Analytical Framework for Coordinated Planning and Operation of Multicarrier Energy Systems

Author(s): Di Somma, Marialaura; Papadimitriou, Christina; Rousis, Anastasios Oulis; Patsidis, Angelos; Shafie-Khah, Miadreza; Shahbazbegian, Vahid; Askeland, Magnus

Title: Analytical Framework for Coordinated Planning and Operation of Multicarrier Energy Systems

Year: 2024

Version: Accepted manuscript

Di Somma, M., Papadimitriou, C., Rousis, A. O., Patsidis, A., Shafie-Khah, M., Shahbazbegian, V. & Askeland, M. (2024). Analytical Framework for Coordinated Planning and Operation of Multicarrier Energy Systems. In M. Di Somma, C. Papadimitriou, G. Graditi, & K. Kok (Eds.). *Integrated Local Energy Communities: From Concepts and Enabling Conditions to Optimal Planning and Operation* (pp. 187-224). Wiley-VCH Verlag. https://doi.org/10.1002/9783527843282.ch6

Chapter 6

Analytical framework for coordinated planning and operation of multi-carrier energy systems

M. Di Somma[1], C. Papadimitriou[2], A. Oulis Rousis[3], A. Patsidis[3], M. Shafie-Khah[4], V. Shahbazbegian[4], M. Askeland[5]

[1] Department of Energy Technologies and Renewable Sources, Italian National Agency for New Technologies, Energy and Sustainable Economic Development, Rome (Italy)
[2] Eindhoven Technical University (The Netherlands)
[3] Smart Power Networks (SMPnet) Ltd. (UK)
[4] University of Vaasa (Finland)
[5] SINTEF Energy Research (Norway)

Abstract

Local multi-carrier energy systems (MCESs) offer a unique opportunity to exploit the synergies from the interplay of multiple energy carriers and utilize local renewables, thus increasing energy efficiency and supply reliability, as well as reducing dependencies from the external networks. To make them sustainable not only from the energetic and environmental perspective but also from the economic one and have a concrete option to the centralized energy systems based on fossil fuels, coordinated planning and operation on multiple time horizons is extremely important. This chapter covers all the transversal aspects related to this issue, by presenting a detailed analytical framework for the optimal design and operation of MCESs. First, the chapter presents the modelling of a wide range of generation, conversion and storage technologies that can be part of MCESs. Then, the optimization frameworks for the design and the operation problems are established, by presenting several types of objective functions, constraints and solution methodologies. The analytical frameworks are structured by covering different time-horizons from long-term system planning to day-ahead and real-time operation. The effectiveness of the tools proposed to address each of these phases will be proved with a proper case study and discussion of simulation results. In addition, a critical overview of the current commercial tools available for the optimal design and operation of MCESs will be presented, by mapping them according to several criteria as type, type of users, coverage of multi-carrier aspects, objective functions, functionalities, mathematical approach, temporal resolution and time horizons as well as pros and cons in their application to MCESs.

Keywords

Multi-carrier energy systems; optimal planning; optimal operation; mathematical programming; optimization tools.

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List of Acronyms

AC	Absorption chiller
ACOPF	AC optimal power flow
BESS	Battery energy storage system
CHP	Combined heat and power
CI	Carbon intensity
CRF	Capital recovery factor
DCOPF	DC optimal power flow
DICOPT	Discrete and continuous optimizer
DR	Demand repsonse
EDR	Incentive-based DR
EV	Electric vehicle
EZ	Electrolyser
FC	Fuel cell
G2V	Grid-to-vehicle
GB	Gas-fired boiler
GHX	Ground heat exchanger
GSHP	Grand-source heat pump
HP	Heat pump
HVAC	Heating, ventilation and air-conditioning
ICE	Internal combustion engine
ILEC	Integrated local energy community
MCES	Multi-carrier energy system
MGT	Micro-gas turbine
MILP	Mixed-integer linear programming
MINLP	Mixed-integer non-linear problem
MIP	Mixed-Integer programming
NLP	Nonlinear programming
O&M	Operation & maintenance
OPF	Optimal power flow
PV	Photovoltaic
RES	Renewable energy sources
SG	Synchronous generator
SOC	State-of-charge
SOCP-ACOPF	Second-order cone programming based ACOPF
ST	Solar thermal
TES	Thermal energy storage
TOU	Time-of-use
V2G	Vehicle-to-grid
WT	Wind turbine

1 Introduction

1.1 Benefits of local multi-carrier energy systems

Sector coupling can increase flexibility of the energy system to cope with the fluctuations in energy demand and variable renewable energy supply, while also avoiding renewable energy sources (RES) curtailment and reducing the need to reinforce existing network infrastructure. [1], [2]. The so-called Power-to-X technologies, that allow for the decoupling of power from the electricity sector for use in other sectors as heating, cooling, transport, chemicals, etc., introduce circularity in the energy system. In fact, excess from RES can be converted into fuel as hydrogen or synthetic methane that can be used on site or stored for later use, as well as re-converted again into electricity when renewable electricity supply is not sufficient to satisfy the loads. Another example of Power-to-X is represented by Power-to-Heat technologies, such as heat pumps, that can lead to cost-effective and efficient heating and cooling of buildings and industrial process heat production, allowing for lower primary energy consumption. If combined with thermal storage, they can allow thermal energy production to be shifted when renewable electricity is in excess thus closing the loop and enabling a circular approach.

Although the several benefits associated to sector coupling solutions, it is also clear that implementing it at large-scale regional or national level is extremely challenging, mainly due to the involvement of too many stakeholders with different and often conflicting goals [3]. Therefore, a bottom-up approach is preferable focusing on local multi-carrier energy systems (MCESs) offering the unique opportunity to implement sector coupling solutions at local level, thereby exploiting synergies among energy carriers available locally and increasing the efficiency in the energy resources use. The MCES paradigm is also fully in line with the ongoing paradigm shift of the energy system from centralized energy generation (largely dependent on fossil-fueled power plants) to decentralized generation, relying on small-scale RES and Combined Heat and Power (CHP) units not connected to the high-voltage or gas grid, namely usually small-scale plants that supply electricity and heat to a building, industrial site or community, potentially selling back surplus electricity. MCESs may offer several benefits deriving from the linking of sector coupling and decentralized generation that are discussed below.

- Producing energy close to where it is used allows **exploiting RES available locally**, such as wind, solar, biomass, geothermal, hydro, waste, etc.

- An **increased energy efficiency** is achievable through: (1) the use of waste heat from power generation processes or reduced transmission losses); (2) the increased use of renewable, carbon-neutral or low-carbon sources of fuel; (3) reduced exchange of energy on large distances that also contributes to delay the need of new infrastructures or their reinforcement.
- **Higher flexibility** for generation matching local demand patterns for electricity and heat is achievable.
- **End-user engagement** is promoted including households, small communities, or businesses that own and operate energy generation and storage assets available locally, including solar photovoltaic (PV) panels, wind turbines (WT), CHP, battery storage and electric mobility (e.g., in electric vehicles (EVs), e-bikes, e-scooters). Moreover, end-user engagement is also fostered through the inclusion of demand response (DR) programs. On the other hand, development of local energy generation contributes to achieve energy self-sufficiency.
- **Addressing energy system vulnerability** since local energy production and consumption increases the energy security in terms of optimal use of local resources, reduction of losses, congestions, reduction or delay in infrastructural investments [4].
- **Addressing energy poverty** as the energy generated locally allows profits remaining in the local system as a community helping to bring down the cost of energy in the long run, whilst also inducing the emergence of local value chains addressing energy poverty in low income, inhabited or marginal areas.

To achieve the aforementioned benefits and make MCES sustainable not only from the energetic and environmental perspective but also from the economic one thus having a concrete option to centralized energy systems, coordinated planning and operation on multiple time horizons is extremely important. As extensively discussed in Chapter 5, planning of MCES is a complex decision-making process aiming at their optimal design namely the identification of the optimal configuration in terms of choice of technologies and sizes by considering one or multiple objective functions. On the other hand, optimal operation planning (day-ahead or real-time) aims at finding the optimized daily or real-time operation strategies of the MCES, also in this case, by considering one or multiple objective functions.

1.2 The optimization framework for coordinated planning and operation of MCES

The aim of this chapter is to cover all the transversal aspects related to the coordinated planning and operation of MCES, by presenting a comprehensive analytical framework for the optimal design and operation problems, structured to cover different time horizons from long-term system planning to day-ahead and real time operation. The system planning framework has the goal to come up with the optimal configuration in MCES, by replying to questions as how to develop the system in terms of types and sizes of technologies. Essential input are: system predefined superstructure with potential technologies to be installed and energy flows needed by the end users; characteristics of potential technologies options; users' demand profiles in representative days; renewables availability. The approach used for the optimal planning can be the economic or the multi-criteria optimization, considering for instance economic and environmental criteria. The day-ahead operation planning framework, represented in Figure 1a) allows achieving the day-ahead scheduling of MCES with the support of forecasting tools for RES generation, energy prices for electricity and gas and users' multi-energy demand or scenario generation tools for the same data aiming at the stochastic optimization of MCES. The short-term operation planning framework represented in Figure 1b) has the main goal to find the optimal real-time scheduling of the MCES, given its configuration, with the support of forecasting tools for RES generation, energy prices and user demand.

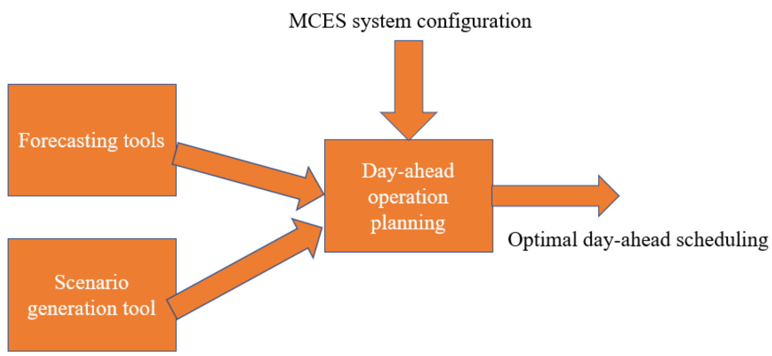
The optimization of MCESs necessitates the establishment of objective functions that capture the desired outcomes and priorities of the system's stakeholders. These objective functions serve as quantitative metrics to guide the optimization process, enabling the efficient utilization of energy resources and the achievement of specific system goals. The choice of objective function(s) is driven by the specific objectives, system characteristics, and stakeholder preferences. Some examples of objective functions that can be used in the context of MCES, are presented as follows:

1. **Cost Minimization**: One of the primary objectives is often to minimize the overall cost of the MCES. This includes minimizing the costs associated with energy generation, storage, conversion and distribution, considering investment and/or operation costs.
2. **Emissions Reduction**: Another important objective is to reduce the environmental impact of the energy system by minimizing greenhouse gas emissions or pollutant emissions. This objective promotes the integration of RES and the efficient utilization of low-carbon technologies.

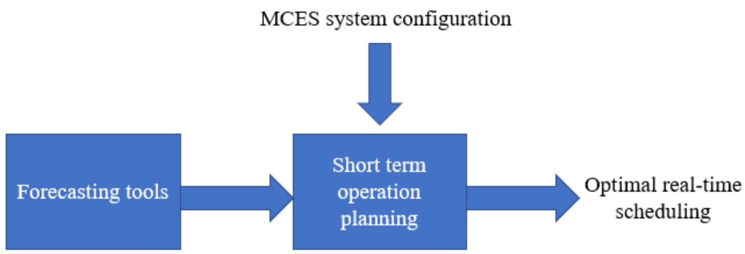
3. **Reliability and Resilience**: This objective function focuses on enhancing the reliability and resilience of the MCES. This may involve minimizing the risk of energy shortages or blackouts, ensuring sufficient energy reserves, or optimizing the response to contingencies and disturbances.
4. **DR and Flexibility**: This objective function aims to incentivize DR programs or flexible energy usage patterns to achieve a more balanced and efficient system operation. This involves optimizing the coordination between energy supply and demand and maximizing the utilization of flexible loads and energy storage.
5. **Renewable Energy Integration**: The objective function prioritizes the integration of RES to maximize their utilization and minimize dependence on fossil fuels. This can include maximizing the share of renewable energy in the overall energy mix or optimizing the utilization of available renewable resources.

It is important to note that the selection of the objective function depends on the specific goals, system characteristics, and stakeholder priorities in each case. The combination and weighting of these objective functions may vary to reflect the unique requirements and objectives of the MCES under consideration. By understanding and appropriately formulating the objective function(s), stakeholders can effectively navigate the trade-offs and complexities inherent in MCESs, paving the way for sustainable and efficient system operation.

In the following, the modelling of a wide range of generation, conversion and storage technologies that can be part of MCESs is presented in Section 2. The detailed optimization frameworks for the design and the day-ahead and the real-time operation problems are discussed in Section 3, 4 and 5, respectively, by also discussive representative case studies to demonstrate the effectiveness of the optimization models. A detailed overview of the current commercial tools available for the optimal planning of MCESs is presented in Section 6, by mapping them according to several criteria as type, type of users, coverage of multi-carrier aspects, objective functions, functionalities, mathematical approach, temporal resolution and time horizons as well as pros and cons in their application to MCESs.



a)



b)

Figure 1: Scheme of the optimization framework for MCES for a) day-ahead scheduling and b) real-time scheduling

2 Modelling of energy technologies in MCES

In this section, modelling of energy technologies that can be part of MCES is analyzed in detail. In particular, the modelled technologies are subdivided into the following categories: RES, primary energy technologies, secondary energy technologies, and storage systems as represented in Figure 2.

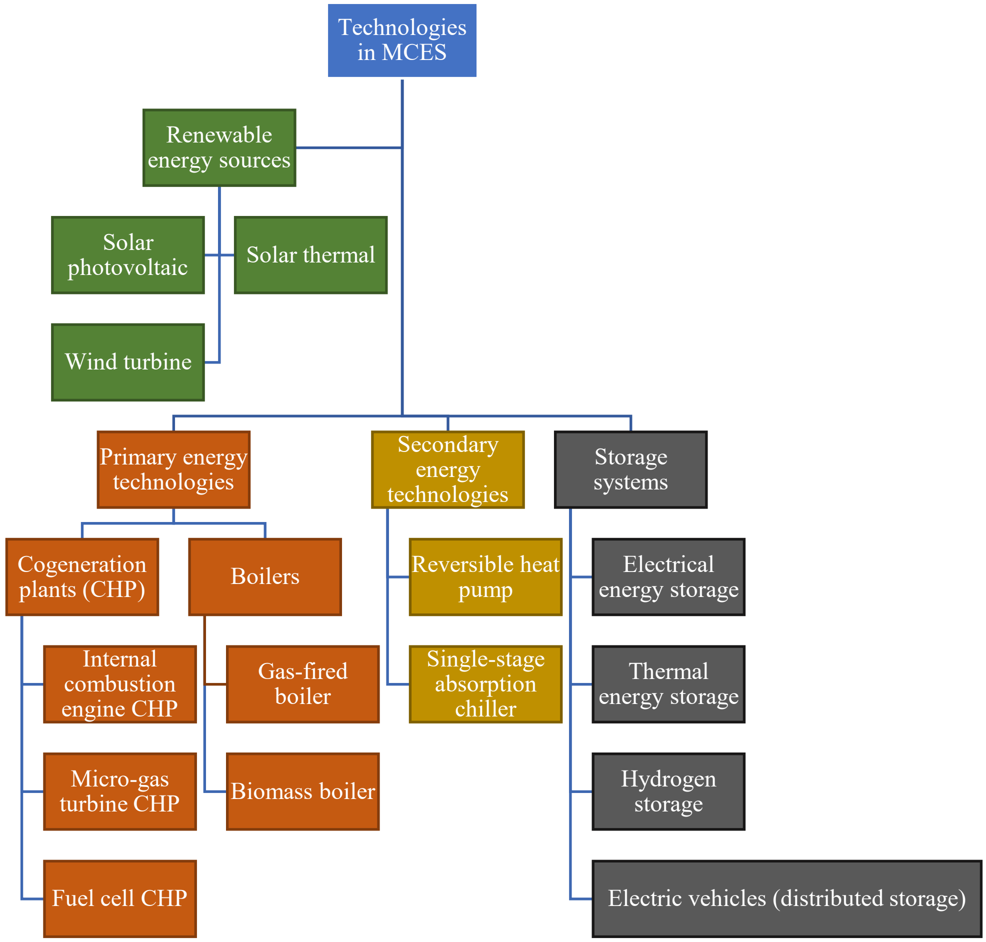


Figure 2: Energy technologies modelled in MCES

2.1 Renewable energy sources (RES)

Photovoltaic systems (PV), solar collectors for domestic hot water production and wind turbines are the RES here considered.

Solar PV

Solar PV can be used to satisfy the user electricity demand within MCES. The model representing the PV system is expressed below:

$$P_{PV,d,t} = A_{PV}\eta_{PV}^{e}I_{d,t}, \forall d,t \quad (1)$$

where $P_{PV,d,t}$ is the generated power at time t of day d, depending on the installed PV area, A_{PV}, the electric efficiency of the PV panels, η_{PV}^{e}, and the solar irradiance at time t of day d, $I_{d,t}$.

Solar thermal

Solar thermal (ST) can be used to satisfy the user domestic hot water within MCES. The model representing the solar thermal system is expressed below:

$$H_{ST,d,t} = A_{ST}\eta_{ST}^{th}I_{d,t}, \forall d, t \tag{2}$$

where $H_{ST,d,t}$ is the generated thermal power at time t of day d, depending on the installed ST area, A_{ST}, the thermal efficiency of the solar collectors, η_{ST}^{th}, and the solar irradiance at time t of day d, $I_{d,t}$.

Wind turbines

Wind turbines (WT) can be used to satisfy the user electricity demand within MCES. For a typical WT, it is assumed that it starts generating at the cut-in wind speed v_c, the generated power increases linearly as the wind speed increases from v_c to the rated wind speed v_R, the rated power is provided when the wind speed varies from v_R to the cut-out wind speed v_F at which the wind turbine will be shut down for safety considerations (all the variables are assumed known based on weather and type). Then, the model of WT generators is expressed below:

$$P_{WT,d,t} = \begin{cases} P_{WT}\frac{v_{d,hr}-v_c}{v_R-v_c} & v_c \leq v_{d,t} \leq v_R \\ P_{WT} & v_R \leq v_{d,t} \leq v_F \\ 0 & v_{d,t} < v_c \quad v_{d,t} > v_F \end{cases} \quad \forall d, t \tag{3}$$

where $P_{WT,d,t}$ is the generated power at time t of day d, whereas P_{WT} is the WT rated power.

2.2 Primary energy technologies

Primary energy technologies include cogeneration plants, gas-fired and biomass boilers.

Cogeneration plants

Cogeneration plants (CHP) may include internal combustion engine (ICE), micro-gas turbine (MGT) and fuel cell (FC) as prime mover and can be used to satisfy the user electricity and thermal demand and the cooling demand through an absorption chiller within MCES. Taking the CHP with an ICE as an example, the amount of natural gas required by the prime mover to produce the power is formulated as:

$$G_{CHP\ ICE,d,t} = \frac{P_{CHP\ ICE,d,t}}{\eta_{CHP\ ICE}^{e}LHV_{NG}}, \forall d, t \tag{4}$$

where $\eta_{CHP\ ICE}^{e}$ is the electrical efficiency of the CHP and LHV_{NG} is the lower heat value of natural gas.

The thermal power recovered from the prime mover is formulated as:

$$H_{CHP\ ICE,d,t} = \frac{P_{CHP\ ICE,d,t}\eta_{CHP\ ICE}^{th}}{\eta_{CHP\ ICE}^{e}}, \forall d, t \tag{5}$$

where $\eta_{CHP\ ICE}^{th}$ is the thermal efficiency of the CHP.

The following equations can be considered to model the CHP FC and electrolyser (EZ) [5].

$$H_{2_{CHP\ FC,d,t}} = \frac{P_{CHP\ FC,d,t}}{(\eta_{CHP\ FC}^{e} LHV_{H_2})}, \forall d,t \tag{6}$$

$$P_{EZ,d,t}^{req} = \frac{H_{2_{CHP\ FC,d,t}} LHV_{H2}}{\eta_{EZ}^{e}}, \forall d,t \tag{7}$$

Eq. (6) allows calculating the amount of hydrogen needed by the CHP FC to produce power and depends on the electrical efficiency of the FC and the hydrogen lower heat value. Eq. (7) allows calculating the power required by the EZ to produce hydrogen and depends on the EZ electrical efficiency.

The thermal power recovered from the CHP FC is formulated as in Eq. (5).

Boilers

Boilers may include gas-fired and biomass boilers and can be used to satisfy the thermal user demand in MCES. Taking the gas-fired boiler (GB) as an example, the amount of natural gas required by the GB to produce the thermal power is formulated as:

$$G_{GB,d,t} = \frac{H_{GB,d,t}}{\eta_{GB}^{th} LHV_{NG}}, \forall d,t \tag{8}$$

where η_{GB}^{th} is the GB thermal efficiency. The model of the biomass boiler can be expressed similarly, by considering the lower heat value of biomass used to feed the boiler.

2.3 Secondary energy technologies

Secondary energy technologies include reversible heat pumps and single-stage absorption chillers.

Reversible heat pump

Reversible heat pump (HP) can be used to satisfy the user thermal or cooling demand within MCES in the heating or cooling mode, respectively. Considering the heating mode, the HP model can be expressed as:

$$P_{HP,d,t}^{HM,req} = \frac{H_{HP,d,t}}{COP_{HP}^{HM}}, \forall d,t \tag{9}$$

which links the power required by the HP, $P_{HP,d,t}^{HM,req}$, to the thermal power provided, $H_{HP,d,t}$, through its coefficient of performance COP_{HP}^{HM}. The model is similar for the HP operating in cooling mode.

Single-stage absorption chiller

Single-stage absorption chiller (AC) can be used to meet the user cooling demand within MCES and can be powered by the CHPs and boilers in the MCES. The general model for the AC is expressed below:

$$C_{AC,d,t} = \left(\sum_{CHP} H_{CHP,d,t}^{SC} + \sum_{GB} H_{GB,d,t}^{SC}\right) COP_{AC} \ \forall d,t \tag{10}$$

where $C_{AC,d,t}$ is the cooling power provided by the AC, depending on the thermal power for space cooling purposes provided by all installed CHPs and the thermal power for space cooling purposes provided by all installed boilers.

2.4 Storage systems

Storage systems include electric and thermal storage and EVs acting as distributed storage, based on the bi-directional charging concept, meaning that they cannot only absorb power from the grid while charging, but also provide vehicle-to-grid services.

Electrical energy storage

Electrical energy storage system may include battery energy storage systems (BESS) as lithium-ion. The model is expressed below:

$$SOC_{BESS,d,t} = SOC_{BESS,d,t-\Delta t} + \frac{P_{BESS,d,t}^{Ch} \eta_{BESS}^{Ch} \Delta t}{Cap_{BESS}} - \frac{P_{BESS,d,t}^{Disch} \Delta t}{\eta_{BESS}^{Dis} Cap_{BESS}}, \forall d,t \tag{11}$$

that defines the battery state-of-charge (SOC) dynamics, where $P_{BESS,d,t}^{Ch}$ and $P_{BESS,d,t}^{Disch}$ are the charging and discharging power respectively, η_{BESS}^{Ch} and η_{BESS}^{Dis} are the charging and discharging efficiencies, respectively; and Cap_{BESS} is the battery capacity.

This model is completed with the additional equations below:

$$SOC_{BESS}^{min} \leq SOC_{BESS,d,t} \leq SOC_{BESS}^{max}, \forall d,t. \tag{12}$$

$$0 \leq P_{BESS,d,t}^{Ch} \leq x_{BESS,d,t}^{Ch} P_{BESS,d,t}^{Ch,max}, \forall d,t \tag{13}$$

$$0 \leq P_{BESS,d,t}^{Disch} \leq x_{BESS,d,t}^{Disch} P_{BESS,d,t}^{Disch,max}, \forall d,t, \tag{14}$$

$$x_{BESS,d,t}^{Ch} + x_{BESS,d,t}^{Disch} \leq 1, \forall d,t, \tag{15}$$

The upper and lower limits of SOC are enforced by Eq. (12), whereas the battery charging/discharging power limits are enforced in Eqs. (13) - (15).

Thermal energy storage

Thermal energy storage (TES) may include thermal storage for heating and cooling purposes. As for the TES for heating, the state dynamic is modelled as:

$$H_{TES-Th,d,t} = H_{TES-Th,d,t-\Delta t}\big(1-\varphi_{TES-Th}(\Delta t)\big) + (H^{Ch}_{TES-Th,d,t} - H^{Disch}_{TES-Th,d,t})\Delta t, \forall d,t \quad (16)$$

meaning that the energy stored at time *t* of day *d*, $H_{TES-Th,d,t}$, depends on the non-dissipated energy stored at time (*t* – Δ*t*) of the same day $H_{TES-Th,d,t-\Delta t}$ (based on the loss fraction of the storage, $\varphi_{TES-Th}(\Delta t)$), and on the net energy flow ($H^{Ch}_{TES-Th,d,t} - H^{Disch}_{TES-Th,d,t}$). The model for TES for cooling is similar.

Hydrogen storage

The state dynamic of the hydrogen storage can be modelled as:

$$H_2{}^{sto}_{Hsto,d,t} = H_2{}^{sto}_{Hsto,d,t-\Delta t}\eta_{Hsto} + \left(H_2{}^{Ch}_{Hsto,d,t} - H_2{}^{Disch}_{Hsto,d,t}\right)\Delta t, \forall d,t. \quad (17)$$

that relates the amount of hydrogen stored at time *t* of day *d* with the one stored at previous time (*t* – Δ*t*) of the same day that depends on the efficiency of the hydrogen storage, η_{Hsto}.

Electric vehicle

As mentioned earlier, EVs can act as distributed storage with bi-directional charging services, namely grid-to-vehicle (G2V) and vehicle-to-grid (V2G).

The EV modelling is discussed below [6]. The EV is characterized by specific value for: (1) battery capacity (2) arrival and departure times at/from the charging stations, (3) the SOC at the arrival time; and (4) the SOC desired at the departure time.

Before the arrival and after the departure at/from the charging stations, the EV can be modeled as:

$$\begin{cases} P^{Ch}_{EV,d,t} = 0 \\ P^{Disch}_{EV,d,t} = 0 \end{cases}, \text{If } t < t^{arrival}_{EV}, and\ t > t^{departure}_{EV}, \forall d \quad (18)$$

where $P^{Ch}_{EV,d,t}$ is the charging power for the EV at time *t* of day *d*; $P^{Disch}_{EV,d,t}$ is the discharging power of EV at time *t* of day *d*; and $t^{arrival}_{EV}$ and $t^{departure}_{EV}$ are the arrival and departure times, respectively, at/from the charging stations for the EV.

During the parking period, the EV can be modeled as:

$$\begin{cases} SOC_{EV,d,t^{arrival}_{EV}} = SOC^{initial}_{EV,d} \\ SOC_{EV,d,t} = SOC_{EV,d,t-\Delta t} + \frac{P^{Ch}_{EV,d,t}\eta^{Ch}_{EV}\Delta t}{Cap_{EV}} - \frac{P^{Disch}_{EV,d,t}\Delta t}{\eta^{Disch}_{EV}Cap_{EV}}, \text{ if } t^{arrival}_{EV} < t < t^{departure}_{EV}, \forall d \\ SOC_{EV,d,t^{departure}_{EV}} \geq SOC^{Desired}_{EV,d} \end{cases} \quad (19)$$

where $SOC_{EV,d,t}$ is the SOC of the battery of EV at time *t* of day *d*; $SOC^{initial}_{EV,d}$ is the SOC of the battery at arrival time at charging station in day *d*; η^{Ch}_{EV} and η^{Disch}_{EV} are the charging and discharging efficiencies, respectively; Cap_{EV} is the battery capacity of EV; $SOC_{EV,d}^{Desired}$ is the desired SOC at departure time from the charging station in day d.

In addition to the EV operating mode expressed in Eq.s (18) and (19), additional operation constraints for EV are defined below:

$$\begin{cases} 0 \le P_{EV,d,t}^{Ch} \le x_{EV,d,t}^{Ch} P_{EV,d,t}^{Ch,max} \\ 0 \le P_{EV,d,t}^{Disch} \le x_{EV,d,t}^{Disch} P_{EV,d,t}^{Disch,max} \\ x_{EV,d,t}^{Ch} + x_{EV,d,t}^{Disch} \le 1 \\ SOC_{EV}^{min} \le SOC_{EV,d,t} \le SOC_{EV}^{max} \end{cases}, \text{ if } t_{EV}^{arrival} < t < t_{EV}^{departure}, \ \forall d \qquad (20)$$

which allow limiting the charging and discharging power for the EV's battery and the battery SOC.

3 The optimal design problem for MCES

Traditionally, optimal design problems considered an economic objective only. As the desired outcome is more complex, the objective formulation of optimal design problems has later been extended to also account for other factors such as environmental outcomes.

3.1 Objective function

The main metric for an economic objective is the total MCES costs, considering both operational costs of the system and investment costs. The economic objective to minimize can be formulated as:

$$C^{Tot} = C^{INV} + C^{O\&M} + C^{Energy} \qquad (21)$$

The investment cost function C^{INV} may be formulated as:

$$C^{INV} = \sum_i CRF_i\left(C_{c,i} S_i\right) \quad CRF_i = r(1+r)^{N_i}/[(1+r)^{N_i} - 1] \qquad (22)$$

The total annualized investment cost of all technologies is represented in Eq. (22). For technology i, the total annualized investment cost is calculated as the product of the capital recovery factor (CRF) (a parameter depending on the lifetime of the technology, N_i, and the interest rate, r), the capital cost (a parameter) and its designed size that is a continuous decision variable of the optimization model.

The total annual O&M cost of the MCES can be formulated as:

$$C^{O\&M} = \Delta_t \sum_i \sum_d \sum_t OM_i R_{i,d,t} \qquad (23)$$

For technology i, the total annual O&M cost is calculated by multiplying its O&M specific cost (a parameter) by its generation level, R, at time t of day d, and the time step (1 hour). For storage systems, the O&M costs can be calculated through their capacities.

The total energy cost can be formulated as:

$$C^{Energy} = \Delta t\left(\sum_i \sum_d \sum_t Pr_{NG,d} G_{i,d,t} + \sum_d \sum_t Pr_{PG,d,t} P_{PG,d,t}\right) \tag{24}$$

It is the sum of the total cost of gas calculated by multiplying the gas price (a parameter) by the total amount of gas consumed by the gas-fired technologies in the MCES, and the total cost of buying grid power calculated by multiplying the time-varying unit price of grid power (a parameter) and the total amount of power taken from the grid.

As already mentioned, a multi-objective approach is often preferable for long-term planning of MCESs to reduce also the environmental impacts represented by carbon emissions.

The environmental objective can be represented by the minimization of the total annual carbon emissions, consisting of the sum of the following functions:

$$Env^{Tot} = Env^{NG} + Env^{PG} \tag{25}$$

$$Env^{NG} = \Delta t \sum_i \sum_d \sum_t G_{i,d,t} CI_{NG} LHV_{NG} \tag{26}$$

$$Env^{PG} = \Delta t \sum_d \sum_t P_{PG,d,t} CI_{PG} \tag{27}$$

In Eq. (26), the total carbon emission associated with the gas consumed by the gas-fired technologies in the MCES and depends on the carbon intensity (CI) of gas, whereas in Eq. (27), the total carbon emission associated with the grid power depends on the carbon intensity of the power grid, which the MCES is connected to.

With the economic and environmental objectives, the optimal planning problem has two types of objective functions to be minimized. To solve this multi-objective optimization problem, the weighted-sum method can be used to have a single objective function formulated as:

$$Fobj = c\omega C^{TOT} + (1-\omega) Env^{Tot}, \tag{28}$$

where c is a constant scaling factor to keep the two objectives at the same order of magnitude, and ω is the weight for the total annual cost varying in the range of 0-1. When $\omega = 1$, it is to find the solution that minimizes the total annual cost of the MCES, and when $\omega = 0$, it is to find the solution that minimizes the total environmental impact of MCES. When varying the weight ω in the range of [0, 1], the Pareto frontier between economic and environmental objectives can be found.

3.2 Constraints

The optimization problem constraints mainly consist of three types of constraint, i.e.:

Design constraints: ensure that the designed size of each energy technology installed in MCES (a continuous decision variable) is within the minimum and maximum size values available in the market.

Operation constraints: for instance, the common operation constraint for technologies in the MCES is the technology capacity constraint.

System balance constraints: ensure that at each time *t*, the multi-energy user demand (electrical, heating and cooling demand) is satisfied by the MCES.

3.3 Solution methodology

The problem is formulated through a mixed-integer linear programming (MILP) approach. It must be mentioned that from the analysis carried out in Chapter 5, it emerged that MILP formulations are the most widely used in the literature for the design optimization of MCES, being these a good compromise between model fidelity and complexity of the optimization process, by also taking advantage of powerful MILP solution methods as branch-and-cut. In detail, the optimization problem is linear and involves both discrete (binary) and continuous variables. The binary decision variables are the existence and the operation on/off status of the energy technologies, whereas the continuous decision variables include the size of the energy technologies with the corresponding energy rate provided (power, heating and cooling), capacity of storage systems, with charging/discharging rate, and power taken from the grid. All the other variables can be classified as dependent variables.

3.4 Case study and simulation results

In case study, the investigated MCES corresponds to an integrated local energy community (ILEC) located in a neighborhood in Turin, Italy. It consists of three multi-energy microgrids, each of them associated with an end-user, namely a supermarket, a hotel, and a residential building cluster of five buildings. The entire year is divided into four seasons (i.e., cold, cold mid-, hot mid-, and hot), each of them with a representative day, and the optimization is conducted on an hourly basis for a representative day per season. It is assumed that each microgrid can be composed by the technologies with related characteristics shown in Table 1 [7], [8]. The distances between the end-users are assumed known, namely 50 m between the supermarket and the residential building clusters, 100 m between the hotel and the supermarket, and 70 m between the residential building cluster and the hotel, whereas the distance between the energy hub and its associated user is assumed null.

Table 1: Technologies candidates for the optimal planning of the ILEC with related characteristics[7] [8]

Energy technology	**Investment cost**	**Efficiency**	
		El	**Th**
CHP ICE	770-1380 €/kW	0.30-0.45	0.43-0.65
CHP MGT	1630-2490 €/kW	0.24-0.31	0.44-0.53
GB	100 €/kW		0.80
PV	2000 €/kWp		0.14
Solar thermal	200 €/m^2		0.60
Heat pump	460 €/kW		3.5/3.0
Absorption chiller	230-510 €/kW		0.80
Battery	400 €/kWh	0.75/0.75	
TES	20 €/kWh		0.95

The multi-objective optimization model is implemented by using ILOG Cplex Optimization Studio, version 12.10.0 and can be solved within 20 hours with a mixed-integer gap lower than 0.15%. The Pareto frontier obtained is shown in Figure 3. With the economic optimization, the total annual cost is minimum, equal to 572.19 k€ and the total annual emissions are maximum, i.e., 1581.05 tons of CO_2. With the environmental optimization, the total annual cost is maximum equal to 680.72 k€ and the total annual emissions are minimum, i.e., 1338.30 tons of CO_2.

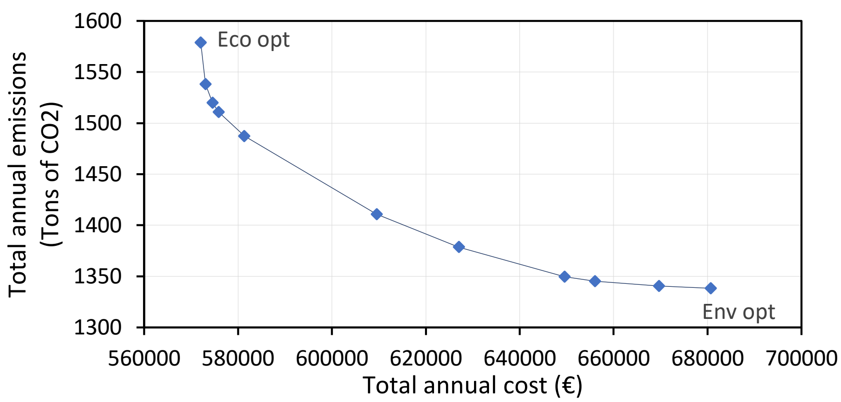


Figure 3: Pareto frontier obtained with the multi-objective optimization model [7] [8]

The optimized configurations obtained for the multi-energy microgrids are shown in Table 2 for the economic and environmental optimization (extreme points of the Pareto frontier), and they are discussed below.

Economic optimization: The PV installed area is maximum for all the users, highlighting the economic benefits coming from the low investment costs of this technology. Large storage for space heating demand is preferred over a large heat pump, since it is more convenient to store a larger amount of heat recovered from CHPs, instead of installing larger heat pumps.

Environmental optimization: The sizes of solar thermal and heat pumps for all users are all at their maximum, highlighting the environmental benefits of solar thermal for thermal purposes and of electric heat pumps supplied by the electricity network characterized in Italy by a low carbon intensity.

Table 2: Optimal configuration of the ILEC [7] [8]

Technology	***Residential building***		***Supermarket***		***Hotel***	
	Eco Opt	***Env Opt***	***Eco Opt***	***Env Opt***	***Eco Opt***	***Env Opt***
CHP ICE (kW_e)	221	22	153	118	106	21
PV (m^2)	750	433	600	408	242	290
Solar thermal (m^2)	0	317	0	192	0	210
Gas-fired boiler (kW_{th})	0	0	0	0.0	0	0
Heat pump (kW_{th})	270	1074	326	482	50	191
Absorption chiller (kW_{th})	500	0	0	0	100	0
Battery (kWh_{el})	0	0	0	0	0	10
TES (DHW) (kWh_{th})	0	522	0	200	14	242
TES (Heat) (kWh_{th})	873	0	160	0	100	0
TES (Cooling) (kWh_{th})	387	31	0	0	20	0

To prove the effectiveness of the optimal planning model, the total costs and emissions are also evaluated for a conventional energy system associated to the three users, where the grid power is used for the electricity demand, gas-fired boilers for thermal demands, and electric chillers fed by grid power for cooling demand. Under the case-specific circumstances, the calculated total annual cost is 838.95 k€ and increases of about 32% as compared with the cost for the MCES obtained with the economic optimization, whereas the calculated total annual emissions are 2003.78 tons of CO_2 and increase of about 33% as compared with the emissions for the MCES obtained with the environmental optimization.

4 Optimal day-ahead scheduling of MCES under uncertainties and by considering DR programs

In this section, the optimal operation of MCES represented by multi-energy microgrids is studied, consisting of the electricity and the natural gas distribution systems. DR programs are also integrated into the operation of the microgrid to effectively manage and optimize energy consumption in response to various conditions, such as peak demand periods when consumption is at the highest or intermittent supply due to the RES integration. The uncertainty in the parameters as electricity demand and output power of RES, are also considered to provide more realistic solutions.

DR programs are initiatives implemented by utility companies and grid operators to adjust energy consumption in response to changes in grid conditions, such as high demand, grid instability, or the need to balance energy supply and demand [9]. These programs aim to incentivize consumers to reduce or shift their electricity usage, contributing to a more reliable and efficient energy system. There are two main types of DR programs: tariff-based and incentive-based. Tariff-based programs involve the use of dynamic pricing, where electricity rates vary based on the time of day or overall grid conditions. In this case, consumers are encouraged to adjust their consumption patterns to take advantage of lower rates during off-peak hours. On the other hand, incentive-based programs offer financial rewards or other benefits to consumers who voluntarily curtail their electricity usage when called upon during peak demand events. These programs encourage consumers to participate actively in DR efforts, fostering a more flexible and responsive electricity grid.

The uncertainty in the problem of optimal operation of a multi-energy microgrid can be effectively captured through various approaches [10]. As already discussed in Chapter 5, the choice of the method depends on the specific characteristics of the microgrid and the nature of the uncertainty involved. In the problem of optimal operation of a multi-energy microgrid, where historical data is available to characterize the uncertainty in parameters, stochastic programming emerges as a more fitting approach. By modeling these uncertain parameters as random variables with known probability distributions and generating scenarios based on historical data, stochastic programming effectively captures the probabilistic nature of uncertainty.

In the following, the problem of optimal day-ahead operation of a multi-energy microgrid under uncertainty in the presence of tariff-based and incentive-based DR programs is discussed.

4.1 Objective function

Equation (29) represents the objective function of the optimal operation of a microgrid, considering both the natural gas and electricity distribution systems. The equation comprises two main terms in which the first term deals with the cost of electricity network operation (equation (30)). It encompasses various factors, such as the cost of purchased electricity from the main grid, the revenue generated by selling excess electricity back to the main grid, the cost associated with load-shedding strategies to manage in emergency cases, and the incentives provided to consumers participating in incentive-based demand response programs. The second term focuses on the cost of operating the natural gas systems within the microgrid (equation (31)). This includes expenses related to purchasing natural gas from the main network, the management cost of stored gas within pipelines, and the cost of gas shedding when necessary.

$$C^{tot} = C^{elec} + C^{gas} \tag{29}$$

$$C^{elec} = \Delta_t \left(\sum_t Pr_{PG,t} \left(P_{PG,t}^{buy} - P_{PG,t}^{sell} \right) + \sum_t C^{lsh} \, P_{PG,t}^{lsh} + \sum_t inc\left(Load_t - Load_t^{DR} \right) \right) \tag{30}$$

$$C^{gas} = \Delta_t \left(\sum_t Pr_{NG} \, G_t + \sum_t C^{gsh} \, G_t^{sh} \right) + \sum_{\Delta_t} C^{lp} \, \Delta G_{\Delta_t} \tag{31}$$

4.2 Constraints

Electricity network constraints

The microgrid scheduling model needs to adhere to various operational constraints to guarantee secure and reliable demand provision. Among these constraints, *active power balance* holds the utmost significance. It mandates that the total active power generated by distributed energy resources, along with imported power from the main grid, must precisely match the aggregate active power consumed, losses in distribution lines, and exported power to the main grid. By adhering to this principle, the microgrid efficiently fulfills the energy demands of its users, preventing any risk of system overload or underload.

In addition to active power balance, another crucial constraint is *reactive power balance* within the microgrid. The scheduling model must ensure that the reactive power generated by distributed energy resources matches the total reactive power consumed by the loads and the reactive power losses in the distribution lines. This equilibrium of reactive power is essential for upholding the voltage stability of the microgrid.

Furthermore, *Kirchhoff's law* presents another fundamental constraint in microgrid scheduling. According to this law, the voltage and current at every node within the microgrid must comply with the principle of energy conservation. The microgrid scheduling model must diligently guarantee that the voltage and current at each node in the system are balanced and satisfy the requisites of Kirchhoff's law. By adhering to this crucial principle, the microgrid can maintain a stable and efficient electrical network, ensuring the proper distribution and utilization of energy throughout the system.

Additionally, the *capacity of dispatchable units* constitutes a vital constraint that necessitates consideration in microgrid scheduling. Dispatchable units, such as diesel generators, must be operated within their designated capacity to prevent overloading or underloading. Thus, the microgrid scheduling model must meticulously consider the output of each dispatchable unit and ensure that it remains within the specified limits. The *ramp-rate limits* of dispatchable units constitute another crucial constraint in microgrid scheduling. These limits govern the rate at which the dispatchable units can ramp up or down their power output.

Gas network constraints

To accurately simulate the natural gas network within the microgrid, a set of constraints is considered. These constraints encompass various aspects of the natural gas distribution system, ensuring its safe and efficient operation. Among the constraints, the *natural gas flow balance* ensures that the amount of purchased natural gas from the main grid must be equal to the consumption at each time step within the microgrid. It guarantees that the energy demands are adequately met without shortages or wastage. *Maximum and minimum pressure at each node* is also considered to maintain the integrity of the natural gas network and limits on the pressure at each node are imposed. Furthermore, *maximum and minimum natural gas flow within pipelines' constraints* are added to restrict the maximum and minimum flow rates of natural gas through pipelines and are set to avoid overloading or underutilization of the pipeline infrastructure. Additionally, linepack refers to the amount of natural gas stored in the pipelines. *Constraints related to linepack changes* help manage the storage of natural gas, allowing the system to respond to demand fluctuations effectively. The *Panhandle equation* is utilized to relate the natural gas flow within pipelines to the pressure at nodes. This equation provides a crucial link between flow rates and pressure, enabling accurate modeling of the natural gas distribution system.

In addition to the previously mentioned constraints, a *coupling constraint* must be taken into consideration to calculate the required amount of natural gas for gas-fired technologies and add it to the gas flow constraint. This coupling constraint establishes the interdependency between the electricity and gas networks within the microgrid.

Demand response constraints

In equation (32), the load in the presence of a Tariff-based and an incentive-based DR is calculated [11]. The former is a time-of-use (TOU) DR program, and the latter is an incentive-based DR program (EDR) in which consumers decide to change their demand based on prices and incentives (INC_i). It should be noted that the cost of incentive payment for the EDR program has been added to the operating cost of the microgrid. For the TOU DR program, distinct electricity prices are considered for specific periods, including valley periods, off-peak periods, and peak periods

($Pr_{PG,t'}^{ini}$ is replaced by $Pr_{PG,t'}$). In contrast, the EDR program entails a fixed electricity purchase rate, complemented by an extra incentive offered during peak periods. In the formulation, $E_{t,t'}$ is a matrix that indicates the elasticity of demand, and $Load_{b,t}^{DR}$ and $Load_{b,t}$ represent the electric load in the presence and absence of the DR program, respectively.

$$Load_{b,t}^{DR} = Load_{b,t}\left(1 + \sum_{t'=1}^{T} E_{t,t'} \frac{\left(Pr_{PG,t'} - Pr_{PG,t'}^{ini}\right) + INC_i}{Pr_{PG,t'}^{ini}}\right) \tag{32}$$

Uncertainty consideration

To capture uncertainty and propose a stochastic model for the problem under study, two-stage stochastic programming is utilized, expressed mathematically in equation (33). In this formulation, in the first stage, a decision is made based on available information, and in the second stage, after observing uncertain factors, an adjustment decision is made. More precisely, the formulation involves defining decision variables, objective functions, and constraints for both stages, while incorporating probabilities for the uncertain factors. This approach helps in finding optimal solutions that balance initial decisions with adjustments to achieve the best possible outcome considering uncertain scenarios.

$$\begin{gathered} \text{Min } z = cx + \sum prob^s\, b^s y^s \\ \text{Subject to } Bx + D^s y^s = h^s\ \forall s \in S \\ x \geq 0\ ,\ y^s \geq 0, \text{ and} \sum prob^s = 1 \end{gathered} \tag{33}$$

Considering the above formulation, the objective function of the stochastic operation of the multi-energy microgrid should be rewritten. The changes must be implemented in the objective function of operation of the electricity subsystem (equation (30)), and constraints should be revised consequently.

$$\begin{aligned} C^{elec} = \Delta t\Bigg(&\sum_{t} Pr_{PG,t}\left(P_{PG,t}^{buy} - P_{PG,t}^{sell}\right) \\ &+ \sum_{s} prob^s\left(\sum_{t} C^{lsh}\, P_{PG,t}^{lsh} + \sum_{t} inc\left(Load_t - Load_t^{DR}\right)\right)\Bigg) \end{aligned} \tag{34}$$

4.3 Solution methodology

The optimization problem developed in the section is in the form of Mixed-Integer Nonlinear Programming (MINLP). The panhandle equation in the gas system's operating model and a set of constraints connecting voltage and current in the electricity system's operating model (i.e., the application of Kirchhoff's voltage law) are nonlinear constraints. Moreover, the binary variables represented the status of generating units. To solve this class of problem, DICOPT (DIscrete and Continuous OPTimizer) solver is employed in the GAMS software, which is based on the extensions of the outer-approximation algorithm for the equality relaxation strategy [12]. The MINLP algorithm inside DICOPT solves a series of Nonlinear Programming (NLP) and Mixed-Integer Programming (MIP) subproblems, which can be solved using any NLP or MIP solver that runs under GAMS. The performance will heavily depend on the choice of the selected subsolvers.

4.4 Case study and simulation results

In this case study, the focus lies on examining the optimal operation of a multi-energy microgrid with DR under uncertainty located in the US. The microgrid is composed of two networks: an 11-node gas distribution network and a 33-bus electricity distribution network. Gas distribution involves 11 nodes interconnected by 13 pipelines, connected to the main grid via node one. Similarly, the electricity network consists of 33 buses and 32 lines, connected to the main grid through bus one. Distributed generators, like PV systems and wind turbines, are linked to specific buses (15, 29, 30, and 32) in the electricity network. Dispatchable units are connected to buses 2 and 9, with gas-powered dispatchable units supplied through nodes 5 and 6 in the gas network. The study aims to optimize the microgrid's operation, accounting for uncertainties, and leverage demand response strategies to manage energy resources effectively. More detailed characteristics of the networks can be found in [13]. To assess DR programs, the baseline scenario without DR assumes a constant grid power price, set at 16 $/MWh. In the case of the TOU DR program, different grid power prices are considered for specific periods: 8 $/MWh during valley periods, 16 $/MWh during off-peak periods, and 21.5 $/MWh during peak periods. On the other hand, the EDR program involves a flat rate of 16 $/MWh for electricity purchases, and an additional incentive of 7 $/MWh is provided during peak periods. More detailed data about the DR programs of can be found in[11].

The optimization of the stochastic model for the operation of the multi-energy microgrid, considering DR, incorporates five scenarios, including a base case and four additional scenarios where the renewable output power and demands can increase and decrease by 5%, resulting in varying conditions to account for uncertainty. However, in practical applications, when relying on historical data, it is essential to perform scenario reduction to identify a concise yet representative set of scenarios. This approach helps capture the key characteristics of uncertainty while ensuring computational feasibility and simplicity in the analysis [15].

Simulation results

Figure 4 illustrates the effects of TOU DR and EDR on consumer electricity demand. During peak hours from 14:00 to 20:00, consumers participating in the TOU program show a modest reduction in electricity consumption, while those in the EDR program demonstrate a more significant decrease of approximately 0.6 MW. This substantial reduction in electricity demand through the EDR program provides valuable support to the grid operator in ensuring a balanced supply-demand provision during critical periods, enhancing grid stability and reliability.

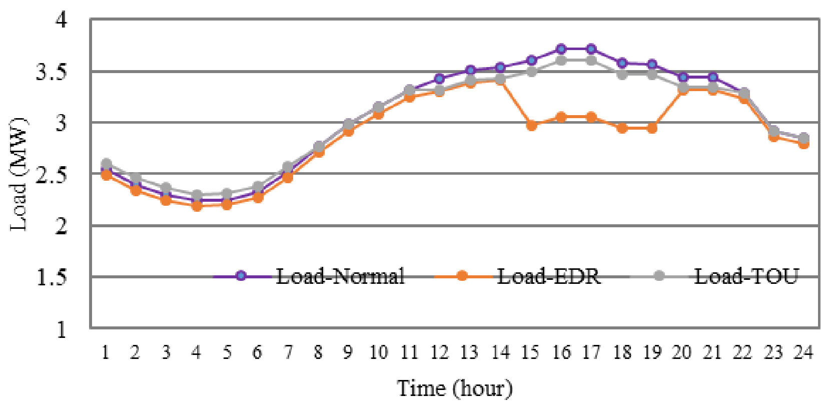
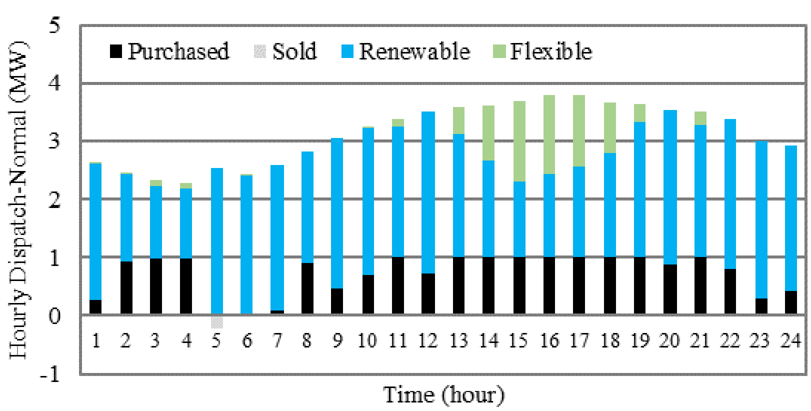


Figure 4: Load profile in the presence and absence of the demand response programs.

Figure 5 presents a comparative examination of the microgrid dispatch in three cases: without DR, with TOU DR, and with EDR. The graph clearly shows that in the presence of the EDR, there is a substantial decrease in the reliance on gas-fired units during peak operational hours compared to the other cases. This advantage of reduced reliance on gas-fired units through the EDR program offers the potential for emission reduction, making the microgrid's operations more environmentally friendly and efficient.



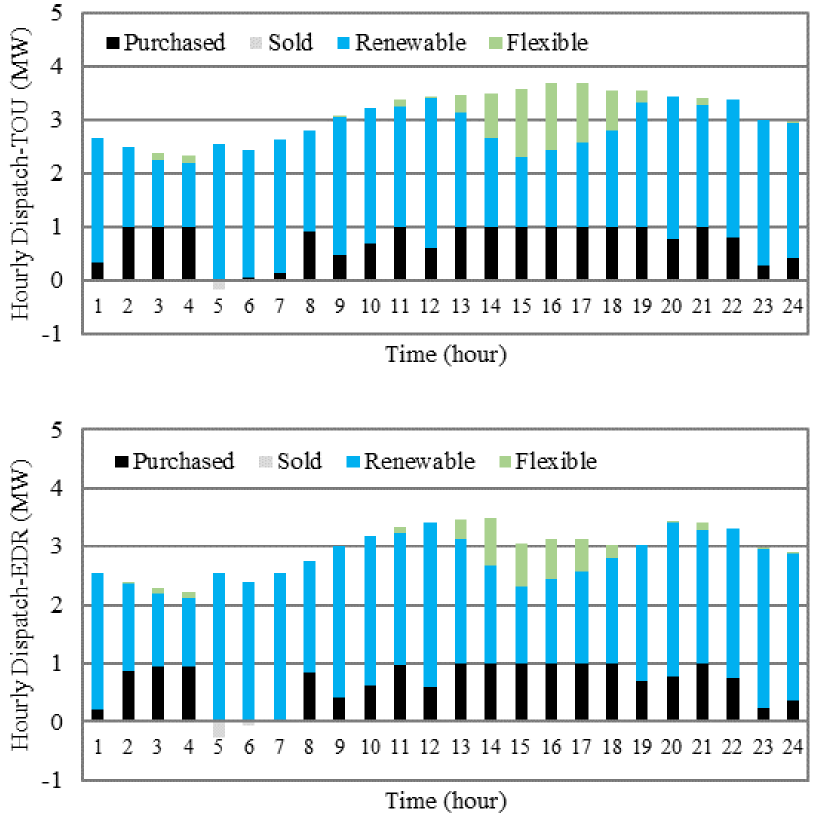


Figure 5: Hourly dispatch of the microgrid in the presence of the demand response programs.

Figure 6 examines the impact of DR programs on the operation of the gas network (i.e., gas supply and linepack), influenced by their effects on the electricity network. The graph illustrates that both the EDR program and the TOU DR program lead to reduced operation of gas-fired units. As a result of this reduction, the consumption of natural gas during peak hours also decreases. The connection between electricity and gas networks through these DR programs creates a favorable outcome, contributing to the optimization of gas network operations and enabling more efficient energy consumption during critical peak hours. Additionally, the EDR program further decreases fluctuations in stored gas within the pipelines of the gas network. This reduction in linepack fluctuations enhances the gas network's capability to effectively cope with sudden changes in demand. By moderating the variations in stored gas, the EDR program optimizes the gas network's responsiveness and resilience, enabling it to efficiently adjust to shifts in demand patterns.

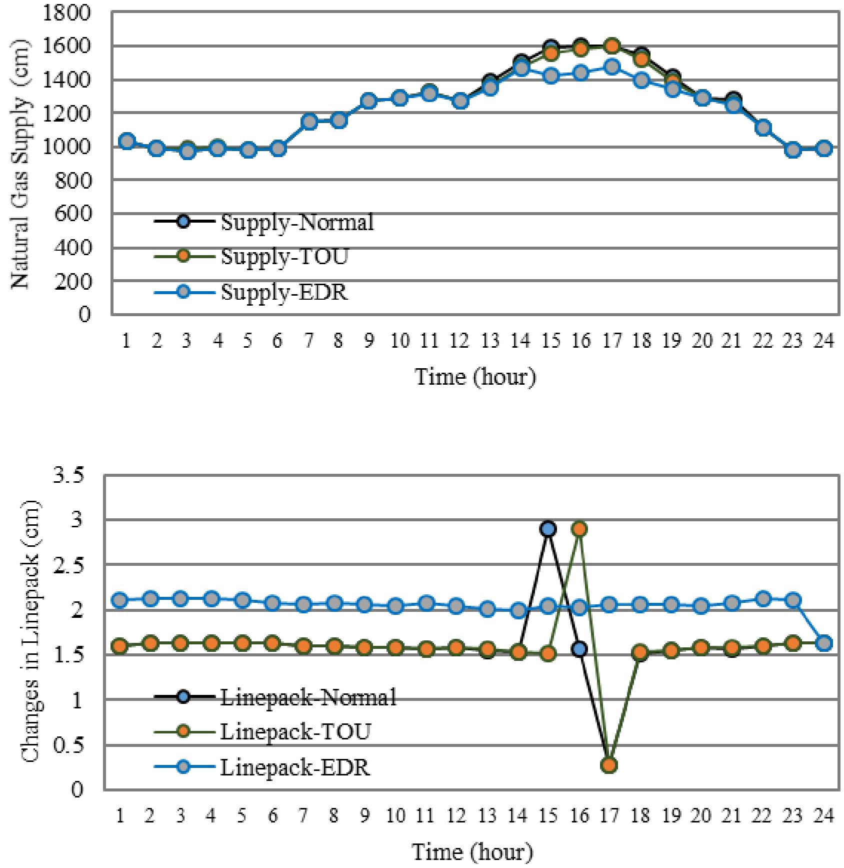
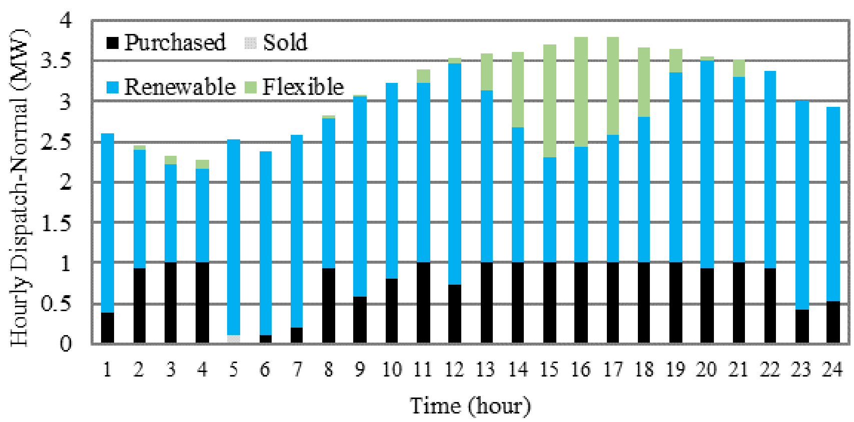
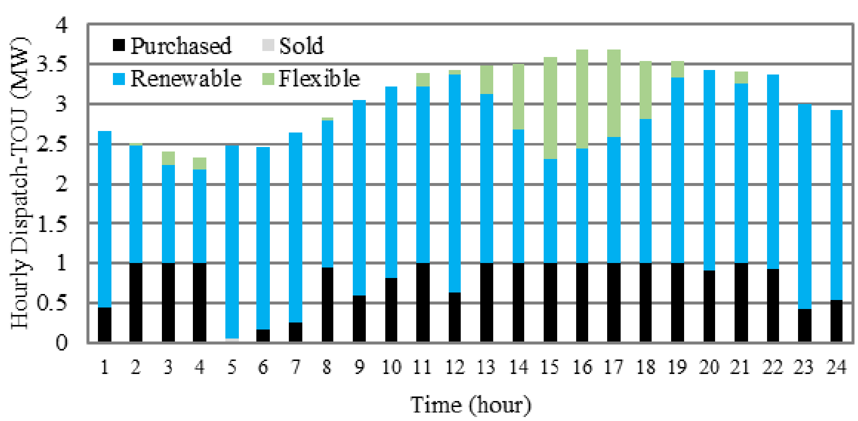


Figure 6: Natural gas supply and changes in linepack in the presence and absence of the DR programs.

Figure 7 showcases the microgrid dispatch when a stochastic model is employed. The graph provides insights into how the microgrid's energy resources are allocated and utilized under the stochastic modeling approach. Furthermore, Table 3 presents the operating costs of the microgrid in different scenarios. It compares the costs when DR programs are incorporated, and when both stochastic and deterministic considerations are considered. The table provides a comprehensive overview of the various operating cost scenarios, allowing for a detailed analysis of cost efficiency under different conditions. Together, Figure 7 and Table 3 offer valuable information regarding the microgrid's dispatch strategy and operating costs, considering the integration of DR programs and stochastic modeling techniques. These insights can be crucial for optimizing the microgrid's performance, cost-effectiveness, and overall energy management. In the microgrid's stochastic model, uncertainty is effectively managed by utilizing gas-fired units, allowing for proper handling of the inherent variability in renewable energy sources. While the stochastic model's operating cost may be higher compared to the deterministic one, it holds a crucial advantage in addressing increased energy demands during periods of limited renewable energy availability. This adaptability to changing conditions and uncertain energy supply equips the stochastic model to handle fluctuating energy demands with greater proficiency. Properly evaluating the expected costs between the stochastic and deterministic models necessitates consideration of uncertainty's value. While the deterministic model may seem more cost-effective, it assumes perfect foresight and it overlooks the dynamic nature of RES and the potential risks associated with varying energy demand. In contrast, the stochastic model provides a more realistic representation of the microgrid's performance and cost-effectiveness, considering the inherent uncertainty in renewable energy generation. In conclusion, the stochastic model's higher operating cost is justified by its ability to effectively manage uncertainties and establish a reliable and resilient energy management strategy. To compare the expected costs of both models accurately, a thorough assessment of uncertainty and the advantages it offers in ensuring flexible and robust microgrid operation is essential.





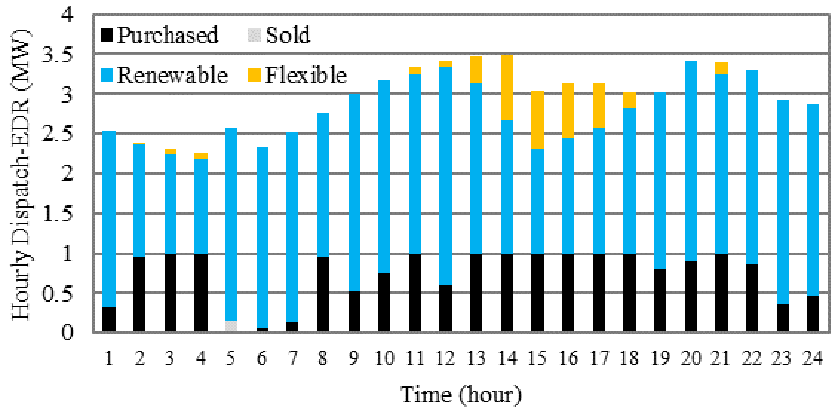


Figure 7: Hourly dispatch of the microgrid considering uncertainty.

Table 4. Operating cost of the microgrid.

DR Program	Deterministic/Stochastic	Cost	
		Electricity network ($)	Gas Network ($)
-	Deterministic	2947.96	10927.12
TOU	Deterministic	2744.84	10476.27
EDR	Deterministic	2043.42	10130.32
-	Stochastic	3066.513	11368.23
TOU	Stochastic	2857.56	10907.40
EDR	Stochastic	2130.34	10561.38

5 Optimal real-time operation of MCES

This section delves into the crucial aspect of formulating the operation of MCESs that include energy assets from three energy carriers, namely electricity, electrified heating and electrified transportation, focusing on the optimization and real-time control.

Managing MCESs creates a unique opportunity to exploit flexibility provided by carriers that until today are heavily underutilized. MCESs are inherently complex and dynamic, and their optimal operation and management encompasses the integration of various assets. These range from traditional electricity assets such as WT, solar PV and BESS, to assets from other energy carriers such as EV, HP, and heating, ventilation and air-conditioning (HVAC). Although significant work has been conducted with respect to managing networks that are penetrated by renewable energy sources and BESSs, assets from other energy carriers introduce a multitude of features, constraints and social considerations that should be accurately modelled in order to be part of a management system [16]. These characteristics render the optimization of MCES a challenging task. For example, EVs, via the appropriate protocols, can be controlled in order to essentially serve as energy storage units capable of storing and discharging electricity to the grid when instructed, however accurately forecasting their charging patterns can be quite challenging. Similarly, HPs and HVAC systems can be appropriately operated to exploit market conditions and participate in other network services, however comfort levels of the end-users shall be considered and not violated in any time.

5.1 Objective function

The objective function of the optimisation problem is formulated as a maximisation problem (expressed as the opposite minimisation problem for computational efficiency) of the renewable energy penetration. Specifically, the objective function is calculated based on Equation (35) and aims to maximise the active power output of both PV and WT units in order to reduce reliance on non-renewable energy sources.

$$\max\Big(\sum_{c\in C}\sum_{t\in T}\sum_{k\in N_{WT}} P_{WT,d,t}(k,c) + \sum_{c\in C}\sum_{t\in T}\sum_{k\in N_{PV}} P_{PV,d,t}(k,c)\Big) \tag{35}$$

where c is the contingency associated with that asset. It should be noted that the problem has been formulated as a mathematical optimization model, which is solved for 24 hours ahead in time steps of 5 minutes. The 24-hour time horizon allows for the consideration of daily trends and patterns in energy consumption and generation, while the 5-minute intervals provide the necessary granularity to capture the dynamic nature of energy demand and supply, as discussed in previous subsections.

5.2 Constraints

The development of a comprehensive mathematical model that considers the characteristics of each asset, their interactions, and finally their constraints, is a prerequisite for the optimization problem formulation. Decision (control) variables represent the controllable aspects of the system that can be adjusted to achieve the optimization goal. Parameters, on the other hand, are fixed values that define the characteristics of the system, such as the capacity of assets or their minimum operating power. By defining decision variables and parameters, constraints can then be formulated to ensure the optimization problem is feasible.

These constraints mainly refer to *technology operation constraints* as capacity constraints. The constraints considered in this work model upper and lower, active and reactive power of conventional synchronous generator, WT, PV, EV and BESS. With respect to the latter asset, other considered constraints are related to the BESS power and energy capacity, the energy conservation law and the efficiency during charging and discharging. Finally, the constraints that relate to the EV have been developed with two main operational designs at the epicenter. First, the EV is based on the bi-directional charging concept, meaning that it can absorb power from the grid while charging, but also provideV2G services as power is drawn from the EV towards the grid. Second, when the EV is charging, it is modelled as a ZIP model. In order to include EV into the operational strategy, the anticipated plug-in period is forecasted and used as an input in the optimization problem. Finally, from the electrified heating energy vector, a grand-source heat pump (GSHP) is modelled, based on a vertical U-pipe Ground Heat Exchanger (GHX) configuration. The modelling of the GSHP unit has been based on heat transfer balance equations, thermal exchange equation between building and external environment, in-building heat transfer equation, and lastly, comfort and capacity limits.

Typical n*etwork constraints* shall also be considered when designing an optimization algorithm for a MCES. These constraints ensure the optimal operation of the system while maintaining safety and stability. The constraints modelled here can be broadly classified into two types: equality constraints and inequality constraints. Equality constraints ensure that the power flow in the system satisfies certain relationships, such as Kirchhoff's laws and power balance equations. Inequality constraints impose limits on the system parameters, such as the voltage magnitude and phase at buses, as well as thermal constraints of the lines. These constraints ensure that the system operates within safe limits and prevents the occurrence of voltage instability or line overloads. Modelling of the network constraints follows well-established mathematical formulations which can be found in [17] and are based upon a fully-detailed AC optimal power flow (ACOPF).

5.3 Solution methodology

Optimal power flow (OPF) has long been recognized as a vital tool employed by network operators in various applications. Over the years, the literature has explored several OPF formulations to achieve optimal operation in distribution networks. These formulations include DC optimal power flow (DCOPF), second-order cone programming based ACOPF (SOCP-ACOPF), and ACOPF. DCOPF serves as a linearized alternative to detailed ACOPF, often employed for large-scale problems or networks where solving an ACOPF formulation would require significant time. ACOPF introduces a comprehensive mathematical representation of the network, encompassing the classical power flow equations that capture the network's physical characteristics. This meticulous modelling approach ensures accurate representation of vital network features, including frequency, voltage, and voltage angles, which are essential considerations in deriving feasible solutions. The need for detailed formulations, especially in the context of MCESs, is further amplified by the need to calculate and investigate network metrics cannot be monitored through alternative optimization modelling (e.g., DCOPF).

The formulation of the constraints and objective functions described previously is implemented using the Python programming language and leverages the Pyomo toolbox [18]. To solve the optimization problem, Pyomo employs the open-source solvers IPOPT and GLPK to solve the resulting mixed-integer non-linear problem (MINLP). Pyomo is a powerful, open-source, tool that can be used to develop mathematical models of MCES and interfaces directly with a wide range of open-source and commercial solvers.

While temporal aspects that can impede the achievement of set-points derived from ACOPF have been explored in the literature, there has been limited investigation on integrating and coordinating the ACOPF considering:

- high-level market mechanisms,
- emerging flexibility provision schemes, and
- real-time changes in network and asset status, and short-term weather and demand forecasts.

The strategy proposed in this section is targeting MCES that require constant dispatch considering the dynamic nature of the above points. The framework includes constant calculation and dispatch of set-points from the ACOPF, executed within a couple of minutes (e.g., 5 minutes). The latter builds upon two main operational directives:

1. At the distribution system level, optimization schemes are developed to dispatch control set-points to energy assets over relatively large time periods. However, to effectively handle the dynamic nature of the system, it becomes necessary to employ more granular timeframes.
2. Traditional optimization schemes operate in an open-loop framework, disregarding sophisticated market products and changes in the network conditions. To address this issue, feedback-based, adaptive optimization algorithms and architectures offer a practical solution by considering the above and constantly re-dispatching the network according to the latest available information.

When combined, a feedback-based, adaptive optimization scheme that is based on a granular, rolling-window operation, demonstrates significant potential and substantial benefits for the system operator. These algorithms, supported by relevant computing and communication systems, can enable effective control of MCESs.

5.4 Case study and simulation results

In order to validate and demonstrate the effectiveness of the proposed analytical framework for the optimal real-time operation of MCESs, a comprehensive case study was conducted. This case study serves as a practical application of the concepts and methodologies discussed thus far, providing valuable insights into the real-world implications of the optimization strategies. Through the use of simulation tools and realistic system data, the performance of the optimized operation strategy was evaluated. By examining the simulation results, the aim is to showcase the practical viability and advantages of the optimized real-time operation approach in MCESs.

To perform the case study, the considered MCES depicted in Figure 8 has been modelled in Python using Pyomo. The MCES is composed of various generation and consumption assets including:

- An interface with the upstream network
- A 33kV/11kV transformer
- Synchronous generator (SG) unit (connected at Bus 1)
- WTs (connected to Bus 1, Bus 3, Bus 4 and Bus 5)
- PVs (connected to Bus 1, Bus 2 and Bus 6)
- A BESS (connected to Bus 5)
- An EV charger (connected to Bus 3)
- A GSHP (connected at Bus 6)

Furthermore, the MCES contains non-controllable demand (connected at Bus 1, Bus 2, Bus 3, Bus 4 and Bus 5) representing typical electricity demand.

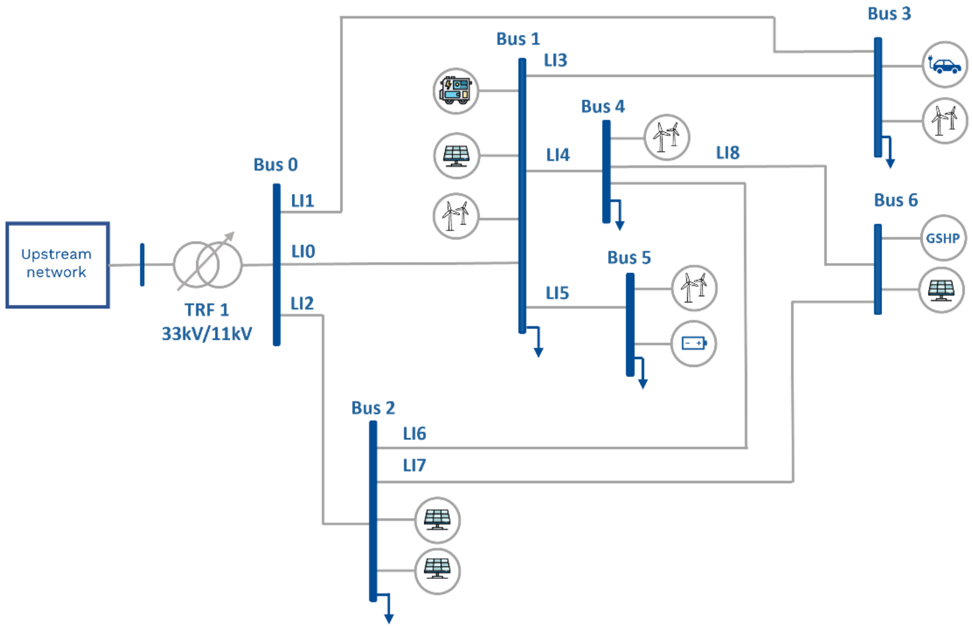


Figure 8: MCES network used in case study.

The studies presented in this section seek to showcase the outcomes of employing a fully detailed ACOPF tailored to the MCES, utilizing the mathematical formulations discussed previously. To benchmark the results, a classical load flow analysis was conducted, using typical real-world input data for all the assets of the MCES (see examples in the figures below).

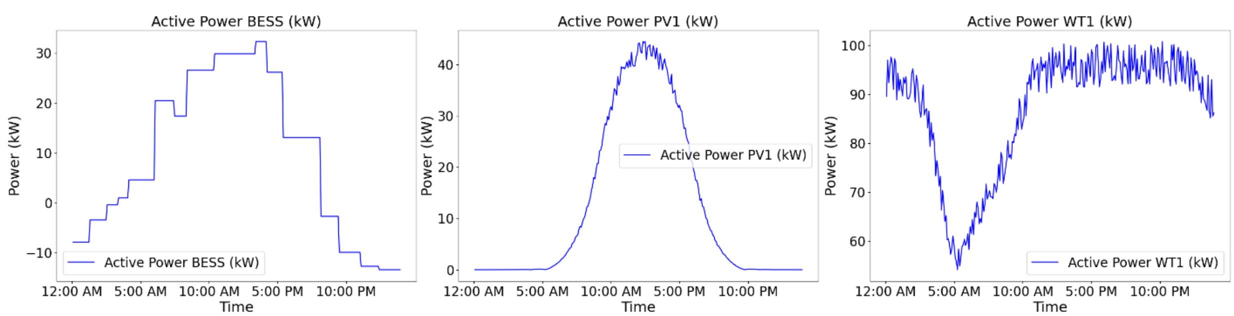


Figure 9: BESS, PV and WT input profiles for load flow analysis.

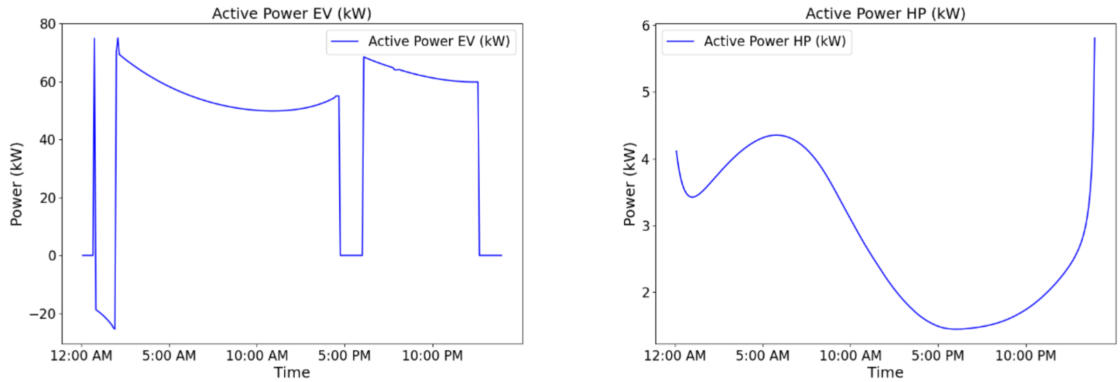


Figure 10: EV and GSHP active power input profiles for load flow analysis.

Based upon the load flow analysis, a power constraint at the substation is expected to be violated (refer to Figure 11). This is mainly due to the non-controllable nature of the RES and the participation of the BESS unit in the electricity market (i.e., pre-defined power profile based upon an assumed contractual agreement). The constraint violation, if not mitigated can lead to congestion issues and render disconnections of units imperative for the operator, meaning that end-users and asset owners operations are affected by disruptions. This underscores the importance of incorporating congestion management strategies in network management approaches, to ensure reliable and efficient operation of the MCES.

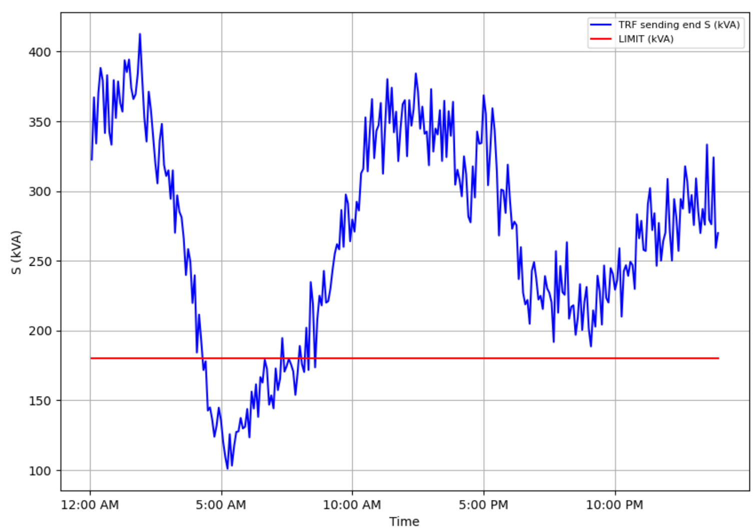


Figure 11: Transformer apparent power profile and limit extracted by load flow analysis.

To benchmark the ACOPF-based approach discussed previously, the problem was formulated with characteristics that are discussed hereafter. The objective function used for this case study is to maximize the penetration of renewable generation while mitigating any congestion challenges at the upstream network (when power flow surpasses the maximum capacity threshold of the transformer). The latter was not modelled through the objective function, but rather expressed as a constraint due to its emergent nature (prevent overloading and potential damage, outages and disconnections).

The resulting apparent power profile at the upstream substation is presented in Figure 12. Note that through the MCES optimization objective function and relevant constraints, three direct and indirect objectives have been realized:

1. Upstream substation expected constraint violation is alleviated.
2. Renewable resources are not curtailed and inject all their available power into the network.
3. Disconnections, outages and possible equipment damages risk are minimized.

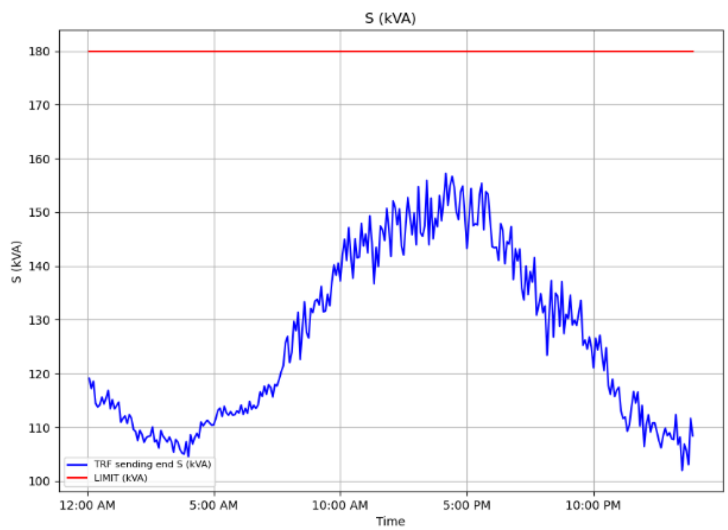


Figure 12: Transformer apparent power expected profile and limit following MCES optimization.

6 Analysis of commercial tools for the optimal design and operation of MCES

Based on the literature review, numerous tools and models exist to tackle the optimal operation and planning of MCESs. Such tools have their distinct advantages and limitations and can be categorized against different criteria. So far, universal categorization is not in place. Instead, energy planning tools can be categorized based on several criteria, including their purpose, scope, level of detail, modularity etc. This section provides a comparison among the different commercial tools based on their characteristics and specifications that are briefly described in the next. [19][20]

1.Purpose: Energy planning tools can be categorized based on their purpose, such as:

- Energy demand forecasting tools: These tools are used to forecast the future energy demand for a region or country based on various economic and demographic factors.
- Energy supply planning tools: These tools are used to determine the optimal mix of energy sources (e.g., coal, gas, renewable energy) to meet the forecasted energy demand.
- Energy efficiency assessment tools: These tools are used to evaluate the potential energy savings that can be achieved through various energy efficiency measures.
- Energy system modeling tools: These tools are used to simulate the operation of the energy system and evaluate the impact of different policies and scenarios on the system's performance.

2.Scope: Energy planning tools can also be categorized based on their scope, which can be regional, national, or global. Some tools are designed for specific regions or countries, while others are used to model the global energy system. So, this specification provides the targeted scale of the system model, which can range from large e.g., national networks to comparatively small structures such as local distribution grids. The scale that each tool targets is related to the intention of use and the included models are developed accordingly. As an example, at a national level network assets/devices or regions energy modeling is relatable where at microgrid level single technologies or buildings energy modeling are important. Also, under this specification the spatial scope is involved. Spatial resolution has a strong impact on which studies a tool can conduct depending on whether component models correspond to individual network assets and devices or aggregated structures like buildings or districts.

3.Level of detail: Energy planning tools can also be categorized based on the level of detail they provide. Some tools provide a high level of detail, such as hourly or daily energy consumption data, while others provide a more aggregated view of the energy system, such as annual energy consumption data. So, this category provides a measure for the temporal resolution of the component models used by a tool. The temporal resolution has strong implications for the potential applications a tool can be applied to. For instance, models for control applications need to address time scales in the order of the dynamics of the underlying process. Other models e.g., the ones focusing on energy balancing or economic studies may require only aggregated or averaged information.

4.Modeling approach: Energy planning tools can be categorized based on their modeling approach, such as:

- *Optimization models:* These models are used to determine the optimal mix of energy sources and technologies that minimize the cost of meeting energy demand while satisfying various constraints. The optimization models may focus on one single objective optimization or more than one.
- *Simulation models:* These models simulate the operation of the energy system over time and can be used to evaluate the impact of different policies and scenarios on the system's performance.
- *Bottom-up models:* These models are used to analyze energy consumption in various sectors (e.g., residential, commercial, industrial) and can provide insights into the potential for energy efficiency improvements.
- *Top-down models:* These models use aggregated data to estimate energy consumption and can be used to forecast future energy demand.

5. Modularity: This is related to the structure of the tool and has an impact on the user-friendliness and expandability of the tool. Three main categories are distinctive:

a. **Chain the different models together through specialized code.** This approach has flexibility and efficiency for one specific pair of tools but expert users are needed and thus it has low modularity.
b. **Monolithic program** This approach means extending one tool by directly including one or more others. For the user, the resulting tool is easy to learn. However, creating such a tool becomes increasingly difficult as the complexity of the system increases.
c. **Workflow management.** This approach focuses on creating an interaction framework where different tools can communicate through a shared database by using standardized data structures. Once established, usage is relatively easy for regular users and offers flexibility and scalability options as well.

The authors of [21], [22] provide an overview of the most popular commercial models and tools. The relevant ones for the multi-carrier systems are briefly described below:

Energy System Planning and Optimization:

- **EnergyPLAN:** A tool for energy system analysis and optimization that evaluates the technical and economic feasibility of various energy supply scenarios. It allows users to model different energy supply technologies and demand-side measures to create optimized energy systems that meet specific objectives[23], [24]

- **Calliope:** A tool for energy system modeling and optimization that analyzes the feasibility and performance of a range of energy supply technologies and demand-side measures. It enables users to simulate and optimize energy systems at a national or regional level.[25], [26]

Energy System Design and Optimization:

- **HOMER Pro:** A tool for energy system design and optimization that is focused on off-grid and grid-connected systems, hybrid renewable energy systems, and microgrids. It allows users to simulate and optimize different energy system configurations and determine the optimal mix of technologies to meet energy demand. [27], [28]
- **SPINE Toolbox:** A tool for energy system modeling and analysis that explores different design options and identifies optimal solutions in the early stages of system design. It is focused on building and district-level energy systems. [29][30]

MCES Modeling and Simulation:

- **Integrate:** A tool for energy system optimization and management that integrates multiple energy carriers and demand sectors to optimize system design and operation based on various objectives. It is designed for district and regional-level energy systems. [31]
- **EnergyExemplar PLEXOS:** A tool for energy system planning and optimization that models and simulates large-scale energy systems at the national or regional level. It enables users to optimize energy system operation based on multiple objectives.[32]

Energy Management and Data Analysis:

- **EnergyCAP:** A tool for utility bill tracking, energy management, and sustainability reporting for building and facility level. It helps users track energy usage and costs and provides basic energy management tools. [33]
- **HYSYS:** A tool for process simulation that models and simulates energy systems at a detailed process level, including process design, optimization, and control.[34]

The above-mentioned tools are summarized and compared in the table below, against the 5 main characteristics analyzed in the first part of this section.

Table 4: A comparison for commercial tools for energy planning of MCES

Tool	Purpose	Scope	Level of Detail	Modeling Approach	Modularity
HOMER Pro	Energy system design and optimization for off-grid and grid-connected systems, hybrid renewable energy systems, and microgrids	Building and facility level	Medium to high	Optimization modeling and simulation	a
EnergyPLAN	Energy system analysis and optimization for evaluating technical and economic feasibility of various energy supply scenarios	National and regional level	Low to high	Mathematical modeling and optimization	a
SPINE Toolbox	Energy system modeling and analysis for exploring different design options and identifying optimal solutions in the early stages of system design	Building and district level	Low to medium	Optimization modeling and simulation	*c*
Integrate	Energy system optimization and management for integrating multiple energy carriers and demand sectors, and optimizing system operation based on various objectives	District to regional level	Medium to high	Optimization modeling	*c*
Calliope	Energy system modeling and optimization for analyzing the feasibility and performance of a range of energy supply technologies and demand-side measures	National and regional level	Low to medium	Mathematical modeling and optimization	*c*
EnergyCAP	Utility bill tracking, energy management, and sustainability reporting for building and facility level	Building and facility level	Low	Data management and analysis	*b*
EnergyExemplar PLEXOS	Energy system planning and optimization for modeling and simulating large-scale energy systems at the national or regional level	National and regional level	High	Optimization modeling and simulation	*a*
HYSYS	Process simulation for modeling and simulating energy systems at a detailed process level, including process design, optimization, and control	Building and facility level to national and regional level	Very high	Process simulation and optimization	b

The first column describes the main purpose or function of each tool. Most of the tools are designed for energy system planning, optimization, and simulation, but they differ in terms of their specific applications and focus. For example, HOMER Pro is designed for designing and optimizing off-grid and grid-connected energy systems, while EnergyPLAN is designed for evaluating the technical and economic feasibility of different energy supply scenarios. Second column describes the scope or scale of the energy systems that each tool can model or analyze. The tools range from building and facility level to national and regional level, with some tools able to model both small and large systems. For example, HOMER Pro and SPINE Toolbox are focused on building and facility level energy systems, while EnergyPLAN and Calliope are designed for analyzing energy systems at a national or regional level. Level of detail column describes the level of detail that each tool can provide in modeling energy systems. The tools range from low to very high levels of detail, depending on their intended use and the complexity of the energy system being modeled. For example, EnergyCAP provides a low level of detail and is designed for utility bill tracking and basic energy management, while HYSYS provides a very high level of detail and is designed for process simulation of complex energy systems. The fifth column describes the modeling approach used by each tool to simulate and optimize energy systems. The last column categorizes the tools against the three categories of the modularity characteristic.

7 Conclusions and lessons learned

Formation, development and operation of MCES is motivated by possible benefits such as producing where energy is consumed, increasing energy efficiency and flexibility, end-user engagement, reducing system vulnerabilities, and addressing energy poverty. Planning and operation of MCES is very complex due to many technical and stakeholder interdependencies in addition to the need for considering several time horizons. As coordination of operation and planning is increasingly important, there is a need for sound methodologies addressing the various aspects of MCES.

The aspects of coordinated planning and operation of MCES is presented both in the form of an analytical framework and with detailed model examples for the planning, operation and real-time aspects that comprise MCES. These aspects represent different problem formulations, and are also interlinked. System configuration needs to consider operational situations when designing the system. Furthermore, when implementing the system that has been designed and evaluated through operational analyses, real-time operation needs to be compatible with the analyses performed. Traditionally cost minimization has been the mostly used approach to optimize MCES, but several other objective functions are relevant to consider. This includes emission reduction, reliability and resilience, demand response and flexibility, and renewable energy integration. Choosing what combination of these to employ depend on the priorities of stakeholders and system characteristics on a case-by-case basis. A crucial point is to be aware of the various objective formulations and their impact on the results to effectively navigate the trade-offs between them.

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