Energy 283 (2023) 128430

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

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

Vahid Shahbazbegian [a,*], Farnam Dehghani [b], Mohammad Agha Shafiyi [b], Miadreza Shafie-khah [a], Hannu Laaksonen [a], Hossein Ameli [c]

[a] School of Technology and Innovations, University of Vaasa, Vaasa, Finland
[b] Department of Electrical Engineering, Shahid Beheshti University, Tehran, Iran
[c] Control and Power Group, Imperial College London, London, UK

ARTICLE INFO

Handling Editor: Henrik Lund

Keywords:
Decomposition
Energy storage systems
Microgrid
Natural gas and electricity systems
Techno-economic analysis

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

* Corresponding author.
E-mail addresses: vahid.shahbazbegian@uwasa.fi (V. Shahbazbegian), f_dehghani@sbu.ac.ir (F. Dehghani), shafiyi@hotmail.com (M.A. Shafiyi), miadreza.shafiekhah@uwasa.fi (M. Shafie-khah), hannu.laaksonen@uwasa.fi (H. Laaksonen), h.ameli14@imperial.ac.uk (H. Ameli).

https://doi.org/10.1016/j.energy.2023.128430
Received 2 February 2023; Received in revised form 6 June 2023; Accepted 12 July 2023
Available online 19 July 2023

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)
v_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.

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

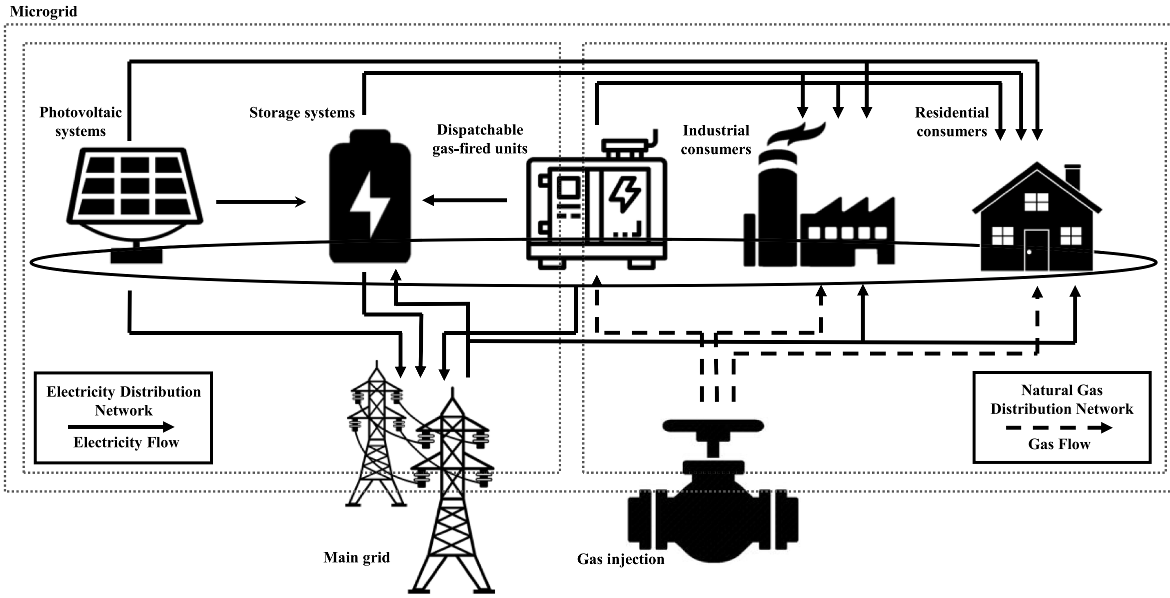

Fig. 1. Illustration of natural gas and electricity distribution subsystems in a multi-energy microgrid.

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 ($\sum_{t=1}^{T}\sum_{y=1}^{Y} C^{g}.G^{buy}_{y,t}$), 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

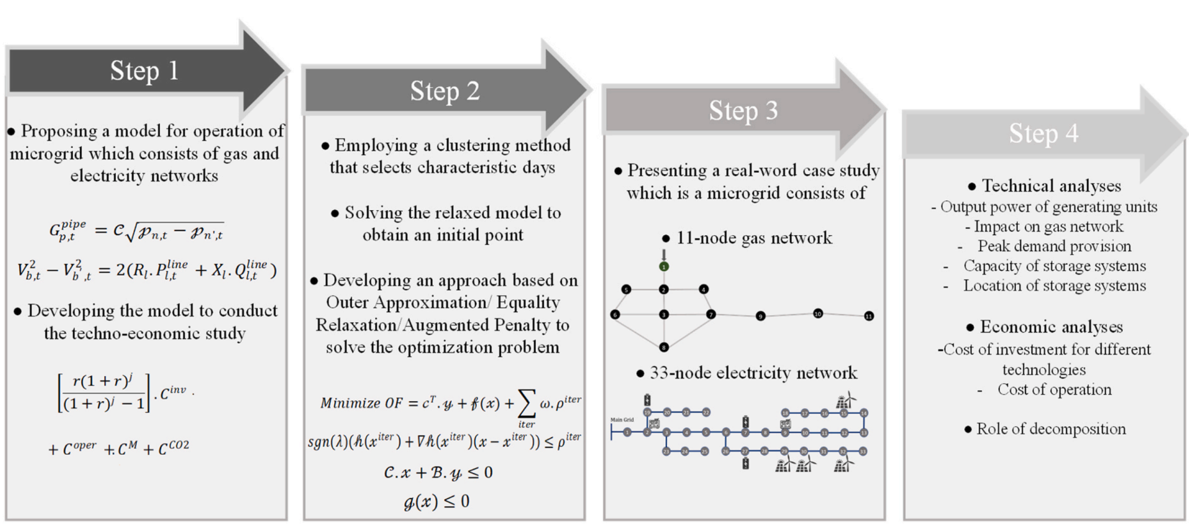

Fig. 2. Main steps of this study-analysis of storage systems in a multi-energy microgrid from technical and economic viewpoints.

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).

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

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

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.

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

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

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.

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

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

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.

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

$$P_k^{ch\ min} \leq P_{k,t}^{ch} \leq P_k^{ch\ max}\ \forall k, \forall t \tag{27}$$

$$P_k^{dch\ min} \leq P_{k,t}^{dch} \leq P_k^{dch\ max}\ \forall k, \forall t \tag{28}$$

$$v_k.SC_k^{min} \leq SC_{k,t} \leq SC_k^{max}.v_k\ \forall k, \forall t \tag{29}$$

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 $\mathrm{H}(\varkappa) = 0$ [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, $\varkappa$ and Υ are continuous and binary decision variables, and $\mathrm{H}(\varkappa) = 0$ and $\mathrm{M}(\varkappa) \leq 0$ are nonlinear and linear constraints.

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

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)).

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

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 ($sgn(\lambda)(\mathrm{H}(\varkappa^{iter}) + \nabla \mathrm{H}(\varkappa^{iter})(\varkappa - \varkappa^{iter})) \leq 0$) and considering Augmented Penalty ($\sum_{iter} \omega.\rho^{iter}$) as indicated in Equation (32).

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

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

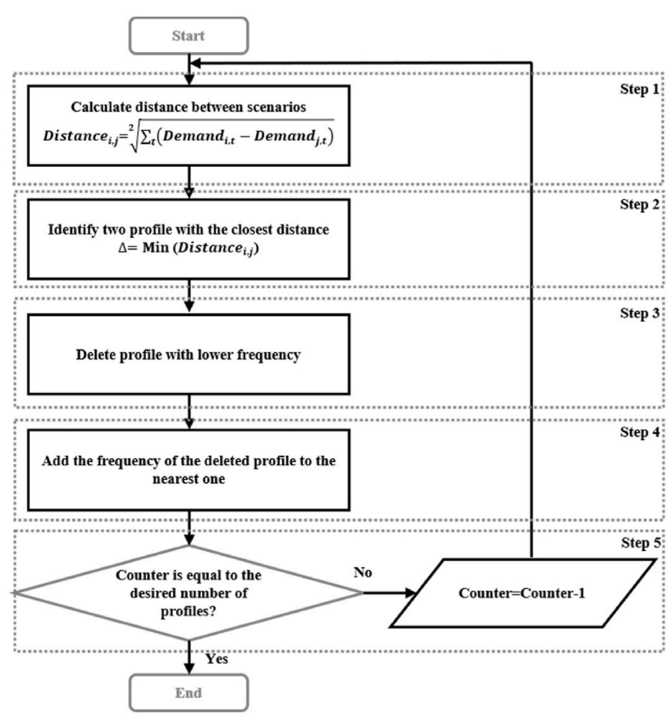

Fig. 3. Main steps of the clustering approach.

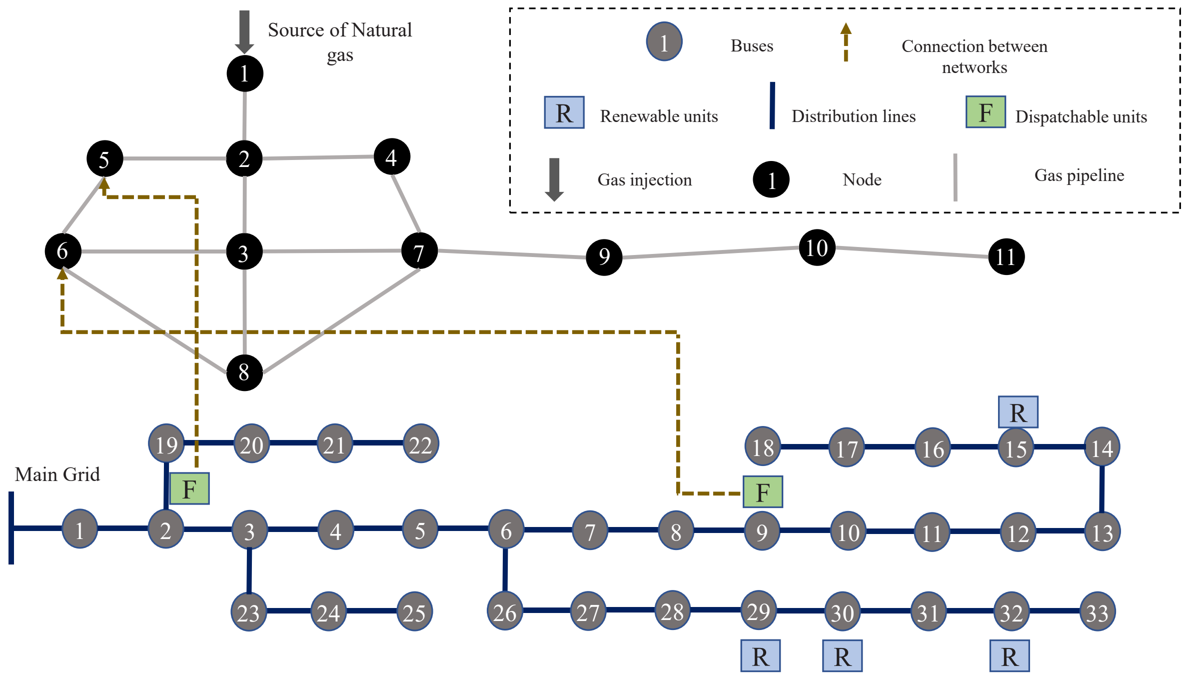

Fig. 4. Case-study-natural gas and electricity subsystems in a microgrid.

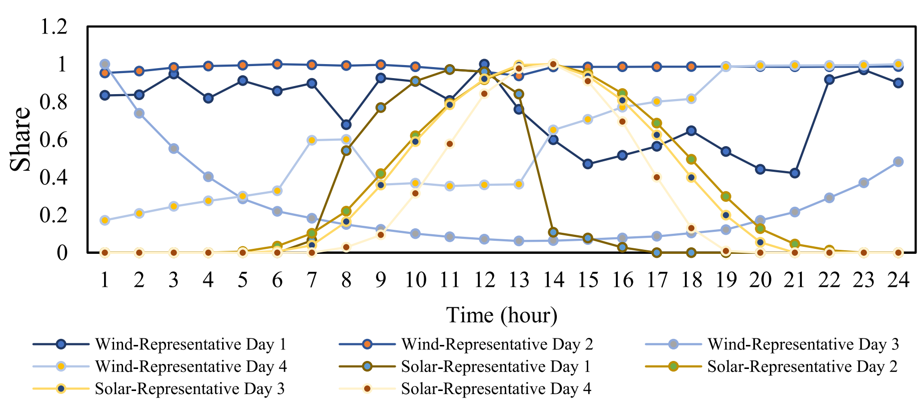

Fig. 5. Wind and solar power availability as a share of the installed capacity.

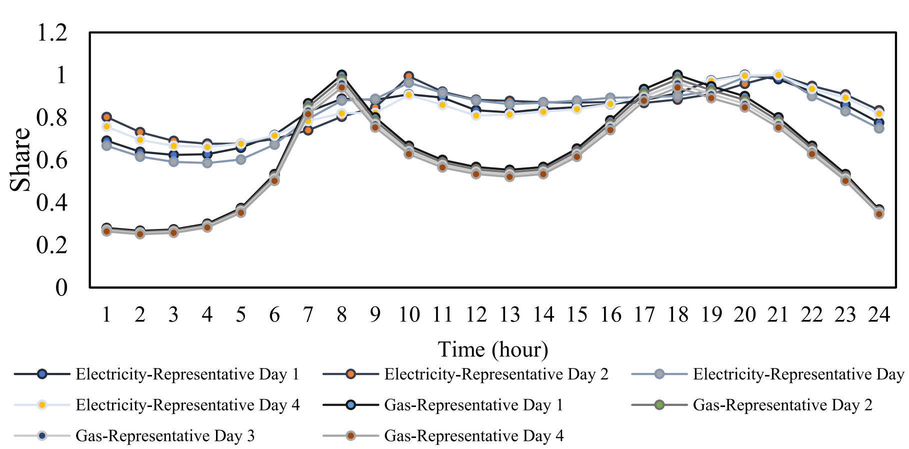

Fig. 6. Gas and electricity demand as a proportion of the peak demand.

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

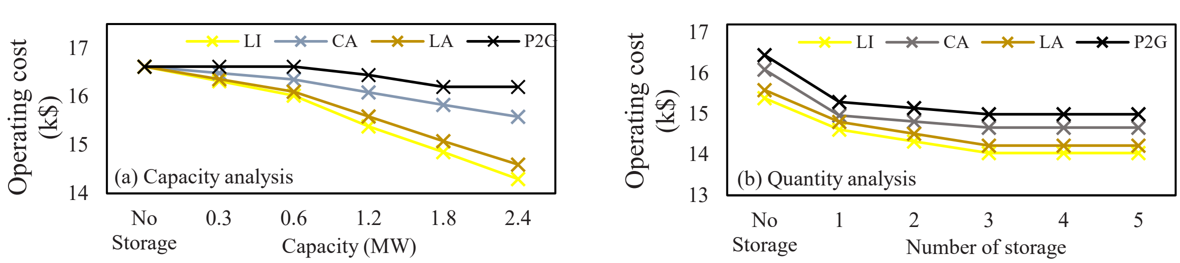

Fig. 7. Operating cost versus installing capacities and quantity of storage systems.

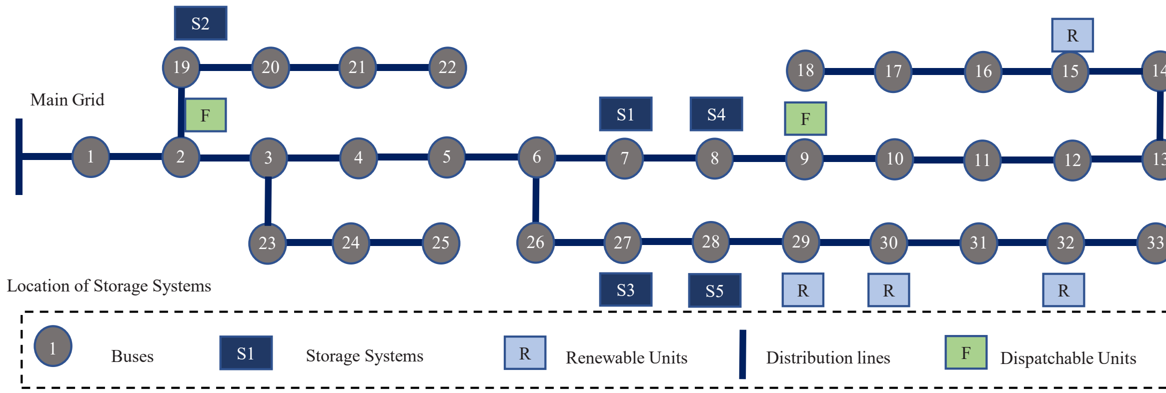

Fig. 8. Location of the energy storage systems to be installed (obtained in the sensitivity analysis).

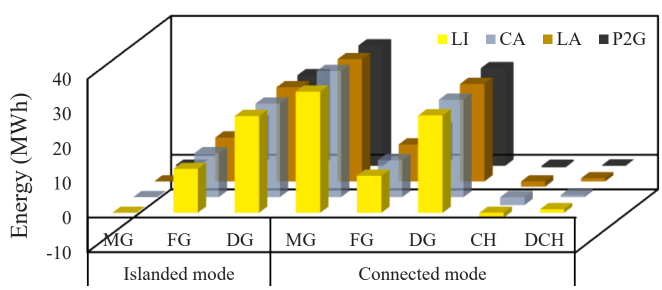

Fig. 9. Role of MG, FGs, DGs, and storage systems in demand provision in the presence of different types of storage systems.

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

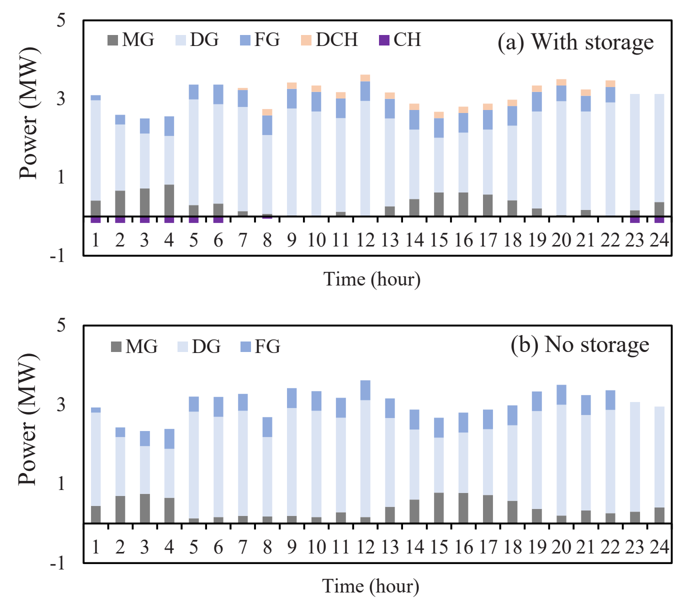

Fig. 11. Hourly dispatch of different components in the microgrid considering LA storage system-a low demand and a high availability of renewable resources.

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

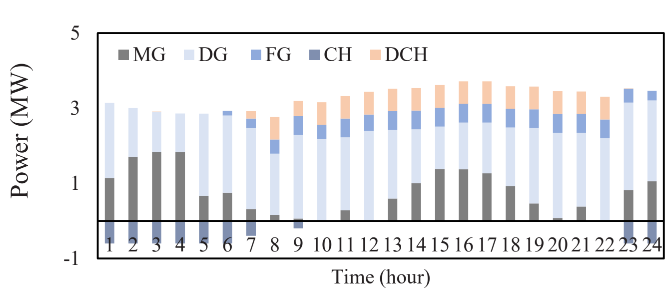

Fig. 10. Hourly dispatch of different components in microgrid considering LA storage system.

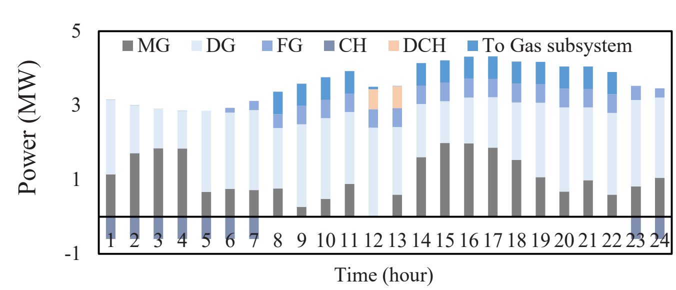

Fig. 12. Hourly dispatch of different components in microgrid considering P2G systems.

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,

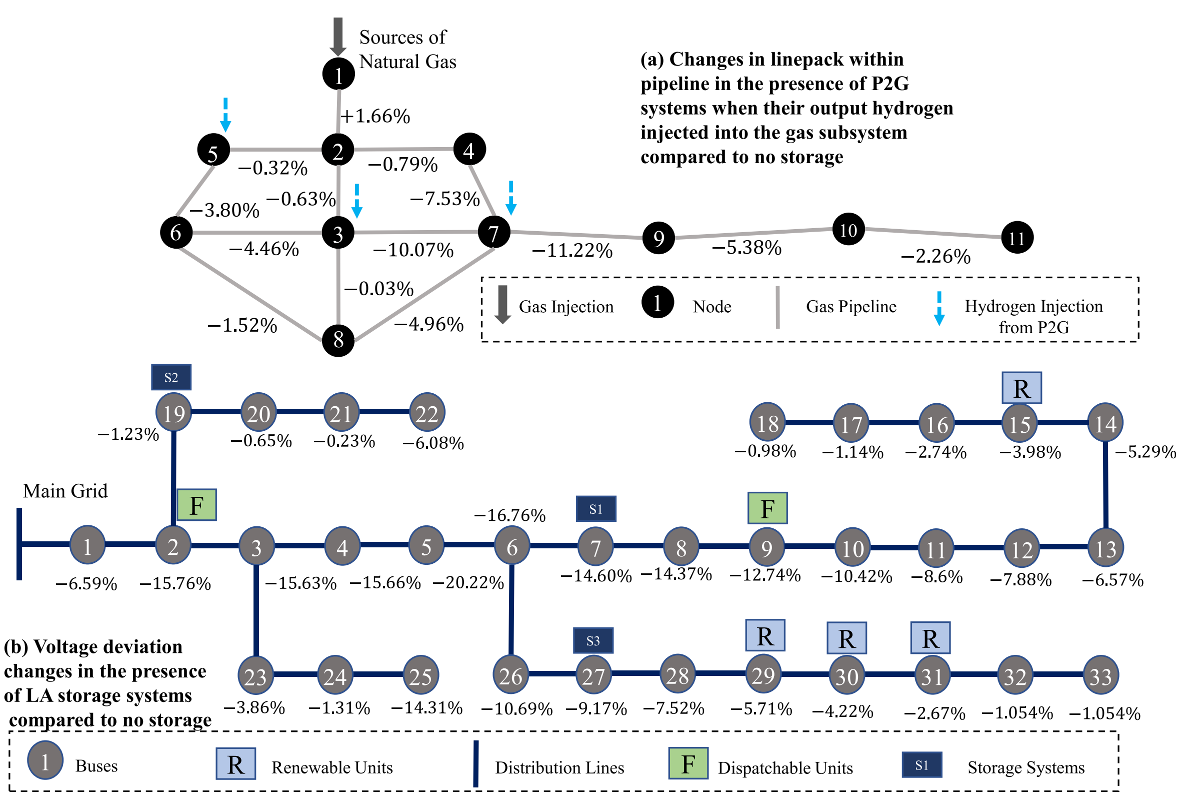

Fig. 13. Voltage deviation and linepack changes compared to when no storage systems exist.

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.

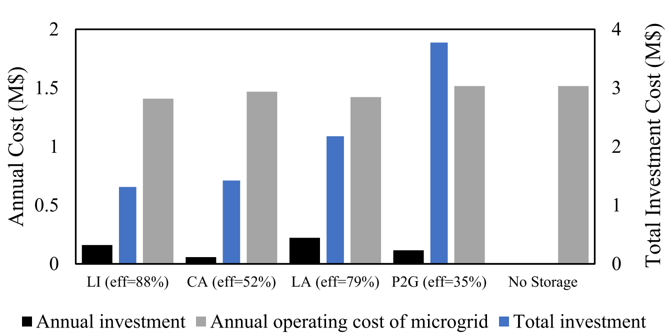

Fig. 14. Comparison of total investment costs, annual cost of investment, and annual operating cost for different storage systems.

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' lifespan, 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.

Acknowledgements

Hossein Ameli gratefully acknowledges the EPSRC-funded programs "High efficiency reversible solid oxide cells for the integration of offshore renewable energy using hydrogen" under grant number EP/W003597/1 as well as the "ZeroCarbon Emission Integrated Cooling, Heating and Power (ICHP) Networks" under award number EP/T022949/1.

References

[1] Guzović Z, Duić N, Piacentino A, Markovska N, Mathiesen BV, Lund H. Paving the way for the paris agreement: contributions of SDEWES science. Energy 2023;263. https://doi.org/10.1016/j.energy.2022.125617.

[2] Breyer C, Khalili S, Bogdanov D, Ram M, Oyewo AS, Aghahosseini A, et al. On the history and future of 100% renewable energy systems research. IEEE Access 2022;10:78176–218. https://doi.org/10.1109/ACCESS.2022.3193402.

[3] Vahedipour-Dahraie M, Rashidizadeh-Kermani H, Anvari-Moghaddam A, Siano P, Catalão JPS. Short-term reliability and economic evaluation of resilient microgrids under incentive-based demand response programs. Int J Electr Power Energy Syst 2022;138:107918. https://doi.org/10.1016/J.IJEPES.2021.107918.

[4] Younesi A, Shayeghi H, Safari A, Siano P. Assessing the resilience of multi microgrid based widespread power systems against natural disasters using Monte Carlo Simulation. Energy 2020;207:118220. https://doi.org/10.1016/J.ENERGY.2020.118220.

[5] Wei W, Chen Y, Wang C, Wu Q, Shahidehpour M. Nodal flexibility requirements for tackling renewable power fluctuations. IEEE Trans Power Syst 2021;36:3227–37. https://doi.org/10.1109/TPWRS.2020.3045223.

[6] Hemmati M, Mirzaei MA, Abapour M, Zare K, Mohammadi-ivatloo B, Mehrjerdi H, et al. Economic-environmental analysis of combined heat and power-based reconfigurable microgrid integrated with multiple energy storage and demand response program. Sustain Cities Soc 2021;69:102790. https://doi.org/10.1016/J.SCS.2021.102790.

[7] Xiang Y, Cai H, Liu J, Zhang X. Techno-economic design of energy systems for airport electrification: a hydrogen-solar-storage integrated microgrid solution. Appl Energy 2021;283. https://doi.org/10.1016/j.apenergy.2020.116374.

[8] Kiptoo MK, Lotfy ME, Adewuyi OB, Conteh A, Howlader AM, Senjyu T. Integrated approach for optimal techno-economic planning for high renewable energy-based isolated microgrid considering cost of energy storage and demand response strategies. Energy Convers Manag 2020;215:112917. https://doi.org/10.1016/J.ENCONMAN.2020.112917.

[9] Mazzola S, Astolfi M, Macchi E. The potential role of solid biomass for rural electrification: a techno economic analysis for a hybrid microgrid in India. Appl Energy 2016;169:370–83. https://doi.org/10.1016/J.APENERGY.2016.02.051.

[10] Herenčić L, Melnjak M, Capuder T, Andročec I, Rajšl I. Techno-economic and environmental assessment of energy vectors in decarbonization of energy islands. Energy Convers Manag 2021;236:114064. https://doi.org/10.1016/J.ENCONMAN.2021.114064.

[11] Martínez Ceseña EA, Good N, Syrri ALA, Mancarella P. Techno-economic and business case assessment of multi-energy microgrids with co-optimization of energy, reserve and reliability services. Appl Energy 2018;210:896–913. https://doi.org/10.1016/J.APENERGY.2017.08.131.

[12] Mukherjee U, Maroufmashat A, Ranisau J, Barbouti M, Trainor A, Juthani N, et al. Techno-economic, environmental, and safety assessment of hydrogen powered community microgrids; case study in Canada. Int J Hydrogen Energy 2017;42:14333–49. https://doi.org/10.1016/J.IJHYDENE.2017.03.083.

[13] Seedahmed MMA, Ramli MAM, Bouchekara HREH, Shahriar MS, Milyani AH, Rawa M. A techno-economic analysis of a hybrid energy system for the electrification of a remote cluster in western Saudi Arabia. Alex Eng J 2022;61:5183–202. https://doi.org/10.1016/J.AEJ.2021.10.041.

[14] Mun H, Moon B, Park S, Yoon Y. A study on the economic feasibility of stand-alone microgrid for carbon-free island in korea. Energies 2021;14:1913. https://doi.org/10.3390/EN14071913. 2021;14:1913.

[15] Tan C, Yu M, Wang J, Geng S, Niu D, Tan Z. Feasibility study on the construction of multi-energy complementary systems in rural areas—eastern, central, and western parts of China are taken as examples. Energy 2022;249:123571. https://doi.org/10.1016/J.ENERGY.2022.123571.

[16] Barberis S, Rivarolo M, Bellotti D, Magistri L. Heat pump integration in a real poly-generative energy district: a techno-economic analysis. Energy Convers Manag X 2022:15. https://doi.org/10.1016/J.ECMX.2022.100238.

[17] Lorestani A, Gharehpetian GB, Nazari MH. Optimal sizing and techno-economic analysis of energy- and cost-efficient standalone multi-carrier microgrid. Energy 2019;178:751–64. https://doi.org/10.1016/J.ENERGY.2019.04.152.

[18] Lorestani A, Ardehali MM. Optimization of autonomous combined heat and power system including PVT, WT, storages, and electric heat utilizing novel evolutionary particle swarm optimization algorithm. Renew Energy 2018;119:490–503. https://doi.org/10.1016/J.RENENE.2017.12.037.

[19] Maleki A, Askarzadeh A. Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system. Int J Hydrogen Energy 2014;39:9973–84. https://doi.org/10.1016/J.IJHYDENE.2014.04.147.

[20] Wasilewski J. Optimisation of multicarrier microgrid layout using selected metaheuristics. Int J Electr Power Energy Syst 2018;99:246–60. https://doi.org/10.1016/J.IJEPES.2018.01.022.

[21] Cao W, Xiao JW, Cui SC, Liu XK. An efficient and economical storage and energy sharing model for multiple multi-energy microgrids. Energy 2022;244. https://doi.org/10.1016/J.ENERGY.2022.123124.

[22] Ehsan A, Yang Q. Scenario-based investment planning of isolated multi-energy microgrids considering electricity, heating and cooling demand. Appl Energy 2019;235:1277–88. https://doi.org/10.1016/J.APENERGY.2018.11.058.
[23] Ak V, Verma A, Talwar R. Optimal techno-economic sizing of a multi-generation microgrid system with reduced dependency on grid for critical health-care, educational and industrial facilities. Energy 2020;208:118248. https://doi.org/10.1016/J.ENERGY.2020.118248.
[24] Fioriti D, Pintus S, Lutzemberger G, Poli D. Economic multi-objective approach to design off-grid microgrids: a support for business decision making. Renew Energy 2020;159:693–704. https://doi.org/10.1016/J.RENENE.2020.05.154.
[25] Lorestani A, Ardehali MM. Optimal integration of renewable energy sources for autonomous tri-generation combined cooling, heating and power system based on evolutionary particle swarm optimization algorithm. Energy 2018;145:839–55. https://doi.org/10.1016/J.ENERGY.2017.12.155.
[26] Dhundhara S, Verma YP, Williams A. Techno-economic analysis of the lithium-ion and lead-acid battery in microgrid systems. Energy Convers Manag 2018;177:122–42. https://doi.org/10.1016/J.ENCONMAN.2018.09.030.
[27] Bhatt A, Ongsakul W, Madhu MN. Optimal techno-economic feasibility study of net-zero carbon emission microgrid integrating second-life battery energy storage system. Energy Convers Manag 2022;266:115825. https://doi.org/10.1016/J.ENCONMAN.2022.115825.
[28] de Aquino CCCB, Vila CU. Optimal dispatch and technical and economic feasibility analysis of residential microgrids considering demand side management. Braz Arch Biol Technol 2021;64:1–14. https://doi.org/10.1590/1678-4324-75YEARS-2021200293.
[29] Khan MJ, Yadav AK, Mathew L. Techno economic feasibility analysis of different combinations of PV-Wind-Diesel-Battery hybrid system for telecommunication applications in different cities of Punjab, India. Renew Sustain Energy Rev 2017;76:577–607. https://doi.org/10.1016/J.RSER.2017.03.076.
[30] Khan FA, Pal N, Saeed SH. Optimization and sizing of SPV/Wind hybrid renewable energy system: a techno-economic and social perspective. Energy 2021;233. https://doi.org/10.1016/J.ENERGY.2021.121114.
[31] García-Vera YE, Dufo-López R, Bernal-Agustín JL. Techno-economic feasibility analysis through optimization strategies and load shifting in isolated hybrid microgrids with renewable energy for the non-interconnected zone (NIZ) of Colombia. Energies 2020;13:6146. https://doi.org/10.3390/EN13226146. 2020; 13:6146.
[32] Heidari M, Parra D, Patel MK. Physical design, techno-economic analysis and optimization of distributed compressed air energy storage for renewable energy integration. J Energy Storage 2021;35:102268. https://doi.org/10.1016/J.EST.2021.102268.
[33] Sawwas A, Chedid R. A techno-economic feasibility study of a green energy initiative for a university campus. Int J Smart Grid Clean Energy 2021. https://doi.org/10.12720/sgce.10.3.203-214.
[34] Singh S, Slowik A, Kanwar N, Meena NK. Techno-economic feasibility analysis of grid-connected microgrid design by using a modified multi-strategy fusion artificial bee Colony algorithm. Energies 2021;14:190. https://doi.org/10.3390/EN14010190. 2021;14:190.
[35] Selvakumar K, Anuradha R, Paul Arunkumar A. Techno-economic assessment of a hybrid microgrid using PSO. Mater Today Proc 2022;66:1131–9. https://doi.org/10.1016/J.MATPR.2022.04.919.
[36] Kharrich M, Mohammed OH, Alshammari N, Akherraz M. Multi-objective optimization and the effect of the economic factors on the design of the microgrid hybrid system. Sustain Cities Soc 2021;65:102646. https://doi.org/10.1016/J.SCS.2020.102646.
[37] Adefarati T, Bansal RC. Reliability, economic and environmental analysis of a microgrid system in the presence of renewable energy resources. Appl Energy 2019;236:1089–114. https://doi.org/10.1016/J.APENERGY.2018.12.050.
[38] Benders JF. Partitioning procedures for solving mixed-variables programming problems. Numer Math 1962;4:238–52. https://doi.org/10.1007/BF01386316/METRICS.
[39] Duran MA, Grossmann IE. An outer-approximation algorithm for a class of mixed-integer nonlinear programs. Math Program 1986;36:307–39. https://doi.org/10.1007/BF02592064/METRICS.
[40] Floudas C. Nonlinear and mixed-integer optimization: fundamentals and applications. 1995.
[41] Rajamand S. Vehicle-to-Grid and vehicle-to-load strategies and demand response program with bender decomposition approach in electrical vehicle-based microgrid for profit profile improvement. J Energy Storage 2020;32:101935. https://doi.org/10.1016/J.EST.2020.101935.
[42] Li X, Zeng Y, Lu Z. Decomposition and coordination calculation of economic dispatch for active distribution network with multi-microgrids. Int J Electr Power Energy Syst 2022;135:107617. https://doi.org/10.1016/J.IJEPES.2021.107617.
[43] da Luz T, Vila C, Ferreira F. New Benders decomposition and rolling horizon optimisation approaches to design isolated microgrids for Amazon region. Elec Power Syst Res 2023;221:109447. https://doi.org/10.1016/J.EPSR.2023.109447.
[44] Shao Z, Cao X, Zhai Q, Guan X. Risk-constrained planning of rural-area hydrogen-based microgrid considering multiscale and multi-energy storage systems. Appl Energy 2023;334:120682. https://doi.org/10.1016/J.APENERGY.2023.120682.
[45] Kim TH, Shin H, Kwag K, Kim W. A parallel multi-period optimal scheduling algorithm in microgrids with energy storage systems using decomposed inter-temporal constraints. Energy 2020;202:117669. https://doi.org/10.1016/J.ENERGY.2020.117669.
[46] Zhou H, Zheng JH, Li Z, Wu QH, Zhou XX. Multi-stage contingency-constrained co-planning for electricity-gas systems interconnected with gas-fired units and power-to-gas plants using iterative Benders decomposition. Energy 2019;180:689–701. https://doi.org/10.1016/J.ENERGY.2019.05.119.
[47] Zhang Y, Huang Z, Zheng F, Zhou R, Le J, An X. Cooperative optimization scheduling of the electricity-gas coupled system considering wind power uncertainty via a decomposition-coordination framework. Energy 2020;194:116827. https://doi.org/10.1016/J.ENERGY.2019.116827.
[48] Khodaei A. Resiliency-oriented microgrid optimal scheduling. IEEE Trans Smart Grid 2014;5:1584–91. https://doi.org/10.1109/TSG.2014.2311465.
[49] Chaudry M, Jenkins N, Strbac G. Multi-time period combined gas and electricity network optimisation. Elec Power Syst Res 2008;78:1265–79. https://doi.org/10.1016/J.EPSR.2007.11.002.
[50] Shahbazbegian V, Ameli H, Shafie-Khah M, Laaksonen H, Ameli MT, Strbac G. Optimal scheduling of gas and electricity distribution networks in microgrids: a decomposition approach. In: IEEE international conference on environment and electrical engineering and 2022 IEEE industrial and commercial power systems europe, EEEIC/I and CPS europe 2022 2022; 2022. https://doi.org/10.1109/EEEIC/ICPSEUROPE54979.2022.9854624.
[51] Osiadacz A. Simulation and analysis of gas networks. 1987.
[52] Macedo LH, Franco JF, Romero R, Rider MJ. An MILP model for the analysis of operation of energy storage devices in distribution systems. IEEE PES Transmission and Distribution Conference and Exposition-Latin America, PES T and D-LA 2016 2017; 2016. https://doi.org/10.1109/TDC-LA.2016.7805610.
[53] Macedo LH, Franco JF, Romero R, Rider MJ. An MILP model for the analysis of operation of energy storage devices in distribution systems. IEEE PES Transmission and Distribution Conference and Exposition-Latin America, PES T and D-LA 2016 2017; 2016. https://doi.org/10.1109/TDC-LA.2016.7805610.
[54] Kocis GR, Grossmann IE. Relaxation strategy for the structural optimization of process flow sheets. Ind Eng Chem Res 1987;26:1869–80. https://doi.org/10.1021/IE00069A026/ASSET/IE00069A026.FP.PNG_V03.
[55] Viswanathan J, Grossmann IE. A combined penalty function and outer-approximation method for MINLP optimization. Comput Chem Eng 1990;14:769–82. https://doi.org/10.1016/0098-1354(90)87085-4.
[56] Burer S, Letchford AN. Non-convex mixed-integer nonlinear programming: a survey. Surveys in Operations Research and Management Science 2012;17:97–106. https://doi.org/10.1016/J.SORMS.2012.08.001.
[57] Ameli H, Qadrdan M, Strbac G. Coordinated operation of gas and electricity systems for flexibility study. Front Energy Res 2020;8:120. https://doi.org/10.3389/FENRG.2020.00120/BIBTEX.
[58] Strbac G, Pudjianto D, Sansom R, Djapic P, Ameli H, Shah N, et al. Analysis of alternative UK heat decarbonisation pathways. London: London, UK: Imperial College; 2018.
[59] Mahdavi M, Alhelou HH, Cuffe P. Test distribution systems: network parameters and diagrams of electrical structural. IEEE Open Access Journal of Power and Energy 2021;8:409–20. https://doi.org/10.1109/OAJPE.2021.3119183.
[60] Abbasi E, Ameli H, Strunz K, Duc NH. Optimized operation, planning, and frequency control of hybrid generation-storage systems in isolated networks. In: IEEE PES innovative smart grid technologies conference europe; 2012. https://doi.org/10.1109/ISGTEUROPE.2012.6465719.
[61] Rahman MM, Oni AO, Gemechu E, Kumar A. Assessment of energy storage technologies: a review. Energy Convers Manag 2020;223:113295. https://doi.org/10.1016/J.ENCONMAN.2020.113295.
[62] Xiang Y, Cai H, Liu J, Zhang X. Techno-economic design of energy systems for airport electrification: a hydrogen-solar-storage integrated microgrid solution. Appl Energy 2021;283:116374. https://doi.org/10.1016/J.APENERGY.2020.116374.
[63] Haas R, Kemfert C, Auer H, Ajanovic A, Sayer M, Hiesl A. On the economics of storage for electricity: current state and future market design prospects, vol. 11. Wiley Interdiscip Rev Energy Environ; 2022. p. e431. https://doi.org/10.1002/WENE.431.
[64] Nikolaidis P, Poullikkas A. A comparative review of electrical energy storage systems for better sustainability. Journal of Power of Technologies 2017; 97: 220-245.
[65] Cruz-Soto J de la, Azkona-Bedia I, Velazquez-Limon N, Romero-Castanon T. A techno-economic study for a hydrogen storage system in a microgrid located in baja California, Mexico. Levelized cost of energy for power to gas to power scenarios. Int J Hydrogen Energy 2022;47:30050–61. https://doi.org/10.1016/J.IJHYDENE.2022.03.026.