Enhancement of flexibility in multi-energy microgrids considering voltage and congestion improvement: Robust thermal comfort against reserve calls

Abstract

In recent years, multi-energy microgrid (MEM) has gained increasing interest, which could use clean and efficient electro-thermal resources, multi-energy storages (MESs) and demand response potential to improve the flexibility of MEM. However, maximizing the flexibility potential of MEM and alongside managing the electrical parameters (EPs) is a challenging modelling problem. In this paper, a probabilistic nonlinear model is presented to maximize the flexibility with all the power grid constraints taking into account EPs constraints using power flow. To this end, voltage profile and congestion improvement, robust thermal comfort provision during reserve call and MESs utilization are the key properties of the proposed model. The outcome of suggested model ensures sustainability in the MEM performance, which is an essential feature in modern smart cities. The presented model is applied to a distribution network in the UK and results illustrate how equipment scheduling and demand response leads to observe the EPs limitation and maximizes MEM flexibility. The achieved results show a decrease in MEM revenue (decrease of 34% and 24% without and with reserve commitment, respectively) and in contrast, a significant increase in flexibility compared to non-compliance with EPs constraints.

Keywords: Electrical parameters, flexibility, multi-energy microgrid, multi-energy storage, reserve commitment, thermal comfort.

Nomenclature

A. Acronyms

CHP	Combined heat and power
DHW	Domestic hot water
EB	Electrical boiler
EHP	Electrical heat pump
EP	Electrical parameter
ES	Electrical storage
GB	Gas boiler
MEM	Multi-energy microgrid
MEMO	Multi-energy microgrid operator
MES	Multi-energy storage
MVA	Mega volt-ampere
PF	Power flow
PV	Photovoltaic
TES	Thermal energy storage
WT	Wind turbine

B.Indices

s	Scenario index
t	Time step index
b, l	Bus index
e	Power transmission equipment index
γ	Set of equipment

C. Constant variables

$\underline{B}_b/\overline{B}_b$	Min/Max ES capacity [kWh]
$\underline{H}_b^{\gamma}/\overline{H}_b^{\gamma}$	Min/Max γ thermal power [kW]
$\underline{P}_b^{\gamma}/\overline{P}_b^{\gamma}$	Min/Max γ electrical power [kW]
$\underline{X}_b/\overline{X}_b$	Min/Max TES temperature [°C]

$\underline{\rho}_{tb}/\overline{\rho}_{tb}$	Max down/up temperature variation [°C]
$\eta_b^{\text{CHPe}}/\eta_b^{\text{CHPth}}$	CHP electrical/thermal efficiency [%]
$\eta_b^{\text{GB}}/\eta_b^{\text{EB}}$	GB/EB efficiency [%]
η_b^{ES}	Round-trip efficiency of ES [%]
CP_{stb}^{EHP}	EHP coefficient of performance [%]
C_e^{TE}	Max transmission equipment current [A]

D. Parameters

$E_{stb}^{\text{ele}}/X_{stb}^{\text{DHW}}$	Electricity/DHW load [kWh]
IG_{stb}/PG_{stb}	Internal/PV heat gains [kWh]
G_{bl}/B_{bl}	Conductance/Susceptance matrix [S]
$O_{stb}/\underline{\kappa}_t$	Binary/Down reserve indicator [∈(0,1)]
$P_{stb}^{\text{PV}}/P_{stb}^{\text{WT}}$	PV/WT electrical power [kW]
$C_b^{\text{B}}/C_b^{\text{TES}}$	Build/TES thermal capacitance [kWh/°C]
$R_b^{\text{B}}/R_b^{\text{TES}}$	Build/TES thermal resistance [°C/kW]
$T_{tb}^{\text{A}}/T_{st}^{\text{E}}$	Adjusted/Environmental temperature [°C]
$\overline{\Lambda}^{\text{RES}}$	Max call length of reserve [h]
ρ_s/ρ^{RES}	Scenario/reserve call probability [%]
Δt	Time interval [h]
$\epsilon_t^{\text{I}}/\epsilon_t^{\text{E}}$	Day-ahead import/export price [£/kWh]
$\pi_{st}^{\text{I}}/\pi_{st}^{\text{E}}$	Imbalance export/import price [£/kWh]
$\delta_t/\underline{\sigma}_t$	Gas/Down reserve availability price [£/kWh]
ξ_t^{d}/ξ_t^{s}	Temperature deficit/surplus penalties [£/°Ch]

E. Variables

$B_{stb}^{\text{ES}}/X_{stb}^{\text{TES}}$	ES/TES energy level [kWh]
$Ft_{stb}^{\text{B}}/Hd_{stb}^{\text{B}}$	Build heat storage footroom/headroom [kW]
$D_t^{\text{I}}/D_t^{\text{E}}$	Day-ahead energy import/export [kW]
$G_{stb}^{\text{GB}}/G_{st}^{\text{I}}$	Gas consumed by GB/MEM [kW]

$H^{GB}_{stb}/H^{CHP}_{stb}$	GB/CHP thermal power [kW]
$X^{I}_{stb}/X^{LOSS}_{stb}$	TES heat import/loss [kWh]
X^{SH}_{stb}	Space heating demand [kWh]
I^{I}_{st}/I^{E}_{st}	Imbalance energy import/export [kW]
P^{M}_{stb}/P^{M}_{st}	Imported power location/MEM level [kW]
$P^{\gamma}_{stb}/\underline{R}^{\gamma}_{stb}$	γ electrical power/down reserve [kW]
$R^{loc}_{stb}/R^{MEM}_{s}$	Down reserve location/MEM level [kW]
$R^{MEM\_a}_{st}$	Auxiliary down reserve MEM level [kW]
T_{stb}	Build temperature [°C]
T^{d}_{stb}/T^{s}_{stb}	Temperature deficit/surplus [°C]
$T^{R\_d}_{stb}/T^{R\_s}_{stb}$	Temperature deficit/surplus of reserve [°C]
Γ_{stb}	Internal/PV gain vent [%]
ν_{stb}	Voltage magnitude at buses [p.u.]
θ_{stb}	Voltage angle at buses [°]
c_{ste}	Transmission equipment current [A]

1. Introduction

1.1. Motivation

Flexibility is the potential and ability to continuously balance the electricity generation and demand in a cost-effective manner that is important in urban economies, while simultaneously maintaining acceptable service quality to the consumers [1]. The demand for flexibility in multi-energy microgrid (MEM), which can be a city or a part of a city, is expected to increase as the application of electric heating/transport in cities, and variable/clean generations grow. However, it is achieved at a compromise between profits and costs [1]. The equipment used in MEM are divided into two categories of resources (including gas boiler (GB), electro-thermal resources such as combined heat and power (CHP), electrical heat pump (EHP), electrical boiler (EB)) and multi-energy storages (such as thermal energy storage (TES), electrical storage (ES) and building fabric). Scheduling these equipment power and also demand response models are the appropriate tools for increasing the flexibility [2]. It is noteworthy that increasing the use of low carbon resources such as EHP and high-efficiency distributed resources such as CHP in the green buildings of smart cities is very important to create a green structure. Also, further expansion of low carbon high-efficiency resources on a larger scale can prevent climate change. Moreover, the demand response synchronizes the load demand locally, making it more convenient to control local generations, eliminate local network capacity limitations and balance the generation with load [3]. Alongside, MEM that includes equipment and demand response sources makes it possible for MEM to participate in both energy/reserve market and provide a safe margin for improving the consumers thermal comfort [2, 4, 5]. To contribute towards the energy/reserve market, provision of consumers thermal comfort and increase in flexibility (service quality improvement), all of MEM parameters must be controlled [6]. To achieve controllability, for instance, the power of equipment and especially the electrical parameters (EPs) must be measurable and limited to their standard range. Here EPs include voltage magnitude and angle, and current in all power transmission equipment such as transformers and lines, resulting from the power flow (PF). If the EPs are not within the standard range, in addition to degrading service quality, it may damage the MEM equipment, resulting in a partial or full stopping of MEM function, and this leads to unsustainable performance [7]. As a result, the control of EPs makes it possible for MEM to sustainability operate over time and develop a sustainable city. The research work related to flexibility improvement are classified into two groups: 1) management of MEM power to increase the flexibility, which provides maximized revenue without implementing the PF. Thus, EPs do not have standard values and the resulting models are not capable to be applied to a realistic MEM technically, 2) management of MEM power which uses PF strategies. Although, some of these works also optimize the revenue, but some parts of MEM revenue (e.g. reserve revenue) are lost. In addition, these works miss the other parts (e.g. thermal comfort). Therefore, EPs are within the standard range, however, these models do not operate economically in MEM and flexibility is not maximized.

1.2. Literature review

So far, various research studies have been carried out for maximizing the MEM flexibility considering the equipment power scheduling specially focused on demand response. Cesena and Mancarella [7] and Coelho et al. [8] present a framework for scheduling of microgrid equipment to increase the flexibility. But, equipment reserve and its impact on consumers thermal comfort (service quality reduction) and also thermal storage of building fabric are not considered. Moreover, temperature profile in thermal load is not modeled separately, which does not analyze the building occupants behavior completely and ignores the impact of its probabilities in MEM power management (selling energy to the upstream network is not investigated in [8], therefore, the optimized MEM revenue is not obtained). Also, the method proposed by Gazijahani et al. [9] deals with the simultaneous scheduling of energy and reserve of microgrid equipment in the market, and the results of which show the reduction of microgrid cost and minimization of pollutant emissions that improves air quality in cities. Due to the probabilities and inherent intermittence of renewable sources, a conditional value-at-risk method is used to reduce the risk of probabilities, however, the consumers thermal comfort and the thermal storage of building fabric are lost. The probabilistic strategies for optimal MEM scheduling so that the MEMO can optimally participate in the three markets of electricity, gas and heat are provided by Lekvan et al. [10] and Ding et al. [11]. Although attention has been paid to new high-efficiency technologies (including power-to-gas units, electric vehicles parking lots and MESs) and demand response programs, but, consumers thermal comfort, reserve generation and EPs are lost. The total cost in [10] and [11] is decreased by 14.2% and 3.51%, respectively (CO_2 emissions is also reduced by 2.36% in [11]). Nasiri et al. [12] present a decentralized approach that uses storage flexibility to achieve optimal market clearing at the regional and local levels for a multi-energy network. In this approach, the linepack model is used to model the gas pipes in the energy hub and also a linear energy hub model is used for multi-energy network modeling, while participation in the imbalanced and reserve market, as well as demand response are not considered. In order to improve the efficiency and reliability of new smart cities, Fontenot et al. [13] provide a control framework to integrate residential and commercial buildings and their internal resources and storages with the distribution network. Applying this model to several standard networks shows that active power losses and building costs are minimized, while voltage regulation and consumer comfort are increased. In this framework, the probabilities of load, environmental parameters and heat gain are considered, while the production of reserve is not considered. Li *et al.* [14] presented two centralized/decentralized frameworks with the aim of maximizing social welfare and minimizing the cost of each player. The result of these frameworks is the optimal dispatch of resources and storage units as well as the determination of the optimal demand response in each of the energy systems. Compared to the centralized framework, the decentralized framework performs better in terms of privacy and dispatches the resources at a lower cost, while carbon emissions value is higher. But these frameworks do not model EPs, reserve generation and thermal comfort. The strategies for aggregating power in the distribution level for combining the flexibility of large and small distributed energy sources, and modeling and quantifying the flexibility of aggregated power are addressed in [6, 15–19]. Chen et al. used a distributed model predictive control framework to implement communications between the distribution network and the upstream network [6], where they mainly address an unbalanced network. Muller et al. use a scalable method in [15] and price aggregated flexibility based on zonotopic sets. This model also allows the aggregator to aggregate the flexibility of a large number of systems at the same time. In addition, control decisions at the aggregated level are distributed among each system in a way that are economically and computationally optimal. The purpose of this method is to reduce costs and provide optimal ancillary services. Yazdani-Damavandi et al. use a multi-layer method for aggregating flexibility, the layers of which include the market, the aggregators of local systems, local systems, as well as loads [16]. The aggregators who participate in the market as a prosumer in this method, in addition to maximizing profits, can reduce their operational risk. The model presented by Majzoobi and Khodaei [17], balances the power changes created by prosumers by power scheduling using aggregated flexibility potential. Moreover, this model eliminates the need for additional investment and considers ramp constraints. The power aggregator proposed by Yazdani-Damavandi et al. [18] for local systems can participate in the retail markets and provide higher integration. This two-layer model has the ability to maximize the profits of aggregators as well as the profits of each local system, and the relationship between the various parts of this model is based on price signals. Lu et al. investigate an aggregation strategy of electrical vehicles flexibility to help the distribution network reduce the impact of probabilities [19]. The aggregators provided in this model allow the distribution network to deal with a smaller number of actors. The robust optimization in this model allows optimal scheduling in the presence of any uncertainties of vehicles average performance. To facilitate the voltage profile and congestion, a flexibility exchange strategy by Liao and Milanovic proposed several factors to minimize the variation of network variables, especially the participation of consumers or aggregators [20]. This strategy is implemented after another model, which considered maximizing the flexibility without considering the voltage profile and current, e.g. [2]. The energy flexibility on the distribution buses provided by flexible loads and controllable inverters based photovoltaic (PV) generation systems (for providing reactive power flexibility) is optimized by Oikonomou et al. [21]. The contribution of each distribution bus in providing the flexibility is determined by the presented index. The TES investigated by Anwar et al. [22] shifts the time of energy consumption, increases demand response potential and thermal comfort of each building, and as a result the flexibility in multi-time scale. Romanchenko et al. [23] performed a techno-economic investigation for the use of thermal load flexibility (by allowing temperature deviations from the set temperature in the buildings) along with the flexibility created by the TES utilization, the result of which is minimum thermal load and cost. They also showed that the increase in temperature was more widespread in multi-family buildings and the decrease in temperature was more widespread in single-family buildings, and the amount of temperature deviations are reduced using TES. But the EPs constraints and the reserve market are not taken into account. Also, according to the works done by Correa-Florez et al. [24] and Iria et al. [25], the equipment power can be optimized from an aggregator's standpoint to participate in day-ahead and local flexibility markets. The objective is to minimize day-ahead operation cost for the aggregator and result in optimized bidding for wholesale and local markets (imbalanced market and electric vehicles are included in [25] as well). The impact of electric vehicles on the energy management of microgrids with respect to the growth of power consumption due to the electric vehicles penetration expansion in smart cities is also investigated by Ahmad et al. [26]. For determining the optimal switching time between generator and pump-mode for the pumped energy storages, the proposed strategy by Liang et al. [27] is specially useful, improving the flexibility and frequency regulation. The water distribution system is optimized by Oikonomou and Parvania [28] and feasible flexible capacity is calculated for the power system operator. The demand response flexibility (based on weather forecast and other data) without depending on smart meter data or detailed consumer surveys can be estimated according to the research implemented by Wang et al. [29]. Furthermore, a direct load control strategy proposed by Tascikaraoglu et al. [30], obtains flexibility from residential heating, ventilation and air conditioning units and optimal management of storage systems with the aim of minimizing energy demand during the demand response event and minimize consumers discomfort. Guo et al. [31] investigate the microgrid equipment scheduling taking into account the flexibility of demand response and plug-in electric vehicles and the results demonstrate a reduction of 3.57% and 3.4% respectively for the cost and emission of pollutants. Also, the real electric vehicles model is improved by using the ac-power flow and Wohler curve, as well as the probabilities are considered in several scenarios based on fuzzy decision making approaches. The model presented by Zeng et al. uses demand response flexibility (based on a price based approach) in MEM planning and scheduling, and with a generalized elasticity strategy, considers consumer behavior in response to price changes [32]. However, the reserve production and consumers thermal comfort are not taken into account in [31, 32] (in addition, heating network and EPs constraints are lost in [31] and [32], respectively). Baldi et al. presented another feedback-based method for load management using smart zoning and according to occupancy patterns [33], which in addition to utilizing renewable resources, improves consumers thermal comfort. Ma et al. presented a model which investigates the impact of environmental parameters including porous pavement and plant transpiration [34]. The results of this model show that the relationship between temperature and ambient temperature and also the relationship between Predicted Mean Vote and humidity increases with increasing building height, and as a result, very tall buildings in the cities do not provide adequate thermal comfort. On the other hand, increasing the space of the building can improve the temperature and the Predicted Mean Vote, thus increasing the thermal comfort. Park and Chang [35] integrated a smart window ventilation system and a central heating, ventilation and air conditioning system into a commercial building, and investigated its impact on indoor air quality and thermal comfort using computational fluid dynamics strategies. The use of smart window ventilation system only improves air quality and thermal comfort in winter, while leading to poor air quality in summer. The investigations performed in [34, 35] do not consider EPs and reserve generation. Korkas et al. in [36], present an energy management system in a microgrid that is connected to the upstream network and includes a heterogeneous occupancy schedule (created due to domestic, commercial and industrial consumers). This system aims to reduce cost and maximize thermal comfort using the potential of occupancy schedule and intermittent power of PV. In addition, a bi-level control algorithm is provided by Korkas et al. in [5] for joint management of scalable and robust demand response as well as optimization of thermal comfort under heterogeneous conditions. This algorithm reduces energy costs compared to previous demand response strategies, and renewable sources are integrated more efficiently. However, Refs. [5, 33, 36] do not consider participation in the reserve market and EPs, as a result of which they lose revenue from reserve sales and the amounts of EPs may not be standard. The reactive power flexibility obtained by tools such as transformers tap is used by Ding et al. [37] to reduce network loss to maintain EPs within the standard range. The reactive power modeling is performed using the conic relaxation strategy. This two-stage model coordinates both types of discrete and continuous reactive power compensators to provide optimal reactive power for any wind power uncertainty. Quantifying the gas network flexibility that can be provided for the power system, as well as the constraints it can impose on the power system is done by Clegg and Mancarella [38]. Because the gas network also provides heat, different heating scenarios are investigated in this flexibility. Moreover, the impacts of gas network inflexibility on local generation and reserve constraints have been checked. Consumers flexibility can be estimated based on offline data for providing day-ahead and real-time ancillary services, which is proved by Zotti et al. [39], given consumers elasticity and technical differences between different types of loads. A chance-constrained model is used to consider the impact of probabilities. In addition, this model is such that it does not require real-time communication to be implemented, and therefore the cost of infrastructure is reduced. Furthermore, Heydarian et al. introduced a techno-economic flexibility index [40] that quantifies the flexibility of generation technologies according to the level of stable minimum generation, performance range, minimum up/down times, and ramp up/down capability. A multi-agent framework is presented by Rahman and Oo [41] to manage microgrid power using distributed power resources equipped with power electronic inverter-interfaced. Electrical vehicles and especially their vehicle-to-home mode have also been considered to ensure the sustainable performance of the microgrid with the uncertainty of the renewable resources and loads. Khan et al. [42] have introduced a distributed multi-agent energy management system that, unlike centralized energy management systems, can satisfy criteria such as adaptability. However, the heating network and its loads have not been taken into consideration in [41, 42] and the consumers thermal comfort has been neglected. Good and Mancarella compared the amount of flexibility and revenue growth that each of the equipment can generate in MEM, considering demand response and effect of reserve call on consumers thermal comfort [2]. But the main problem is that in this model, sometimes the voltage is in the non-standard range and congestion occurs in some network transmission equipment.

1.3. Contributions

To the best knowledge of the authors, there is no systematic model that maximizes the flexibility of an MEM participating in the energy and reserve market, while its EPs are also monitored. Furthermore, some of the models presented in

Section 1.2 do not control the thermal comfort of consumers living in buildings located in MEM. Table 1 provides an at-a-glance view of the previous papers and shows their defects. Given the above, several gaps have been identified in the existing literature, and are listed as follows:

1. Although there are a lot of power management models which aggregate the flexibility from different resources. However, there is lack of a model that systematically considers EPs constraints in flexibility issue at the same time with participation in reserve market (e.g. [7]). Also, the relationship between equipment power and power input from the market with the EPs amount per hour has not been studied.
2. The developed works on flexibility consider the impact of reserve commitment on consumers thermal comfort, but there is no comprehensive model that considers thermal comfort at the same time as EPs and studies changes in thermal comfort alongside EPs.

This paper presents an MEM power management model using PF that not only considers the EPs for sustainable performance of MEM, but also maximizes the flexibility to create a flexible and sustainable city. The multi-energy model allows using different flexibility resources (including MESs, energy vector/equipment substitution and end-user service curtailment). Based on the literature discussed, the major contributions of this paper are as follows:

1. Consideration of EPs constraints for setting them in a standard range, and check their changes hour by hour according to the equipment power changes, market price signals, as well as the level of reserve
2. Presenting a comprehensive multi-energy model including reserve commitment effect on thermal comfort (as a service) alongside the EPs to manage the MEM power optimally for balancing power (in the presence of uncertainties of renewable resources, loads and market prices), creating robust thermal comfort for consumers and increasing the consumers services quality, as well as investigating the interaction of thermal comfort and EPs values in MEM

Table 1: A comparative summary of this study and previous papers

Ref.	EPs	Electricity market			Thermal comfort	Network	Storage	Demand response	Thermal load	
		Day-ahead	Imbalanced	Reserve					Temperature	DHW
[7]	✓	✓	No	No	No	electricity/gas/heat	ES/TES	No	as a single load	
[8]	✓	✓	No	No	No	electricity/gas/heat	ES/TES	✓	as a single load	
[10]	No	✓	No	No	No	electricity/gas/heat	ES/TES/electrical vehicle	✓	as a single load	
[11]	No	✓	No	No	No	electricity/gas/heat	ES/TES/electrical vehicle	✓	as a single load	
[15]	No	✓	No	No	No	electricity/heat	ES	No	✓	No
[16]	No	wholesale market		No	No	electricity/gas/heat	ES/TES	No	as a single load	
[17]	No	✓	No	No	No	electricity	ES	No	No	No
[18]	No	✓	No	No	No	electricity/gas/heat	TES	No	as a single load	
[20]	✓	No	No	No	No	electricity	✓	✓	No	No
[22]	No	✓	No	✓	✓	electricity/heat	ES/TES	✓	✓	No
[24]	No	✓	✓	No	No	electricity/heat	ES/TES	No	as a single load	
[25]	No	✓	✓	✓	✓	electricity/heat	No	✓	✓	No
[26]	No	No	No	No	No	electricity	electrical vehicle	✓	No	No
[27]	No	No	No	✓	No	electricity	pumped energy storage	No	No	No
[28]	No	No	No	No	No	electricity	No	✓	No	No
[29]	No	No	No	No	No	electricity	No	✓	No	No
[30]	✓	No	No	No	✓	electricity/heat	ES	✓	✓	No
[33]	No	No	No	No	✓	electricity/heat	No	✓	✓	No
[36]	No	✓	No	No	✓	electricity/heat	No	✓	✓	No
[5]	No	No	No	No	✓	electricity/heat	ES	✓	✓	No
[37]	✓	No	No	No	No	electricity	ES	No	No	No
[38]	No	No	No	✓	No	electricity/gas/heat	No	No	✓	No
[40]	✓	✓	No	✓	No	electricity	bulk energy storage	✓	No	No
[2]	No	✓	✓	✓	✓	electricity/gas/heat	ES/TES/building fabric	✓	✓	✓
[23]	No	No	No	No	✓	electricity/heat	TES	✓	✓	✓
[12]	✓	✓	No	No	No	electricity/gas/heat	ES/TES	No	as a single load	
[13]	✓	No	No	No	✓	electricity/heat	ES	✓	✓	No
[14]	No	✓	No	No	No	electricity/heat	ES/TES	✓	as a single load	
[34]	No	No	No	No	✓	electricity/heat	No	No	✓	No
[35]	No	No	No	No	✓	electricity/heat	No	No	✓	No
This study	✓	✓	✓	✓	✓	electricity/gas/heat	ES/TES/building fabric	✓	✓	✓

2. Model and problem formulation

2.1. Power exchange of different equipment

Each building in the MEM has a set of equipment and multi-energy microgrid operator (MEMO) manages them to observe MEM constraints. Figure 1 shows the energy deal of equipment under the MEMO control in terms of energy type (electricity, gas and heat). The heat from resources must first be stored in the TES to supply the thermal loads. The operational constraints of each of these equipment are described in detail in Section 2.4 and 2.5. Also, the operational equations of the buildings and the relationship between the power of the equipment and the building loads as well as the markets are explained in Section 2.6 and 2.8, respectively.

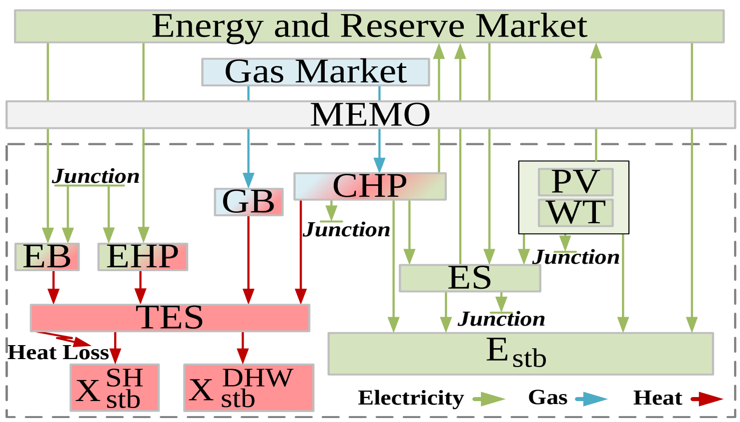


Figure 1: The connection between equipment based on the type of energy in the building.

2.2. Flowchart of the proposed model

The proposed model is shown schematically in Figure 2. The procedure given in Figure 2 is implemented by MEMO, which is a unit in MEM that manages its performance. After receiving the input data, MEMO executes a scenario reduction algorithm. The proposed nonlinear optimization model (due to nonlinear EPs constraints in Section 2.9) is solved using a solver named IPOPT, which is a nonlinear computational (non-heuristic) optimization solver (IPOPT is described in detail in [43]). In this step, the non-EPs constraints are modeled and calculated according to the structure required for IPOPT solver. Then, in each scenario, the link data are sent to OpenDSS in a 24-hour time series. After performing PF calculations, MATLAB receives the values of v_{stb}, θ_{stb} and c_{ste} and uses them to models EPs constraints in the appropriate form to the solver. Finally, the objective function is calculated and then, the solver is used. This solver calculates the error quantity for the constraints as well as the objective function in each iteration. If these error quantity are less than the predetermined threshold, the optimal result is obtained, otherwise the values of the variables in the next iteration must be checked. The novelties of our paper are parts A, B and C of the flowchart. The EPs constraints (1^{st} novelty in Section 1), which need PF calculation, are modelled in part A by OpenDSS (see Eqs. (34)-(39)). The objective function also minimizes the thermal discomfort (2^{nd} novelty) in Part B (Eq. (1)). The other constraints which are named as non-EPs constraints, including reserve and thermal comfort (2^{nd} and part of 1^{st} novelty) are modeled in part C using MATLAB (see Eqs. (2)-(33)). The link data, which are the values of electrical load and power of CHP, EHP, EB, ES, PV and wind turbine (WT), are written in the CSV file and are transferred from MATLAB to OpenDSS in each iteration. It should be noted that the proposed optimization model is a two-stage model that optimizes the performance of each MEM equipment (Eqs. (2)-(29)) at the lower stage and the total MEM performance (Eq. (1) and Eqs. (30)-(39)) at the upper stage (Figure 2).

2.3. Objective function

The objective function of the proposed model in Eq. (1), optimizes the MEM profit. Terms 1 and 2 model energy purchasing/selling in the day-ahead market, respectively. Purchasing/selling energy in the imbalanced market is modeled in terms 3 and 4, respectively . Therefore, the proposed model, by modeling the day-ahead and imbalanced markets separately (unlike some papers in Table 1 that do not consider the imbalanced market), allows the study of the impact of each market, such as probabilities of the imbalanced market price. MEMO purchases gas (term 5) and sells the provided reserve in reserve market (term 6). Also, the temperature deviation from the set temperature of building is penalized (terms 7 and

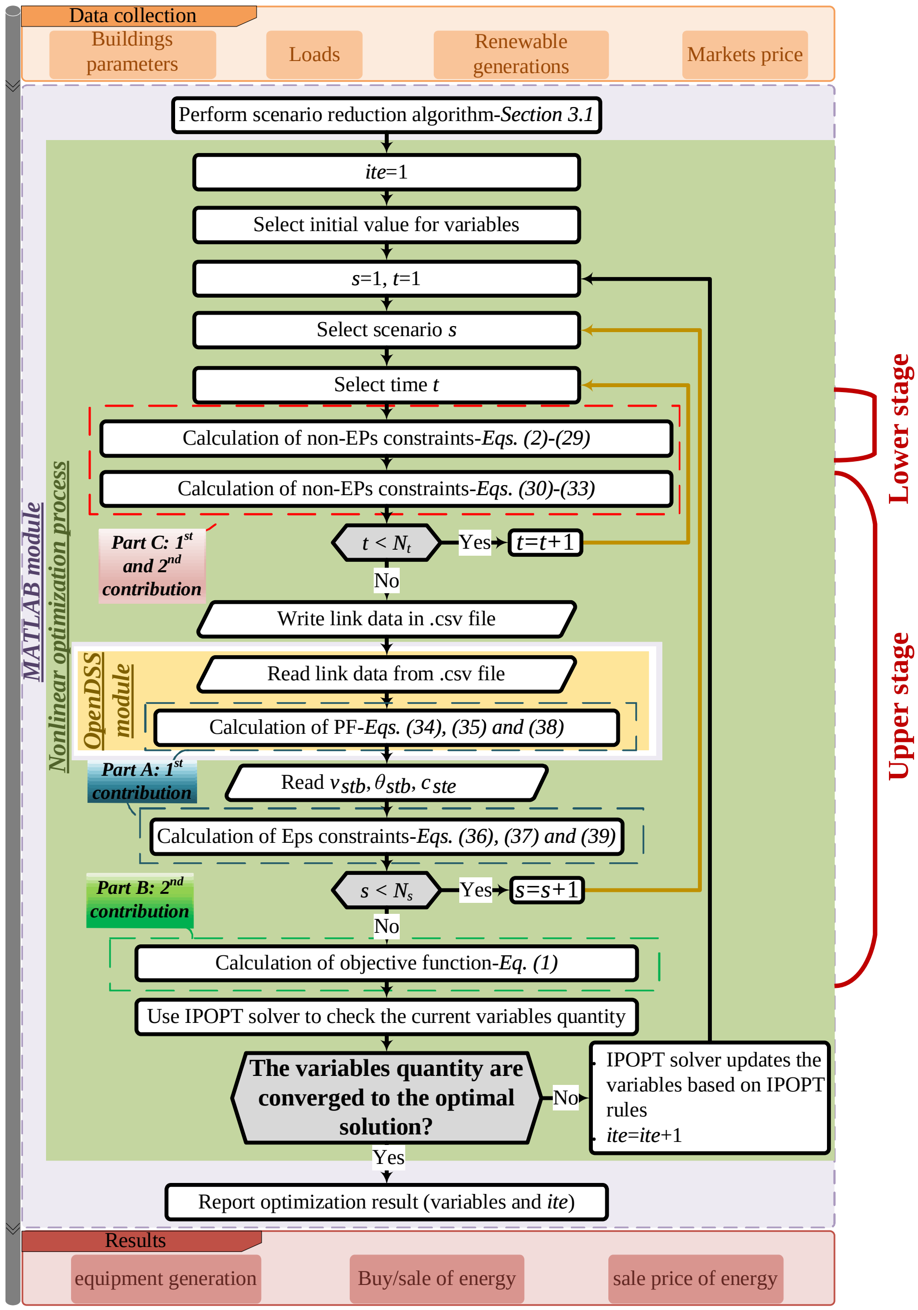


Figure 2: Flowchart of the proposed model.

8) which is paid by MEMO to the consumer for failure to provide consumers thermal comfort (2^{nd} novelty). Similarly, temperature deviation due to reserve call is investigated with the probability of reserve call (ρ^{RES}) in terms 9 and 10. Considering the impact of tax and other tariffs on the imported electricity price, make it different compared to exported electricity price. The probability of occurrence of each scenario is determined by parameter ρ_s.

$$\begin{aligned} &\text{Min}\left\{\sum_{s=1}^{N_s}\left[\rho_s\sum_{t=1}^{N_t}\left(\epsilon_t^I D_t^I \Delta t - \epsilon_t^E D_t^E \Delta t + \pi_{st}^I I_{st}^I \Delta t\right.\right.\right. \\ &-\pi_{st}^E I_{st}^E \Delta t + \delta_t G_{st}^I \Delta t - \underline{\sigma}_t R_{st}^{MEM\_a} \Delta t + \sum_{b=1}^{N_b} \Delta t \left(\xi_t^s T_{stb}^s\right. \\ &+\xi_t^d T_{stb}^d + \rho^{RES} \xi_t^s T_{stb}^{R\_s} + \rho^{RES} \xi_t^d T_{stb}^{R\_d} \end{aligned} \tag{1}$$

2.4. Resources constraints

Eqs. (2)-(5) determine resources limits in MEM.

$$\underline{H}_b^{GB} \leqslant H_{stb}^{GB} \leqslant \overline{H}_b^{GB}\ \forall_{stb},\ H_{stb}^{GB} = G_{stb}^{GB}\eta_b^{GB} \tag{2}$$

$$\underline{H}_b^{CHP} \leqslant H_{stb}^{CHP} \leqslant \overline{H}_b^{CHP}\ \forall_{stb},\ H_{stb}^{CHP} = \frac{P_{stb}^{CHP}\eta_b^{CHPth}}{\eta_b^{CHPe}} \tag{3}$$

$$\underline{P}_b^{EHP} \leqslant P_{stb}^{EHP} \leqslant \overline{P}_b^{EHP}\ \forall_{stb} \tag{4}$$

$$\underline{H}_b^{EB} \leqslant P_{stb}^{EB}\eta_b^{EB} \leqslant \overline{H}_b^{EB}\ \forall_{stb} \tag{5}$$

2.5. Storage equipment

The limits of energy stored in MESs are determined in Eqs. (6)-(7). Eq. (8) determines the allowed P_{stb}^{ES} which is positive or negative when ES is charging or discharging, respectively. Eqs. (10)-(11) respectively show stored energy in TES and ES at next time-step, depends on their energy value and imported energy (12) at the current time-step. The energy stored in TES also relies on its energy loss (9) in the building and thermal load (including building temperature provision and domestic hot water (DHW)).

$$\left(\underline{X}_b - T_{stb}\right) C_b^{TES} \leqslant X_{stb}^{TES} \leqslant \left(\overline{X}_b - T_{stb}\right) C_b^{TES}\ \forall_{stb} \tag{6}$$

$$\underline{B}_b \leqslant B_{stb}^{ES} \leqslant \overline{B}_b\ \forall_{stb} \tag{7}$$

$$\underline{P}_b^{ES} \leqslant P_{stb}^{ES} \leqslant \overline{P}_b^{ES}\ \forall_{stb} \tag{8}$$

$$X^{LOSS}_{stb} = \frac{\left(\frac{X^{TES}_{stb}}{C^{TES}_{b}} - T_{stb}\right)\Delta t}{R^{TES}_{b}} \; \forall_{stb} \tag{9}$$

$$X^{TES}_{s(t+1)b} = X^{TES}_{stb} + X^{I}_{stb} - X^{LOSS}_{stb} - X^{SH}_{stb} - X^{DHW}_{stb} \; \forall_{stb} \tag{10}$$

$$B_{s(t+1)b} = B^{ES}_{stb} + \left(\frac{P^{ES}_{stb}}{\eta^{ES}_{b}}\right)\Delta t \; \forall_{stb} \tag{11}$$

$$\left(H^{GB}_{stb} + H^{CHP}_{stb} + P^{EHP}_{stb} CP^{EHP}_{stb} + P^{EB}_{stb}\eta^{EB}_{b}\right)\Delta t = X^{I}_{stb} \; \forall_{stb} \tag{12}$$

To ensure zero distortion in the obtained results, the value of energy stored at initial time-step in MESs must be set equal to the last time-step.

$$X_{s0b} = X_{sN_t b} \; \forall_{sb} \tag{13}$$

$$B_{s0b} = B_{sN_t b} \; \forall_{sb} \tag{14}$$

2.6. Building equations

Eqs. (15) and (16) show that the building temperature must stay within the allowed band, which is determined by $\underline{\rho}_{tb}$ and $\overline{\rho}_{tb}$ (zero at all conditions and can be set to nonzero values when the model fails to converge for a particular MEM condition), where T^{d}_{stb} and T^{s}_{stb} enable thermal comfort capability. These parameters are used when model fails to meet thermal comfort constraints. In Eq. (17), which defines building temperature, the role of PV heat and consumers depends on consumers actions (for instance opening doors) that is defined by Γ_{stb}. In fact, O_{stb}, T^{A}_{tb} and Γ_{stb} model the behavior of consumers living in MEM. To ensure the achieved results are not distorted, the building temperature at the initial time-step must be set as equal to the last time-step by Eq. (19) [44].

$$O_{stb}\left(T_{stb} - T^{s}_{stb}\right) \leqslant O_{stb}\left(T^{A}_{tb} + \overline{\rho}_{tb}\right) \; \forall_{stb} \tag{15}$$

$$O_{stb}\left(T^{A}_{tb} - \underline{\rho}_{tb}\right) \leqslant O_{stb}\left(T_{stb} + T^{d}_{stb}\right) \; \forall_{stb} \tag{16}$$

$$\begin{aligned} T_{s(t+1)b} = T_{stb} + \Big(& X^{SH}_{stb} + (1 - \Gamma_{stb})\left(IG_{stb} + PG_{stb}\right) \\ & - \left(T_{stb} - T^{E}_{tb}\right)\Delta t {R^{B}_{b}}^{-1} + X^{LOSS}_{stb} {C^{B}_{b}}^{-1} \; \forall_{stb} \end{aligned} \tag{17}$$

$$X^{SH}_{stb} \geqslant 0 \; \forall_{stb} \tag{18}$$

$$T_{s0b} = T_{sN_t b} \; \forall_{sb} \tag{19}$$

2.7. Reserve modelling

2.7.1. The resources of reserve

The reserve commitment of equipment (part of 1^{st} novelty) is limited by Eqs. (20)-(24). Based on Eqs. (21) and (22), the reserve of EHP and EB cannot be greater than the footroom. Whereas, CHP reserve stays below its headroom, given by Eq. (23). ES reserve cannot be greater than up-limit of its discharge power by Eq. (24).

$$R^{loc}_{stb} = \underline{R}^{EHP}_{stb} + \underline{R}^{EB}_{stb} + \underline{R}^{CHP}_{stb} + \underline{R}^{ES}_{stb} \ \forall_{stb} \tag{20}$$

$$0 \leqslant \underline{R}^{EHP}_{stb} \leqslant P^{EHP}_{stb} - \underline{P}^{EHP}_{b} \ \forall_{stb} \tag{21}$$

$$0 \leqslant \underline{R}^{EB}_{stb} \leqslant P^{EB}_{stb} - \frac{\underline{H}^{EB}_{b}}{\eta^{EB}_{b}} \ \forall_{stb} \tag{22}$$

$$0 \leqslant \underline{R}^{CHP}_{stb} \leqslant \frac{\overline{H}^{CHP}_{b}\eta^{CHPe}_{b}}{\eta^{CHPth}_{b}} - P^{CHP}_{stb} \ \forall_{stb} \tag{23}$$

$$0 \leqslant \underline{R}^{ES}_{stb} \leqslant \overline{P}^{ES}_{b} + P^{ES}_{stb} \ \forall_{stb} \tag{24}$$

2.7.2. Reserve commitment and thermal comfort

The robust thermal comfort (2^{nd} novelty) means that the proposed model is able to provide adjusted temperature to the consumers even during reserve call in any of the possible scenarios considered for probabilistic parameters. Due to the complexity of the problem and due to the low impact of air velocity and humidity in this problem, only air temperature is considered in the assessment of thermal comfort. The building temperature (T_{stb}) closer to the adjusted temperature (T^{A}_{tb}) by consumers, increases consumers satisfaction and thus enhances the thermal comfort. Therefore, in the proposed model, air quality control and management which is the parameter of air temperature in MEM buildings, is also discussed. To this end, it is essential to have enough energy in TES and building fabric, or to have enough heat sources on stand-by (Eqs.(25)-(26)). Eq. (25) confines the resources reserve by the TES and building fabric footroom, and the GB up-limit. The CHP heat produced with its reserve must also be able to store in TES and building fabric or replace with reduced GB heat, given in Eq. (26). Eqs. (25)-(26) exist only when the building is actively occupied, which is indicated by the parameter O_{stb}.

Eqs. (27)-(28) determine the building fabric storage footroom/headroom, respectively, where $T^{R\_d}_{stb}$ and $T^{R\_s}_{stb}$ permit reduction in thermal comfort during a reserve call. ES reserve up-limit is set by Eq. (29) in such a way to deal during reserve call without any problem [44].

$$\begin{aligned}&O_{stb}\left(\underline{R}^{EHP}_{stb}CP^{EHP}_{stb}+\underline{R}^{EB}_{stb}\eta^{EB}_{b}-\underline{R}^{CHP}_{stb}\eta^{CHPth}_{b}/\eta^{CHPe}_{b}\right)\\ &\leqslant O_{stb}\left(\left(\frac{\left(\frac{X^{TES}_{stb}}{C^{TES}_{b}}+T_{stb}-\underline{X}_{b}\right)C^{TES}_{b}+Ft^{B}_{stb}}{\overline{\Lambda}^{RES}}\right)\right.\\ &\left.+\left(\overline{H}^{GB}_{b}-H^{GB}_{stb}\right)\right)\ \forall_{stb}\end{aligned}\tag{25}$$

$$\begin{aligned}&O_{stb}\underline{R}^{CHP}_{stb}\eta^{CHPth}_{b}/\eta^{CHPe}_{b}\leqslant O_{stb}\\ &\left(\frac{\left(\overline{X}_{b}-\frac{X^{TES}_{stb}}{C^{TES}_{b}}-T_{stb}\right)C^{TES}_{b}+Hd^{B}_{stb}}{\overline{\Lambda}^{RES}}+H^{GB}_{stb}\right)\ \forall_{stb}\end{aligned}\tag{26}$$

$$0\leqslant Ft^{B}_{stb}=O_{stb}\left(T_{stb}-\left(T^{A}_{tb}-\underline{\rho}_{tb}\right)+T^{R\_d}_{stb}\right)C^{B}_{b}\ \forall_{stb}\tag{27}$$

$$0\leqslant Hd^{B}_{stb}=O_{stb}\left(\left(T^{A}_{tb}+\overline{\rho}_{tb}\right)-T_{stb}+T^{R\_s}_{stb}\right)C^{B}_{b}\ \forall_{stb}\tag{28}$$

$$\underline{R}^{ES}_{stb}\leqslant B^{ES}_{stb}/\overline{\Lambda}^{RES}\ \forall_{stb}\tag{29}$$

2.8. Power, gas and reserve balance

As per the power balance, the produced and consumed electrical powers in the entire MEM must be equal, given by Eq. (30). On the other hand, Eq. (31) defines a gas balance.

$$\begin{aligned}&D^{I}_{t}-D^{E}_{t}+I^{I}_{st}-I^{E}_{st}=\textstyle\sum_{b=1}^{N_b}\left(\frac{E^{ele}_{stb}}{\Delta t}+P^{EHP}_{stb}+P^{EB}_{stb}\right.\\ &\left.-P^{CHP}_{stb}-P^{PV}_{stb}-P^{WT}_{stb}+P^{ES}_{stb}\right)\ \forall_{st}\end{aligned}\tag{30}$$

$$G^{I}_{st}=\sum_{b=1}^{N_b}\left(\frac{P^{CHP}_{stb}}{\eta^{CHPe}_{b}}+G^{GB}_{stb}\right)\ \forall_{st}\tag{31}$$

$$D^{I}_{t},\ D^{E}_{t},\ I^{I}_{st},\ I^{E}_{st},\ G^{I}_{st}\geqslant 0\ \forall_{st}\tag{32}$$

The provided reserve by MEM (R^{MEM}_{s}) must be the same, at all times during reserve call (Eq. (33)) [44], whereas the produced reserve by each building equipment can vary by scenario and time-step. This improves the optimization value and thermal comfort in each building, where $R^{MEM\_a}_{st}$ makes the reserve in a proper form for the objective function.

$$\underline{\kappa}_t R_s^{MEM} = \underline{\kappa}_t \sum_{b=1}^{N_b} R_{stb}^{loc}\ \forall_{st},\ \underline{\kappa}_t R_{st}^{MEM\_a} = \underline{\kappa}_t \sum_{b=1}^{N_b} R_{stb}^{loc}\ \forall_{st} \tag{33}$$

2.9. EPs constraints

These constraints (Eqs. (34), (35) and (38)) calculate the EPs based on equipment power (including P_{stb}^{CHP}, P_{stb}^{EHP}, P_{stb}^{EB}, P_{stb}^{ES}, P_{stb}^{PV}, P_{stb}^{WT}), E_{stb}^{ele} and MEM properties (e.g. line impedance), which are PF equations and implemented by OpenDSS. Afterwards, Eqs. (36), (37) and (39) limit the EPs to their standard range, satisfying the 1^{st} novelty.

2.9.1. Voltage profile

The standard range of the voltage magnitude and angle are defined in Eq. (36) and (37), respectively. Being in standard range, improves the service quality for consumers and thus, increases the flexibility.

$$P_{stb}^{M} = \begin{cases} D_t^I - D_t^E + I_{st}^I - I_{st}^E & b = 250 \\ 0 & \text{otherwise} \end{cases} \tag{34}$$
$$\forall_{stb}, P_{st}^{M} = \textstyle\sum_{b=1}^{N_b} P_{stb}^{M}$$

$$\begin{aligned} &P_{stb}^{M} + P_{stb}^{CHP} - P_{stb}^{EHP} - P_{stb}^{EB} + P_{stb}^{PV} + P_{stb}^{WT} \\ &-P_{stb}^{ES} - E_{stb}^{ele} = \textstyle\sum_{l=1}^{N_b} v_{stb} v_{stl} \Big[G_{bl} \cos\left(\theta_{stb} - \theta_{stl}\right) \\ &+B_{bl} \sin\left(\theta_{stb} - \theta_{stl}\right)\ \forall_{stbl} \end{aligned} \tag{35}$$

$$0.95 \leqslant v_{stb} \leqslant 1.05\ \forall_{stb} \tag{36}$$

$$-180 \leqslant \theta_{stb} \leqslant 180\ \forall_{stb} \tag{37}$$

2.9.2. Congestion

Eq. (39) prevents the current from violating the allowed values in each power transmission equipment and congestion occurrence. It is worth mentioning that congestion damages power transmission equipment and disrupts the MEM performance. As a result, it can stop services to consumers, resulting in decreased flexibility.

$$c_{ste} = \Big[(v_{stb}\cos\theta_{stb} - v_{stl}\cos\theta_{stl}) + i(v_{stb}\sin\theta_{stb} \\ -v_{stl}\sin\theta_{stl})\,[G_{bl} + iB_{bl}]\ \forall_{stble},\ e \text{ is from } b \text{ to } l. \tag{38}$$

$$0 \leqslant c_{ste} \leqslant C_e^{TE}\ \forall_{ste} \tag{39}$$

3. Case study applications

A conceptual simulation study is conducted to demonstrate the ability of proposed model. The MEM under study (is based on the UK [45]), comprises of 720 well-insulated residential detached buildings and 237 buses with domestic, commercial and industrial loads, connected to the upstream network at a point by 850 MVA limit, as shown in Figure 3. The main objective is to maximize the MEM flexibility using equipment power and imported power scheduling, while EPs limitation are also considered, compared through several case studies (given in Table 2). Case study 0 (CS0) is considered as a reference for comparing the other. CS1 considers EPs constraints to observe the limitation of voltage profile and congestion. In CS2 and CS3, the reserve market is also taken into consideration to increase the flexibility and MEM revenue by reserve production. CS3 includes the EPs constraints as well. Table 3 shows the parameters used in these case studies.

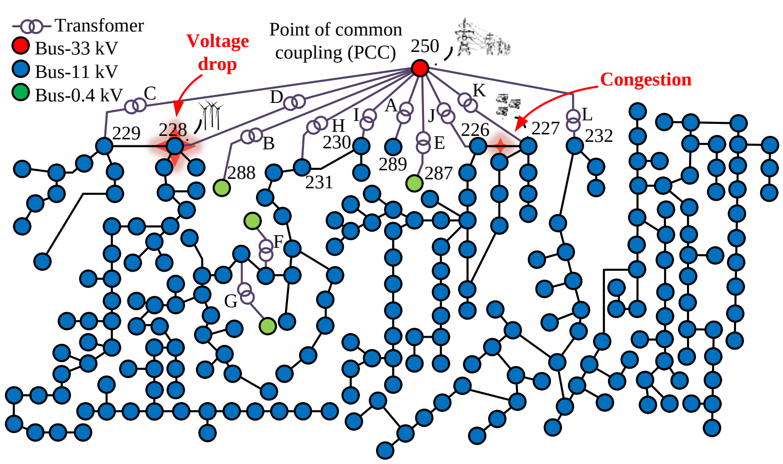


Figure 3: Single line diagram of the MEM under study.

Table 2: Case studies definition

Case study	Markets	Voltage regulation	Congestion
CS0 (reference)	Energy	No	No
CS1	Energy	Yes	Yes
CS2	Energy/Reserve	No	No
CS3	Energy/Reserve	Yes	Yes

Table 3: Parameters used in case studies

	Parameters
GB	$\overline{H}_b^{GB}$=24, η_b^{GB}=75, b=226,228
CHP	η_b^{CHPth}=72, η_b^{CHPe}=24, $\overline{H}_b^{CHP}$=4.9, b=1-N_b
TES	C_b^{TES}=0.35, R_b^{TES}=568, $\underline{X}_b$=55, $\overline{X}_b$=80, b=1-N_b
ES	η_b^{ES}=90, $\overline{P}_b^{ES}$=65.85, $\overline{B}_b$=109.75, b=226
PV	Maximum power=275 kW, b=227
WT	Maximum power=869.1 kW, b=228
MEM	T_{tb}^{A}=21, T_{tb}^{E}=-4, C_b^{Build}=13.89, R_b^{Build}=5.63, ξ_t^d/ξ_t^s=1000

3.1. Probabilistic parameters (scenario generation)

Day-ahead and reserve market prices [46] as well as the gas price [47] are taken according to UK market rules. Because of the uncertain price of the imbalanced market, all possible prices should be considered in a number of scenarios and are based on the previous seasons prices [46]. The day-ahead market is a market in which the price is significant for the next 24 hours and the buy/sell contract for energy is determined based on this price. However, in the imbalanced market, the price for the next 24 hours is not clear and the shortage or excess of energy is compensated. To reduce the volume and increase the speed of computations, the simultaneous backward reduction algorithm [48] used for imbalanced market price takes four scenarios for winter, spring, summer and autumn, respectively. In addition, it determines the probability of occurrence of each scenario (ρ_s). The sce-

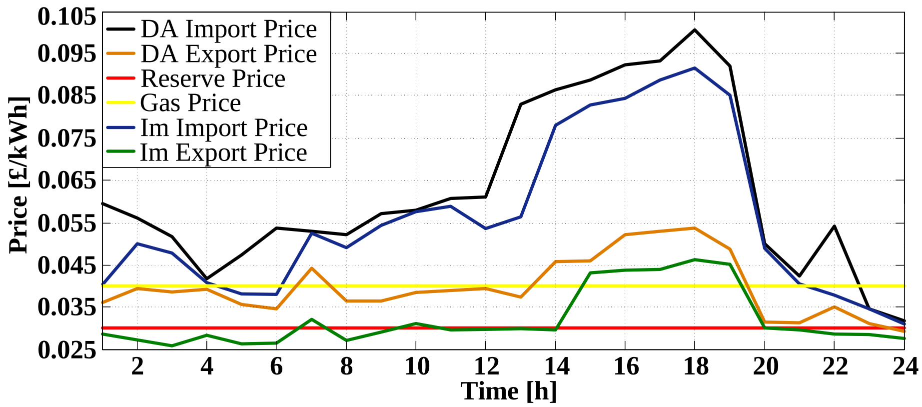


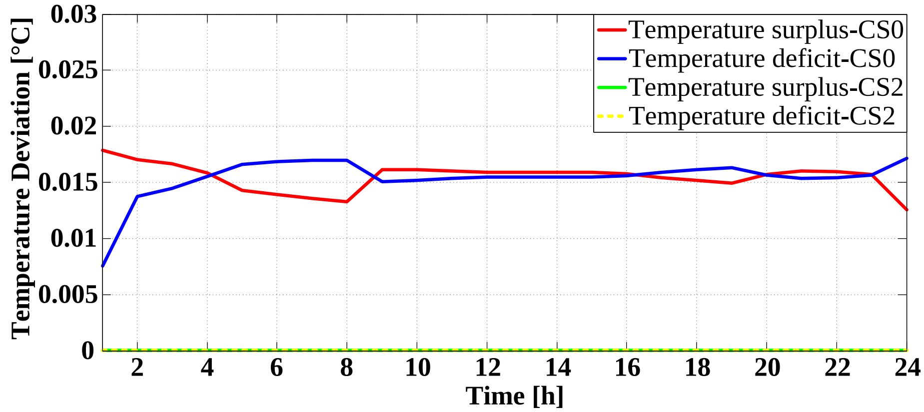
Figure 4: Electricity, reserve and gas prices on a winter day.

narios corresponding to these four selected scenarios are then considered for other probabilistic parameters including occupancy, environmental conditions (temperature, as well as PV and WT generation), electrical load and DHW profiles using their past data. As a result, the application of the simultaneous backward reduction algorithm to consider probabilities has converted the proposed model into a decision making system that supports existing uncertainties. These four scenarios (N_s=4 which is considered in Eq. (1)) are investigated to create robust thermal comfort in the proposed model (Section 2.7.2). The prices for a typical winter day are shown in Figure 4.

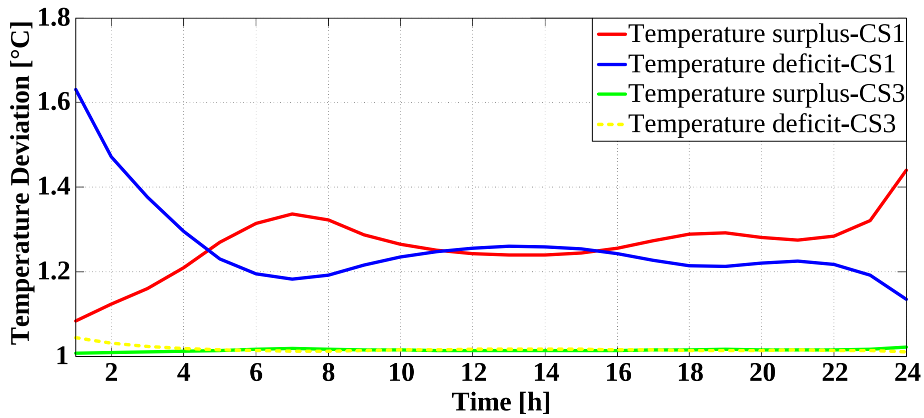
3.2. Results

3.2.1. Equipment power and thermal comfort

The thermal comfort is shown for case studies with and without EPs constraints in Figures 5(b) and 5(a), respectively. The EPs constraints reduce the thermal comfort, which however, is an expected result. It is because the new constraints (EPs) added to the MEM restrict it to operate optimally. However, the amount of thermal comfort reduction is unnoticeable by consumers. As a result, compared to some previous works such as [8, 12, 24] which did not consider thermal comfort, in this model, the amount of temperature deviation is in a range that does not significantly reduce consumer satisfaction. Comparison between CS2 and CS0, or CS3 and CS1



(a) CS0 and CS2

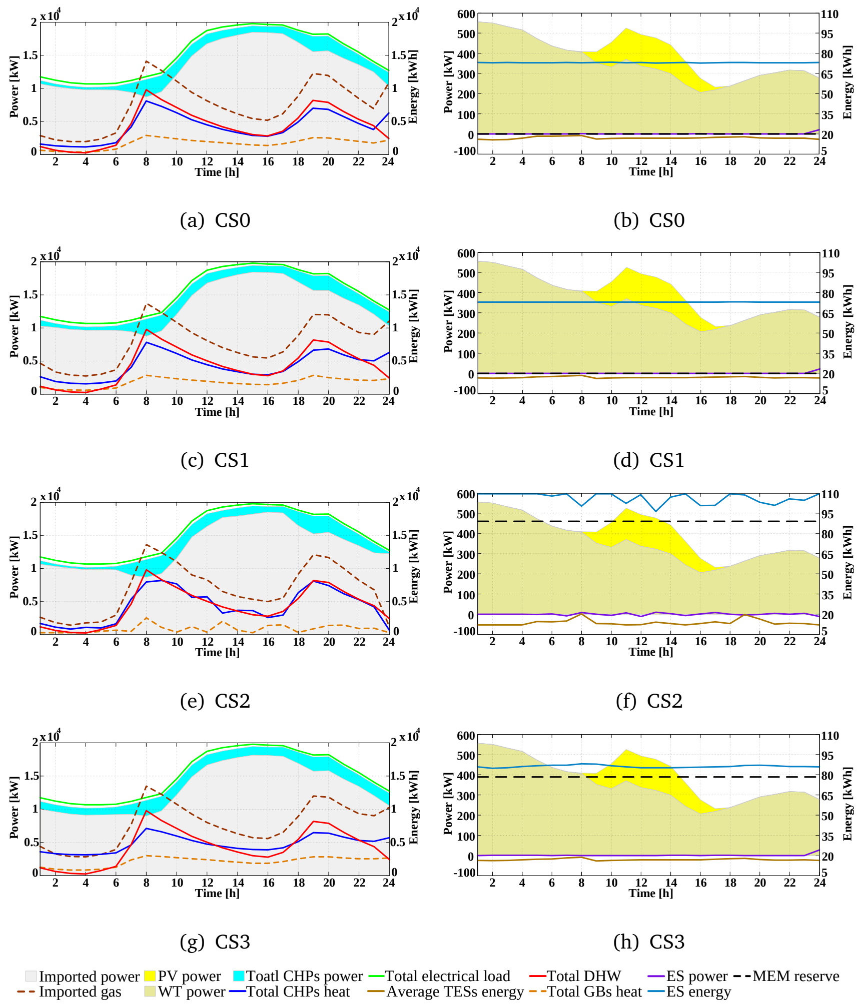


(b) CS1 and CS3

Figure 5: Temperature deviation at bus 226 on a winter day.

in Figure 5 shows that in addition to being robust with respect to thermal comfort, reserve increases it. Therefore, reserve consideration has increased thermal comfort compared to model such as [8, 36] that have not modeled reserve generation.

Figure 6 shows electrical load, DHW profile, equipment power, imported power to MEM from market and imported gas. All the case studies show that the equipment power and imported power is scheduled to maximize the revenue and avoid the MEM constraints. Figure 6(a) shows a part of electrical load is supplied by equipment and the rest of load is imported from the energy markets. The thermal load (adjusted temperature and environmental temperature are constant, conse-



(a) CS0 (b) CS0

(c) CS1 (d) CS1

(e) CS2 (f) CS2

(g) CS3 (h) CS3

Figure 6: On a winter day, imported electrical power from energy markets, power of equipment, imported gas, reserve and load.

quently, X^{SH}_{stb} is constant (Eq. (17)) and only DHW consumption varies) during the day is provided only by CHPs and GBs. Because of this and also the lack of constraint of imported gas and flat gas price, their generated power curve follows DHW consumption. Thus, imported gas also follows DHW consumption and there is no motivation to shift gas consumption time. CHPs heat is more in contrast to GBs heat, because CHPs are the only source of electricity in MEM and must supply a part of electrical load. In the early hours of the morning, CHPs heat is more than DHW consumption to supply electrical load and thus, it increases the TESs energy of each building. Here, it is assumed the buildings are actively occupied all the hours. In DHW peak hours (such as 07:00-11:00), TESs are discharged, but they are charged again in low DHW consumption hours (13:00-18:00) to be discharged over the evening DHW peak (18:00-22:00). At the final day hours (23:00-24:00), CHPs and GBs heat is increased in order to equalize the initial and final energy of TESs. It is important to mention that because of more electrical power of CHPs, imported power is reduced. The ES power is very low and it is charged significantly at 23:00-24:00, when CHPs power is increased (Figure 6(b)). Comparing Figures 6(c) and 6(a), at 01:00-07:00, 13:00-17:00, and 22:00-24:00 periods, CHPs produce more electrical power to compensate the voltage drop and eliminate the congestion (Figure 7(a) and Figure 8), thus, imported power is reduced. The extra heat produced by CHPs is stored in TESs and building fabric, increasing thus the TESs energy. Also, the temperature deviation (comparing Figure 5(b) with Figure 5(a)) is increased and reaches up to 1.6 °C, which in CS0 was below 0.02°C. Because of the increased CHPs power at noted hours, more gas is imported and gas revenue decreases (Table 4). Figure 6(d) is the same as Figure 6(b) and ES energy does not vary significantly.

Comparing Figure 6(e) with Figure 6(a), in the early hours of the day (01:00-06:00), CHPs power decreases to increase its reserve (Eq. (23)). At 13:00, due to lower energy sale price (compared to reserve price), CHPs power is reduced for increasing its reserve. Also, in 17:00-19:00 period, energy purchase price is high and imported power is lower. Consequently, CHPs power cannot be reduced. The CHPs power increases compared to CS0 at this period to charge ES and increase its reserve

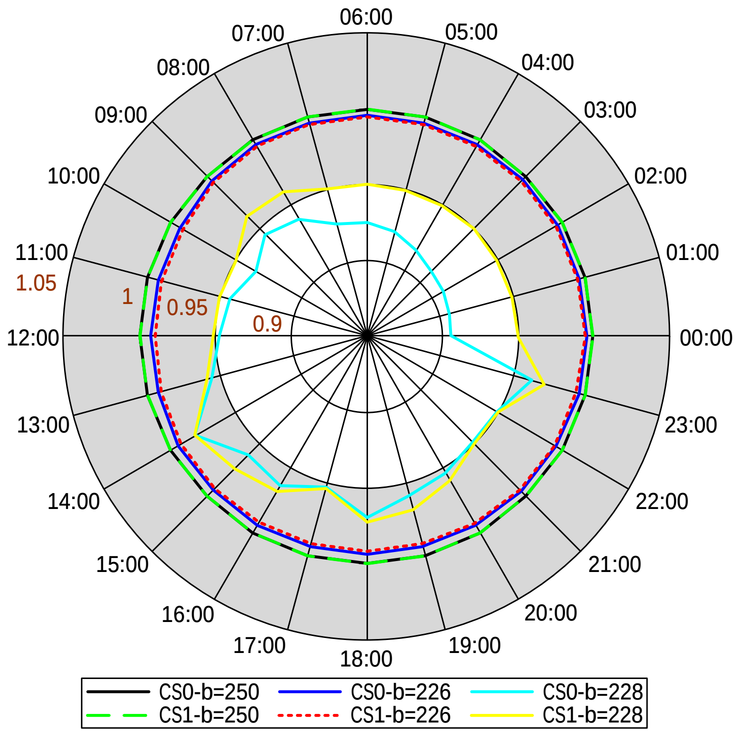
(Eqs. (24) and (29)), as shown in Figure 6(f). Increasing the number of CHPs and ESs can increase the level of MEM reserve. GBs heat compensate the rest of thermal load, which is not supplied by CHPs. The availability of more CHPs power in most of the hours reduces the imported power, As a result, electricity revenue is increased (Table 4). Comparing Figure 6(f) and Figure 6(b), TESs energy is reduced as they are more involved in supplying thermal load. Thus, CHPs and GBs heats are lower and the dependence on them is reduced. Also, gas revenue increases (Table 4). More TESs involvement is due to GBs heat limitation. Figure 5(a) shows temperature deviation is very low compared to CS0, whilst the MEM provides reserve. The reserve has a fixed value of 459.8 kW at all hours of the day. Comparing Figure 6(g) with Figure 6(e), at the 01:00-07:00, 13:00-17:00, and 22:00-24:00, CHPs power increases to compensate voltage drop and eliminate the congestion (Figure 7(b) and Figure 8), and reduces the imported power. The rise in CHPs heat, increase the energy stored in TESs and building fabric. As a result, temperature deviation is more (Figure 5) in contrast to CS2. Because of maintaining the initial and final TESs energy (Eq. (13)), at DHW peak (07:00-12:00 and 18:00-21:00), TESs are discharged and CHPs heat is reduced. Consequently, imported power increases and its revenue decreases compared to CS2 (Table 4). Observing the limitations of voltage profile and congestion in CS3 does not allow the CHPs power to decrease for supplying more reserve or transmitted for charging ES to increase ES reserve. Thus, MEM reserve decreases ((reduced 16.2% compared to CS2), Figure 6(h) compared to Figure 6(f)). It is worth noting that the imported gas is increased, and gas revenue is reduced.

3.2.2. EPs

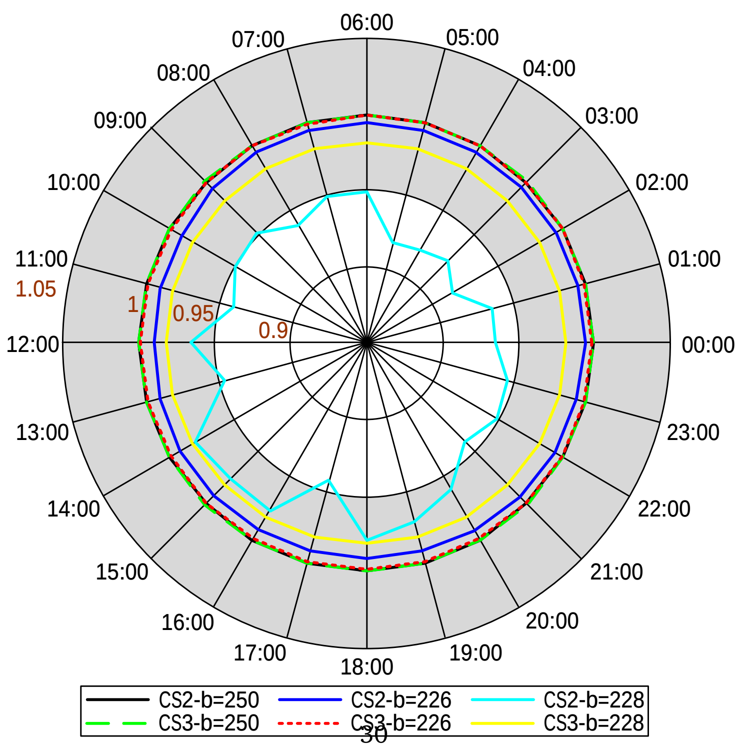
Based on Figure 7(a), bus 228 of Figure 3 has voltage drop in CS0 for most of hours in the day. The gray area shows the standard voltage range, which is between 0.95p.u. and 1.05p.u.. The reason of voltage drop at 00:00-06:00 and 23:00-24:00 (electrical load off-peak hours) is the low DHW, thus, CHPs cannot produce the required power. Comparing CS1 and CS0, given EPs constraints, the voltage of bus 228 is set within standard range, and is achieved by scheduling the CHPs and imported power (Figure 6(c)). As of Figure 7(b), in CS2 a voltage drop has occurred at bus 228 outside the standard range as it was in CS0. Comparing CS3 and CS2, the voltage profile is improved even with reserve commitment considering the EPs constraints. Comparing CS2 to CS0, shows that the reserve has helped in improving voltage at some hours, but at other hours voltage regulation is jeopardized. It is because the reserve commitment in CS2 changes the voltage profile by changing the equipment power and imported power for optimized reserve commitment (Figure 6(e)). But comparing CS3 and CS1, when reserve commitment is alongside the EPs constraints, it can improve the voltage profile at all the hours. The improved voltage profile in CS1 and CS3 results in consumers service quality enhancement and consequently, the flexibility is enhanced. Figure 8 demonstrates the line current between buses 226 and 227, as shown in Figure 3, is more than its rated current (1000 A [45]), implying that it is in the non-standard range. Given the congestion improvement in CS1 (Eqs. (38) and (39)), the congestion in the noted line is eliminated by changing the CHPs and imported powers (Figure 6(c)). Considering reserve commitment in CS2 compared to CS0, the current is changed only at 10:00-13:00 period. The current in CS3 shows that even with reserve commitment, applying EPs constraints set the current in standard range and congestion is eliminated. As it was observed, the proposed model maintains the voltage and current profiles in the standard range by considering the EPs constraints (in CS1 and CS3) in comparison with some models in Table 1 (such as the models provided by Good and Mancarella [2] and Iria et al. [25]), which do not consider the EPs (as modeled in CS0 and CS2). Therefore, the results obtained for CS1 and CS3 in Figure 7 and Figure 8 show that the EPs are within the standard range and according to Section 1, the city has a sustainable performance using the proposed model.

3.2.3. Cash flow results

Table 4 shows the revenue as per case study for the winter day. In CS2, a revenue is added from selling the reserve and the imported power falloffs, increasing the electricity revenue compared to CS0. In addition, because of reducing CHPs and GBs heat totally, gas revenue is also increased. Thus, the total revenue and as a



(a) CS0 and CS1



(b) CS2 and CS3

Figure 7: The voltage magnitude at 250, 226 and 228 on a winter day.

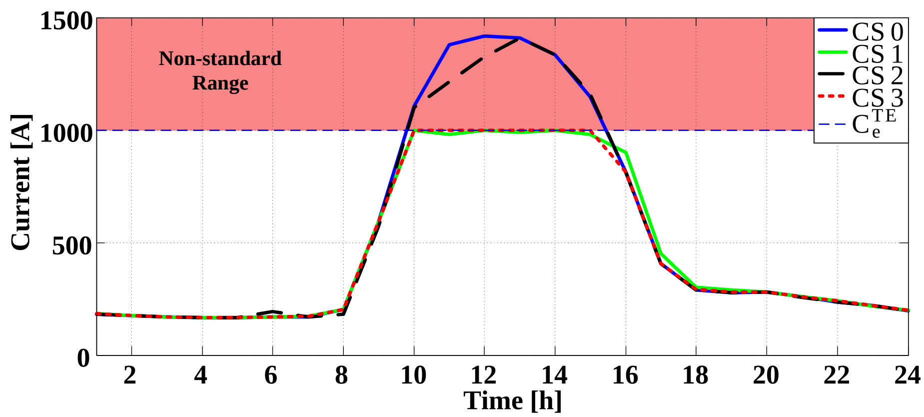


Figure 8: Current in line 226 to 227 on a winter day.

result, the flexibility is enhanced. This is the ability of the proposed model to uses the reserve flexibility for improving the types of revenue compared to the models presented by Coelho et al. [8] and Korkas et al. [36], which do not consider the reserve (Table 1). However, the total revenue of CS1 and CS3 dropped compared to CS0. Because the EPs constraints limit the optimal performance of equipment as well as the imported power. In these case studies, the MEMO may have to buy or sell electricity, when electricity price is high or low, respectively. In addition, shifting the time of consumption and storing may not be feasible considering the EPs constraints. Therefore, given the EPs constraints, although the service quality and thus flexibility increases, but MEMO revenue decreases. As it is noted, flexibility is not cost free. Reserve commitment, however, decreases the revenue reduction because of observing the EPs constraints (decreases 10% the total revenue reduction compared to case studies that do not include reserve commitment). Thus, according to the results for CS2 and CS3, MEM participation in the reserve market improves the urban economics.

Results demonstrate that the scheduling of equipment power and also the imported power from markets improve the voltage profile and congestion. Overall, unlike the models presented by Coelho et al. [8], Correa-Florez et al. [24] and Korkas et al. [36] (Table 1) which did not model the reserve generation, reserve

Table 4: Cash flow results, case study on a winter day

	Case studies			
	CS0	CS1	CS2	CS3
Gas revenue	-113.99	-119.57	-104.28	-119.05
Reserve revenue	0.00	0.00	331.08	277.45
Electricity revenue	52721.00	34627.96	62759.00	47632.00
Total revenue	52606.82	34508.39	62985.65	47790.71

Note: Revenues are in £/day

commitment (which does not compromise consumers thermal comfort) improves thermal comfort, flexibility (increases revenue and service quality such as more standard voltage for consumers appliances). Although EPs constraints considered in this model, unlike the models presented by Good and Mancarella [2], Lekvan et al. [10], Anwar et al. [22] and Iria et al. [25] which do not consider these constraints, improve flexibility (service quality), but revenue, as well as thermal comfort are reduced. However, their decrease is low and voltage profile and congestion improvement are more valuable for supplying the loads and multi-energy services, sustainability.

4. Conclusion

In this paper, a detailed and comprehensive two-stage multi-energy stochastic optimization model has been presented for MEM power management to optimize the flexibility. The MEM considered in the proposed model could be a city or part of it. The buses voltage are maintained within standard range and congestion is avoided using the EPs constraints. Also, the produced reserve by equipment is managed in such a way that the consumers thermal comfort is not degraded during reserve call. The reduction in MEM revenue which is the result of EPs constraints consideration, is decreased 10% by reserve commitment. Moreover, the current could be reduced to 50% during the congestion. The various case studies on a distribution network illustrated practical application of the model. The most important results of the proposed model are:

1. Optimized flexibility and compliance with EPs limitation.
2. EPs constraints and voltage regulation have reduced MEM revenue and the thermal comfort slightly, but increasing the flexibility significantly.
3. Reserve consideration has increased MEM revenue, flexibility and thermal comfort.

These have resulted in the sustainability of MEM performance and also maximized flexibility. Therefore, the application of the proposed model has created a sustainable city with improved urban economics.

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