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Optimal Operation and Planning of Multi-Energy Microgrids with Hydrogen Carriers Integration

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Tiivistelmä

Tämä väitöskirja tarkastelee ilmastonmuutoksen hillintään ja kasvihuonekaasupäästöjen vähentämiseen liittyen nollapäästöisten monienergiamikroverkkojen käyttöä ja suunnittelua, korostaen erityisesti vedyn roolia puhtaana ja joustavana energialähteenä Toisin kuin fossiilisiin polttoaineisiin perustuvat järjestelmät, esitetty ratkaisu korostaa vetyteknologioiden integrointia resilienssin ja kustannustehokkuuden parantamiseksi. Väitöskirjassa kehitettiin mallinnusperiaate sähkö- ja kaasunjakeluverkkojen yhteiskäytölle, jossa kaasun virtaus- ja painerajoitteet huomioidaan yhdessä mikroverkon sähkönjakeluverkon vaatimusten kanssa. Maakaasun ohella tarkastellaan vedyn jakelua vetyputkiston kautta ja ehdotetaan uusia näkökulmia kierrätettävien kiinteäoksidikennojen käyttöön jouston ja pitkäaikaisen varastoinnin tarjoajina. Työssä tarkasteltu monienergiamikroverkko sisältää uusiutuvaa tuotantoa, elektrolyysereitä, polttokennoja, akkuvarastoja, sähköajoneuvoja ja kysyntäjousto-mekanismeja, mikä mahdollistaa sektoreiden välisen jouston hyödyntämisen.

Väitöskirjan keskeisiä kontribuutioita ovat (i) integroidun mallinnusmenetelmän kehittäminen monienergiamikroverkoille, (ii) resilientit optimointistrategiat, (iii) vedyn tarkastelu ohjattavana energiavektorina, (iv) edistyneet ratkaisut laajamittaisten suunnittelu- ja käyttö-optimointiongelmien ratkaisemiseksi, (v) epävarmuuden mallintaminen vaihtelevaa uusiutuvaa energiaa tarkasteltaessa sekä (vi) tapaustutkimukset, jotka osoittavat mikroverkkojen teknis-taloudellisen ja ympäristöllisen arvon. Tulokset osoittavat, että esitetty mallinnusmenetelmä vähentää merkittävästi käyttökustannuksia ja päästöjä sekä parantaa järjestelmän resilienssiä verrattuna perinteisiin yksienergiajärjestelmiin. Lisäksi löydökset korostavat vedyn integroinnin, uusiutuvan energian hyödyntämisen ja joustoratkaisujen synergioita, tarjoten käytännön polkuja kestävien energiajärjestelmien toteuttamiseen. Saatu tieto on merkityksellistä päätöksentekijöille, sääntelystä vastaaville viranomaisille ja energiasektorin suunnittelijoille tarjoten suuntaviivoja puhtaiden, luotettavien ja taloudellisesti kannattavien resilienttien monienergiajärjestelmien suunnitteluun, jotka tukevat globaalia hiilineutraaliustavoitetta.

Asiasanat: elektrolyyseri, vety, mikroverkko, käytön ja suunnittelun optimointi, mahdollistava ohjelmointi (possibilistinen ohjelmointi), hajautusmenetelmät, varastointijärjestelmät, sähköajoneuvot, kysyntäjousto.

Abstract

In response to the global need to mitigate climate change and reduce greenhouse gas emissions, this thesis addresses the operation and planning of low-emission multi-energy microgrids with a particular focus on the role of hydrogen as a clean and flexible energy source. Unlike traditional systems reliant on fossil fuels, the proposed framework emphasizes the integration of hydrogen-based technologies to enhance sustainability, resilience, and cost efficiency. A modelling approach is developed for coupled electricity and gas distribution networks, in which gas flow and pressure constraints are explicitly considered alongside the operational requirements of the electricity distribution system in a microgrid. Aside from natural gas, hydrogen is examined as a dispatchable energy vector, with feasibility assessments of pipeline-based distribution and novel insights into the role of reversible solid oxide cells in providing flexibility and long-duration storage. The microgrid can integrate renewable generation, electrolyzers, fuel cells, battery storage systems, electric vehicles, and demand response mechanisms, thereby enabling sector coupling and cross-vector flexibility.

This thesis makes several key contributions: (i) an integrated modelling framework for multi-energy microgrids, (ii) resilience-oriented optimization strategies, (iii) novel treatment of hydrogen as a central dispatchable energy vector, (iv) advanced solution approaches for large-scale planning and operation optimization problems, (v) robust uncertainty modelling under renewable variability, and (vi) case studies that demonstrate the techno-economic and environmental value of microgrids. The results demonstrate that the proposed framework significantly reduces operational costs while improving system resilience compared to conventional single-energy systems. The findings also highlight the synergies between hydrogen integration, renewable energy utilization, and flexibility options, offering practical pathways for the transition to sustainable energy systems. The insights generated are highly relevant for policy-makers, regulators, and energy system planners, guiding the design of clean, reliable, and economically viable energy systems that support the global decarbonization agenda.

Keywords: electrolyzer, hydrogen, microgrid, optimal operation and planning, possibilistic programming, decomposition, storage systems, electric vehicles, demand response.

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Abbreviations

MES	Multi-Energy System
MEM	Multi-Energy Microgrid
MG	Microgrid
RE	Renewable Energy
RES	Renewable Energy Sources
ESS	Energy Storage System
DR	Demand Response
EV	Electric Vehicle
Electrolyzer	ELZ
Fuel Cell	FC
GBD	Generalized Benders Decomposition
OAER	Outer Approximation with Equality Relaxation
rSOC	Reversible Solid Oxide Cell
HILP	High Impact Low Probability

Publications

Publication I: Shahbazbegian, V., Ameli, H., Strbac, G., Laaksonen, H., & Shafie-khah, M. (2025). Optimal Possibilistic-Robust Operation of Multi-Energy Microgrids Considering Infrastructures' Hydrogen Storage Capability. Results in Engineering, 108167. https://doi.org/10.1016/j.rineng.2025.108167. Copyright © 2025

Publication II: Shahbazbegian, V., Ameli, H., & Laaksonen, H. (2025). Role of Hydrogen in Optimal Operational Planning of Multi-Energy Microgrids. Presented at the IEEE Innovative Smart Grid Technologies (ISGT) 2025 Conference. Copyright © 2025, IEEE. https://doi.org/10.1109/ISGTEurope64741.2025.11305299

Publication III: Shahbazbegian, V., Ameli, H., Laaksonen, H., Shafie-Khah, M., & Strbac, G. (2024). Optimizing the resilient operation of microgrids against natural phenomena and extreme events. In Future Modern Distribution Networks Resilience (pp. 215-238). Elsevier. https://doi.org/10.1016/B978-0-443-16086-8.00008-7. Copyright © 2024 Elsevier Inc.

Publication IV: Shahbazbegian, V., Dehghani, F., Shafiyi, M. A., Shafie-khah, M., Laaksonen, H., & Ameli, H. (2023). Techno-economic assessment of energy storage systems in multi-energy microgrids utilizing decomposition methodology. Energy, 283, 128430. https://doi.org/10.1016/j.energy.2023.128430. Copyright © 2023

Publication V: Shahbazbegian, V., Shafie-Khah, M., Laaksonen, H., Strbac, G., & Ameli, H. (2023). Resilience-oriented operation of microgrids in the presence of power-to-hydrogen systems. Applied Energy, 348, 121429. https://doi.org/10.1016/j.apenergy.2023.121429. Copyright © 2023

Publication VI: Shahbazbegian, V., Laaksonen, H., Ameli, H., Strbac, G., & Shafie-Khah, M. (2023, June). Techno-Economic Analysis of Electric Vehicle Parking Lots in Microgrids. In the 2023 International Conference on Future Energy Solutions (FES) (pp. 1-6). IEEE. https://doi.org/10.1109/FES57669.2023.10182744. Copyright ©2023 IEEE.

Publication VII: Shahbazbegian, V., Ameli, H., Shafie-khah, M., Laaksonen, H., Ameli, M. T., & Strbac, G. (2022, June). Optimal scheduling of gas and electricity distribution networks in microgrids: a decomposition approach. In 2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe) (pp. 1-6). IEEE. https://doi.org/10.1109/EEEIC/ICPSEurope54979.2022.9854624.

Author’s contributions

Publication I: Vahid Shahbazbegian: Methodology, Software, Investigation, Data, Writing-Original Draft, Visualization Miadreza Shafie-khah: Conceptualization, Validation, Writing–Review & Editing, Supervision Hannu Laaksonen: Conceptualization, Validation, Writing–Review & Editing Goran Strbac: Writing–Review & Editing, Supervision Hossein Ameli: Methodology, Investigation, Writing-Original Draft, Visualization

Publication II: Vahid Shahbazbegian: Methodology, Software, Investigation, Data, Writing-Original Draft, Visualization. Hossein Ameli: Methodology, Investigation, WritingOriginal Draft, Visualization. Hannu Laaksonen: Conceptualization, Validation, Writing–Review & Editing

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Other Relevant Studies

The following is the list of the author's relevant publications that are not included in the thesis:

i. Di Somma, M., Papadimitriou, C., Rousis, A. O., Patsidis, A., Shafie-Khah, M., Shahbazbegian, V., & Askeland, M. (2024). Analytical framework for coordinated planning and operation of multicarrier energy systems. Integrated Local Energy Communities: From Concepts and Enabling Conditions to Optimal Planning and Operation, 187-224.

ii. Shahbazbegian, V., Barroso-Pereira, J., Shafie-khah, M., Osório, G. J., & Catalão, J. P. (2024, June). Optimal Operation of Renewable Energy Resources and Electric Vehicles in Microgrids. In 2024 IEEE International Conference on Environment and Electrical Engineering and 2024 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe) (pp. 1-6). IEEE.

1 INTRODUCTION

1.1 Motivation

The urgent global response to climate change has led countries to set ambitious targets for greenhouse gas emission reductions and transition toward zero-emission energy systems. For example, Finland aims to become carbon-neutral by 2035, while the United Kingdom targets full decarbonization by 2050 (Cui et al., 2023; Laurikko et al., 2020). While these goals are necessary, they are complicated by economic recovery efforts following the COVID-19 pandemic and geopolitical disruptions, such as the Russia-Ukraine conflict. The energy sector, as one of the largest contributors to greenhouse gas emissions, also remains central to any decarbonization strategy. Policymakers have implemented regulatory and financial instruments to promote the uptake of renewable and zero-emission energy systems. However, achieving long-term sustainability requires addressing the structural and operational limitations of current infrastructure.

A primary technical obstacle in high-renewable power systems is their inherent intermittency and unpredictability, which can jeopardize grid stability. While solar and wind technologies have witnessed increased deployment, they need to be connected to a flexible and reliable system to maintain supply-demand balance. Microgrids (MGs) have emerged as a promising response, offering localized energy management, islanding capability, and improved resilience against grid failures. By reducing transmission losses and dependency and integrating distributed generation, MGs can play a pivotal role in enhancing the reliability and flexibility of the system to host the renewables, especially under conditions of uncertainty and extreme events (J. J. Chen et al., 2021; Koivunen et al., 2023).

Realizing the full potential of MGs requires advanced operational strategies to integrate diverse technologies. The control and operational strategies consider photovoltaics, wind turbines, Energy Storage Systems (ESSs), and dispatchable backup units. However, it requires optimization frameworks capable of handling numerous and various nonlinearities, discrete variables, and time-dependent constraints. Moreover, considering Multi-Energy Systems (MESs) within MGs, incorporating electrical and gas-based energy forms, can improve flexibility and resource utilization. Investigating the integrated systems from a techno-economic perspective is essential to identify cost-optimal configurations and control schemes. It is of great importance when accounting for the high capital and operational costs of storage and conversion technologies (Ehsan & Yang, 2019; Koivunen et al., 2023).

The integration of hydrogen into future energy systems and MGs presents another compelling avenue for addressing renewable intermittency while reducing reliance on fossil fuels. Hydrogen can be produced using excess renewable electricity via Electrolyzers (ELZs), stored, and later utilized in Fuel Cells (FCs) or gas turbines to ensure demand provision during peak demand periods. Leveraging existing gas infrastructure for hydrogen distribution allows for reduced capital expenditures and a faster transition to cleaner fuels. Moreover, the linepack capacity of gas pipelines introduces a form of intrinsic storage, enabling dynamic balancing between supply and demand without immediate infrastructure expansion. Yet, the coupling of gas and electricity networks introduces modelling and operational complexities that require integrated optimization (Evans et al., 2022).

In addition to the above-mentioned solutions, Demand Response (DR) programs have gained prominence as a means to enhance grid flexibility and integrate higher shares of Renewable Energy (RE). By incentivizing consumers to adjust their electricity usage in response to supply conditions, DR can help balance demand with variable renewable generation. Recent initiatives in the UK have demonstrated the potential of DR to reduce peak demand and support grid stability, though challenges remain in ensuring consumer participation and effective implementation (Sustain & 2022, 2022).

Another emerging solution to enhance flexibility in renewable-rich systems involves leveraging electric vehicles (EVs) as distributed storage units. EVs can provide bi-directional energy services, offering peak-shaving capabilities and ancillary support when connected to the grid. Their coordinated operation within MG environments has the potential to not only reduce energy costs but also increase the effective penetration of renewables. Designing the coordinated operation that accounts for user behaviour, vehicle mobility patterns, and grid constraints is vital to unlock the full value of vehicle-to-grid technologies (Abeysekera et al., 2016).

In summary, the study of integrated operational models for coupled gas and electric MGs is of significant importance in facilitating the transition toward carbon-neutral, resilient, and economically sustainable energy systems. These models are instrumental in enabling the coordinated integration of RE sources, ELZs, FCs, ESSs, DR mechanisms, and flexible loads, such as EVs. Applying the models to practical case studies offers valuable insights for policymakers, grid operators, and energy planners, thereby contributing to the formulation of strategies for a secure and sustainable energy future.

1.2 Background

The operation and planning of integrated Multi-Energy Microgrids (MEMs) have received significant attention due to the global push for resilient, low-carbon, and economically viable energy systems. Recent efforts have focused on the coordination of electricity and gas systems (i.e., natural gas or hydrogen transmission or distribution), integration of Renewable Energy Sources (RESs), ESSs, hydrogen-based solutions, and the involvement of flexible resources, such as EVs and DR programs. The literature spans a wide range of modelling approaches, optimization methods, and techno-economic assessments, which collectively inform the development of future MESs.

Among the studies, a considerable share has explored the role of technologies like ELZs and FCs in enhancing operational flexibility and enabling the integration of RE. A comparative evaluation of ELZs and gas storage technologies under different levels of RES penetration is provided in (Faisal, 2020), while in (Aljabery et al., 2021), a broader analysis is offered with a focus on enhancing resilience and reducing emissions. The potential of hydrogen as a storage medium is discussed in (Son et al., 2021), highlighting its role in decarbonizing MESs. It is shown in (Z. Liu et al., 2022), that ELZs and FCs systems can improve utilization and reduce curtailment of renewable power, especially in isolated or coastal regions. Similarly, a cooperative game-theoretic framework for ELZs and FCs operation in MGs is proposed in (Bo Li et al., 2022) to optimize hydrogen production and distribution. It is demonstrated, in (H. Chen et al., 2021; Ding et al., 2020), that MGs contribute to higher RES penetration and support EV charging. The integration of DR and combined heat and power systems with ELZs and FCs is explored in (Guo, Nojavan, et al., 2021; Y. Yang et al., 2020), emphasizing cost and emission reductions. Additionally, the inclusion of ELZs and FCs, heat storage, and EVs in MGs is examined in (Mobasseri et al., 2022; Yuwei Wang et al., 2022; Z. Zhang et al., 2023), where the role of such combinations in improving flexibility and peak load management is emphasized. Optimal scheduling methods that coordinate ELZs and FCs with EV charging, combined heat and power units, and DR are investigated in (J. J. Chen et al., 2021; Y. Li et al., 2021; Tabar et al., 2023), indicating noticeable improvements in both economic performance and energy balance.

Enhancing system resiliency through flexible and multi-layered architectures is another recurring theme. The ability of MGs to withstand disruptions by leveraging diesel generators, ESSs, and hydrogen storage is assessed in (MansourLakouraj et al., 2021; Masrur et al., 2021). In (J. Liu et al., 2021; Silva et al., 2021; Vahedipour-Dahraie et al., 2021, 2022), resilience is studied under different contingency scenarios, including grid-connected and islanded operations, showing that integrated energy systems with appropriate flexibility mechanisms can ensure critical load supply. The importance of robust scheduling and flexibility planning under uncertainty is highlighted in (Jia et al., 2021; G. Liu et al., 2020).

Addressing the computational challenges of the integrated models of MESs, several researchers have adopted heuristic and meta-heuristic approaches, such as Particle Swarm Optimization, Genetic Algorithms, Grey Wolf Optimizer, and Differential Evolution, as illustrated in (Dey et al., 2020; Ghiasi et al., 2021; Gholami & Dehnavi, 2019; Jiao et al., 2020; Mandal & Mandal, 2020; Phani Raghav et al., 2021; Roy & Das, 2021). Although these methods offer scalability and simplicity, their convergence to global optimal is not guaranteed. More exact methods, such as Benders Decomposition and the Alternating Direction Method of Multipliers, are utilized in (Luo et al., 2020; J. Yang & Su, 2021) to improve tractability and solution accuracy. An agent-based optimization model is introduced in (Khaligh et al., 2022) for coordinating decentralized decision-making across various system components.

A parallel stream of research focuses on the techno-economic planning of MESs. Studies, such as (Hemmati et al., 2021; Herenčić et al., 2021; Kiptoo et al., 2020; Martínez Ceseña et al., 2018; Mazzola et al., 2016; Mukherjee et al., 2017; Xiang et al., 2021) which assess investment and operation strategies for combined-heat and power units, RESs, and ESSs in the UK, Canada, and Denmark, emphasizing hydrogen's role in enhancing system reliability and reducing emissions. In contrast, (Barberis et al., 2022; Mun et al., 2021; Seedahmed et al., 2022; Tan et al., 2022) use software to evaluate MGs, confirming that hybrid renewable systems can deliver cost-effective energy solutions, particularly in remote and underserved areas.

Hydrogen transmission or distribution modelling has also been addressed in some previous studies. Hydrogen's integration into electricity and gas networks is further discussed in (Lux et al., 2022; Pellegrino et al., 2017; C. Wang et al., 2024), where hydrogen injection into gas pipelines and the use of linepack as a storage method are explored. The economic and technical feasibility of such approaches is affirmed, although system-level modelling remains limited. Scheduling and market participation strategies for hydrogen production are addressed in (Marzi et al., 2023; J. Wang et al., 2023), while (H. Ameli et al., 2019; Fambri et al., 2022) present frameworks that couple gas and electricity systems using ELZ and FC technologies for the purpose of decarbonization. These contributions highlight the importance of joint gas-electric optimization but often neglect long-term hydrogen storage and transport considerations. A gap is evident in fully integrated models that consider hydrogen generation, storage, distribution, and end-use under uncertainty.

To improve the reliability of MG planning under renewable variability, various uncertainty modelling techniques have been adopted. Stochastic programming is used in (Rezaei & Pezhmani, 2022; Sun et al., 2023) for hydrogen-enabled MGs, while robust optimization frameworks are presented in (Y. Qiu et al., 2022) to handle peak demand and resource intermittency. In (G. Zhang et al., 2023), possibilistic modelling is applied to address epistemic uncertainty in wind, ELZ, FC, and heat systems, offering an alternative to purely probabilistic methods.

Aside from already mentioned aspects, the role of EVs as flexible demand assets is extensively analyzed (De Cauwer et al., n.d.; Figueiredo et al., 2017; Guo, Liang, et al., 2021; Ivanova et al., 2020; C. Li et al., 2022; Marasciuolo et al., 2022). It is demonstrated that smart charging and discharging strategies significantly improve load shaping, reduce operational costs, and support the integration of solar PV in parking lot MGs. Nevertheless, most studies omit the constraints imposed by electricity distribution networks and do not consider their interaction with gas-based generation. As such, integrated planning that captures EV-gas-electricity interactions received less attention. DR programs have also been shown to enhance energy system performance through load shifting and peak shaving. As noted in (H. Qiu et al., 2022; Stanelyte et al., 2022), these programs are categorized into tariff-based and incentive-based schemes and can be especially effective when implemented in MGs with high renewable shares.

In summary, while the existing literature offers valuable insights into ELZs and FCs integration, resilience strategies, and optimization of MESs, several critical gaps remain. These include the lack of comprehensive models that co-optimize energy systems under uncertainty, limited treatment of hydrogen's role beyond local storage or injection, and the absence of scalable frameworks that incorporate EVs, DR programs, and hydrogen distribution infrastructure within constrained distribution networks. The model needs to be solved through an optimization framework that provides a more optimal solution. This thesis aims to address these gaps by developing integrated frameworks for the optimal planning and operation of hydrogen-based, economical, and resilient MEMs.

1.3 Research questions and objectives of the thesis

This thesis aims to support the development of resilience, cost-efficient, and low-carbon energy systems by advancing the operation and planning of integrated MEMs. This thesis is focused on and tries to answer the following sets of research questions:

Q1. How can electricity and gas distribution networks in MEMs be co-optimized simultaneously? How can resilience be integrated into MEMs' operational planning to ensure a secure and reliable energy supply?

Q2. In what ways can hydrogen enhance operational flexibility within MEMs? What are the technical limits of transporting hydrogen through existing natural-gas distribution infrastructure from the viewpoint of supply-demand balance? What are the impacts of other emerging technologies, such as EVs, DR programs, and ESSs, on MGs' flexibility?

Q3. Which optimization and algorithmic approaches can be developed to optimize operational and planning models of MEMs? How can the uncertainty consideration approach be employed to provide more realistic optimal solutions?

Q4. What are the insights that can assist decision-makers and policymakers in moving toward carbon-neutral energy systems?

With respect to the above-mentioned research questions, the specific objectives of the thesis are as follows:

O1. The first objective is to improve the operational coordination of electricity and gas distribution systems within the MEMs and enhance the resilience of the system. For this purpose, a framework is developed that captures their interdependencies, along with the integration of RE sources and hydrogen technologies (Publication IV and Publication VII). The potential for hydrogen transport is investigated through existing gas infrastructure by evaluating its technical feasibility and demand provision (Publication I). To enhance the resilience of MEMs, resilience measures are considered in operational planning, ensuring energy supply even under disruptions in the electricity grid (Publication II, Publication III, and Publication V).

O2. The second objective is to improve the flexibility of energy systems by exploring the role of hydrogen as both a storage medium and an end-use energy, especially in industrial applications (Publication V). In addition to hydrogen, the use of other emerging technologies is also optimized, such as EVs, DR programs, and ESSs, in achieving better energy balance, cost-effectiveness, and emission reductions within MEMs (Publication IV and Publication VI).

O3. The third objective is to ensure the practical applicability of the proposed models by employing solution approaches that are computationally efficient and scalable to realistic systems (Publication III, Publication IV, and Publication VII). Then, it focuses on improving the handling of uncertainties in RE production, energy demand, and market prices through the use of robust and flexible modelling approaches (Publication I).

1.4 Main contributions

Figure 1 categorizes the publications on which the dissertation is based, according to their energy systems under study, theme, focus, and most importantly their contributions.

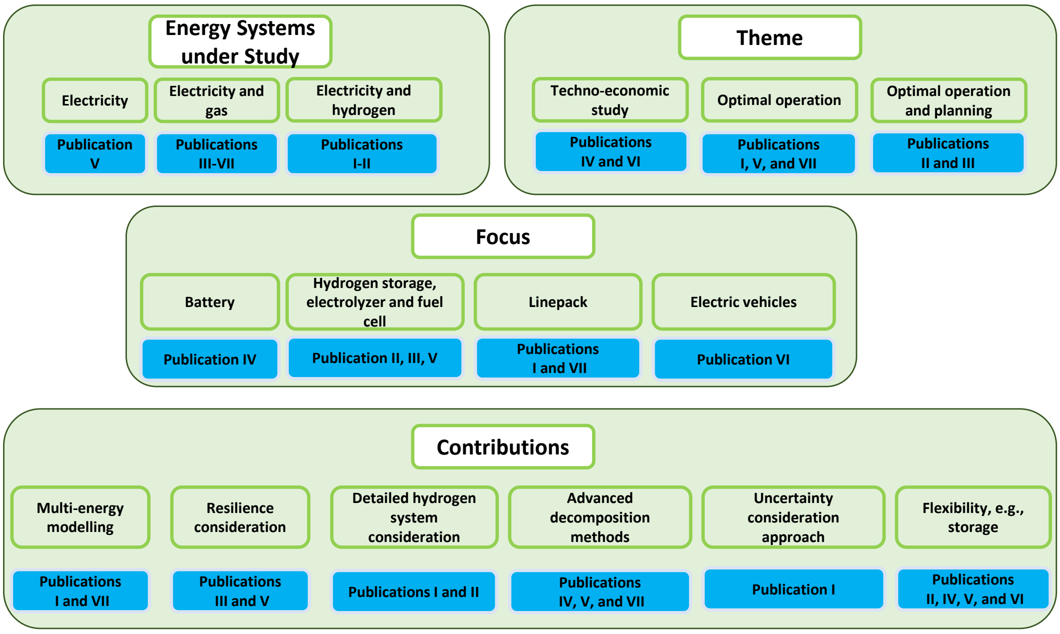

Figure 1. Categorization of the publications of this dissertation.

More precisely, this research makes the following contributions to the field of MESs, MGs, and hydrogen-integrated energy systems:

- Integrated MEM modelling (Publication IV and Publication VII)

A unified modelling framework is developed that captures the operational dynamics of electricity and gas distribution networks, considering AC power flow, gas flow equations, linepack effects, and pressure constraints. The model also integrates RE sources, market interaction, and hydrogen systems, thereby extending existing models to a fully coupled MES.

- Resilience-oriented multi-objective optimization (Publication III and Publication V)

A bi-objective optimization framework is developed that jointly considers the cost and system resilience, an aspect rarely addressed in prior works. Resilience can be quantified through three new performance indicators, which are a weighted sum of (1) reduced energy-not-supplied, (2) increased hydrogen reserve levels, and (3) reduced dependency on the upstream main grid.

- Hydrogen as a dispatchable vector (Publication II)

Unlike previous studies that treat hydrogen only as a storage medium, this work incorporates the distribution of hydrogen in industrial processes into the optimization problem. The hydrogen produced via ELZ can be used for electricity generation, stored, or sold to industrial consumers, providing a new dimension of flexibility in MG operation.

- Advanced decomposition-based solution strategy (Publication IV and Publication VII)

Generalized Benders Decomposition (GBD) and Outer Approximation with Equality Relaxation (OAER) algorithms are customized for the problem and augmented with a pre-processing strategy. The pre-processing includes initial point generation and convexification of the original problem to enhance solver performance and convergence reliability.

- Possibilistic-robust uncertainty modelling (Publication I)

A hybrid uncertainty quantification technique is proposed that combines fuzzy logic (possibility theory) with robust optimization to address uncertainty in RE production, market prices, and demand. This approach captures the ambiguity and variability in real-world data, without increasing the complexity compared to traditional stochastic or robust-only methods.

- EV, DR, and BSS integration in MG scheduling (Publication IV and Publication VI)

A framework is presented for the optimal operation of EV parking lots, employment of DR programs, and employment of ESSs, considering both investment and operational costs and their impact on energy balance and emissions within the MG.

- Pipeline-based hydrogen transport feasibility (Publication I)

A detailed feasibility analysis is performed for utilizing low-pressure natural gas infrastructure for hydrogen distribution, including tests for supply-demand satisfaction, pressure-drop effects, and compatibility with current pipe specifications.

- Policy and decision-making implications

Results of the thesis provide insights for policymakers, energy companies, and local authorities in Finland as they navigate the transition toward carbon neutrality (Figure 2). The integration of MEMs with hydrogen offers both technical opportunities and regulatory challenges. The outputs of this research can support decision-making in the following ways: (i) This thesis quantifies how MEMs improve system flexibility, reliability, and efficiency under various climatic and infrastructural conditions. The findings can assist policymakers in evaluating whether the localized energy solutions can complement the centralized market. (ii) By modelling the interaction of wind and hydrogen systems, the thesis provides insights into how to accommodate rapidly growing renewable capacity. Regulators and transmission system operators can use these results when designing incentive mechanisms for distributed resources and storage. (iii) The thesis demonstrates the technical feasibility and system-level value of hydrogen in addressing seasonal demand-supply imbalance. These results can inform the development of the hydrogen roadmaps, particularly in identifying conditions under which hydrogen is more cost-effective than alternatives such as battery storage. (iv) MGs with hydrogen integration can enhance resilience against extreme weather and geopolitical risks. The thesis provides data on how decentralized systems can maintain supply during grid disruptions. This evidence is valuable for authorities responsible for national security of supply and regional emergency planning. (v) The thesis highlights potential synergies between industrial decarbonization and local energy systems. Regional development agencies and municipalities can draw on these insights to design hydrogen hubs and energy-industrial symbiosis strategies, strengthening competitiveness in the emerging hydrogen economy.

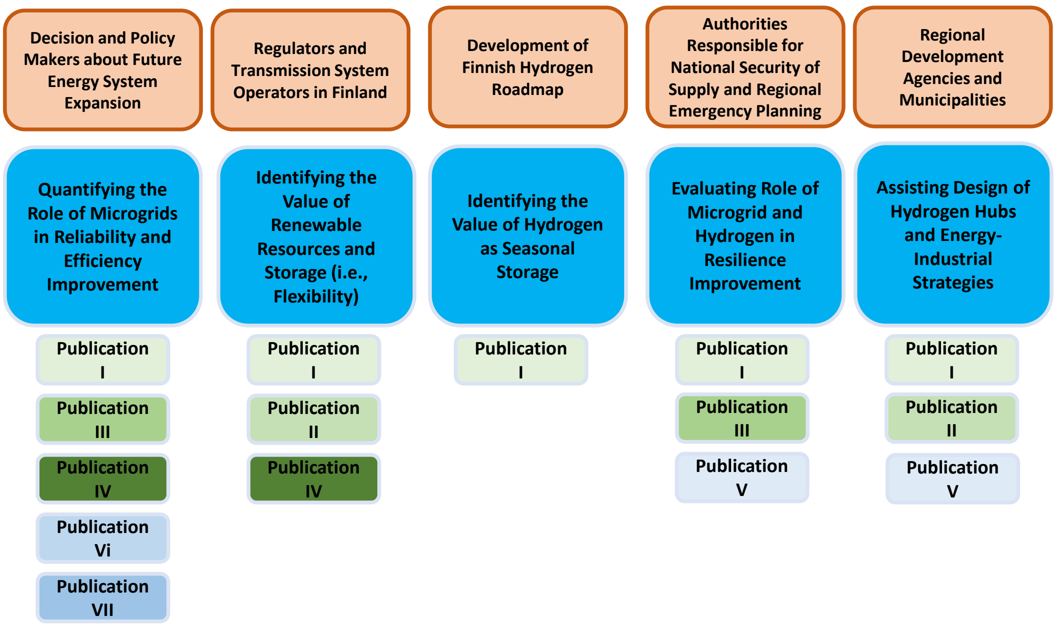

Figure 2. Provided insights from the thesis.

2 FUTURE MICROGRIDS AND ENERGY SYSTEMS IN FINLAND

2.1 MGs-production, storage, and distribution

MGs are decentralized energy systems capable of operating either in connection with the main utility grid or in isolation. When interconnected, an MG can draw electricity from the main grid during times of local generation shortage and feed surplus energy back when local production surpasses demand. In scenarios, such as main grid outages or remote locations with limited grid access, MGs can even function autonomously, called islanded mode (Yi Wang et al., 2024).

Key components form the foundation of MG functionality, ensuring efficient and reliable energy production, storage, and distribution. MGs utilize a variety of local generation sources, broadly classified into renewable and conventional categories (i.e., energy production) (P. Chen et al., 2024). Renewable sources, including solar photovoltaic panels, small wind turbines, and occasionally small hydro units, are fundamental to modern MGs due to their environmental benefits and alignment with decarbonization goals. Among these, solar photovoltaic systems are widely deployed due to their scalability and high availability in sun-rich regions. Wind energy, while more intermittent, also serves as a crucial source in windy areas. To provide operational reliability during periods of low renewable output, conventional generation units, such as diesel generators or small gas-fired plants, are integrated into the system.

ESSs can be essential in stabilizing the variability inherent to renewable sources and improving the robustness of MGs (Irfan et al., 2024). The ESSs are extensively employed for their ability to absorb surplus electricity during low-demand periods and supply it back during peak times, thus mitigating generation fluctuations and serving as backup during outages. Hydrogen-based storage adds another layer of flexibility; here, excess RE is used to produce green hydrogen via ELZs. This hydrogen can later be stored and converted back to electricity through FCs or utilized directly for transportation and heating, supporting long-duration storage and decarbonization.

Effective operation of an MG depends significantly on advanced control and communication systems (D. Qiu et al., 2023). These systems manage power flows, ensure real-time balancing of supply and demand, and uphold system stability (i.e., energy distribution). Cutting-edge MGs often implement real-time monitoring, data analytics, artificial intelligence, and automated control to dynamically adjust to system conditions. Switchgear and protection devices, such as circuit breakers and switches, serve a protective role by isolating faults and preventing cascading failures (Chawda et al., 2024). Transformers adjust voltage levels across various parts of the network to maintain efficient power distribution (Uddin et al., 2023), while load controllers optimize energy delivery by coordinating consumption and avoiding overloading.

MGs are classified based on various parameters, such as generation capacity, energy sources, operational modes, current type, and intended application (see Figure 3 (M. T. Ameli et al., 2021)). Small-scale MGs, with capacities up to 10 MW, often rely on renewables and are suited for residential, rural, or island settings. Medium-scale systems, generating between 10 and 100 MW, typically support industrial applications using a mix of renewables and conventional sources like natural gas and/or diesel. Large-scale MGs exceed 100 MW and are typically deployed in industrial complexes, powered by a considerable share of fossil fuels. Additionally, MGs may adopt different architectures and control schemes, depending on whether they operate as AC or DC systems, use hybrid generation, or are managed centrally or in a distributed fashion, all of which influence their performance and sustainability.

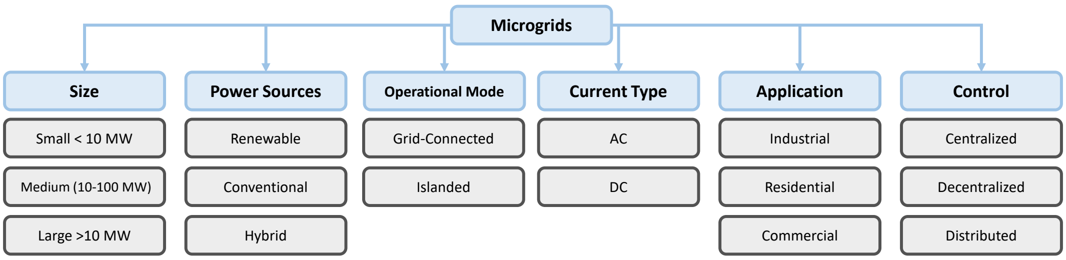

Figure 3. Different categories for MGs.

MGs can operate in various modes, including grid-connected, where they remain linked to the utility network; islanded, functioning autonomously; and grid-interactive, which allows seamless transitioning between connected and standalone operations depending on prevailing conditions and operational requirements. Power distribution within MGs can be managed through Alternating Current (AC), Direct Current (DC), or a hybrid AC/DC configuration. Each option is selected based on the intended application and has implications for infrastructure efficiency and complexity. MGs are adaptable to a wide array of uses, residential, commercial, industrial, and community-scale deployments, each designed to address specific energy demands and resilience requirements.

In terms of control strategies, MGs may employ centralized, decentralized, or distributed (hierarchical) control schemes, which dictate how energy generation and distribution are coordinated and optimized. Centralized control systems deliver globally optimal solutions and facilitate comprehensive system coordination but require robust communication infrastructure, involve high computational demands, limit scalability, and are sensitive to communication failures. In contrast, decentralized control operates independently at the local level without the need for communication infrastructure, resulting in lower complexity and greater scalability, though it may fail to achieve system-wide optimality. Distributed control aims to combine the strengths of both approaches by enabling collaboration among distributed controllers. It improves scalability and reliability while reducing computational burden, although it still relies on communication networks and may lead to suboptimal outcomes. These operational modes and control architectures are fundamental in determining how an MG is structured, how it functions under varying conditions, and how well it aligns with specific energy requirements and application contexts.

2.2 MESs - hydrogen integration and sector coupling

The incorporation of hydrogen into energy systems or MESs is enabled through components, such as hydrogen-fired units, ELZs, and FCs (Zainal et al., 2024). Hydrogen-fired units contribute to grid stability and serve as a backup power source during supply shortages. ElZs play a critical role by transforming excess electrical energy into hydrogen, which can then be stored for future applications. Meanwhile, FCs convert the stored hydrogen back into electricity when needed. This hydrogen integration improves the efficiency, reliability, and adaptability of MESs, facilitating optimized energy management and catering to a variety of energy demands. Despite these potential advantages, hydrogen currently plays a marginal role in the power sector, largely as a by-product of industrial processes. However, the rapid deployment of RE and the falling cost of electrolysis technologies suggest a much larger impact in the future.

The large-scale deployment of ELZs can affect electricity grids in several ways. Their additional load needs to be managed through coordinated grid planning, with careful future scenario consideration. At the operational level, ELZs can act as flexible demand, absorbing surplus renewable generation or reducing consumption during peak demand. Therefore, they can provide ancillary services, including fast frequency response and voltage support. Beyond short-term balancing, hydrogen storage offers long-duration flexibility, enabling seasonal energy shifting and complementing variable renewable generation (European Commission, 2023). Overall, the integration of hydrogen into grids transforms it from a negligible energy vector into a strategic source of flexibility and resilience. Its effective role, however, can depend on coordinated planning between hydrogen projects and grid operators, context-specific infrastructure investments, and policies that support sector coupling and system-level optimization.

Beyond its technical role in supporting electricity grids, hydrogen is also expected to shape emerging energy markets. As mentioned, current use is concentrated in industrial processes such as refining, steelmaking, and ammonia production, but decarbonization policies and falling RE costs are opening new opportunities. Future markets are likely to expand in three main directions: (i) as a feedstock for low-carbon industrial production, (ii) as a transport fuel in sectors where direct electrification is difficult, and (iii) as a cross-border commodity traded through pipelines, shipping of liquid hydrogen, or hydrogen-derived carriers such as ammonia and methanol (Kalis, 2024). The hydrogen market is expected to enable dynamic trading of different hydrogen variants while creating value across the value chain. This market is designed to maximize the benefits of sector integration by allowing flexible operation at the interface of electricity, gas, transport, and industrial systems. The evolution of these markets requires not only technological advances but also appropriate market mechanisms.

With respect to the above-mentioned issues, an overview of the hydrogen production, delivery or transports, storage, and utilization is depicted in Figure 4 and discussed in the following subsections.

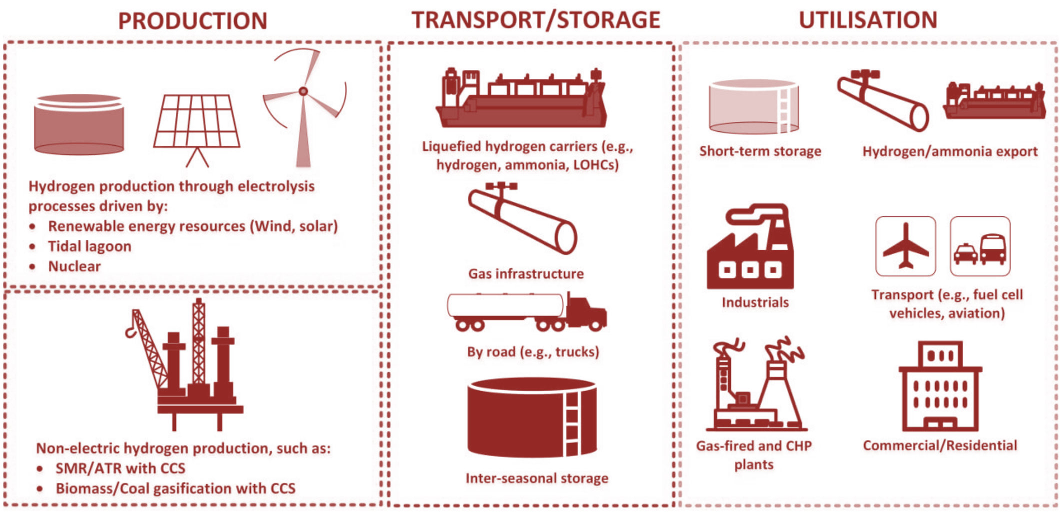

Figure 4. Production, storage, distribution, and utilization of hydrogen.

2.2.1 Hydrogen production

Hydrogen can be produced through several methods, each with its benefits and challenges (Bosu & Rajamohan, 2024). For instance, electrolysis is a process that uses electrical energy to split water into hydrogen and oxygen. The primary components include an ELZ, which contains an anode and a cathode separated by an electrolyte. When an electric current is applied, water molecules are split into positively charged hydrogen ions and oxygen gas in the anode ($2H_2O \rightarrow O_2 + 4H^+$). Moving through the electrolyte to the cathode, hydrogen ions combine with electrons from the external circuit and form hydrogen gas ($4H^+ + 4e^- \rightarrow 2H_2$). Electrolysis is particularly favourable when powered by RE sources, such as wind or solar, resulting in green hydrogen with minimal carbon emissions. It should be noted that the comparison of the hydrogen production cost through various methods that use renewable power for this purpose is indicated in (Kalis, 2024). Steam methane reforming is the most widely used method for hydrogen production, particularly in industrial settings. It involves reacting methane from natural gas with steam at high temperatures under 3-25 bar pressure to produce hydrogen, carbon monoxide through the steam methane reforming reaction ($CH_4 + H_2O \rightarrow CO + 3H_2$), and carbon dioxide through a water-gas shift reaction ($CO + H_2O \rightarrow CO_2 + H_2$). While steam methane reforming is known for its efficiency and cost-effectiveness, it results in considerable greenhouse gas emissions, making it less environmentally sustainable than electrolysis. Partial oxidation involves partially oxidizing hydrocarbons like natural gas using oxygen to produce hydrogen and carbon monoxide. Although not as prevalent as steam methane reforming, this method enables hydrogen production from a range of hydrocarbon inputs. Gasification is a technique that transforms solid fuels, such as coal or biomass, into hydrogen through high-temperature reactions with steam and oxygen. This method is typically used in large-scale operations and benefits from the ability to utilize renewable biomass as a feedstock. In contrast, rSOCs represent an advanced, dual-mode hydrogen technology. These systems can function as solid oxide electrolyzer cells, splitting water into hydrogen and oxygen using electricity, or as solid oxide fuel cells, which generate power by consuming hydrogen. This bidirectional capability allows rSOCs to store excess electricity as hydrogen during low-demand periods and regenerate electricity when needed. Their high efficiency and operational versatility make them a compelling choice for integrating RE into future energy systems (Giap et al., 2020).

2.2.2 Hydrogen storage

The ability to store hydrogen effectively is vital due to its low energy density and the engineering challenges it presents (F. Li et al., 2024). One common method is compressed gas storage, typically in high-pressure cylinders operating between 350 and 700 bar. This well-established method offers quick refuelling and is especially practical for transport applications, although the need for durable, high-strength materials increases cost. Another approach is cryogenic liquid storage, where hydrogen is stored at ultra-low temperatures (~-253°C). This improves volumetric energy density, but it introduces technical hurdles such as boil-off losses and the requirement for advanced insulation. Solid-state storage involves absorbing hydrogen into metal hydrides, such as magnesium or lanthanum-nickel alloys. These provide a compact and safe storage solution with high volumetric density and lower operational pressures, but suffer from slower absorption/desorption kinetics and added system weight. In chemical hydrogen storage, hydrogen is embedded in compounds like ammonia, formic acid, or liquid organic hydrogen carriers. Hydrogen can be extracted via chemical reactions or catalysis, offering high storage density and simplified handling, though the energy required for release and regeneration remains a concern. Novel storage approaches under active research include nanomaterials, porous structures like metal-organic frameworks, and advanced composite materials, which aim to improve capacity, reduce system weight, and enhance safety. Most of these technologies are still under development and have yet to reach commercial maturity.

2.2.3 Hydrogen delivery

The transportation of hydrogen is a critical enabler for its widespread deployment in multiple sectors (Osiadacz, 1987a). Pipeline delivery is central to building a viable hydrogen infrastructure. Adapting existing natural gas networks to carry hydrogen, either blended with methane or in pure form, offers a cost-effective solution by leveraging already established infrastructure. However, hydrogen's small molecular size poses challenges such as permeation, embrittlement of pipeline materials, and the need for specialized compression systems. With appropriate material upgrades and safety protocols, current pipelines can be retrofitted for hydrogen transport. Pipeline networks are generally categorized by pressure level: low-pressure systems (0–75 mbar) are used for residential and commercial distribution, offering easier adaptation to hydrogen due to their lower operational risks. Medium-pressure networks (below 7 bar) serve as an intermediary between long-distance transmission and end-users, typically delivering gas to industrial facilities or city gate stations. These systems require a balance between material integrity and pressure control. High-pressure pipelines (above 7 bar and up to ~85 bar) are essential for long-distance transmission, linking production hubs with demand centers. Due to hydrogen’s properties, these pipelines must address risks such as embrittlement and incorporate robust sealing and joint designs. For modelling gas flow within these networks, equations like Panhandle can be used, which factors in pipe diameter, pressure drop, and flow rate, and Weymouth, which simplifies flow estimation based on pipe roughness and compressibility. These models are instrumental in optimizing pipeline design and ensuring operational safety (Hai et al., 2024).

Beyond pipelines, hydrogen can also be delivered via compressed cylinders or cryogenic liquid trucks, which are practical for areas without pipeline access or for decentralized applications. For international transport, hydrogen may be shipped either as a liquid or chemically bound in carriers like ammonia or methylcyclohexane, enabling large-scale and long-distance shipment. Hydrogen refuelling stations form a critical part of the supply chain, especially for fuel cell vehicles, and are typically equipped to store, compress, and dispense hydrogen safely in urban and transport corridors.

2.2.4 Hydrogen utilization

In industrial applications, which account for a large share of global emissions, hydrogen provides a path to decarbonize high-temperature processes. Sectors such as steel, cement, and chemical manufacturing, traditionally reliant on carbon-intensive fuels, can adopt low-carbon hydrogen (especially from renewable sources) to replace fossil energy. Hydrogen is also integral in industrial processes like ammonia and methanol production and refining, where its use can significantly curb the carbon footprint. The shift toward hydrogen in industry aligns with global climate goals and supports sustainable manufacturing systems (Shahabuddin et al., 2023).

Hydrogen is increasingly recognized as a versatile and clean energy carrier suitable for a variety of sectors, including heating, industry, and transportation (Capurso et al., 2022). In the heating sector, hydrogen can be integrated with combined heat and power systems using FCs to simultaneously generate electricity and useful heat, ideal for residential and commercial use. Additionally, hydrogen enhances the adaptability of reconfigurable MGs by facilitating thermal power recovery, thus improving overall system efficiency and reducing emissions.

In the transportation sector, hydrogen offers a powerful alternative to conventional fuels, particularly for heavy-duty and long-haul vehicles. Hydrogen fuel cell electric vehicles benefit from short refuelling times and extended range, making them more suitable than battery electric vehicles in freight and industrial transport. The move from diesel-powered trucks to hydrogen-fuelled vehicles plays a key role in reducing emissions and mitigating the environmental impact of logistics. MGs, self-sufficient, localized energy networks capable of functioning autonomously or alongside the main grid, can accommodate hydrogen stations as both energy consumers and ESSs, enhancing their operational flexibility and sustainability (Bei Li et al., 2023).

Hydrogen refuelling stations have significant electricity requirements, particularly for compression and liquefaction processes, and their integration with broader energy systems offers multiple technical, economic, and environmental benefits. By sourcing electricity from RESs such as solar or wind when available, stations can reduce dependence on grid power, lower emissions, and align with decarbonization strategies, while energy systems can prioritize supply to the stations during peak demand without overloading local networks. Moreover, the role of hydrogen as an energy storage medium enables excess renewable electricity to be converted through electrolysis and stored on-site, later used for vehicle fuelling or reconverted into electricity via FCs, thus supporting energy balancing and enhancing flexibility. In cases of central grid failures, hydrogen stations integrated into energy systems can maintain autonomous operation, ensuring uninterrupted fuel availability for hydrogen-powered vehicles and providing backup electricity to critical infrastructure. Beyond resilience, such integration delivers cost advantages by leveraging on-site renewable generation and contributes to broader sustainability objectives by reducing fossil fuel reliance and lowering the carbon footprint of hydrogen production and distribution.

2.3 MEMs

With respect to the above-mentioned explanation, in Figure 5, an MEM is illustrated, which is going to be studied in this thesis and future works. The MEM integrates different energy systems and technologies to provide a reliable, flexible, and low-carbon energy system. At its core, the system connects electricity, natural gas/hydrogen, and heat networks in order to serve the energy needs of transport, residential and commercial buildings, and industry. Electricity enters the system from the high-voltage transmission grid, which is stepped down through substations to medium voltage for distribution. In addition to grid supply, renewable sources such as wind turbines and photovoltaic panels feed electricity directly into the network. Natural gas/hydrogen is another important input, delivered through medium or low-pressure pipelines, and is used for both electricity and heat generation.

Within the MG, several conversion and storage technologies transform and manage these energy inputs. Combined Heat and Power units use natural gas/hydrogen to generate electricity while simultaneously capturing useful heat for district heating and industrial processes, significantly increasing efficiency. Boilers provide additional heating capacity when needed, while electrically driven heat pumps extract low-temperature heat from the environment and upgrade it for space heating in buildings. Surplus electricity can be directed to ELZs, which split water into hydrogen that can be stored and later reconverted into electricity and heat using FCs or boilers. This hydrogen pathway not only balances fluctuating renewable electricity but also supports hydrogen mobility and industrial use. Thermal ESSs further enhance flexibility by storing heat for later use during peak demand periods.

The MG supplies energy to three major demand sectors. The transport sector benefits from both electricity, through EVs and charging infrastructure, and hydrogen, through vehicles. Residential and commercial buildings rely on the system for electricity, heating, and cooling, with an increasing trend toward full electrification in the coming decades. Industry is supported with electricity, heat, and hydrogen, facilitating the shift toward cleaner production processes. The integration of these different energy vectors allows the system to optimize flows across sectors, making use of RE whenever possible and relying on storage to smooth out variability.

The figure emphasizes the interaction between resources, technologies, and demands. Electricity, natural gas, hydrogen, and heat are not treated as separate systems but rather as interconnected networks that complement each other. By combining renewable generation, traditional fuels, and innovative storage solutions, the MEM ensures that energy can be provided efficiently, sustainably, and reliably. This approach can reduce dependence on fossil fuels, enhance energy security, and support long-term decarbonization goals across all major areas of consumption.

In the publications of this dissertation, MEMs are studied in which an AC electricity distribution network is interconnected with a natural gas or hydrogen distribution network. More precisely, the possibility of repurposing a natural gas network to be used to supply the same amount of demand through hydrogen is investigated. In the studies, it is assumed that the electricity network can buy/sell electricity from/to the upstream grid (i.e., a transmission system). The natural gas or hydrogen network can also interact with the upstream grid (i.e., a high-pressure network). In the output studies, the role of hydrogen in operational planning and system flexibility is extensively studied, where hydrogen storage systems, ELZs, and FCs are shown to enhance resilience, provide balancing for renewables, and serve as a clean fuel for transport and industry. The resilience dimension of MEMs is also addressed, focusing on the ability of integrated electricity, gas, or hydrogen flows to withstand natural phenomena and extreme events while ensuring critical load support. The techno-economic aspects of ESSs in MEMs are explored, including both electricity and hydrogen, and the transport sector is considered through the analysis of EVs' parking lots within MEMs. However, other elements of MESs remain open for future work, particularly the role of heat networks, such as boilers, heat recovery, and thermal storage, the integration of heat pumps with environmental sources, as well as hydrogen mobility.

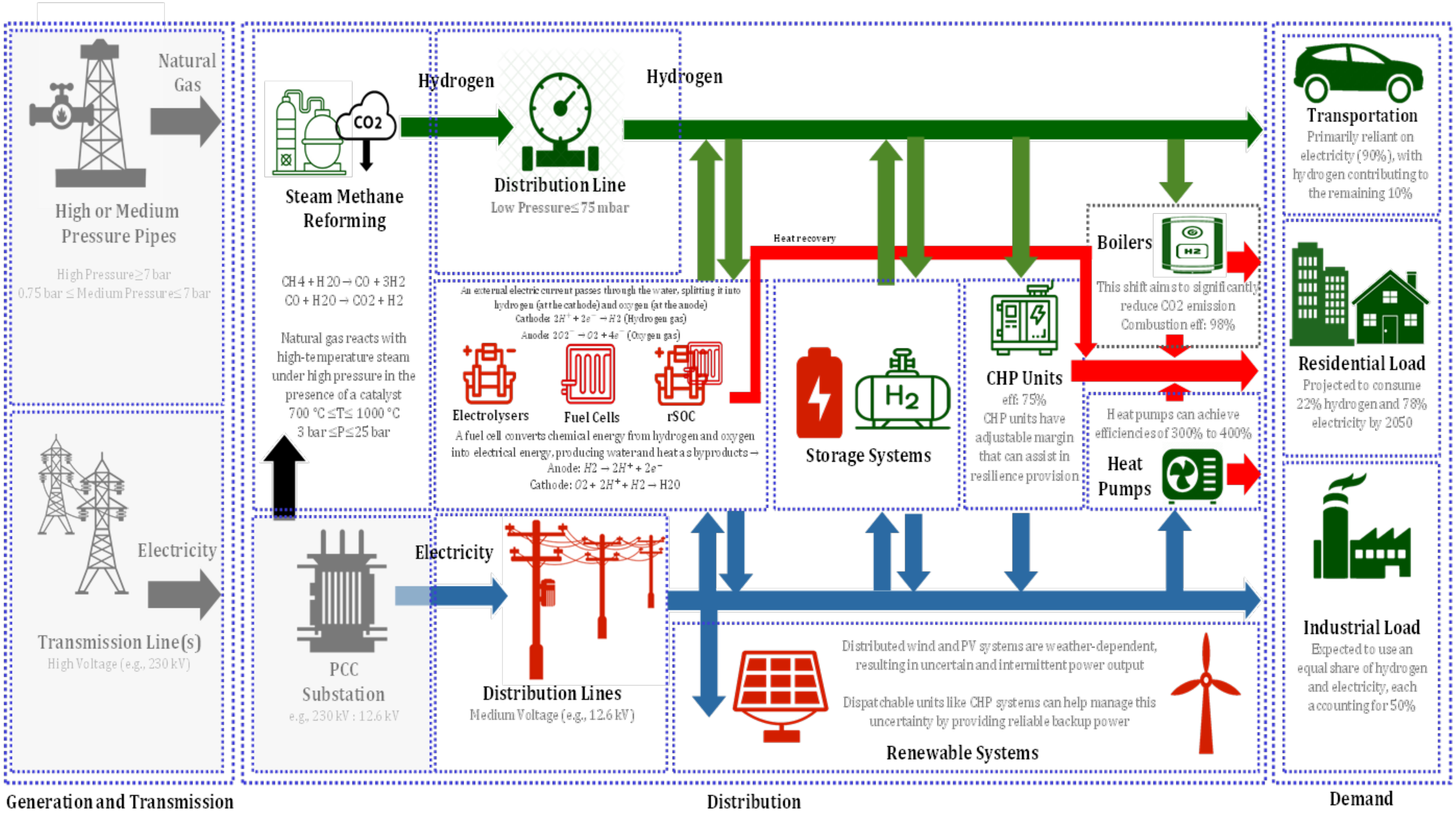

Figure 5. Role of hydrogen in a multi-energy microgrid.

2.4 RE in Finland

Finland has committed to becoming carbon neutral by 2035, a legally binding objective under the national Climate Change Act (Ministry of the Environment, 2022a). This target exceeds the European Union's collective ambition of climate neutrality by 2050 and requires a structural transformation of the Finnish energy system. Achieving this goal depends on a significant expansion of RE production and its integration across electricity, heating, and transport sectors.

The Finnish energy mix is distinct compared to most European Union member states. In 2022, renewables accounted for 43% of total final energy consumption, one of the highest shares in the European Union (Statistics Finland - Energy, 2020). Bioenergy is the single largest contributor, primarily from forest residues, wood-based fuels, and black liquor, reflecting Finland's globally significant forestry industry. Hydropower contributes approximately 15 TWh annually, while wind power has expanded rapidly, with installed capacity exceeding 5 GW in 2023 and projected to surpass 14 GW by 2030. Solar energy currently plays a smaller role, with less than 1% of total electricity generation, but is expanding due to declining costs and targeted support schemes.

District heating systems also occupy a central role in Finland's energy transition. A considerable share of the population is connected to district heating networks. Traditionally based on fossil fuels, these networks are being decarbonized through large-scale heat pumps, geothermal sources, and biomass (Ministry of the Environment, 2022b). The scale and integration of these heating systems provide a strong basis for multi-energy optimization, which is directly relevant for future MG planning.

2.5 MGs' potential in Finland

Finland's power system is part of the synchronous Nordic grid and is strongly interconnected with Sweden, Norway, Estonia, and Russia (until 2022). The reliability of supply is high, with an average annual outage time of less than an hour per customer (Statistics Finland - Energy, 2020). However, the increasing share of variable RE introduces challenges in balancing generation and consumption.

MGs offer a solution by enabling localized control, flexibility, and resilience. Their relevance in Finland can be justified on three grounds. First, Finland's geography creates distinct challenges: sparsely populated rural and Arctic regions rely on long transmission lines, which are costly to maintain and vulnerable to weather disruptions. Locally managed MGs can reduce dependence on central infrastructure and improve resilience in these areas. Second, Finland has exceptionally high heating demand, with heating accounting for approximately 25% of total final energy use (Finland - Countries & Regions - IEA, 2020). MEMs, which integrate the gas sector (e.g., hydrogen or biogas) and potentially transport energy, can therefore deliver substantial efficiency and emission benefits. Third, Finland faces climate-related reliability challenges, including severe winter storms and icing conditions. MGs with distributed storage and local generation can provide islanding capability, ensuring security of supply during outages.

In Finland, several pilot MGs have been developed to support the energy transition, with the Sundom Smart Grid in Vaasa being one of the most notable examples. This project turned the village of Sundom into a testbed for smart-grid solutions, combining RE, smart meters, and digital tools to study DR and flexible electricity use. It was carried out through collaboration between local energy companies, universities, and technology firms, and became a model for future smart grid development.

2.6 Hydrogen integration into Finland's energy system

Hydrogen is central to Finland’s long-term decarbonization strategy. The Finnish Hydrogen Roadmap 2020, published by VTT Technical Research Center of Finland, identifies green hydrogen as a key enabler for reaching carbon neutrality and for positioning Finland as a competitive hydrogen economy in the Nordic-Baltic region (Government Resolution on Hydrogen, 2020). The Roadmap estimates that by 2035, Finland could produce a considerable amount of renewable hydrogen annually, primarily from wind power-based electrolysis.

Hydrogen integration is particularly relevant for MGs due to its multi-functional role. First, hydrogen provides long-duration storage. While batteries are suitable for short-term balancing, Finland’s seasonal variations in demand and renewable output require storage solutions that extend from weeks to months. Hydrogen enables this by storing surplus electricity in chemical form for later use in FCs, turbines, or heating applications. Second, hydrogen can be used as a sector-coupling medium, linking electricity, heating, transport, and industry. In Finnish MGs, hydrogen can be converted into electricity, injected into district heating networks through hydrogen boilers, or utilized in industrial processes. Third, hydrogen strengthens the strategic resilience of the Finnish energy system by reducing dependence on imported fossil fuels and aligning with industrial decarbonization pathways.

Finland's industrial base further amplifies the relevance of hydrogen MGs. The steel industry in Raahe, the chemical clusters in Porvoo, and the paper and pulp industries across the country are actively exploring hydrogen as a replacement for fossil-based feedstocks and fuels (Statistics Finland - Energy, 2020). Co-locating hydrogen production with MGs not only supports local energy balance but also provides industrial symbiosis opportunities.

3 OPERATION AND PLANNING OF ENERGY SYSTEMS

This section sheds light on the operation and planning models that are used for the MEMs, as indicated in Figure 6.

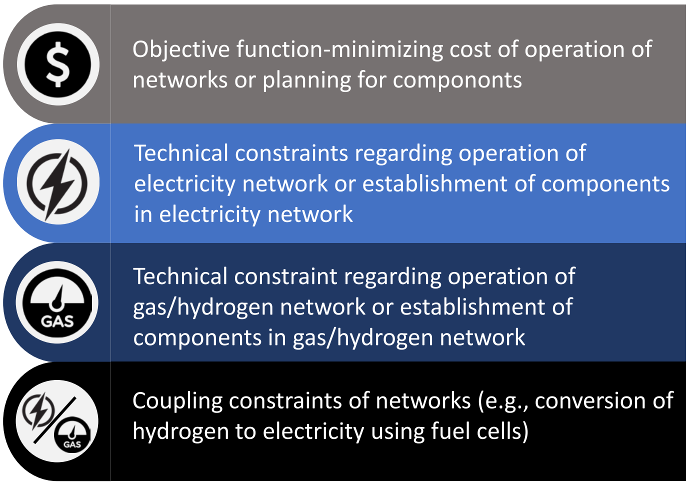

Figure 6. Problem of operation and planning of MEMs.

The objective function and constraints of the optimization problem are indicated in Figure 7 and discussed in detail in the following subsections.

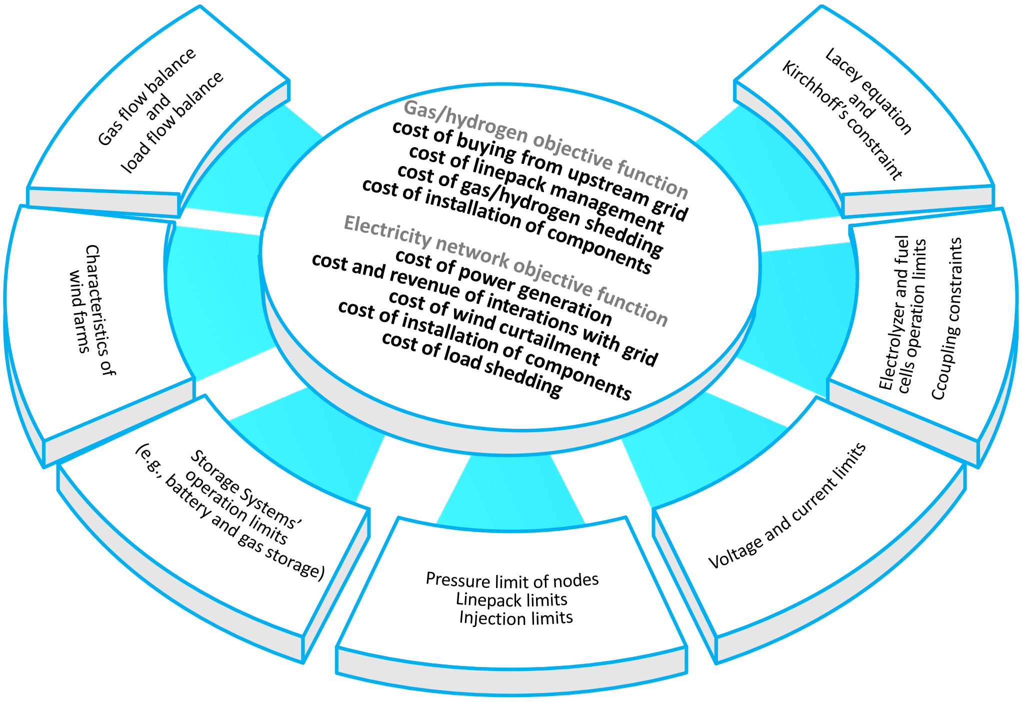

Figure 7. Objective function and constraints of the operation and planning of MEMs.

3.1 Operation of the electricity distribution network in MGs

This section presents the operational model of the electricity distribution network within an MG as part of a coordinated scheduling framework for the operation of MEMs. The goal of this model is to ensure that electricity supply and demand are balanced in a cost-effective and technically feasible manner, while also capturing the interdependence between electrical and gas infrastructures.

The electricity distribution network is modelled with practical assumptions, discussed in Publication VII, to reduce computational complexity while retaining system characteristics, as follows:

Constant Demand: The active and reactive power demands at each bus are assumed to remain constant throughout each scheduling period. This simplifies the load representation and reflects typical short-term planning scenarios.

Simplified Loss Representation: Power losses in distribution lines are accounted for at the beginning of each branch. This approach approximates resistive losses while maintaining model tractability.

Single-Phase, Balanced Network: The electricity distribution network is represented as a single-phase equivalent model and is assumed to be balanced. This is a common simplification in distribution system studies, especially in planning and optimization contexts.

Day-Ahead Market Participation: The MG is assumed to interact with the main electricity grid through a day-ahead market. This allows the grid-connected MG to buy electricity when internal generation is insufficient and sell electricity when there is surplus.

These assumptions lay the foundation for the detailed mathematical formulation of the electricity distribution network operation, which is described in the following. The model seeks to minimize the total cost of electricity supply while ensuring that all operational constraints of the network are satisfied. The model is grouped into the objective function and a set of system constraints, discussed in the following.

3.1.1 Objective function

The objective function represents the total cost associated with operating the electricity distribution network over the scheduling horizon. It includes three main components:

Electricity Purchase Cost and Electricity Sale Revenue: The MG may purchase electricity from the main grid at time-dependent market prices. This cost accounts for the total energy imported to meet local demand when internal generation is insufficient or less economical. The MG may also sell surplus electricity back to the main grid. This term reflects the income from exported electricity and appears as a negative cost, effectively reducing the total operational cost.

Non-Renewable Generation Cost: Non-renewable distributed generators (such as gas-fired combined heat and power units) incur operating costs. These include fuel-related costs and start-up costs, which depend on whether the unit is active.

Load Shedding Cost: The MG may not be able to meet the demand due to various reasons, which causes the cost of the load not supplied.

Together, these terms ensure that the MG operates economically, leveraging market participation, local generation, and demand management. A more precise explanation about the electricity subsystem's costs and operational constraints being discussed in the following can be found in Publication IV, Publication VI, and Publication VII.

3.1.2 Constraints

To ensure a realistic operation of the electricity distribution network, a series of constraints is applied:

Active Power Balance: At each bus and every time step, the sum of power generated locally, wind generation, and power purchased from the grid must equal the sum of the local demand, power losses, and any electricity sold to the main grid. This ensures energy balance at all nodes.

Wind Generation Limits: The power generated by wind units is capped at their available capacity, which can vary over time due to resource variability.

Non-Renewable Generation Limits: The output of non-renewable generators is bounded by their minimum and maximum operational limits. A binary status variable determines whether the unit is online and hence capable of producing power.

Ramping Constraints: Non-renewable generators cannot change their output arbitrarily between consecutive time steps. These constraints enforce realistic up and down ramp rates based on the technical limitations of the units.

Reactive Power Balance: Similar to active power, the reactive power supplied by generators and the reactive component of power flows must match the reactive power demand at each bus.

Reactive Power Generation Limits: Generators and substations must supply reactive power within their technical capability limits.

Voltage Drop Equations (Kirchhoff's Voltage Law): In these two constraints, equations (1)-(2), the application of Kirchhoff's voltage law is presented. These two nonlinear constraints, often referred to as voltage drop equations, model the relationship between voltages at the sending and receiving ends of a branch while accounting for real and reactive power flows, line impedance, and current magnitude. They directly couple voltage and current, or equivalently, active and reactive power, thereby ensuring voltage consistency throughout the network and capturing the interdependence between electrical variables. Due to their critical role in linking these variables, they are included in this section, whereas other network constraints are only explained. However, the other equations and their description can be found in the publications of this thesis.

$$V_{l,t}^{in\,2} - V_{l,t}^{out\,2} = 2\left(R_l . P_{l,t}^{line} + X_l . Q_{l,t}^{line}\right) + Z_l^2 . I_{l,t}^2 l \subseteq (i,i') \; and \; \forall t \quad (1)$$

$$V_{l,t}^2 . I_{l,t}^2 = Q_{l,t}^{line\,2} + P_{l,t}^{line\,2} l \subseteq (i,i') \; and \; \forall t \quad (2)$$

Where,

T	Periods
L	Electric lines
I	Nodes in MG
R_l	Resistance
X_l	Reactance
Z_l	Impedance
$P_{i,t}^{line}$	Active power
$Q_{i,t}^{line}$	Reactive power
$I_{l,t}$	Electricity current
$V_{i,t}$	Voltage magnitude

It should be noted that equation (1) is non-convex in its current form, which means that the solution method may lead to local optimum solutions. While decomposition methods are an appropriate solving method to deal with the mixed-integer nonlinear problem, a pre-processing is also implemented to prepare the optimization problem by reformulating equation (1) into (3), which transforms the non-convex optimization problem of optimal power flow into a convex one by a conic program based on (Farivar & Low, 2013). More precisely, by converting the model into a convex optimization problem, achieving a unique solution is guaranteed.

$$V_{l,t}^2 \,.\, I_{l,t}^2 \geq Q_{l,t}^{line\ 2} + P_{l,t}^{line\ 2} \quad \forall l \ and\ \forall t \tag{3}$$

Power Flow Equations: Real and reactive power flows are constrained by the product of current and voltage magnitudes, maintaining consistency with electrical laws.

Voltage Limits: The bus voltages are restricted to stay within permissible operational bounds to maintain power quality and system stability.

Current Limits: The current in each distribution line is limited to avoid thermal overloading and ensure safe operation.

3.2 Operation of gas distribution network in MGs

This subsection presents the mathematical model used to describe the operation of the gas/hydrogen distribution network within the MG. The model aims to minimize the overall cost associated with natural gas/hydrogen supply while ensuring the physical and operational constraints of the gas network are respected. More precise explanations about the subsystem's costs (either natural gas or hydrogen) and operational constraints being discussed in the following can be found in Publication I and Publication II.

3.2.1 Objective function

The objective function in the gas/hydrogen network model consists of three main components:

Natural Gas/Hydrogen Injection Cost: This term accounts for the cost of injecting natural gas or hydrogen into the distribution network from upstream supply sources over the scheduling period (e.g., gas transmission network).

Linepack Cost: Linepack refers to the volume of gas (e.g., natural gas and hydrogen) stored within the pipelines themselves. Because gas transportation is not instantaneous, linepack acts as a buffer to balance fluctuations between supply and demand. This component reflects the cost related to changes in linepack levels.

Gas/Hydrogen Not Supplied Cost: This term represents penalties or costs associated with any shortfall in meeting the gas demand at network nodes, often referred to as gas-not-supplied.

Together, these components guarantee the scheduling of gas injections and flow management to operate the network economically and reliably.

3.2.2 Constraints

The gas network operation is governed by several key constraints:

Natural Gas/Hydrogen Injection Limits: The amount of gas injected by each source is limited by its minimum and maximum capacity. This ensures that injections stay within physically feasible and contractual bounds.

Gas Flow Balance: At every node and time step, the difference between gas injection and pipeline flow leaving the node must satisfy the local gas demand adjusted for any unmet gas demand. This ensures continuity of supply throughout the network.

Pressure-Flow Relationship-Lacey's Equation: Lacey's equation serves as a key link between hydrogen flow through pipelines and the corresponding pressures at network nodes, enabling precise simulation of hydrogen distribution systems (Osiadacz, 1987b). In equation (4), Lacey's equation is adapted for a low-pressure hydrogen network operating between 0 and 75 mbar gauge:

$$H_{n,n',t}^{pipe} = 0.023\sqrt{\left[\frac{\left(\pi_{n,t}-\pi_{n',t}\right)D_{n,n'}^{5}}{f_{n,n'}SL_{n,n'}}\right]}\quad p\epsilon(n,n'), \forall t \tag{4}$$

Where,

$L_{n,n'}$	Pipe lengths
$D_{n,n'}$	Pipe diameters
$\pi_{n,t}$	Nodal pressures
$H_{n,n',t}^{pipe}$	Hydrogen flow rates within pipes

Unwin's low-pressure formula can be used to determine the value of f, represented in equation (5).

$$f_{n,n'} = 0.0044\left(1+\frac{12}{0.276D_{n,n'}}\right)\quad p\epsilon(n,n'), \tag{5}$$

Alternatively, by replacing the value of 0.0065 with $f_{n,n'}$ for all pipes, equation (4) can be replaced by equation, called Pole's equation (6).

$$H_{n,n',t}^{pipe} = 0.0071\sqrt{\left[\frac{\left(\pi_{n,t}-\pi_{n',t}\right)D_{n,n'}^{5}}{SL_{n,n'}}\right]}\quad p\epsilon(n,n'), \forall t \tag{6}$$

Considering S equal to 0.0695 for hydrogen, the equation can be rewritten in the following (equations (7)-(8))

$$\pi_{n,t} - \pi_{n',t} = K_{n,n'} {H^{pipe}_{n,n',t}}^2 \quad p\epsilon(n,n'), \forall t \tag{7}$$

$$K_{n,n'} = \frac{1378.69\, L_{n,n'}}{D^5_{n,n'}} \quad p\epsilon(n,n') \tag{8}$$

However, for natural gas distribution, as the S is equal to 0.589, the constant is calculated, as indicated in equation (9) (Publication IV).

$$K_{n,n'} = \frac{11684.19\, L_{n,n'}}{D^5_{n,n'}} \quad p\epsilon(n,n') \tag{9}$$

A more precise description of the equations can be found in Publication II and Publication IV.

Pipeline Flow Limits: Gas flow through each pipeline segment is constrained within minimum and maximum allowable flow rates to avoid operational issues, such as pressure drops or pipeline damage.

Linepack Variation: Linepack at any time is calculated based on an initial level plus the cumulative net inflow (difference between gas entering and leaving the pipeline). This model shows that the storage capacity within pipelines is utilized to manage supply-demand imbalances over time.

This gas network model supports operational decisions that balance supply costs, storage utilization, and demand fulfilment while adhering to the physical laws governing gas flow. For detailed mathematical formulations, including the objective function and constraints, the reader is referred to Publication I, Publication II, and Publication IV.

It should be highlighted here that, as mentioned earlier, gas distribution network model, originally designed for natural gas, can be effectively adapted to operate a hydrogen network within an MEM. In this adapted model, the coefficients of Lacey's equation should be changed. It is aside from the safety measures that are required to be implemented to prevent the leakage risks of hydrogen.

3.3 Planning of MGs

Planning is a critical phase in the development of an MG, wherein strategic decisions regarding infrastructure investment, operational strategy, and system architecture are made. In this stage, long-term uncertainties, particularly in load demand and RE generation, must be accounted for to ensure a robust and cost-effective MG configuration. Unlike operational or real-time control phases, which take from seconds to hours, the planning phase typically spans several years and thus places significant emphasis on economic and technical sustainability.

3.3.1 Objective function in the planning stage

A fundamental aspect of the planning phase is the formulation of an objective function that differs from that used in real-time or short-term operational models. While operational models often aim to minimize immediate fuel or dispatch costs, the planning-stage objective function is designed to account for both capital investment and long-term operational performance under uncertainty. While the objective can be framed as a multi-year expected cost minimization that balances economic feasibility and technical efficiency, another approach can be annualizing both operating and planning costs to conduct meaningful analyses of costs versus savings.

Key components of the planning objective function include:

Capital Expenditure (CapEx): Costs associated with the installation of Distributed Energy Resources and flexibility components, including photovoltaic systems, wind turbines, ESSs, and ELZs and FCs.

Operational Expenditure (OpEx): Long-term costs related to fuel consumption, maintenance, and equipment wear, particularly for dispatchable resources such as hydrogen-fired units.

Mathematically, this objective is typically expressed in a way that the expected value of total cost is minimized across a set of future scenarios, each weighted by its probability or number of occurrences. These scenarios capture variability in uncertain parameters and are essential for ensuring that the selected MG design performs reliably under diverse conditions. More detailed information about the planning model can be found in Publication II, Publication IV, and Publication VI.

As an example, the objective function of planning for components studied in the publications is explained here, in which all costs are annualized. Here, the objective is to minimize the total operating and investment costs of electricity and hydrogen systems.

$$OF^{tot} = OF^{Op} + OF^{inv} \tag{10}$$

$$OF^{op} = OF^{ELC} + OF^{H_2} \tag{11}$$

To reduce computational complexity in evaluating annual operational costs, representative days are employed. The electricity-related component of the objective function aims to minimize the total costs of electricity imports, exports, and load shedding, scaled by the corresponding number of representative days. The formulation of this objective function is presented in equation (12).

$$OF^{ELC} = \sum_{d=1}^{D} \omega_d \, (\sum\nolimits_{t=1}^{T} \psi_{t,d}.E_{t,d}^{buy} - \sum\nolimits_{t=1}^{T} \psi'_{t,d}.E_{t,d}^{sell} + \sum\nolimits_{t=1}^{T} \sum\nolimits_{b=1}^{B} \psi''_{t,d}.E_{b,t,d}^{shed}) \tag{12}$$

Where:

ϕ ϕ' ϕ''	Costs of purchasing hydrogen, linepack changes, and penalty for imbalance and unmet hydrogen demand
$H_{t,d}^{buy}$	Hydrogen bought
$HNS_{n,t,d}$	Hydrogen imbalance
$\Delta H_{n,t,d}$	Changes in the linepack

The hydrogen-related component of the objective function minimizes annual costs associated with hydrogen purchased from external sources, the cost of linepack management, and unmet demand. The costs are presented and weighted by the number of representative days in equation (12).

$$OF^{H_2} = \sum_{d=1}^{D} \pi_d \left(\sum\nolimits_{t=1}^{T} \phi_d.H_{t,d}^{buy} + \sum\nolimits_{t=1}^{T} \sum\nolimits_{n=1}^{N} \phi'_d.\,\Delta H_{n,t,d} + \sum\nolimits_{t=1}^{T} \sum\nolimits_{n=1}^{N} \phi''_d.HNS_{n,t,d}\right) \tag{13}$$

Where,

ϕ ϕ' ϕ''	Costs of purchasing hydrogen, linepack changes, and penalty for imbalance and unmet hydrogen demand
$H_{t,d}^{buy}$	Hydrogen bought
$HNS_{n,t,d}$	Hydrogen imbalance
$\Delta H_{n,t,d}$	Changes in the linepack

In the objective function, the investment cost is also annualized using a capital recovery factor and includes cost contributions from every planned component (e.g., ELZs, FCs, hydrogen-fired units, and rSOC), in equations (14)-(15).

$$INV = \left[\frac{r(1+r)^j}{(1+r)^j - 1}\right].C^{inv} \tag{14}$$

$$C^{inv} = \sum_{k=1}^{K} C^{investment}.Cap_k \tag{15}$$

Where,

r	Discount rate
j	Lifetime (years)
Cap_k	Installed capacity of technology
$C^{investment}$	Unit investment cost
C^{inv}	Investment cost
INV	Annualized investment cost

3.3.2 Scenario generation and reduction

To incorporate uncertainty into the planning model, a scenario-based framework is employed in Publication II and Publication IV. In this framework, the uncertainty of variables, such as wind generation and electrical and gas demand over the planning horizon, is represented by a finite set of discrete scenarios. These scenarios are generated based on the reduction of historical data to provide representative days that preserve the statistical properties of the original time series.

The scenario reduction process, indicated in Table 1, focused specifically on wind generation, electricity demand, and gas demand, which are the most influential stochastic parameters in the system. In this case, the annual time series for both variables were clustered and reduced into four representative scenarios, each corresponding to a distinct seasonal or operational pattern observed throughout the year. This reduction was achieved using a clustering-based approach that groups similar days and selects a representative profile for each group, as follows:

Table 1. Pseudocode for scenario reduction and providing representative days in a year.

Pseudocode
Input:
Set of demand and wind profiles H
Number of desired profiles Ndp
Initial frequency of each profile (equal for all = 1)
Output:
Reduced set of representative profiles with updated frequencies
Procedure:
Set Hp ← total number of profiles in H

line	Pseudocode
9	While Hp> Ndp do
10	a. Calculate the distance between every pair of profiles
11	b. Identify the two closest profiles
12	c. Compare their frequencies
13	- Delete the profile with lower frequency
14	- Add its frequency to the remaining profile
15	d. Update Hp ← Hp - 1
16	End While
17	Return the final set of representative profiles and their frequencies

The resulting four scenarios serve as the basis for representing a whole year in an optimization model. Each scenario is assigned some days based on its relative frequency, and the optimization seeks a design that minimizes the annual cost across all scenarios. This approach ensures that the planning model remains computationally efficient while still capturing the impact of seasonal and stochastic variations in demand and renewable generation.

4 FLEXIBILITY OPTIONS

The integration of flexibility resources within MGs is essential to enhance their ability to manage variability, uncertainty, and intermittency, particularly those arising from RES and dynamic demand profiles. Flexibility mechanisms enable a more resilient, efficient, and responsive MG operation, thereby supporting long-term sustainability goals. In this chapter, three major categories of flexibility options considered in the proposed model in the publication of this thesis are elaborated: (i) ESSs, (ii) EVs, and (iii) DR strategies.

4.1 Storage systems

ESSs are among the most critical components for enabling flexibility in modern MGs. They provide temporal decoupling between electricity generation and consumption, allowing excess energy, especially from renewable sources, to be stored and dispatched as needed.

ESSs are characterized by their charging and discharging behaviours, modelled via state-of-charge (SOC) dynamics. The SOC at each time step is a function of the initial stored energy and the net energy flow, considering respective charging and discharging efficiencies. To ensure operational feasibility, the charging and discharging power is constrained within defined upper and lower bounds. Moreover, the SOC is subject to technical limits, bounded by the minimum and maximum storage capacities.

Equations (16)-(19) define the operational constraints of the storage systems. Equation (16) represents the variation in the storage energy level (i.e., state of charge ($SC_{k,t}$)) while accounting for charging and discharging efficiencies (eff^{ch} and eff^{dch}, respectively). Equations (17) and (18) impose limits on the charging and discharging power of the storage units ($P_{k,t}^{ch}$ and $P_{k,t}^{dch}$, respectively). Furthermore, equation (19) restricts the maximum allowable stored energy within the system. It is of importace to note that a binary decision variable is included in the state of charge constraint to indicate whether the installation of candidate storage systems is part of the optimal solution (i.e., not necessary in only the operation of MGs).

$$SC_{k,t} = SC_{k,t}^{0} + \sum_{1}^{T} (eff^{ch}.P_{k,t}^{ch} - P_{k,t}^{dch}/eff^{dch}) \quad \forall k \text{ and } \forall t \tag{16}$$

$$P_k^{ch\,min} \le P_{k,t}^{ch} \le P_k^{ch\,max} \quad \forall k \text{ and } \forall t \tag{17}$$

$$P_k^{dch\,min} \le P_{k,t}^{dch} \le P_k^{dch\,max} \quad \forall k \text{ and } \forall t \tag{18}$$

$$v_k.SC_k^{min} \le SC_{k,t} \le SC_k^{max}.v_k \quad \forall k \text{ and } \forall t \tag{19}$$

Where,

k	Index of storage systems
$eff^{dch/ch}$	Efficiency of discharge/charge (%)
$P_k^{ch\ min/max}$	Minimum/maximum charging power into storage systems (kW)
$P_k^{dch\ min/max}$	Minimum/maximum discharging power from storage systems (kW)
$SC_k^{min/max}$	Minimum/maximum stored energy within storage systems (kWh)
$SC_{k,t}^0$	Initial stored energy within storage systems (kWh)
$SC_{b,t}$	Energy stored in storage systems (kWh)
$P_{k,t}^{ch}$	Charged power (kW)
$P_{k,t}^{dch}$	Discharged power (kW)
v_k	Binary variable indicates whether a storage system is installed (0/1)

In addition to conventional battery storage, hydrogen-based storage is incorporated as a long-duration energy flexibility solution. Surplus electrical energy in the MG can be directed toward hydrogen production through ELZs. The produced hydrogen is compressed and stored in tankers to be used in the later horizon. The level of hydrogen stored is updated dynamically, considering the previously stored quantity and the net balance of hydrogen inflow and outflow. This stored hydrogen can subsequently be used in two ways: (i) conversion back into electricity through FCs, or (ii) direct sale to industrial customers.

The key technical constraints of storage systems encompass their maximum capacity, charging and discharging rates, charging and discharging efficiencies, and the allowable number of charge-discharge cycles (equations (20)-(24)).

$$Gl_{q,t}^{min} \leq GL_{q,t} \leq GL_{q,t}^{max} \quad \forall q \ and\ \forall t \tag{20}$$

$$Gl_{q,t} = Gl_{q,t-1} + (GL_{q,t}^{wd}.\eta^{ch} - GL_{q,t}^{inj}.\eta^{dch}) \quad \forall q \ and\ \forall t \tag{21}$$

$$0 \leq GL_{q,t}^{wd} \leq GL_{q,t}^{wd,max}.I^{ch} \quad \forall q \ and\ \forall t \tag{22}$$

$$0 \leq GL_{q,t}^{inj} \leq GL_{q,t}^{inj,max}.I^{dch} \quad \forall q \ and\ \forall t \tag{23}$$

$$I^{dch} + I^{dch} \leq N^{max} \quad \forall q \ and\ \forall t \tag{24}$$

Where,

q	Set of gas storage
$GL_{q,t}$	Gas level in gas storage systems
$GL_{q,t}^{max/min}$	Maximum/minimum gas level in gas storage systems
$GL_{q,t}^{wd/inj}$	Withdrawal/injected gas
$GL_{q,t}^{wd/inj,max}$	Maximum withdrawal/injected gas
$\eta^{ch/dch}$	Charging/discharging efficiency
$I^{ch/dch}$	State of charging/discharging
N^{max}	Maximum number of charge/discharges during the operation period

For each gas storage system, the maximum withdrawal and injection rates of natural gas vary proportionally with the storage level. Equations (25)-(26) indicate the maximum gas withdrawal and the maximum gas injection, in which K_s, K_s^1, and

K_s^2 depend on the type and dimension of these systems. However, it can be simplified and considered as it was indicated in the previous equations.

$$GL_{q,t}^{wd,max} = K_q\sqrt{GL_{q,t}} \quad \forall q \text{ and } \forall t \tag{25}$$

$$GL_{q,t}^{inj,max} = -K_q^1\sqrt{\frac{1}{GL_{q,t} + GL_{q,t}^{cush}} + K_q^2} \quad \forall q \text{ and } \forall t \tag{26}$$

Where,

K_q	Coefficient of maximum withdrawal gas from gas storage systems
$K_q^{1/2}$	Coefficient of maximum injection gas into gas storage systems
$GL_{q,t}^{cush}$	Cushion gas capacity of gas storage systems (cm)

4.2 Scheduling EVs

EVs offer bidirectional flexibility, serving both as energy consumers and as distributed energy storage resources when discharge to the grid is available. In general, EV flexibility is modelled based on battery capacity, arrival and departure times, energy demand at departure, and allowable charging/discharging rates. EVs can be charged during off-peak or high renewable generation periods and potentially discharge energy during peak demand hours, contributing to load levelling, voltage support, and renewable integration.

The aggregated behaviour of EV fleets can provide substantial flexibility without requiring additional investment in stationary storage systems. Their inherent mobility and load-shifting potential make them a promising asset in future smart MGs, especially as EV adoption rates continue to rise. The following formulation is used to model EV parking lots: Equation (27) implies that a parking lot can either be charged or discharged, but not both simultaneously. Equations (28)-(29) define the boundaries for the charging and discharging power. Taking into consideration the same as for batteries, the minimum limits deviate from zero, constituting 20% of the maximum discharging and charging power.

$$U_{k,t}^{Dch,EVPL} + U_{k,t}^{Ch,EVPL} \leq 1 \tag{27}$$

$$0.2P_{k,t}^{Max,Ch,EVPL}.U_{k,t}^{Ch,EVPL} \leq P_{k,t}^{Ch,EVPL} \leq P_{k,t}^{Max,Ch,EVPL}.U_{k,t}^{Ch,EVPL} \tag{28}$$

$$0.2P_{k,t}^{Max,Dch,EVPL}.U_{k,t}^{Dch,EVPL} \leq P_{k,t}^{Dch,EVPL} \leq P_{k,t}^{Max,Dch,EVPL}.U_{k,t}^{Dch,EVPL} \tag{29}$$

Where,

$U_{k,t}^{Ch/Dch,EVPL}$	Status of charging/discharging of EVs' parking lot (binary variable)
$P_{k,t}^{Ch/Dch,EVPL}$	Charging/discharging power of EVs' parking lot
$P_{n,t}^{Max/Min,Ch/Dch,BSS}$	Maximum/minimum charging/discharging power of the battery storage system

Equation (30), as presented below, plays a crucial role in quantifying the energy level of each parking lots over time. Like BSS, this equation considers the energy level of the previous time and the charging and discharging power within that specific hour. However, there are notable distinctions when applying this equation to the EV parking lots. Since this case is dealing with a dynamic load, it becomes imperative to consider the energy that enters and exits the parking lots, which involves carefully considering the arrivals and departures that occur during each period. These factors are crucial in accurately assessing the energy dynamics of EV charging infrastructure and provide a comprehensive understanding of the energy flow within the parking lot.

$$El_{k,t}^{EVPL} = \begin{cases} t \geq 1 \;\; El_{k,t-1}^{EVPL} + El_{k,t}^{Arv} - El_{k,t}^{Dpt} + (P_{k,t}^{Ch,EVPL}.\lambda^{Ch,EVPL}) - \dfrac{P_{k,t}^{Dch,EVPL}}{\lambda^{Dch,EVPL}} \\ t = 1 \;\; El_{k,1}^{EVPL} \end{cases} \tag{30}$$

Where,

$El_{k,t}^{EVPL}$	EV's parking lot energy level
$El_{k,t}^{Arv/Dpt}$	Arrival/departure energy level of EVs
$P_{k,t}^{Ch/Dch,EVPL}$	Charging/discharging power of the EV parking lot
$\lambda^{Ch/Dch,EVPL}$	Charging/discharging efficiency of the EV parking lot

To accurately assess the energy dynamics within the EV parking lots infrastructure, it is necessary to consider the energy levels associated with the vehicle's arrival and departure. Equation (31) captures the energy level upon vehicle arrival at each time. Similarly, equation (32) calculates the energy level upon vehicle departure.

$$El_{k,t}^{Arv} = \begin{cases} if\ El_{k,t} \leq El_{k,t-1} & 0 \\ if\ El_{k,t-1} \leq El_{k,t} & El_{k,t} - El_{k,t-1} \end{cases} \tag{31}$$

$$El_{k,t}^{Dpt} = \begin{cases} if\ El_{k,t-1} \leq El_{k,t} & 0 \\ if\ El_{k,t} \leq El_{k,t-1} & El_{k,t-1} - El_{k,t} \end{cases} \tag{32}$$

The energy level of each parking lot can be obtained by input scenarios, and it is formulated by equation (33). The energy level is limited by equation (34), where it has been considered a minimum SOC of 20% and a maximum of 80% for each EV that enters or leaves the parking lots.

$$El_{k,t}^{EVPL} = Cap_{k,t}^{EV}\ .SOC_{k,t}^{EV}.n_{k,t}^{EV} \tag{33}$$

$$Cap_{k,t}^{EV}.n_{k,t}^{EV}.0.2 \leq El_{k,t}^{EVPL} \leq Cap_{k,t}^{EV}.n_{k,t}^{EV}.0.8 \tag{34}$$

Where,

$SOC_{k,t}^{EV}$	EVs' battery state of charge
$n_{k,t}^{EV}$	Number of EVs parked in the parking
$Cap_{k,t}^{EV}$	Power capacity of each EV

4.3 DR

Demand-side flexibility is addressed through the implementation of DR programs. These programs incentivize end-users to adjust their consumption patterns based on price signals or direct incentive mechanisms, thereby improving the alignment between supply and demand and mitigating the need for costly infrastructure upgrades.

Two types of DR mechanisms are modelled: time-of-use pricing and incentive-based DR.

4.3.1 Time-of-use pricing

This program categorizes the operational timeline into distinct periods: valley, off-peak, and peak, with corresponding electricity tariffs. These varying prices act as economic signals to encourage consumers to shift consumption toward lower-cost periods. The model incorporates a price elasticity matrix to quantify the responsiveness of demand to these temporal price variations.

4.3.2 Incentive-based DR

In this scheme, consumers are offered direct monetary incentives to reduce or reschedule consumption during critical periods, such as peak load hours or contingencies. Unlike time-of-use pricing, which relies on pre-set tariffs, incentive-based DR is event-driven and provides more dynamic control over demand. The model reflects this mechanism by adjusting the baseline demand based on the offered incentives and the corresponding elasticity values. Importantly, the cost of these incentives is integrated into the operating cost function of the MG, ensuring that the optimization captures the trade-off between supply-side costs and demand-side flexibility.

4.3.3 Integrated demand-side management

The integration of both time-of-use and incentive-based mechanisms provides a comprehensive framework for demand-side management. The final load profile in the presence of DR is calculated based on both the baseline demand and its responsiveness to prices and incentives. This dual mechanism allows for more accurate modelling of consumer behaviour and better utilization of flexibility at the demand level. The impact of DR is reflected in the system's operational and economic performance, contributing to peak load reduction, improved system reliability, and enhanced renewable integration.

In equation (35), the load in the presence of a time-of-use and an incentive-based DR is calculated (Heydarian-Forushani et al., 2020a). The former is a time-of-use DR program, and the latter is an incentive-based DR program in which consumers decide to change their demand based on prices and incentives (INC_i). It should be noted that the cost of incentive payment is added to the operating cost of the MG. For the time-of-use DR program, distinct electricity prices are considered for specific periods, including valley periods, off-peak periods, and peak periods ($Pr^{ini}_{PG,t'}$ is replaced by $Pr^{ini}_{PG,t'}$). In contrast, the incentive-based program entails a fixed electricity purchase rate, complemented by an extra incentive offered during peak periods. In the formulation, $E_{t,t'}$ is a matrix that indicates the elasticity of demand, and $Load^{DR}_{b,t}$ and $Load_{b,t}$ represent the electric load in the presence and absence of the DR program, respectively (Heydarian-Forushani et al., 2020b).

$$Load^{DR}_{b,t} = Load_{b,t}\left(1 + \sum_{t'=1}^{T} E_{t,t'}\frac{\left(Pr_{PG,t'} - Pr^{ini}_{PG,t'}\right) + INC_i}{Pr^{ini}_{PG,t'}}\right) \tag{35}$$

Where,

$Load^{DR}_{b,t}$	Electric load in the presence of DR program
$Load_{b,t}$	Electric load in the absence of DR program
$E_{t,t'}$	Matrix that indicates the elasticity of demand
$Pr_{PG,t'}$	Prices for specific periods
$Pr^{ini}_{PG,t'}$	Uniform Price
INC_i	Incentive

Considering the above formulation, the objective function of the operation of the MEM should be rewritten. The changes must be implemented in the objective function of the operation of the electricity subsystem in equation (36).

$$C^{elec\prime} = C^{elec} + \sum_{t} inc(Load_t - Load^{DR}_t) \tag{36}$$

Where,

$C^{elec\prime}$	Cost of electricity network operation with DR
C^{elec}	Cost of electricity network operation without DR

For more information about DR programs discussed above, readers are suggested to check Publication i.

5 MATHEMATICAL METHODS

In this section, the mathematical methods used in the publications of the thesis are reviewed, with a primary focus on the motivation for their adoption.

5.1 Uncertainty consideration

Uncertainty is an inherent aspect of many real-world optimization problems. In particular, the integration of RE sources, ELZs for hydrogen production, and the coupling of electricity and gas networks (i.e., natural gas or hydrogen) introduce significant uncertainty into the operation of MEM. In the following, firstly, the methods are explained and compared, as represented in Table 2.

Table 2. Comparison of uncertainty handling approaches.

Approach	Uncertainty Representation	Strengths	Limitations	Relevance to MEMs
Stochastic Programming	Probability distributions/scenarios	Captures randomness explicitly; well-established	Requires reliable data; scenario explosion	Limited (future RES adoption data is scarce)
Robust Programming	Bounded uncertainty sets (interval/polyhedral)	Ensures feasibility under all realizations	Often conservative; light-robust reduces but still worst-case oriented	Useful, but may yield overly cautious solutions
Possibilistic / Fuzzy Programming	Fuzzy sets, membership functions	Handles epistemic/imprecise data; no need for probabilities	Lacks explicit worst-case protection	Suitable for uncertain RES penetration and demand
Robust Fuzzy Programming	Hybrid: fuzzy + robust sets	Balances robustness and imprecision handling	More complex; requires parameter tuning	Strong candidate for energy applications
Proposed Possibilistic Robust Programming	Hybrid: light-robust + fuzzy membership	Balanced trade-off between robustness and optimality; less conservative	New approach; validation needed	Highly suitable for MEMs under evolving uncertainty

5.1.1 Stochastic programming

Stochastic programming represents uncertainty through probability distributions and scenarios (Shabazbegian et al., 2020). It provides solutions that perform well on average and are effective when sufficient historical data are available. However, it becomes impractical when data are scarce or when future conditions.

5.1.2 Robust programming

Robust optimization considers bounded uncertainty sets to guarantee feasibility under all possible realizations. Early methods were highly conservative, often sacrificing optimality. Later refinements, such as light-robust optimization, reduced this conservatism by introducing protection levels, though the focus remained on worst-case scenarios (Fischetti et al. 2009).

5.1.3 Fuzzy and robust fuzzy programming

Fuzzy set theory and possibilistic programming model imprecise data using membership functions rather than probabilities. These methods are particularly suited for epistemic uncertainty. Robust fuzzy Programming integrates fuzzy and robust programming to combine their strengths. This approach has also been extended to address flexibility in objectives and constraints (Pishvaee et al., 2012). Fuzzy programming is generally categorized into:

- Flexible programming, which manages imprecision while introducing flexibility in objectives and constraints.
- Possibilistic programming, which directly handles vague or imprecise input parameters.

5.1.4 Robust possibilistic programming

One of the contributions of this thesis is the development of a Possibilistic Robust Programming approach (Publication I). It combines light-robust optimization with possibility theory. While classical robust methods often sacrificed optimality for guaranteed feasibility, this approach extends the interval representation of uncertain parameters through fuzzy membership functions. This enables a more nuanced trade-off between robustness and optimality, resulting in practical and less conservative solutions.

In the case of MEMs, where electricity demand is uncertain due to the high penetration of renewables, hydrogen integration, and evolving consumer behavior, this uncertainty consideration approach provides an effective tool to optimize MG operations under uncertain and evolving conditions.

5.2 Decomposition

The planning and operation of MEMs lead to a Mixed-Integer Nonlinear Programming (MINLP) problem. The binary decisions (e.g., unit commitment, equipment on/off states) and nonlinear constraints arising from gas flow equations and Kirchhoff's laws in electricity networks make direct solution highly challenging. In the following, different solving approaches are compared to highlight the reason for applying decomposition methods, as represented in Table 3.

Table 3. Comparison of solving approaches.

Approach	Characteristics	Strengths	Limitations
Classical Exact (e.g., Branch-and-Bound)	Enumerative algorithms exploring the full solution space	Guarantee an optimal solution	Computationally prohibitive for large MEMs
Heuristic / Metaheuristic [e.g., GA, PSO]	Search-based, problem-driven algorithms	Flexible; fast; easy to implement	No guarantee of optimality; sensitive to tuning
GBD	Decomposition into master (integer) + subproblems (nonlinear)	Handles large-scale MINLPs; converges to exact solution	Iterative; may require many cuts
OA/ER	Iterative outer approximation of nonlinear constraints	Effective for convex problems	Can be trapped in local optimal under non-convexity
OA/ER/AP	Enhanced OA/ER with augmented penalty terms	Expands feasible region; ensures global solution	More complex implementation

5.2.1 Classical and heuristic approaches

guarantee global optimality, and their performance is often problem-dependent, requiring significant calibration.

5.2.2 Decomposition approaches

To address both tractability and solution quality, decomposition methods are employed. These approaches divide the MINLP into smaller, structured subproblems that are solved iteratively, thereby reducing computational complexity while maintaining rigorous optimality properties (Floudas, 1995).

5.2.2.1 Generalized Benders Decomposition (GBD)

Generalized Benders Decomposition (GBD) is one of the most widely applied techniques for MINLPs. It separates the model into a master problem, which handles discrete (integer) variables, and subproblems, which handle the nonlinear continuous components. The method iteratively refines the feasible region using Benders cuts and converges in a finite number of iterations. GBD is particularly effective in MEM applications where nonlinear physical constraints make direct optimization difficult.

5.2.2.2 Outer Approximation with Equality Relaxation Decomposition

The OAER method was originally introduced to solve nonlinear optimization problems by approximating nonlinearities with linear representations while relaxing equalities. It can be adapted for MEM studies that involve nonlinear network constraints. However, because OAER relies on convexity assumptions, it may yield local rather than global solutions when applied to non-convex systems. To address this, the OAER with the Augmented Penalty method [55] can be developed for optimal MEM operation and planning. By enlarging the feasible region and penalizing invalid linearization, it increases robustness and ensures convergence to the global optimal solution. This makes OAER a reliable approach for MEM planning and operation problems.

5.3 Multi-objective programming

Multi-Objective Goal Programming (MOGP) is an optimization technique designed to handle problems with multiple, often conflicting objectives. In the context of optimal MG's planning and operation, MOGP allows decision-makers to simultaneously consider different performance criteria, such as cost minimization, emission reduction, and resilience enhancement. The primary advantage of MOGP is its ability to quantify trade-offs between objectives, providing a set of solutions that reflect varying levels of satisfaction for each goal. This feature enables operators to make informed decisions by selecting solutions that best align with their priorities. Additionally, MOGP can reduce computational complexity in multi-objective problems by converting them into a single aggregated optimization framework, which often decreases the number of iterations and solving time compared to solving multiple objectives separately (Hosseini-Motlagh et al., 2020).

6 PLANNING AND OPERATION OF MEMS WITH FOCUS ON REVERSIBLE SOLID OXIDE CELLS

Hydrogen technologies, such as ELZs, FCs, and hydrogen-fired power units, are studied extensively for their ability to balance supply-demand mismatches and enhance system resilience in publications of the thesis. Here, in addition to a combination of ELZs and FCs, rSOCs are also studied, which is a promising technology in this context, offering both high efficiency and bidirectional operation. Unlike conventional systems where ELZs and FCs operate separately, rSOCs can switch between ELZ mode (producing hydrogen) and FC mode (generating electricity), thus providing enhanced flexibility and resilience to the MEM.

This chapter investigates the operational planning and integration of hydrogen technologies in renewable-based MEMs, emphasizing the role of rSOCs. A detailed mathematical model that captures electricity and hydrogen network constraints, component operations, and resilience strategies is used for this purpose (Publication I and Publication II). The chapter draws insights from a comprehensive study evaluating various hydrogen integration scenarios, including conventional hydrogen-fired units, separate ELZs and FCs, and rSOC-based systems, under both normal and High Impact Low Probability (HILP) conditions, such as the upstream grid outages.

6.1 Role of reversible solid oxide cells in MEMs

6.1.1 Overview of reversible solid oxide cell technology

rSOCs are advanced electrochemical devices capable of operating in two modes: solid oxide electrolysis cell mode for hydrogen production and solid oxide fuel cell mode for electricity generation. Their high-temperature operation (~700–900°C) enables superior efficiency compared to low-temperature ELZs and FCs, owing to better thermodynamic integration and lower overpotentials (Publication I).

In MEMs, rSOCs serve as flexible interface components between electrical and hydrogen subsystems. They can absorb excess renewable electricity during periods of high generation by producing hydrogen (ELZ mode) and can generate electricity from stored hydrogen during periods of high demand or grid outages (FC mode). This bidirectional capability reduces the need for separate ELZs and FCs, potentially lowering capital costs and improving system efficiency. The upsides to the incorporation of rSOCs into MEMs can be as follows:

Elimination of renewable curtailment: As discussed, by converting surplus renewable electricity into hydrogen, rSOCs can prevent wastage of RE, thereby maximizing utilization of installed RES capacity.

Reduction of load shedding: During periods of high electricity demand or main grid outages, rSOCs can generate electricity from stored hydrogen, significantly reducing load shedding and enhancing supply continuity.

Enhanced operational flexibility: The ability to switch modes can provide MEMs with an adaptive response to variable renewable generation and fluctuating demand patterns.

Improved economic performance: Although rSOCs have higher upfront investment costs compared to separate ELZ-FC systems, their higher efficiency can be translated into lower annual operating costs.

Resilience under upstream grid failure: During extreme conditions such as simultaneous high demand, low renewable availability, and grid failure, rSOCs, combined with hydrogen storage, can help maintain MG autonomy and avoid blackouts.

However, optimizing the operation and planning of MEMs with rSOCs need to a comprehensive approach that accounts for:

Network constraints: Electrical power flows are modelled using second-order cone approximations of AC power flow equations, respecting voltage, current, and thermal limits. Hydrogen flows within pipelines are captured using Lacey's equation to represent pressure drops and pipeline linepack dynamics.

Component constraints: Operational limits on rSOC capacity, mode-switching dynamics, efficiency losses, and hydrogen storage tank capacities are enforced to ensure feasible and realistic system behaviour.

Economic objectives: The total cost function includes electricity and hydrogen operating costs, capital investments (annualized), and penalties for unmet demand or load shedding.

Resilience scenarios: The model includes High Impact Low Probability (HILP) events such as main grid outages and peak demand conditions, ensuring the MG can sustain operations autonomously.

The model and formulation have been discussed in more detail in the publications (e.g., Publication I and Publication II).

6.1.2 Case study insights

A case study involving a multi-node hydrogen distribution network coupled with an electricity grid is examined under various technology deployment scenarios. The hydrogen and electricity networks under study are indicated in Figure 8. Demand from different sectors and availability of wind are also represented in Figure 9 and Figure 10. The impact of extreme weather events is studied, which includes HILP, e.g., low renewable-high demand when there is a failure in the main grid (i.e., representative day four).

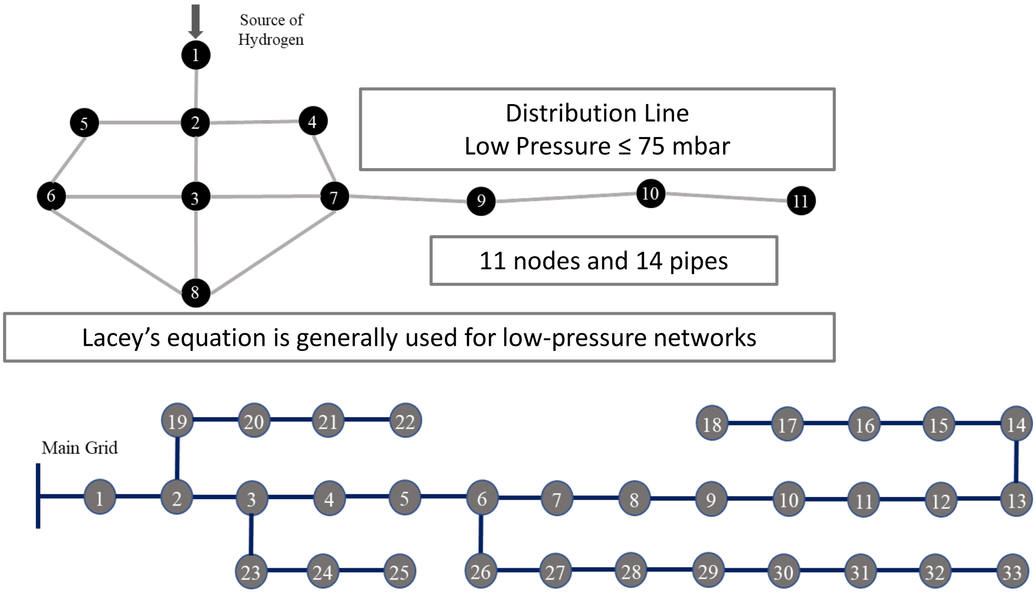

Figure 8. Hydrogen and electricity networks under study.

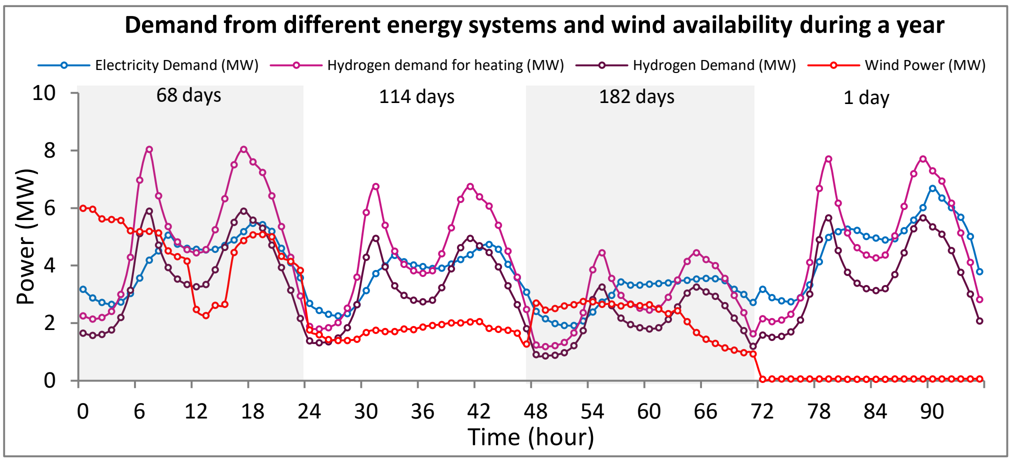

Figure 9. Demand from hydrogen and electricity networks under study and wind power availibility.

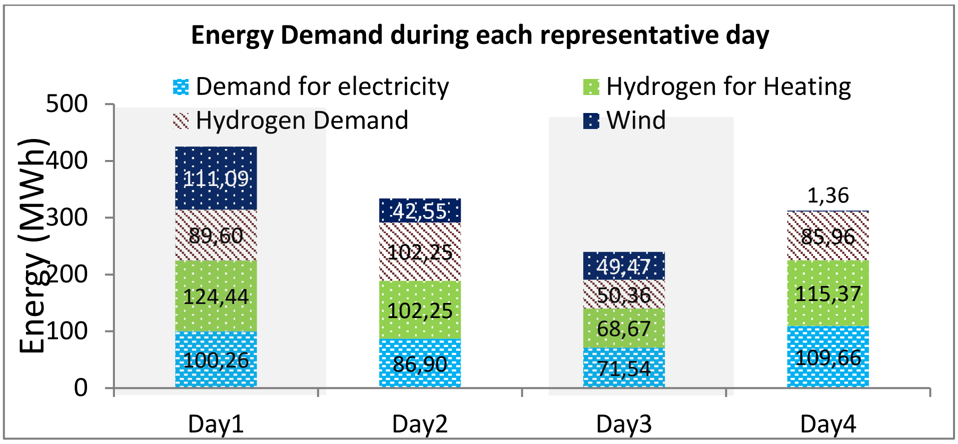

Figure 10. Energy demand from hydrogen and electricity networks under study.

Scenarios for planning are studied, which are listed in the following. It should be noted that, in the resilience scenario, the planning assumes the main grid outage during the fourth representative day, simulating HILP events. By planning and considering the HILP event, this approach provides resilience solutions, taking advantage of the employment of ELZs and FCs or rSOC. The following is a list of scenarios that are studied in this chapter.

i. *Only Renewables and Interaction with Main Grid (Base)*

ii. *Presence of Hydrogen-Fired Units (H2P)*

iii. *ELZ and FCs (ELEC+FC)*

iv. *rSOC*

v. *Resilience*

6.1.3 Implications for future MEM

In scenario (i), a total of 5.23 MW of renewable capacity is installed within the MG. The performance is analyzed over representative operating days to evaluate the balance between demand, renewable generation, and reliance on the main grid. On the representative day 1, a significant amount of renewable power is curtailed due to the mismatch between generation and demand (more power is available compared to the required power), coupled with the absence of storage in the system. The curtailed energy amounts to 13 MWh during the day and approximately 925 MWh over the year. It should be noted that this power cannot be sold to the main grid due to current limits of lines. On representative day 4, load shedding occurs as a result of insufficient renewable availability, leading to an unmet demand of 37 MWh.

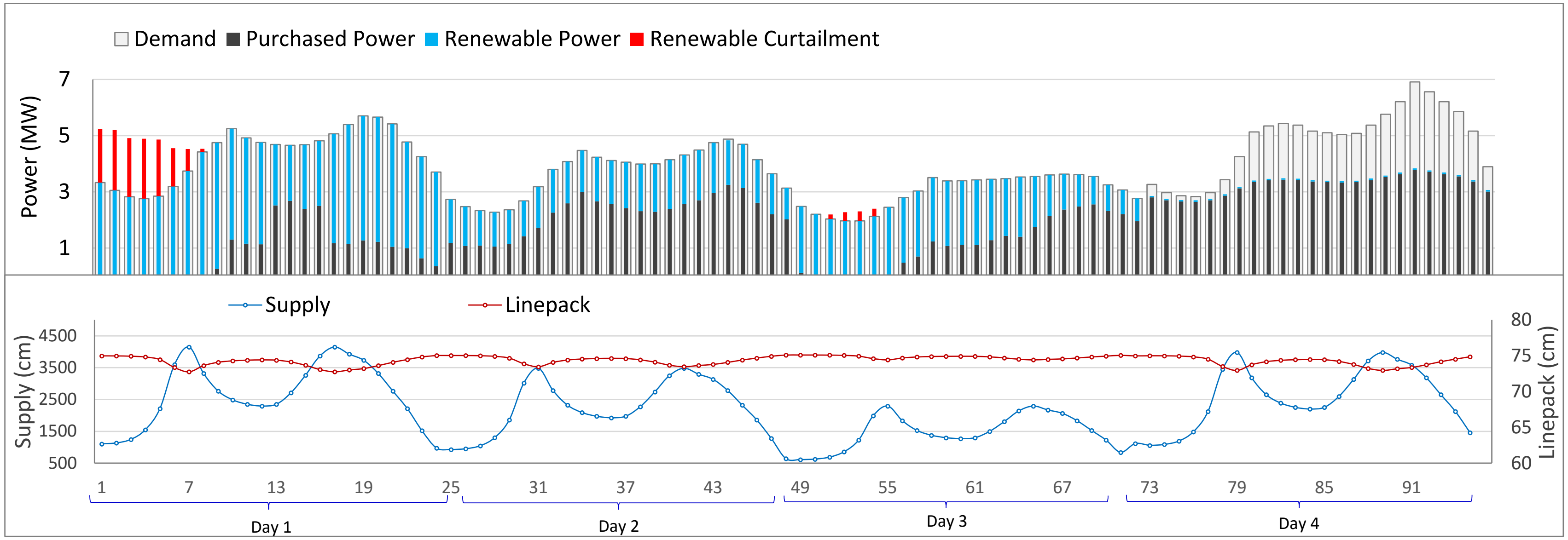

Figure 11. Dispatch of MEM and hydrogen supply and linepack within pipelines (only renewables are available, and electricity and hydrogen can be purchased from upstream grids).

In this scenario, the system shows a high dependence on the main grid for energy supply, with 99% reliance during day 4. This highlights a strong vulnerability in the case of the main grid failure. The dispatch of the MEM, in Figure 11, shows that only renewable generation is available locally, while electricity and hydrogen are purchased from upstream grids. This results in curtailment during periods of excess renewable generation and load shedding when the renewable supply is inadequate. The hydrogen supply and linepack dynamics within pipelines further illustrate fluctuations across operating days, with variations in supply and storage (linepack) that can impact system reliability.

A comparison of total supply during the four operating days emphasizes the contribution of RE, purchased electricity, curtailment, and load shedding to the overall energy balance (Figure 12).

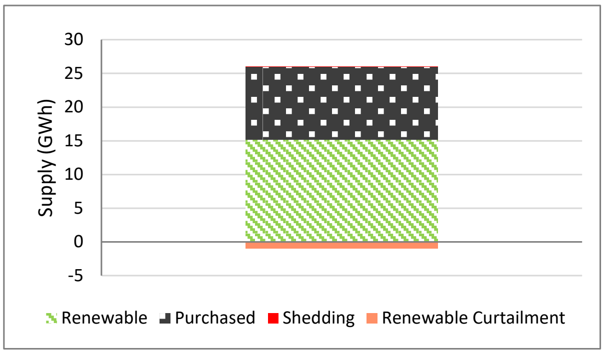

Figure 12. Total Supply During the Four Operating Days- Only Renewables are available, and electricity and hydrogen can be purchased from upstream grids (Shedding 37 MWh in representative day 4).

In scenario (ii), 4 MW of existing fuel-fired units are renovated to operate with hydrogen (i.e., results of solving the planning problem). In this scenario, on representative day 4, load shedding is reduced by 60%, decreasing from 37 MWh in the base case to 14 MWh. The dependency on the main grid drops significantly, from 99% in the base case to 38%, highlighting a notable improvement in system autonomy. The renovated hydrogen-fired units provide additional flexibility and help mitigate demand shortfalls. However, they do not completely resolve curtailment, particularly during periods, such as the first operating hour. The dispatch of the MG and hydrogen supply, and linepack are indicated in Figure 13.

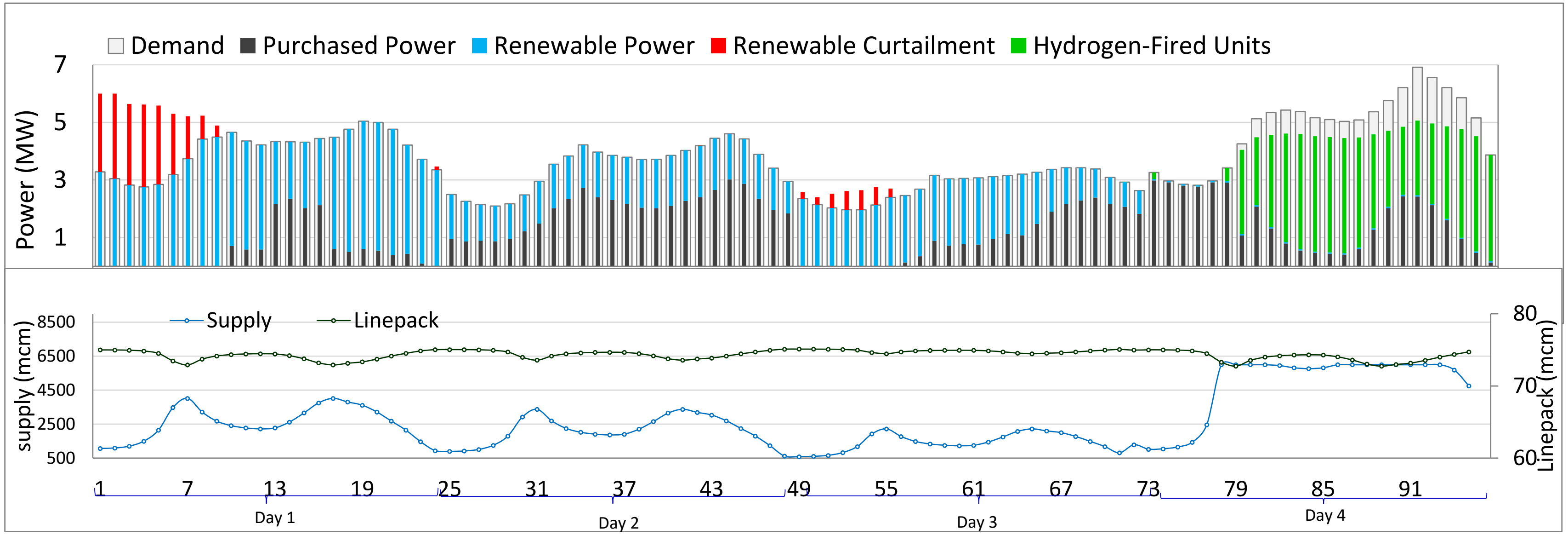

Figure 13. Dispatch of MEM and hydrogen supply and linepack within pipelines (renewables and hydrogen-fired units).

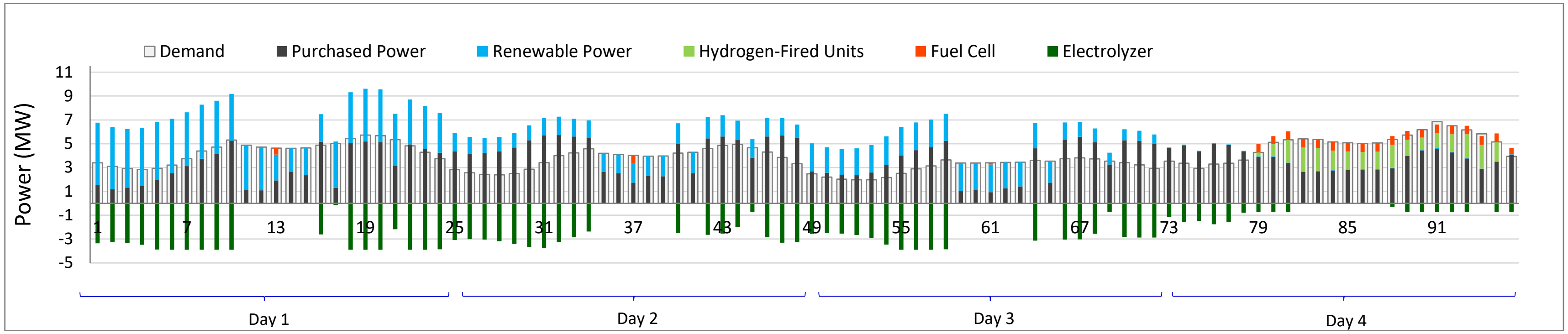

Figure 14. Dispatch of MEM and hydrogen supply and linepack within pipelines (presence of hydrogen-fired units, ELZs, and FCs).

It should be noted that the operation of hydrogen-fired units introduces a dependency on hydrogen supply. A consistent and sufficient supply is essential, but it can be challenging to guarantee, especially during periods of high demand. The efficiency of hydrogen-fired units is relatively low, which leads to higher hydrogen consumption. This results in a decrease in linepack levels, as observed in pipeline dynamics, and poses challenges for long-term system stability.

In scenario (iii), Figure 14, the system integrates 3.89 MW of ELZs and 0.95 MW of FCs, enhancing the role of hydrogen in balancing supply and demand. The presence of ELZs enables green hydrogen production during periods of high renewable availability, ensuring that renewable power is fully utilized.

In this case, only 9.75 MWh of load shedding occurs in ELEC+FC, which represents a 30% reduction compared to H2P. Around 800 k€ reduction in hydrogen network operating costs is observed in this scenario (20% decrease). Moreover, a 267 k€ reduction in electricity network operating costs (2% decrease) compared to scenario (ii). However, the capital cost is 210 k€ higher than H2P (26% increase) due to the inclusion of ELZs and FCs. The investment and operating costs of this scenario are indicated in Figure 15.

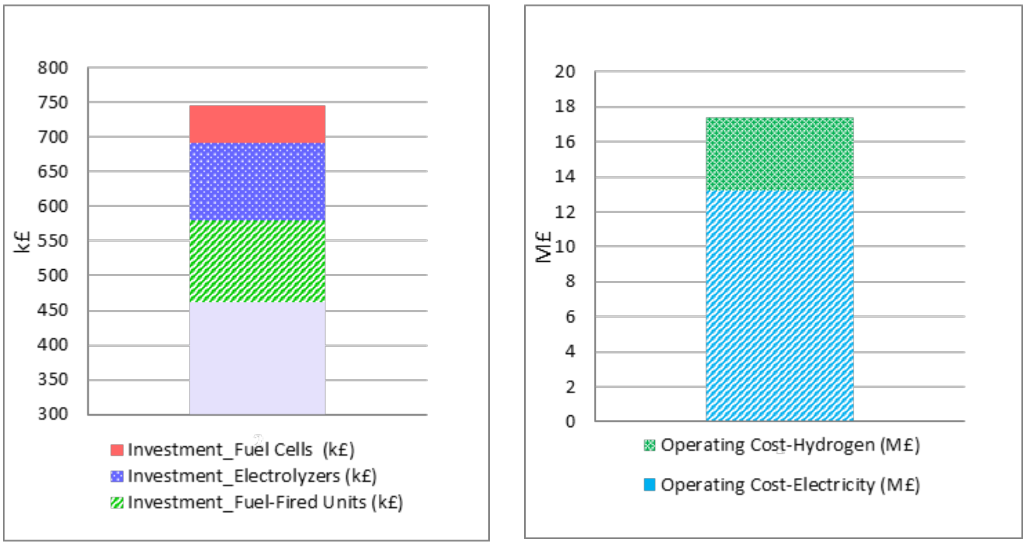

Figure 15. Investment and operating costs (presence of hydrogen-fired units, ELZs, and FCs versus rSOC).

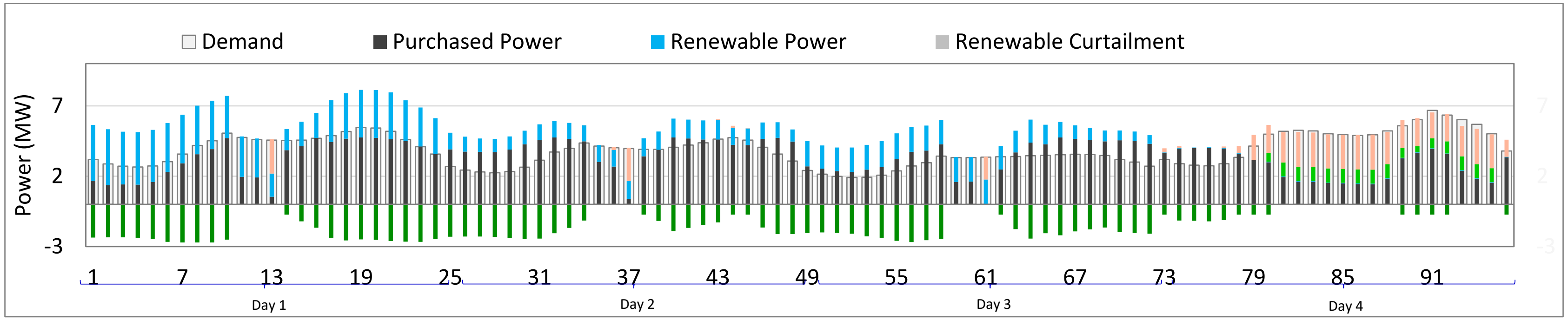

Figure 16. Dispatch of the MEM-rSOC.

In scenario (iv), a total of 2.78 MW of rSOCs were installed within the MG system. The dispatch profile over four days (Figure 16) highlights the contributions of renewable generation, hydrogen-fired units, rSOC power production, and hydrogen production. Importantly, no renewable curtailment was observed due to the capability of the rSOC to utilize excess green electricity for hydrogen production during periods of high renewable availability.

A key advantage of the rSOC configuration lies in its ability to reduce load shedding. Compared to conventional ELZ and FC (ELEC+FC) systems, where load shedding amounted to 9.75 MWh and 14 MWh in H2P, respectively, the rSOC scenario required only 5.34 MWh. However, this comes at the cost of higher storage requirements, approximately 40% greater than in the ELEC+FC configuration.

From an economic perspective, rSOC operation demonstrates improved efficiency, leading to a reduction of approximately 426 k€ in annual operating costs compared to ELEC+FC. Nevertheless, this efficiency gain is offset by higher capital investment costs: 42.8 k€ greater than the ELEC+FC configuration. When both investment and operational expenditures are accounted for, the rSOC scenario results in a total annual operating cost saving of 258 k€ (a 1.5% reduction) relative to ELEC+FC (Figure 17). Overall, the rSOC scenario provides a technically robust and economically favourable option for MG integration, particularly in contexts with high renewable penetration and the need to minimize curtailment

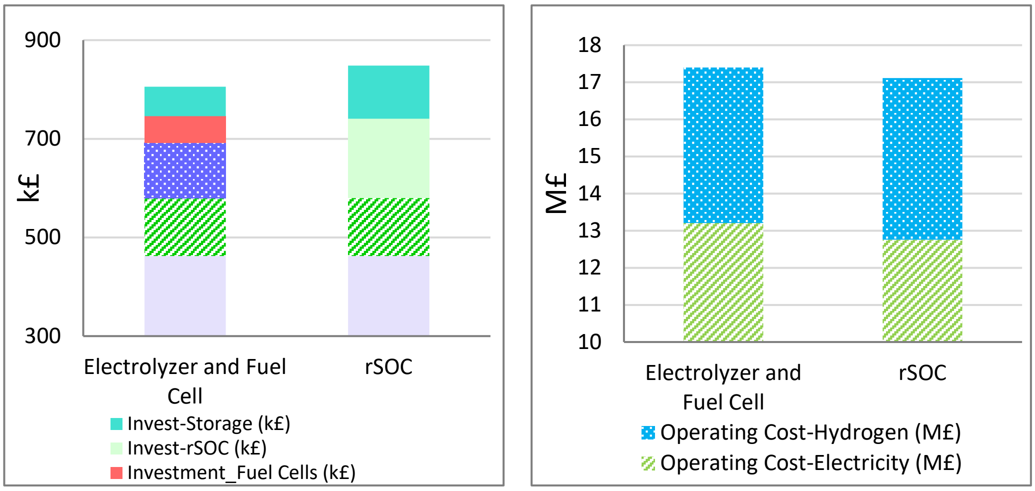

Figure 17. Investment and operating costs (presence of hydrogen-fired units, ELZs, and FCs versus rSOC).

In scenario 5, the role of advanced storage technologies in enhancing system resilience during extreme conditions is investigated. Specifically, it simulates a main grid outage on the fourth representative day, representing an HILP event. The analysis evaluates the performance of two configurations: ELZ and FC (ELEC+FC), and reversible solid oxide cells (rSOC). The changes in operating cost, load shedding and curtailment, and investment costs are indicated in Figure 18.

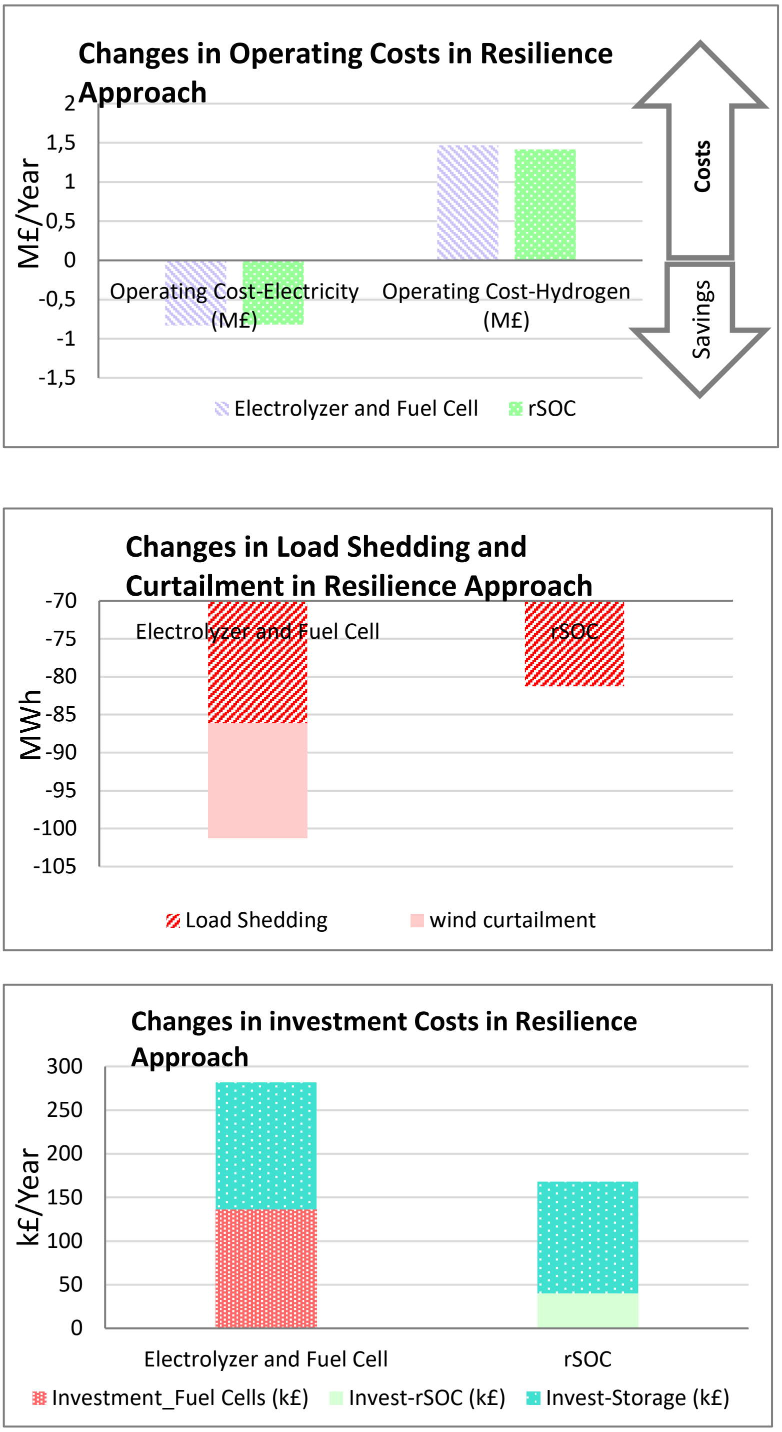

Figure 18. Changes in operating cost, load shedding and curtailment, and investment costs.

The results indicate significantly higher storage requirements in both configurations under the resilience approach. For ELEC+FC, storage requirements increase by 243%, while rSOC requires 118% more storage compared to the baseline. Additionally, ELZ and FC requirements are 82% higher for the ELEC+FC system and 25% higher for rSOC, reflecting the increased reliance on these technologies to sustain demand during prolonged outages. From a cost perspective, the resilience approach yields mixed outcomes. On the one hand, electricity network costs are reduced by approximately 800 k€ in both cases due to reduced dependency on external power supply. On the other hand, the hydrogen network costs increased, as both H2P and FC technologies became critical in meeting demand during the outage. Importantly, the resilience approach eliminates load shedding. While baseline configurations experienced notable load shedding, resilience planning required an additional investment of around 500 k€ in both scenarios to ensure zero loss of load. This additional expenditure reflects the value of resilience-oriented planning, where cost increases are justified by improved resilience and uninterrupted supply.

Overall, the findings emphasize that incorporating resilience into energy planning significantly alters system requirements and cost structures. While both ELEC+FC and rSOC configurations incur higher investment and operational costs, they provide critical resilience benefits under HILP events by preventing load shedding and ensuring continuity of supply.

7 CONCLUSION

7.1 Summary of contributions

This thesis has addressed the modelling of operation and planning of low-emission MEMs with a particular emphasis on the role of hydrogen as a flexible and dispatchable energy system. A comprehensive framework was developed to integrate electricity and gas networks, explicitly modelling hydrogen flows, pressures, and interactions with electricity distribution system operations. The framework enabled the incorporation of renewable generation, ELZs, FCs, battery storage, DR, and EVs into a unified optimization environment, thereby enhancing the flexibility, resilience, and sustainability of future energy systems with focusing on emissions reduction.

The methodological contributions of this work include the development of possibilistic-robust programming techniques for uncertainty handling, multi-objective optimization approaches to balance economic, environmental, and resilience objectives, and advanced decomposition-based solution strategies for solving large-scale planning and operation problems. The thesis also examined the role of hydrogen beyond storage, including its use as a distribution medium via pipelines and as an enabling technology for rSOCs, which can provide long-duration storage and sector coupling services.

7.2 Answers to research questions

The research questions posed at the outset of this thesis were addressed through the development of integrated frameworks, advanced optimization methods, and validation via case studies. The findings demonstrate that electricity and gas networks, including hydrogen infrastructures, can be co-optimized within a unified framework, yielding lower operational costs, reduced emissions, and greater reliability compared with independent operation. Incorporating resilience criteria into the models further ensured the security of supply during disturbances, with hydrogen playing a central role as a flexible and dispatchable energy vector.

The work also established that hydrogen integration enhances operational flexibility by enabling higher renewable penetration, providing large-scale storage, and supporting industrial end-use applications. To make these models computationally viable, decomposition-based algorithms and multi-objective methods were developed, which proved effective in handling the complexity of MEM planning and operation. Furthermore, robust and possibilistic uncertainty modelling was shown to produce solutions that remain valid under fluctuating renewable output, market prices, and demand conditions, thereby improving the realism and applicability of the results.

In addition, the analysis highlighted the contribution of emerging technologies such as EVs, DR programs, and ESSs in enhancing flexibility, reducing emissions, and improving economic performance. The feasibility assessment of hydrogen transport through existing natural gas pipelines revealed both technical constraints and potential for blending as a transitional option. Collectively, these findings not only addressed the technical research questions but also provided actionable insights for policymakers and decision-makers, underlining the role of hydrogen-integrated MEMs in advancing towards secure, cost-effective, and carbon-neutral energy systems.

In the following table, a summary is represented that how research questions were answered in the publications.

Table 4. Connecting research questions to the publications.

Research Question	Solution	Chapter	Publication
Q1	-Developing a model for operational and planning of MEMs -Integrating resilience measure	-Chapter 3 -Chapter 6	Publication II Publication III Publication IV Publication V Publication VII
Q2	-Modelling hydrogen with pipelines -Developing MEMs' model to consider EVs, ESSs, and DRs	-Chapter 3 -Chapter 4	Publication IV Publication V Publication VI
Q3	-Designing an applicability test for hydrogen to be used instead of natural gas -Developing an uncertainty consideration approach -Developing a framework for integrating rSOCs into low emission MEMs	-Chapter 3 -Chapter 5 -Chapter 6	Publication I Publication III Publication IV Publication VII
Q4	-Providing decision makers with useful insights	-Chapter 1 -Chapter 2	Publication I-VII

7.3 Limitations of the research and future research direction

While the thesis provided new methodological and practical insights into the planning and operation of hydrogen-integrated MEMs, some limitations should be acknowledged. For example, the models relied on simplifying assumptions regarding market behaviour and optimizing the problem from the viewpoint of the MG operator, which may limit their direct applicability when there are various owners. Moreover, more practical limitations and constraints can be integrated, such as inverter capacity to provide various services (e.g., frequency control, short circuit current provision, and mimicking inertia of synchronous machines by advanced controllers).

One further step beyond the thesis can be the development of a multi-level framework that accounts for various owners and participants in markets. Future research can also extend the developed framework to more accurately represent the growing share of inverter-based resources, such as wind turbines, battery systems, and power-electronic hydrogen technologies. These units introduce challenges related to fault current contribution, voltage stability, and reactive power support, which demand more advanced modelling of inverter dynamics and the design of grid-forming and grid-following control strategies.

Beyond electricity and gas systems, future work can advance sector coupling by integrating thermal networks and considering interactions across electricity, gas, heating, and mobility sectors. Incorporating life-cycle assessment and circular economy principles into planning models would further align technical optimization with environmental and sustainability goals. Finally, pilot projects and demonstration cases are necessary to bridge the gap between modelling insights and practice, offering empirical validation and facilitating the adoption of hydrogen-integrated MEMs in real-world contexts.

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Optimal possibilistic-robust operation of multi-energy microgrids considering infrastructure hydrogen storage capability

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ABSTRACT

In sustainable energy transitions, the utilization of hydrogen is crucial, providing flexibility in the operation of net-zero emission renewable-based energy systems. This paper presents a study on the optimal operation of net-zero emission multi-energy future microgrids that utilize hydrogen as an alternative fuel instead of natural gas. The electrolyzers' output is injected into the hydrogen grid to meet demand or converted back to electricity later using generating units, owing to the storage capability of pipes, called linepack. For this purpose, a detailed mathematical model is developed to simulate the main characteristics of grids (e.g., voltage, current, hydrogen flow, and pressure) as well as various components (e.g., renewable systems, electrolyzers, and hydrogen-fired units). To become more realistic, a possibilistic-robust approach is developed to account for the uncertainty arising from the lack of real-world implementation. By representing a case study, a test is performed to evaluate the possibility of employing a low-pressure gas grid to meet the demand for hydrogen. After that, the effects of electrolyzers are analyzed in the presence and absence of the uncertainty consideration approach. The result indicates that, despite hydrogen's lower energy density compared to natural gas, it is still feasible to satisfy the same energy demand level, considering the technical characteristics of the grid. The integration of electrolyzers can reduce wind curtailment by 2 % and supplement hydrogen demand by 50 %. A higher level of conservatism in the possibilistic-robust approach leads to an increase in the mean value of the objective function and a reduction in the standard deviation under the realization of uncertain parameters, which provides the decision-makers with a more realistic insight.

Nomenclature

Indices			
t	Time step	b	Bus in electricity grid
n	Node in hydrogen grid	l	Electric line
p	Pipe		
Parameters			
ψ_t	Import price for electric power	ψ'_t	Export price for electric power
ψ''_t	Shedding cost for electric demand	ϕ	Import price for hydrogen
ϕ'	Cost of linepack management	ϕ''	Shedding cost for hydrogen demand

(*continued on next column*)

(*continued*)

$E^{load}_{b,t}/Er^{load}_{b,t}$	Active/reactive power demand	$V^{\max}_b$	Voltage limit
$R_{l,t}/X_l$	Resistance/reactance of electric line	$I^{\max}_l$	Current limit
$E^{dg,min/max}_b$	Minimum/maximum available renewable power	$T^{on/off}$	Minimum up/down time of generating units
$Ramp_b$	Ramp limit	$H^{load}_{n,t}$	Hydrogen consumption
$\pi^{min/max}_n$	Minimum/maximum pressure	$H^{line,\ min/max}_p$	Minimum/maximum flow within pipe
$LP^0_{p,t}$	Initial linepack (stored hydrogen) within pipe	$D_{n,n'}$	Diameter of pipe

(*continued on next page*)

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$L_{n,n'}$	Length of pipe	ξ	Hydrogen required for electricity production using generating unit
ζ	Electricity required for hydrogen production using electrolyzer	$f_{n,n'}$	Friction factor
S	Slope or gradient of pipe	c_{ij}	Cost coefficient
$\widetilde{a}_{ij}$	Imprecise constraint coefficients	b_i	Right-side coefficient
ρ_0	Fixed tolerance	$\widehat{c}$	Optimal value of objective function without uncertainty
z	Control parameter of decision maker	γ	Weighted coefficient
Decision Variables			
OF^{MEM}	Operating cost of multi-energy microgrid	OF^{ELC}	Operating cost of electricity grid
OF^{H_2}	Operating cost of hydrogen grid	E_t^{buy}	Purchased power
E_t^{sell}	Sold power	$E_{b,t}^{shed}$	Load shedding
H_t^{buy}	Purchased hydrogen	$\Delta H_{n,t}$	Changes in hydrogen within pipe
$HNS_{n,t}$	Hydrogen-not-supplied	$E_{b,t}^{dg}$	Electric power from renewable resources
$E_{b,t}^{rnw}$	Electric power of gas-fired unit	$E_{l,t}^{line}/Er_{l,t}^{line}$	Active/reactive power within line
$E_{b,t}^{elz}$	Electric power consumption of electrolyzer	$V_{b,t}$	Voltage
Er_t	Reactive power from the main grid	$I_{l,t}$	Current
$\Gamma_{i,t}$	On/off status of generating units	$H_{n,t}^{elz}$	Hydrogen production of electrolyzers
$\pi_{n,t}$	Pressure	$H_{p,t}^{line}$	Hydrogen flow within pipe
$LP_{p,t}$	Linepack (stored hydrogen within pipes)	$H_{p,t}^{pipe,in/out}$	Hydrogen flow to/from pipe
$H_{n,t}^{dg}$	Hydrogen required for generating units	z	Objective function
x_{ij}	Decision variables	Γ_i	Protection level
Abbreviations			
RES	Renewable Energy Systems	MEM	Multi-Energy Microgrids
PRP	Possibilistic-Robust Programming	DICOPT	Discrete and Continuous Optimizer
GAMS	General Algebraic Modeling System	NG	Natural Gas
NGL	Natural Gas-Low Initial Linepack	H2	Hydrogen
mcm	Million Cubic Meter	kcm	Thousand Cubic Meters
H2L	Hydrogen-Low Initial Linepack	MINLP	Mixed-Integer Nonlinear Programming

1. Introduction

Currently, a considerable share of emissions stems from the energy sector as there is still dependency on burning fossil fuels for energy demand provision. To address this concern, governments of different countries set targets to increase their renewable energy share in their final energy consumption [1]. This objective is being pursued through various policies promoting the adoption and development of Renewable Energy Systems (RESs). These policies include financial incentives like feed-in tariffs, investment grants, and tax credits to encourage the installation of RESs [2]. However, despite their efforts, the key challenge still includes the intermittent nature of renewable sources impacting the grid [3]. A solution can be to utilize flexible gas-fired units burning hydrogen to manage intermittency and address supply-demand provisions without emissions [4]. The existing gas grid infrastructure can be repurposed to transport and distribute hydrogen to the gas-fired units, reducing the need for new investments [5]. The hydrogen produced by electrolyzers can also be injected into the grid to supply these units or provide hydrogen demand for other purposes, leading to reduced emissions and moving toward a carbon-neutral energy sector [6].

In order to study the role of hydrogen in the operation of energy systems, it is of great importance to consider the time that it takes to transfer gas from the supply point to the demand point. However, the gas stored within the pipes, known as linepack, can help manage sudden changes in demand by compensating for the mentioned time delay. Linepack also serves as a form of storage, allowing gas to be reserved for later use, which optimizes the need for additional storage systems to provide flexibility [7]. A growing number of studies focus on the incorporation of alternative fuels within natural gas grids, employing steady-state models to inform their analyses with respect to the linepack within pipes. For instance, in [8], the distributed injection of alternative fuels, such as hydrogen and biogas, into transmission gas grids was examined. The findings indicated the potential to supplement demand by injecting alternative fuels up to a 10 % mixture. In [9], a case study in Germany was considered to examine the impact of hydrogen on the supply of energy. This study provided insight into the capacity of electrolyzers, hydrogen storage systems, and fuel cells used in future scenarios, which showed that hydrogen is still expensive due to the high loss factor of conversions. While highlighting the role of hydrogen and linepack management on the supply side of natural gas systems, the above-mentioned studies did not focus on its conversion for use in the power sector.

Some other studies focused on the electricity grid operation, considering the production and/or sale of hydrogen in the market. For instance, in [10], a risk-averse operating model was developed for a grid-connected energy system, which consisted of photovoltaic systems, wind turbines, diesel generators, and hydrogen storage systems. The results indicated the potential cost savings of interactions with electricity and hydrogen markets. In [11], an operating model for a microgrid was developed and optimized to improve the resilience in the islanded mode. It indicated that the capability of the integration of electrolyzers, fuel cells, and hydrogen storage systems to reduce the load shedding in the case of an unexpected failure in the upstream grid. In [12], the role of hybrid hydrogen and battery storage systems in the optimal dispatch of an isolated electricity grid was studied. By analysis of a case study indicated that the hybrid system facilitated the integration of renewable resources. In [13], a stochastic model was developed for the dispatching of energy systems, analyzing the role of power-to-gas systems for seasonal storage. The output demonstrated the seasonal storage capability to improve the operation of the energy system. In [14], the optimal operation of a transmission electricity grid was optimized considering power-to-gas systems. The results addressed the economic and environmental improvement obtained by scheduling the integration of the power-to-gas systems. In [15], the integration of fuel cells into photovoltaic and wind units is studied by developing a model for a multi-microgrid. Developing a heuristic solving approach, this studies reduce the allocation cost by developing a framework for this purpose. In [16], energy management of microgrids that rely on renewable and hydrogen storage is optimized using artificial intelligence. However, in [17], the optimal operation of stand-alone and photovoltaic-based microgrids is examined, which are equipped with hydrogen storage systems. The results of the studies indicate the more efficient and economical energy management through the devised frameworks. The main drawback of the reviewed studies was that they did not model the gas or hydrogen grids, and their mathematical models of the optimization problems were neither detailed nor realistic.

Multiple research efforts have explored both gas and electricity grids, specifically investigating the viability of injecting produced green hydrogen, generated via electrolyzers, into natural gas grids. Notably, in [18], the potential of power-to-hydrogen systems to enhance flexibility within both natural gas and electricity grids was highlighted. This study anticipated future energy scenarios, where surplus RESs' output could be converted into hydrogen using power-to-hydrogen technologies. This surplus hydrogen could also be integrated into the natural gas grid to meet demand requirements. Alternatively, during instances of demand exceeding supply in the electricity grid, the stored hydrogen could be reconverted into electricity through the fuel cells, offering a flexibility option that provides cost savings. In [19], the planning for flexibility options was conducted to facilitate the operation of natural gas and electricity grids for future energy resources. The outputs indicated that the integration of flexibility options, such as flexible gas-fired units and compressors, provided operating cost savings. Although these studies focused on the operation of multi-energy systems considering flexibility options, they only focused on the natural gas grid. None of them focused on a net-zero emission future grid that fully supplies hydrogen through pipes to meet demand.

Aside from the recapped issues, the development of a method to deal with intermittent and vague parameters makes the output more realistic. For instance, in [20], a planning approach is conducted to allocate a microgrid integrated into a hydrogen grid using a stochastic approach. In [21] and [22], a scenario-based stochastic method is employed to operate multi-microgrids connected to the hydrogen grid. In [23], hydrogen storage planning is implemented to reach peak shaving and valley filling utilizing robust programming. In [24], a possibilistic approach is used to dispatch different parties in a microgrid, such as wind turbines, hydrogen storage systems, and heat storage systems. In [25], the operation and configuration of a microgrid are optimized, which relies on electrolyzers and fuel cells. This study uses robust programming to capture the uncertainty in renewable resources and demand. Although uncertainty has been considered in the existing literature, most proposed approaches are scenario-based according to the reviewed studies, which increases the computational complexity of solving the optimization problem. This underscores the need for non-scenario-based methods to effectively reduce the complexity associated with the optimal operation of MEMs.

Following the examination of existing studies in the related subjects (Table 1), the main objectives of this study are as follows:

- Primary Objective: to develop a comprehensive framework for assessing the applicability of existing gas infrastructure for hydrogen distribution, and to investigate the role of electrolyzers, flexible hydrogen-fired units, and the storage capability of pipelines (i.e., linepack) within MEMs. For this purpose, a detailed operating model of the hydrogen grid is developed, considering constraints such as hydrogen pressure limits, hydrogen flow limits, and linepack variations. Additionally, a test is proposed to evaluate the adaptability of previously used low-pressure natural gas grids for hydrogen distribution, taking into account supply-demand balance. The framework is further enhanced to simulate and optimize MEM operation by integrating the electric grid, incorporating parameters, such as voltage at connection points, current flow through lines, and active/reactive power.
- Secondary Objective: to propose a novel Possibilistic-Robust Programming (PRP) approach that captures uncertainty in key parameters and provides a more realistic decision-making environment based on possibility and necessity theories within fuzzy logic and robust optimization. This approach simulates uncertainties to assist decision-makers, whose performance is evaluated through the realization of uncertain parameters and the comparison of mean values and standard deviations.

By representing a case study, the test is conducted to evaluate the capability of the former low-pressure natural gas grid to be used for hydrogen. The role of electrolyzers in producing hydrogen to be injected into the hydrogen grid is examined. The produced green hydrogen can be either used to assist hydrogen supply-demand provision or converted back to electricity by hydrogen-fired units, owing to the linepack. More precisely, the interaction between the grids, the effects of hydrogen on the operation of the electricity grid, and the role of the uncertainty consideration approach are studied in detail.

2. Methodology

In this section, the operating model for the MEM, which consists of an electricity grid and a hydrogen grid utilized for hydrogen transportation, is presented (Step I). Afterward, integrating the uncertainty consideration approach based on possibilistic and robust programming is explained to be more realistic (Step II). Then, the solving approach and the test for the applicability of the natural gas grid to be used for hydrogen are introduced (Step III), as demonstrated in Fig. 1. It should be noted that, after the methodology, the main steps are case study representation and determination of scenarions (i.e., Step IV), represented in Section 3. At the end, the results and analyses are conducted in Section 4 (i.e., Step V).

Before developing an operational model, the definition of a microgrid is introduced in this section. A microgrid is a localized energy system that can operate autonomously or in conjunction with the main grid, integrating various energy sources to meet the needs of a specific community or facility. Microgrids are key components in the transition to resilient and sustainable energy systems because they enhance energy security, reduce transmission losses, and facilitate the integration of renewable energy sources such as wind and solar [26]. In contrast to traditional microgrids, multi-energy microgrids go a step further by incorporating multiple forms of energy, such as electricity, heat, and gas, allowing for a more flexible and efficient energy exchange. These systems leverage diverse energy carriers, like hydrogen, to optimize overall energy efficiency and reliability, while balancing supply and demand across different energy vectors. By coupling sectors and enabling energy storage through systems, such as hydrogen linepack, multi-energy microgrids play a critical role in advancing net-zero emission goals and improving the resilience of future energy infrastructures [27].

The following subsection presents a detailed mathematical model of a multi-energy microgrid that integrates electricity and hydrogen systems. It should be noted that in the hydrogen grid's model, the continuity and momentum equations are employed to represent gas flow, with the primary assumption that variations in kinetic energy along the pipeline resulting from changes in velocity and density are negligible. In the electricity distribution network model, the demand is represented as constant active and reactive power, power losses along each branch are assumed to occur at the sending end, and the network is modeled as a single-phase balanced equivalent. Furthermore, the microgrid is assumed to interact with the main grid within a day-ahead market framework, and renewable generation output is assumed to follow the forecasted day-ahead profile [11].

2.1. Operational model

To optimize the operation of an MEM, the objective function consists of two terms indicated in (1): (i) the operating cost of the electricity grid and (ii) the operating cost of the hydrogen grid. The operating cost of the electricity grid depends on three terms (Eq. (2)), including (a) the expense of buying electricity from the main grid, (b) the earnings from selling surplus electricity back to the main grid, and (c) the cost of load shedding during emergencies. The cost of operating the hydrogen grid is also influenced by three terms (Eq. (3)), including (a) the cost of purchasing hydrogen from the market, (b) the expenses associated with storing hydrogen within pipes, and (c) the cost of hydrogen shedding when it is required. To ensure a cost-effective operation of the MEM, the summation of the objective functions is minimized subject to a set of constraints, which are introduced in the following.

$$OF^{MEM} = OF^{ELC} + OF^{H_2} \tag{1}$$

$$OF^{ELC} = \sum_{t=1}^{T} \psi_t \cdot E_t^{\mathrm{buy}} - \sum_{t=1}^{T} \psi'_t \cdot E_t^{\mathrm{sell}} + \sum_{t=1}^{T} \sum_{b=1}^{B} \psi''_t \cdot E_{b,t}^{\mathrm{shed}} \tag{2}$$

Table 1
A systematic review of previously conducted studies considering various energy carriers.

No.	Ref.	Objective	Solution Method		Grid Consideration			Transmission/ Distribution Level	Solver	Uncertainty Consideration Approach	Components		
			Numerical analysis or simulation	*Exact optimization*	*Electricity*	*Gas*	*Hydrogen*				*Renewable*	*P2G*	*Fuel cell/ gas-fired unit*
1	[8]	-Examining the injection of green hydrogen into gas grids	✓	-	-	✓	-	Transmission	-	-	✓	✓	-
2	[9]	-Examining Germany's hydrogen strategy	✓	-	-	-	✓	Transmission	-	-	✓	✓	✓
3	[10]	-Improve the operation of electricity grids	-	✓	✓	-	-	Transmission	CPLEX	Stochastic	✓	✓	-
4	[11]	-Improve the resilience of microgrids	-	✓	✓	-	-	Distribution (Microgrid)	DICOPT	-	✓	✓	✓
5	[12]	-Improve the integration of renewable resources	-	✓	✓	-	-	Distribution (Microgrid)	GUROBI	-	✓	✓	✓
6	[13]	-Improve the operation of electricity grids	-	✓	✓	-	-	Distribution	CBC	Stochastic	✓	✓	✓
7	[14]	-Improve the operation of electricity grids	-	✓	✓	-	-	Transmission	CPLEX	-	✓	✓	✓
S	[15]	-Improve energy management of microgrids	-	✓	✓	-	-	Distribution (Microgrid)	Huristics	-	✓	✓	✓
9	[16]	-Improve energy management of microgrids	-	✓	✓	-	-	Distribution (Microgrid)	Artificial inteligence	Stochastic	✓	✓	✓
10	[17]	-Improve energy management of microgrids	-	✓	✓	-	-	Distribution (Microgrid)	Huristics	-	✓	✓	✓
11	[18]	-Examining power-to-gas systems from techno-economic aspect	✓	-	✓	✓	-	Distribution	-	-	✓	✓	✓
12	[19]	-Improve the flexibility of gas and electricity grids	-	✓	✓	✓		Transmission	OA/ER	-	✓	✓	✓
13	[20]	-Planning a microgrid with net-zero target	-	✓	✓	-	✓	Distribution (Microgrid)	GUROBI	Stochastic	✓	✓	✓
14	[21]	-Improve the operation of microgrids	-	✓	✓	-	-	Distribution (Microgrid)	CPLEX	Stochastic	✓	✓	✓
15	[22]	-Improve operation and configuration	-	✓	✓			Distribution (Microgrid)	CPLEX	Robust	✓	✓	✓
16	[23]	-Improve the operation of electricity grids	-	✓	✓	-	-	Transmission	CPLEX	Robust	✓	✓	✓
17	[24]	-Improve the operation of electricity grids	-	✓	✓	✓	-	Distribution	CPLEX	Possibilistic	✓	✓	✓

(*continued on next page*)

Table 1 (*continued*)

No.	Ref.	Objective	Solution Method		Grid Consideration			Transmission/ Distribution Level	Solver	Uncertainty Consideration Approach	Components		
			Numerical analysis or simulation	*Exact optimization*	*Electricity*	*Gas*	*Hydrogen*				*Renewable*	*P2G*	*Fuel cell/ gas-fired unit*
18	[25]		-	✓	✓	-	-	Distribution (Microgrid)	GUROBI	Robust	✓	✓	✓
19	*	-Evaluating a net-zero emission multi-energy microgrid	-	✓	✓	-	✓	Distribution (Microgrid)	DICOPT	Possibilistic-Robust	✓	✓	✓

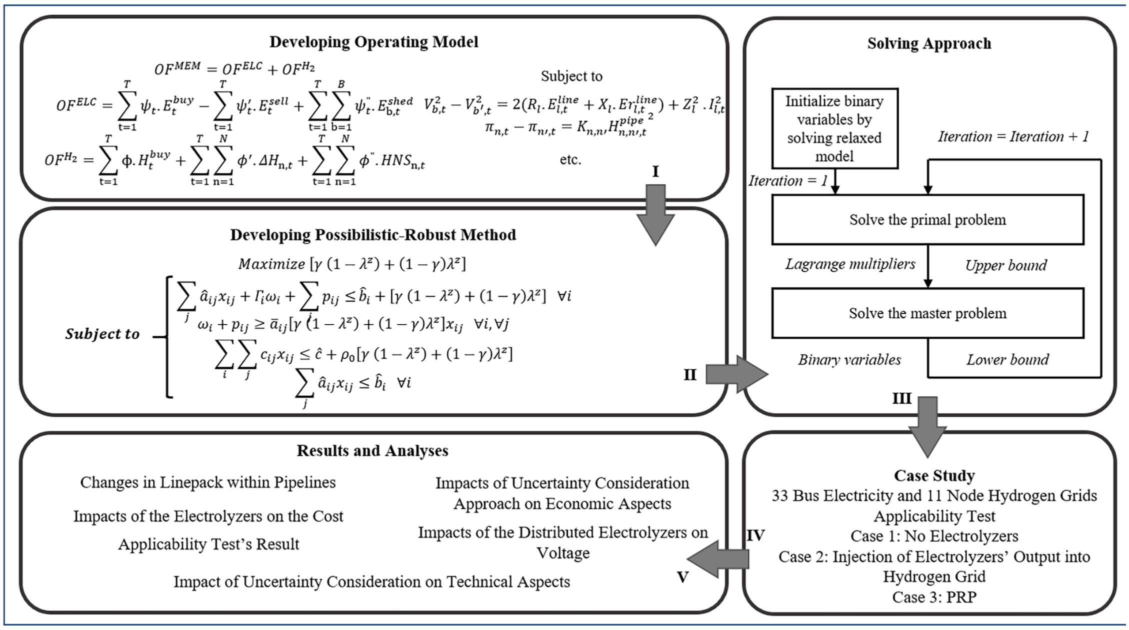

Fig. 1. Overview of the methodology for optimizing microgrid operation with hydrogen energy carrier.

$$OF^{H_2} = \sum_{t=1}^{T} \phi.H_t^{buy} + \sum_{t=1}^{T}\sum_{n=1}^{N} \phi'.\ \Delta H_{n,t} + \sum_{t=1}^{T}\sum_{n=1}^{N}\phi''.HNS_{n,t} \tag{3}$$

2.1.1. Operating constraints of the electricity grid

To fulfill the energy demands of consumers and avoid any risk of system overload or underload when operating an electricity grid, it is important to adhere to technical constraints. In (4), active power balance is presented, which means that the total active power generated by distributed energy resources and renewable resources, along with imported power from the main grid, must match the aggregate active power consumed, losses in distribution lines, power consumption of electrolyzers to produce hydrogen, and exported power to the main grid.

$$E_{b,t}^{dg} + E_{b,t}^{rnw} + E_t^{buy} = E_{b,t}^{load} + \sum_{b'=1}^{B}\left(E_{l,t}^{line} + R_{l,t}.I_{l,t}^2\right) + E_{b,t}^{elz} + E_t^{sell}\ \forall b,\ l\epsilon(b,b'),\forall t \tag{4}$$

Apart from maintaining a balance in active power, the reactive power balance is a crucial constraint that must be taken into consideration in the operation of the electricity grid (Eq. (5)). The operating model should guarantee that the reactive power flow from the main grid matches the total reactive power consumed by the loads and the reactive power losses in the distribution lines. This balance of reactive power is essential in maintaining the voltage stability of the grid.

$$Er_t + \sum_{b'=1}^{B}\left(Er_{l,t}^{line}+X_{l,t}.I_{l,t}^2\right) = Er_{b,t}^{load}\ \forall b,\ l\epsilon(b,b'),\forall t \tag{5}$$

Kirchhoff's law presents another fundamental constraint that should be considered in the electricity grid. According to this law, the voltage and current at every node within the grid must comply with the principle of energy conservation (Eqs. (6)-(7)).

$$V_{b,t}^2 - V_{b',t}^2 = 2\left(R_l.E_{l,t}^{line}+X_l.Er_{l,t}^{line}\right)+Z_l^2.I_{l,t}^2\ l\epsilon(b,b'),\ \forall t \tag{6}$$

$$V_{b,t}^2.I_{l,t}^2 = E_{l,t}^{line\ 2} + Er_{l,t}^{line\ 2}\ l\epsilon(b,b'),\ \forall t \tag{7}$$

The maximum and minimum limits for voltage at nodes and current within lines are also necessary, as represented in Eq. (8) and Eq. (9), respectively.

$$V_b^{min}\le V_{b,t}\le V_b^{max}\ \forall b,\ \forall t \tag{8}$$

$$0\le I_{l,t}\le I_l^{max}\ l\epsilon(b,b'),\ \forall t \tag{9}$$

Additionally, dispatchable and renewable generating units must be operated within their designated or available power limits, as indicated in Eq. (10). However, the ramp-rate limits of dispatchable units constitute another crucial constraint in the operation, indicated in Eq. (11). These limits govern the rate at which the dispatchable units can ramp up or down their power output. Another set of operating constraints that need to be considered is related to the minimum up/down time of these generating units. As proposed in Eq. (12) and Eq. (13), these constraints refer to the minimum amount of time that a dispatchable unit must remain either on or off after being started or stopped.

$$\Gamma_{i,t}E_b^{min} \leq E_{b,t}^{dg} \leq \Gamma_{i,t}E_b^{max}\ \forall b,\ \forall t \tag{10}$$

$$\left|E_{b,t}^{dg} - E_{b,t-1}^{dg}\right| \leq Ramp_b\ \forall b,\ \forall t \tag{11}$$

$$\Gamma_{i,t'} - \Gamma_{i,t'-1} \leq \Gamma_{i,t}\ t'\epsilon[t - T^{on} + 1, t-1] \tag{12}$$

$$\Gamma_{i,t'-1} - \Gamma_{i,t'} \leq 1 - \Gamma_{i,t}\ t'\epsilon\left[t - T^{off} + 1, t-1\right] \tag{13}$$

2.1.2. Operating constraints of hydrogen grid

To optimize the operation of the MEM, a set of constraints is also considered for the hydrogen grid. These constraints cover various aspects of the hydrogen distribution system, ensuring its safe and efficient operation. A set of constraints is related to the hydrogen flow balance, indicated in Eq. 14. This constraint ensures that the amount of purchased hydrogen from the upstream, besides the distributed production by electrolyzers, must be equal to the consumption at each time step within the microgrid. By maintaining this balance, the constraint guarantees that the hydrogen demand is adequately met.

$$H_{n,t}^{elz} + H_t^{buy} = H_{n,t}^{dg} + H_{n,t}^{load} + \sum_{n'=1}^{N} H_{p,t}^{line}\ \forall n,\ \forall t \tag{14}$$

To maintain the integrity of the hydrogen grid, the maximum and minimum pressure at each node are limited in Eq. (15). These constraints impose limits on the pressure at each node to ensure that the grid is operated within safe pressure levels.

$$\pi_n^{min} \leq \pi_{n,t} \leq \pi_n^{max}\ \forall n,\ \forall t \tag{15}$$

The maximum and minimum hydrogen flow within pipes is limited in Eq. (16) to avoid overloading.

$$H_p^{line,min} \leq H_{p,t}^{line} \leq H_p^{line,\ max}\ p\epsilon(n,n'),\forall t \tag{16}$$

Additionally, linepack refers to the amount of gas stored within the pipes. Eq. (17) is also included, which is related to linepack changes to help manage the storage of hydrogen, allowing the system to respond to demand fluctuations effectively.

$$LP_{p,t} = LP_{p,t}^0 + \sum_0^t \left(H_{p,t}^{pipe,in} - H_{p,t}^{pipe,out}\right)\ p\epsilon(n,n'),\ \forall t \tag{17}$$

Lacey's equation plays a significant role in linking hydrogen flow within pipes to the pressure at nodes, enabling accurate modeling of the hydrogen distribution system [28]. In Eq. (18), Lacey's equation is adapted for a low-pressure hydrogen grid, with an operating pressure between 0 and 75 mbar gauge [29]. In the formulation pressure at nodes (π), the diameter of pipes (D), the length of pipes (L), and the hydrogen flow within pipes (H^{pipe}) are measured in mbar gauge, mm, m, cm/h, respectively.

$$H_{n,n',t}^{pipe} = 0.023\sqrt{\left[\frac{(\pi_{n,t} - \pi_{n',t})D_{n,n'}^5}{f_{n,n'}SL_{n,n'}}\right]}\ p\epsilon(n,n'),\ \forall t \tag{18}$$

Unwin's low-pressure formula [30] can be used to determine the value of f, represented in Eq. (19).

$$f_{n,n'} = 0.0044\left(1 + \frac{12}{0.276D_{n,n'}}\right)\ p\epsilon(n,n'), \tag{19}$$

Alternatively, by replacing the value of 0.0065 with $f_{n,n'}$ for all pipes, Eq. (18) can be replaced by Eq. (20), called Pole's equation.

$$H_{n,n',t}^{pipe} = 0.0071\sqrt{\left[\frac{(\pi_{n,t} - \pi_{n',t})D_{n,n'}^5}{SL_{n,n'}}\right]}\ p\epsilon(n,n'),\ \forall t \tag{20}$$

Considering S equal to 0.0695 for hydrogen, the equation can be rewritten in the following (Eqs. (21)-(22)).

$$\pi_{n,t} - \pi_{n',t} = K_{n,n'}{H_{n,n',t}^{pipe}}^2\ p\epsilon(n,n'),\ \forall t \tag{21}$$

$$K_{n,n'} = \frac{1378.69\ L_{n,n'}}{D_{n,n'}^5}\ p\epsilon(n,n') \tag{22}$$

However, for natural gas distribution, as the S is equal to 0.589, the constant is calculated, as indicated in Eq. 23 [27].

$$K_{n,n'} = \frac{11684.19\ L_{n,n'}}{D_{n,n'}^5}\ p\epsilon(n,n') \tag{23}$$

2.1.3. Linking constraints

In Eq. (24) and Eq. (25), the constraints that link the hydrogen and electricity grids are indicated. The former calculates the hydrogen required for distributed generating units, which is added to the hydrogen flow balance. The latter indicates the electricity consumption to produce hydrogen by electrolyzers, added to the load flow balance.

$$H_{n,t}^{dg} = \phi E_{b\to n,t}^{dg}\ \forall n,\ \forall t \tag{24}$$

$$H_{n\to b,t}^{elz} = \psi E_{b,t}^{elz}\ \forall b,\ \forall t \tag{25}$$

2.2. PRP approach

A PRP approach is proposed to handle the uncertainty in the parameters of the optimization problem. This method is based on the combination of the light-robustness counterpart [31] and possibility theory [32]. In robust programming, Soyster's method ensured feasibility within a convex set but was conservative, leading to a significant loss of optimality [33]. Fischetti and Monaci's light robust method addressed this by introducing a protection level to manage conservatism, but it only considered worst-case scenarios [34]. This developed PRP approach extends the interval representation of uncertain parameters using a fuzzy membership function, allowing decision-makers to better balance robustness and optimality, resulting in more practical solutions under various uncertain conditions.

In the context of MEMs, the electricity demand is an uncertain parameter. The electricity demand is subject to epistemic uncertainty when considering the integration of electrolyzers into the future microgrid, a high penetration of renewable resources in the future, which affects the demand profile of prosumers, and the gas grid, which is employed for hydrogen. More precisely, this uncertainty arises from limited data on future RESs' impacts on electricity demand. Integrating electrolyzers, which produce hydrogen from water using electricity, introduces complexity as it depends on variable RESs like solar and wind. The increasing adoption of renewables alters traditional demand patterns, impacting when and how much electricity prosumers consume and generate. Employing hydrogen within existing gas infrastructure necessitates coordination and adaptation, further complicating future demand forecasting and grid management. To address these challenges, the possibilistic method is efficient in optimizing the microgrid operation under uncertain and evolving energy conditions.

Considering an optimization problem presented in Eq. (26), the goal is to minimize the total cost, which is expressed as a double summation over all decision variables (x_{ij}) and their corresponding cost coefficients (c_{ij}).

$$\begin{aligned} & \textit{Minimize } z = \sum_i \sum_j c_{ij} x_{ij} \\ & \quad \textit{Subject to} \\ & \quad \sum_j \widetilde{a}_{ij} x_{ij} \le b_i \ \forall i \\ & \quad x_{ij} \ge 0 \ \forall i,\ \forall j \end{aligned} \tag{26}$$

In the above-mentioned optimization problem, as discussed, c_{ij} and x_{ij} indicate cost coefficients and decision variables, respectively. However, imprecise constraint coefficients and the right-hand side of constraints are indicated by $\widetilde{a}_{ij}$ belongs to $[\widehat{a}_{ij} - \overline{a}_{ij}, \widehat{a}_{ij} + \overline{a}_{ij}]$ and b_i, respectively. The robust counterpart of the above-mentioned optimization problem is indicated in Eq. (27) [35].

$$\begin{aligned} & \textit{Minimize } ||\lambda|| \\ & \quad \textit{Subject to} \\ & \sum_j \widehat{a}_{ij} x_{ij} + \Gamma_i \omega_i + \sum_j p_{ij} \le b_i + \gamma_i \ \forall i \\ & \quad \omega_i + p_{ij} \ge \overline{a}_{ij} x_{ij} \ \forall i,\ \forall j \\ & \quad \sum_j \widehat{a}_{ij} x_{ij} \le b_i \ \forall i \\ & \quad \sum_i \sum_j c_{ij} x_{ij} \le \widehat{c} + \rho_0 \\ & \quad x_{ij},\ p_{ij},\ \omega_i \ge 0 \ \forall i,\ \forall j \end{aligned} \tag{27}$$

In the robust formulation, the protection level allowing decision makers to set the level of conservatism is indicated by Γ_i. The price of robustness is limited by a fixed tolerance, indicated by ρ_0. The optimal value of the objective function without uncertainty consideration is represented by $\widehat{c}$. The formulation allows decision-makers to make a tradeoff between the price of robustness and the feasibility of robustness [36]. To develop the possibilistic method, a fuzzy membership function is replaced with the uncertainty interval. The formulation of the fuzzy membership function is indicated in Eq. (28). Decision makers can change the z to reach the most preferred membership function [37].

$$\begin{aligned} & \textit{Probability}(a_{ij}(\lambda)) = \overline{a}_{ij}(1 - \lambda^z) \\ & \quad z \ge 0 \textit{and} \lambda \in (0, 1] \end{aligned} \tag{28}$$

This possibilistic method considers both the most optimistic and pessimistic possible level for data occurrence (*Possibility* in Eq. (29) and *Necessity* in Eq. (30)). A tradeoff between possibility and necessity is developed, which is called *Mean* in Eq. (31) and Eq. (32) [37].

$$\textit{Possibility}(a) = \textit{sup}(\textit{Probability}(a)) \tag{29}$$

$$\textit{Necessity}(a) = 1 - \textit{Possibility}(a) \tag{30}$$

$$\textit{Mean}(a) = \gamma \textit{Possibility}(a) + (1 - \gamma)\textit{Necessity}(a) \tag{31}$$

$$\textit{Necessity}(a) \le \textit{Mean}(a) \le \textit{Possibility}(a) \tag{32}$$

Considering *Possibility*, *Necessity*, and *Mean*, the optimization problem in Eq. (26) can be reformulated as shown in Eq. (33) as *Mean* is greater than $[\gamma(1 - \lambda^z) + (1 - \gamma)\lambda^z]$ if and only if $\sum_j \widetilde{a}_{ij} x_{ij} \le b_i$ is maximized.

$$\begin{aligned} & \textit{Maximize } [\gamma\ (1 - \lambda^z) + (1 - \gamma)\lambda^z] \\ & \quad \textit{Subject to} \\ & \sum_j \widehat{a}_{ij} x_{ij} + \Gamma_i \omega_i + \sum_j p_{ij} \le b_i + \varsigma_i \ \forall i \\ & \omega_i + p_{ij} \ge \overline{a}_{ij}[\gamma\ (1 - \lambda^z) + (1 - \gamma)\lambda^z] x_{ij} \ \forall i,\ \forall j \\ & \quad \sum_j \widehat{a}_{ij} x_{ij} \le b_i \ \forall i \\ & \quad \sum_i \sum_j c_{ij} x_{ij} \le \widehat{c} + \rho_0 \\ & \quad x_{ij},\ p_{ij},\ \omega_i \ge 0 \ \forall i,\ \forall j \end{aligned} \tag{33}$$

In the case of uncertainty in b_i, optimization problem proposed in Eq. (33) is replaced by Eq. (34), which indicates the generalized formulation of the PRP approach.

$$\begin{aligned} & \textit{Maximize } [\gamma\ (1 - \lambda^z) + (1 - \gamma)\lambda^z] \\ & \quad \textit{Subject to} \\ & \sum_j \widehat{a}_{ij} x_{ij} + \Gamma_i \omega_i + \sum_j p_{ij} \le \widehat{b}_i + [\gamma\ (1 - \lambda^z) + (1 - \gamma)\lambda^z] \ \forall i \\ & \quad \omega_i + p_{ij} \ge \overline{a}_{ij}[\gamma\ (1 - \lambda^z) + (1 - \gamma)\lambda^z] x_{ij} \ \forall i,\ \forall j \\ & \quad \sum_j \widehat{a}_{ij} x_{ij} \le \widehat{b}_i \ \forall i \\ & \quad \sum_i \sum_j c_{ij} x_{ij} \le \widehat{c} + \rho_0[\gamma\ (1 - \lambda^z) + (1 - \gamma)\lambda^z] \\ & \quad x_{ij},\ p_{ij},\ \omega_i \ge 0 \ \forall i,\ \forall j \end{aligned} \tag{34}$$

In the optimal operation of the MEM, the PRP model is written in Eq. (35).

2.3. Solving approach and applicability test

To solve the developed problem in this study, Discrete and Continuous Optimizer (DICOPT) is employed using General Algebraic Modeling System (GAMS) software [37]. Based on the iterative approach described in Fig. 2(a), the solving method involves generating upper and lower bounds in each iteration to tackle the Mixed-Integer Nonlinear Programming (MINLP) problem effectively [38]. The upper bound is derived from the primal problem, utilizing initialized binary variables from the relaxed problem solution in the first iteration and the master problem in subsequent iterations. The lower bound is obtained by solving the master problem, where nonlinear equality constraints are linearized at the current solution to generate a cutting plane. The process iterates between solving the primal and master problems, gradually refining the solution until convergence is achieved. Additionally, a geometrical interpretation of the linearizations in the master problem

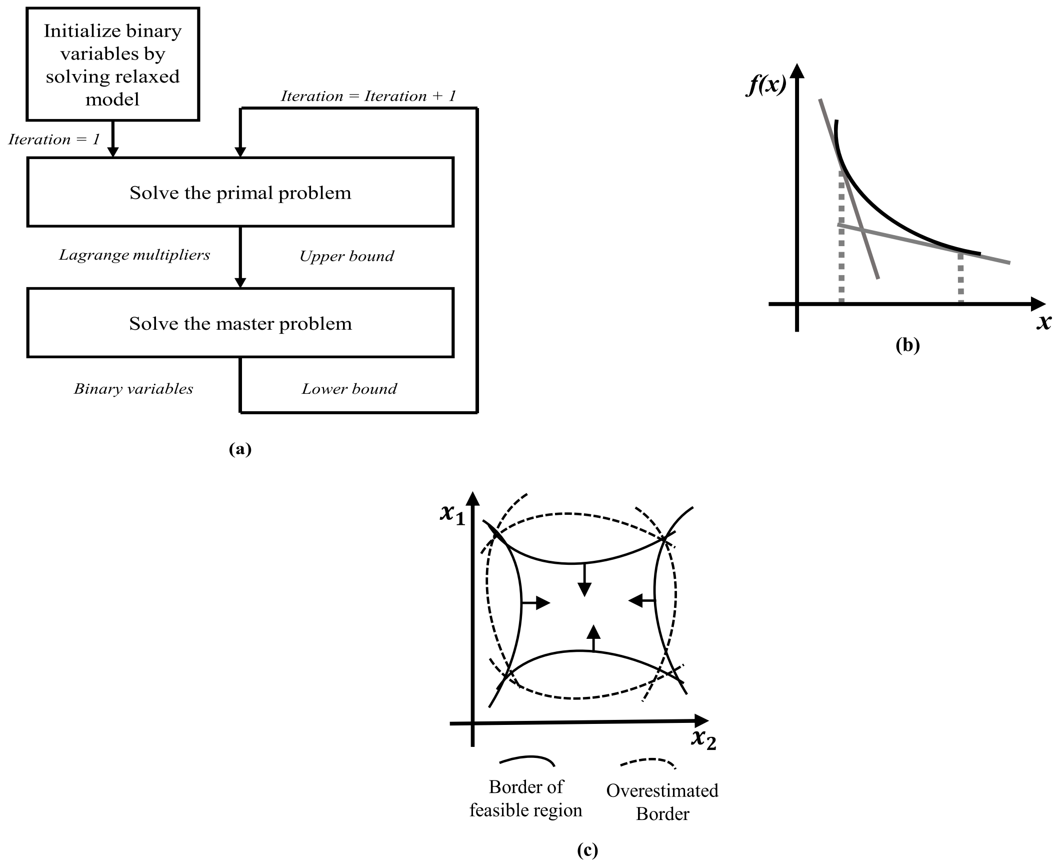

Fig. 2. Solving approach for the operation of MEMs ((a) iterative approach utilized by DICOPT solver, (b) objective function underestimation, and (c) feasible region overestimation).

illustrates how the objective function is underestimated while the feasible region is overestimated, aiding in the efficient solving of the optimization problem (Fig. 2(b) and (c)) [11].

$$
\begin{aligned}
&\textit{Maximize}\ [\gamma\ (1-\lambda^z)+(1-\gamma)\lambda^z]\\
&\textit{Subject to}\\
&-E^{dg}_{b,t}-E^{rnw}_{b,t}-E^{buy}_{t}+\sum_{b'=1}^{B}\left(E^{line}_{l,t}+R_{l,t}.I^2_{l,t}\right)+E^{elz}_{b,t}+E^{sell}_{t}+\Gamma_{b,t}\omega_{b,t}+\sum_{t}p_{b,t}\leq\\
&\overline{E^{load}_{b,t}}+[\gamma\ (1-\lambda^z)+(1-\gamma)\lambda^z]\ \forall b,\forall t\\
&\omega_{b,t}+p_{b,t}\geq\\
&\left(-E^{dg}_{b,t}-E^{rnw}_{b,t}-E^{buy}_{t}+\sum_{b'=1}^{B}\left(E^{line}_{l,t}+R_{l,t}.I^2_{l,t}\right)+E^{elz}_{b,t}+E^{sell}_{t}+\Gamma_{b,t}\omega_{b,t}+\sum_{t}p_{b,t}\right)[\gamma\ (1-\lambda^z)+(1-\gamma)\lambda^z]\forall b,\forall t\\
&-E^{dg}_{b,t}-E^{rnw}_{b,t}-E^{buy}_{t}+\sum_{b'=1}^{B}\left(E^{line}_{l,t}+R_{l,t}.I^2_{l,t}\right)+E^{elz}_{b,t}+E^{sell}_{t}+\Gamma_{b,t}\omega_{b,t}+\sum_{t}p_{b,t}\leq-E^{load}_{b,t}\ \forall b,\ \forall t\\
&OF^{MEM}\leq OF^{MEM^*}+\rho_0[\gamma\ (1-\lambda^z)+(1-\gamma)\lambda^z]\\
&\omega_{b,t}\ \textit{and}\ p_{b,t}\geq 0
\end{aligned}
\tag{35}
$$

Eqs. (5)-(17), (21), and (23)-(24).

The potential for repurposing the natural gas grid for hydrogen distribution involves evaluating key grid characteristics, such as the pipe's diameter and length. Given the energy density differences, supplying the same load with hydrogen requires three times the volume compared to natural gas. In this study, load shedding for hydrogen demand is tested when the natural gas demand is on the verge of shedding.

If hydrogen can supply the load without shedding, it indicates the feasibility of using the natural gas grid for hydrogen distribution. Further analysis includes checking load shedding when natural gas demand is on the verge of shedding, and there is low linepack within the pipe. The successful supply of hydrogen without load shedding demonstrates the feasibility of utilizing the natural gas grid for hydrogen. Additionally, a more detailed analysis considers initial linepack requirements within the pipe. The absence of load shedding in hydrogen distribution during this assessment further validates the suitability of adapting existing natural gas infrastructure to support hydrogen distribution. It should be noted that, in this study, the risk associated with the leakage of hydrogen and explosion is not considered.

3. Case study

The case study is an MEM, consisting of hydrogen and electricity distribution grids. In this study, the potential for hydrogen to serve as an alternative to natural gas is examined under conditions where the natural gas demand is high. The focus is on evaluating whether hydrogen can maintain the load without requiring load shedding when (i) the natural gas supply is on the verge of shedding (energy demand is high) and (ii) there is a low linepack conditions within the pipeline. In both cases, hydrogen supply without load shedding supports the feasibility of utilizing the natural gas grid for hydrogen from the viewpoint of supply-demand provision. After that, three cases are examined in this study, as follows:

Case 1. In the first case, the operation of the MEM is studied when there is no electrolyzer.

Case 2. In the second case, there are electrolyzers in the microgrid, and the output hydrogen of these systems is injected into the hydrogen grid.

Case 3. In the third case, in addition to the existence of the electrolyzers, the proposed PRP approach is integrated to deal with the uncertainty in electricity demand and output power of renewable resources.

3.1. Hydrogen grid

The hydrogen grid consists of 11 nodes and 14 pipes, connected to the upstream grid through node one, which can import or export hydrogen. An illustration of the hydrogen grid is indicated in Fig. 3. More detailed information about the hydrogen grid under study, such as diameter and length of pipes, pressure and flow limits, supply limit, and costs, can be found in [39]. For natural gas, the purchasing cost is assumed to be \$350/kcm, the linepack management cost is \$3.5/kcm, and the load shedding cost is \$3500/kcm. For hydrogen, the purchasing cost is assumed to be \$540.5/kcm, the linepack management cost is \$5.25/kcm, with the load shedding cost, assumed to be the same.

3.2. Electricity grid

The electricity grid under study is illustrated in Fig. 4. This grid consists of 33 nodes and 32 electric lines. The flexible generating units and electrolyzers are connected to buses numbered two and nine. The buses are connected to the hydrogen distribution grid. The wind turbines are connected to the buses numbered 15, 29, 30, and 32. The installed capacity of the components installed in the electricity grid is also indicated in Table 2. More detailed data about the electricity system, such as electricity price and characteristics of lines, can be found in [11]. The proposed model for the operation of the MEM, consisting of hydrogen and electricity grids, is solved in the General Algebraic Modeling System, GAMS software, using a computer with an Intel Core i7 processor and 8 GB of RAM.

4. Results and discussions

In Fig. 5(a), the supply curve analysis over 24 h reveals significant insights into the performance of natural gas and hydrogen under varying conditions (Natural gas (NG), Natural Gas-Low Initial Linepack (NGL), Hydrogen (H2), and Hydrogen-Low Initial Linepack (H2L)). Under high demand, the natural gas supply meets demand without experiencing load shedding. In the scenario where the initial linepack is low, the system requires increased injections of natural gas to sustain demand. Conversely, hydrogen supply demonstrates robustness in both normal and low initial linepack conditions. Although the volume of hydrogen required is inherently higher due to its lower energy density, it also meets demand without load shedding. Notably, in the low linepack scenario, the hydrogen supply requires a slight increase compared to normal linepack conditions, but still maintains system stability and demand fulfillment. These findings indicate the potential of repurposing existing natural gas infrastructure for hydrogen distribution, with appropriate adjustments to account for hydrogen's volumetric and linepack characteristics. The linepack within the pipe indicates that, in the case of natural gas supply, more injections are required to compensate for the low initial linepack (Fig. 5(b)). However, for hydrogen supply, the linepack remains lower throughout the entire operating period. Hydrogen transfers faster than natural gas due to its smaller and lighter molecules, resulting in higher diffusion and flow rates. Consequently, even with a lower linepack, hydrogen can maintain a consistent supply, demonstrating the feasibility of using existing natural gas infrastructure for hydrogen distribution.

The obtained results from Case 1 and Case 2 (without and with electrolyzers, respectively), including wind power, purchased power from the main grid, and output of gas-fired units, are indicated in Fig. 6. In Fig. 6(a), it is indicated that there is wind curtailment without electrolyzers, especially from 01:00 to 07:00. In case 2, the total amount of wind curtailment during the operating period is about 800 kW. In Figs. 6 (b) and (c), the power purchased from the main grid and the output power of the gas-fired generating units are indicated. In case 1, a

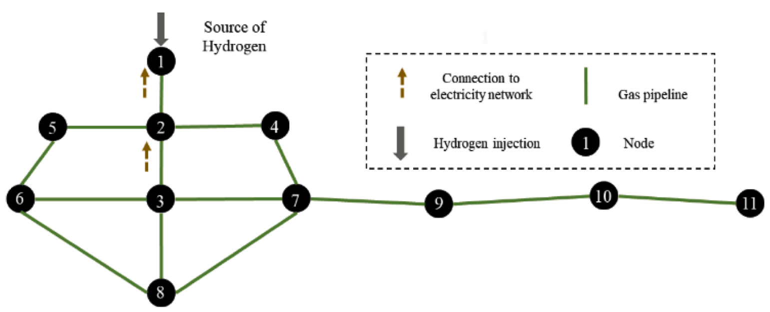

Fig. 3. Case study - hydrogen grid [39].

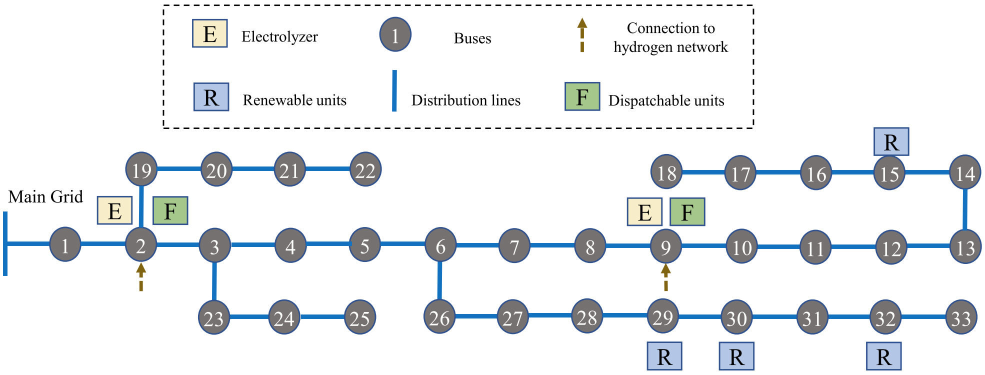

Fig. 4. Case study - electricity grid [40].

Table 2
Characteristics of components in the electricity grid.

Component	Location	Characteristics
Wind	Node 15, Node 29, Node 30, and Node 32	Capacity=2800 kW [41]
Flexible units	Node 2 and Node 9	Capacity=600 kW, Efficiency=55 %, Conversion Rate= 0.00027 MW/mcm, and Ramp rate=50 % [42]
Electrolyzers	Node 2 and Node 9	Capacity=5000 kW and Efficiency=60 % [43]

considerable amount of power is purchased from the main grid, as indicated in Fig. 6(b). The purchased power in Case 1 is about 50 MW more than the purchased power in Case 2. However, in the presence of electrolyzers, more power is produced utilizing gas-fired generating units. The produced power utilizing gas-fired units in Case 2 is around 40 MW more than the generated power in Case 1. The reason is the availability of Hydrogen in the case of the presence of electrolyzers, which assists the transition to a lower-carbon energy system.

In Fig. 7, the maximum voltage deviation in the electricity grid is compared during the operating period in the absence and presence of the electrolyzers (Case 1 and Case 2, respectively). The graph shows the lower voltage deviation in the presence of the electrolyzers. More voltage drops in the absence of electrolyzers are evident from 13:00 to 19:00. When there is a voltage drop, it is possible for various components that use electricity to become overheated. Voltage deviation is an important indicator of power quality and grid stability; excessive deviations can lead to equipment malfunction, reduced efficiency, and potential damage to sensitive electrical devices.

The hydrogen purchased from the market supplied into the hydrogen distribution grid is indicated in Fig. 8. The figure shows a greater dependency on purchasing hydrogen in the absence of electrolyzers. The

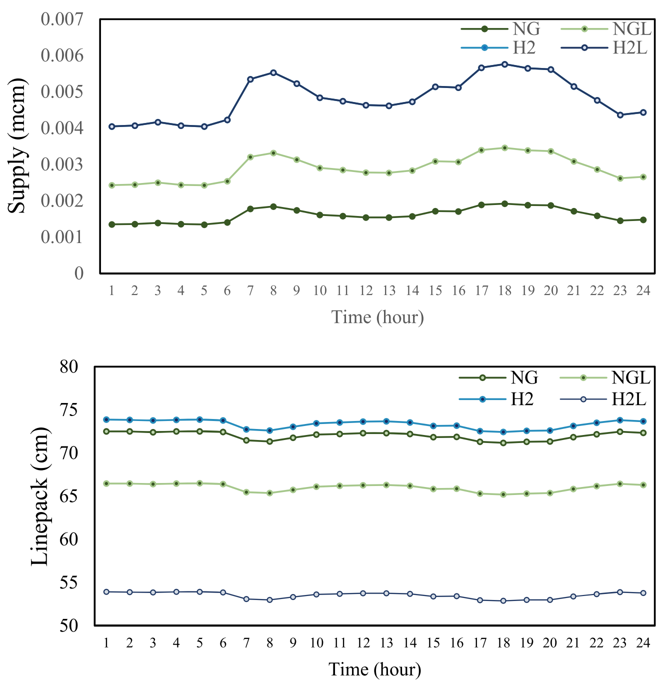

Fig. 5. Supply (a) and linepack (b)-utilization of gas grid for hydrogen (Natural gas (NG), Natural Gas-Low Initial Linepack, Hydrogen (H2), and Hydrogen-Low Initial Linepack (H2L)).

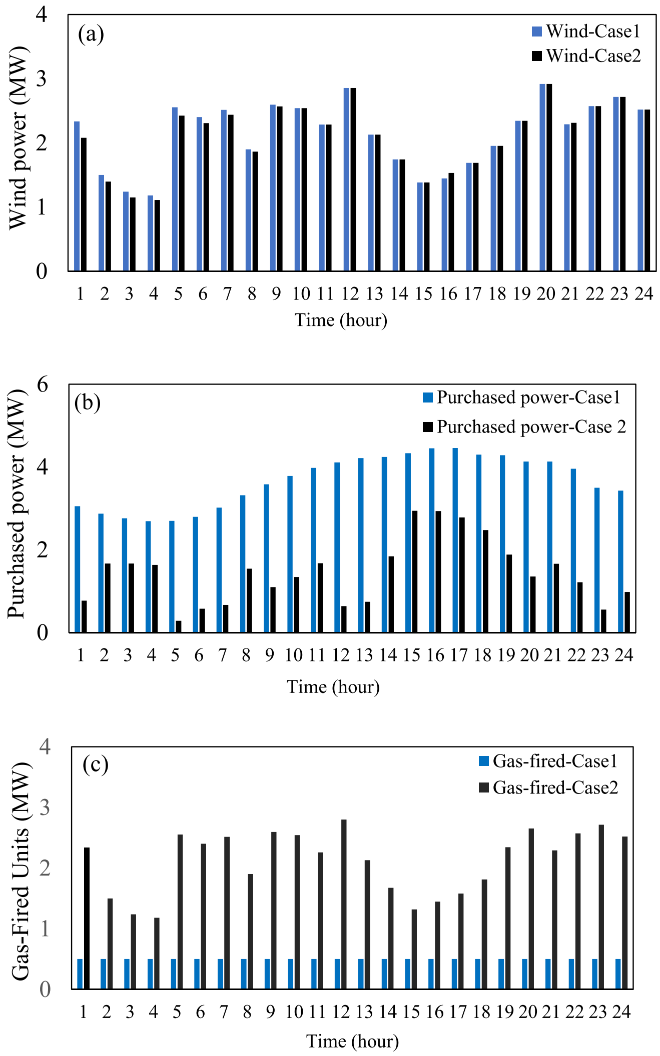

Fig. 6. Output of the optimization problem ((a) wind power, (b) purchased power from the main grid, and (c) gas-fired units' output power, Case 1 without electrolyzer versus Case 2 with presence of electrolyzers).

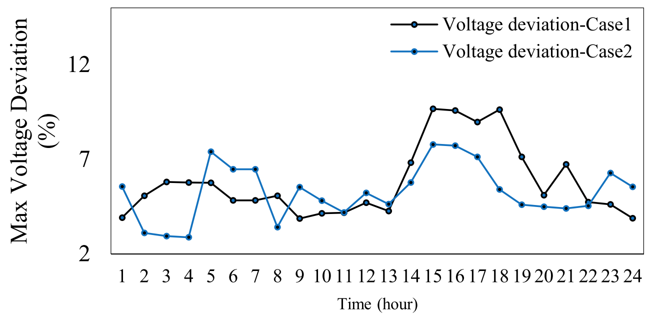

Fig. 7. Maximum voltage deviation - Case 1 (no electrolyzer) versus Case 2 (presence of electrolyzers).

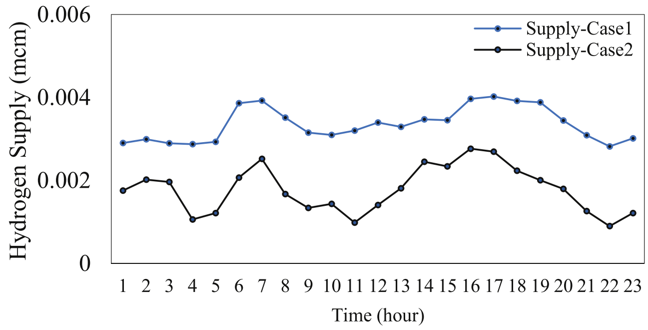

Fig. 8. Hydrogen supply - Case 1 (no electrolyzer) versus Case 2 (presence of electrolyzers).

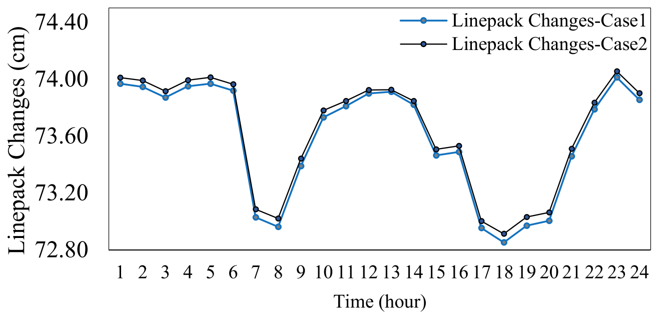

Fig. 9. Linepack changes - Case 1 (no electrolyzer) versus Case 2 (presence of electrolyzers).

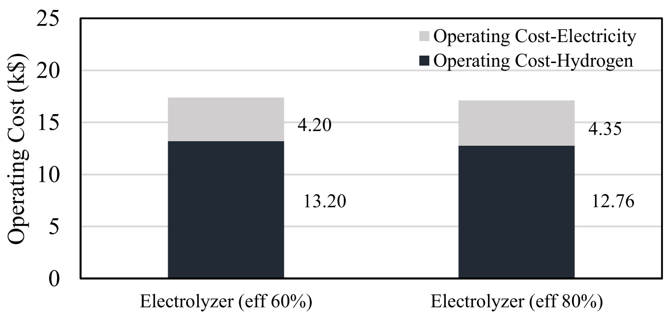

Fig. 10. Analysis of the operating cost of hydrogen and electricity grids when the efficiency increases from 60 % to 80 %.

total amount of purchased hydrogen is about 38,000 cm higher when there are no electrolyzers connected to the grid. Relying on locally generated hydrogen can be advantageous as it increases the reliability of the hydrogen supply. In the event of a failure in the upstream grid, there would be no issues. Moreover, it can lead to cost savings and emission reduction as hydrogen can be produced from accessible renewable sources in the electricity grid. Finally, in Fig. 9, the changes in linepack, which is hydrogen stored within pipes, are indicated during the 24-hour operating period. Based on the results, there are more changes in the linepack in the presence of electrolyzers (or Case 2). It indicates the operation of this grid is more efficient, and the linepack assists supply-demand provision. More precisely, more efficient utilization of the stored hydrogen within pipes has the potential to reduce the operating cost of the hydrogen grid significantly.

In addition to the analysis conducted on the system performance with and without the electrolyzer, a further investigation is performed to examine the sensitivity of system operation to electrolyzer efficiency and the electrification of heat demand supplied through the electricity grid instead of the hydrogen grid. The results show that increasing electrolyzer efficiency from 60 % to 80 % leads to a noticeable shift in the cost distribution between the two energy grids. Specifically, the operating cost of the electricity grid increases due to higher power purchases required to operate the electrolyzers, while the hydrogen grid cost decreases considerably as more hydrogen is generated locally. This trade-off highlights the system's sensitivity to electrolyzer efficiency, emphasizing that higher efficiency improves overall hydrogen production economics but imposes additional stress and cost on the electricity grid, as illustrated in Fig. 10.

Aside from what has already been discussed, in Case 3, the problem of optimal operation of hydrogen and electricity distribution grids is considered utilizing the PRP approach. To evaluate the performance of the proposed method in this study, the costs and standard deviations are compared ten times, generating random values for uncertain parameters (i.e., electricity demand). This ten-time random data generation is

Table 3
Analyses of uncertainty consideration approach.

Conservatism Level	Uncertainty interval (Z)	Operating cost ($)		Mean value	Standard deviation
		Electricity grid	Hydrogen grid		
$\Gamma = 0.1$	2	5675.69	14,720.23	22,231.55	566.86
$\Gamma = 1$	2	5806.23	15,058.79	22,742.87	508.62
$\Gamma = 10$	2	6212.66	15,152.43	23,287.95	475.27
$\Gamma = 0.1$	3	6078.66	14,821.79	20,522.90	565.55
$\Gamma = 1$	3	6305.56	15,171.73	21,094.22	508.01
$\Gamma = 10$	3	6784.22	14,287.29	21,769.08	474.79
$\Gamma = 0.1$	1	5663.69	13,839.21	24,057.78	617.57
$\Gamma = 1$	1	5887.54	14,165.94	24,682.33	553.94
$\Gamma = 10$	1	6334.47	14,273.84	25,460.93	519.77

chosen because, after ten iterations, there are no significant changes in the mean values and standard deviations, indicating the knee point. The output of the examination is indicated in Table 3. Based on the results, by increasing the conservatism level from 0.1 to 10, the mean value increases by around 5 % while the standard deviation decreases by around 16 %, highlighting a better performance in dealing with uncertainty. It is important to recognize that the rise in operating costs is primarily due to the increased purchases of electricity from the main electricity grid, as indicated in Fig. 11. In this figure, as the conservatism level increases from 0.1 to 10, the total purchased power also increases from 37 MW to over 40 MW. Another sensitivity analysis is conducted by changing the uncertainty interval (i.e., changing z). The results indicate that a higher value of z causes the membership function to decline more rapidly, representing a more conservative decision. Conversely, a lower value of z produces a flatter membership function, reflecting more optimistic assumptions. The conservative case yields lower mean values and smaller standard deviations in the realization of uncertain parameters, resulting in more robust but higher-cost operational outcomes.

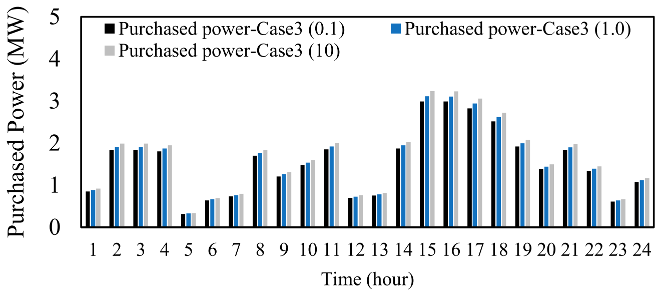

Fig. 11. Purchased power - Case 3 (with uncertainty consideration $z = 2$).

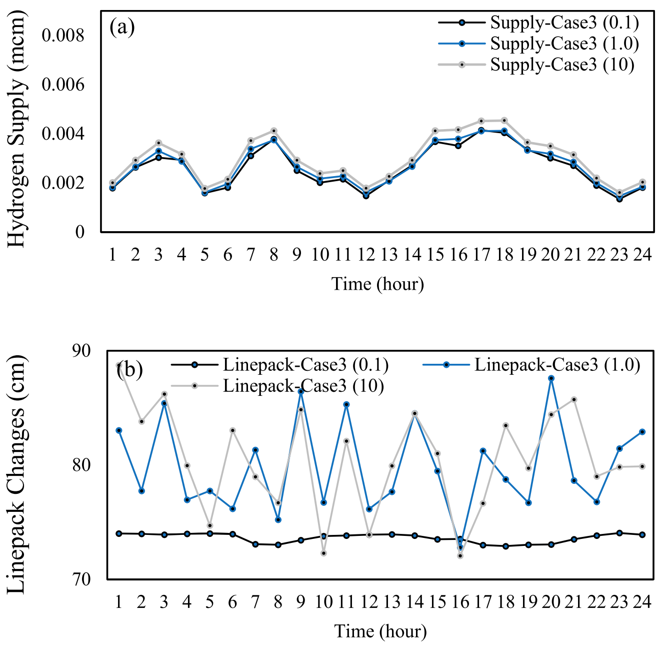

Fig. 12. (a) Hydrogen supply and (b) linepack changes - Case 3 (with uncertainty consideration).

As illustrated in Fig. 12(a) and (b), another reason for the increase in operating costs is related to a greater hydrogen supply and linepack within the pipes. During the operational period, as the level of conservatism increases from 0.1 to 1, there is a corresponding increase of approximately 8000 cm in the hydrogen supply and 1600 cm in the linepack. Although this increases the cost of operations, it is a necessary measure to adapt to changes in demand. For example, having more linepack enables a quicker supply of hydrogen during times of varying demand, as well as meeting the demand for gas-fired units that assist with varying electricity demand provision. The reason for this is that the transfer of hydrogen within pipes from supply nodes to demand nodes takes time. Moreover, a higher linepack requires more injection of hydrogen from supply nodes, which in turn increases operating costs. In the case of increased linepack (Case 3 (1.0) and (10)), the stored hydrogen is used to supply demand, causing oscillations in linepack levels, as indicated in Fig. 12(b). For these two conversion levels, the oscillations are in the same direction, while the total changes in linepack are greater at a conversion level of 10, indicating more efficient use of linepack.

Overall, the findings of this study have significant practical implications for microgrid owners, particularly those considering the integration of hydrogen into their energy systems. In relation to the primary objective of this research, the results demonstrate the robustness of hydrogen supply in maintaining supply-demand balance even under low initial linepack conditions. Hydrogen's ability to transfer faster than natural gas due to its smaller and lighter molecules results in higher diffusion and flow rates, which allows for faster response to the changes. This efficiency can be advantageous for microgrid operators, as it allows for a consistent supply even with lower linepack levels. Consequently, microgrid owners can consider investing in hydrogen infrastructure without the need for significant increases in storage capacity, thus optimizing the use of existing pipes and linepack management that reduces capital expenditure. Furthermore, the role of electrolyzers, also central to the primary objective, is shown to be crucial in integrating RESs into the microgrid. Electrolyzers reduce wind curtailment and enhance the utilization of locally generated hydrogen, thereby improving both the reliability of hydrogen supply and the overall energy efficiency of the system. This integration supports a stable and flexible operation of the MEM while facilitating progress toward a net-zero emission energy system.

In relation to the secondary objective, which introduces the PRP approach to capture uncertainties, the findings highlight the stability of system performance under uncertain operating conditions. The PRP-based model ensures robust decision-making despite fluctuations in renewable generation and demand, resulting in consistent operational outcomes and reduced standard deviation under the realization of uncertain parameters as key performance indicators. This confirms the effectiveness of the proposed approach in managing uncertainty and enhancing the reliability and resilience of MEM operations.

Overall, these results collectively demonstrate that the developed framework and uncertainty modeling approach successfully meet the primary and secondary objectives of this study, offering a practical, adaptable, and robust solution for the integration of hydrogen in multi-energy microgrids.

5. Conclusion

This research aimed to optimize microgrid operations for a cleaner energy future by examining hydrogen as a substitute for natural gas. In line with the primary objective of this research, a comprehensive mathematical framework was developed to evaluate the applicability of existing gas infrastructure for hydrogen distribution and to assess the roles of electrolyzers, gas-fired units, and linepack within Multi-Energy Microgrids. The developed applicability test demonstrated that existing low-pressure natural gas pipelines can be effectively repurposed for hydrogen transport from demand provision aspect. This finding confirms the technical feasibility of hydrogen integration with minimal additional investment in new infrastructure, though our work extends prior findings by incorporating both the electrical and gas subsystems in a unified optimization model. The results further revealed that incorporating electrolyzers significantly improved renewable energy utilization, reducing wind curtailment by approximately 2 % and enhancing system voltage stability by about 8 %. These outcomes directly address the primary objective's focus on evaluating electrolyzers' contributions to flexible operation. The observed efficiency gains are consistent with earlier findings on electrolyzer-based grid balancing. However, this model also highlighted the unique advantage of leveraging linepack as a temporary hydrogen storage mechanism, an aspect that remains underexplored in previous studies. Addressing the secondary objective, the proposed Possibilistic-Robust Programming approach effectively managed uncertainties in renewable generation and demand, yielding solutions with reduced standard deviation and improved cost stability under varying conditions. This demonstrates the approach's capacity to provide realistic and reliable decision-making under uncertainty, complementing and extending previous PRP-based studies by explicitly incorporating hydrogen-related variability. Overall, this study successfully meets both its primary and secondary objectives, demonstrating that repurposing existing gas infrastructure for hydrogen use, supported by robust optimization techniques, can enable a cost-effective, reliable, and sustainable energy transition.

The findings contribute to the growing body of research advocating for hydrogen-integrated microgrids and provide actionable insights for policymakers, energy planners, and microgrid operators seeking to advance toward net-zero energy systems. While these findings are promising, the study acknowledges several limitations and assumptions. The current model does not explicitly address hydrogen leakage or explosion risks, which could affect both system safety and economic feasibility. In addition, uncertainties related to infrastructure retrofitting costs, material compatibility of existing pipelines, and hydrogen purity requirements were not explicitly modeled. These aspects, along with the simplified representation of renewable variability and aggregated operational constraints, present important directions for future work. Incorporating these real-world constraints and cost uncertainties will enhance the robustness and applicability of the proposed framework in practical planning contexts.

Declaration of generative AI and AI-Assisted technologies in writing process

During the preparation of this work, the authors used ChatGPT in order to improve the readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Vahid Shahbazbegian: Writing – original draft, Software, Methodology, Investigation, Data curation. **Hossein Ameli:** Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Goran Strbac:** Writing – review & editing, Supervision. **Hannu Laaksonen:** Writing – review & editing, Validation, Conceptualization. **Miadreza Shafie-khah:** Writing – review & editing, Validation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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Role of Hydrogen in Optimal Operational Planning of Multi-Energy Microgrids

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***Abstract*— To support decarbonization and enhance energy resilience, this study investigates how hydrogen technologies can be effectively integrated into renewable-based microgrids. For this purpose, a detailed operational planning model is proposed for a multi-energy microgrid that combines electricity and hydrogen distribution networks. This model captures network constraints, various technologies, and high-impact low-probability events, such as upstream grid outages. Four scenarios are investigated, including the renovation of gas-fired units to burn hydrogen, ELZs and fuel cells combinations, and reversible solid oxide cells, both with and without resilience planning. Results show that rSOC integration eliminates 100% of renewable curtailment, reduces load shedding by up to 85%, and achieves 1.5% lower annual operating costs compared to conventional hydrogen systems.**

Keywords—Hydrogen, Microgrid, ELZ, Fuel Cell, Reversible Solid Oxide Cells

I. Introduction

Decarbonization of energy systems is a critical pillar in the response to mitigate climate change. Microgrids (MGs) offer a viable pathway for localized energy autonomy, enhanced resilience, and reduced emissions by integrating distributed renewable energy resources [1] However, managing the variability of renewables like wind and solar requires flexibility that can be addressed by multi-energy solutions that bridge electricity with other vectors, such as gas or hydrogen.

In recent years, Multi-Energy Microgrids (MEMGs) have been studied to coordinate the interaction between electricity and gas networks. Technologies, such as storage systems, Electrolyzers (ELZs), and Fuel Cells (FCs), have been explored for their role in improving system flexibility, economic efficiency, and carbon neutrality [2] Nevertheless, challenges remain in optimizing these systems under operational constraints, network limitations, and disruptive events.

Various studies have been conducted that investigate topics related to the operation and planning of MEMGs. The dynamic behavior of natural gas systems, particularly the role of linepack, the gas stored within pipelines, has been recognized for enhancing system flexibility and compensating for time lags in supply [3]. Several studies have examined the integration of alternative fuels like hydrogen into natural gas networks, typically using steady-state models. For example, in [4], the distributed injection of hydrogen and biogas into gas grids is explored, finding up to a 10% blending potential. In [5], future scenarios are analyzed in Germany and highlight the high cost of hydrogen due to conversion losses. However, these studies largely neglected the power sector interface. On the power side, studies such as [6–10] incorporate hydrogen technologies, e.g., ELZs, FCs, and storage, into MGs or grid-connected systems, often to improve cost-efficiency or resilience. However, detailed modeling of gas or hydrogen grids is lacking. A more integrated perspective is offered in [11] and [12], where ELZs are utilized to balance supply-demand mismatches in both gas and electricity grids. While these studies demonstrate hydrogen's value for multi-energy system flexibility, they overlook fully decarbonized, hydrogen-supplied networks.

Aside from overlooking fully hydrogen-supplied networks, rSOCs have received limited attention in studies on the operation and planning of multi-energy systems. Unlike conventional ELZs and FCs, rSOCs combine both functionalities in a single device, allowing hydrogen production during periods of surplus renewable generation and electricity supply during peak demand. This bidirectional capability improves overall system efficiency, reduces the need for separate infrastructure, and enhances the flexibility of multi-energy networks in [13].

A. Research Gap and Contribution

Although the literature on MEMGs has evolved significantly, some critical gaps remain. Most existing studies either focus solely on electricity and gas or electricity and heat systems, without fully exploring the operational dynamics of coupled electricity-hydrogen networks. While some recent models incorporate hydrogen production and usage, they typically treat the hydrogen subsystem in a simplified manner, ignoring the complexities of pipeline-based storage (linepack) or the bidirectional flexibility offered by technologies like rSOCs. Furthermore, resilience has not been systematically embedded into the operational planning models. Only a few works address high-impact, low-probability (HILP) events such as grid outages.

In this context, this study contributes by developing a detailed operational planning model for electricity and hydrogen distribution systems in MGs. Hydrogen in the MG is distributed through the network at a nominal pressure of 20–100 mbar, ensuring safe and efficient interaction with the rSOCs, ELZs, and FCs. The model explicitly accounts for linepack dynamics and enables simultaneous investment and dispatch of ELZs, FCs, and rSOCs. The model evaluates four practical scenarios involving upstream grid outages to address resilience planning. This framework benchmarks hydrogen-enabled flexibility and resilience in decarbonized microgrids.

II. METHODOLOGY

This section presents the optimization model developed to optimize the operational planning of a MEMG that integrates electricity and hydrogen distribution systems. The objective function considers the total annual operating cost of the system, composed of electricity and hydrogen-related costs. However, investment costs are included as annuitized expenditures for infrastructure, such as ELZs, FCs, hydrogen-fired units, and rSOCs. The system is constrained by both electrical and hydrogen network limitations, as well as the operational characteristics of key components.

A. Objective function

The objective is to minimize the total operating and investment costs of electricity and hydrogen systems (1)-(2).

$$OF^{tot} = OF^{Op} + OF^{inv} \tag{1}$$

$$OF^{op} = OF^{ELC} + OF^{H_2} \tag{2}$$

1) Electricity System Operating Cost:

To evaluate annual operational costs with reduced computational complexity, representative days are used. The electricity-related component of the objective function minimizes the total cost associated with electricity imports, exports, and load shedding, weighted by the number of representative days. This term of the objective function is formulated in (3).

$$OF^{ELC} = \sum_{d=1}^{D} \omega_d \Big(\sum_{t=1}^{T} \psi_{t,d}.E_{t,d}^{buy} - \sum_{t=1}^{T} \psi'_{t,d}.E_{t,d}^{sell} + \sum_{t=1}^{T}\sum_{b=1}^{B} \psi''_{t,d}.E_{b,t,d}^{shed}\Big) \tag{3}$$

Where:
D is the representative days,
ω_d is the total number of days represented by day d,
T is the time steps in each day (i.e., 24 hours),
$E_{t,d}^{buy}$ and $E_{t,d}^{sell}$ are electricity bought and sold at time t on day d,
$E_{b,t,d}^{shed}$ is the load shedding at bus b, time t, and day d,
$\psi_{t,d}$, $\psi'_{t,d}$, and $\psi''_{t,d}$ are the electricity buying price, the electricity selling price, and the load-shedding penalty.

2) Hydrogen System Operating Cost:

The hydrogen-related term of the objective function represents annual costs associated with hydrogen purchased from external sources, the cost of linepack management, and unmet demand. The costs are presented and weighted by the number of representative days in (4).

$$OF^{H_2} = \sum_{d=1}^{D} \pi_d \Big(\sum_{t=1}^{T} \phi_d.H_{t,d}^{buy} + \sum_{t=1}^{T}\sum_{n=1}^{N} \phi'_d.\ \Delta H_{n,t,d} + \sum_{t=1}^{T}\sum_{n=1}^{N} \phi''_d.HNS_{n,t,d}\Big) \tag{4}$$

Where:
ϕ is the cost of purchasing hydrogen,
ϕ' is the cost associated with linepack changes,
ϕ'' is the penalty for imbalance and unmet hydrogen demand,
$H_{t,d}^{buy}$ is hydrogen bought at node n, day d, and time t,
$HNS_{n,t,d}$ is the imbalance at node n, day d, and time t,
$\Delta H_{n,t,d}$ is the changes in the linepack at node n, day d, and time t.

B. Investment Cost

The investment cost is annualized using a capital recovery factor and includes cost contributions from ELZs, FCs, hydrogen-fired units, and rSOC, in (5)-(6).

$$INV = \left[\frac{r(1+r)^j}{(1+r)^j - 1}\right].C^{inv} \tag{5}$$

$$C^{inv} = \sum_{k=1}^{K} C^{investment}.Cap_k \tag{6}$$

Where:
r is the discount rate,
j is lifetime (years),
Cap_k is the installed capacity of technology k,
$C^{investment}$ is the unit investment cost,
C^{inv} is the investment cost,
INV is the annualized investment cost.

C. System Constraints

1) Electrical Network Constraints:

The electrical network is modeled to ensure the physical and operational feasibility of power flow, including the following key constraints:

- Import and export limits for electricity exchanged with the main grid
- Power balance at each bus, ensuring that total generation, imports, storage dispatch, and load match
- Line flow limits, to respect the thermal capacities of transmission elements
- Voltage magnitude constraints, typically bounded within operational ranges to maintain power quality
- Current limits, ensuring safe line operation

The nonlinear AC power flow is modeled using a second-order cone approximation in (7)-(8) [14].

$$V_{b,t}^2 - V_{b',t}^2 = 2(R_l.E_{l,t}^{line} + X_l.Er_{l,t}^{line}) + Z_l^2.I_{l,t}^2 \tag{7}$$

$$V_{b,t}^2.I_{l,t}^2 = E_{l,t}^{line\,2} + Er_{l,t}^{line\,2} \tag{8}$$

Where:
$V_{b,t}$ is the voltage at bus b at time t,
$E_{l,t}^{line}$ and $Er_{l,t}^{line}$ are active and reactive power flows on line l at time t,
R_l and X_l are the resistance and reactance of line l at time t,
$I_{l,t}$ is the current flow through line l at time t.

2) Hydrogen Network Constraints:

The hydrogen network operation is constrained by physical laws and infrastructure limitations, including pipeline capacities, nodal pressure bounds, and linepack dynamics. The hydrogen flow between two connected nodes is modeled using Lacey's equation (i.e., for low pressure gas network), which relates the pressure drop to the square of the hydrogen flow through the pipe, given by (9) [15]. The linepack in the pipeline, representing the stored hydrogen volume, evolves according to the net flow into and out of the pipe (10).

$$\pi_{n,t} - \pi_{n',t} = K_{n,n'}H_{n,n',t}^{pipe\,2} \tag{9}$$

$$LP_{p,t} = LP_{p,t}^0 + \sum_0^t (H_{p,t}^{pipe,in} - H_{p,t}^{pipe,out}) \tag{10}$$

Where:

$\pi_{n,t}$ is the pressure at the hydrogen node n at time step t,
$H_{n,n',t}^{pipe}$ is the hydrogen flow through the pipeline from node n to n' at time t,
$K_{n,n'}$ is the pipe-specific coefficient in Lacey's equation, which accounts for the pipe's diameter, length, roughness, and gas properties,
$LP_{p,t}$ is linepack (i.e., the volume of hydrogen stored in pipeline p at time step t,
$LP_{p,t}^{0}$ is the initial linepack in pipeline p at the beginning of the time horizon.

3) Component Operational Constraints:

The operational feasibility of system components in the MEMG is ensured through a set of constraints that include generation and consumption limits for ELZs, FCs, rSOCs, and storage tank operation constraints, such as charging/discharging efficiencies and capacity of tanks [9]. These constraints enable coordinated and realistic operation of the integrated electricity and hydrogen networks within the optimization model.

D. Resilience

To enhance the reliability of the MEMG under extreme conditions, the proposed model incorporates resilience-oriented planning by simulating HILP events [15]. These scenarios reflect simultaneous occurrences of low renewable generation, peak demand, and main grid outage conditions representative of severe weather or infrastructure failures. The model prepares for such disruptions by planning flexibility based on worst-case forecasts for demand and renewable availability (i.e., the fourth operating day), ensuring system autonomy when islanded from the grid. Key technologies, including hydrogen storage, FCs, and rSOCs, are strategically dispatched to maintain energy balance and minimize load shedding. This ensures that the MG remains operational and serviceable during critical events, contributing to overall system resilience.

E. Solving Approach

To solve the proposed MINLP model, the DICOPT is employed within the GAMS environment [14]. The solution converges after approximately 1600 seconds, depending on the components considered as candidates for establishment. DICOPT uses a decomposition-based iterative algorithm that alternates between solving a relaxed master MILP and a subproblem to refine the nonlinear solution. In each iteration, upper and lower bounds are generated based on fixed binary decisions and linearized constraints using Lagrange multipliers. This approach ensures convergence to an optimal or near-optimal solution within a finite number of steps and provides a practical balance between solution accuracy and computational tractability.

It is worthwhile to mention that, in this study, a scenario reduction algorithm is used to extract the representative days of a year and solve the optimization problem. This algorithm reduces annual demand (i.e., electricity, heat, hydrogen) and wind profiles into a few representative scenarios by iteratively merging the most similar profiles, updating their frequencies, until the desired number of profiles is obtained, preserving the main seasonal and operational patterns [16].

III. CASE STUDY

This study investigates the performance of a MEMG under various planning scenarios, including its ability to respond to HILP events. Four scenarios are analyzed in addition to the base case (i.e., only renewable energy sources), as follows: (1) presence of hydrogen-fired units (H2P), (2) ELZs and FCs (ELEC+FC), (3) rSOC; and (4) Resilience. The MG comprises a low-pressure hydrogen distribution network with 11 nodes and 14 pipes as well as 33 nodes electricity distribution network, as illustrated in Fig. 1. The source of hydrogen is centralized, and distribution is governed by Lacey's equation, which is typically used for low-pressure gas networks (⩽75 mbar). Assumptions around ELZ, FC, and rSOC efficiency and lifetime are summarized in TABLE I [9].

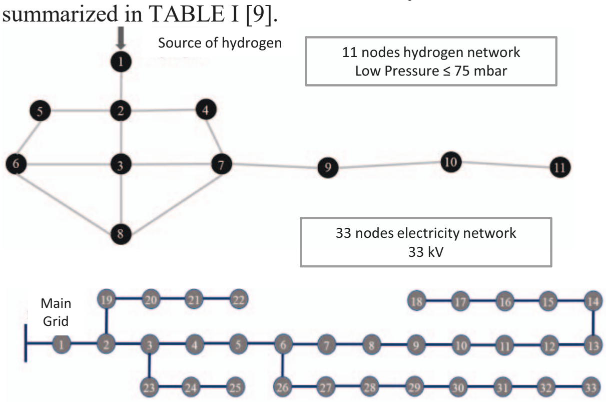

Figure 1. Hydrogen and electricity distribution networks under study

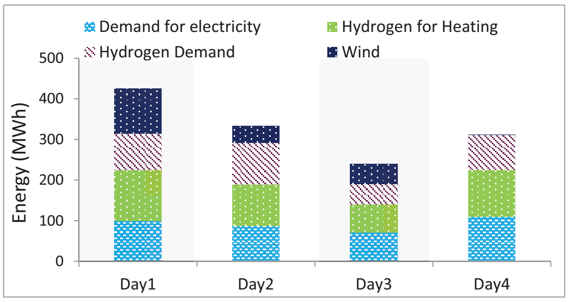

Figure 2. Total demand during a year for the four representative days

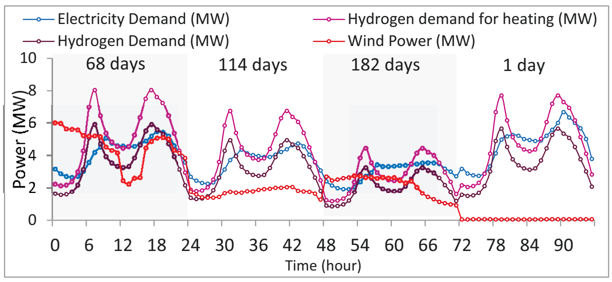

Figure 3. Time series for electricity demand, hydrogen demand, and wind availability

TABLE I. EFFICIENCY AND LIFETIME OF ELZ AND FC

Technology	Efficiency (%)	Lifetime (year)
ELZ	65	15
FC	80	10
rSOC-ELZ	90	20
rSOC-FC	60	20

The total demand during a year for the four representative days is indicated in Fig. 2. The time series for electricity demand, hydrogen demand, and wind availability are shown in Fig. 3. These profiles represent seasonal fluctuations and energy system interactions over a year as a result of scenario reduction algorithm implementation [9].

IV. Results and Analyses

In Scenario 1, 4 MW of existing fuel-fired units are renovated, aiming to reduce reliance on the main grid. It results in a significant reduction in load shedding on representative day 4, dropping by 60% (from 37 MWh to 14 MWh), and grid dependency fell from 99% to 38%. Figure 4 (top) illustrates the power dispatch across different sources. While the renovated hydrogen-fired units contributed effectively to reducing unmet demand, periods of renewable curtailment still occurred, especially during the early hours of the day, indicating the generators alone did not fully address excess renewable production. Figure 4 (bottom) shows the hydrogen supply and linepack levels. Although hydrogen supply remained steady, a noticeable dip in linepack was observed toward the end of day 4, suggesting that maintaining adequate hydrogen storage is critical for sustained operation. This also underscores potential challenges in fuel availability and generator efficiency, especially when the system faces high demand and limited flexibility.

Figure 5 illustrates the hourly dispatch of the MEMG over the four days for Scenario 2, installing 3.89 MW of ELZs and 0.95 MW of FCs. The power balance is managed using renewable energy, hydrogen-fired units, FCs, and external electricity purchases. ELZs operate flexibly to absorb excess renewable power, resulting in zero renewable curtailment. Load shedding is limited to 9.75 MWh, representing a 30% reduction compared to the H2P scenario.

Figure 6 presents the capital and operating expenditures for Scenario 2 in comparison with Scenario 3. It should be noted that, in this scenario, the total investment is 210 k€ higher than in the H2P scenario (a 26% increase), attributed mainly to the addition of ELZs and FCs. Despite this, the scenario achieves significant cost savings: a 20% (800 k€) reduction in hydrogen network operating costs and a 2% (267 k€) reduction in electricity network operating costs. An additional investment of 220 k€ in hydrogen storage results in a 6% operating cost saving. However, the capital and operating costs of Scenario 3 is also indicated, which features 2.78 MW of rSOCs, against the ELZ and FC configuration (ELEC+FC). The total investment in rSOC is 42.8 k€ higher than ELEC+FC, primarily due to increased storage capacity and rSOC system costs. However, rSOC achieves a total operating cost reduction of approximately 426 k€ (2%) per year, owing to higher system efficiency. The net operating cost saving is 258 k€ annually (1.5%) compared to ELEC+FC.

To assess system robustness under extreme grid outage scenarios, a resilience-based planning approach was simulated assuming an HILP event. Figure 7 presents the impacts of this strategy on key economic and operational metrics. Figure 8 (a) illustrates the changes in operating costs, where electricity-related expenditures are reduced, while hydrogen-related

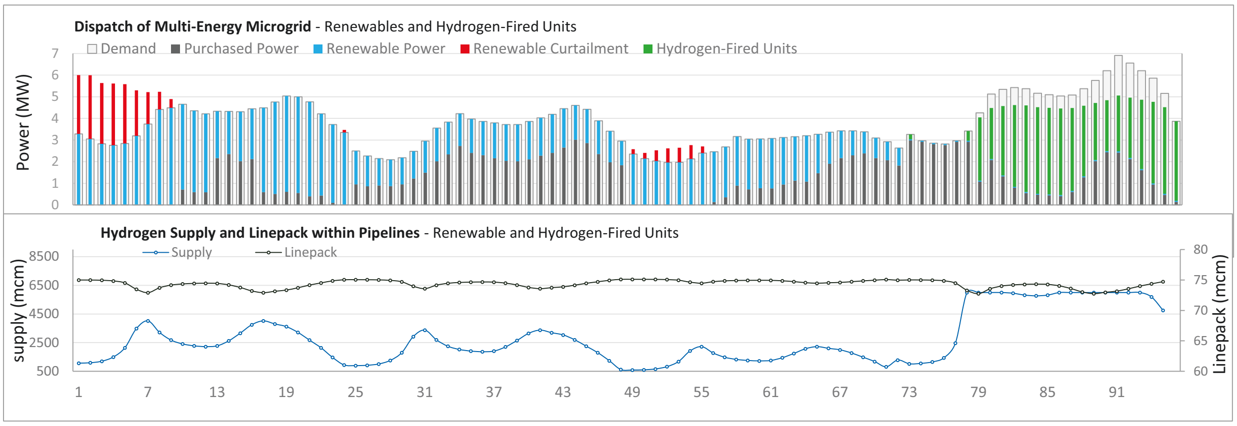

Figure 4. Dispatch of microgrid and hydrogen supply and linepack in scenario 2 (H2P)

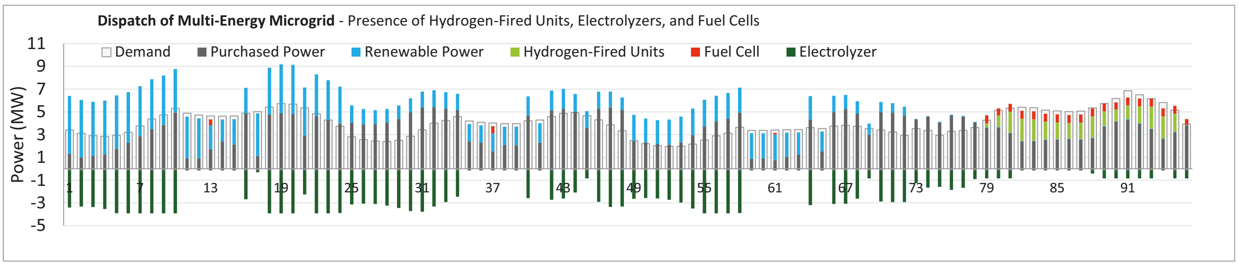

Figure 5. Dispatch of MEMG for Scenario 3 (ELEC+FC)

operating costs rise due to greater reliance on hydrogen infrastructure. Figure 8 (b) demonstrates significant reductions in load shedding and wind curtailment, reflecting enhanced supply continuity. Figure 8 (c) shows that achieving zero load shedding necessitates increased capital investment, particularly in storage, ELZs, and FCs. Overall, the resilience strategy incurs higher upfront and operational hydrogen costs but delivers substantial reliability improvements, including the complete elimination of load shedding during outages.

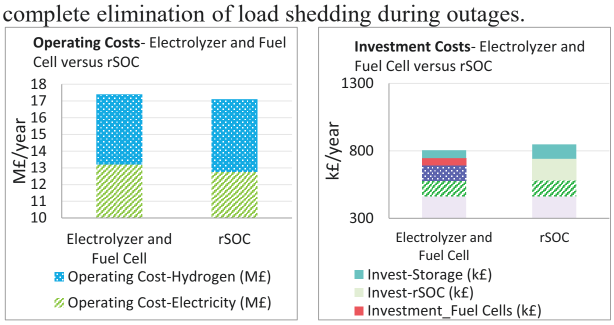

Figure 6. Investment and operating costs for Scenario 3 compared to scenario 2 (rSOC)

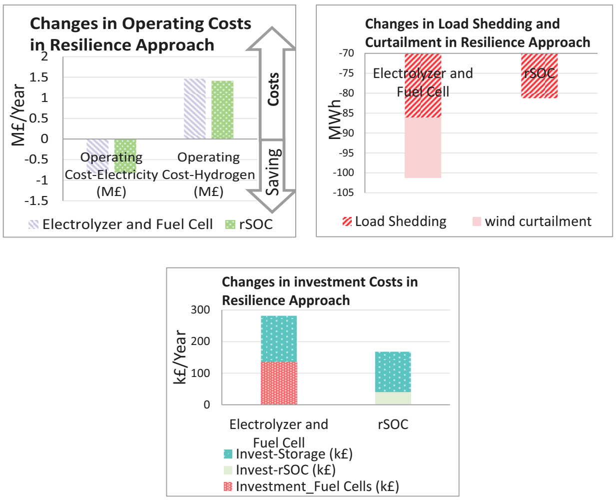

Figure 7. Results of Scenario 4 (Resilience)

V. Conclusion

In conclusion, this study investigated four technological scenarios of future multi-energy microgrids. These included planning for hydrogen-fired units, ELZ and FC systems, and rSOCs, both with and without resilience planning. The results demonstrated that integrating rSOCs provided the most cost-effective and flexible solution, eliminating renewable curtailment and minimizing load shedding. Specifically, rSOCs reduced annual operating costs by approximately 1.5% and offered complete elimination of load shedding during main grid outages. While rSOCs require higher upfront investment, certain use cases, such as areas far from the main grid or regions like Finland prone to winter outages, can reap greater cost savings and resilience benefits over time. As a future research direction, the computational burden of the formulation could be addressed by evaluating solver convergence, scalability, and testing decomposition techniques to improve tractability for larger microgrid cases.

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Optimizing the Resilient Operation of Microgrids against Natural Phenomena and Extreme Events

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Abstract

It is still challenging to determine the best operational strategies for microgrids to cope with extraordinary, high-impact, and low-probability events. This book chapter aims to address this challenge by categorizing the different methodologies developed to consider the impact of such events on energy system scheduling and proposing a scheduling approach to improve the resilience of microgrids during events. The previous methods to enhance the resilience of microgrids and/or distribution energy systems against natural events and phenomena are broadly classified into three categories: considering outage scenarios, employing flexible components as backup, and using a mixed strategy that combines the previous strategies. This chapter also proposes a scheduling approach to improve the resilience of microgrids during events, which involves maximizing the energy in the storage system and minimizing the imported power from the main grid, added to the microgrid scheduling model to improve its resilience. The results show that the proposed approach effectively reduces load shedding and improves the resilience of microgrids during events.

Keywords: Resilience; Microgrids; Operation; Natural Events; Natural Phenomena and Extreme Events.

1. Introduction

1.1. Motivation

A substantial number of studies are conducted worldwide each year to mitigate climate change and prevent extreme weather conditions. Climate change refers to long-term shifts in average weather patterns that have come to define earth's local and global climates. These shifts are primarily driven by human activities, particularly the burning of fossil fuels (e.g., coal, oil, and natural gas), which release large amounts of carbon dioxide and other greenhouse gases into the atmosphere. These gases trap heat from the sun, causing the planet's temperature to rise, leading to changes in precipitation patterns, sea levels, and other elements of the climate system (Figure 1) [1]. Climate change is a significant global challenge, with potential impacts ranging from more frequent and severe weather events to rising sea levels. To mitigate its effects, researchers, governments, and organizations are constantly working on finding solutions [2]. This includes developing new technologies, promoting renewable energy, improving energy efficiency, and reducing greenhouse gas emissions. The goal is to minimize the impact of human activities on the planet and prevent extreme weather conditions, such as storms, earthquakes, droughts, hurricanes, and heat waves.

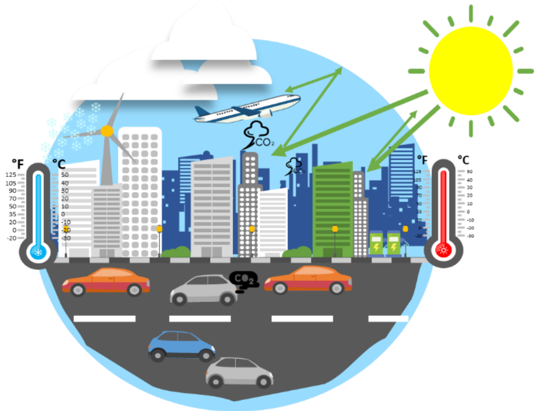

Figure 1. Illustration of climate change and global warming in the world.

Severe weather conditions and phenomena are the leading cause of interruption in energy systems worldwide. They can cause power outages, damage to infrastructure, such as power plants and transmission lines, and disrupt fuel supplies. This can lead to temporary or long-term interruptions in the energy supply, which can have far-reaching impacts on economies, communities, and individuals [3]. To minimize the impact of these events, energy companies are working to improve the resilience and reliability of energy systems, e.g., by investing in backup power sources and strengthened infrastructure. These events have a considerable cost, and the statistics show that their frequency of occurrence has increased in the past few years. As greenhouse gas emissions rise worldwide, these events are likely to become more intense, frequent, and prolonged. The impact of natural phenomena and extreme weather conditions on energy systems has also raised awareness about strengthening their resiliency [4]. Resiliency refers to the ability of the energy systems to withstand high-impact and low-probability incidents by efficiently minimizing interruption in demand provision and quickly facilitating restoration to the normal status [5].

1.2. Development of microgrids to enhance resiliency

The development of microgrids as an alternative to centralized and bulk energy systems is an approach to address resiliency in energy systems [6]. Microgrids are scaled-down decentralized energy systems that consist of distributed energy resources, loads, and flexibility options (e.g., storage systems and demand response programs). They allow for local control of energy generation, making the energy supply more reliable and resilient. Microgrids are an appropriate solution to facilitate the integration of distributed energy resources as well as supply customers who seek to reduce their dependency on the main grid and/or benefit from locally generated energy. More precisely, when the main grid fails and a microgrid is operated independently (i.e., islanded mode), the customers can benefit from locally generated energy. This makes microgrids a promising solution for improving the stability and reliability of energy systems, particularly in areas with weak or unreliable grid infrastructure [7]. An illustration of a typical microgrid is also indicated in Figure 2.

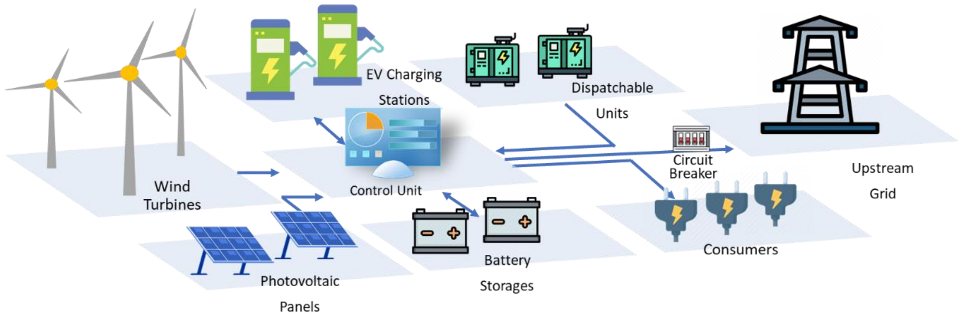

Figure 2. Demonstration of climate change and global warming in the world.

1.3. Aims and objectives

It is still challenging to practically determine the best operational strategies for microgrids to cope with extraordinary, high-impact, and low-probability events. The reason is that the frequency and intensity of the events are subject to uncertainty in the future paradigm, and taking into consideration the high impact of these events would be challenging. More precisely, climate change and global warming evolve low probability events and worsen the problem. Therefore, the first aim of this chapter is to recap and categorize the different methodologies developed to consider the impact of the occurrence of the events on the scheduling of energy systems (e.g., microgrids, distribution networks, or transmission networks). To this aim, a literature review is also conducted to examine the studies and allocate them to appropriate categories. In light of this, a modeling framework is finally suggested for enabling the development of weather-related resilience studies after introducing an operating model of microgrids. Finally, by introducing a case study, the developed approach is investigated to assess the effectiveness in reducing the load shedding in the case of these events.

2. Resilience measures

In this section, firstly, we introduce a more precise demonstration of microgrids and compare them with conventional power grids. After that, we will focus on exploring scheduling and management strategies that can be employed to improve the resilience of microgrids.

2.1. Microgrids versus power grid

As illustrated in Figure 3, a visual comparison of microgrids and conventional power grids is provided, highlighting the key differences between the two systems.

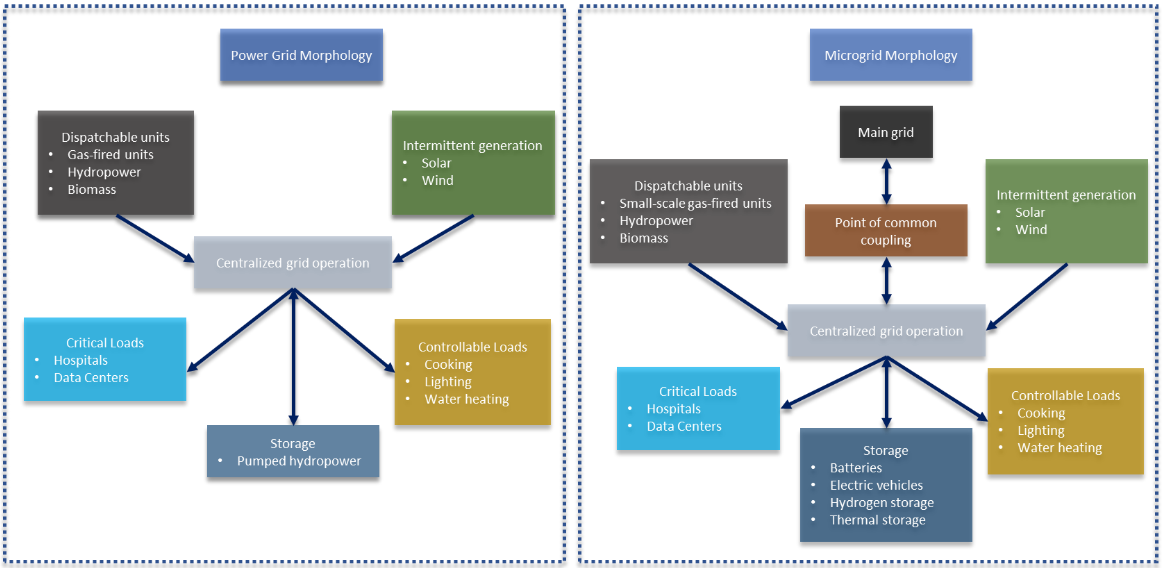

Figure 3. Design of microgrids versus conventional power grids.

In the power grid, intermittency and fluctuations, which affect the voltage and frequency in the grid, are the primary challenges of renewable energy power generation [8]. For instance, solar power production relies on sunlight, while wind power production depends on wind conditions. These factors can fluctuate significantly over time, making it difficult to maintain the stability and reliability of the power system, particularly during peak demand periods. More precisely, the increasing adoption of renewable energy sources can result in problems such as conductor overcapacity, frequency deviation, voltage fluctuations, harmonics, and flicker [9]. However, these challenges can be tackled by adopting on-grid energy storage, such as high-power batteries and more advanced weather forecasting to anticipate solar and wind energy outputs.

Moreover, photovoltaic and wind power generations have both advantages and disadvantages. One benefit is that solar and wind energy offers a diverse mix of power sources, which can boost the reliability of the power system. Furthermore, renewable energy sources are generally more resistant to supply disruptions compared to traditional fossil fuels, as they do not depend on fuel transportation. Aside from that, in regions with hot climates, the solar photovoltaic output can correspond to the daily electricity demand driven by air-conditioning load and therefore contributes to system stability during the peak demand period in the afternoon.

On the other hand, microgrids are distinct from traditional power grids, as they are composed of controllable units that contain flexible power components, such as distributed power-generation units, wind turbines, and photovoltaics [10]. Additionally, they contain circuit breakers and control units for the local network. Distributed renewable energy systems, which are typically small-scale wind or solar installations located near the point of use, can mitigate the power system's vulnerability to high-impact, low-frequency events. These systems are less constrained geographically than large-scale power plants, which can be susceptible to extreme weather conditions or natural disasters. These microgrids offer greater flexibility and self-sufficiency in terms of energy supply and consumption within their service area. As a result, they can mitigate the vulnerability of power supply from centralized generation and long-distance transmission, which is particularly significant during power system restoration following extreme weather events [11]. More precisely, a microgrid is an adaptable and manageable component of the distribution network that can integrate the output of distributed generation through energy management systems. The effects of renewable energy fluctuations can be reduced by combining demand-side management and energy storage systems [12]. Furthermore, because the timing and location of potential threats to the power system are uncertain and their impacts may not be evenly distributed, linking microgrids to the distribution network can greatly enhance network resilience. As the entire microgrid is less likely to be destroyed, it can provide support as an independent power source. During an emergency, a single microgrid can also assist nearby critical loads, resulting in reduced losses [13]. Additionally, the growing adoption of electric vehicles, heating, and cooling is expected to drive up the electricity demand further, necessitating a distribution network system that can sustain sufficient capacity and high-quality power. While microgrids offer inherent advantages in terms of resilience and reliability, advanced scheduling and management strategies can further enhance the performance of these systems. By optimizing the operation of microgrids under various dynamic and uncertain conditions, such as changes in weather patterns, power demand, and equipment failures, scheduling and management strategies can improve the overall efficiency, stability, and resilience of the system. In the following, the scheduling and management strategies for microgrids or even other types of energy systems that previous studies have introduced and devised are recapped and categorized.

2.2. Resilience consideration methods

The methods employed to improve the resiliency of energy systems can be categorized based on different criteria. One way is to categorize them based on the time frame in which they are employed [14]. In this regard, we can categorize resilience methods into short-term, medium-term, and long-term methods (Figure 4). Short-term resilience methods are employed to deal with immediate disruptions or shocks in the system. Examples of short-term resilience methods include backup generators, energy storage systems, and load shedding. These methods are designed to ensure that the energy supply is maintained in the event of immediate disruptions or failures in the system. Medium-term resilience methods are those that are employed to deal with disruptions or stresses that may last for a few hours to a few days. Examples of medium-term resilience methods include demand response programs and flexible generation technologies. These methods are designed to help the system cope with changes in demand and supply and adjust accordingly. Finally, long-term resilience methods are those that are employed to deal with disruptions or stresses that may last for several weeks, months, or even years. Examples of long-term resilience methods include infrastructure upgrades, diversification of energy infrastructure sources, and research and development of new technologies. These methods are designed to ensure that the system is resilient to long-term stresses and disruptions and can adapt to changes in the energy landscape.

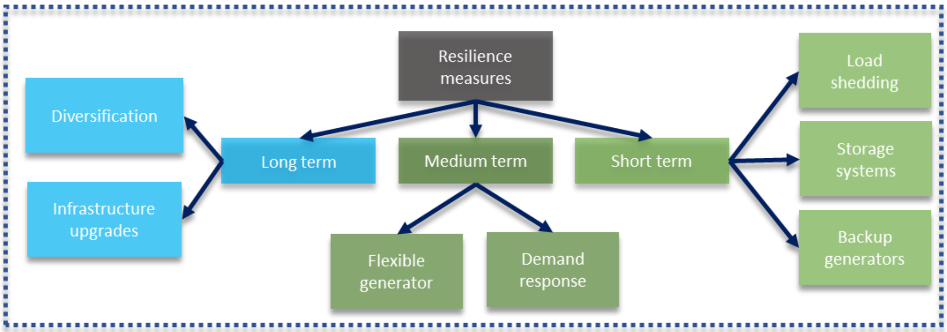

Figure 4. Categorizing resiliency measures based on the time frames in which they are employed.

On the other hand, resiliency improvement approaches in energy systems can be categorized into pre-event and post-event methods (Figure 5) [15]. Pre-event resiliency improvement approaches refer to those that are implemented before a disruption occurs in the energy system. These approaches are designed to mitigate the potential impacts of disruption and minimize the system's downtime. Examples of pre-event resiliency improvement approaches in energy systems include redundancy, system hardening, situational awareness, and flexibility. Redundancy refers to the provision of backup capacity and resources that can be used in the event of a disruption in the system. Redundancy can be achieved through various means, such as having backup generators, energy storage systems, and multiple transmission lines. Redundancy is an important pre-event resiliency improvement approach because it helps ensure that the energy supply is maintained even if one or more components of the system fail. Another example is system hardening, which refers to the process of making the energy system more robust and resilient to withstand potential disruptions. System hardening can involve the use of more durable materials in the system's infrastructure, the implementation of stronger cybersecurity measures, and the use of physical barriers to protect critical infrastructure. System hardening is an important pre-event resiliency improvement approach because it helps to reduce the vulnerability of the energy system to potential disruptions. Situational awareness refers to the ability of the energy system operators to monitor the system and detect potential disruptions before they occur. Situational awareness can be achieved through the use of advanced monitoring and sensing technologies, such as remote sensors and smart meters. Situational awareness is an important pre-event resiliency improvement approach because it enables energy system operators to take proactive measures to mitigate potential disruptions before they occur. Another method that is employed in the scheduling of energy systems to enhance resilience is flexibility. Flexibility refers to the ability of the system to adjust to changes in demand and supply quickly. Flexibility can be achieved through various means, such as demand response programs, energy storage systems, and flexible generation technologies. The advantage of flexibility is that it can help to ensure that the system can cope with changes in demand and supply and adjust accordingly.

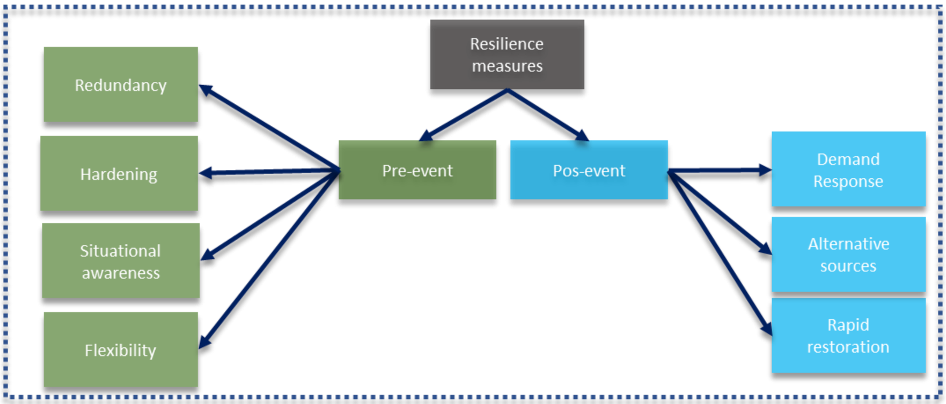

Figure 5. Categorizing resilience measures into pre-event and post-event.

Post-event resiliency improvement approaches also refer to those that are implemented after a disruption occurs in the energy system. These approaches are designed to restore the system's functioning as quickly as possible and minimize the impacts of the disruption on society. Examples of post-event resiliency improvement approaches in energy systems also include rapid restoration, alternative energy sources, and demand response. Rapid restoration refers to the process of quickly repairing or replacing the components of the energy system that were affected by the disruption. Rapid restoration can involve the use of specialized repair crews, pre-positioned equipment, and streamlined repair processes. Rapid restoration is an important post-event resiliency improvement approach because it helps to minimize the system's downtime and restore the energy supply as quickly as possible. Alternative energy sources refer to the use of energy sources that are not dependent on the disrupted components of the energy system. Alternative energy sources can include renewable energy sources, such as wind and solar, and portable generators. Alternative energy sources are an important post-event resiliency improvement approach because they can help to maintain the energy supply even if the primary energy sources are disrupted. Demand response refers to the process of reducing the energy demand in response to a disruption in the energy system. Demand response can involve the use of time-of-use pricing, which incentivizes consumers to shift their energy usage to off-peak hours, and the use of smart grid technologies, which enable energy system operators to remotely control energy usage. Demand response is an important post-event resiliency improvement approach because it helps to reduce the strain on the energy system and minimize the impacts of the disruption on society.

In this chapter, however, previous methods to enhance the resilience of microgrids and/or distribution energy systems against natural events and phenomena are classified into three categories: (i) considering outage scenarios, (ii) employing flexible components as backup, and (iii) using a mixed strategy that combines the two (Figure 6). The first approach involves analyzing the microgrid's behavior during outages and identifying strategies to maintain or restore power supply to critical loads. For instance, one of previous studies proposes a step-by-step approach to enhance the resilience of integrated gas and electricity networks against natural hazards [16]. For this purpose, at first, the potential occurrence of natural hazards in the area is evaluated, and the failure probability of components is calculated. After that, robust programming is devised to optimize decisions and enhance the resiliency of critical infrastructure when there is a limited amount of budget. In [17], an approach is developed to improve the resilience of gas and electricity systems against sequential extreme weather events. The proposed approach consists of hardening to reduce the impact of extreme weather as a preventive measure and rescheduling the system using robust programming to minimize the cost after the event. In [18], a method is proposed to enhance the resiliency of electricity distribution systems and restore the system after the event (post-disaster measure). To reach this aim, it uses the flexibility of both supply and demand-side to reschedule and restore the systems. This method uses options like mobile emergency generators, prosumer communities, photovoltaic systems, and demand response programs. In [19], the flexibility provided by power-to-gas systems and gas-fired units is utilized to enhance the resiliency of natural gas and electricity distribution systems. This study recognizes the worst-case scenario for the outage of components before the occurrence of a natural event and schedules different parties (i.e., *n-k* examination). In [20], a framework is proposed for scheduling the integration of electricity distribution and transportation systems to enhance resilience against natural hazards. To this aim, this study, after widespread events, uses mobile energy storage systems for restoration and supply a technically possible amount of demand.

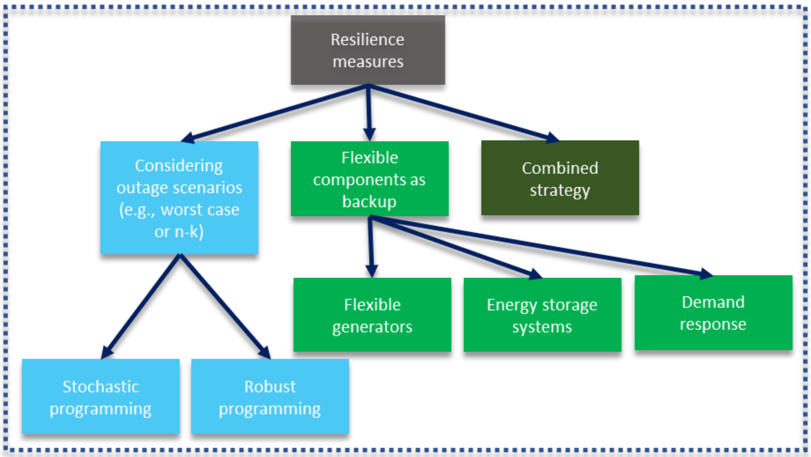

Figure 6. Categorizing resilience measures from the viewpoint of this chapter.

The second approach focuses on using flexible and modular components that can be reconfigured to provide backup power during an outage. For example, an approach is proposed to improve resilience against extreme weather events consisting of hardening and smart scheduling methods in [21]. In [22], another method is presented to enhance the resilience of the distribution electricity network against floods. The developed approach of this study is based on the long-term adaptability of components and adding flexibility to the electricity distribution network. Another research investigates the potential of photovoltaic systems and vehicles with the capability of vehicle-to-grid to enhance the resilience of microgrids against extreme weather events [23]. In [24], a model is presented to evaluate the resiliency of microgrids against harsh weather events based on the fragility of components and event model. In [25], a methodology is proposed that consists of predicting vulnerable components of distribution electricity networks against wind storms and optimizing the operation benefiting from wind turbines, photovoltaic systems, diesel generators, and energy storage systems.

The third approach is a hybrid approach that combines the benefits of both strategies to provide a robust and resilient microgrid system. In the following, previous studies that enhance the operation of energy systems by employing advanced scheduling and management strategies are reviewed and categorized. In previous studies, some scenarios are considered for incidents of failure as a consequence of natural hazards and use demand response programs to improve the resilience of microgrids after the occurrence of the incident [26]. In [27], scheduling of distributed energy resources, demand response programs, and shunt capacitors, are employed to enhance the resilience of a distribution network after incidents. In [28] and [29], an approach is developed based on swathing and mobile energy storage systems to facilitate the restoration of distribution networks. In [30], a method is developed that allocates underground lines before an event and optimizes and coordinates swathing and mobile storage systems after events.

3. Methodology, case study, and simulation results

The occurrence and severity of natural disasters vary by location and can have significant impacts on human populations and the environment. For instance, earthquakes are most common in areas near tectonic plate boundaries, but small earthquakes can happen anywhere [31]. The majority of the approximately 20,000 earthquakes that occur worldwide each year are small to be felt while larger earthquakes can cause extensive damage and loss of life. Volcanic eruptions are more likely in areas with active volcanoes, with about 50-70 eruptions happening worldwide each year [32]. Tsunamis, while relatively rare, can occur in any coastal area near a fault zone or volcanic region, with about two per year causing significant damage or loss of life [33]. The likelihood of hurricanes and cyclones depends on the location and season, with areas in the Atlantic and Pacific Oceans being most susceptible from June to November [34]. Floods can occur in any area with a high amount of precipitation or a risk of storm surges, affecting an estimated 250 million people each year worldwide[35]. Wildfires are most common in hot, dry climates and are becoming more frequent and severe in many regions due to climate change and land use changes [36]. As discussed, natural phenomena and extreme events can cause significant interruptions and harm to energy systems as well. To improve the resilience of microgrids against the natural phenomena and extreme events, a methodoly is suggested in this section of the study.

3.1. Methodology

In this section, a scheduling approach is suggested to improve the resilience of the operation of microgrids. For this purpose, at the first stage, an operating model of microgrids is proposed, which is an optimization problem consisting of the objective function(s) and constraints. Microgrid scheduling involves optimizing the operation of distributed energy resources in the microgrid and interactions with the upstream grid to meet the energy demand of the loads while minimizing the costs [37]. The microgrid can include various energy sources, such as solar, wind, biomass, and dispatchable units like diesel generators, gas turbines, and even battery energy storage systems. It should be noted that battery storage systems can provide flexibility in microgrids by storing excess energy during times of low demand and low price and then releasing it during times of high demand and high price. This helps to balance the supply and demand of energy and achieve cost savings, which can be especially important in systems that rely heavily on intermittent renewable energy sources.

3.1.1. Objective function

The objective function of the microgrid scheduling model is to minimize the total operating cost of the microgrid (Equation (1)). The total cost includes the cost of dispatchable units, the cost of load shedding, and the cost of interactions with the main grid. The cost of interaction with the main grid includes the cost of importing and revenue of exporting power.

$$Z = \sum_{t=1}^{T}\sum_{b=1}^{B} \alpha_t . P_{b,t}^{buy} - \sum_{t=1}^{T}\sum_{b=1}^{B} \beta_t . P_{b,t}^{sell} + \sum_{t=1}^{T}\sum_{b=1}^{B} \gamma_b . P_{b,t} + \sum_{t=1}^{T}\sum_{b=1}^{B} \delta . P_{b,t}^{lsh} \tag{1}$$

, where

b	Buses
t	Periods
α_t	Price of purchasing from the main grid
β_t	Price of selling to main grid
γ_b	Cost of power production using dispatchable units
δ	Cost of load shedding
Z	Objective function
$P_{b,t}^{buy}$	Purchased power from the main grid
$P_{b,t}^{sell}$	Sold power to the main grid
$P_{b,t}$	Output power of dispatchable units
$P_{b,t}^{lsh}$	Load shedding

3.1.2. Constraints

Microgrids consist of distributed energy resources, such as solar panels, wind turbines, and batteries that are connected to a local distribution network. Microgrids can operate in grid-connected or islanded mode, depending on whether they are connected to the main grid or not. In either mode, the microgrid scheduling model must satisfy various operational constraints to ensure the safe and reliable operation of the microgrid. One of the most important operational constraints in microgrid scheduling is active power balance (Equation (2)). The sum of active power produced by the distributed dispatchable units, imported power from the main grid, output power of renewable resources, discharging power of storage systems, load shedding must be equal to the active power consumed by the loads plus the active power losses in the distribution lines, charging power of energy storage systems, and exported power to the main grid. This ensures that the microgrid is meeting the energy demand of its users without overloading or underloading the system. The microgrid scheduling model must consider the active power consumption and production of each distributed energy resource and ensure that the system is balanced at all times.

$$P_{b,t} + P_{b,t}^{DG} + P_{b,t}^{buy} + P_{k,t}^{dc} + P_{b,t}^{lsh} = P_{b,t}^{load} + P_{b,t}^{sell} + P_{k,t}^{c} + \sum_{b'=1}^{B} (P_{l,t}^{line} + R_l . I_{l,t}^2) \qquad \forall b, l\epsilon(b,b'), \forall t \qquad (2)$$

, where

L	Distribution lines
$P_{b,t}^{DG}$	Output power of distributed renewable resources
$P_{k,t}^{dc}$	Discharging power of storage systems
$P_{k,t}^{c}$	Charging power of storage systems
R_l	Resistance of distribution lines
$P_{b,t}^{load}$	Load
$P_{l,t}^{line}$	Power through distribution line
$I_{l,t}$	Current through distribution line

Another important constraint is reactive power balance, indicated in Equation (3). The reactive power produced by the distributed energy resources must be equal to the reactive power consumed by the loads plus the reactive power losses in the distribution lines. Reactive power is important for maintaining the voltage stability of the microgrid. The microgrid scheduling model must consider the reactive power consumption and production of each distributed energy resource and ensure that the system is balanced at all times.

$$Q_{b,t} + \sum_{b'=1}^{B} (Q_{l,t}^{line} + X_l . I_{l,t}^2) = Q_{b,t}^{load} \qquad \forall b, l\epsilon(b,b'), \forall t \qquad (3)$$

, where

$Q_{b,t}$	Reactive power produced by the distributed energy resources
$Q_{l,t}^{line}$	Reactive power through distribution line
X_l	Reactance
$Q_{b,t}^{load}$	Reactive power load

Kirchhoff's law is also a crucial constraint in microgrid scheduling. It states that the voltage and current at each node in the microgrid must satisfy the law of conservation of energy [38]. The microgrid scheduling model must ensure that the voltage and current at each node in the system are balanced and meet the requirements of Kirchhoff's law (Equations (4)-(5)).

$$V_{b,t}^2 - V_{b',t}^2 = 2(R_l . P_{l,t}^{line} + X_l . Q_{l,t}^{line}) + Z_l^2 . I_{l,t}^2 \qquad l\epsilon(b,b'), \forall t \qquad (4)$$

$$V_{b,t}^2 . I_{l,t}^2 = Q_{l,t}^{line\,2} + P_{l,t}^{line\,2} \qquad l\epsilon(b,b'), \forall t \qquad (5)$$

,where

$Z_{l,t}$	Impedance
$V_{b,t}$	Voltage

The output of the dispatchable units is another constraint that must be considered in microgrid scheduling (Equation (6)). The dispatchable units, such as diesel generators, must operate within their minimum and maximum limits to ensure that they do not overload or underload the system. The microgrid scheduling model must consider the output of each dispatchable unit and ensure that it is within the required limits.

$$P_b^{min} \leq P_{b,t} \leq P_b^{max} \qquad \forall b, \forall t \qquad (6)$$

, where

P_b^{min} Minimum output power limit

P_b^{max} Maximum output power limit

The active and reactive power flowing through the distribution lines must also be within their rated limits (Equations (7)-(8)). This constraint ensures that the distribution lines are not overloaded and that they operate within their rated capacity. The microgrid scheduling model must consider the active and reactive power flowing through each distribution line and ensure that it is within the required limits.

$$P_l^{line\ min} \leq P_{l,t}^{line} \leq P_l^{line\ max} \qquad l\epsilon(b,b'),\ \forall t \qquad (7)$$

$$Q_l^{line\ min} \leq Q_{l,t}^{line} \leq Q_l^{line\ max} \qquad l\epsilon(b,b'),\ \forall t \qquad (8)$$

, where

$P_l^{line\ min}$ Minimum power through line

$P_l^{line\ max}$ Maximum power through line

$Q_l^{line\ min}$ Minimum reactive power through line

$Q_l^{line\ max}$ Maximum power through line

Finally, the dispatchable units must ramp up or down within their ramp rate limits (Equations (9)-(10)). This constraint ensures that the dispatchable units can respond quickly to changes in the energy demand of the system. The microgrid scheduling model must consider the ramp rate limits of each dispatchable unit and ensure that they are not exceeded.

$$P_{b,t} - P_{b,t-1} \leq Rmp_b^{up\ max} \qquad \forall b, \forall t \qquad (9)$$

$$P_{b,t-1} - P_{b,t} \leq Rmp_b^{dn\ max} \qquad \forall b, \forall t \qquad (10)$$

, where

$Rmp_b^{up\ max}$ Maximum ramp up

$Rmp_b^{dn\ max}$ Maximum ramp down

In addition to these constraints, storage systems, such as batteries must also be considered in microgrid scheduling (Equations (11)-(14)). The scheduling model must consider the changes in the state of charge of the batteries, the limitations of charging and discharging power, and the limitation of the state of charge. These constraints ensure that the batteries are used efficiently to meet the energy demands of the microgrid. It is of crucial importance that the charging and discharging power of storage systems are added to the active power balance.

$$SC_{k,t} = SC_{k,t}^0 + \sum_1^T (ef^c . P_{k,t}^c - P_{k,t}^{dc}/ef^{dc}) \qquad \forall k,\ \forall t \qquad (11)$$

$$P_k^{c\ min} \leq P_{k,t}^c \leq P_k^{c\ max} \qquad \forall k,\ \forall t \qquad (12)$$

$$P_k^{dc\ min} \leq P_{k,t}^{dc} \leq P_k^{dc\ max} \qquad \forall k,\ \forall t \qquad (13)$$

$$SC_k^{min} \leq SC_{k,t} \leq SC_k^{max} \qquad \forall k,\ \forall t \qquad (14)$$

, where

$SC_{k,t}^{0}$	Initial state of charge of storage systems
ef^{c}	Efficiency of charging
ef^{dc}	Efficiency of discharging
$P_{k}^{c\,min}$	Minimum charging limit
$P_{k}^{c\,max}$	Maximum charging limit
$P_{k}^{dc\,min}$	Minimum discharging limit
$P_{k}^{dc\,max}$	Maximum discharging limit
SC_{k}^{min}	Minimum state of charge
SC_{k}^{max}	Maximum state of charge
$SC_{k,t}$	State of charge

3.1.3. Resilience consideration

Adding additional objective functions to the microgrid scheduling model can help improve the resilience of the microgrid during times of uncertainty or unpredictability [39]. Two such objective functions that could be added to the model are maximizing the energy in the storage system and minimizing the imported power from the main grid (Equations (15)-(16)).

$$Z' = \sum_{t=1}^{T}\sum_{k=1}^{K} SC_{k,t} \tag{15}$$

$$Z" = \sum_{t=1}^{T}\sum_{b=1}^{B} P_{b,t}^{buy} \tag{16}$$

Maximizing the energy in the storage system is an important objective function for improving the resilience of the microgrid. During times when there is a shortage of power from the distributed energy resources or when the electricity demand is high, the storage system can provide backup power to the microgrid. By maximizing the energy in the storage system, the microgrid can ensure that it has sufficient backup power to meet the demand in case of an emergency. This can be achieved by adding another objective function that maximizes the energy in the storage system.

Minimizing the imported power from the main grid is another important objective function for improving the resilience of the microgrid. During times when the main grid is experiencing a failure or is unable to supply power to the microgrid, the microgrid must rely on its resources to meet the electricity demand. By minimizing the imported power from the main grid, the microgrid can reduce its dependence on the main grid and ensure that it can operate independently in case of an emergency. This can be achieved by adding another objective function that minimizes the imported power from the main grid subject to the constraint of the minimum and maximum output of the dispatchable units.

It should be noted that normalizing the objective functions ensures that they are on the same scale so that they can be combined using a weighted sum. The weights represent the relative importance of each objective and can be adjusted to find different trade-offs between the objectives (w_1, w_2, and w_3, respectively). It should be noted that the sum of weighted coefficients is equal to zero.

$$OF = w_1\left(\frac{Z^{nis} - Z}{Z^{nis} - Z^{pis}}\right) + w_1\left(\frac{Z' - Z'^{\,nis}}{Z'^{\,pis} - Z'^{\,nis}}\right) + w_1\left(\frac{Z''^{\,nis} - Z''}{Z''^{\,nis} - Z''^{\,pis}}\right) \tag{14}$$

, where

OF	Total objective function
w_1	Weighted coefficient
Z^{pis}	Maximizing Z provides a positive ideal solution
Z^{nis}	Maximizing Z' or minimizing Z'' that provides the worst solution for Z, called non-idea solution

Last but not least, to evaluate the effectiveness of the proposed approach, the step-by-step algorithm is illustrated in Figure 7. As indicated, in the first step, the resilience operation of a microgrid is optimized when a failure in the upstream grid is predicted. After that, the optimal scheduling of the microgrid is saved, including the dispatch of renewable and non-renewable resources and storage systems. Then, it is assumed that failure in the main grid has occurred and the energy-not-supplied is obtained considering the dispatch provided in the last step. It should be noted changing the weighted coefficients and reconducting these steps provide the dispatch that leads to minimum load shedding (i.e., maximum resilience by employing this method).

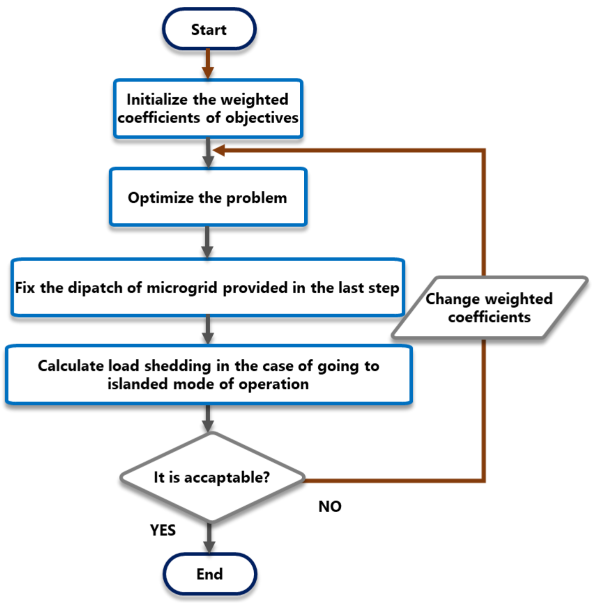

Figure 7. Step-by-step algorithm to evaluate the effectiveness of the proposed approach.

3.2. Case study

A microgrid that includes 33 buses, 32 lines, wind generators, battery storage systems, and dispatchable units, is considered to validate the proposed approach (Figure 8) [40]. In microgrids, the control unit plays a critical role in ensuring optimal energy management and grid stability. The control unit acts as the brain of the microgrid, monitoring and managing energy flow, frequency, voltage, and other key parameters to ensure the microgrid operates efficiently and reliably. With advanced control algorithms and real-time data analysis, the control unit can optimize energy use, minimize grid disruptions, and respond quickly to changing conditions, making it an essential component of any modern microgrid system.

The microgrid can be simulated under normal operating conditions as well as natural hazards or failures in the main grid when it goes to islanded mode. More data about the case study, including characteristics of electricity networks, dispatchable units as well as load and availability of wind power, are available in [37].

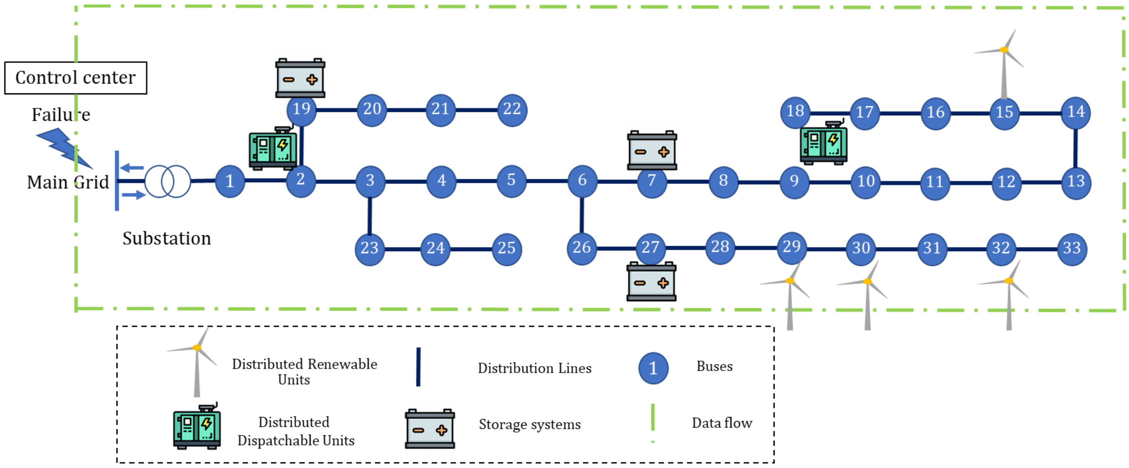

Figure 8. Case study: validating the effectiveness of resilience improvement approach in a Microgrid.

This case study involves a set of lithium-ion battery storage systems, each with a capacity of 3 MW. They systems are connected to buses 7, 19, and 27, to be charged and discharged and assist the operation of the microgrid. One notable aspect of these batteries is their high efficiency, meaning that they can quickly and effectively store and release energy, helping to balance the grid and ensure a reliable power supply. With their impressive capabilities, these battery storage systems are an exciting example of how cutting-edge technology can help to transform the energy landscape [41]. For this reason, this study investigates whether they can improve the resilience operation of microgrids.

3.3. Simulation results

At first, it is indicated whether the integration of the storage systems has any impact on the scheduling of the microgrid. To reach this aim, a case is investigated in which the scheduling of the microgrid is compared in the presence and absence of battery storage systems (Figure 9). As indicated, the battery storage systems are charged during off-peak hours of the operating horizon and discharged during the peak hours of the operating period. The reason is that the price of imported power from the main grid is low during the off-peak hours and high during the peak hours, respectively. So, it is beneficial that the batteries are operated in this manner from the viewpoint of the microgrid operator.

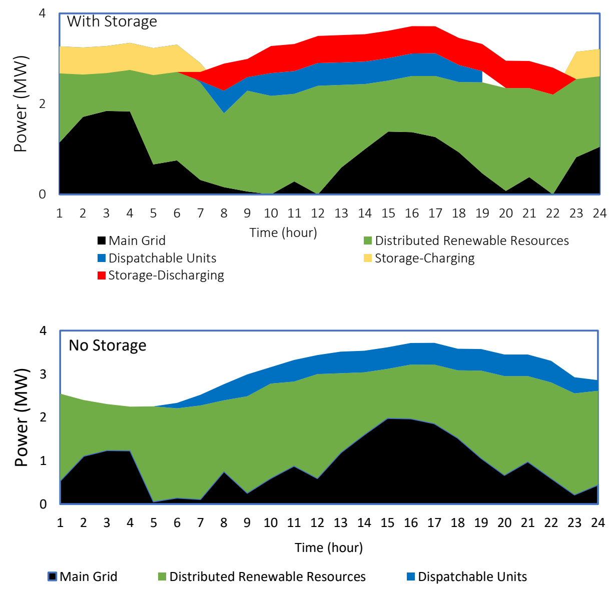

Figure 9. Dispatching of the microgrid in the presence and absence of battery storage systems.

The next analysis that is conducted is the investigation of the role of the battery in the case of low wind power availability (i.e., around 25 % of the previous case). As indicated in Figure 10, in the low availability of wind, the microgrid operation considerably relies on the imported power from the main grid. However, the battery storage systems fully charged during the last operating horizon can assist in addressing supply-demand provision.

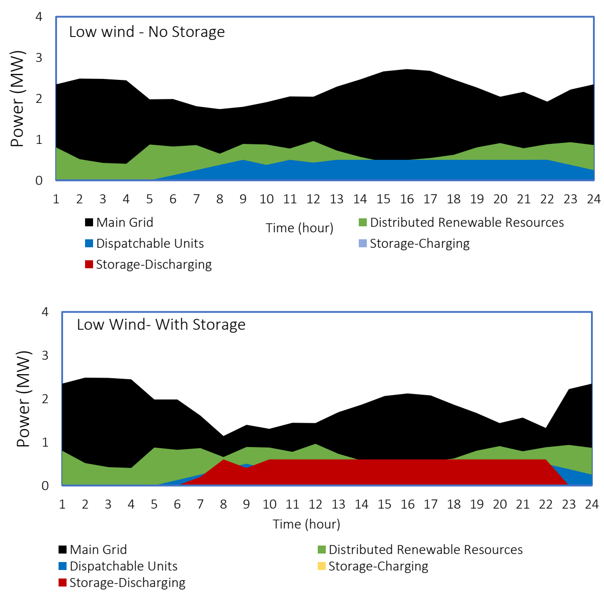

Figure 10. Dispatching of the microgrid in low wind power availability.

Moreover, a sensitivity analysis is conducted to study the effect of considering the second and the third objective functions to improve the resilience of the operation (i.e., the proposed method in Figure 7). As indicated, the increase in the weighted coefficients of the second and third objective functions reduces the amount of energy-not-supplied (Table 1). As a justification, the previous analyses should be recapped that indicated the role of battery storage systems in providing flexibility in the microgrid. When the the sum of weighted coefficients of the second and the third objective function are equal to one (i.e., the most resilience approach), there is no load shedding. It addresses the effectiveness of the suggested resiliency consideration methodology to improve the resiliency of the microgrid. In the case of the prediction of natural hazards, if the microgrid is operated considering resiliency, there will be no load shedding. However, it increases operating costs, so the operator must evaluate the trade-off between resilience and economic operation.

Table 1. Load shedding versus weighted coefficients of resilient improvement objective functions.

Weighted coefficients	Load shedding (kW)	Weighted coefficients	Load shedding (kW)
$w_2 = w_3$=0	18124	$w_2 = w_3$=0.3	11554
$w_2 = w_3$=0.05	14386	$w_2 = w_3$=0.35	7043
$w_2 = w_3$=0.15	1338	$w_2 = w_3$=0.4	6938
$w_2 = w_3$=0.2	13838	$w_2 = w_3$=0.45	6518
$w_2 = w_3$=0.25	13838	$w_2 = w_3$=0.5	0

4. Conclusion

The development of microgrids as an alternative to centralized and bulk energy systems is a promising approach to address resiliency in energy systems. However, determining the best operational strategies for microgrids to cope with extraordinary, high-impact, and low-probability events remains a challenge. This book chapter aimed to address this challenge by categorizing the different methodologies developed to consider the impact of such events on energy system scheduling and proposing a scheduling approach to improve the resilience of microgrids during events.

The chapter categorized the previous methods to enhance the resilience of microgrids and/or distribution energy systems against natural events and phenomena into three categories: considering outage scenarios, employing flexible components as backup, and using a mixed strategy that combines the two. Moreover, the chapter proposed a scheduling approach to improve the resilience of microgrids during events. The approach involved an operating model of microgrids, which was an optimization problem consisting of the objective function(s) and constraints. The microgrid scheduling optimized the operation of distributed energy resources in the microgrid and interactions with the upstream grid to meet the energy demand of the loads while minimizing the costs. The chapter concluded by suggesting that additional objective functions, such as maximizing the energy in the storage system and minimizing the imported power from the main grid, could be added to the microgrid scheduling as a preventive measure to improve its resilience during the occurrence of events. The proposed approach was investigated in a case study to assess its effectiveness in reducing load shedding during events. The results showed that the proposed approach effectively reduced load shedding and improved the resilience of microgrids during events.

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Techno-economic assessment of energy storage systems in multi-energy microgrids utilizing decomposition methodology

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ABSTRACT

Renewable resources and energy storage systems integrated into microgrids are crucial in attaining sustainable energy consumption and energy cost savings. This study conducts an in-depth analysis of diverse storage systems within multi-energy microgrids, including natural gas and electricity subsystems, with a comprehensive focus on techno-economic considerations. To achieve this objective, a methodology is developed, comprising an optimization model that facilitates the determination of optimal storage system locations within microgrids. The model considers various factors, such as operating and emission costs of both gas and electricity subsystems, and incorporates a sensitivity analysis to calculate the investment and maintenance costs associated with the storage systems. Due to the incorporation of voltage and current relations in the electricity subsystem as well as gas pressure and flow considerations in the natural gas subsystem, the developed model is classified as a mixed-integer nonlinear programming model. To address the inherent complexity in solving, a decomposition approach based on Outer Approximation/Equality Relaxation/Augmented Penalty is developed. This study offers scientific insights into the costs of energy storage systems, potential operational cost savings, and technical considerations of microgrid operation. The results of the developed decomposition approach demonstrate significant advantages, including reduced solving time and a decreased number of iterations.

1. Introduction

Increasing energy consumption without proper management and planning can result in increased pollution and waste of natural resources. Harnessing green renewable energy resources has become increasingly important to cope with the mentioned problem [1]. It is due to their potential to control the negative effects of carbon dioxide emissions and help the environment, which is experiencing alarming global warming [2]. Research on microgrids has grown in recent years as a result of their ability to assist in the integration of renewable energy sources into electricity systems while also enhancing flexibility, reliability, efficiency, and reducing environmental impact [3]. Another important potential of microgrids is a wide opportunity to use multi-carrier energy systems for energy generation and conversion. Integrating different energy carriers in an optimal framework can also facilitate progress toward a reliable, cost-effective, and environmentally friendly energy system [4]. However, even in a multi-energy microgrid, a significant part of the cost still comes from supporting technologies that are necessary to deal with the variability and uncertainty of renewable resources, such as storage systems that charge energy when there is excess supply and discharge during peak periods [5]. Researchers are always looking for solutions to either eliminate or reduce the existing challenges in front of the high penetration of renewable energy sources. Therefore, techno-economic studies of energy storage systems can play an important role in reducing costs and increasing the use of renewable energy sources.

A considerable number of studies have been conducted to investigate microgrids from a techno-economic point of view. These studies can be divided into two main groups, including the analysis of multi-energy systems and single-energy systems. While some studies propose linear models for examining this problem, others consider more precise and nonlinear models. In the studies with linear models, Mixed-Integer Linear Programming (MILP) solvers are mainly used to solve the

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Nomenclature

Indices

b	Index of buses in electricity system
j	Index of years
n	Index of nodes in natural gas system
y	Index of injection nodes in natural gas system
p	Index of pipes in natural gas system
l	Index of lines in electricity system
k	Index of storage systems
m	Index of distributed renewable energy systems
$iter$	Index of iterations
t	Period

Parameters

D^{day}	Total energy demand during a day (kWh)
D^{year}	Total energy demand during a year (kWh)
C^{g}	Cost of purchased volume of natural gas from main grid (\$/kcm)
C^{lp}	Cost of changes in volume of natural gas within pipelines in gas system (\$/kcm)
C^{Co2}	Cost of emission produced by dispatchable units (\$/kW)
C^{sh}	Cost of gas shedding in natural gas system (\$/kW)
C^{BS}	Cost of investment for energy storage systems (\$/kW)
Cap_k	Capacity of storage systems (kW)
C^{MBS}	Maintenance cost of energy storage systems (\$/kW)
$G_y^{buy\ lim}$	Limitation of volume of purchased natural gas from main grid (kcm)
ψ_t	Price of purchasing electricity from main grid (\$/kW)
$\psi'_{b,t}$	Price of selling electricity to main grid (\$/kW)
α_b	Variable cost of electricity production using non-renewable dispatchable units (\$/kW)
β_b	Fixed cost of electricity production using non-renewable dispatchable units (\$)
r	Interest rate (%)
C_p	Coefficient of Lacey's Equation for low-pressure natural gas $\left(\sqrt{\frac{Dia_p^5}{11700\ Le_p}}\right)$
Dia_p	Diameter of pipelines (mm)
Le_p	Length of pipelines (m)
r	Lifespan (year)
$D_{n,t}^{gas}$	Demand in gas system (kcm)
$GP_{p,t}^{0}$	Initial volume of natural gas within pipeline in gas system (kcm)
$P_{b,t}^{DG\ max}$	Maximum output of renewable distributed energy resources (kW)
$P_b^{min/max}$	Minimum/maximum output of non-renewable distributed generating units (kW)
$Ramp_b^{down/up\ max}$	Maximum ramp down/up (kw)
I_l^{max}	Maximum magnitude of current through electrical lines (Ampere)
$V_b^{min/max}$	Minimum/maximum magnitude of voltage (Volt)
R_l	Resistance (ohm)
X_l	Reactance (ohm)
Z_l	Impedance (ohm)
υ	Coefficient of calculating required amount of natural gas to produce electricity using gas-fired units (kcm/kW)
η_i	Efficiency of non-renewable gas-fired units to produce electricity (%)
$p_n^{min/max}$	Minimum/maximum pressure (mbar)
$P_k^{ch\ min/max}$	Minimum/maximum charging power into storage systems (kW)
$P_k^{dch\ min/max}$	Minimum/maximum discharging power from storage systems (kW)
$eff^{dch/ch}$	Efficiency of discharge/charge (%)
$SC_k^{min/max}$	Minimum/maximum stored energy within storage systems (kWh)
$SC_{k,t}^{0}$	Initial stored energy within storage systems (kWh)

Decision variables

OF	Objective function (\$)
C^{inv}	Cost of investment (\$)
C^{M}	Cost of Maintenance (\$)
C^{oper}	Cost of operation (\$)
C^{CO2}	Cost of emissions (\$)
C^{gas}	Cost of natural gas system operation (\$)
C^{elec}	Cost of electricity system operation (\$)
$GNS_{n,t}$	Natural gas-not-supplied (kcm)
$\Delta GP_{n,t}$	Changes in volume of natural gas within pipelines (kcm)
$G_{p,t}^{pipe}$	Transmitted volume of natural gas through pipelines (kcm)
$p_{n,t}$	Gas pressure (mbar)
$GP_{p,t}$	Volume of natural gas within pipelines (kcm)
$G_{y,t}^{buy}$	Purchased volume of natural gas from main grid (kcm)
$Q_{l,t}^{line}$	Reactive power within lines (kVAR)
$G_{n,t}$	Transmitted gas from gas system to supply non-renewable dispatchable generating units to produce electricity (kcm)
$P_{b,t}^{buy}$	Purchased power from main grid (kw)
$G_{b,t}$	Gas consumption of non-renewable dispatchable generating units to produce electricity (kcm)
$P_{b,t}^{sell}$	Electric power sold to main grid (kW)
$P_{b,t}$	Output power of non-renewable dispatchable generating units (kcm)
$u_{b,t}$	Status of non-renewable dispatchable generating units (0/1)
$P_{b,t}^{DG}$	Output power of distributed renewable energy resources (kW)
$Q_{b,t}$	Reactive power (kVAR)
$I_{l,t}$	Magnitude of current (Ampere)
$V_{b,t}$	Magnitude of Voltage (Volt)
$SC_{b,t}$	Energy stored in storage systems (kWh)
$P_{k,t}^{ch}$	Charged power (kW)
$P_{k,t}^{dch}$	Discharged power (kW)
$P_{l,t}^{line}$	Active power within lines (kW)
ν_k	Binary variable indicates whether storage system is installed (0/1)

Abbreviations

MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
GAMS	General Algebraic Modeling System
P2G	Hydrogen storage
LI	Lithium-Ion
LA	Lead-Acid
PSO	Particle swarm optimization
GBD	Generalized Benders Decomposition
mbar	Millibar
CH	Charge
DG	Distributed renewable resources
MW(h)	Megawatt (hours)
HOMER	Hybrid Optimization of Multiple Energy Resources
DICOPT	Discrete and Continuous Optimizers
CA	Compressed air storage
PV	Photovoltaic
WT	Wind turbine

OA/ER	Outer Approximation/Equality Relaxation	cm	Cubic meter
OA/ER/AP	Outer Approximation/Equality Relaxation/Augmented Penalty	DCH	Discharge
		FG	Flexible dispatchable unit
kW(h)	Kilowatt (hours)	MG	Main grid

problem using General Algebraic Modeling System (GAMS) software or Hybrid Optimization of Multiple Energy Resources (HOMER) software. However, solving nonlinear optimization problems is challenging so that heuristic methods are usually used to solve this class of problems. Among the studies on multi-energy microgrids, in Ref. [6], optimal microgrid planning is examined by developing a Mixed-Integer Nonlinear Programming (MINLP) formulation to consider combined heat and power units, compressed air storage systems (CA), renewable resources, and thermal storage systems. The results prove that the simultaneous integration of the technologies significantly reduces the operation and emission costs. In Ref. [7], by developing an MILP model, techno-economic analysis is conducted to study the integration of photovoltaic (PV) systems and hydrogen storage systems (P2G) into a microgrid of an airport. A sensitivity analysis is also performed, which indicates the cost reduction by the P2G integration. In Ref. [8], techno-economic allocation of different devices in a microgrid, optimal operation, and demand side management are studied to achieve an efficient renewable-based microgrid. Mathematical modeling is in the form of MILP, and the results show a significant reduction in the operating cost of microgrids due to demand-side management. In Ref. [9], another MILP model is introduced with the objective of economic evaluation of isolated microgrids with biomass technology integration for rural electrification of India. The results show that the integration of this technology is beneficial and improves the cost of operation in an isolated microgrid. In Ref. [10], another MILP model is introduced to provide new indicators for estimating multi-energy microgrids' techno-economic and environmental potential in island mode. Considering two microgrids in Denmark and Croatia, the results show the significant role of energy storage in adding flexibility. In Ref. [11], an MILP model is also proposed for the analysis of the impact of battery and thermal storage systems on microgrids in England. It concludes that the storage systems improve the economic operation of the microgrid. In Ref. [12], an MILP model is introduced to optimize the size and operation of renewable energy resources, P2G systems, and fuel cell systems for a microgrid in Canada. It proves that the economic design of the microgrid based on renewable energy and P2G devices can be a cost-effective option.

In [13–16], the techno-economic study of microgrids is conducted using HOMER software. In Ref. [13], the role of hybrid distributed resources is examined to supply electricity in remote areas and find an optimal solution. It concludes that the combination of wind/fuel cell/-diesel generation/battery systems is an optimal option. In Ref. [14], an economic feasibility study is conducted to study different scenarios to design an isolated renewable-based microgrid in Korea. The results indicate the inverse relationship between reliability and energy costs. In Ref. [15], another economic feasibility study of multi-energy microgrids in rural areas is conducted. The simulation results demonstrate pollution reduction, job creation, and cost reduction. In Ref. [16], a techno-economic analysis is conducted to install heat pumps that convert excess electricity production into thermal energy in a microgrid at the University of Genoa. The output addresses that the presence of the heat pump increases energy efficiency.

The following studies investigate multi-energy microgrids with non-linear models from techno-economic aspects [17–22]. These studies typically employ meta-heuristic algorithms to solve the optimization problem. For instance, in Ref. [17], an optimization approach is presented based on particle swarm optimization (PSO) for techno-economic analysis and optimal sizing of the multi-energy microgrid in Iran. The total annual cost is presented as the objective function of the problem, which covers investment, operation, and maintenance costs. In Ref. [18], an optimization model is developed in which thermal and electrical loads are supplied using PV panels, Wind Turbines (WT), thermal storage, and battery storage. This problem is optimized by a novel approach, called Evolutionary PSO. In Ref. [19], the performance of different Artificial Intelligence techniques is evaluated for optimal sizing of a PV/Wind/Fuel cell hybrid system to continuously meet load demand with minimum annual total cost. For this purpose, four heuristic algorithms, including PSO, Tabu Search, Simulated Annealing, and Harmony Search are applied. In Ref. [20], another heuristic method is presented to optimize a multi-carrier energy microgrid operating cost. This study indicates that an energy hub is an appropriate solution to reach this aim. In Ref. [21], a hybrid energy storage model is presented for a multi-carrier energy microgrid, which consists of batteries and heat storage systems. Then, the operating cost of the microgrid is optimized using Lagrange Method. In Ref. [22], a scenario-based expansion planning model is proposed for a multi-energy microgrid. It determines the optimal combination of distributed energy resources, their location, and their size while minimizing the overall costs of the microgrid and carbon emissions.

Other reviewed studies are related to the techno-economic optimization of single-energy microgrids. As previously mentioned, techno-economic analysis is performed using linear and non-linear models. In Ref. [23], a techno-economic study is presented to reduce the dependence of microgrids on the upstream grid and address the critical demand. This model is in the form of MILP and finds the optimal size for batteries, PV systems, and biomass and diesel generators in a microgrid. In Ref. [24], a multi-objective approach to optimizing different economic indicators of microgrids is presented. Sensitivity analysis is also implemented and indicates the effects of electricity price, load shedding cost, and dispatching strategy considering an isolated microgrid in Uganda. In Ref. [25], a model is developed to determine an optimal and economic design of combined heat and power systems, PV, WT, storage systems, electric chiller, absorption chiller, and electric heater in a remote microgrid. The Evolutionary PSO algorithm is also developed in this study, whose convergence and solving time are compared to PSO, Differential Evolution, Genetic Algorithm, and Harmony Search algorithms.

In [26–31], simulation is conducted using HOMER software to implement techno-economic analyses of microgrids. In Ref. [26], the analysis of Lithium-Ion (LI) and Lead-Acid (LA) batteries is conducted in a microgrid, which consists of PV systems, WTs, and diesel and biodiesel generators. The outputs demonstrate that LI batteries are technically and economically more beneficial than LA batteries. In Ref. [27], a techno-economic assessment is implemented using HOMER software to compare different scenarios of battery systems for a microgrid in Thailand. The results show using second-life LI batteries in microgrids can be a cost-effective and technically acceptable solution compared to fresh LI batteries. In Ref. [28], the study is conducted considering a microgrid that consists of WTs, PV systems, storage systems, electric vehicles, and controllable loads. The results show that the operation of distributed resources and storage devices, along with the optimal management of controllable loads, significantly reduces energy costs. In Ref. [29], to carry out a techno-economic study, different configurations of various sources of energy production in microgrids are considered using HOMER software. Examining a microgrid in India, it is concluded that the economic configuration is a combination of solar, wind, diesel generator, and battery systems. In Ref. [30], a multi-objective sizing model is developed using HOMER software, which considers technical, environmental, and social indicators. The results prove that multi-criteria analysis can provide an optimal combination of different sources more efficiently. In Ref. [31], another techno-economic analysis is implemented considering six isolated microgrids with renewable energy production located in Colombia. This study determines the optimal operating and emission costs and introduces LI batteries as a suitable alternative to LA batteries due to their lifespan and efficiency.

As mentioned, in the literature, some studies are related to single-energy microgrids with non-linear optimization models [32–37]. In Ref. [32], a techno-economic analysis of CA storage and PV systems is optimized using Genetic Algorithm for a microgrid in Switzerland. It concludes that CA systems with a higher nominal power are more cost-effective compared to lower power ones. In Ref. [33], a techno-economic assessment of replacing PV systems and batteries is studied. The results of solving by Genetic Algorithm show the operating cost saving in the presence of replaced PV systems. In Ref. [34], to maintain a continuous energy supply to a rural area, a grid-connected microgrid is designed, consisting of PV and battery systems. Using the Artificial Bee Colony Algorithm, the optimal size of different components in the microgrid is determined. In Ref. [35], another techno-economic study examines a hybrid microgrid with renewable resources to reduce the final cost of energy and the probability of loss of load. The PSO is utilized to optimize the problem, whose results indicate a hybrid microgrid that consists of PV, wind, and storage systems reduces costs and the probability of loss load. In Ref. [36], a novel approach is introduced to deal with the problem of the economic sizing of a PV/wind/diesel/battery microgrid. Three different multi-objective meta-heuristic algorithms are introduced to determine an optimal design considering different economic aspects. In Ref. [37], a model is developed to minimize annual loss of load, emission, and battery life cycle costs in a microgrid. It indicates that the number of people without access to electricity can be significantly reduced by using distributed renewable energy sources.

Although the recapped studies utilize heuristic methods to deal with the complex optimization problems of techno-economic analysis, decomposition methods can also be employed when there is a complex MINLP or even MILP Model. The main advantage of decomposition methods is that they generally use precise mathematical methods and divide the main problem into two parts (i.e., a master problem and a subproblem). This approach reduces the computational burden significantly. While there are different methods of decomposition, Banders Decomposition [38] and Outer Approximation/Equality Relaxation (OA/ER) [39] methods have received significant attention. Benders Decomposition and its variants have great potential to cope with the complex MILP and MINLP optimization problems. However, the OA/ER has shown even superior performance when the problem being examined has nonlinear constraints in the form of equality [40]. The Outer Approximation decomposes the original problem into a master problem and a subproblem. The master problem deals with continuous variables, while the subproblem handles binary variables. The master problem provides an initial feasible solution, and the subproblem generates valid cuts to enhance the solution. Equality Relaxation involves relaxing certain constraints in the problem by converting them from strict nonlinear equalities to linear inequalities, and the obtained solution is used to guide the resolution of the original problem. A variant of OA/ER, called Outer Approximation/Equality Relaxation/Augmented Penalty (OA/ER/AP), is a method used to handle complex constraints in optimization problems. It adds a penalty term to the objective function that penalizes violations of the constraints. By adjusting the penalty term, the algorithm balances the objective function with the constraint violations, encouraging convergence toward feasible solutions. To be more specific, the Augmented Penalty broadens the feasible region, thereby reducing the likelihood of truncating feasible solutions due to invalid linearization. Among the studies in the related fields, in Ref. [41], the charging and discharging power of electric vehicles in a microgrid are scheduled to assist demand provision. The mathematical model is in the form of MILP, which, due to the high computational burden, the Benders Decomposition method is used to be solved. With the emergence of active distribution networks, there has been a notable rise in the integration of distributed energy resources within these systems. As a result, the problem of economic dispatch is faced with complexity to be solved. In Ref. [42], Benders Decomposition is utilized to improve the calculation accuracy of the economic dispatch problem. In Ref. [43], an optimization model based on Benders decomposition is introduced for the techno-economic study of microgrids for the Brazilian Amazon region. In Ref. [44], a risk-constrained method is purposed for the optimal planning of a hydrogen-based zero-carbon multi-energy microgrid. This model is designed to meet the energy requirements (electricity, heating, and cooling) in rural areas. To solve the complex MILP model, Benders Decomposition is used in this study. In Ref. [45], the optimization of microgrids operation and charging/discharging schedule of storage systems is formulated as an MINLP problem. To find the optimal solutions for the problem, a parallel computing method is presented based on Generalized Benders Decomposition. The simulation results show that the proposed method has considerable potential to facilitate the ability of parallel computing in microgrid operation. In Ref. [46], a MILP model is presented for the planning of the electricity and gas network. In order to solve this model, Benders Iterative Decomposition method is developed to divide the problem into a main investment problem and three operating sub-problems. The iterative process between the main problem and each sub-problem is continued until a practical, economic, and reliable solution is obtained. In Ref. [47], the scheduling of gas and electricity transmission networks is optimized considering different wind profiles using Generalized Benders Decomposition. The obtained results of the problem indicate the effectiveness of the solving approach.

Previously mentioned papers have conducted techno-economic analyses of microgrids with various assumptions and considering different case studies (Table 1). By reviewing these studies, it is crystal clear that no techno-economic study compares the economic feasibility of different high-energy-density storage systems in microgrids. Furthermore, the scarcity of techno-economic studies that simulated energy systems (e.g., natural gas distribution system, electricity distribution system, etc.) highlights the need for attention to make the models more realistic. Addressing the research gap in the field, this paper introduces an economic feasibility model specifically designed for high-energy density storage devices within a multi-energy microgrid. The model takes into account both gas and electricity subsystems, with a particular focus on scenarios featuring a substantial penetration of renewable energy resources, such as wind turbines (WTs) and photovoltaic (PV) systems. The main contribution of this paper is explained in the following.

- Proposing a mathematical model to perform a comprehensive techno-economic analysis of various types of energy storage systems, including LI, CA, LA, and P2G systems. The model incorporates the investment and maintenance costs of these storage systems through sensitivity analysis. Moreover, it takes into account the optimal operation of a multi-energy microgrid, encompassing both gas and electricity distribution grids. Notably, the optimization model considers active and reactive power in the electricity subsystems, as well as pressure and flow dynamics in the natural gas subsystem. By incorporating these factors, the model provides a more realistic depiction of the system's operational dynamics.
- Developing a solving approach based on a decomposition method, called OA/ER/AP, to solve the proposed model. In the developed solving approach, to tackle the computational complexity associated with analyzing a multi-energy microgrid over an entire year, a clustering method is employed. This method selectively identifies characteristic days that effectively represent the behavior and patterns of the entire year, significantly reducing the computational burden while still capturing the essential dynamics of the system. After that, as the main contribution, an extra step is integrated into

Table 1
Systematic review of studies in the field of techno-economic analysis on microgrids.

Ref.	Objective	Solution method		Decomposition	Network consideration		Solver	Class of optimization (linear or nonlinear)/ Simulation software	Type of storage		
		Exact	Heuristic		Electricity	Others			BES	CA	P2G
[6]	- Minimize operation cost - Minimize emission	✓	–	–	✓	–	DICOPT	MINLP	–	✓	–
[7]	- Minimize investment, operation, and emission costs	✓	–	–	–	–	–	MILP	✓	–	✓
[8]	- Minimize investment, operation, and emission costs	✓	–	–	–	–	INTLINPROG	MILP	✓	–	–
[9]	- Minimize investment, operation, maintenance, and emission costs	✓	–	–	–	–	Gurobi	MILP	✓	–	–
[10]	- Minimize cost of operation	✓	–	–	–	–	Gurobi	MILP	✓	–	✓
[11]	- Minimize cost of operation	✓	–	–	–	Hydrogen	FICO Xpress	MILP	✓	–	–
[12]	- Minimize cost of operation	✓	–	–	–	–	–	MILP	–	–	✓
[13]	- Investment, operation, and maintenance costs	–	–	–	–	–	–	HOMER	✓	–	✓
[14]	-Investment, operation, and maintenance costs	–	–	–	–	–	–	HOMER	✓	–	✓
[15]	-Minimize investment, operation, maintenance, and emission costs	–	–	–	–	–	–	HOMER	✓	–	✓
[16]	- Cost of operation	–	–	–	–	–	–	W-ECOMP	–	–	–
[17]	- Minimize cost of investment, operation, and maintenance	–	✓	–	–	–	PSO	MINLP	✓	–	–
[18]	- Minimize cost of investment, operation, and maintenance	–	✓	–	–	–	PSO	MINLP	✓	–	–
[19]	- Minimize cost of operation and maintenance	–	✓	–	–	–	PSO	MINLP	✓	–	✓
[20]	- Minimize cost of operation and maintenance	–	✓	–	–	–	PSO	MINLP	✓	–	–
[21]	- Minimize cost of operation	–	✓	–	–	–	Lagrange	MINLP	✓	–	–
[22]	- Minimize Cost of operation and maintenance	✓	–	–	–	–	PSO	MINLP	✓	–	–
[23]	- Minimize cost of investment, operation, and maintenance	✓	–	–	✓	Heat	GLPK	MILP	✓	–	–
[24]	- Minimize investment, operation, maintenance, and emission costs	–	✓	–	–	–	GA	MILP	✓	–	–
[25]	- Cost of investment and operation	–	✓	–	–	–	PSO	MINLP	✓	–	–
[26]	- Minimize investment, operation, maintenance, and emission costs	–	–	–	–	–	–	HOMER	✓	–	–
[27]	- Minimize investment, operation, and maintenance costs	–	–	–	–	–	–	HOMER	✓	–	–
[28]	- Investment, operation, and maintenance costs	–	–	–	–	–	–	HOMER	✓	–	–
[29]	-Investment, operation, and maintenance costs	–	–	–	–	–	–	HOMER	✓	–	–
[30]	-Investment, operation, and maintenance costs	–	–	–	–	–	–	HOMER	✓	–	–
[31]	- Investment, operation, and maintenance costs	–	–	–	–	–	–	HOMER	✓	–	–
[32]	- Cost of investment and operation	–	✓	–	–	–	GA	MINLP	–	✓	–
[33]	- Cost of operation	–	✓	–	–	–	GA	MINLP	✓	–	–
[34]	- Minimize costs of investment, operation,	–	✓	–	–	–	BC	MINLP	✓	–	–

(continued on next page)

Table 1 (*continued*)

Ref.	Objective	Solution method		Decomposition	Network consideration		Solver	Class of optimization (linear or nonlinear)/ Simulation software	Type of storage		
		Exact	Heuristic		Electricity	Others			BES	CA	P2G
	maintenance, and emission										
[35]	Minimize costs of investment, operation, and maintenance	–	✓	–	–	–	PSO	MINLP	✓	–	–
[36]	- Minimize costs of investment, operation, and maintenance	–	✓	–	–	–	PSO	MINLP	✓	–	–
[37]	- Minimize costs of operation, maintenance, and emission	✓	–	–	–	–	FMINCON	MINLP	✓	–	–
[41]	- Minimize operation cost - Maximizing profit	✓	–	✓	✓	–	Benders	MILP	✓	–	–
[42]	- Minimize cost of operation	✓	–	✓	✓	–	Benders	MINLP	–	–	–
[43]	- Minimize cost of planning	✓	–	✓	–	–	Benders	MILP	✓	–	–
[44]	- Minimize cost of planning	✓	–	✓	✓	–	Benders	MILP	✓	–	✓
[45]	- Minimize cost of operation	✓	–	✓	✓	–	Benders	MINLP	✓	–	–
[46]	- Minimize cost of planning	✓	–	✓	✓	Natural Gas	Benders	MILP	–	–	–
[47]	-Minimize cost of operation				✓	Natural Gas	Benders	MINLP	–	–	–
Our Study	- Minimize costs of investment, operation, maintenance, and emission	✓	–	✓	✓	Natural Gas	OA/ER/AP	MINLP	✓	✓	✓

*BC: Bee Colony; *GA: Genetic Algorithm; *PSO: Particle Swarm Optimization; *BES: Battery Energy Storage (LI and LA storage systems); *CA: Compressed Air Energy Storage; *W-ECOMP: Web-Based Economic Cogeneration Modular Program; *GLPK: GNU Linear Programming Kit; *HOMER: Hybrid Optimization of Multiple Energy Resources; *FMINCON: Find Minimum of Constrained Nonlinear Multivariable Function; and *ADMM: Alternating Direction Method of Multipliers.

the process, which involves solving the relaxed model to acquire an initial point, thereby enhancing the overall efficiency of the problem-solving process. Then, the decomposition approach effectively divides the problem into a master problem and a subproblem. Through an iterative process, these problems are solved sequentially, resulting in a reduction of complexity and computational time required for solving the overall problem. This decomposition method proves to be an effective strategy for tackling the challenges associated with the MINLP problems. It also utilizes Augmented Penalty to reach a global optimal solution and prevent trapping into local optimal solutions.

Finally, the techno-economic analysis is conducted to examine the role of different storage systems in a real-world case study which is a microgrid consisting of an 11-node natural gas subsystem and a 33-bus electricity subsystem.

2. Model and formulation

A microgrid refers to a set of suppliers and consumers at the distribution level, such as distributed renewable energy sources (e.g., PV systems and WTs), dispatchable units (e.g., small-scale gas-fired units, diesel generators, fuel cells), energy storage systems, and residential and industrial consumers [48]. A block is also located in microgrids to control and coordinate different components. The short distance between suppliers and consumers reduces the loss of transmission and increases the reliability of the system. Although a microgrid interacts with the main grid during normal situations (i.e., purchasing and selling electricity), it can be independently operated, called island mode, during failure in the main grid. An illustration of a microgrid considering both natural gas and electricity subsystems as well as different components is indicated in Fig. 1. As demonstrated, the dispatchable gas-fired units link gas and electricity distribution subsystems as they are utilized beside the storage systems to deal with the variable output of renewable systems owing to their fast ramping rate. Therefore, the variability of renewable resources transmits to the gas subsystem, which can make the coordinated operation beneficial.

Considering the mentioned issues, the main steps of this study, including proposing the methodology to conduct techno-economic analysis of storage systems (Subsection 2.1), developing the solving approach (Subsection 2.2), introducing the case study (Section 3), and technical and economic analyses (Section 4), are illustrated in, Fig. 2. More precisely, in the first step, a methodology for the techno-economic assessment of storage systems is proposed. In the second step, a solving approach is developed, based on OA/ER/AP, to solve the optimization problem. In the third step, a case study is introduced to examine the proposed approach, consisting of gas and electricity distribution grids. In the fourth step, analyses are conducted, and the obtained results are discussed from technical and economic viewpoints.

2.1. *Objective function and constraints of techno-economic analysis of energy storage systems in multi-energy microgrids*

The objective function of the problem consists of four terms (Equation (1)), including annual investment cost for energy storage systems ($\left[\frac{r(1+r)^j}{(1+r)^j-1}\right]C^{inv}$), cost of operation of the microgrid (C^{oper}), the annual cost of maintenance (C^M), and the cost of emissions (C^{CO2}). It should be noted that r and j refer to the annual rate of return and lifespan of the project, respectively.

$$OF = \left[\frac{r(1+r)^j}{(1+r)^j - 1}\right] \cdot \frac{D^{day}}{D^{year}} . C^{inv} + C^{oper} + \frac{D^{day}}{D^{year}} . C^M + C^{CO2} \tag{1}$$

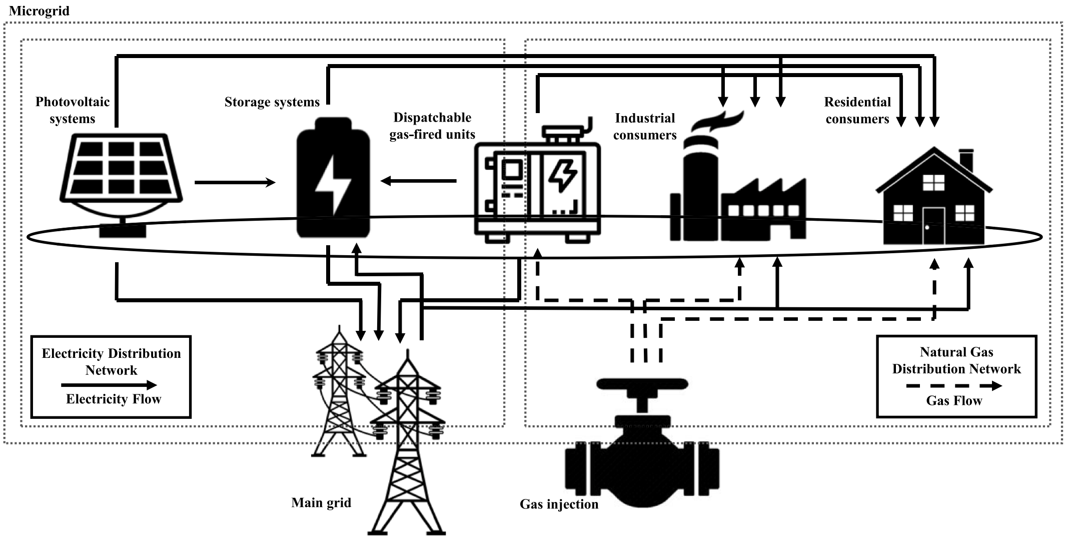

Fig. 1. Illustration of natural gas and electricity distribution subsystems in a multi-energy microgrid.

As discussed, the first term is the cost of investment for the storage system, which is appropriate to the installed capacity multiplied by a binary variable that indicates whether the storage system is installed or not (Equation (2)). It is noteworthy to mention that this term includes the cost of construction, purchased equipment, and installation. The second term is the cost of microgrid operation (Equation (3)), including the cost of electricity subsystem operation (C^{elec}) and the cost of natural gas subsystem operation (C^{gas}). The third term is the cost of maintenance of the energy storage systems (Equation (4)). The last term is also the emission cost that is appropriate to the output power of non-renewable units and purchased power from the main grid (Equation (5)).

$$C^{inv} = \sum_{k=1}^{K} C^{BS}.Cap_k.v_k \tag{2}$$

$$C^{oper} = C^{gas} + C^{elec} \tag{3}$$

$$C^{m} = \sum_{k=1}^{K} C^{MBS}.Cap_k.v_k \tag{4}$$

$$C^{CO2} = \sum_{t=1}^{T}\sum_{b=1}^{B} C^{Co2}.P_{b,t} \tag{5}$$

The cost of operation is the summation of the gas distribution system operation cost and electricity distribution system operation cost in the microgrid, indicated in Equations (6) and (7). The gas system operation cost includes the cost of purchasing natural gas from the main system ($\sum_{t=1}^{T}\sum_{y=1}^{Y} C^{g}.G_{y,t}^{buy}$), the cost of changes in the amount of natural gas stored within pipelines (i.e., cost of linepack management ($\sum_{t=1}^{T}\sum_{n=1}^{N} C^{lp}.\ \Delta GP_{n,t}$)), and the cost of gas-not-supplied (i.e., cost of gas shedding ($\sum_{t=1}^{T}\sum_{y=1}^{Y} C^{sh}.GNS_{n,t}$)). The cost of linepack management is considered due to the characteristic of natural gas that takes time to be transmitted from the supply nodes to the demand nodes. Natural gas in pipelines can effectively handle demand variations, similar to storage systems. The cost of gas-not-supplied is also considered to calculate the amount of gas demand that can be supplied. However, as the corresponding penalty is considerably high, the priority is to fulfill demand as much as possible, while in emergency cases, gas shedding would be an

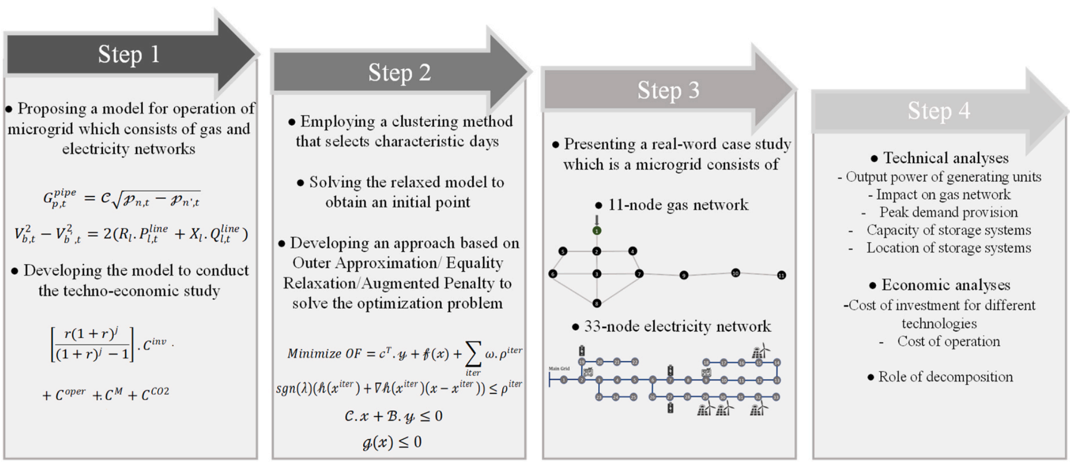

Fig. 2. Main steps of this study-analysis of storage systems in a multi-energy microgrid from technical and economic viewpoints.

option. In optimization, gas-shedding can also help achieve convergence when demand exceeds supply. It means the model can make informed decisions on which loads to shed and how to allocate the available resources optimally [49]. The electricity system operation cost in the microgrid consists of three terms, including the cost of purchasing electricity from the main grid ($\sum_{t=1}^{T}\sum_{b=1}^{B}\psi_{b,t}.P_{b,t}^{buy}$), the revenue from selling electricity to the main grid ($-\sum_{t=1}^{T}\sum_{b=1}^{B}\psi_t^{'}.P_{b,t}^{sell}$), and the cost of producing electricity using non-renewable generating units ($\sum_{t=1}^{T}\sum_{b=1}^{B}(\alpha_b.P_{b,t}+\beta_b.u_{b,t})$). In the last term of electricity system operation cost, gas-fired dispatchable units are not considered as the cost of the required amount of natural gas for these units is in gas network operation cost (e.g., only diesel generating units are considered). More precisely, the amount of required fuel for gas-fired units is added to the gas flow balance. It should be noted that, in the third term, the first part represents the variable cost of operation, while the second part denotes the fixed cost of operation [50]. The fixed cost is multiplied by a binary variable that indicates the status of dispatchable units (on or off).

$$C^{gas}=\sum_{t=1}^{T}\sum_{y=1}^{Y}C^{g}.G_{y,t}^{buy}+\sum_{t=1}^{T}\sum_{n=1}^{N}C^{lp}.\Delta GP_{n,t}+\sum_{t=1}^{T}\sum_{y=1}^{Y}C^{sh}.GNS_{n,t} \tag{6}$$

$$C^{elec}=\sum_{t=1}^{T}\sum_{b=1}^{B}\psi_t.P_{b,t}^{buy}-\sum_{t=1}^{T}\sum_{b=1}^{B}\psi_t^{'}.P_{b,t}^{sell}+\sum_{t=1}^{T}\sum_{b=1}^{B}(\alpha_b.P_{b,t}+\beta_b.u_{b,t}) \tag{7}$$

In Equations (8) and (9), the volume of purchased natural gas is limited ($G_{y,t}^{buy}$), and the output and input natural gas from/to each node is addressed (i.e., gas flow balance), which guarantees natural gas demand provision.

$$G_{y,t}^{buy}\le G_{y}^{buy\ lim}\ \forall y,\forall t \tag{8}$$

$$\begin{aligned}&G_{y,t}^{buy}-G_{p,t}^{pipe}=D_{n,t}^{gas}+G_{n,t}-GNS_{n,t}\\&\quad\forall n,p\epsilon(n,n^{'}),y\subseteq n,\forall t\end{aligned} \tag{9}$$

In Equation (10), Lacey's Equation for the natural gas subsystem is indicated that connects the volume of natural gas within the pipelines ($G_{p,t}^{pipe}$) to the pressure in nodes ($p_{n,t}$) [51]. This equation works for low-pressure natural gas subsystems whose pressure is between 0 and 75 (mbar gauge). It is worthwhile to mention that assuming that $p_{n,t}$ (mbar gauge), we get $G_{p,t}^{pipe}$ (cm). In Equation (11), the pressure of each node in the natural gas distribution system is limited.

$$G_{p,t}^{pipe}=C_p\sqrt{p_{n,t}-p_{n^{'},t}}\ \forall p\epsilon(n,n^{'}),\forall t \tag{10}$$

$$p_n^{min}\le p_{n,t}\le p_n^{max}\ \forall n,\forall t \tag{11}$$

In Equations (12) and (13), the volume of natural gas within pipelines ($G_{p,t}^{pipe}$) is limited, and the changes in the volume of the stored natural gas within the pipelines are indicated, respectively.

$$G_p^{pipe\ min}\le G_{p,t}^{pipe}\le G_p^{pipe\ max}\ \forall p,\forall t \tag{12}$$

$$GP_{p,t}=GP_{p,t}^{0}+\sum_{1}^{T}\left(G_{n^{'},n,t}^{pipe}-G_{n,n^{'},t}^{pipe}\right)\forall p\epsilon(n,n^{'}),\forall t \tag{13}$$

In Equation (14), the output and input electricity flow from/to each bus is indicated, which guarantees that the active electric load is satisfied. In the formulation, the power loss is assumed as a load at the beginning of the lines. It is noteworthy to mention that Equation (14) illustrates the ability to charge excess supply in the electricity subsystems, such as renewable or nonrenewable power, into storage systems. This stored energy can then be utilized later to assist in meeting demand requirements [52]. In Equations (15) and (16), the output power of distributed energy resources ($P_{b,t}^{DG}$) and dispatchable units ($P_{b,t}$) are constrained based on their characteristics. In Equation (17), the required amount of natural gas to produce electricity using non-renewable dispatchable units ($G_{b,t}$) is indicated.

$$\begin{aligned}&P_{b,t}+P_{b,t}^{DG}+P_{b,t}^{buy}+P_{k,t}^{dch}-P_{k,t}^{ch}\\&-\sum_{b^{'}=1}^{B}\left(P_{l,t}^{line}+R_{l,t}.I_{l,t}^{2}\right)=P_{b,t}^{load}+P_{b,t}^{sell}\forall b,l\epsilon(b,b^{'}),\forall t\end{aligned} \tag{14}$$

$$P_{b,t}^{DG}\le P_{b,t}^{DG\ max}\ \forall b,l\epsilon(b,b^{'}),\forall t \tag{15}$$

$$u_{b,t}.P_b^{min}\le P_{b,t}\le u_{b,t}.P_b^{max}\ \forall b,\forall t \tag{16}$$

$$G_{b,t}=\frac{P_{b,t}}{\eta_b}.\upsilon\ \forall b,\forall t \tag{17}$$

In Equations (18) and (19), the changes in output power of dispatchable generating units are limited, called ramping rate. More precisely, it is the speed at which dispatchable units can increase and decrease their output based on their characteristics (i.e., ramp up and ramp down, respectively ($Ramp_b^{up\ max}$ and $Ramp_b^{down\ max}$).

$$P_{b,t}-P_{b,t-1}\le Ramp_b^{up\ max}\ \forall b,\forall t \tag{18}$$

$$P_{b,t-1}-P_{b,t}\le Ramp_b^{down\ max}\ \forall b,\forall t \tag{19}$$

In Equations (20) and (21), reactive power flow from/to each bus and the limitation of reactive power ($Q_{b,t}$) at each node are addressed. The mentioned constraint is necessary to guarantee that reactive power is satisfied.

$$\begin{aligned}&Q_{b,t}+\sum_{b^{'}=1}^{B}\left(Q_{l,t}^{line}+X_{l,t}.I_{l,t}^{2}\right)=Q_{b,t}^{load}\\&\quad\forall b,l\epsilon(b,b^{'}),\forall t\end{aligned} \tag{20}$$

$$Q_b^{min}\le Q_{b,t}\le Q_b^{max}\ \forall b,\forall t \tag{21}$$

In Equations (22) and (23), Kirchhoff's Voltage Law is indicated that connects voltage ($V_{b,t}$) and current ($I_{l,t}$) together (i.e., reactive and active power) [53]. In Equations (24) and (25), the limitations of voltage and current in the system are indicated.

$$\begin{aligned}&V_{b,t}^{2}-V_{b^{'},t}^{2}=2\left(R_l.P_{l,t}^{line}+X_l.Q_{l,t}^{line}\right)\\&\quad+Z_l^{2}.I_{l,t}^{2}\ l\epsilon(b,b^{'}),\forall t\end{aligned} \tag{22}$$

$$V_{b,t}^{2}.I_{l,t}^{2}=Q_{l,t}^{line\ 2}+P_{l,t}^{line\ 2}\ \ l\epsilon(b,b^{'}),\forall t \tag{23}$$

$$V_b^{min}\le V_{b,t}\le V_b^{max}\ \forall b,\forall t \tag{24}$$

$$0\le I_{l,t}\le I_l^{max}\ \ l\epsilon(b,b^{'}),\forall t \tag{25}$$

In Equations (26)–(29), some constraints about the storage systems operation are declared. Equation (26) shows the changes in the energy level within the storage systems (i.e., state of charge ($SC_{k,t}$)) considering charging and discharging efficiency (eff^{ch} and eff^{dch}, respectively). Equations (27)-(28) constrain the charged and discharged power of these components ($P_{k,t}^{ch}$ and $P_{k,t}^{dch}$, respectively). Equation (29) is also the limitation of stored energy within the storage systems. It is worthwhile to mention that the binary variable multiplied by the limitation of the state of charge is added to indicate whether the installation of candidate storage systems is an optimal decision or not.

$$\begin{aligned}&SC_{k,t}=SC_{k,t}^{0}+\sum_{1}^{T}\left(eff^{ch}.P_{k,t}^{ch}-P_{k,t}^{dch}\middle/eff^{dch}\right)\\&\quad\forall k,\forall t\end{aligned} \tag{26}$$

$$P_k^{ch\ min} \le P_{k,t}^{ch} \le P_k^{ch\ max}\ \forall k, \forall t \quad (27)$$

$$P_k^{dch\ min} \le P_{k,t}^{dch} \le P_k^{dch\ max}\ \forall k, \forall t \quad (28)$$

$$v_k.SC_k^{min} \le SC_{k,t} \le SC_k^{max}.v_k\ \forall k, \forall t \quad (29)$$

2.2. Solving approach based on OA/ER/AP

Due to the reason that the problem of techno-economic analysis of microgrids is in the class of mixed-integer nonlinear programming, a decomposition method, called OA/ER/AP, is developed in this section to solve the problem. OA/ER was first introduced by Kocis and Grossmann in 1987 to solve optimization problems with nonlinear constraints in the form of $\mathrm{H}(x) = 0$ [54]. As the problem of techno-economic analysis of energy storage systems in microgrids has some nonlinear constraints (Equation (10), (22), and (23)), this decomposition can be developed to find an optimal solution. However, this approach can be trapped into a local solution when there is a non-convex constraint (i.e., this method is based on the convexity of constraints). To cope with this problem, OA/ER/AP is utilized, proposed by Viswanathan and Grossmann in 1990 [55]. This decomposition approach expands the feasible region, which reduces the probability of cutting off the feasible region as a result of invalid linearization, which guarantees reaching a globally optimum solution.

The main steps of the algorithm of OA/ER/AP are introduced in this section. For this purpose, consider an optimization problem, indicated in Equation (30). In this problem, x and y are continuous and binary decision variables, and $\mathrm{H}(x) = 0$ and $\mathrm{M}(x) \le 0$ are nonlinear and linear constraints.

$$\begin{aligned} &Minimize\ OF = \mathbb{C}^T.Y + F(x) \\ &\quad Subject\ to\ \mathrm{H}(x) = 0 \\ &\qquad \mathrm{M}(x) \le 0 \\ &\qquad \mathbb{C}.x + \mathrm{B}.Y \le 0 \end{aligned} \quad (30)$$

To solve the mentioned optimization problem via OA/ER/AP, in the first step, binary variables are initialized, resulting in the primal problem (Equation (31)).

$$\begin{aligned} &Minimize\ OF = \mathbb{C}^T.Y^* + F(x) \\ &\quad Subject\ to\ h(x) = 0 \\ &\qquad \mathrm{M}(x) \le 0 \\ &\qquad \mathbb{C}.x + \mathrm{B}.Y^* \le 0 \end{aligned} \quad (31)$$

Solving the primal problem provides an upper bound (UB) and optimal multipliers (λ) for the next step. Then, the master problem is solved by relaxing the nonlinear equality constraints ($sgn(\lambda)(\mathrm{H}(x^{iter}) + \nabla\mathrm{H}(x^{iter})(x - x^{iter})) \le 0$) and considering Augmented Penalty ($\sum_{iter}\omega.\rho^{iter}$) as indicated in Equation (32).

$$\begin{aligned} &Minimize\ OF = \mathbb{C}^T.Y + F(x) + \sum_{iter}\omega.\rho^{iter} \\ &(\lambda)\left(\mathrm{H}\left(x^{iter}\right) + \nabla\mathrm{H}\left(x^{iter}\right)\left(x - x^{iter}\right)\right) \le \rho^{iter} \\ &\qquad \mathrm{M}(x) \le 0 \\ &\qquad \mathbb{C}.x + \mathrm{B}.Y \le 0 \end{aligned} \quad (32)$$

The outputs of the master problem give binary variables for the next iteration as well as a lower band (LB). When the lower band and upper band converge ($UB - LB = 0$), an optimal solution is obtained. According to discussed issues, to solve the techno-economic analysis of storage systems in multi-energy microgrids, in the master problem, Equations (10) and (22)-(23) (i.e., nonlinear equality constraints) should be relaxed as explained in Equation (32). Furthermore, initializing binary variables would be challenging, and solving the relaxed model could be helpful before utilizing the decomposition method [56]. In the relaxed model, binary variables are treated as continuous variables constrained between zero and one, allowing for fractional values between one and zero. Then, using the relaxed model, rounding up its output to the nearest integer (zero or one) can provide the initial points for the decomposition method.

Aside from what is already mentioned, analyzing the multi-energy microgrid for an entire year (i.e., 8760 h) poses significant computational challenges. As a solution, a clustering method is employed for the selection of characteristic days which represent the whole year [57]. These selected days' net electricity demand profiles, obtained by subtracting renewable electricity generation from demand, are used for analysis. In the following, the clustering algorithm is introduced to facilitate this process. In the first step of the algorithm (Step 1), the distance between different net demand profiles is calculated. The distance is computed by summing the squared differences between net demand values for each time step. In Step 2, the two profiles with the closest distance are identified. Step 3 involves comparing the frequency of occurrence of the profiles to determine which profile has a lower frequency, which is then deleted. In Step 4, the frequency of the deleted profile is added to the closest profile, and the counter is decreased. If the frequency of the first profile is greater than or equal to the frequency of the second profile, the second profile is deleted, and the frequency of the first profile is updated accordingly. Conversely, if the frequency of the first profile is less than the frequency of the second profile, the first profile is deleted, and the frequency of the second profile is updated. Step 5 checks if the counter is equal to the desired number of profiles. If it is, the algorithm terminates; otherwise, it returns to Step 1 for further processing. The flowchart of this algorithm is also indicated in Fig. 3 [57].

3. Case study

In this section, a case study is presented to examine the role of storage systems from technical and economic aspects (Fig. 4). A multi-energy microgrid is considered, consisting of an 11-node gas distribution system (more detailed data in Ref. [58]) and a 33-bus electricity distribution system (more detailed data in Ref. [59]). The natural gas system consists of 11 nodes and 13 pipelines, and it is connected to the natural gas transmission system via node one. The electricity distribution system consists of 33 buses and 32 lines, and it is also connected to the main grid via bus one. As depicted, distributed renewable generators

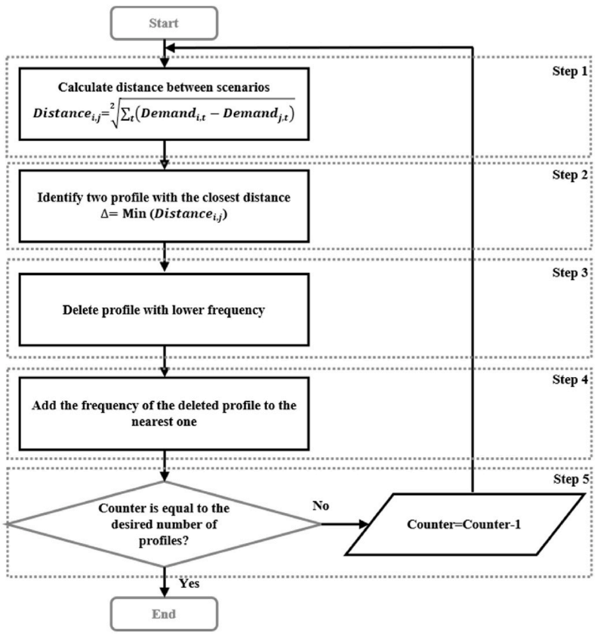

Fig. 3. Main steps of the clustering approach.

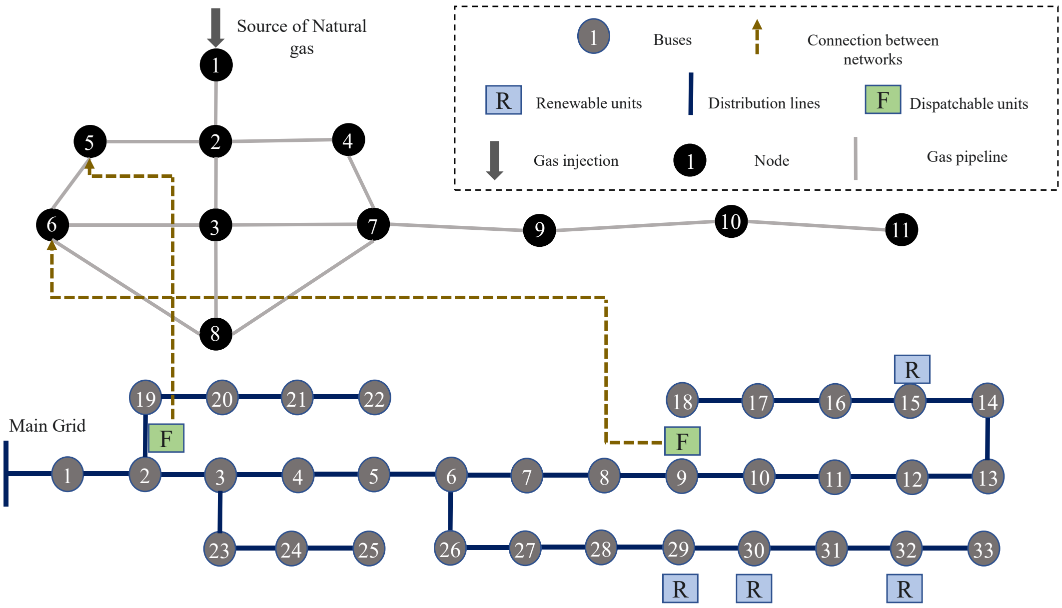

Fig. 4. Case-study-natural gas and electricity subsystems in a microgrid.

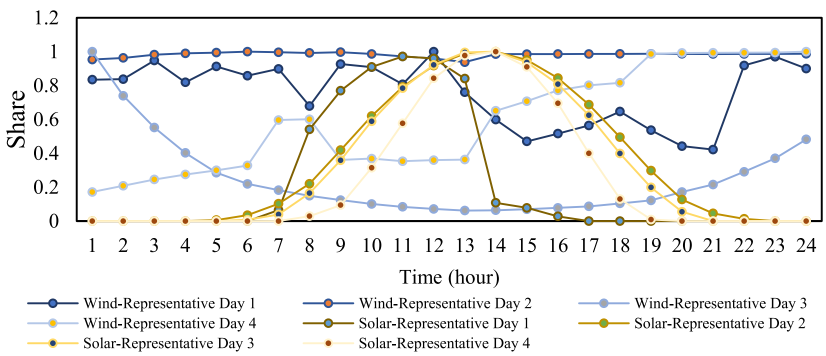

Fig. 5. Wind and solar power availability as a share of the installed capacity.

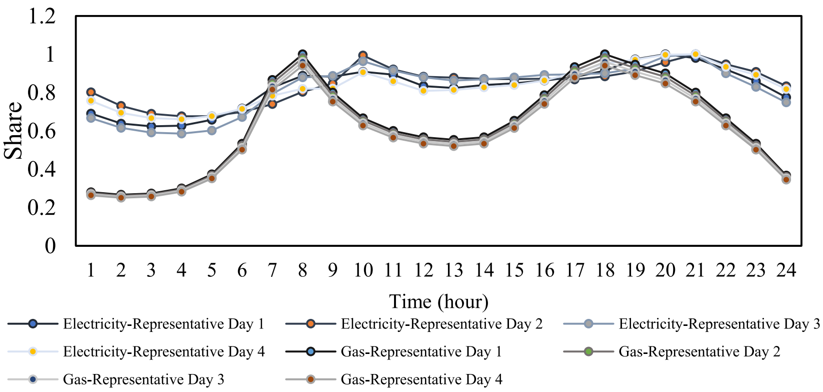

Fig. 6. Gas and electricity demand as a proportion of the peak demand.

Table 2
Characteristics of storage systems.

Parameter	LI [62,63]	CA [63,64]	LA [62,63]	P2G [62,65]
Investment cost	1.09 $/W	1.17 $/W	1.8 $/W	3.12 $/W
Maintenance cost	3.70 $/kW	16.12 $/kW	5.90 $/kW	28.51 $/kW
Life	10 year	30 year	12 year	40 year
Efficiency	88%	52%	79%	35%

(i.e., PV systems and WTs) are connected to bus 15, bus 29, bus 30, and bus 32 in the electricity system. Dispatchable units are also connected to bus 2 and bus 9 in the electricity system. The dispatchable units in bus 2 and bus 9 in the electricity distribution system are supplied through node 5 and node 6 in the natural gas distribution system, respectively [50]. The required gas system's data include the length and diameter of lines, supply limitations, and natural gas demand, and in the electricity system, generating units' characteristics, load, electricity price, resistance, reactance, and capacity of lines are necessary. While this study assumes a scenario where the prices are the same, in real-world situations, the selling and purchasing prices may differ. However, in the optimization model, different parameters for the prices are determined for further implication and analysis.

Based on the step-by-step method represented in Subsection 2.2., Figs. 5 and 6 illustrate the distribution of wind and solar power availability as a share of the installed capacity and the gas and electricity demand as a proportion of the peak demand during four characteristics days, respectively ([57] and [60]). More precisely, this study conducts a comprehensive analysis that investigates the behavior and characteristics of the microgrid system throughout the year by examining four selected days representing the whole year.

Different types of storage systems are also investigated in this paper, whose characteristics are demonstrated in Table 2. The characteristics include efficiency of charge and discharge, investment cost, operation and maintenance costs, and lifespan of the components [61]. During the sensitivity analysis focused on the capacity and quantity of storage installations, the capacity of storage systems is systematically incremented. Concurrently, the sensitivity analysis also includes an increase in the number of permissible nodes for storage installation. This enables an examination of operating costs across various scenarios, with the aim of evaluating the cost implications under a wide range of potential conditions.

It is worthwhile to mention that DICOPT (Discrete and Continuous Optimizers) solver is employed to solve this problem, and the results of solving the optimization problem are compared using the mentioned solver versus the developed solving method based on OA/ER/AP. To this aim, the problem is solved using a computer with Intel Core i7, 2.5 GHz CPU with 12 GB of RAM.

4. Results and analyses

In this section, different analyses are conducted in three main subsections, including (i) sensitivity analysis of the capacity and location of storage systems (Subsection 4.1), (ii) analysis of the operation of the multi-energy microgrid (Subsection 4.2), (iii) analysis of different types of storage systems and technology integration (Subsection 4.3), and (iv) computational analysis (Subsection 4.4), as follows.

4.1. Sensitivity analysis of the capacity and number of storage systems

In this subsection, an analysis is conducted to gain insights into the location and capacity of storage systems to be installed (the third step of solving approach). This analysis is conducted by considering the four operating days which represent a year. The reason is to capture the variations in load and the availability of renewable resources in different seasons. In Fig. 7, the sensitivity analysis is conducted to examine the impact of the installed capacity and the location of storage systems on the operating cost of the electricity distribution subsystem in the microgrid. In Fig. 7 (a), the vertical axis shows the operating cost of the electric subsystem in the microgrid while the horizontal axis shows the capacity of a type of energy storage system. In this stage, the number of storage systems that can be installed is limited to one. By optimizing the problem, it is determined that the optimal location for the storage system is at node 7. Furthermore, the analysis shows that increasing the capacity of the storage system leads to a reduction in the operating cost of the electricity subsystem. Based on the outputs, when the installed capacity of storage systems increases, the operation cost of the electricity distribution subsystem decreases. For instance, the integration of 2.4 MW of LI storage systems reduces the cost of operation from \$16.62k to \$14.29k. In comparison with LA, CA, and P2G systems, the installation of the LI system is more beneficial as its charging and discharging efficiency is higher. The storage systems are charged during the valley and off-peak hours when the price of electricity is low and excess supply is available by renewable energy resources. Then, these systems are discharged to supply demand during peak hours of operation. It is evident that energy storage systems with a higher efficiency provide the operating cost of the microgrid with more cost savings (e.g., LI and LA storage systems). Another analysis is conducted in Fig. 7 (b), in which the operating cost of the electricity subsystem is investigated versus the number of storage systems to be installed in different locations. The analysis indicates that integrating three storage systems at buses 7, 19, and 27 results in efficient operating cost savings. Increasing the number of storage systems beyond this point does not yield significant additional benefits in terms of cost reduction. The total installed capacity of the storage systems, which is 1.2 MW, is evenly distributed among different locations in this examination. It should be noted that the optimal locations of the storage systems are determined through the optimization of the techno-economic analysis model proposed in this study. In Fig. 8, the location of the storage systems to be installed is also indicated. The optimal locations are situated in various branches and adjacent to renewable resources and/or flexible dispatchable units, allowing for strategic positioning and leveraging sustainable energy sources.

4.2. Analysis of the operation of the multi-energy microgrid

Another analysis is conducted in this subsection to examine how the integration of energy storage systems leads to operating cost reduction in the microgrid. For this purpose, in Fig. 9, the dispatch of the microgrid is indicated for both the islanded and connected modes. When the

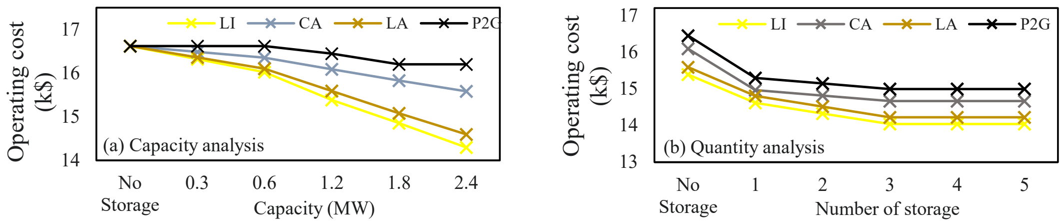

Fig. 7. Operating cost versus installing capacities and quantity of storage systems.

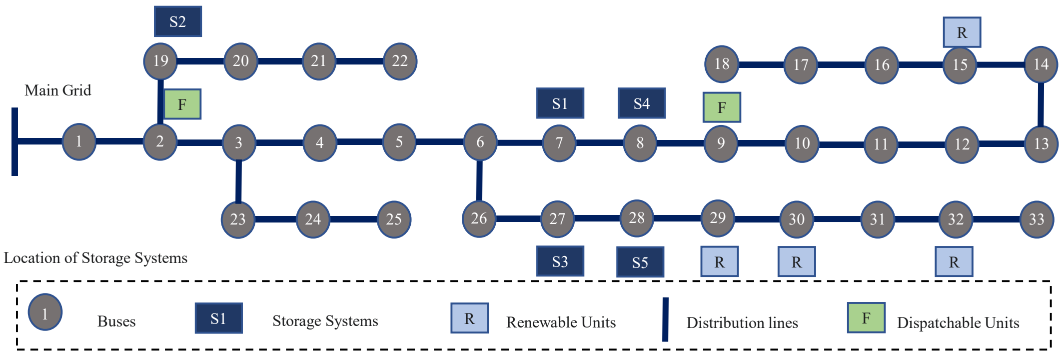

Fig. 8. Location of the energy storage systems to be installed (obtained in the sensitivity analysis).

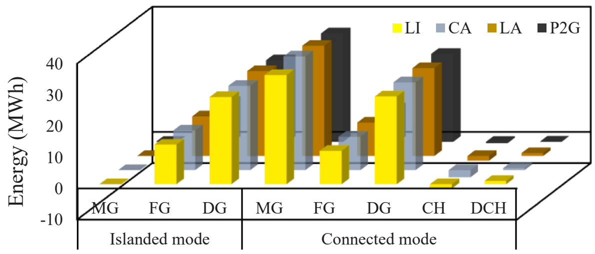

Fig. 9. Role of MG, FGs, DGs, and storage systems in demand provision in the presence of different types of storage systems.

microgrid is connected to the main grid, the summation of interactions with the main grid (MG), the output of distributed renewable (WTs and PV systems) resources (DG), the output of flexible dispatchable units (FG), and charged and discharged power of storage systems (CH and DCH), are indicated during the one-day operating period (i.e, the first representative day). In this case, in the connected mode, the output power of flexible generating units and DGs are equal when different types of storage systems are integrated into the electricity subsystem (10.72 MW and 28.14 MW, respectively). The main difference is in the interactions with the main grid. However, in the islanded mode, the dispatch of the microgrid is discussed, when there is no interaction with the main grid. In this case, only critical loads or a portion of the demand can be supplied. As the microgrid is isolated, the interactions with the MG are equal to zero. However, in the presence of storage systems, it is indicated that the operation of renewable resources within the microgrid is more beneficial, as a result of the reduced loss of available renewable power. For instance, as the efficiency of LI systems is higher than others, it reduces the renewable power spillage by 2 MW. The charged and discharged energy of the storage systems during the operating period is also indicated. A higher discharge of power is evident for

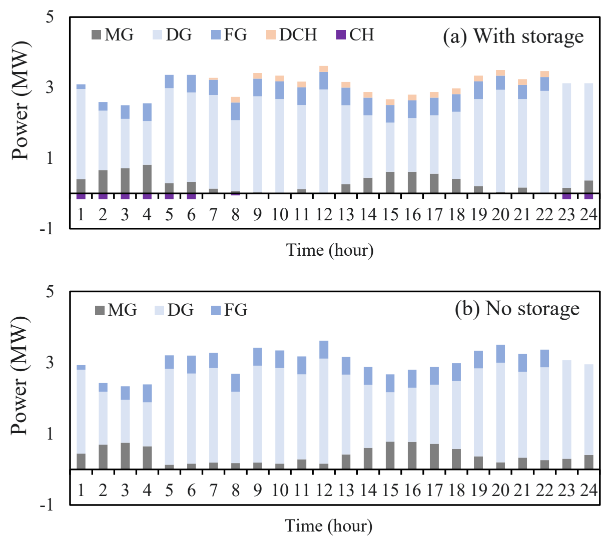

Fig. 11. Hourly dispatch of different components in the microgrid considering LA storage system-a low demand and a high availability of renewable resources.

storage systems with higher efficiency, like LI and LA storage systems (1.06 MW and 0.95 MW, respectively). It concludes that, in the connected mode, when the efficiency of a type of storage system is lower, a higher amount of energy is charged from the main grid. However, the efficiency of the P2G system is considerably lower that is not economical to be charged that much. In other cases (LI, CA, and LA systems), the power is charged during the valley and off-peak hours of demand, and storage systems are discharged into the microgrid to provide demand

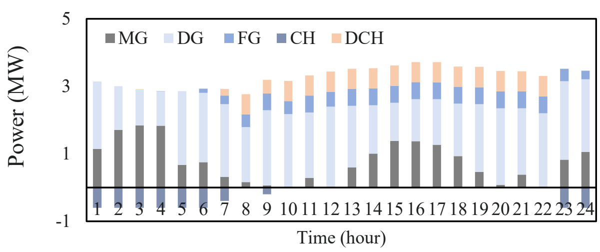

Fig. 10. Hourly dispatch of different components in microgrid considering LA storage system.

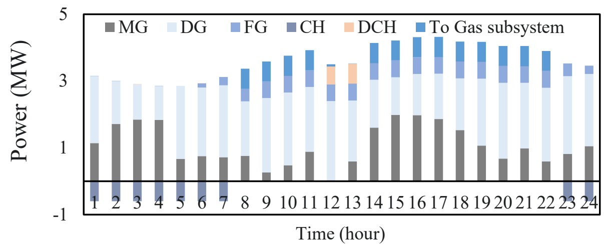

Fig. 12. Hourly dispatch of different components in microgrid considering P2G systems.

Table 3
Impact of P2G system integration into gas subsystem on operating cost.

Installed capacity (MW)	Operating cost of gas subsystem (k$)	Installed capacity (MW)	Operating cost of gas subsystem (k$)
0.3	10.73	1.5	10.56
0.6	10.66	1.8	10.42
0.9	10.60	2.1	10.40
1.2	10.54	2.4	10.30

during peak hours. As an example, in Fig. 10, the hourly interaction of different parties in the microgrid is shown when LA systems are included in the microgrid. According to the results, storage systems are charged from 01:00 to 08:00 and 23:00 to 24:00 (i.e., valley and off-peak hours) and discharged from 10:00 to 22:00 (i.e., peak hours) which leads to the operating cost saving.

Another analysis is conducted to examine the role of this specific storage system when the demand is approximately 10% lower and the availability of renewable resources is 20% higher. The results, considering both the presence and absence of this type of storage system, are indicated in Fig. 11. The comparison also demonstrates how the storage systems contribute to meeting the supply-demand balance from 07:00 to 22:00. Additionally, at the beginning and end of the one-day operating period, the charging of storage systems helps prevent the curtailment of available renewable power (from 01:00 to 05:00 and from 20:00 to 24:00).

Aside from the mentioned issues, the output of P2G systems can be injected into the gas subsystem. It should be noted that it cannot be more than 10% of natural gas supply or demand due to practical constraints. More precisely, it is due to characteristics of hydrogen that can cause leakage in the gas subsystem. Based on the explanations, the interactions with the main grid, output power of distributed energy resources, and charging and discharging of P2G systems are indicated during the one-day operating period (i.e., the first representative day) considering P2G systems and their capability to inject hydrogen into the natural gas subsystem, in Fig. 12. As demonstrated, the P2G systems are charged from 00:00 to 07:00 and 23:00 to 24:00 (i.e., valley and/or off-peak hours of the operating period). As the output hydrogen of the P2G systems can be discharged into the gas system, it occurs from 08:00 to 11:00 and 13:00 to 15:00. However, from 12:00 to 13:00, as the price of electricity is high, the hydrogen is used to regenerate electricity.

In order to study the impact of P2G systems on the operating cost of natural gas subsystems during the four-day operating period, different levels of installed capacity of these systems are examined in Table 3. According to the analysis, the integration of the P2G systems into the microgrid reduces the operating cost of the natural gas system from $10.73k to $10.30k by increasing the installed capacity from 0.3 MW to 2.4 MW. Although, in this case, increasing the operating cost of the electricity subsystem as installed capacity of distributed renewable resources is less than demand, integration of P2G systems does not have any impact on the operating cost when there is a considerable share of renewable resources and spillage.

As discussed, the proposed optimization model considers voltage and current in the electricity subsystem as well as natural gas flow and pressure in the natural gas subsystem to provide a more realistic solution. In this regard, another analysis is conducted to examine voltage deviation in the electric subsystem and changes in linepack within pipelines in the gas subsystem in the presence of different storage systems as the stored gas within pipelines is directly proportional to pressure. As an example, in Fig. 13, changes in linepack within the pipelines are demonstrated in the presence of P2G systems while the variation of the voltage deviation is indicated when LA storage systems are integrated into the microgrid compared to no storage systems. The linepack within the pipeline between node one and node two experiences a 1.66% increase, attributed to the utilization of hydrogen injection to meet the demand in nodes three, five, and seven. Nevertheless, due to the variable nature of the injected hydrogen, which is produced by renewable resources, it results in higher utilization of linepack within other lines by 11.22%. The reduction in the amount of linepack within pipelines leads to reduce in the operating cost of the natural gas subsystem. Moreover,

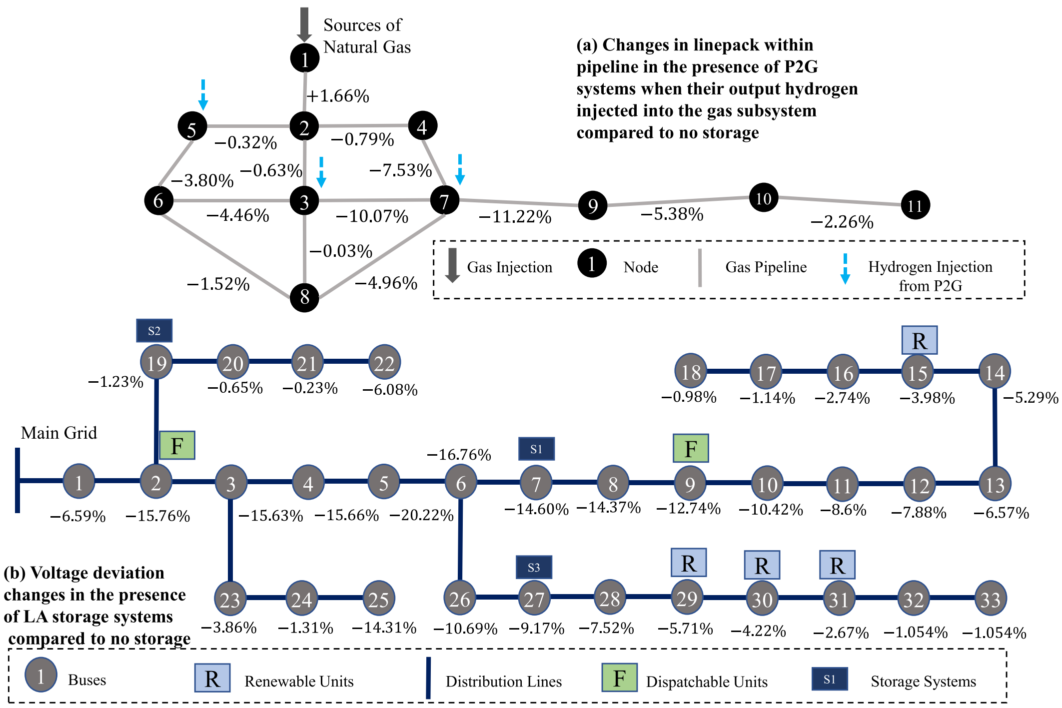

Fig. 13. Voltage deviation and linepack changes compared to when no storage systems exist.

the integration of LA storage systems into electricity systems leads to improvement in voltage deviation, ranging from approximately 1%–29% across different nodes. This improvement in voltage deviation is attributed to the more effective utilization of active power within the network, resulting in more efficient use of reactive power. Reducing the voltage deviation in the electricity distribution subsystem brings benefits, such as improved equipment performance, enhanced power quality, energy efficiency, effective voltage regulation, mitigation of equipment stress, and increased customer satisfaction.

4.3. Analysis of different types of storage systems and technology integration

In this subsection, the costs of investment and operation, are studied considering different types of storage systems. Fig. 14 shows the comparison of (a) total investment costs (b) annual cost of investment, and (c) annual operating cost of the electricity subsystem in the microgrid, when LI, CA, LA, and P2G systems are integrated. It should be mentioned that, at this stage, the installed capacity is 1.2 MW at buses 7, 19, and 27.

Based on the figure, the LI and CA systems have the lowest total cost of investment among the storage systems, which is around $1.35M. The total cost of investment for LA systems is more than $2.00M. However, P2G systems have a higher cost, which is $3.77M. It is worthwhile to mention that storage systems have different lifespans. Therefore, when comparing the investment cost of the storage systems, the lifespan can be taken into consideration. The annual cost of investment also is indicated, considering the lifespan of the energy storage systems. Based on the analysis, CA and P2G systems have $58.12k and $115.83k annual costs of investment. However, LI and LA systems have $160.60k and $115.83k annual costs of investment, respectively. Aside from that, the impact of each type of storage system on the operation of the electric subsystem in the microgrid is examined. Based on the results, LI systems provide microgrid owners with an operating cost saving of around 7% compared to using P2G systems or no storage systems. The LA systems also reduce the operating cost of the microgrid by around 6% compared to using P2G systems or no storage systems. However, comparing CA systems with P2G and no storage system indicates around 3% operating cost saving. It should be noted that the investment cost saving by employing P2G systems is negligible although P2G systems can provide the natural gas subsystem with other benefits discussed previously.

4.4. Computational analysis

In the following, the obtained results of applying developed OA/ER/AP are compared to other decomposition methods and the GAMS software's solver, DICOPT [4]. In Table 4, the value of the objective function refers to total costs, including investment cost for energy storage systems allocated to the operating period (i.e., the first term of the objective function), cost of operation of gas and electricity subsystems in the microgrid (i.e., the second term of the objective function), cost of maintenance (i.e., the third term of the objective function), and cost of emissions (i.e., the fourth term of the objective function). The solution gap refers to the difference between the upper bound and the lower bound when the solution approach convergent to the optimal solution. The last column of the table also indicates the number of iterations that takes until the upper and lower bound of the solution convergent. The results demonstrate that the developed method based on OA/ER/AP method converges to optimal solutions faster than other decomposition methods, with a notable time of 38.45 s. However, OA/ER provides the solutions at approximately the same time (41.84 s). On the contrary, the solving time of the problem using the Generalized Benders Decomposition (GBD) is around double of the latter method, which is 73.12 s. Solving the problem using GAMS software's solver takes a considerable amount of time in comparison with the decomposition methods which is 103.22 s. Another difference is that the solution gap when the DICOPT solver is employed is also 0.1. All in all, based on the conducted analysis, the developed decomposition approach to solve the problem has priority in comparison with the other methods.

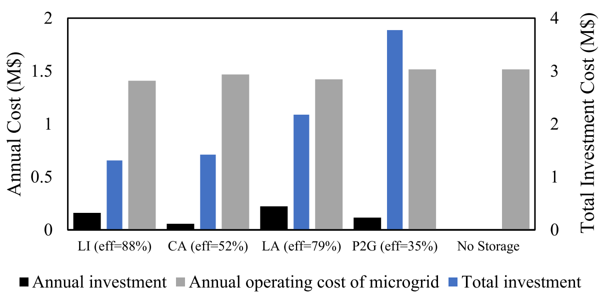

Fig. 14. Comparison of total investment costs, annual cost of investment, and annual operating cost for different storage systems.

Table 4
Comparison of different solving methods for techno-economic analysis of energy storage systems in the multi-energy microgrid.

Solver or solving approach	Type of storage systems	Value of objective function (M $)	Solving time (Second)	Solution Gap (%)	Number of iterations
DICOPT	LI	7.96	103.22	0.10	–
	CA	8.16	103.22	0.10	–
	LA	9.03	103.22	0.10	–
	P2G	8.07	103.22	0.10	–
GBD	LI	7.96	73.12	0	8
	CA	8.16	73.12	0	8
	LA	9.03	73.12	0	8
	P2G	8.07	73.12	0	8
OA/ER	LI	7.96	41.84	0	3
	CA	8.16	41.84	0	3
	LA	9.03	41.84	0	3
	P2G	8.07	41.84	0	3
OA/ER/AP	LI	7.96	38.45	0	3
	CA	8.16	38.45	0	3
	LA	9.03	38.45	0	3
	P2G	8.07	38.45	0	3

*DICOPT: Discrete and Continuous Optimizers; * GBD: Generalized Benders Decomposition; * OA/ER: Outer Approximation/Equality Relaxation; and * OA/ER/AP: Outer Approximation/Equality Relaxation/Augmented Penalty.

5. Conclusion

To ensure a reliable and efficient supply-demand balance, various types of storage systems can be integrated into microgrids. These systems play a crucial role in absorbing excess energy during periods of supply surplus and releasing stored energy during times when supply falls short of demand. In line with this, the present study undertook a comprehensive techno-economic analysis of multiple storage system options within multi-energy microgrids. Specifically, the analysis encompassed lithium-ion battery storage, compressed air energy storage, lead-acid storage, and hydrogen energy storage systems. To reach this aim, a comprehensive methodology was introduced, incorporating an optimization model to identify the optimal placement of storage systems, determine the microgrid's operating cost and schedule. Furthermore, a sensitivity analysis was carried out to assess investment and maintenance expenses associated with the storage systems. To effectively solve the mixed-integer nonlinear problem of the integrated model for gas and electricity subsystems, a decomposition approach based on Outer Approximation/Equality Relaxation/Augmented Penalty was developed and implemented.

The analyses indicate valuable insights into the investment costs associated with energy storage systems in microgrids. By conducting a case study involving the installation of storage systems with a capacity of 1.2 MW at three buses within the electricity subsystem, the analysis revealed compelling results. Among the various storage systems considered, compressed air storage systems demonstrated the lowest total investment cost, amounting to approximately $1.35M. In contrast, lead-acid storage systems incurred a higher investment cost, exceeding $2.00M. Finally, hydrogen energy storage systems exhibited the highest cost, reaching $3.77M. To account for variations in the lifespan of the storage systems, a separate analysis was performed to compare the annual investment costs. When considering the storage systems' life-span, the annual costs of investment were found to be $58.12k for compressed air energy storage and $115.82k for hydrogen energy storage systems. In contrast, lithium-ion and lead-acid storage systems incurred higher annual costs of investment, amounting to $160.60k and $226.63k, respectively. Aside from the mentioned issues, it was studied that energy storage systems could be charged during hours when electricity prices were lower and discharged during hours when electricity prices were higher, resulting in operating cost savings of approximately 7%. Besides, the capability of hydrogen energy storage systems to inject compressed hydrogen into natural gas subsystems was taken into consideration which assisted natural gas demand provision by charging during off-peak hours of electricity demand and discharging to the gas system during peak hours of natural gas demand. Despite certain limitations imposed by safety considerations, the integration of power-to-gas systems and the injection of compressed hydrogen into the natural gas system proved to be beneficial in terms of reducing system operating costs. Specifically, over the course of one operating day, the integration led to a decrease in operating costs from $10.73k to $10.30k. Furthermore, the integration of lead-acid storage systems and power-to-gas systems yielded favorable outcomes for microgrid operators, with a maximum reduction of 15.7% in voltage deviation and a maximum decrease of 10.07% in linepack requirements. Moreover, the development of the decomposition method resulted in notable improvements, including a reduced solving time and fewer iterations compared to other solvers and decomposition methods, achieving a reduction of approximately 60%. These advancements signify the efficiency and effectiveness of the proposed methodology in addressing complex optimization challenges within microgrid systems.

CRediT authorship contribution statement

Vahid Shahbazbegian: Methodology, Software, Writing – original draft, Visualization. **Farnam Dehghani:** Software, Investigation, Data, Writing – original draft. **Mohammad Agha Shafiyi:** Validation, Writing – review & editing, Supervision. **Miadreza Shafie-khah:** Conceptualization, Validation, Writing – review & editing, Supervision. **Hannu Laaksonen:** Writing – review & editing. **Hossein Ameli:** Methodology, Software, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Resilience-oriented operation of microgrids in the presence of power-to-hydrogen systems

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HIGHLIGHTS

- A model to operate PtH in microgrids considering industry demand for hydrogen.
- A novel approach to improve resiliency of microgrids in islanded mode.
- A bi-objective operation cost and resilience measures optimization model (MINLP).
- A solving approach based on the integration of GBD and MOGP methods.

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ABSTRACT

This study presents a novel framework for improving the resilience of microgrids based on the power-to-hydrogen concept and the ability of microgrids to operate independently (i.e., islanded mode). For this purpose, a model is being developed for the resilient operation of microgrids in which the compressed hydrogen produced by power-to-hydrogen systems can either be used to generate electricity through fuel cells or sold to other industries. The model is a bi-objective optimization problem, which minimizes the cost of operation and resilience by (i) reducing the active power exchange with the main grid, (ii) reducing the ohmic power losses, and (iii) increasing the amount of hydrogen stored in the tanks. A solution approach is also developed to deal with the complexity of the bi-objective model, combining a goal programming approach and Generalized Benders Decomposition, due to the mixed-integer nonlinear nature of the optimization problem. The results indicate that the resilience approach, although increasing the operation cost, does not lead to load shedding in the event of main grid failures. The study concludes that integrating distributed power-to-hydrogen systems results in significant benefits, including emission reductions of up to 20 % and cost savings of up to 30 %. Additionally, the integration of the decomposition method improves computational performance by 54 % compared to using commercial solvers within the GAMS software.

1. Introduction

1.1. Motivations and aims

The deployment of renewable energy resources is an option to mitigate the emissions of greenhouse gases which have become one of the major concerns on a global scale. Taking advantage of renewable resources, the federal government of the United States has set a goal of reaching a net-zero electricity sector by 2050 [1]. Likewise, the European Union plans to become climate-neutral by 2035, which will require the utilization of renewable resources, as energy production accounts for a substantial portion of global greenhouse gas emissions [2]. In order to ensure a reliable electricity supply using renewable resources, deploying distributed energy resources, such as rooftop photovoltaic panels and small-scale wind turbines, are potential options [3]. These units are installed in low-voltage electricity distribution networks near the consumers, which reduces transmission loss. It also increases the reliability of supply compared to traditional generators that are typically located far from consumers and mounted on high-

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Nomenclature

Sets

I	Nodes in microgrid ($i \in I$)
T	Periods ($t \in T$)
L	Electric lines ($l \in L \subseteq (i, i')$)
C	Power-to-hydrogen systems consist of electrolyzers, hydrogen storage systems, and fuel cells ($c \in C \subseteq I$)

Parameters

$\delta_{i,t}$	Purchased energy price ($/kW)
$\delta'_{i,t}$	Sold energy price ($/kW)
δ'_{c}	Sold hydrogen price ($/m^3)
α_i	Variable cost of generating power using non-renewable dispatchable units ($/kW)
β_i	Cost of emissions ($/Ton)
ζ_i	Produced emissions of dispatchable units (Ton/kW)
γ_i	Fixed cost of generating power using non-renewable dispatchable units ($)
υ_i	Cost of load shedding ($/kW)
$P_i^{min/max}$	Minimum/maximum produced power by non-renewable units or supplied by substations (kW/h)
$R_i^{max\ up/down}$	Maximum ramp up/down of non-renewable units (kW/h)
$Q_i^{min/max}$	Minimum/maximum active power of non-renewable units or substations (kVAr)
$P_{i,t}^{load}$	Active demand (kW)
$Q_{i,t}^{load}$	Reactive demand (KVAr)
R_l	Resistance (Ω)
X_l	Reactance (Ω)
Z_l	Impedance (Ω)
$V_i^{min/max}$	Minimum/maximum voltage (kV)
I_l^{max}	Maximum current (kA)
$P_{i,t}^{wind,\ max}$	Maximum available power by wind generators (kW)
$\lambda, \mathscr{L}, \mathscr{L}', \wp, \mathscr{M}$	Optimal multipliers of optimization problem
ϕ_c	Efficiency of power-to-hydrogen (%)
φ_c	Efficiency of hydrogen-to-power (%)
ψ_c	Coefficient of hydrogen-to-power (kW/m^3)
$HL_{c,t}^{max}$	Maximum level of hydrogen through hydrogen storage systems (m^3)
HL_c^0	Initial level of hydrogen through hydrogen storage systems (m^3)
PN	Penalty

Decision variables

Z	Objective function
$\mathscr{R}$	Resiliency measures
$P_{i,t}^{buy/sell}$	Purchased/sold energy from/to day-ahead market (kW)
$P_{i,t}$	Generated power of non-renewable units (kW)
$Q_{i,t}$	Reactive power of generating units or substations (kVAr)
$P_{i,t}^{wind}$	Output power of wind turbines (kW)
$P_{i,t}^{line}$	Active power (kW)
$Q_{i,t}^{line}$	Reactive power (kVAr)
$I_{l,t}$	Electricity current (kA)
$V_{i,t}$	Voltage magnitude (kV)
$P_{c,t}^{E \to H_2}$	Electricity power used to produce hydrogen (kW)
$P_{c,t}^{H_2 \to E}$	Produced power using hydrogen (kW)
$H_{c,t}^{in/out}$	Input/output volume of hydrogen (m^3)
$HL_{c,t}$	Volume of hydrogen through hydrogen storage systems (m^3)
$H_{c,t}^{E}$	Volume of hydrogen used to produce electricity (m^3)
$H_{c,t}^{sell}$	Volume of hydrogen sold to industries (m^3)
$P_{j,t}^{lsh}$	Load shedding (kW)
$SV_{i,t}^{s/d}$	Slack variables on supply/demand side

Binary variables

$u_{i,t}$	Status of non-renewable dispatchable units {1,0}
$\rho_{c,t}$	Injecting output power of fuel cells into microgrid using compressed hydrogen {1,0}
$\varrho_{c,t}$	Selling hydrogen to industries {1,0}

voltage transmission networks.

In order to operate distributed energy resources more efficiently, the sources and loads can be considered in an interconnected energy system called a "microgrid". Despite being generally connected to the main grid, the microgrid can operate autonomously, called islanded mode, when the upstream grid fails [4]. In this way, microgrids can improve the resilience of the electricity system by reducing the amount of energy-not-supplied. The term resiliency refers to the systems' ability to resist low-frequency and high-impact incidents efficiently and provide quick recovery and restoration [5]. Besides, excess microgrid generation can be sold to the main grid to provide customers with financial benefits, such as reductions in electricity bills. These factors make microgrids increasingly attractive to customers who cannot rely on the main grid and/or seek economic benefits from locally generated electricity. In the United States, microgrids operate in different states, and according to the forecasts, the capacity is expected to double to a total of 320 in the next three years [6]. There are also over 160 microgrids in India that mainly rely on solar panels for their power supply [7]. In addition to developed countries, microgrids can be an effective solution to connect people in developing and underdeveloped countries to electricity.

In addition to distributed energy resources, other options can come together in a microgrid, such as flexible small-scale generating units and power-to-hydrogen (PtH) systems. The flexible and dispatchable generating units are an appropriate option to handle the variability of renewable energy resources benefiting from their flexible ramping capability [8]. Moreover, PtH systems are flexible technologies that can convert the excess output of renewable energy resources and/or excess supply in electricity networks to hydrogen. This gas can be either consumed in other industries or converted to electricity to provide supply–demand balance during peak hours (e.g., using fuel cells) [9].

Despite the already-mentioned issues, solving the optimal operation of microgrids for the dispatch of different components is still challenging. The first reason would be the complexity of modeling different components, such as distributed generators, PtH systems, and storage systems. The second one would be difficulty with modeling power flow within the electricity network in microgrids, which involves a set of nonlinear constraints. Therefore, it would be more efficient to break the original problem into smaller ones and solve the subproblems, which decreases complexity compared to solving the original problem [10]. However, a solving procedure that finds optimal solutions to the problem should not sacrifice optimally and accuracy [11].

1.2. Review of related literature

A few review papers published recently investigating the operation of microgrids when distributed sources of renewable energy and Power-to-Gas (PtG) systems are highly prevalent. For instance, in [12], the role of different technologies and shares of PtG systems integrated into energy systems are investigated and compared. In particular, different types of electrolyzers and storage systems were examined, along with a high and low penetration of the PtG systems. In [13], distinct aspects of energy systems, including PtG systems integration, resiliency consideration, pollution reduction, and operation objectives, are investigated. In [14], the operation of different storage systems, such as hydrogen storage systems, is recapped in energy systems. In the following, a systematic review of the recent research works in this field is also conducted as well. In this section, the studies in this field are divided based on their objectives, including examination of the role of PtG systems, resiliency consideration, or development of solving methods (e.g., heuristic and exact methods).

Among the previous studies, in [15], the role of PtG systems was studied costal microgrids in coastal areas considering water resources and wind power as energy input and raw material input, respectively. It concluded that the integration of PtG systems was an efficient solution to handle fluctuations of wind power by peak shaving and valley filling. In [16], a considerable number of PtG systems were examined in islanded microgrids applying a game that involves different parties, including wind turbines, storage systems, and photovoltaic systems. The results indicated the integration of hydrogen and methane reduced wind curtailment and improved the income of each party. In [17], the effect of PtG systems and fuel cells was examined in the optimal operation and planning of microgrids. It was demonstrated that the integration of the PtG systems improved the penetration level of renewable resources to supply demand. In [18], the role of PtG systems besides fuel-cell electric vehicles was investigated to mitigate the growth in energy demand due to the development of the transportation system. It indicated that the integration of PtG systems assisted in the integration of electric vehicles by decreasing renewable energy curtailment. In [19], the study focused on assessing the effects of PtG and power-to-heat technologies on the operation of industrial microgrids, with the aim of providing affordable energy supply to meet the demand. The operator of the industrial parks interacted with different markets (e.g., the heat market), which provided operating cost savings. Some studies also examined the effect of PtG systems in conjunction with the combined heat and power systems. For instance, in [20] and [21], the role of PtG systems and combined cooling and heating systems were examined to enhance clean production in microgrids. In [22] and [23], the joint dispatch of PtG systems and combined heat and power systems were considered to handle the variability of renewable energy resources and demand. These studies also demonstrated that integrating PtG systems into microgrids reduced operating costs and emissions. In [24] and [25], the problem of optimal operation of microgrids was examined by considering PtG systems, combined heat and power systems, and fuel cell electric vehicles. The obtained results indicated that the combination of the technologies and electric vehicles reduced the operating costs of microgrids. In [26] and [27], the effect of PtG systems and demand response programs on scheduling microgrids was studied by considering combined heat and power units. In [28], the impacts of PtG systems and demand response programs were studied on scheduling microgrids coupled with wind turbines, photovoltaic systems, and storage systems. These studies showed that the integration of PtG systems into demand response programs or storage systems was an appropriate solution to reach peak shaving and valley filling that leads to operating cost savings. Besides, some other studies consider other subsystems' constraints in operating microgrids to examine the impact of PtG systems (e.g., gas, hydrogen, and heat networks). In [29], the role of PtG facilities was examined by considering a hydrogen subsystem to be utilized for the charging station of electric vehicles in microgrids. In [30], the impact of PtG systems was studied on microgrids considering congestion in the natural gas network. The results of the studies indicated that the output hydrogen of PtG systems supplied electric vehicles and injected into the gas network, respectively, which concluded cost savings. In [31], the variation of market price and wind power, as well as the role of hydrogen storage systems in microgrids, were studied, which consisted of the electricity network, gas network, and heat network. In [32], the optimal scheduling of microgrids was analyzed in electricity markets considering PtG systems, demand response programs, and energy storage systems. The outputs of these studies also addressed the capability of PtG systems besides demand response and energy storage systems for an efficient demand provision using distributed energy resources.

On the other hand, some other studies focus on improving the resilience of the microgrid. These studies consider the failure of the main grids in different scenarios or use flexible components, such as PtG systems, to reach this aim. For instance, in [33], microgrid operation was optimized under conditions of failure in the main grid that increased load shedding risk. This study introduced a trade-off between resilient and economic operation, as resilient operation increased the operating costs of microgrids. In [34], different outage scenarios were considered for an airport microgrid (e.g., failures of the main grid during peak hours and off-peak hours), and the resiliency of the system considering storage systems and diesel generators was evaluated. It indicated that the integration of storage systems and diesel generators reduced operating costs as well as the duration of network failure in case of an outage. In [35], different scenarios were considered, including grid-connected and islanded ones, to optimize the operation of microgrids to enhance resiliency. This study concluded the proposed approach maximized the profits of microgrids considering the possibility of islanding. In [36], different scenarios for outages in industrial microgrids were taken into consideration in the presence of fuel cells, hydrogen storage tanks, and battery and heat storage systems to improve resiliency. This study demonstrated the use of hydrogen as a backup for generating power and the stochastic scheduling of microgrids to consider outage scenarios reduced load shedding risks. In [37], the role of incentive-based changes in the demand of customers was examined to improve the resiliency of microgrids in islanded mode. It concluded that the flexibility obtained by customers improved the profit of microgrids in both normal and resilient operations. In [38], an unbalanced microgrid was studied considering random variables, such as demand and output power of renewable resources, and examined the resiliency considering contingency constraints that indicated the islanded mode. It concluded the resilient scheduling of microgrids minimized costs and maximized the use of distributed renewable resources. In [39], both failures of the main grid and uncertainty in microgrid resources were considered to enhance resiliency by examining the level of flexibility provided by distributed resources. In [40], the economic mode of operation and a determined resilient mode based on the charge and discharge of energy storage systems were compared in the case of contingency and main grid failure. Based on the results of the reviewed studies, it was necessary to employ a resilient approach using flexibility options to reduce load shedding and provide a technically possible portion of demand when the main grid fails, and microgrids go into islanded mode.

As discussed earlier, solving the optimal operation of microgrids is challenging due to the complexity of the problem, which can be in the form of mixed-integer nonlinear programming (MINLP). Various heuristic methods have been developed to address this problem, such as the Improved Multi-Objective Differential Evolutionary Optimization algorithm [41], an approach based on Differential Evolution and Chaos Theory [42], the Quantum Version of Teaching Learning Based Optimization [43], the Conventional Particle Swarm [44], the Modified Bat Algorithm [45], a Co-Evolutionary algorithm [46], and a hybrid approach based on the Gray Wolf Optimizer, Sine Cosine Algorithm, and Crow Search Algorithm [47]. While heuristic techniques were able to find satisfactory optimal solutions more rapidly using a computational procedure, they often compromised optimality and accuracy. However, a few recent studies focused on the exact methods to solve the optimization problem. For instance, to solve the robust operation of microgrids, a dual Benders Decomposition approach was developed in [48]. The decomposition approach is based on splitting a large optimization problem into smaller subproblems that can be solved independently and combining the results to find a solution to the original problem. Another

Table 1
Systematic review of related work to this study.

Reference	Single-Objective	Multi-Objective	Objectives	Resiliency Consideration			Modeling Approach	Solution Method		Decomposition Approach	Power-to-Hydrogen Systems			
				Failure of the main grid	Flexible components	Another objective		Exact	Heuristic		Gas-to-industry or market	Power-to-gas	Gas-to-power	Gas storage
[15]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	–	✓	✓	✓
[16]	✓	–	-Income maximization	–	–	–	MINLP	–	✓	–	–	✓	✓	✓
[17]	–	✓	-Cost minimization -Wind-curtailment minimization	–	–	–	MINLP	–	✓	–	–	✓	✓	✓
[18]	✓	–	-Profit maximization	–	–	–	MILP	✓	–	–	✓	✓	–	–
[19]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	–	✓	–	–
[20]	–	✓	-Cost Minimization -Emission minimization	–	–	–	MILP	✓	–	–	–	✓	–	–
[21]	–	✓	-Cost minimization -Emission minimization	–	–	–	MILP	✓	–	–	✓	✓	✓	–
[22]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	–	✓	–	✓
[23]	–	✓	-Cost minimization -Emission minimization	–	–	–	MINLP	✓	–	–	✓	✓	✓	–
[24]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	✓	✓	–	–
[25]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	✓	✓	✓	✓
[26]	✓	–	-Cost minimization	–	–	–	MILP	–	✓	–	✓	✓	–	–
[27]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	✓	✓	✓	✓
[28]	✓	–	-Cost minimization	–	–	–	MINLP		✓	–	–	✓	✓	–
[29]	✓	–	-Profit maximization	–	–	–	MILP	–	✓	–	✓	✓	✓	✓
[30]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	✓	✓	✓	✓
[31]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	✓	✓	✓	✓
[32]	✓	–	-Cost minimization	–	–	–	MILP	✓	–	–	✓	✓	–	✓
[33]	✓	–	-Cost minimization	✓	✓	–	MILP	✓	–	–	–	–	–	–
[34]	✓	–	-Cost minimization	✓	✓	–	MILP	✓	–	–	–	–	–	–
[35]	–	✓	-Cost minimization -Resiliency maximization	✓	✓	✓	MILP	✓	–	–	–	–	–	–
[36]	–	✓	-Cost minimization -Resiliency maximization	✓	✓	✓	MILP	–	✓	SOCR	✓	–	✓	✓
[37]	✓	–	-Cost minimization	✓	✓	–	MILP	✓	–	–	–	–	–	–
[38]	✓	–	-Cost minimization	✓	✓	–	MINLP	✓	–	–	–	–	–	–
[39]	✓	–	-Cost minimization	✓	–	–	MILP	✓	–	–	–	–	–	–
[40]			-Cost minimization -Resiliency maximization	✓	✓	–	MILP	✓	–	–	–	–	–	–
[41]	✓	–	-Cost Minimization	–	–	–	MINLP	–	✓	–	–	–	–	–
[42]	✓	–	-Cost Minimization	–	–	–	MINLP	–	✓	–	–	–	–	–
[43]	✓	–	-Cost Minimization	–	–	–	MILP	–	✓	–	–	–	–	–
[44]	✓	–	-Cost Minimization	–	–	–	MINLP	–	✓	–	–	–	–	–
[45]	✓	–	-Cost Minimization	–	–	–	MINLP	–	✓	–	–	–	–	–
[46]	✓	–	-Cost Minimization	–	–	–	MINLP	–	✓	–	–	–	–	–
[47]	✓	–	-Cost Minimization	–	–	–	MINLP	–	✓	–	–	–	–	–

(continued on next page)

Table 1 (*continued*)

Reference	Single-Objective	Multi-Objective	Objectives	Resiliency Consideration			Modeling Approach	Solution Method		Decomposition Approach	Power-to-Hydrogen Systems			
				Failure of the main grid	Flexible components	Another objective		Exact	Heuristic		Gas-to-industry or market	Power-to-gas	Gas-to-power	Gas storage
[48]	✓	–	-Cost Minimization	–	–	–	MINLP	–	✓	–	–	–	–	–
[49]	✓	–	-Cost Minimization	–	–	–	MINLP	✓	–	BD	–	–	–	–
[50]	✓	–	-Cost Minimization	–	–	–	MILP	✓	–	ADMM	–	–		
[51]	✓	–	-Profit maximization of agents	–	–	–	MILP	–	✓	ADMM	✓	✓	✓	✓
Thisresearch	–	✓	-Cost minimization -Resiliency maximization	✓	✓	✓	MINLP	✓	–	GBD	✓	✓	✓	✓

*MILP: Mixed Integer Linear Programming; * MINLP: Mixed Integer Nonlinear Programming; *SOCR: Second Order Conic Relaxation; *BD: Benders Decomposition; *GBD: Generalized Benders Decomposition; *ADMM Alternating Direction Method of Multipliers.

study applied Benders Decomposition to optimize the profit of microgrids during the islanded mode of operation [49]. In [50], a model was proposed to maximize the profit of supply and flexible loads on the demand side in microgrids. This study developed the Alternating Direction Method of Multipliers, which divided the original objective function and constraints to reduce the complexity of the problem like Benders Decomposition. In [51], agent-based scheduling was studied for microgrids considering PtH systems (e.g., electricity and hydrogen systems agents). This study also developed the Alternating Direction Method of Multipliers to solve the optimization problem. It concluded that, in the reviewed studies, the solving methods provided precise solutions benefiting from splitting the problem into smaller subproblems, which decreased complexity compared to solving the original problem.

1.3. *Research gaps and contributions*

Considering the literature listed above, the comparison of related studies with the proposed approach in this research is given in Table 1. Previous studies have examined the operation of microgrids in the presence of PtH systems, taking into account the conversion of excess electricity to hydrogen and the storage of the hydrogen produced, but the consumption of hydrogen for industrial use has not been fully investigated. Furthermore, the role of PtH systems in enhancing resilience and reducing energy-not-supplied has not been adequately investigated. Nonetheless, current resilience methods primarily focus on failure scenarios of the main grid or the utilization of flexible components like storage systems. Previous studies have not given enough attention to the potential of exact mathematical solutions, such as decomposition methods, in effectively solving the operation model for microgrids in the presence of PtH systems. Given that the problem is formulated as an MINLP problem, exploring these mathematical approaches could yield more accurate solutions.

In view of the above problem, this study proposes a bi-objective model for the resilient operation of industrial microgrids in the presence of PtH systems consisting of electrolyzers, hydrogen storage systems, and fuel cells. In this model, the first objective is the cost of microgrid operation, and the output hydrogen from these systems can either be sold to industry, stored in tanks (i.e., hydrogen storage systems), or consumed to generate electricity using fuel cells. The second objective considers three measures to enhance the resilience of the microgrid by reducing the interaction with the main grid, increasing hydrogen levels in storage systems, and reducing power losses. As the model of resilient operation of microgrids in the presence of PtH systems is bi-objective and in the form of MINLP, a solution approach is developed in which Generalized Benders Decomposition (GBD) is integrated into the Multi-Objective Goal Programming (MOGP) approach. A pre-processing approach is also developed to facilitate the convergence of the solution method. This approach involves two key steps: initializing points for the decomposition method and convexifying the MINLP problem. These steps aim to streamline the optimization process and improve the overall efficiency of the solution approach.

Finally, through the introduction of case studies, various technical analyses are carried out to examine the role of PtH systems in the operation of a microgrid. Analyses are performed with the aim of providing insight into the resilience and economic operation of the microgrid in the presence of PtH systems. The developed solution approach's significance in addressing the complexity of the optimization model for the resilient operation of the microgrid is examined.

1.4. *Paper organization*

The remainder of this study is structured as follows: In Section 2, an optimization model is proposed for the resilient operation of microgrids considering distributed renewable energy resources, flexible generating units, and PtH systems composed of electrolyzers, hydrogen storage systems, and fuel cells. Subsequently, the solving method is presented,

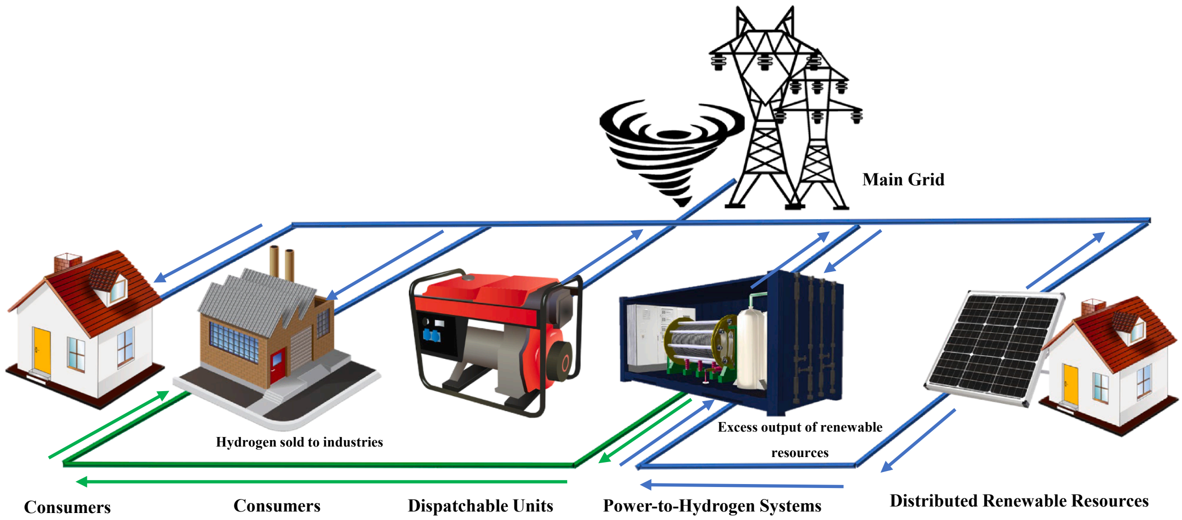

Fig. 1. The illustration of a microgrid connected to the main grid consists of consumers, dispatchable units, PtH systems, and distributed renewable energy resources (blue lines and green lines indicate power flow and hydrogen transmission, respectively). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

which involves combining the MOGP approach with the GBD method. In Section 3, a case study is illustrated to examine the applicability and performance of the proposed model, and an analysis is conducted to assess the effectiveness of the proposed model and provide insights for operators in Section 4. Finally, the main conclusions and future research directions are presented and recapped in Section 5.

2. Model and formulation

A configuration of an industrial microgrid connected to the main grid is illustrated in Fig. 1. As depicted, it consists of consumers, distributed renewable energy resources, flexible natural gas-fired units, and PtH systems. When the output power of distributed energy resources in this microgrid exceeds local demand, the excess power can be consumed by PtH systems' electrolyzers to produce hydrogen from the water. These systems consume electricity to split hydrogen and oxygen from the water through electrolysis. ($2H_2O \rightarrow 2H_2 + O_2$) [52]. In the microgrid, the compressed hydrogen can be either sold to industries or filled into storage tanks of the PtH systems for later use (e.g., generating electricity using PtH systems' fuel cells). Moreover, in the case of any failures in the main grid, the microgrid is disconnected and operated independently in islanded mode. Therefore, it is of significant importance to schedule it considering resilience when any failure in the main grid is predicted. For instance, predicting the level of hydrogen in tanks and being independent of imported power from the main grid could be beneficial as preventive measures when local supply is lower than demand. These measures help local demand provision during a specific period improving the system's resilience.

It should be noted that although the PtH systems, including electrolyzers, hydrogen storage systems, and fuel cells, are cost-intensive, they can be valuable in the scheduling of industrial microgrids from several perspectives. The first one is that hydrogen is necessary for different industries in the area, including metalworking, flats glass production, and electronic industries [53]. Hydrogen sales to industries can provide the operator with revenue that can be used to offset other operating costs. The second one is that these systems are designed to provide the storage capability for excess renewable energy, which can be used during periods of low renewable energy availability or high energy demand. In this way, fuel cells that are used in conjunction with electrolyzers and hydrogen storage systems can be a flexible option to convert hydrogen into power. The last point to consider is that PtH technologies are rapidly advancing, which will improve their efficiency and reduce the costs associated with their deployment [54]. Therefore, the PtH systems can play a key role in achieving decarbonization in the future of energy systems, where all energy needs are met by low/net-zero emission sources.

2.1. *Model for the resilient operation of microgrid considering PtH systems*

The model for the resilient operation of single-phase and balanced electricity distribution networks of microgrids is indicated in this subsection. It is noteworthy to mention that demand is considered as constant active and reactive power for each hour of operation in the model, and the power loss is also assumed at the beginning of each line. Besides, the microgrid can exchange power with the main grid in electricity markets; hence it is assumed that the day-ahead electricity market was operated to determine electricity price based on the supply and demand (i.e., day-ahead electricity price is determined). In this study, the optimal operation of the microgrids is investigated, meaning all components were previously installed, including PtH systems. The resilient operation of microgrids in the presence of PtH systems is formulated as a bi-objective optimization problem. The reason is that there are two objectives with different scales, including minimizing cost ($) and minimizing de-resilience (kWh). The objective functions and the constraints are explained in the following.

2.1.1. *Objective functions*

Equation (1) addresses the objective function of the optimal operation of the microgrid considering PtH systems. The objective function consists of five terms: cost of purchasing electricity from the main grid, costs of producing electricity and emissions production using non-renewable dispatchable units (e.g., microturbines), cost of load shedding, the revenue of selling electricity to the main grid, and revenue of selling hydrogen to industries. It is assumed that the day-ahead electricity market has already been operated, and as a result, the price of electricity has been determined based on the interaction between electricity suppliers and consumers.

$$\text{Minimize } Z_1 = \sum_t \sum_i \delta_{i,t}.P^{buy}_{i,t} + \sum_t \sum_i ((\alpha_i + \beta_i.\zeta_i).P_{i,t} + \gamma_i.u_{i,t}) + \sum_t \sum_i \upsilon_i.P^{lsh}_{i,t} - \sum_t \sum_i \delta^{'}_{i,t}.P^{sell}_{i,t} - \sum_t \sum_c \delta^{''}_c.H^{sell}_{c,t} \tag{1}$$

Three measures are also determined as another objective function to improve the resiliency of the microgrid against predicted events in Eq. (2). More precisely, considering the second objective function improves the operation of the microgrid to be more efficient when it goes to islanded mode. Each term of the objective function is precisely explained in the following.

$$\text{Minimize } Z_2 = \mathscr{R}_1 - \mathscr{R}_2 + \mathscr{R}_3 \tag{2}$$

- *The first term: decrease interactions with the main grid.*

As a resiliency measure, it is necessary to reduce power imports from the main grid (Eq. (3)). The purpose of this measure is to ensure that the microgrid is independent and ensure power supply by locally generated power. When a microgrid operates independently, it can function more reliably in cases of contingency (i.e., in islanded mode).

$$\mathscr{R}_1 = \sum_t \sum_i P^{buy}_{i,t} \tag{3}$$

- *The second term: increase available power through tanks.*

A microgrid can achieve improved operation when the available local supply falls short of demand, if it has sufficient hydrogen supply that can be converted to electricity in the event of contingencies in the main grid. Therefore, the second term of this objective is gas level through tanks multiplied by the efficiency of electricity production, as indicated in Eq. (4).

$$\mathscr{R}_2 = \sum_t \sum_c \varphi_{c,t} HL_{c,t} \tag{4}$$

- *The third term: decrease power loss.*

When the power loss is minimized, consumers are supplied by the nearest suppliers, which improves the reliability of the supply. For this purpose, the third term of the second objective (i.e., the third resiliency measure) is considered to reduce the power loss (Eq. (5)).

$$\mathscr{R}_3 = \sum_t \sum_l R_l.I^2_{l,t} \tag{5}$$

2.1.1.1. Constraints. In addition to objective functions, constraints of the problem are determined, including active power balance, maximum/minimum output power of renewable and non-renewable generating units, ramp up/down, reactive power balance, Kirchhoff's voltage law and voltage and current limitations, and PtH systems' technical constraints, in the following.

- *Active power balance.*

In Eq. (6), the active power balance for the microgrid is indicated by considering dispatchable and renewable generating units, interactions with the main grid, charge and discharge power of PtH systems, and power loss within the lines [55]. More precisely, it declares that the supply should match the demand in each hour of the operation period [56].

$$P_{i,t} + P^{wind}_{i,t} - P^{E\rightarrow H_2}_{c,t} + P^{H_2\rightarrow E}_{c,t} + P^{lsh}_{i,t} + P^{buy}_{i,t} - P^{sell}_{i,t} - \sum_{i'} (P^{line}_{l,t} + R_l.I^2_{l,t}) = P^{load}_{i,t} \quad \forall i, \forall l, \forall t \tag{6}$$

- *Maximum/minimum output power of renewable and non-renewable generating units.*

In Eqs. (7)-(8), the maximum/minimum output power of different generating units is demonstrated. The binary variable $u_{i,t}$ represents the status of dispatchable generating units which is equal to one when the units are on and is zero otherwise.

$$P^{wind}_{i,t} \le P^{wind,max}_{i,t} \quad \forall i, \forall t \tag{7}$$

$$u_{i,t}.P^{min}_i \le P_{i,t} \le u_{i,t}.P^{max}_i \quad \forall i, \forall t \tag{8}$$

- *Ramp up/down.*

In Eqs. (9)-(10), the ramp-up and ramp-down constraints of dispatchable generating units are indicated, which refers to their capability to change their output power. A fast ramping rate capability is appropriate to deal with the variable output power of renewable generating units, called flexibility measure.

$$P_{i,t} - P_{i,t-1} \le R^{maxup}_i \quad \forall i, \forall t \tag{9}$$

$$P_{i,t-1} - P_{i,t} \le R^{maxdown}_i \quad \forall i, \forall t \tag{10}$$

- *Reactive power balance.*

In Eq. (11), the reactive power balance in the network is presented.

$$Q_{i,t} + Q^{wind}_{i,t} + \sum_{i'} (Q^{line}_{l,t} + X_l.I^2_{l,t}) = Q^{load}_{b,t} \quad \forall i, \forall l, \forall t \tag{11}$$

- Kirchhoff's voltage law and voltage & current limitations.

In Eqs. (12)-(13), Kirchhoff's voltage law for each time step is indicated [57]. Eqs. (14)-(15) indicate the voltage limitation at each node and the current limitation through each line.

$$V^{in\,2}_{l,t} - V^{out\,2}_{l,t} = 2\left(R_l.P^{line}_{l,t} + X_l.Q^{line}_{l,t}\right) + Z^2_l.I^2_{l,t} \quad \forall l, \forall t \tag{12}$$

$$V^2_{l,t}.I^2_{l,t} = Q^{line2}_{l,t} + P^{line2}_{l,t} \quad \forall l, \forall t \tag{13}$$

$$V^{min}_i \le V_{i,t} \le V^{max}_i \quad \forall i, \forall t \tag{14}$$

$$|I_{l,t}| \le I^{max}_l \quad \forall l, \forall t \tag{15}$$

- *PtH systems' technical constraints.*

In Eqs. (16)-(20), constraints are indicated related to the operation of PtH systems in microgrids. According to Eq. (16), excess power from a microgrid ($P^{E\rightarrow H_2}_{c,t}$) can be used to produce hydrogen utilizing electrolyzers. Hydrogen produced ($H^{in}_{c,t}$) is compressed and stored within tanks, as indicated in Eq. (17). It should be noted that, in this equation, the stored amount of hydrogen from the previous operating period is also taken into consideration (HL^0_c). More precisely, the amount of hydrogen stored within tanks at the end of each operating period will be used as the initial amount at the beginning of the next operating period. The stored amount of hydrogen can either be used in generating electricity for later uses by fuel cells ($H^{E}_{c,t}$) or sold for use in other industries ($H^{sell}_{c,t}$), as indicated in Eqs. (18)-(19). Additionally, Eq. (20) indicates the level of hydrogen stored within the tanks ($HL_{c,t}$) cannot exceed its maximum ($HL^{max}_{c,t}$). The discharge of hydrogen to produce electricity in microgrids and the sale of hydrogen to industries are also limited by Eqs. (21)-(22). Binary variables are also defined ($\rho_{c,t}$ and $\varrho_{c,t}$), and another constraint is introduced to prevent that each storage can be discharged to produce electricity in the microgrid and supply industries, simultaneously (Eq. (23)). The reason is that fuel cells need hydrogen at a specific pressure to operate efficiently. Therefore, the simultaneous discharge of hydrogen from storage systems should be avoided so that fuel cells can operate properly [58,59].

$$P^{E\rightarrow H_2}_{c,t}\rho_{c,t} = H^{in}_{c,t} \quad \forall c, \forall t \tag{16}$$

$$HL_{c,t} = \begin{cases} HL^{0}_{c} & if \quad \forall c, t = 1 \\ HL_{c,t-1} + \left(\phi_c.H^{in}_{c,t} - \dfrac{H^{out}_{c,t}}{\varphi_c}\right) & if \quad \forall c, \forall t \geq 2 \end{cases} \tag{17}$$

$$H^{out}_{c,t} = H^{E}_{c,t} + H^{sell}_{c,t} \quad \forall c, \forall t \tag{18}$$

$$H^{E}_{c,t}.\psi_c = P^{H_2\rightarrow E}_{c,t} \quad \forall c, \forall t \tag{19}$$

$$HL_{c,t} \leq HL^{max}_{c,t} \quad \forall c, \forall t \tag{20}$$

$$H^{E}_{c,t} \leq \rho_{c,t}.HL^{maxE}_{c,t} \quad \forall c, \forall t \tag{21}$$

$$H^{sell}_{c,t} \leq \varrho_{c,t}.HL^{maxsell}_{c,t} \quad \forall c, \forall t \tag{22}$$

$$\rho_{c,t} + \varrho_{c,t} \leq 1 \quad \forall c, \forall t \tag{23}$$

2.2. Solving approach based on GBD and MOGP

To address the resilient operation of microgrids with PtH systems, a solving method is devised that combines the GBD technique with the MOGP approach. This combination provides an effective solution for optimizing microgrid operations under various scenarios and enables efficient utilization of PtH systems. An upside to the MOGP method is the reduction in the number of iterations and solving time of the MINLP model [60]. Different satisfaction levels for each objective function can be considered using MOGP to provide insights for the operators. The first step of the MOGP is to calculate the positive ideal and negative ideal solutions for each objective function. After that, using the obtained results in the last step, membership functions are determined for the objective functions. In the third step, the weighted sum of objective functions is optimized to find the maximum level of satisfaction of constraints for each objective. Finally, MOGP is added as a constraint, and the model is solved iteratively, which provides a set of solutions to be opted by operators. However, to solve the resilient operation of microgrids in the presence of PtH systems using the four-step MOGP approach, the problem contains binary variables and nonlinear constraints, which makes the model an MINLP problem. To handle this issue, an approach based on Benders Decomposition, called GBD, is combined with the MOGP method for solving this MINLP problem. Proposed a few decades ago [61,62], GBD has often been employed to solve optimization problems in different fields, such as telecommunication, energy, and transport. As non-convexity is often associated with MINLP problems, within a finite number of iterations, the GBD fixes the non-convexity problem and converges to the exact solution [49,50]. Therefore, this approach is an appropriate option to optimize the resilient operation of microgrids due to the nonlinear constraints (Eqs. (12)-(13)) and binary decision variable ($u_{i,t}$, $\rho_{c,t}$, and $\varrho_{c,t}$).

In the following, at first, the main step of the MOGP method to solve the problem of resilient operation of microgrids in the presence of PtH systems is determined step-by-step. Then, it is explained how the GBD method is integrated into the MOGP method to solve the optimization problem.

- *MOGP: the first step*.

The first step involves finding ideal and non-ideal solutions by solving the optimization problem considering only one of the objective functions and ignoring the other one at any time [63]. For instance, in Eqs. (24), minimizing the first objective function provide an ideal and a non-ideal solution for the resilient operation of microgrids in the presence of PtH systems (Z_1^+ and Z_2^-, respectively (Eq. (25)). In Eq. (26), the other ideal and non-ideal solutions are also determined for the problem studied (Z_2^+ and Z_1^-, respectively (Eq. (27)). More precisely, when the optimization problem is solved by considering only one objective function, it provides an ideal solution for that objective function and a non-ideal solution for the other objective function.

$$\begin{array}{l} \text{Minimize } Z_1 \\ \text{Subject to} \\ \text{Equations } (6) - (23) \end{array} \tag{24}$$

$$Z_1^+ = Z_1^* \text{ and } Z_2^- = Z_2^* \tag{25}$$

$$\begin{array}{l} \text{Minimize } Z_2 \\ \text{Subject to} \\ \text{Equations } (6) - (23) \end{array} \tag{26}$$

$$Z_2^+ = Z_2^* \text{ and } Z_1^- = Z_1^* \tag{27}$$

- *MOGP: the second step*

A membership function (ψ_1 and ψ_2) is determined for each objective function as indicated in Eq. (28). In this way, the membership functions are determined for the problem of the resilient operation of the microgrids.

$$\begin{array}{l} \psi_1 = \begin{cases} 1 & if \ Z_1 \leq Z_1^+ \\ \dfrac{Z_1^- - Z_1}{Z_1^- - Z_1^+} & if \ Z_1^- \leq Z_1 \leq Z_1^+ \\ 0 & if \ Z_1 \geq Z_1^- \end{cases} \\ \psi_2 = \begin{cases} 1 & if \ Z_2 \leq Z_2^+ \\ \dfrac{Z_2^- - Z_2}{Z_2^- - Z_2^+} & if \ Z_2^- \leq Z_2 \leq Z_2^+ \\ 0 & if \ Z_2 \geq Z_2^- \end{cases} \end{array} \tag{28}$$

- *MOGP: the third step*

A maximum level of satisfaction for the constraints is determined by solving a crisp model indicated in Eq. (29). In the optimization problem, ς, ω_h, and h respectively indicate the maximum level of satisfaction for the constraints, weighted coefficients ($\sum_h \omega_h = 1$) determined by decision-makers (i.e., microgrid operator in the problem of resilient operation of microgrids), and a set of objective functions.

$$\begin{array}{l} \text{Maximize} \sum_h \omega_h \varsigma_h \\ \text{subject to} \\ \psi_h \geq \varsigma \quad h = 1 \text{ and } 2, \ \varsigma \in [0,1] \\ \text{Equations } (6)\text{–}(23) \end{array} \tag{29}$$

- *MOGP: the fourth step*

Table 2
Main steps of GBD to solve an MINLP optimization problem.

Loop
Initialization $Iteration := 1$ $Upperbound = \infty$ Initializing binary variables $y^{(k)}$
The first step: nonlinear programming subproblem Minimize $Z^{primal} = C^T y^{(k)} + f(x)$ Subject to $h(x) = 0,\ g(x) \le 0,\ Cx + By^{(k)} \le b,\ Ay \le \alpha, x \in R^n$ The solutions are optimal multipliers ($\lambda^{(k)}$) and decision variable ($x^{(k)}$) if $Z^{primal} \le Upperbound$ $Upperbound := Z^{primal}$ $\lambda^{new} := \lambda^{(k)}$ $x^{new} := x^{(k)}$ End
The second step: mixed integer programming master problem Minimize $Z^{master} = \mu$ Subject to $\mu \ge C^T y + f(x^k) - \lambda^{(k)}(C^T x^{(k)} + By - b)$ $Ay \le \alpha,$ $y \in \{0, 1\}$ The solution is $y^{(k+1)}$
The third step: convergence checking If $Z^{master} \ge Upperbound$ Stop Else $Iteration := Iteration + 1$ Go to step 1 End

Finally, goal programming is integrated into the approach to solving the resilient operation of microgrids by adding a constraint ($\psi_h^{new} \ge \psi_h$) into the model proposed in the last step (Eq. (30)). This step is repeated until it provides an appropriate level of satisfaction (ς) for the microgrid operator. Meanwhile, an analysis of weighted coefficients is carried out by modifying the weights assigned to each objective function. This analysis aims to provide decision-makers with valuable insights by exploring the impact of different weightings on the overall optimization results.

$$
\begin{aligned}
&\text{Maximize} \sum_h \omega_h \varsigma_h \\
&\text{subject to} \\
&\psi_h \ge \varsigma_h \quad h = 1 \text{ and } 2, \varsigma_h \in [0, 1] \\
&\psi_h^{new} \ge \psi_h \\
&\text{Equations (6)–(23)}
\end{aligned} \tag{30}
$$

Despite using the MOGP approach to solve the bi-objective problem presented in this study, challenges remain in solving the Mixed-Integer Nonlinear Programming (MINLP) problems encountered in the first, third, and fourth steps. For this purpose, GBD is integrated into the MOGP to cope with this issue. The concept of GBD is to solve the primal problem first and then the master problem, which generates an upper bound and a lower bound. Firstly, the primal problem is solved by initializing the binary variables in the first iteration that provides the upper bound and Lagrange Multipliers related to constraints. After that, the master problem is determined by employing duality theory and Lagrange Multipliers of the previous step. The solution to the master problem provides a lower bound and binary variable for the next iteration. The procedure converges in a finite number of iterations when the upper bound is greater or equal to the lower bound. Considering an MINLP problem in the form of Eq. (31), the main steps of this decomposition approach are represented in detail in Table 2.

Table 3
Main steps of GBD to solve the resilient operation of microgrids in the presence of PtH systems.

Loop
Initialization $Iteration := 1$ $Upperbound = \infty$ Initializing binary variables $u_{i,t}^{(k)}, \rho_{c,t}^{(k)}$, and $\varrho_{c,t}^{(k)}$
The first step: nonlinear programming subproblem Minimize $Z^{primal} = \sum_t \sum_i (\gamma_i . u_{i,t}^{(k)}) + \sum_t \sum_i \delta_{i,t} . P_{i,t}^{buy} + \sum_t \sum_i ((\alpha_i + \beta_i . \zeta_i) . P_{i,t}) + \sum_t \sum_i \upsilon_i . P_{i,t}^{lsh} - \sum_t \sum_i \delta'_{i,t} . P_{i,t}^{sell} - \sum_t \sum_c \delta''_{c,t} . H_{c,t}^{sell}$ Subject to Equations (6), (7), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), and (20) $u_{i,t}^{(k)} . P_i^{min} \le P_{i,t} \le u_{i,t}^{(k)} . P_i^{max}, \mathscr{L}_{i,t}^{(k)}, \mathscr{L}'^{(k)}_{i,t}, \forall i, \forall t$ $H_{c,t}^{E} \le \rho_{c,t}^{(k)} . HL_{c,t}^{maxE}$ $\wp_{c,t}^{(k)}, \forall c, \forall t$ $H_{c,t}^{sell} \le \varrho_{c,t}^{(k)} . HL_{c,t}^{maxsell}, \mathscr{R}_{c,t}^{(k)}, \forall c, \forall t$ $\rho_{c,t}^{(k)} + \varrho_{c,t}^{(k)} \le 1, \varkappa_{c,t}^{(k)}, \forall c, \forall t$ The solutions are optimal multipliers of constraints and continuous decision variables if $Z^{primal} \le Upperbound$ $Upperbound := Z^{primal}$ ${P_{i,t}^{buy}}^{new} := {P_{i,t}^{buy}}^{(k)}$ ${P_{i,t}}^{new} := {P_{i,t}}^{(k)}$ ${P_{i,t}^{lsh}}^{new} := {P_{i,t}^{lsh}}^{(k)}$ ${P_{i,t}^{sell}}^{new} := {P_{i,t}^{sell}}^{(k)}$ ${H_{c,t}^{sell}}^{new} := {H_{c,t}^{sell}}^{(k)}$ and$\cdots$ $\mathscr{L}^{new} := \mathscr{L}_{i,t}^{(k)}$ $\mathscr{L}'^{new} := \mathscr{L}'^{(k)}_{i,t}$ $\wp^{new} := \wp_{c,t}^{(k)}$ $\mathscr{M}^{new} := \mathscr{M}_{c,t}^{(k)}$ End
The second step: mixed integer programming master problem Minimize $Z^{master} = \mu$ Subject to $\mu \ge \sum_t \sum_i (\gamma_i . u_{i,t}^{(k)}) + \sum_t \sum_i \delta_{i,t} . {P_{i,t}^{buy}}^{(k)} + \sum_t \sum_i ((\alpha_i + \beta_i . \zeta_i) . {P_{i,t}}^{(k)}) + \sum_t \sum_i \upsilon_i . {P_{i,t}^{lsh}}^{(k)} - \sum_t \sum_i \delta'_{i,t} . {P_{i,t}^{sell}}^{(k)} - \sum_t \sum_c \delta''_{c,t} . {H_{c,t}^{sell}}^{(k)} + \sum_t \sum_i \mathscr{L}'^{(k)}_{i,t} . ({P_{i,t}}^{(k)} - u_{i,t} . P_i^{max}) + \sum_t \sum_c \wp_{c,t}^{(k)} . (H_{c,t}^{E(k)} - \rho_{c,t} . HL_{c,t}^{maxE}) + \sum_t \sum_c \mathscr{R}_{c,t}^{(k)} . (H_{c,t}^{sell(k)} - \varrho_{c,t} . HL_{c,t}^{maxsell});$ $\rho_{c,t} + \varrho_{c,t} \le 1$ $u_{i,t}, \rho_{c,t},$ and $\varrho_{c,t} \in \{0, 1\}$ The solutions are $u_{i,t}^{(k+1)}, \rho_{c,t}^{(k+1)}$, and $\varrho_{c,t}^{(k+1)}$
The third step: convergence checking If $Z^{master} \ge Upperbound$ Stop Else $Iteration := Iteration + 1$ Go to step 1 End

$$
\begin{aligned}
&\text{Minimize } C^T y + f(x) \\
&\text{Subject to} \\
&h(x) = 0,\ g(x) \le 0,\ Cx + By \le b \\
&x \in R^n,\ y \in \{0, 1\}
\end{aligned} \tag{31}
$$

As demonstrated, initialization of iteration ($Iteration := 1$), upper bound ($Upperbound = \infty$), and binary variables ($y^{(k)}$) are implemented, and after that, the primal problem is solved in the form of nonlinear programming (i.e., the first step). The output of solving the primal problem provides an upper bound ($Upperbound := Z^{primal}$), Lagrange Multipliers ($\lambda^{(k)}$), and continuous variables ($x^{(k)}$) for the next step. In the second step, the master problem is solved, as demonstrated in the above table (i.e., the second step). The third step is also convergence checking

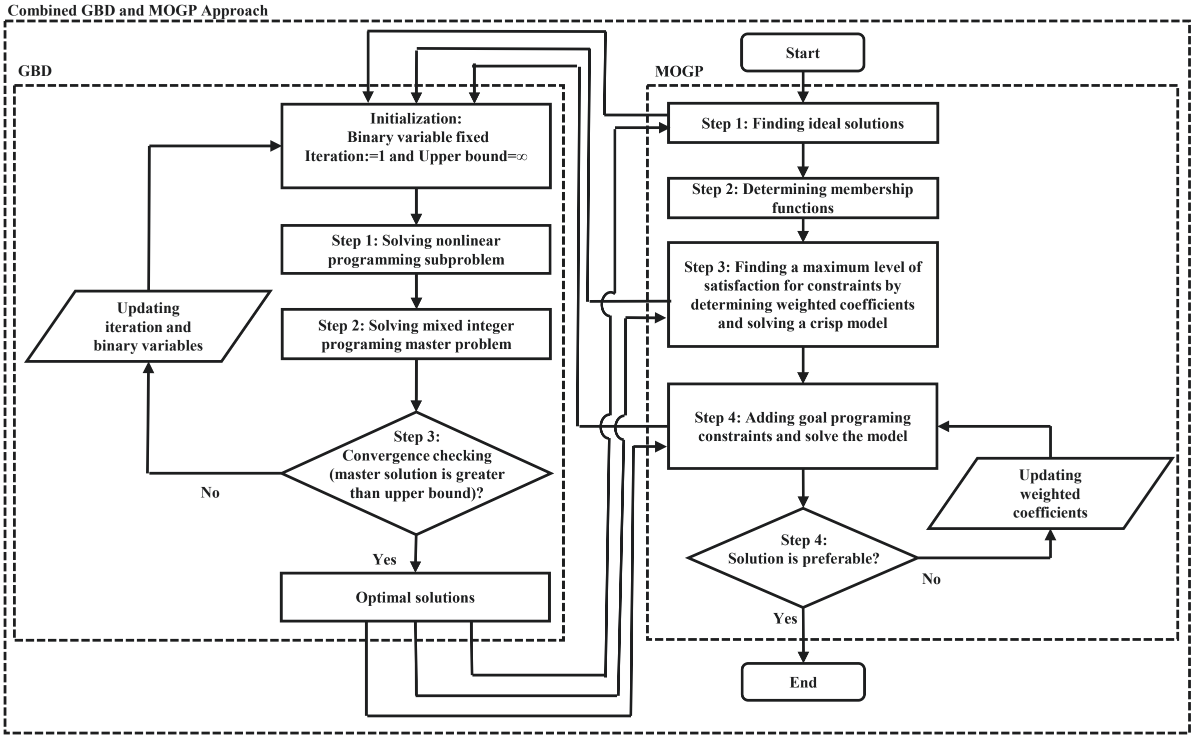

Fig. 2. Main steps of the developed solving approach to optimize the resilient operation of microgrids in the presence of PtH systems.

($Z^{master} \geq Upperbound$) and updating iteration ($Iteration := Iteration + 1$) when another iteration is required. As an example, in Table 3, the main steps of this decomposition approach to solve the operation of PtH systems in microgrids are demonstrated (i.e., solving the optimization problem discussed at the first step of MOGP (Eq. (24)).

Fig. 2 illustrates the main stages involved in solving the resilient operation of microgrids with PtH systems using the developed solving approach. More precisely, this figure indicates the flowchart of solving the optimization problem using the developed approach. As depicted, on the right side of the figure, the main steps of MOGP are demonstrated as discussed previously. Based on this approach, in the first, third, and fourth steps of the MOGP approach, the GBD method is integrated to solve the optimization problems, indicated on the left side of the figure, as discussed earlier (See Fig. 3.)

It should be noted that the model is non-convex in its current form, which means that the solution method may lead to local optimum solutions. While GBD is an appropriate solving method to deal with the MINLP problem, a pre-processing technique could help to achieve a unique solution. The first step of this technique is to prepare the optimization problem by reformulating Eq. (13) into Eq. (32), which transforms the non-convex optimization problem of optimal power flow into a convex one by a conic program based on [64]. More precisely, by converting the model into a convex optimization problem, achieving a unique solution is guaranteed. The second step of pre-processing is to solve the relaxed optimization problems in which binary variables are considered as continuous variables between zero and one. After solving the relaxed problem, initial points for solving the original problem using GBD are obtained by rounding the value of these continuous variables. As a result, this method prevents initializing the binary variable inappropriately. The third step of this method is based on adding slack variables to the power flow balance equation (Eq. (33)), adding the corresponding considerable penalty to the objective function (Eq. (34)), and solving the obtained optimization problem. It also prevents trapping into local optimum or infeasible solutions by overestimating the feasible region, as demonstrated in Fig. 4 [65]. The main reason is that the initializing binary variable may still lead to infeasible solutions in the early iterations of the proposed solving approach. Although the third step assists in coping with the problem, the value of the slack variable must be zero if a unique solution is to be obtained. On the other hand, the initial points and penalties must be updated to reach this aim [66].

$$V_{l,t}^2 . I_{l,t}^2 \geq Q_{l,t}^{line2} + P_{l,t}^{line2} \quad \forall l, \forall t \tag{32}$$

$$P_{i,t} + P_{i,t}^{wind} - P_{c,t}^{E\rightarrow H_2} + P_{c,t}^{H_2\rightarrow E} + P_{i,t}^{lsh} + P_{i,t}^{buy} - P_{i,t}^{sell} - \sum_{i'} (P_{l,t}^{line} + R_l . I_{l,t}^2) + SV_{i,t}^s = P_{i,t}^{load} + SV_{i,t}^d \quad \forall i, \forall l, \forall t \tag{33}$$

$$Z' = Z + \sum_t \sum_i PN.(SV_{i,t}^s + SV_{i,t}^d) \tag{34}$$

It should be noted that, as this study examines the resilience operation of microgrids in the presence of PtH systems, developing the method based on the decomposition provide more accurate solutions in comparison with linearization. The reason is that the linearization techniques are an approximation around specific points and provide a less accurate solution when the distance from the points increases [67,68]. Therefore, in this case, applying the GBD method leads to a more accurate solution and guarantees a globally optimal solution.

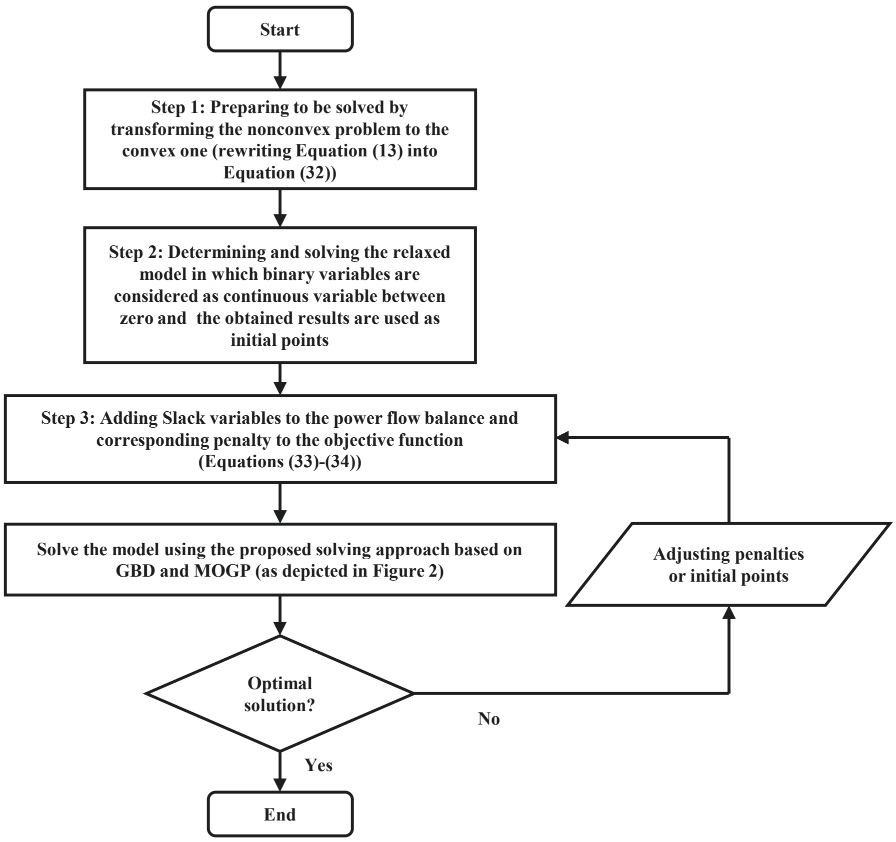

Fig. 3. Main steps of the developed preprocessing approach to optimize the resilient operation of microgrids in the presence of PtH systems.

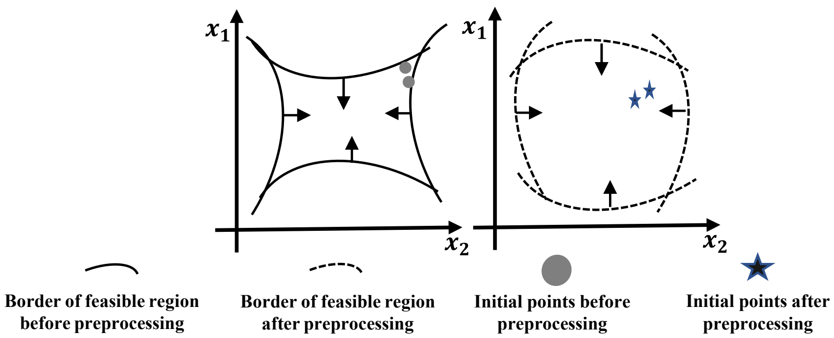

Fig. 4. Feasible solution and initial points for the solving method with and without preprocessing.

3. Case study

In this study, based on real-world data, an industrial microgrid is taken into consideration to analyze the role of PtH systems, the resiliency consideration approach, and the solving approach from technical and economic aspects. As depicted in Fig. 5, a microgrid is studied, which consists of 33-node, 32-line, four connections to wind generators, three connections to PtH systems, and two connections to dispatchable units. In a normal situation, the microgrid can sell/buy electricity to/from the main grid. While the microgrid is connected to the main grid in the normal operation mode, in case of a contingency in the main grid (e.g., equipment failure caused by severe weather), this microgrid operates independently in the islanded mode.

It is worthwhile to mention that, in the paper, PtH systems are examined that consist of alkaline electrolysis technology, known for its robustness and long-standing presence in the industry [69].

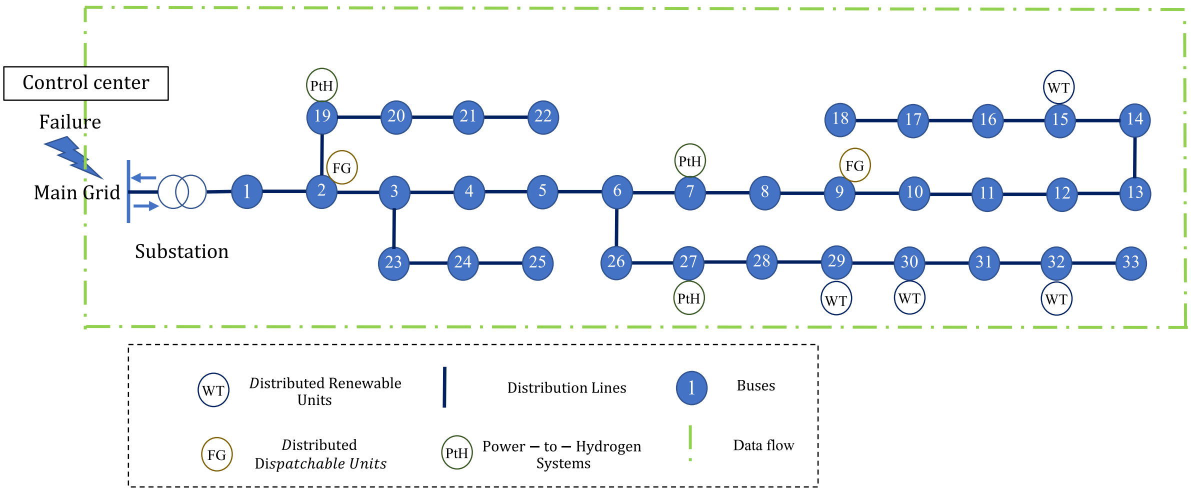

Fig. 5. Illustration of the microgrid examined in this study, including PtH systems, dispatchable units, and distributed renewable resources.

Table 4
Characteristics of different systems installed in the microgrid.

System	Location	Installed capacity	Characteristics of each unit
Windturbines	Node 15, Node 29, Node 30, and Node 32	2400 kW	$P_{i,t}^{wind,max} = 600 \text{ kW}$
Dispatchable units	Node 9	100 kW	$\alpha_i = 0.04\,\$/\text{kW}$, $P_i^{min} = 10\,\text{kW}$, $P_i^{max} = 100 \text{ kW}$, $R_i^{maxup/down} = 50 \text{ kW}$, $\beta_i = 5 \text{ \$/Ton}$, and $\zeta_i = 0.0003 \text{ Ton/kW}$
Dispatchable units	Node 2	500 kW	$\alpha_i = 0.25\,\$/\text{kW}$, $P_i^{min} = 100\,\text{kW}$, $\beta_i = 65 \text{ \$/Ton}$, and $P_i^{max} = 500\,\text{kW}$, $\zeta_i = 0.000417 \text{ Ton/kWh}$ [72] $R_i^{maxup/down} = 125\,\text{kW}$,
PtH systems	Node 7, Node 19, and Node 27	1200 kW	$\phi_c = 60\%$, $\varphi_c = 36\,\%$, $HL_{c,t}^{max} = 2000\,\text{m}^3$, and $\delta'_c = 6\$/\text{m}^3$

Table 5
Scenarios examined in the study.

No.	Scenario	Further explanations
1	Different prices of hydrogen	• 100 %, 10 %, and 1 % of real prices of hydrogen
2	Distributed PtH systems and a centralized PtH system	• Centralized PtH system capacity is equal to the sum of distributed PtH systems Centralized PtH system is connected to node 7
3	No PtH systems	
4	Low wind availability	• 20 % wind availability Hydrogen storage full at the start of the operating period

Additionally, proton exchange membrane (PEM) fuel cells are integrated to convert the stored hydrogen back into electricity, with the added benefit of a fast start-up time, albeit with a higher cost due to the required catalyst [70]. The produced hydrogen is also compressed to be stored in steel-made cylinders under high pressure. By combining these technologies, PtH systems can transform surplus electrical energy into a storable and versatile form of fuel that can be utilized for power generation or in various industrial applications.

In Table 4, the location, capacity, and characteristics of the components installed in this microgrid are addressed [71]. All required data to simulate the electricity network in the microgrid are also presented in Appendix.

Considering the case study, different scenarios are investigated (Table 5), including various prices of hydrogen (Scenario 1), a centralized PtH system versus distributed PtH systems (Scenario 2), no PtH systems (Scenario 3), and a low wind power availability, as an example of extreme weather events (Scenario 4). It should be noted that the proposed model for the resilient operation of microgrids in the presence of PtH systems is implemented in General Algebraic Modeling System (GAMS) using a computer with an Intel Core i8 processor and 8 GB of RAM.

4. Result and analysis

The results and analyses presented in this section are divided into two main subsections. The role of PtH systems is examined in the operation of the microgrid from technical and economic viewpoints in Subsection 4.1 (Scenario 1 and Scenario 2). In Subsection 4.2, the role of the resiliency consideration approach to mitigate load shedding in the microgrid is examined along with the output of the developed approach to solve the optimization problem (Scenario 3 and Scenario 4).

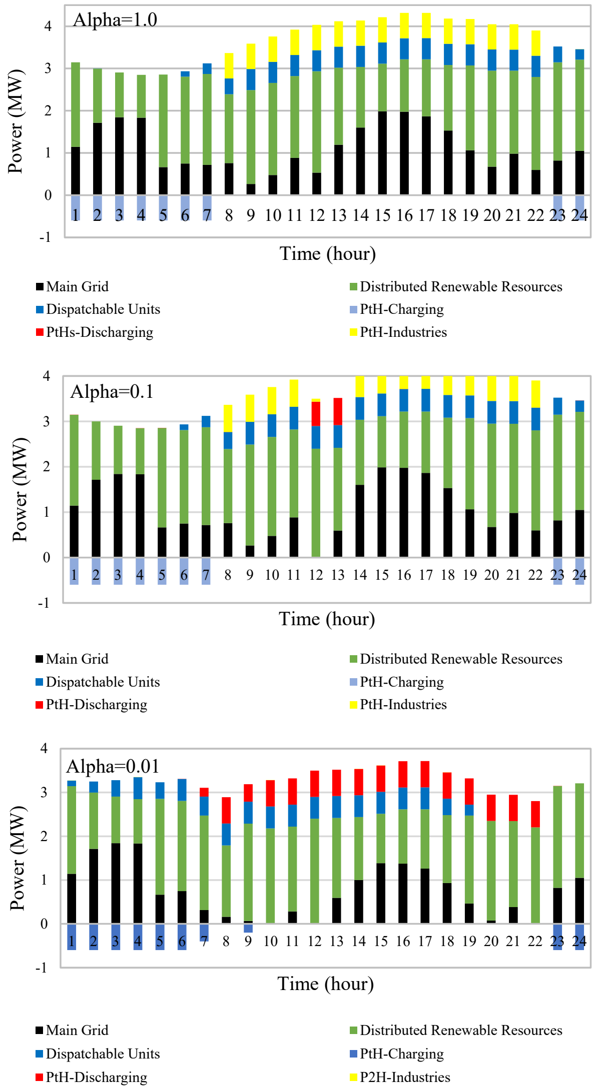

Fig. 6. Examining the scheduling of the microgrid considering different prices for hydrogen during normal operation.

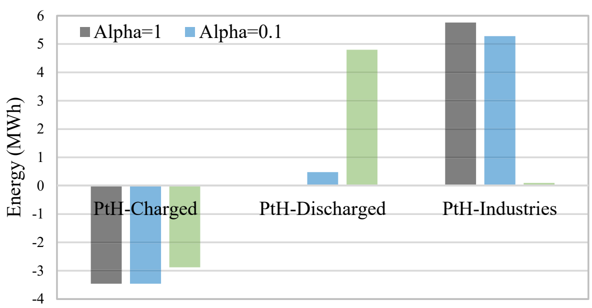

Fig. 7. Charge and discharge of PtH systems in the microgrid.

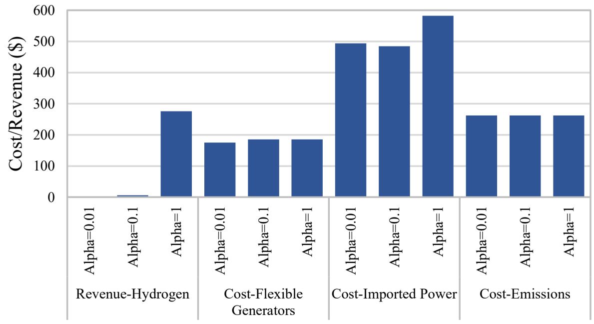

Fig. 8. Different terms of the first objective function considering various prices for hydrogen during normal operation.

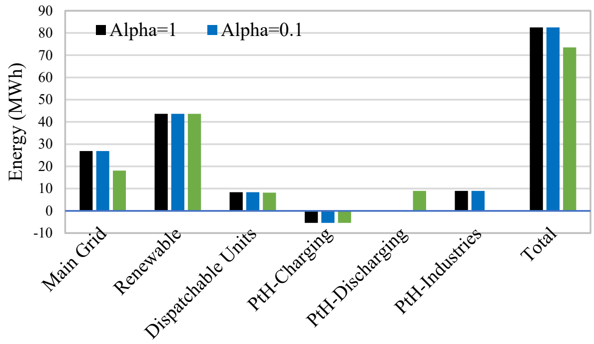

Fig. 9. Energy supply in the microgrid.

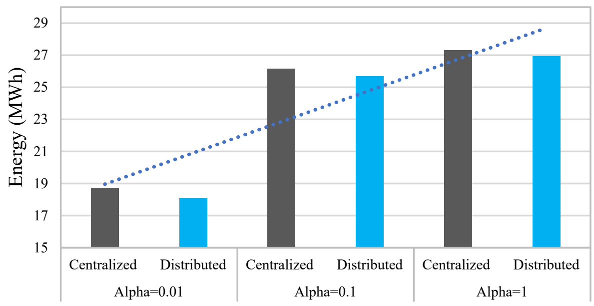

Fig. 10. Imported power from the main grid- a centralized PtH system versus distributed PtH systems.

4.1. PtH systems techno-economic analysis

In this subsection, firstly, an analysis is conducted to examine the optimal operation of the microgrid versus different hydrogen prices (i.e., Scenario 1). The main reason is that the price of hydrogen is decreasing

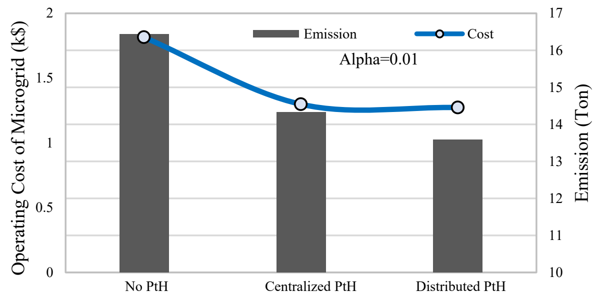

Fig. 11. Operating cost of microgrid versus the produced amount of emissions.

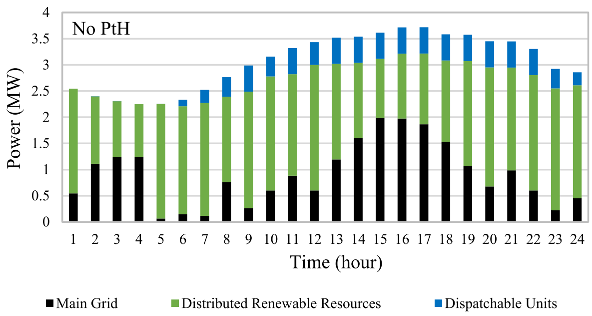

Fig. 12. Scheduling of microgrid without PtH systems.

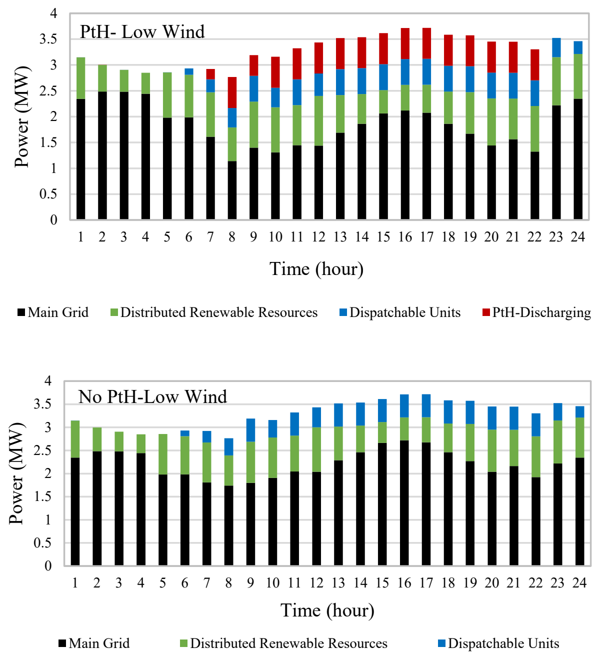

Fig. 13. Scheduling of microgrid when low wind power is available in the presence and absence of PtH systems.

mainly due to improvements in production technologies, the promotion of the use of renewable resources, and government policies to use clean energy. For this purpose, the output and/or input power of different components as well as interactions with the main grid are illustrated in Fig. 6. It demonstrates that the excess electricity in the microgrid is converted to hydrogen during off-peak hours of operation (from 00:00 to 07:00 and from 23:00 to 24:00), and the amount of stored hydrogen within tanks of PtH systems is used for either electricity production or industries' demand provision during peak hours of operation (from 08:00 to 22:00). When the price of hydrogen is high, the stored hydrogen within tanks is continuously sold to industries (Alpha = 1.0). Examination of a low price of hydrogen shows that, in this case, the stored hydrogen is persistently converted to electricity to supply peak demand (Alpha = 0.01). However, when Alpha is equal to 0.1, only at the beginning of peak hours, the stored hydrogen is converted to electricity, and it is mostly used to supply the required amount of hydrogen for industries.

Fig. 7 further illustrates the total charged and discharged energy of the PtH systems as part of the overall solving approach for the resilient operation of microgrids. It shows that the charged energy is less than 4 MWh, and the PtH systems are discharged either to provide hydrogen for industry or supply energy in the microgrid according to the price of hydrogen. However, in the case of high hydrogen prices, the hydrogen sold to the industry is much higher than in other cases. It is due to a substantial revenue stream from hydrogen sales at high prices, which makes importing power from the main grid and converting it into hydrogen using PtH systems a beneficial option. It is supported by an illustration of different terms of the first objective function for different prices of hydrogen, indicated in Fig. 8. This figure indicates the revenue of selling hydrogen to industry, the cost of imported power from the main grid, the cost of emission, and the cost of flexible generating units operation. Based on the examination, when the price of hydrogen is high, the cost of imported power from the main grid is high as converting to hydrogen and selling to industry provides a significant revenue that offsets a portion of operating costs.

In Fig. 9, the total imported and exported energy to/from the microgrid is also illustrated, including imported energy from the main grid, supplied energy by renewable and dispatchable systems, and charged and discharged energy of PtH systems. It indicates that renewable energy sources provide a substantial portion of electricity demand (about 40 MWh). However, the main grid still provides about 20 MWh of electricity demand. The flexible generating units only supply the electricity demand during peak hours. Due to the lower price of the main grid compared to the operating costs of flexible generating units (i. e., based on Table 9 and Table 4), imported power from the grid is given priority over flexible generating units. Due to the technology of dispatchable units connected to node 2, the variable cost of operation is 0.25 $/kWh, while the maximum price of electricity is 0.16 $/kWh. For resilient operations, however, dispatchable units in the microgrid would supply the energy to minimize dependence on the main grid.

To analyze the role of PtH systems, another examination is also conducted that compares the operation of distributed against centralized PtH systems in this microgrid (i.e., Scenario 2). It is worthwhile to mention that the capacity of the centralized PtH system is equal to the sum of the installed capacity of the distributed systems represented in the case study, and it is connected to node 7. The examination shows that the distributed PtH systems reduce the total amount of power imported from the main grid, as indicated in Fig. 10. For instance, for Alpha equal to 0.01, 0.1, and 1, the amount of imported energy reduces

Table 6
Sensitivity analysis of the MOGP approach.

Weighted coefficients	Z_1($)	Z_2(kWh)	Weighted coefficients	Z_1($)	Z_2(kWh)
$\omega_1 = 1$ and $\omega_2 = 0$	1272.95	18219.13	$\omega_1 = 0.4$ and $\omega_2 = 0.6$	1740.12	11649.59
$\omega_1 = 0.8$ and $\omega_2 = 0.2$	1314.47	14434.91	$\omega_1 = 0.2$ and $\omega_2 = 0.8$	2816.43	7027.54
$\omega_1 = 0.6$ and $\omega_2 = 0.4$	1359.71	13934.74	$\omega_1 = 0$ and $\omega_2 = 1$	6566.00	−115.08

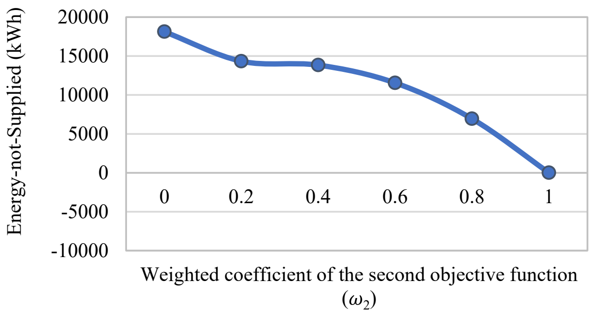

Fig. 14. Energy-not-supplied versus different weighted coefficients for resiliency consideration objective function.

by 610 kWh, 470 kWh, and 410 kWh, respectively. It shows a more efficient operation of the PtH systems to deal with changes in demand when installed in a distributed way compared to a centralized one. More precisely, in the distributed installation of the PtH systems, more output power of renewable energy resources is converted and charged into hydrogen storage systems. As a result, this can assist demand provision more efficiently and reduce the dependency on the main grid. On the other hand, when the price of hydrogen increases, the amount of imported energy rises as well, from 18.12 MWh to 26.92 MWh. However, the reason is that the hydrogen production to be sold to industries is more beneficial when there is a high price of hydrogen and compen-

Table 7
Examining different weighted coefficients for each term of the second objective function.

Weighted coefficient of $\mathscr{R}_1$	Weighted coefficient of $\mathscr{R}_2$	Weighted coefficient of $\mathscr{R}_3$	Z_2
0.2	0.4	0.4	9996.470
0.5	0.25	0.25	3481.525
0.8	0.1	0.1	2238.990
0.4	0.2	0.4	1858.448
0.25	0.5	0.25	1161.530
0.1	0.8	0.1	464.612
0.4	0.4	0.2	1791.199
0.25	0.25	0.5	1245.591
0.1	0.1	0.8	699.982

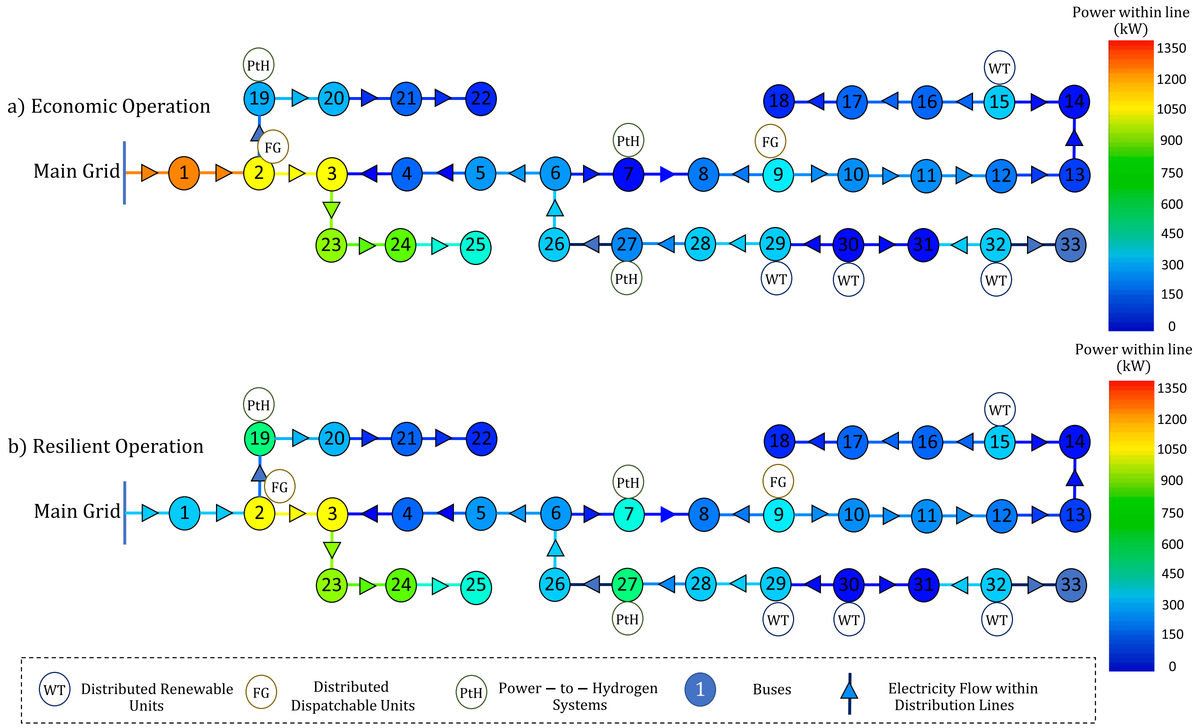

Fig. 15. Load flows through microgrid with and without resiliency consideration ((a) economic operation and (b) resilient operation).

Table 8
Comparison of costs and solving time using GAMS software versus GBD.

Weighted coefficients	Solver	Z_1 ($)	Solving Time (sec)
$\omega_1 = 1$ *and* $\omega_2 = 0$	DICOPT	1009.50	733
	GBD	1009.51	330
$\omega_1 = 0.8$ *and* $\omega_2 = 0.2$	DICOPT	1314.47	954
	GBD	1314.47	418
$\omega_1 = 0.6$ *and* $\omega_2 = 0.4$	DICOPT	1359.71	987
	GBD	1359.70	433
$\omega_1 = 0.4$ *and* $\omega_2 = 0.6$	DICOPT	1740.12	1263
	GBD	1740.12	558
$\omega_1 = 0.2$ *and* $\omega_2 = 0.8$	DICOPT	2816.43	1244
	GBD	2816.42	550
$\omega_1 = 0$ *and* $\omega_2 = 1$	DICOPT	6566.00	1800
	GBD	6566.00	810

sating operating costs. To go into greater depth, the operating cost of the microgrid and the amount of produced emission in this scenario is indicated in Fig. 11. In the figure, in addition to the centralized and distributed PtH systems, another case is examined without the PtH systems when Alpha is equal to 0.01. Based on the obtained results, the distributed integration of PtH systems, compared to when there are no PtH systems, reduces the emissions by two tons and the cost of operation by $540. It is due to the reduction in the amount of imported power from the main grid due to the more efficient operation of PtH systems to deal with the variable output of renewable resources and changes in demand. More precisely, the distributed PtH systems are more efficiently charged in off-peak hours and discharged during peak hours which assists demand provision in this case. However, it should be noted that the centralized PtH systems can normally provide a higher efficiency due to economies of scale, optimized operation, and large-scale production, which should not be ignored [73].

All in all, the analyses in this subsection can provide microgrid operators with proper insights into the operation of the PtH systems. Firstly, the analyses show that the integration of the PtH systems can supply either the demand of industries for hydrogen or electricity demand during peak hours. It depends on the strategy of the operators and the price of hydrogen whether the hydrogen must be sold to industries to increase the revenue (i.e., compensate the cost of operation) or consumed in the microgrid for other purposes, such as peak shaving that prevent the establishment of extra capacity of suppliers. Besides, the analyses prove that the installation of the system in a distributed way makes these systems operate more efficiently. It concludes with more cost-saving and emission reduction compared to a centralized high-capacity PtH system.

4.2. *Resiliency analysis and computational performance of the decomposition approach*

In this subsection, at first, analysis is conducted to examine the potential of PtH systems in the resilient operation of the microgrid. To this aim, the scheduling of the microgrid in the absence of PtH systems is indicated in Fig. 12 (i.e., Scenario 3). The hourly scheduling of the microgrid indicates that it is more dependent on the main grid (especially during the peak operating hours) instead of charging PtH systems during off-peak and valley hours of demand and discharging them during peak hours. In comparison with Fig. 6, it is evident that wind curtailment occurred from 00:00 to 07:00 and from 23:00 to 24:00. It means that although wind power is available, it cannot be used in the microgrid due to some limitations (e.g., congestion). However, as discussed earlier, the output power of turbines could be converted to hydrogen to be used during peak hours of the operating period. It should be noted that, in this case, the total wind curtailment during the operating period is 4.5 MWh.

The scheduling of the microgrid with and without PtH systems in a day with a low wind power availability is also indicated in Fig. 13 to investigate the value of PtH systems in extreme conditions (i.e., Scenario 4). It is assumed that, in the presence of PtH systems, at the beginning of the operating period, the hydrogen storage systems are full (e.g., due to the availability of wind power and/or low price of energy in previous days). It shows that when a low amount of wind power is available, the microgrid supplies a large portion of demand by purchasing from the main grid (especially when there are no PtH systems). However, the microgrid's dependency on hydrogen-to-power to supply demand is evident from 07:00 to 21:00. It indicates the positive role of PtH systems in the energy management of microgrids to enhance resilience.

In this subsection, the obtained results of the resiliency consideration approach are investigated. In Table 6, the sensitivity analysis of weighted coefficients of the MOGP approach is indicated. When the weighted coefficient of the first objective (i.e., Cost minimization (Z_1)) increases from zero to one, the cost of operation reduces from $6566.00 to $1272.95. However, the resiliency reduces due to some reasons, such as dependency on the main grid and low levels of hydrogen within the tanks. On the other hand, the increase in the weighted coefficient of the second objective function (i.e., de-resilience minimization (Z_2)) reduces the de-resilience from 18219.13 to −115.08. It is noteworthy to mention that the greater the weighted coefficient is given to the second objective (i.e., resiliency consideration), the more cost of operation increases. For instance, when ω_2 increases from 0 to 0.6, the operating cost goes up from $1272.95 to $1740.12. However, when the weighted coefficient is equal to 0.8 and 1, the operating cost is considerably elevated, matching $2816.43 and $6566.00, respectively. The reason is that a considerable amount of hydrogen within tanks is stored when the weighted coefficient of the second objective is high. It also highlights the role of the PtH systems in the economic operation of the microgrid. As the cost of operation surges when a considerable level of hydrogen is stored within the tanks, the most resilient approach would not be preferable from the economic perspective, although improving the resiliency of the microgrid.

In Fig. 14, the changes in the amount of energy-not-supplied versus the weighted coefficient of the resiliency consideration objective function are demonstrated in the case of the main grid failure. This analysis is conducted by fixing all decision variables based on the obtained result from the optimization problem (i.e., scheduling of microgrid) except the

Table 9
Data of demand, wind output power, and electricity price during a day.

Time (hour)	Electricity (%)	Wind (%)	Electricity price ($/kWh)	Time (hour)	Electricity (%)	Wind (%)	Electricity price ($/kWh)
1	0.6843	0.8345	0.0300	13	0.9460	0.7601	0.1600
2	0.6451	0.5361	0.0200	14	0.9515	0.5987	0.0850
3	0.6198	0.4424	0.0300	15	0.9721	0.4704	0.0820
4	0.6044	0.4220	0.0250	16	0.9991	0.5162	0.0700
5	0.6057	0.9124	0.0250	17	1.0000	0.5641	0.0800
6	0.6268	0.8579	0.0310	19	0.9638	0.6466	0.0650
7	0.6773	0.8981	0.0450	19	0.9608	0.8375	0.0550
8	0.7437	0.6792	0.0470	20	0.9271	0.9480	0.0650
9	0.8029	0.9266	0.0490	21	0.9269	0.8187	0.0750
10	0.8484	0.9083	0.0620	22	0.8872	0.9185	0.0500
11	0.8930	0.8075	0.0900	23	0.7853	0.9699	0.0450
12	0.9222	1.0000	0.1300	24	0.7685	0.9002	0.0350

load shedding and the objective function value. The amount of interactions with the main grid is also equal to zero in the case of this failure to simulate islanded mode of operation. As demonstrated in the figure, as far as the weighted coefficient of the second objective function increases from zero to one, the amount of energy-not-supplied reduces when there is an interruption in the main grid. Although having a considerable amount of cost (see the last table), when ω_2 is equal to one, there is no load shedding during the islanded mode, which is preferable from the resiliency viewpoint.

Additional analysis is conducted to investigate the underlying reasons for the no load shedding during resilient operation scenarios. This analysis aims to identify the factors and conditions that contribute to the successful avoidance of load shedding, providing insights into the effectiveness of the resilient operation strategy. In Fig. 15, the load flow within the microgrid is indicated for the most economic strategy of operation versus the most resilient one in the peak hour ($t = 17$). It is worthwhile mentioning that the microgrid is still connected to the main grid. The analysis shows that the amount of power imported from the main grid reduces in the resilient operation (b) in comparison with the economic operation (a). In this mode, the dispatchable generating units connected to node two operate to supply a considerable portion of demand. However, the cost of these generating units is more than the price of the main grid. Moreover, in the resilient operation, the maximum volume of hydrogen is stored within tanks connected to nodes 7, 19, and 27 to deal with the predicted failure of the main grid. As a result, when the microgrid goes to the islanded mode in the case of failure in the main grid, no load shedding occurs.

Another analysis is also conducted to examine the impact of each term of the second objective function on the resiliency (i.e., the impact of $\mathscr{R}_1$, $\mathscr{R}_2$, and $\mathscr{R}_3$ on Z_2). This analysis is conducted considering the most resilient approach, examined above ($\omega_1 = 0$ and $\omega_2 = 1$). For this purpose, determining a weighted coefficient for each term of the second objective function, the value of this objective function (de-resiliency) is examined as demonstrated in Table 7. Based on the analysis, when the weighted coefficient of the second term is higher than other ones (weighted coefficient of $\mathscr{R}_2$ is equal to 0.8), the maximum resiliency (i.e., minimum de-resiliency) is achieved. It highlights the impact of the availability of hydrogen to be converted to electricity in emergency cases (e.g., islanded model when local supply is lower than demand). Moreover, this term makes the objective function exclusive, as when the amount of hydrogen stored in storage systems increases, it concludes the increase in the operating cost of the microgrid. The reason is that the microgrid should purchase more power from the main grid and/or dispatch gas-fired units.

To sum up, it should be declared that it is beneficial to sell hydrogen to industries in a normal situation. However, when a failure in the main grid is predicted, and local supply is lower than demand, it is not reasonable. In the case of prediction of failure in the main grid, the hydrogen produced by PtH systems must be stored within tanks to be converted to electricity after the failure occurrence. It prevents or reduces energy-not-supplied in the microgrid in the case of the occurrence of the predicted event. Aside from the mentioned strategy, two other measures are employed in this research that prevent load shedding, including the reduction in interactions with the main grid and power loss. The former decreases the dependency on the main grid and the latter causes supply demand from the nearest producers. Therefore, whenever a microgrid goes to islanded mode, if the strategies are implemented beforehand, the amount of shedding reduces significantly, which prevents harming the industries. Industries are negatively affected by a shortage of electrical power, as material is lost, equipment breaks down, and productivity is lost.

Aside from the discussed issues, the cost of microgrid operation versus various levels of resilience is examined. For this purpose, both the GAMS DICOPT solver and the GBD method are integrated into the MOGP method to solve the optimization problem considering different weighted coefficients. It should be noted that this GAMS solver is mainly

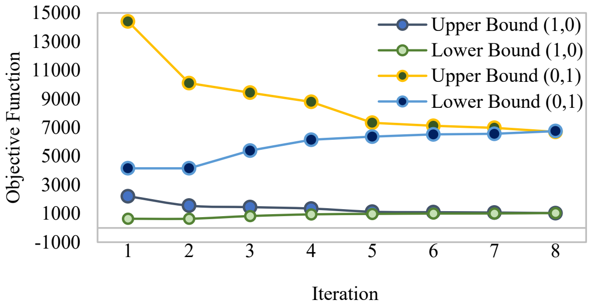

Fig. 16. Convergence of upper and lower bounds using the GBD.

used to solve complex problems, whose benefits are generating high-quality solutions and faster computation. Table 8 compares the value of the objective function and the solving time between the GBD method and DICOPT to ensure that the proposed approach yields unique solutions. This comparison serves to evaluate the performance of both methods in terms of solution quality and computational efficiency. It is demonstrated that the integration of GBD provides better or similar solutions in a shorter time. When the economic aspect is only considered ($\omega_1 = 1$), the decomposition approach reduces the solving time from 733 s to 330 s. However, in the most resilient approach ($\omega_2 = 1$), the integration of the GBD to solve the problem decreases the solving time from 1800 s to 810 s. It should be noted that when$\omega_1 = 0.8$, 0.6, 0.4, and 0.2, the GBD reduces the solving time by 536, 554, 678, and 694 s, respectively. Besides, when the problem is solved using the GBD approach, upper and lower bounds converge between eight to ten iterations. For instance, in Fig. 16, the convergence to the optimal solution is depicted in eight iterations when $\omega_1 = 1$ and $\omega_2 = 0$ as well as $\omega_1 = 0$ and $\omega_2 = 1$.

5. Conclusion

This study introduced a bi-objective optimization model formulated as a mixed-integer nonlinear programming problem. The model was specifically designed for the resilient operation of microgrids that incorporate power-to-hydrogen systems which include electrolyzers, hydrogen storage systems, and fuel cells. The power-to-hydrogen systems produced hydrogen from excess electricity in the microgrid, which could either be sold to industry or stored in tanks for future use. Three resilience measures were considered in this study to improve microgrid operation during main grid failures: (i) decreasing imported power, (ii) reducing power loss, and (iii) increasing hydrogen levels in the tanks. The decrease in the amount of imported power from the main grid and power loss measures reduced the dependency of the microgrid on the main grid. As a result, the electricity was supplied from the nearest resources, improving the reliability of supply. The increase in hydrogen level in the tanks improved the ability of the microgrid to supply the demand in the islanded mode by utilizing the stored hydrogen for conversion to electricity. To address the complexity of the mixed-integer nonlinear programming bi-objective model for the operation of the industrial microgrid, a novel method was developed. This method integrated the Generalized Benders Decomposition technique with the Multi-Objective Goal Programming approach. The aim was to handle the model's complexity while improving computational performance effectively.

Based on the results, the integration of the power-to-hydrogen system into the microgrid could either facilitate the provision of peak electricity demand or supply the required amount of hydrogen in the industries. The price of hydrogen plays a crucial role in determining the most beneficial course of action: whether to sell hydrogen to industries (in the case of a high hydrogen price) or convert it into electricity (in the case of a low hydrogen price). The price directly influences the economic viability and profitability of these options, allowing decision-makers to optimize their strategy based on prevailing market conditions. Furthermore, three cases of (i) no power-to-hydrogen system, (ii) a centralized power-to-hydrogen system, and (iii) distributed power-to-hydrogen systems were considered, and cost and emissions analyses were carried out. It was demonstrated that the distributed integration of power-to-hydrogen systems reduced the emissions by about 20 % and the operating cost by about 30 % compared to the no power-to-hydrogen system case, due to the reduction in the amount of power imported from the main grid. In the low wind power availability scenario, it was indicated that the power-to-hydrogen systems were important in maintaining the security of supply and enhancing system resilience. The study investigated the impact of different weighted coefficients on the role of resilience measures. Furthermore, the computational performance of the problem was evaluated with respect to the solution approach used. The approach of resilience consideration indicated that the most resilient weighted coefficients increased the operation cost by more than four times. However, in this case, the amount of load shedding in the case of failure of the main grid was zero. It was also demonstrated that the solution time of this mixed-integer nonlinear programming problem was reduced by 54 % using the developed approach compared to GAMS commercial solver.

While this study offers valuable insights into the resilient operation of microgrids with power-to-hydrogen systems, there are additional areas that warrant further exploration. One such aspect is the incorporation of costs associated with the establishment and maintenance of power-to-hydrogen system components, including electrolyzers, storage systems, and fuel cells. Future research can delve into integrating these cost considerations into the optimization model to provide a more comprehensive analysis of the economic feasibility and viability of such systems in ensuring a reliable and sustainable energy supply. Besides, future studies can focus more on incorporating uncertainty in the model. This can involve exploring the effects of different sources of uncertainty, such as availability of renewable power and electricity demand.

CRediT authorship contribution statement

Vahid Shahbazbegian: Data curation, Investigation, Methodology, Software, Writing – original draft. **Miadreza Shafie-khah:** Conceptualization, Supervision, Validation, Writing – review & editing. **Hannu Laaksonen:** Conceptualization, Supervision, Validation, Writing – review & editing. **Goran Strbac:** Supervision, Writing – review & editing. **Hossein Ameli:** Investigation, Methodology, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Electricity network data

The shares of electricity demand (hourly demand/peak demand) and wind output power (available power/installed capacity) as well as electricity price during the day are indicated in Table 9 [49].

In Table 10 and Table 11, the characteristics of the electricity network and the electricity demand are demonstrated, respectively. It is noteworthy to mention that the demand is indicated as active and reactive powers, and it is assumed all loads have the same profile [74].

Table 11
Microgrid’s load.

Node	Load (kW + jkVar)	Node	Load (kW + jkVar)
2	100 + j60	18	90 + j40
3	90 + j40	19	90 + j40
4	120 + j80	20	90 + j40
5	60 + j30	21	90 + j40
6	60 + j20	22	90 + j40
7	200 + j100	23	90 + j40
8	200 + j100	24	420 + j200
9	60 + j20	25	420 + j200
10	60 + j20	26	60 + j25
11	45 + j30	27	60 + j25
12	60 + j35	28	60 + j20
13	60 + j35	29	120 + j70
14	120 + j80	30	200 + j600
15	60 + j10	31	150 + j70
16	60 + j20	32	210 + j100
17	60 + j20	33	60 + j40

Table 10
Electricity network data.

Branch	From Node	To node	Resistance (Ω)	Reactance (Ω)	Branch	From Node	To node	Resistance (Ω)	Reactance (Ω)
1	1	2	0.0922	0.0470	17	17	18	0.7320	0.5740
2	2	3	0.4930	0.2511	18	2	19	0.1640	0.1565
3	3	4	0.3660	0.1864	19	19	20	1.5042	1.3554
4	4	5	0.3811	0.1941	20	20	21	0.4095	0.4784
5	5	6	0.8190	0.7070	21	21	22	0.7089	0.9373
6	6	7	0.1872	0.6188	22	3	23	0.4512	0.3083
7	7	8	0.7114	0.2351	23	23	24	0.8980	0.7091
8	8	9	1.0300	0.7400	24	24	25	0.8960	0.7011
9	9	10	1.0440	0.7400	25	6	26	0.2030	0.1034
10	10	11	0.1966	0.0650	26	26	27	0.2842	0.1447
11	11	12	0.3744	0.1238	27	27	28	1.0590	0.9337
12	12	13	1.4680	1.1550	28	28	29	0.8042	0.7006
13	13	14	0.5416	0.7129	29	29	30	0.5075	0.2585
14	14	15	0.5910	0.5260	30	30	31	0.9744	0.9630
15	15	16	0.7463	0.5450	31	31	32	0.3105	0.3619
16	16	17	1.2890	1.7210	32	32	33	0.3410	0.5302

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Techno-Economic Analysis of Electric Vehicle Parking Lots in Microgrids

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***Abstract* — This study aims to analyze the techno-economic utilization of electric vehicle parking lots in microgrids under a considerable penetration of renewable energy resources. For this purpose, an optimization model is proposed considering the investment and maintenance costs of the parking lots as well as the operation and emission costs of microgrids. In the model, natural gas and electricity distribution systems are simulated in a grid-connected microgrid with a considerable share of wind turbines. A scenario generation technique is also utilized to determine the number and arrival state of charge of electric vehicles in parking lots. A microgrid, which consists of a 33-bus electricity system and an 11-node gas system, is studied to investigate the charging and discharging of electric vehicles in parking lots. It concludes that electric vehicles in parking lots offer flexibility that offsets investment costs and reduces the amount of emission. Owing to the flexibility, the natural gas system can also respond the changes in natural gas demand more efficiently due to more natural gas within pipelines.**

Keywords — electric vehicles, microgrid, natural gas and electricity systems, techno-economic analysis, electric vehicle parking lots

NOMENCLATURE

Sets

b	Index of bus in electricity system
n	Index of node in gas system
y	Index of injection node in gas system
t	Index of time
k	Index of parking lot
p	Index of pipeline in gas system
l	Index of electric line in electricity system
m	Index of electric vehicles

Parameters

r	Annual rate of return (%)
j	Lifespan (year)
$Demand^{day/year}$	Total energy demand in a day or year (kWh)
$Cost^{pl}$	Cost of investment on a parking lot ($/kW)
$Cost^{Mpl}$	Cost of maintenance for parking lot ($/kW)
Cap_k	Capacity of parking lot (kW)
$Cost^{Gas}$	Cost of purchasing natural gas ($/cubic meter)
$Cost^{lp}$	Cost of linepack management ($/cubic meter)
$Cost^{sh}$	Shedding cost ($/cubic meter)
$Cost^{co2}$	Cost of emission ($/kw)
$Price_t$	Price of purchasing electricity from main grid ($/kW)
$Price'_t$	Price of selling electricity to main grid ($/kW)
α_b	Variable cost of operation ($/kW)
β_b	Fixed cost of operation ($)
$Gas^0_{p,t}$	Initial volume of natural gas within pipeline (cubic meter)
R_l	Resistance (ohm)
X_l	Reactance (ohm)
Z_l	Impedance (ohm)
$eff^{ch/dch}$	Efficiency of charge or discharge (%)
$SC^0_{k,t}$	Initial state of charge of parking lot (kWh)
$P_k^{ch/dch\ min/max}$	Minimum or maximum charged or discharged power (kW)
$SC_{k,t}^{min/max}$	Minimum or maximum state of charge of parking lot (kWh)
$\mathrm{Number}^{ev\ max}$	Maximum number of electric vehicles in parking lot
$t^{arv/dep}$	Arrival or departure time of electric vehicles (hour)
σ	Standard deviation
μ	Mean value

Variables

$Cost^{inv}$	Cost of investment ($)
$Cost^{oper}$	Cost of operation ($)
$Cost^{M}$	Cost of maintenance ($)
$Cost^{CO2}$	Cost of emission ($)
$Cost^{gas}$	Cost of natural gas system operation ($)
$Cost^{elec}$	Cost of electricity system operation ($)
$P_{b,t}$	Output power of generating unit (kW)
$Gas^{buy}_{y,t}$	Purchased volume of natural gas (cubic meter)
$\Delta Gas_{n,t}$	Changes in natural gas volume within pipeline (cubic meter)
$GNS_{n,t}$	Volume of natural gas-not-supplied (cubic meter)
$u_{b,t}$	Status of generating unit {0,1}
$Gas^{pipe}_{n,t}$	Natural gas flow within pipeline (cubic meter/hour)
$\mathcal{C}$	Lacey's equation constant (cubic meter/$mbar^{1/2}$)
$\wp_{n,t}$	Pressure (mbar)
$V_{b,t}$	Voltage magnitude (Volt)
$I_{l,t}$	Current magnitude (Ampere)
$P^{line}_{l,t}$	Active power within line (kW)
$Q^{line}_{l,t}$	Reactive power within line (kVAR)
$SC_{k,t}$	State of charge of parking lot (kWh)
$P^{ch/dch}_{k,t}$	Charged/discharged power (kW)
$y_{k,t}$	Status of charge or discharge {0,1}
$SC^{arv/dep}_{p,k,t}$	State of charge of arrived/departed vehicles to/from parking lot (kWh)
Number^{ev}	Number of electric vehicles

I. Introduction

A. Motivation

Moving to supply energy from renewable energy resources has been started due to the benefits, such as not emitting greenhouse emissions [1]. The global target is to supply the total energy demand using zero-emission renewable energy resources by 2050. However, the problem is still the variability of renewable energy resources' output power (e.g., the output power of photovoltaic systems and wind turbines) that is dependent on different parameters, such as weather conditions. A solution would be the deployment of microgrids that can help with the integration of intermittent renewable energy resources [2]. Microgrids are small-scale energy systems, which consist of a group of loads and distributed energy resources (e.g., distributed renewable resources and/or distributed dispatchable units) that works either connected or disconnected (i.e., island mode) to/from the main grid. More precisely, while being connected normally to the main grid to buy and sell electricity from/to, a microgrid can be disconnected and work independently when there is a failure in the upstream grid.

To reach the carbon neutrality targets, the transportation system is another sector that needs to be decarbonized as it contributes to producing a considerable amount of emissions [3]. A solution would be the integration of electric vehicles into modern energy systems, which do not emit carbon dioxide or other harmful pollutants at the point of use. The integration of electric vehicles increases energy demand, which increases also the need to invest in renewable energy resources to supply vehicles without burning fossil fuels and producing emissions. However, a scheduled charging and discharging strategy for electric vehicles would be helpful, as it reduces the peak of energy demand and prevents heavy investment in generation and distribution network expansion [4]. More precisely, the scheduled charging can smooth out the energy demand curve, reducing the need for new renewable and nonrenewable energy generation and network infrastructures to meet peak demand. As the integration of electric vehicles also needs adequate infrastructure, it is of great importance to conduct a techno-economic assessment and examine their impact on energy systems.

B. Literature review

Among previous studies, in [5], the economic feasibility of renewable resources was studied for charging stations of electric vehicles in different locations in China. The results of this study showed that a hybrid system, which, consists of wind turbines, photovoltaic systems, and battery storage systems, is the most effective response to facilitating large-scale integration of electric vehicles into the power system. In [6], [7], the techno-economic feasibility of electric vehicle parking lots coupled with photovoltaic systems was taken into consideration. It concluded that the integration of photovoltaic systems into parking lots reduces the net present cost of parking lots. In [8], a techno-economic study of supply infrastructure for electric vehicles in a microgrid was implemented considering different weather conditions and levels of electric vehicle integration. The output of the study indicated that optimal scheduling of electric vehicles improved the operation of the microgrid. In another study [9], the potential of electric vehicle fleets was studied to provide both active and reactive supply-demand balance. The results of the study also showed voltage profile improvement, released capacity of generating units, and reduction in the cost of operation. In [10], the role of demand response programs and electric vehicle integration into a microgrid was examined. It concluded that the demand response of electric vehicles integration into the microgrid can provide economic and environmental benefits. In [11], the economic and environmental benefits of electric vehicles with bi-directional chargers were studied in a microgrid. It also concluded that discharging electric vehicles in a scheduled strategy provided economic and environmental through peak shaving. In [12], a techno-economic assessment was conducted to study the role of electric vehicles in a multi-energy microgrid that consists of electricity and hydrogen networks. The output of this study also demonstrated cost savings and ensures less grid reliance. In another study [13], a techno-economic model was developed for the assessment of electric vehicle operation in cold weather conditions. The results of the study indicate the effects of different parameters, such as ambient temperature, on the operation of electric vehicles from different technical and economic points of view.

C. Research gap and contributions

Despite the increasing interest in electric vehicle adoption and the potential for electric vehicle parking lots to provide a convenient and sustainable charging solution, the techno-economic feasibility of electric vehicle parking lots has been under-researched in the literature. Moreover, existing studies have not adequately accounted for the realistic limitations of electricity network infrastructure, which can have a significant impact on the feasibility and cost-effectiveness of electric vehicle parking lots. Some components of the electricity system that are used in conjunction with electric vehicle parking lots, such as distributed dispatchable gas-fired units, are connected to the natural gas system. Therefore, a coordinated operation of these systems can provide significant benefits although this has not been explored in the literature. The research gaps need to be addressed to provide decision-makers with valuable insights to support the development of sustainable and cost-effective electric vehicle charging solutions. The main contributions of this study to fill this gap are discussed in the following.

The main contribution of this paper is the development of an optimization model that integrates the investment and maintenance costs of electric vehicle parking lots and the operation and emission costs of microgrids. The proposed model uses a scenario generation technique to randomly determine the arrival time, departure time, and arrival state of charge of electric vehicles in the parking lots. The model is also extended to consider the natural gas system supplying components in the electricity system, and a case study is conducted on an 11-node natural gas system coupled with a 33-bus electricity system to examine the impact of parking lots on supply-demand provision besides the economic analysis. The microgrid can buy and sell electricity to/from the main grid, and different cases are analyzed, including scheduled and unscheduled charging, various sizes of parking lots, and the absence of parking lots, providing a comprehensive analysis from both technical and economic perspectives.

II. Methodology

The multi-energy microgrid represented in Fig. 1 is a system that combines natural gas and electricity distribution systems, with gas-fired dispatchable units connecting the systems. The gas-fired units allow for the conversion of natural gas into electricity and provide a source of power that can be dispatched, or controlled, as needed to meet the demand for energy within the microgrid. The microgrid also includes renewable energy sources, such as wind turbines and photovoltaic systems, and it allows electric vehicles to be charged and discharged at the electric vehicle parking lots.

The mathematical model used for conducting a techno-economic assessment of electric vehicle parking lots in the multi-energy microgrid is based on certain assumptions. For instance, the gas distribution system model uses the continuity and momentum equations to simulate gas flow, with the assumption that variations in kinetic energy due to changes in velocity and density are negligible. In the electricity distribution system's model, the demand during each operating hour is considered constant active and reactive power. Power losses along a branch are assumed at the beginning of that branch, the network is addressed in a single-phase and balanced equivalent, and the microgrid interacts with the main grid in a day-ahead market. It should be noted it is also assumed that the day-ahead electricity market has been operated based on supply and demand, and the price of electricity has been determined by the interaction between electricity suppliers (generators) and consumers (buyers).

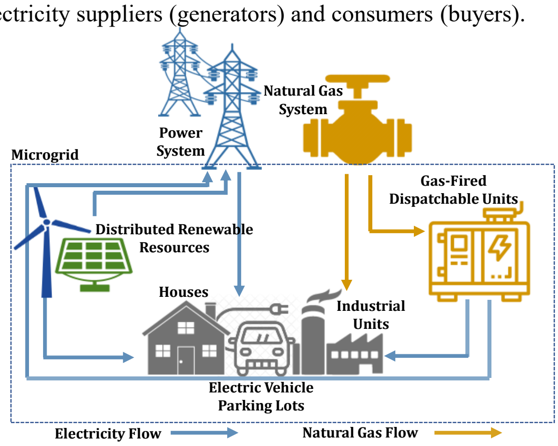

Fig. 1. Illustration of multi-energy microgrid

The model and formulation, including objective function and constraints as well as the scenario generation method for electric vehicles in parking lots and the solving method, are discussed in the following.

A. Optimization problem

The model and formulation for the techno-economic assessment of parking lots with power-to-grid capability are discussed in this section. In (1), the objective function of the optimization problem is discussed, which consists of four terms. The first term indicates the investment costs in a day for the establishment of the electric vehicle parking lots, including infrastructure and equipment. To calculate the cost in a day, the total investment cost is multiplied by $\left[\frac{r(1+r)^j}{(1+r)^j-1}\right] \cdot \frac{Demand^{day}}{Demand^{year}}$. The second term represents the operation cost of the microgrid consisting of natural gas and electricity systems operating costs. The third term addresses the cost of maintenance for the parking lots in the microgrid. Additionally, the last term demonstrates the fine for producing carbon dioxide (i.e., carbon dioxide emission cost).

$$OF = \left[\frac{r(1+r)^j}{(1+r)^j - 1}\right] \cdot \frac{Demand^{day}}{Demand^{year}} \cdot Cost^{inv} + Cost^{oper} + Cost^{M} + Cost^{CO2} \tag{1}$$

The total investment cost is appropriate to the capacity of parking lots which is indicated in (2). The operation cost of the microgrid consists of the natural gas distribution system operating cost and the electricity distribution system operating cost, indicated in (3). In (4), the maintenance cost of parking lots is addressed, which is also appropriate to the capacity of parking lots. The cost of carbon dioxide production for dispatchable gas-fired units is also indicated in (5).

$$Cost^{inv} = \sum_{k=1}^{K} Cost^{pl} . Cap_k \tag{2}$$

$$Cost^{oper} = Cost^{gas} + Cost^{elec} \tag{3}$$

$$Cost^{M} = \sum_{k=1}^{K} Cost^{Mpl} . Cap_k \tag{4}$$

$$Cost^{CO2} = \sum_{t=1}^{T} \sum_{b=1}^{B} Cost^{co2} . P_{b,t} \tag{5}$$

In (6)-(7) the operating costs of natural gas and electricity systems are indicated, respectively. The operation cost of the gas system consists of the cost of purchasing natural gas from the main grid, the cost of linepack management, and the cost of gas shedding. It should be noted that the linepack means the amount of natural gas within pipelines, and it may be used to deal with the changes between supply and demand [14]. The operating cost of the electricity system includes the cost of purchased and sold power from/to the main grid as well as the cost of generating power using dispatchable gas-fired units.

$$Cost^{gas} = \sum_{t=1}^{T} \sum_{y=1}^{Y} Cost^{Gas} . Gas_{y,t}^{buy} + \sum_{t=1}^{T} \sum_{n=1}^{N} Cost^{lp} . \Delta Gas_{n,t} + \sum_{t=1}^{T} \sum_{y=1}^{Y} Cost^{sh} . GNS_{n,t} \tag{6}$$

$$Cost^{elec} = \sum_{t=1}^{T} \sum_{b=1}^{B} Price_t . P_{b,t}^{buy} - \sum_{t=1}^{T} \sum_{b=1}^{B} Price'_t . P_{b,t}^{sell} + \sum_{t=1}^{T} \sum_{b=1}^{B} (\alpha_b . P_{b,t} + \beta_b . u_{b,t}) \tag{7}$$

Some constraints are taken into consideration, including natural gas flow balance, active and reactive power flow balance, maximum/minimum gas injection through injection nodes, maximum/minimum purchased electricity from the main grid, maximum/minimum pressure at nodes, maximum/minimum voltage at nodes, and maximum/ minimum active and reactive power flow and current within lines in the electricity system.

In addition to the already mentioned constraints, in (8), the changes in linepack within pipelines are demonstrated. In (9), Lacey's equation is indicated which is used to simulate the low-pressure natural gas system by connecting gas flow within pipelines and pressure at nodes [15]. In (10)-(11), Kirchhoff's voltage law is represented that connects voltage and current in the electricity distribution system (i.e., connect active and reactive power) [16].

$$Gas_{p,t} = Gas_{p,t}^{0} + Gas_{p,t-1} + Gas_{n,t}^{pipe} - Gas_{n',t}^{pipe} \qquad \forall p \epsilon \subset (n,n'), \forall t \qquad (8)$$

$$Gas_{p,t}^{pipe} = \mathcal{C}\sqrt{\wp_{n,t} - \wp_{n',t}} \qquad \forall p \subset (n,n'), \forall t \qquad (9)$$

$$V_{b,t}^{2} - V_{b',t}^{2} = 2(R_l . P_{l,t}^{line} + X_l . Q_{l,t}^{line}) + Z_l^2 . I_{l,t}^2 \qquad l\epsilon(b,b'), \forall t \qquad (10)$$

$$V_{b,t}^{2} . I_{l,t}^{2} = Q_{l,t}^{line\,2} + P_{l,t}^{line\,2} \qquad l\epsilon(b,b'), \forall t \qquad (11)$$

In the following, some constraints are discussed, related to the operation of electric vehicles' parking lots. The state of charge of electric vehicle parking lots is indicated in (12). It is calculated considering the state of charge in the previous hour, the state of charge of arrived and departed electric vehicles, and charging and discharging the energy of the vehicle parking lots considering the efficiency of charge and discharge. Charged and discharged power of electric vehicles' parking lots are limited in (13)-(16). A binary variable is also determined to avoid the charge and discharge of a parking lot at the same time (i.e., from a parking lot to the distribution system or vice versa). The state of charge of electric vehicle parking lots is also limited to prevent overcharging or undercharging of vehicles' batteries (17).

$$SC_{k,t} = SC_{k,t}^{0} + SC_{k,t-1} + \sum_{p}(SC_{p,k,t}^{arv} - SC_{p,k,t}^{dep}) + (eff^{ch}.P_{k,t}^{ch} - P_{k,t}^{dch}/eff^{dch}) \qquad \forall k, \forall t \qquad (12)$$

$$P_{k,t}^{ch} \leq P_{k}^{ch\,max}.y_{k,t} \qquad \forall k, \forall t \qquad (13)$$

$$P_{k,t}^{ch} \geq P_{k}^{ch\,min}.y_{k,t} \qquad \forall k, \forall t \qquad (14)$$

$$P_{k,t}^{dch} \leq P_{k}^{dch\,max}.(1 - y_{k,t}) \qquad \forall k, \forall t \qquad (15)$$

$$P_{k,t}^{dch} \geq P_{k}^{dch\,min}.(1 - y_{k,t}) \qquad \forall k, \forall t \qquad (16)$$

$$SC_{k}^{min} \leq SC_{k,t} \leq SC_{k}^{max} \qquad \forall k, \forall t \qquad (17)$$

B. Scenario generation

It should be noted that, in this model, it is assumed that a contract is signed between electric vehicles and parking lot owners to allow vehicle-to-grid. To study the problem, a scenario is required, which represents the hourly state of charge of electric vehicles in each parking lot. For this purpose, the Gaussian Distribution Function is utilized to generate the scenario for the arrival time of electric vehicles as well as the state of charge at arrival, represented in (18) [17]. It is noteworthy to mention that time of departure should be greater than the time of arrival in the scenario generation (19). The number of electric vehicles is also limited according to the capacity of parking lots (20). Considering the capacity of parking lots, the maximum/minimum state of charge and charging/discharging power of parking lots are limited (21)-(22).

$$f(x,\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (18)$$

$$t^{arv} \leq t^{dep} \qquad (19)$$

$$Number^{ev} \leq Number^{ev\,max} \qquad (20)$$

$$SOC_{k,t}^{min/max} = \sum_{m=1}^{Number^{ev}} SOC_{m,t}^{min/max} \qquad \forall k, \forall t \qquad (21)$$

$$P_{k,t}^{ch/dch\,min/max} = \sum_{m=1}^{Number^{ev}} P_{m,t}^{ch/dch\,min/max} \qquad \forall k, \forall t \qquad (22)$$

C. Solving method

The techno-economic model is a mixed-integer nonlinear programming (MINLP) problem, which can be challenging to solve due to the presence of both nonlinear equations and binary variables. Relaxing the integer decision variable in the model transforms the MINLP into a nonlinear programming (NLP) problem, which can be easier to solve. By using the solution from the relaxed model as an initial point, the original MINLP problem can be solved using optimization algorithms, such as branch-and-bound or branch-and-cut. The scaling of the gas and electricity operation subproblems can also help to overcome the difficulties in solving the MINLP problem [18]. The main steps of the discussed solving method are demonstrated in detail in Table I.

TABLE I. PSEUDOCODE OF DISCUSSED SOLVING METHOD

Line	Algorithm
1	Iteration: =1;
2	Relaxing binary variables in the model;
3	Solving the relaxed model which is NLP;
4	If an optimal solution found;
5	Stop;
6	Else adding load shedding to electricity and natural gas flow and
7	corresponding penalty into the objective function, going to line 1, and
8	Iteration ≔ Iteration + 1;
9	End
10	Setting output of the previous problem as initial points;
11	Solving the original problem which is MINLP;
12	If an optimal solution found;
13	Stop;
14	Else scaling natural gas and electricity operating problem, going to line 1, and
15	Iteration ≔ Iteration + 1;
16	End

III. Case study

Illustrations of electricity and natural gas systems are represented in Fig. 2 and Fig. 3, respectively [16]. The electricity system is formed of 33 buses, 32 lines, four distributed renewable resources at buses 15, 29, 30, and 32, and two distributed dispatchable gas-fired units at buses 2 and 9, and three electric vehicles parking lots. The natural gas system is also formed of 11 nodes and 12 pipelines. The electricity system is connected to the main grid through a substation. The gas-fired dispatchable units also connect the electricity system to the natural gas system. More precisely, the gas-fired units at bus two and bus nine in the electricity system are connected to node five and node six in the natural gas system, respectively, to be supplied.

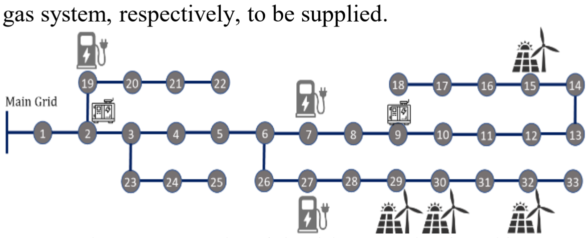

Fig. 2. Demonstration of electricity system in microgrid

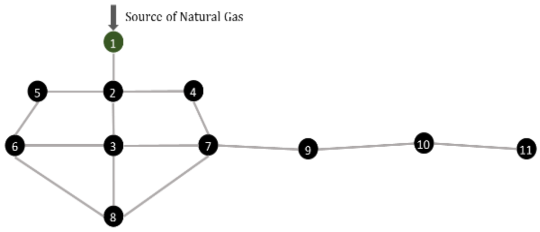

Fig. 3. Demonstration of natural gas system in microgrid

The shares of electric load (hourly to peak), natural gas loads (hourly to peak) as well as the output power of distributed wind turbines (available power/installed capacity) are demonstrated in Table II.

As discussed, the Gaussian Distribution Function is utilized to generate the scenario for arrival time, departure time, and state of charge of electric vehicles at parking lots. The scenario generation is conducted by considering the represented data in Table III.

TABLE II. SHARE OF ELECTRIC AND NATURAL GAS LOADS AND WIND POWER

Time (hour)	Electricity (%)	Gas (%)	Wind (%)	Time (hour)	Electricity (%)	Gas (%)	Wind (%)
1	0.6843	0.77	0.8345	13	0.9460	0.94	0.7601
2	0.6451	0.74	0.5361	14	0.9515	0.94	0.5987
3	0.6198	0.7	0.4424	15	0.9721	0.92	0.4704
4	0.6044	0.71	0.4220	16	0.9991	0.94	0.5162
5	0.6057	0.72	0.9124	17	1.0000	1	0.5641
6	0.6268	0.74	0.8579	19	0.9638	0.99	0.6466
7	0.6773	0.85	0.8981	19	0.9608	0.99	0.8375
8	0.7437	0.86	0.6792	20	0.9271	0.96	0.9480
9	0.8029	0.94	0.9266	21	0.9269	0.91	0.8187
10	0.8484	0.96	0.9083	22	0.8872	0.82	0.9185
11	0.8930	0.96	0.8075	23	0.7853	0.72	0.9699
12	0.9222	0.94	1.0000	24	0.7685	0.74	0.9002

TABLE III. PARAMETERS OF PARKING LOTS [17]

Parameter	μ	σ	Min	Max
Initial state of charge (%)	50	25	30	90
Arrival time (hour)	8	3	5	17
Departure time (hour)	16	3	11	24

According to the above-mentioned case study, this paper is modeled under the environment of General Algebraic modeling system (GAMS) software using the Discrete and Continuous Optimizer (DICOPT) solver. The operating system is Windows 10 64bit, and the hardware environment of the simulation test is Intel Core I7 CPU, 2.20 GHz, 8 GB memory.

IV. RESULTS AND ANALYSES

A. *Scenario generation*

Based on the model formulation, to conduct the techno-economic analysis of electric vehicles parking lot, a scenario for arrival time, departure time, and arrival state of charge of electric vehicles are generated. The generated scenario for each parking lot in the case study is indicated in Fig. 4. It should be noted that the cumulative arrival state of charge of electric vehicles in each parking lots are indicated. According to the generated scenarios, electric vehicles are in parking lots almost between 04:00 and 18:00.

B. *Economic analysis*

Considering the generated scenario that represents the state of charge of electric vehicle parking lots, the problem of techno-economic analysis is optimized. In this step, five cases are taken into consideration. In the first case, it is assumed that the parking lots can use arrived electric vehicles to improve the electricity system operation. More precisely, there is no limit to utilizing the stored energy in electric vehicles' batteries. In the second and third cases, there are two and one electric vehicle parking lot(s) in the microgrid, respectively. In the fourth case, the electric vehicles' state of charge must be more than 90% when they are going to leave the parking lots. In the fifth case study, there are no electric vehicle parking lots. The operation cost of the electricity system and emission cost in each case is indicated in Fig. 5. It is evident that, in the first case, the scheduled changing and discharging of electric vehicles in parking lots reduces the cost of operation by 15% (i.e., the first case in comparison with the fourth case). Moreover, the scheduled operation of electric vehicles reduces the emission by 33% due to less operation of fossil fuel-fired generating units (the first case in comparison with the fourth case). Moreover, it is worthwhile to mention that the total investment cost for each parking, allocated to a one-day operating period, is 385$. Therefore, the flexibility provided by electric vehicles in parking lots can compensate for a considerable portion of the investment costs.

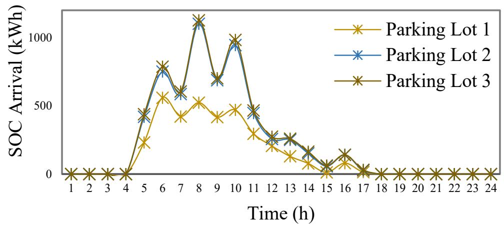

Fig. 4. Generated scenario for state of charge of each electric vehicle parking lot

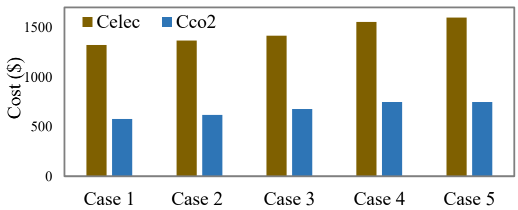

Fig. 5. Cost of electricity system operation and emission cost considering different cases

C. *Technical analysis*

To examine the reason for cost and emission reduction when the scheduled electric vehicles operation is considered, the output power of flexible dispatchable units (FG), distributed wind turbines (DG), interactions with the main grid (Deal), and charge/discharge of electric vehicles (Evch/Evdch) in the first case and the fourth case are indicated to be compared in Fig. 6. As demonstrated, the output power of wind turbines is utilized to supply demand during the whole operation period. In the first case, the electric power is purchased from the main grid during the period from 00:00 to 10:00 and from 14:00 to 24:00. However, in the fourth case, it is purchased from 00:00 to 04:00 and from 14:00 to 24:00. In these two cases, the main difference is charging electric vehicles in parking lots. More precisely, in the fourth case, unscheduled charging of electric vehicles increases the peak load that leads to an increase in costs of operation and emissions.

Figure 7 shows the injection of natural gas through the main grid and the amount of linepack within pipelines in the gas system. The maximum natural gas injection in the fourth case is higher compared to the first case (from 17:00 to 22:00). It is concluded that the natural gas system is able to supply a higher amount of load during peak hours of operation since it is a scheduled integration of electric vehicles (from 06:00 to 09:00 and from 17:00 to 22:00). On the other hand, in the first case, the volume of linepack within the pipelines is more in comparison with the fourth case. As a result, this system can deliver natural gas to the demand node more efficiently (e.g., demand for gas-fired units). Gas transmission from the main grid to demand nodes takes some time, and a higher volume of linepack allows it to provide supply-demand balance in the gas system more effectively. In conclusion, in the first case, the natural gas system is more flexible in dealing with changes between supply and demand and addressing demand provision.

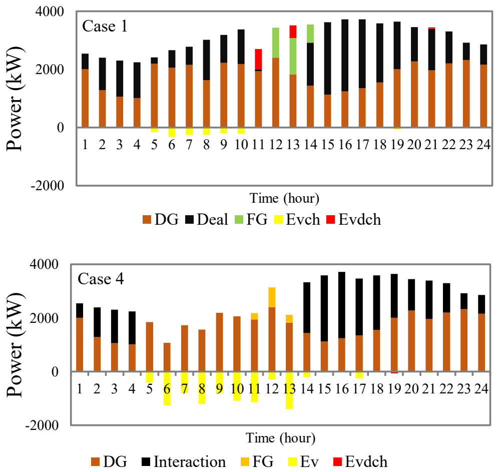

Fig. 6. Scheduling of electric system in microgrid (Case 1 vs. Case 4)

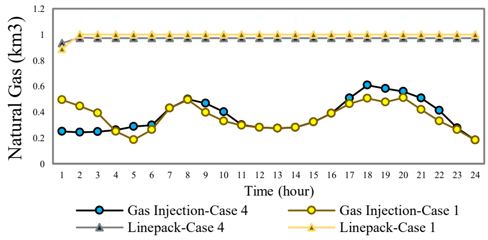

Fig. 7. Gas injection through main grid and linepack within pipelines in natural gas system

V. Conclusion

This study presented a model to analyze the role of electric vehicles parking lots in microgrids from technical and economic points of view. To this aim, a mathematical model was proposed for natural gas and electricity systems in a microgrid. The objective function of the model included the costs of investment, operation, maintenance, and emission. To model the electric vehicles in parking lots, a scenario was generated for arrival and departure time as well as the arrival state of charge of electric vehicles at each parking using the Gaussian Distribution Function. The results of the study provided insights with microgrid owners, such as the impact of the scheduled and unscheduled operation of electric vehicles in parking lots, the required cost of investment, and the flexibility provided by the scheduled integration of electric vehicles. It showed that scheduled operation of electric vehicle parking lots could reduce the costs of operation and emission by 15% and 33%, respectively, compared to when there is no parking lot. Due to its inherent flexibility provided by electric vehicle parking lots, the natural gas system can efficiently adapt to changes in demand for natural gas, which is further supported by the higher stored natural gas within pipelines.

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Optimal Scheduling of Gas and Electricity Distribution Networks in Microgrids: A Decomposition Approach

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Abstract— **The transition towards increasingly renewables-based energy system is ongoing. During this transition microgrids are seen as a key concept and sub-system which can enable the transition and improve the security of supply at distribution network level. From generation perspective, flexible and rapidly controllable gas-based generation units can be utilized to deal with the variable output of weather-dependent renewable energy resources. Due to these complementary characteristics, it is of interest to study the integrated operation of gas and electricity distribution networks also in future microgrids. In this paper, the optimized scheduling of resources in a microgrid with gas and electricity distribution networks is studied. For this purpose, a mathematical model is first determined. After that, due to the complexity of this model, a decomposition method is developed to solve the optimization problem. This method splits the original problem into two subproblems, which reduces the complexity of solving. In order to validate the efficacy of the proposed model, a case study is derived based on a 15-node gas distribution network and a 13-node electricity distribution network. Based on the results, integrated scheduling improves the costs compared to separated scheduling, and the decomposition method reduces the solving time considerably.**

Keywords—microgrid, scheduling, gas and electricity distribution networks, decomposition

NOMENCLATURE

Sets	
Y	Set of sources in gas distribution network ($y \subseteq N$)
N	Set of nodes in gas distribution network ($n \in N$)
P	Set of pipelines in gas distribution network ($p \subseteq (n, n')$)
B	Set of nodes in electricity network ($b \in B$)
T	Set of periods ($t \in T$)
L	Set of distribution lines ($l \subseteq (b, b')$)
Parameters	
$\mathrm{C}^{\mathrm{gas}}$	Cost of natural gas (\$/km^3)
C^{lp}	Cost of changes in linepack (\$/km^3)
$\mathrm{C}^{\mathrm{gsh}}$	Cost of gas not-supplied (\$/km^3)
$F_y^{\mathrm{sup\ min/max}}$	Minimum /maximum gas injection (km^3)
$D_{n,t}^{\mathrm{gas}}$	Gas demand (km^3)
Le_p	Pipeline length (km)
Dia_p	Pipeline diameter (mm)
$F_p^{\mathrm{pipe\ min/max}}$	Minimum/maximum gas flow (km^3)
$\pi_{p,t}^{\mathrm{min/max}}$	Minimum/maximum gas pressure (Pascal)
$LP_{p,t}^{0}$	Initial linepack (km^3)
$\gamma_{b,t}$	Purchased energy prices (\$)
$\gamma'_{b,t}$	Sold energy prices (\$)
α_b	Variable cost of generating power using non-renewable distributed generators (\$/kW)
β_b	Fixed cost of generating power using non-renewable distributed generators (\$)
$Pg_b^{\mathrm{min/max}}$	Minimum/maximum produced power by non-renewable generators or supplied by substations (kW/h)
$R_b^{\mathrm{max\ up/down}}$	Minimum ramp up/down of non-renewable generating units (kW/h)
υ	Energy conversion coefficient (m^3/W)
η_b	Energy efficiency of non-renewable generators
$Qt_b^{\mathrm{min/max}}$	Minimum/maximum active power of non-renewable generators or substations (kVAr)
$P_{b,t}^{\mathrm{load}}$	Active load (kW)
$Q_{b,t}^{\mathrm{load}}$	Reactive load (KVAr)
R_l	Resistance (Ω)
X_l	Reactance (Ω)
Z_l	Impedance (Ω)
$V_b^{\mathrm{min/max}}$	Minimum/maximum voltage (kV)
I_l^{max}	Maximum current (kA)
$Pw_{b,t}^{\mathrm{max}}$	Maximum available generated power by wind generators (kW)
f	Friction factor for pipelines
S	Specific gravity of natural gas (kg/m^3)
λ	Optimal multipliers of optimization problem
Decision variables	
$F_{y,t}^{\mathrm{sup}}$	Gas injection (km^3)
$\Delta LP_{n,t}$	Change in linepack (km^3)
$GNS_{n,t}$	Gas-not-supplied (km^3)
$F_{p,t}^{\mathrm{pipe}}$	Gas flow within pipelines (km^3)
$F_{p,t}^{\mathrm{pipe\ in/out}}$	Input/output gas flow of pipelines (km^3)
$\pi_{p,t}^{\mathrm{in/out}}$	Input/output pressure of gas within pipelines (Pascal)
$LP_{p,t}$	Linepack (km^3)
$P_{b,t}^{\mathrm{buy/sell}}$	Purchased/sold energy from/to day-ahead market (kW)
$Pg_{b,t}$	Generated power of non-renewable generators (kW)
$Fg_{b,t}$	Required natural gas of non-renewable generators (km^3)

$Qt_{b,t}$	Reactive power of generating non-renewable generating units or substations (kVAr)
$Pw_{b,t}$	Output power of wind generators (kW)
$Pl_{l,t}$	Active power (kW)
$Ql_{l,t}$	Reactive power (kVAr)
$I_{l,t}$	Electricity current (kA)
$V_{b,t}$	Voltage magnitude (kV)
Binary variables	
$u_{b,t}$	Status of non-renewable generators

I. Introduction

The increasing proportion of renewable-resource in supplying the amount of energy demand in the world has different benefits, such as decreasing greenhouse emissions and increasing energy supplies diversification, which leads to reduction of dependency on fossil fuels [1]. The worldwide analyses show that transition to a zero-emission energy supply by employing renewable energy resources has been started, and the resources will be the largest sources of energy in the world by 2050 [2]. For instance, the government of the United States of America has set goals to achieve a zero-emission economy by no later than 2050 [3]. The European Union's objective is also to become a zero-emission continent by 2050 to benefit from the sustainable and green transition [4]. Although having significant challenges, such as flexibility requirement and inefficiency resulting from the backup capacity requirement due to the variable output of renewable resources, the electricity sector can accommodate a large share of these recourses by employing an appropriate strategy of scheduling and operation [5].

In moving toward a zero-emission energy system, microgrids can help manage supply-demand balance, reduce energy loss through transmission lines, and improve the resiliency of grids in extreme conditions [6]. Microgrids are local and controllable energy systems composed of a few renewable and non-renewable generating units connected to nearby consumers. The short distance between supply and demand helps manage electricity demand and alleviate congestion and energy loss through lines that reduce the peak demand and energy price. Moreover, microgrids can autonomously operate in island mode when the main grid is off, which enhances resiliency in extreme conditions as well as function as a resource for recovery [7]. A considerable number of previous studies have also investigated scheduling electricity distribution networks in a microgrid. For instance, in [8], a method is proposed to deal with uncertainty in the scheduling microgrids, which is independence in forecasting. The results of this study show cost-saving and being computationally effective in comparison with other approaches which are based on forecasting uncertain data. In [9], this problem is taken into consideration, focusing on the demand response of electric vehicles. It concludes that electric vehicles demand response encourages the owners to participate in the scheduling microgrid that is beneficial in providing supply-demand balance. In [10], the scheduling of microgrids is studied considering a high share of distributed energy resources and energy storage systems. This study shows optimizing this problem considerably contributes to reducing greenhouse gas emissions.

In moving to the producing energy from renewable energy resources, scheduling multi-energy systems is also beneficial. Some components, such as gas-fired units, heat storage systems, and combined heat and power units, integrate gas, electricity, and heat networks and make the integration operation necessary. Therefore, simultaneous scheduling energy systems can lead to cost reduction as a result of finding an optimal solution for the operation of these networks [11]. Among recent studies, in [12], optimal scheduling of integrated heat and electricity microgrids is studied due to a considerable proportion of combined heat and power units. However, in addition to the heat system, cooling system operation is investigated to study the interactions in multi-energy microgrids in [13]. These studies also show the optimal solutions to prevent being exposed to a high scheduling cost. Moreover, in [14] and [15], due to the presence of natural gas-fired units to deal with distributed renewable resources' variable output, scheduling electricity distribution networks coupled with the natural gas network is studied. It is connected to the characteristics of gas-fired units, such as fast-ramping rate, enabling them to cope with the variable output of renewable resources. The results demonstrate cost-saving and the ability of peak shaving when both networks are taken into consideration.

Aside from the already mentioned, solving the integrated operation of energy systems is difficult since the optimization problem is complex. Although linearization [16] and applying heuristic approaches [17] can improve problem solving, decomposition techniques are other options for dealing with the complexity of the optimization. The decomposition method splits the original problem into a few subproblems and solves them iteratively. In recent years, only a few studies have employed decomposition methods to examine the operation of the multi-energy system. For example, in [18], a decomposition method based on Benders Decomposition is developed to solve the complex problem of scheduling multi-energy systems in microgrids considering energy storage systems. In [19], in order to solve the problem of scheduling microgrids quickly and convergently, a relaxation method is employed that provides a convex model. In [20], the problem of scheduling microgrids is examined under a high proportion of distributed renewable energy considering both islanded and grid-connected modes of operation. Furthermore, this study applies Benders Decomposition to solve the optimization problem quickly.

Considering the upsides and downsides of the earlier studies in this field, first of all, a novel mathematical model of gas and electricity distribution networks operation is introduced precisely. In the gas distribution network, constraints such as gas supply limits for the sources, gas flow balance, and linepack and pressure constraints are considered. In the electricity distribution network, an AC model for the scheduling of the electricity distribution network is introduced, which takes into accounts load flow balance, renewable energy resources, and interactions with the market. Then, a decomposition approach is also developed to solve the complex optimization problem. As far as we are aware, it is for the very first time that this method is applied to deal with the complexity of solving the scheduling gas and electricity distribution networks in a microgrid. For validation of the efficacy of the proposed model, a case study is derived based on a 15-node gas distribution network and a 13-node electricity distribution network.

II. Model Formulation

In this section, at first, a mathematical model is introduced for the integrated scheduling of gas and electricity distribution networks in a microgrid. It is worth noting that, in the gas network's model, continuity and momentum equations are used to show gas flow [21]. The main assumption in the gas distribution network simulation is that the variation in kinetic energy along a pipeline as a consequence of changes in velocity and density is negligible.

The key assumptions in the electricity distribution network's model are also represented as follows:

- The demand is indicated as constant active and reactive power;
- The power loss along a branch is assumed at the beginning of that;
- This network is addressed in a single-phase and balanced equivalent;
- The microgrid interacts with the main grid in a day-ahead market.

A. Gas distribution network model

In this subsection, the operation model of a gas distribution network is indicated (1)-(6). In (1), the objective function of the scheduling gas distribution network is shown, composed of three terms. These terms indicate the cost of natural gas injection through sources, the cost of linepack changes, and the cost of gas not-supplied, respectively. It is important to highlight that linepack refers to the amount of stored natural gas within the pipelines, employed to deal with variation between supply and demand. Linepack is important since it takes a while to transmit natural gas from sources to demand nodes [22].

$$Z_{gas} = \sum_t \sum_y \mathrm{C}^{\mathrm{gas}}.F_{y,t}^{\mathrm{sup}} + \sum_t \sum_n \mathrm{C}^{\mathrm{lp}}.\Delta LP_{n,t} + \sum_t \sum_n \mathrm{C}^{\mathrm{gsh}}.GNS_{n,t} \quad (1)$$

In (2), the gas injection through sources is constrained, and the natural gas balance is shown in (3).

$$F_y^{\mathrm{sup\,min}} \le F_{y,t}^{\mathrm{sup}} \le F_y^{\mathrm{sup\,max}} \qquad \forall y, \forall t \quad (2)$$

$$F_{y,t}^{\mathrm{sup}} - F_{p,t}^{\mathrm{pipe}} = D_{n,t}^{\mathrm{gas}} - GNS_{n,t} \qquad \forall n, \forall t \quad (3)$$

In (4), Lacey's equation is indicated, employed to simulate the low-pressure gas networks and shows the relation between gas flow and pressure [23].

$$\pi_{p,t}^{\mathrm{out}} - \pi_{p,t}^{\mathrm{in}} = 0.00117\, Le_p.\left(F_{p,t}^{\mathrm{pipe}}\right)^2 / Dia_p^5 \qquad \forall l, \forall t \quad (4)$$

The natural gas through distribution pipelines is constrained in (5), and the variation of linepack through distribution pipelines is demonstrated in (6).

$$F_p^{\mathrm{pipe\,min}} \le F_{p,t}^{\mathrm{pipe}} \le F_p^{\mathrm{pipe\,max}} \qquad \forall p, \forall t \quad (5)$$

$$LP_{p,t} = LP_{p,t}^0 + \sum_0^t (F_{p,t}^{\mathrm{pipe\,in}} - F_{p,t}^{\mathrm{pipe\,out}}) \qquad \forall p, \forall t \quad (6)$$

B. Electricity network model

In this subsection, the operating model of an electricity distribution network is indicated (7)-(18). The objective function, which consists of three terms, is presented in (7). The first two terms show the cost of interactions with the main grid, and the last one indicates the cost of generating power from non-renewable distributed generators (e.g., combined heat and power units).

$$Z_{elec} = \sum_t \sum_b \gamma_{b,t}.P_{b,t}^{\mathrm{buy}} - \sum_t \sum_b \gamma'_{b,t}.P_{b,t}^{\mathrm{sell}} + \sum_t \sum_b (\alpha_b\,.Pg_{b,t} + \beta_b.u_{b,t}) \quad (7)$$

In (8), the active power balance is represented, and available wind generation and maximum/minimum limitation of non-renewable generators are shown in (9)-(10), respectively.

$$Pg_{b,t} + Pw_{b,t} + P_{b,t}^{\mathrm{buy}} - (Pl_{l,t} + R_{l,t}.I_{l,t}^2) = P_{b,t}^{\mathrm{load}} + P_{b,t}^{\mathrm{sell}} \qquad \forall b, l\epsilon(b,b'), \quad (8)$$

$$Pw_{b,t} \le Pw_b^{\mathrm{max}} \qquad \forall b, l\epsilon(b,b'), \forall t \quad (9)$$

$$u_{b,t}.Pg_b^{\mathrm{min}} \le Pg_{b,t} \le u_{b,t}.Pg_b^{\mathrm{max}} \qquad \forall b, \forall t \quad (10)$$

The ramping rate of the none-renewable generating units is also indicated in (11)-(12).

$$Pg_{b,t} - Pg_{b,t-1} \le u_{b,t-1}.R_b^{\mathrm{max\ up}} \qquad \forall b, \forall t \quad (11)$$

$$Pg_{b,t-1} - Pg_{b,t} \le u_{b,t}.R_b^{\mathrm{max\ down}} \qquad \forall b, \forall t \quad (12)$$

The reactive power balance is demonstrated in (13), and the limitation of reactive power from the generating units and substations is demonstrated in (14).

$$Qt_{b,t} + Qw_{b,t} + (Ql_{l,t} + X_{l,t}.I_{l,t}^2 = Q_{b,t}^{\mathrm{load}} \qquad \forall b, l\epsilon(b,b'), \forall t \quad (13)$$

$$Qt_b^{\mathrm{min}} \le Qt_{b,t} \le Qt_b^{\mathrm{max}} \qquad \forall b, \forall t \quad (14)$$

In (15)-(16), the application of Kirchhoff's voltage law is presented [24]. In (17)-(18), the limitations of voltage and current are also indicated.

$$V_{l,t}^{\mathrm{in}^2} - V_{l,t}^{\mathrm{out}^2} = 2(R_l.Pl_{l,t} + X_l.Ql_{l,t}) + Z_l^2\,.I_{l,t}^2 \qquad l\epsilon(b,b'), \forall t \quad (15)$$

$$V_{l,t}^2\,.I_{l,t}^2 = Q_{l,t}^2 + P_{l,t}^2 \qquad l\epsilon(b,b'), \forall t \quad (16)$$

$$V_b^{\mathrm{min}} \le V_{b,t} \le V_b^{\mathrm{max}} \qquad \forall b, \forall t \quad (17)$$

$$0 \le I_{l,t} \le I_l^{\mathrm{max}} \qquad l\epsilon(b,b'), \forall t \quad (18)$$

C. Coupled gas and electricity distribution networks

The non-renewable distributed generators couple the electricity and natural gas distribution networks. The distributed generators mainly burn natural gas to produce electricity (e.g., combined heat and power units). The amount of natural gas that these units need to produce electricity is calculated in (19). This is noteworthy to mention that the amount of required natural gas should be added to the gas flow balance (3) when the operation of both networks is considered. Furthermore, the integrated operation is optimized subject to all constraints ((2)-(6) and (8)-(19)) whose objective function is the sum of electricity and natural distribution networks' objective functions [25]. However, in the separated operation (Fig. 1), the scheduling electricity distribution network is optimized at the first stage. Secondly, the required amount of natural gas in the electricity distribution network is considered in addition to natural gas demand. After that, the problem of gas distribution network operation is optimized, and if there is any problem with supply-demand, the maximum output of gas-fired units is constrained [26].

$$Fg_{b,t} = \frac{Pg_{b,t}}{\eta_b}.\upsilon \qquad \forall b, \forall t \qquad (19)$$

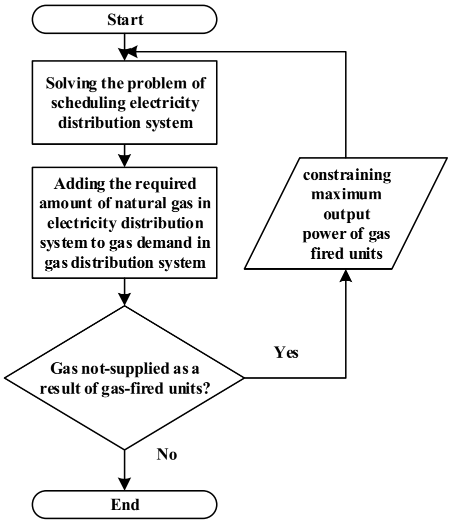

Fig. 1. Separated operation of natural gas and electricity distribution networks

III. DECOMPOSITION METHOD

In this section, the key steps of the decomposition method, called Outer Approximation/Equality Relaxation, are explained (Fig. 2). This should be mentioned that this method was introduced to cope with the nonlinear equality constraints in the form of $f(x) = 0$ in optimization problems [27].

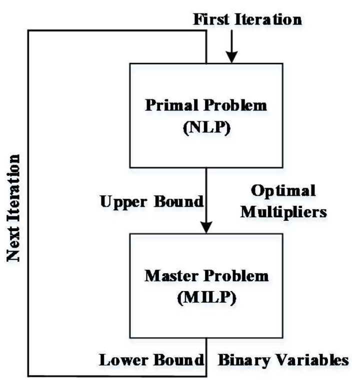

Fig. 2. Structure of Outer Approximation/Equality Relaxation based on [25]

In this method, firstly, the primal problem is solved by initializing binary variables (nonlinear problem). Solving this problem provides upper bound as well as optimal multipliers for the equality constraints. After that, the master problem is solved by relaxing the nonlinear equality constraints and using the optimal multipliers (mixed-integer linear problem). The outputs of the master problem give binary variables for the next iteration as well as a lower band. When the upper band and lower band converge, this is an optimal solution. Therefore, the method splits the main problem into two subproblems, which reduces the complexity of solving. This is noteworthy to mention that, in the problem of scheduling electricity and gas distribution networks in a microgrid, the nonlinear constraints include Lacey's equation in the gas distribution network (4) and the constraint related to Kirchhoff's voltage law in the electricity distribution network (16) that must be relaxed as indicated in (20).

$$sgn(\lambda)(f(x^k) + \nabla f(x^k)(x - x^k)) \leq 0 \qquad (20)$$

In the aforementioned formulation, $f(x)$, λ, and x^k indicate the nonlinear constraints, the optimal multipliers, and the optimal solution of primal problem in kth iteration, respectively. Moreover, $sgn()$ shows the sign function.

IV. CASE STUDY

The proposed methodology is examined on a 15-node gas distribution network and 13-node electricity distribution network, depicted in Fig. 3 and Fig. 4, respectively. As depicted, the gas distribution network consists of one injection node, 15 nodes, and 17 pipelines. The electricity distribution network also consists of one gas-fired unit, three renewable distributed energy resources, 13 nodes, and 13 lines. It should be mentioned that gas-fired units connect node two in the electricity distribution network to node five in the gas distribution network. For this purpose, the operation of the microgrid is optimized through the integrated and separated strategies with and without employing the decomposition method during a day (24 hours). The results of the study are presented in the next section, and analyses are conducted to validate the results.

It is noteworthy to mention that, the characteristics of the gas and electricity distribution networks have been presented in [28] and [29], including the maximum injection through the terminal, and the length and diameter of pipelines, the capacity of lines, the characteristics of generating units, and gas and electricity demand.

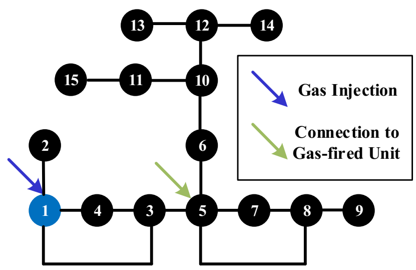

Fig. 3. Representation of natural gas distribution network

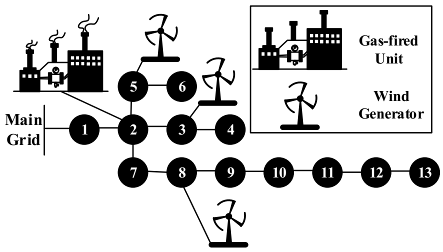

Fig. 4. Representation of electricity distribution network

V. Results and Analyses

In this section, the analytical findings of the proposed methodology are analyzed using the fifteen-node gas distribution network and the thirteen-node electricity distribution network.

A. *Gas distribution network analysis*

The injection of natural gas through the sources and the variation of linepack within the pipelines are depicted in Fig. 5. It is evident that maximum natural gas injection in the separated strategy of operation is higher compared to when the integrated strategy of operation is employed (from 17:00 to 22:00). Therefore, the natural gas distribution network can supply more demand in peak hours as a result of choosing the integrated strategy (from 06:00 to 09:00 and from 17:00 to 22:00). On the other side, when the integrated strategy of operation is conducted, the amount of linepack within the pipelines is higher in comparison with applying the separated strategy. Therefore, it increases the ability of this network to supply changes in demand (e.g., the growth in the required amount of natural gas for gas-fired units). It is worth noting that it takes a while to transmit natural gas from sources to demand nodes, and a higher level of linepack allows to address the supply-demand balance in the gas distribution network effectively. Due to these reasons, employing the integrated strategy to optimize the problem, the natural gas distribution network is more flexible in dealing with changes and supplying excess demand.

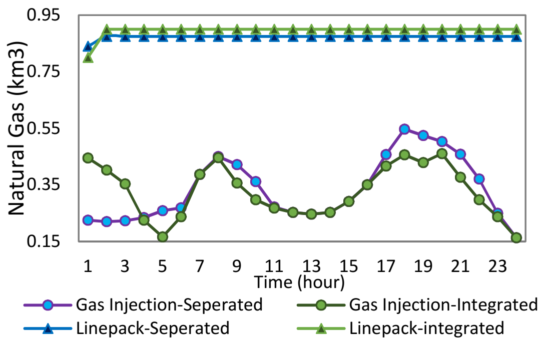

Fig. 5. Amount of gas injection and sum of linepack in gas distribution network

B. *Electricity distribution network analysis*

The power output of distributed renewable generators and gas-fired units as well as the imported power from the main grid is demonstrated in Fig. 6. It is evident that when the integrated strategy is employed to solve the problem, more wind power can be used to supply the demand by 2293 kW. It is due to the flexibility of the natural gas distribution network that facilitates employing gas-fired units to deal with variable output of the renewable distributed generators in peak hours (from 06:00 to 09:00 and from 17:00 to 22:00). On the other side, the imported power from the main grid and power output of gas-fired units is higher when the separated strategy is employed by 100 kW and 1956 kW, respectively, which increases the cost of operation and emissions.

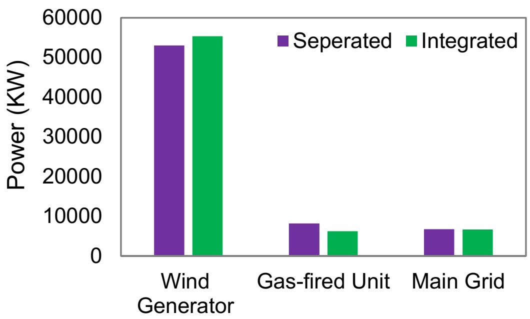

Fig. 6. Output power of different generating units and interactions with the main grid

C. *Cost and decomposition method analyses*

In this subsection, the scheduling cost of natural gas and electricity distribution networks are examined under both strategies of operation. Furthermore, the solving time is compared considering solving by GAMS solvers and Outer Approximation/Equality Relaxation method. Table I shows the economic analyses of the operation of electricity and natural gas distribution networks. It is a fact that employing the integrated strategy decreases the operating costs in natural gas and electricity distribution systems by $60.69 and $125.82, respectively. The reason is to use more renewable distributed energy resources to address supply-demand balance.

TABLE I. ECONOMIC ANALYSIS AND SOLVING TIME OF OPTIMIZATION PROBLEM

Solver		Operating cost ($)		Time (Sec)
		Gas Network	*Electricity Network*	
GAMS Solvers	Separated Operation	2797.691	1787.971	452.23
	Integrated Operation	2737.022	1662.156	770.13
Decomposition Method	Separated Operation	2797.691	1787.971	150.21
	Integrated Operation	2737.021	1661.993	370.85

On the other side, the solving time decreases by 51.8% when Outer Approximation/Equality Relaxation decomposition is employed to solve the problem. The reason is that this decomposition method solves the optimization problem iteratively and splits the original problem into the primal problem and the linearized master problem. This is noteworthy to mention that the GAMS solvers, employed to conduct this comparison, are SBB and BARON. Both solvers are based on the Branch and Bound method, improved with some constraints, such as interval analysis and duality techniques [30].

VI. CONCLUSION

In reaction to the growing proportion of distributed energy resources in electricity systems, such as photovoltaic systems and wind turbines, this study investigates the operation of gas and electricity distribution systems in a microgrid. In this context, gas-fired units are employed to cope with the variable output of renewable resources and dependence on the operation of these networks. For this purpose, in the first step, a mathematical model is introduced for the operation of natural gas and electricity distribution systems. In the electricity system, AC load flow is employed, and Lacey's equation is considered to simulate the low-pressure gas systems. Furthermore, a decomposition method known as Outer Approximation/Equality Relaxation is developed to solve the proposed mixed-integer non-linear model. This approach reduces the solving time by splitting the original problem into two subproblems. The obtained results of this study demonstrate the increase in the participation of renewable distributed generators by about 5% as a result of the integrated scheduling of both natural gas and electricity distribution systems. It concludes cost reduction by 2.3% and 7.5% in the gas and electricity distribution systems, respectively. Moreover, the decomposition method reduces the solving time by 52% in the integrated scheduling of these networks.

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