Management of Renewable-based Multi-Energy Microgrids in the Presence of Electric Vehicles

Miadreza Shafie-khah [1,*], Morteza Vahid-Ghavidel [2], Marialaura Di Somma [3], Giorgio Graditi [3], Pierluigi Siano [4], João P.S. Catalão [2]

[1] School of Technology and Innovations, University of Vaasa, 65200 Vaasa, Finland
[2] Faculty of Engineering of the University of Porto, and INESC TEC, 4200-465 Porto, Portugal
[3] ENEA - Italian National Agency for New Technologies, Energy and Sustainable Economic Development - CR Portici, 80055 Portici, Italy
[4] Department of Management & Innovation Systems, University of Salerno, Fisciano (SA), 84084 Salerno, Italy
[*]mshafiek@univaasa.fi

Abstract: This paper proposes a stochastic optimization programming for scheduling a microgrid considering multiple energy devices and the uncertain nature of renewable energy resources and parking lot-based electric vehicles (EVs). Both thermal and electrical features of the multi-energy system are modeled by considering combined heat and power (CHP) generation, thermal energy storage, and auxiliary boilers. In addition, price-based and incentive-based DR programs are modeled in the proposed multi-energy microgrid to manage a commercial complex including hospital, supermarket, strip mall, hotel and offices. Moreover, a linearized AC power flow is utilized to model the distribution system including EVs. The feasibility of the proposed model is studied on a system based on real data of a commercial complex, and the integration of DR and EVs with multiple energy devices in a microgrid is investigated. The numerical studies show the high impact of EVs on the operation of the multi-energy microgrids.

Nomenclature

Indexes

Sc	Index of scenarios
N	Number of EVs
n	Index of EVs
B	Number of buses
b, b'	Index of buses

Superscripts

TES	Thermal energy storage
Ch	Charging
Dch	Discharging

Parameters

ρ_{sc}	Probability of scenarios
η_{el}^{CHP}	Electric efficiency of CHP
η_{th}^{CHP}	Thermal efficiency of CHP
$SOC_{n,t,sc}^{\max}$	Maximum state-of-charge of EV n at time t scenario sc
$SOC_{n,t,sc}^{\min}$	Minimum state-of-charge of EV n at time t scenario sc
$P^{CHP\max}$	Maximum generation of CHP
$P^{CHP\min}$	Minimum generation of CHP
$P_{t,sc}^{W,\max}$	Maximum generation of wind unit
$P_{t,sc}^{PV,\max}$	Maximum generation of photovoltaic unit
$H_{\max}^{TES}$	Maximum heat of thermal energy storage
$H^{Boil\min}$	Minimum heat of boiler
η_{th}^{Boil}	Thermal efficiency of boiler
$V_{\max}, V_{\min}, V^{Nom}$	Maximum and minimum voltage, nominal voltage
$R_{nn'}, X_{nn'}$	Distribution lines resistance and reactance
$\Delta S_{nn'}$	Upper limit in the discretization of quadratic flow (kVA).

Variables

$P_t^{req,HP}$	Electric power required by the heat pump
H_t^{CHP}	Heat rate recovered by the CHP
$P_{b,t,s}^{L}$	Customers' demand
PEN_t	Penalty of DR programs
DR^{CHP}	ramp-down power generation of CHP
$H_t^{Dis,TES}$	Discharging heat rate of thermal energy storage
$H_t^{Ch,TES}$	Charging heat rate of thermal energy storage
$P^{Boil\max}$	Minimum power of boiler
$P_{Sb,t,sc}^{Wh}$	The injected power from the upper grid
$P_{n,t,sc}^{Ch,EV}$	Charging power of EVs
$P_{t,sc}^{W}$	Power generation of wind unit
$P_{t,sc}^{PV}$	Power generation of PV unit
$P_{b,t,sc}^{Load}$	Electric load at bus b

$\Pr_t^L$	Electricity price after DR
H_t^{Boil}	Heat rate of boiler
$\Pr^{Wh,gas}$	Price of natural gas
$\Pr_t^{EV}$	Price of energy purchased by EVs
COP^{HP}	Coefficient of performance of the heat pump
x_t^{Boil}	Commitment binary variable of boiler
A_t	Incentive of DR programs
UR^{CHP}	Ramp-up power generation of CHP
x_t^{CHP}	Commitment binary variable of CHP
$\Pr_t^{Dch}$	Discharging tariff of EVs
$\Pr_t^{Wh,el}$	Price of buying electricity from the wholesale market
P_t^{CHP}	Generation of CHP
LHV_{gas}	lower heat value of natural gas
$P_{n,t,sc}^{Dch,EV}$	Discharging power of EVs
$P_{b,t,s}^{L,DR}$	Customers' demand by implementing DR
$P_{b,t,s}^{Con}$	Contracted power in DR programs
$SOC_{n,t,sc}^{EV}$	State-of-charge of EV n at time t scenario sc
$X_{n,t,sc}^{Ch,EV}$ $X_{n,t,sc}^{Dch,EV}$	Auxiliary binary variables to guarantee the EV is not charge and discharged simultaneously
H_t^{TES}	Stored heat at thermal energy storage
$P_{t,sc}^{Loss}$	Power loss of the system
$\varphi_{\Delta t}^{TES}$	Loss fraction of thermal energy storage
I,I2	Current flow, Squared current flow
P+	Active power flows in downstream directions
P-	Active power flows in upstream directions
Q+	Reactive power flows in downstream directions
Q-	Reactive power flows in upstream directions
V,V2	Voltage, Squared voltage

1. Introduction

1.1. Motivation

Distributed energy resources (DER) are being widely used as a suitable option for energy supply more reliable and sustainable [1]–[3]. A DER system can be introduced as an energy system with multiple input and output in which electricity and thermal energy is supplied near customers [2], [3]. DER systems are supposed to have certain policies related to several DERs integration and some useful incentives regarding economic benefits and recovering waste heat from thermal power generations [2]-[7]. To take the advantages of DER systems, it is essential to schedule their operation in an optimum way which may have some challenges in modelling [8]. During operation scheduling of DERs, supply and balance balancing should be taken into account because of not only regular variation of weather-dependent DERs like photovoltaic system (PVs) and wind generators (WG) as well as electric vehicle (EVs) and but also limited operation condition [3], [4], [8]. Considering all above mentioned conditions leads to achieve the best operation strategy which can satisfy electrical and thermal loads of customers [4].

1.2. Literature review

Some mathematical models were suggested for DER optimization procedure that concentrated mostly on a certain DER technology, such as Combined Heat and Power (CHP) or Combined Cooling Heat and Power (CCHP) systems, while taking economic aspects into consideration [9]–[15]. In [16], a price-based decomposition has been developed as well as a coordination optimization approach which shows a reduction in the daily energy costs. And as stated in [17], multiple DERs are taken into account in the model while energy cost minimization procedure has been carried out.

Moreover, using parking lot (PL)-based EVs are being widely spread. In [18], various standards for EVs, vehicle to grid (V2G) concept and its advantages, the effect of charging strategy, as well as the comparison among uncoordinated and coordinated strategies for charging have been studied. In [19], the current conditions of EV technologies, effects of EV penetration, and the relation among EV and the smart grids have been investigated. In [20], a review has been provided for scheduling of plug-in EV along with different optimization approaches for EVs integration in the electrical systems. This review has involved an assessment on different charging strategies, objective functions, earlier mathematical modeling, heuristic algorithm methods, along with a comparison of these approaches.

Since demand response (DR) is another effective way to provide cost-efficient balance among supply and demand, combination of DR, EV and other DERs are being investigated recently. In [21]-[23], different studies on EVs and DR programs have been conducted. In [24], using an optimal strategy in both price-based demand response (PBDR) and incentive-based demand response (IBDR) programs and several subgroups, the behavior of PL-based EVs has been assessed. The objective function was to maximize the profit of PLs while taking into account the uncertainties of PLs and the electricity market. The amount of participation of EVs in several DR programs is also being optimized. In [25], a stochastic framework has been introduced for the operation of distribution systems considering DERs. In the proposed method, the stochastic nature of electricity prices and the amount of generation of DERs have been also taken into account. In [26], total operation cost and emission have been minimized applying a stochastic approach considering renewable energy resources (RERs) and several DR programs.

One of the main challenges of the data centers in the deregulated electricity market is choosing the utility company as well as scheduling the workload. These challenges are addressed in [27]. The authors in [28] propose a two-stage procedure that allocates the electric vehicles' parking lots and distributed renewable generation simultaneously. A centralized energy trading is modeled through a bi-level optimization approach in Ref. [29]. The effects of uncertainty in [29] are managed through considering probabilistic load model and assuming the risk of renewable generation storage. In order to minimize the generation and discomfort cost of end-users in an optimal power flow optimization problem, authors has proposed a model in Ref. [30] considering voltage and power balance constraints using semidefinite programming relaxation technique. The role of DR programs in smart grids development is studied deeply in [31] such as load participation models in DR programs, integration of demand-side generation into the current power system.

As stated in [32], by employing an IBDR program, PLs' location and size have been accomplished for raising the reliability of distribution system. Meanwhile the Energy Not Supplied (ENS) and system average interruption duration indices (SAIDI) have been calculated. The objective function has been solved by genetic algorithm while considering four scenarios regarding EVs availability. Reference [33] applies IBDR programs and a proper EVs' charging and discharging strategy; a new methodology for a microgrid (MG) has been introduced. The proposed program has aimed to minimize the total operation cost of MG. In [34], for the distribution systems scheduling including EVs and RERs, a model to minimize the whole cost has been presented involving the cost of power supply, EVs and ENS as the reliability costs.

To schedule the operation of DERs, various kinds of uncertainties like RERs generation uncertainty, and EV's owner behavior should be considered. Otherwise, the proper strategies for DER operation might not be optimum one [8]. Uncertainties handling of DERs modeling has been increased in recent studies. A sensitivity analysis on load demands variations has been conducted in [35] to assess the impact on the CCHP systems. A CCHP system has been analyzed in [36] for the various operation strategies while considering inputs as the uncertain parameters like load demand and process efficiency. In Ref. [37], a new modelling is introduced to optimize a CCHP system with uncertain demand. According to [38], there are different methods to overcome uncertainties of network's element. Moreover, to combine stochastic variables, the existence approaches have been reviewed. Likewise, scenarios generation methods to apply in optimization programs for power system operation have been discussed. Although various reports studied the multi-energy systems, to the best of the authors' knowledge a microgrid considering DR, multi-energy systems and EVs that distributed across the network has not been addressed in the literature.

1.3. Contributions

The main contributions of this work are written as follows:

- Proposing a stochastic optimization programming for scheduling a microgrid considering heat loads and electrical loads by considering the stochastic nature of PV generation, wind power generation and PL-based EVs;
- Developing the distribution system model including EVs empowered by a linearized AC power flow;
- Modeling price-based and incentive-based DR programs in a multi-energy microgrid.

1.4. Paper organization

The rest of this paper is organized as follows. Section 2 express the mathematical modeling of the uncertainties and demand response. Section 3 presents the formulation of the multi-energy microgrids. Section 4 devoted to numerical results and discussion. Section 5 concludes the paper.

2. Uncertainty characterization and DR modeling

2.1. Uncertainty handling

In this section, intermittent nature of PVs, wind generation and PL-based EVs are modeled. This modeling aims to tackle uncertainties caused inaccurate results. It should be noted that since in this study well-addressed and well-known uncertainty models have been applied, the exact distribution exists. Therefore, the stochastic optimization is chosen in this model.

2.1.1 PV

Solar irradiance is the source of uncertainty in PV systems. To predict solar irradiance, a statistical approach is employed in this paper. To model the solar irradiance uncertainty, Beta probability distribution functions (PDFs) is utilized. It is noteworthy to mention that according to [39] and [38], this function is a famous probability distribution for solar irradiance uncertainty modeling. To define a suitable PDF, via the expected value of the solar irradiance, the relative PDF for each duration is produced. A normal day, i.e. 24 hours is assumed for defining the random solar irradiance. The data which is corresponding to the same times of the day are employed to achieve the PDF related to each time horizon. A lot of scenarios can be generated through fitting uniform random variables to the PDFs with same probability. This approach is repeated for a certain volume of iterations. For the generation of a Beta PDF for each time interval the hourly solar irradiance data are considered. Thus, the PDF that corresponds to the solar irradiance is determined as follows:

$$f_b(\zeta)=\begin{cases}\dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)}\zeta^{(\alpha-1)}(1-\zeta)^{\beta-1} & 0\le\zeta\le 1,\alpha\ge 0,\beta\ge 0\\ 0 & otherwise\end{cases} \tag{1}$$

In the above equation, $f_b(\zeta)$ indicates the Beta distribution function, the parameters of the Beta function are denoted by α and β, which can be calculated through the historical data and ζ is the random variable. Finally, the power production is calculated with the following equation.

$$P_{PV}=\begin{cases}P_{PV-Rated}\cdot\dfrac{SI}{SI_r} & 0\le SI\le SI_{\mathrm{r}}\\ P_{PV-Rated} & SI_{\mathrm{r}}\le SI\end{cases} \tag{2}$$

where SI is solar irradiance and SI_r is rated to solar irradiance. Moreover, $P_{PV\text{-}Rated}$ is rated power production of PV. Accordingly, for solar irradiance less than rated one the power production is a percentage of the rated one. While for the solar irradiance more than rated one, the power production is equal the rated one [40].

2.1.2 Wind generation

For wind generation, wind speed is the uncertain variable. Similar to solar generators, the application of a statistical approach is considered to determine wind speed forecast. Therefore, Rayleigh probability distribution functions (PDFs) is applied to model the wind speed uncertainty. It is worthy to declare that Rayleigh is one of the famous probability distributions that are used for wind speed [41]. The related hourly PDF is generated through the *r* forecasted wind speed. Since horizon time is 24 hours in a day, the related data for this horizon time are engaged to produce 24 PDF corresponding to each hour. Many scenarios can be formed by combining random variables with the same probability in the PDFs. For a number of iterations this approach is repeated. For generating a Rayleigh PDF the hourly wind speed data is employed for each period. To this end, the PDF of the Rayleigh is evaluated through:

$$f_r(\zeta) = \left(\frac{2\zeta}{c^2}\right) e^{-\left(\frac{\zeta}{c}\right)^2} \tag{3}$$

In the above equation, $f_r(\zeta)$ indicates the Rayleigh distribution function, the parameters of the Beta function are denoted by α and β, which can be calculated through the historical data and ζ is the random variable.

Electricity is generated based on wind speed as (4) explains, where V_{ci} V_{co} V_r and P_r are cut-in, cut-out, rated wind speeds and rated power output of WT, respectively. Accordingly, when the wind speed is more than cut-out wind speed, no electricity is produced. While, if the wind speed is between cut-out and rated wind speeds, the maximum electricity is produced. In case the wind speed is variated among cut-in and rated wind speed, the generation is linearly dependent to wind speed [44].

$$P_w = \begin{cases} 0 & 0 \le \mathrm{V} \le \mathrm{V_{ci}}, V_{co} \le V \\ P_{W-Rated} \cdot \dfrac{V - V_{ci}}{V_r - V_{ci}} & \mathrm{V_{ci}} \le V < V_r \\ P_{W-Rated} & \mathrm{V_r} \le \mathrm{V} \le \mathrm{V_{co}} \end{cases} \tag{4}$$

2.1.3 EV

Different parameters of EVs include the initial state of charge (SOC), presence duration of EVs in PL, charge/discharge rate, the capacity of EVs' batteries as well as the desired final SOC. These are necessary to model the EV mathematically. However, considering the stochastic behavior of each EV owner, the output for EVs scheduling would be more precise. Therefore, for modelling the EV's behavior the truncated Gaussian distribution is implemented [18]. For generating each scenario, the aforementioned method must be utilized as stated in (5) – (7).

$$SOC_n^{ini} = f_{TG}\left(X; \mu_{SOC}; \sigma_{SOC}^2; \left(SOC_n^{ini,\min}; SOC_n^{ini,\max}\right)\right) \quad \forall n \tag{5}$$

$$t_n^{arv} = f_{TG}\left(X; \mu_{arv}; \sigma_{arv}^2; \left(t_n^{arv,\min}; t_n^{arv,\max}\right)\right) \quad \forall n \tag{6}$$

$$t_n^{dep} = f_{TG}\left(X; \mu_{dep}; \sigma_{dep}^2; \left(\max(t_n^{dep,\min}, t_n^{arv}); t_n^{dep,\max}\right)\right), \forall n \tag{7}$$

2.1.4 Scenario generation

The available solar irradiance correlation and wind speed and EV behavior is taken into account by using the historical data from the same period and a correlated approach to scenario generation. As stated in [43], product moment correlation is utilized when the distribution functions are not normal. Moreover, a rank correlated procedure is considered which is not the measurement of the correlation between the real values of the random variables. In this method, the models are sorted ranging from the lowest to the highest values; then for the corresponding ranks, the product moment correlation is measured. It catches the monotonic relationship among the random variables. As well, the rank correlation from a population of *N* pairs of samples (xi, yi) is calculated straightforward. The amount of xi is taken over by the amount of its rank amongst the other models (i.e. 1, 2, …, N). In case the samples are all distinct, each integer takes place only once. While the mean of the ranks is assigned, if some of the samples have identical values with slight difference.

For scenario generation, using historical data, hourly different PDFs are produced. Thus though implementing the scenario tree technique, different output states are explained. Initial output scenarios set will be carried out through employing the interval method. Since dealing with all generated scenarios leads to computation burden, constructing a scenario reduction method is required. The basic concept of scenario reduction is to select a reference scenario and compare this scenario with other scenarios and remove the closest scenario. In this paper, the Kantorovich distance (K-distance) is introduced to calculate the distance among the different scenarios. The scenario with the minimum K-distance is deleted and the probability of a deleted scenario should be added to the reference scenario. Thus, the latest version of scenarios can be obtained as well as the probability of all scenarios. In ref. [42], the scenario reduction model is explained.

2.2. DR Model

Two DR programs are applied in this paper in one equation to implement DR. One DR program is TOU from price-based DR (PBDR) programs and the other is emergency DR program from incentive-based DR (IBDR) programs. To deal with PBDR programs, price elasticity, which is load reaction to electricity price, should be introduced as follows[43]:

$$E = \frac{\mathrm{Pr}_0}{P_0} \cdot \frac{\partial P}{\partial \mathrm{Pr}} \tag{8}$$

Some loads can be reduced without recovering named fixed loads. The sensitivity of those loads is only in a single period called "self-elasticity" with a negative value which is presented as follows:

$$E(t,t) = \frac{\mathrm{Pr}_0(t)}{P_0(t)} \cdot \frac{P(t) - P_0(t)}{\mathrm{Pr}(t) - \mathrm{Pr}_0(t)} \le 0 \tag{9}$$

The other types of loads can be shifted and recovered from the peak periods to off-peak periods called flexible loads. They have multi period sensitivity and are introduced by “cross elasticity”. This value is always positive.

$$E(t,t^{'})=\frac{\Pr_0(t^{'})}{P_0(t)}.\frac{P(t)-P_0(t)}{\Pr(t^{'})-\Pr_0(t^{'})}\geq 0 \tag{10}$$

The following formulation is a combination of TOU and EDRP while considering elasticity, incentive and penalty concept to implement DR programs and obtain the amount of reduced load. This model is extracted from [43].

$$P(t)=P_0(t). \left\{1+\sum_{t^{'}\varepsilon \mathrm{T}}\frac{\Pr(t^{'})-\Pr_0(t^{'})+A(t^{'})+PEN(t^{'})}{\Pr_0(t^{'})}.E(t,t^{'})\right\} \tag{11}$$

The cost of DR implementation is also calculated by the following equation from ISO’s viewpoint.

$$C^{DR}=\left(A(t).\left(P_0(t)-P(t)\right)\right)- \left(PEN(t).\left(P_{con}(t)-\left(P_0(t)-P(t)\right)\right)\right) \tag{12}$$

3. Problem Formulation of Multi-Energy Microgrid

In the proposed model, the objective function is the maximization of operator’s profit that is achieved by revenue and cost terms. Operator’s revenue includes energy selling to EV owners and energy selling to loads. Operator’s cost is also gas and power procurement from wholesale market, power purchase from EV owners, the cost of buying DR from customers, and battery depreciation. According to Fig. 1, there are two sources of heat productions including combined heat and power (CHP) and auxiliary boiler (AB) both supplied by gas. The sources of electricity production are upstream network, CHP, PV, Wind, as well as EVs. The main players that are correlated to the operation of the system are the EV owners. They tend to charge their vehicle with the lower cost or exit from PL with the desired SOC. The EVs have the capability of power injection into the system especially during peak times and the system can manage EVs charging/discharging scheduling. Moreover, the system can implement the DR programs. All these facilities in the system lead to achieve the important objectives such as loss reduction, voltage profile improvement, increasing reliability index, avoiding feeder or transformer congestion, etc.

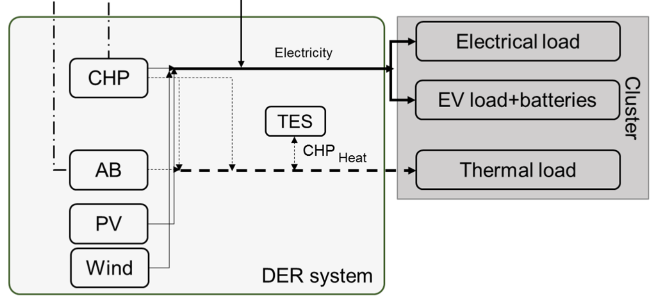


Fig. 1. *Scheme for the optimization problem*

3.1. Objective Function

The objective function includes 6 items as follows:

1) Revenue from the EV owners’ energy purchases.
2) Revenue from the load’s energy purchase.
3) Cost for providing power and gas through the wholesale market.
4) Cost of buying energy from EV owners for delivering to the load.
5) Cost that belongs to the battery depreciation.
6) Cost of buying DR from customers.

The first term refers to the revenue from the selling energy to EVs owner because of charging, i.e. (13). It is an expected function with different scenarios in 24-hour horizon time with one hour time period. The decision variable, EV power charging $P_{n,t,sc}^{Ch,EV}$, is obtained based on EV charging price $\Pr_t^{EV}$.

$$F_1=\sum_{sc=1}^{Sc}\rho_{sc}\sum_{n=1}^{N}\sum_{t=1}^{24}P_{n,t,sc}^{Ch,EV}.\Pr_t^{EV}.\Delta t \tag{13}$$

The second term refers to the revenue from selling energy to loads including commercial, industrial and residential sectors which is presented in (14). Decision variable, load supply $\mathrm{P}_{\mathrm{b,t,sc}}^{\mathrm{Load}}$, is optimized based on load supply price $\Pr_t^L$ in an expected function.

$$F_2=\sum_{sc=1}^{Sc}\rho_{sc}\sum_{b=1}^{B}\sum_{t=1}^{24}P_{b,t,sc}^{Load}\Pr_t^L\,\Delta t \tag{14}$$

The third term refers to cost of the purchased energy (electricity and gas) from the wholesale market to supplying several load and EV charging, i.e. (15). The first term of F_3 is the cost of buying electricity with decision variable $P_{Sb,t,sc}^{Wh}$ and the electricity price $\Pr_t^{Wh,el}$. The second term of F_3 includes the cost of buying gas for producing heat in CHP and boiler based on gas price $\Pr^{Wh,gas}$ and decision variables P_t^{CHP} and H_t^{Boil}, which are the power from CHP and the heat rate from boiler, respectively.

$$F_3= \sum_{sc=1}^{Sc}\rho_{sc}\sum_{Sb=1}^{Sb}\sum_{t=1}^{24}\left[\begin{array}{l}\left(P_{Sb,t,sc}^{Wh}\Pr_t^{Wh,el}\right)+\\ \left[\begin{array}{l}\left(P_t^{CHP}/\left(\eta_{el}^{CHP}LHV_{gas}\right)\right)+\\ \left(H_t^{Boil}/\left(\eta_{th}^{Boil}LHV_{gas}\right)\right)\end{array}\right]\Pr^{Wh,gas}\end{array}\right]\Delta t \tag{15}$$

The term 4 refers to the cost of the EVs offer to the market, which is resulting from discharging the EVs’ batteries in the peak hours. This cost that is paid to EV owner is given by (16). The decision variable is power discharging of EV and it is obtained based on discharging price through this expected function.

$$F_4=\sum_{sc=1}^{Sc}\rho_{sc}\sum_{n=1}^{N}\sum_{t=1}^{24}P_{n,t,sc}^{Dch,EV}\times\Pr_t^{Dch}\times\Delta t \tag{16}$$

Cost that belongs to the battery depreciation is taken into account in term 5. As stated in [23, 24], EV battery's life usually influenced by the depth of discharge. This is calculated based on the amount of energy taken from EV batteries and sold to the system. Therefore, at each discharge situation, operator is charged with another cost based on the certain price for battery depreciation C^{cd}. This cost that is paid to EVs owner is presented in (17).

$$F_5 = \sum_{sc=1}^{Sc} \rho_{sc} \sum_{n=1}^{N} \sum_{t=1}^{24} P_{n,t,sc}^{Dch,EV} C^{cd} \Delta t \tag{17}$$

Finally, the last term, i.e. 6, refers the cost of employment of the DR programs as presented in (18). In this DR model, EDRP and TOU programs are combined to implement in this problem.

$$F_6 = \sum_{s=1}^{NS} \rho_s \sum_{b=2}^{Nb} \sum_{t=1}^{24} \begin{pmatrix} A_t \left(P_{b,t,s}^{L} - P_{b,t,s}^{L,DR}\right) - \\ PEN_t \left(P_{b,t,s}^{Con} - P_{b,t,s}^{L} + P_{b,t,s}^{L,DR}\right) \end{pmatrix} \Delta t \tag{18}$$

After a description of revenue and cost, the objectives function in this part is presented as follows (19).

$$MAX \;\; \mathrm{OF} = F_1 + F_2 - F_3 - F_4 - F_5 - F_6 \tag{19}$$

Note that the purchased electricity from the wholesale market is consumed for supplying load, charging of EVs and losses. Therefore presenting a program for operational scheduling of system is a technical and economic model.

3.2. Constraints

All constraints regarding the objective function are presented in (20) – (55). These constraints are for renewable sources, DERs, network constraints and EVs.

3.2.1 RERs generation

Based on (20) – (21), the output of the solar and wind generation units have limitations that is forecasting the generation in the time period corresponding to solar radiation and wind speed.

$$0 \le P_{t,sc}^{W} \le P_{t,sc}^{W,\max} \tag{20}$$

$$0 \le P_{t,sc}^{PV} \le P_{t,sc}^{PV,\max} \tag{21}$$

3.2.2 DERs generation

The continuous decision variables are the generation levels of all devices, charging and discharging heat rates of storage, whereas the binary decision variables are the ON/OFF status of all devices, as presented below:

3.2.2.1 CHP system

The total electrical power, P_t^{CHP} (continuous decision variable) provided by the CHP has to be within the limitation of power output, if the device is on:

$$x_t^{CHP} P^{CHP\min} \le P_t^{CHP} \le x_t^{CHP} P^{CHP\max}, \;\; \forall t \tag{22}$$

The variation of power generation between two successive time steps within the ramp-down, DR^{CHP}, and ramp-up, UR^{CHP} limits is considered as the ramp rate constraint as follows:

$$DR^{CHP} \le P_t^{CHP} - P_{t-\Delta t}^{CHP} \le UR^{CHP}, \;\; \forall t \tag{23}$$

The heat rate recovered by the CHP is formulated as:

$$H_t^{CHP} = P_t^{CHP} \times \eta_{th}^{CHP} / \eta_{el}^{CHP}, \;\; \forall t \tag{24}$$

3.2.2.2 Auxiliary Boiler

The heat rate, H_t^{Boil} (continuous decision variable) provided by the boiler is limited, if the device is on, as follows:

$$x_t^{Boil} H^{Boil\min} \le H_t^{Boil} \le x_t^{Boil} P^{Boil\max}, \;\; \forall t \tag{25}$$

3.2.2.3 Thermal Storage

The amount of energy that is kept at time interval t depends on the non-dissipated energy stored at the previous time interval (based on the storage loss fraction), and on the net energy flow, i.e.:

$$H_t^{TES} = H_{t-\Delta t}^{TES}\left(1 - \varphi_{\Delta t}^{TES}\right) + \left(H_t^{Ch,TES} - H_t^{Dis,TES}\right)\Delta t, \; \forall t \tag{26}$$

where $\varphi_{\Delta t}^{TES}$ is stating the loss fraction, which considers the dissipated thermal energy in the time interval Δt. Further, $H_t^{Ch,TES}$ is the charging heat rate and $H_t^{Dis,TES}$ is discharging heat rate, (continuous decision variables). Additional constraints for the thermal storage are in (27) - (31).

$$H_t^{TES} \le H_{\max}^{TES}, \forall t \tag{27}$$

$$H_t^{TES} \ge 0, \forall t \tag{28}$$

$$H_t^{Ch,TES} \ge 0, \forall t \tag{29}$$

$$H_t^{Dis,TES} \ge 0, \forall t \tag{30}$$

$$H_t^{Ch,TES} \le H_t^{CHP}, \forall t \tag{31}$$

3.2.3 Network Constraints

Equations (32) – (33) present power balance for active and reactive power. Voltage balance is indicated in (34). The limitations of active and reactive power are calculated in (35) – (36), respectively. Linearized branch power flow for radial networks is presented in (37) – (44). Linearization of active and reactive power is conducted by (37) and piecewise linearization of constraints is performed by (38) – (44) [44]. Power factor constraint is brought in inequality in (45).

$$\begin{aligned} & P_{Sb,t,sc}^{Wh} + P_{b,t,sc}^{PV} + P_{b,t,sc}^{W} + P_{b,t,sc}^{CHP} + \sum_{\mathrm{EV}} P_{n,t,sc}^{Dch,EV} - \sum_{\mathrm{EV}} P_{n,t,sc}^{Ch,EV} \\ & + \sum_{b' \in B} (P_{t,b,b'}^{+} - P_{t,b,b'}^{-}) - \sum_{b' \in B} [(P_{t,b,b'}^{+} - P_{t,b,b'}^{-}) + R_{b,b'} I2_{t,b,b'}] \\ & = P_{b,t,Sc}^{\mathrm{Load}} \qquad \forall t, \forall b. \end{aligned} \tag{32}$$

$$Q^{Wh}_{Sb,t,sc} + Q^{PV}_{b,t,sc} + Q^{W}_{b,t,sc} + Q^{CHP}_{b,t,sc} + \sum_{EV} Q^{Dch,EV}_{n,t,sc} - \sum_{EV} Q^{Ch,EV}_{n,t,sc}$$
$$+\sum_{b'\in B}(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'}) - \sum_{b'\in B}[(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'}) + X_{b,b'} I2_{t,b,b'}] \tag{33}$$
$$= Q^{Load}_{b,t,Sc} \qquad \forall t, \forall b.$$

$$V2_{t,b} - 2R_{b,b'}(P^{+}_{t,b,b'} - P^{-}_{t,b,b'}) - 2X_{b,b'}(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'})$$
$$-(R^{2}_{b,b'} + X^{2}_{b,b'}) I2_{t,b,b'} - V2_{t,b'} = 0 \qquad \forall t, \forall b. \tag{34}$$

$$P^{+}_{t,b,b'} + P^{-}_{t,b,b'} \le V^{Nom} I^{Max}_{b,b'} \qquad \forall t, \forall b. \tag{35}$$

$$Q^{+}_{t,b,b'} + Q^{-}_{t,b,b'} \le V^{Nom} \times I^{Max}_{b,b'} \qquad \forall t, \forall b. \tag{36}$$

$$V2^{Nom}_{t,b} I2_{t,b,b'} =$$
$$\sum_{\tau}(2\tau - 1)\Delta S_{t,b,b'} \Delta P_{t,b,b'} + \sum_{\tau}(2\tau - 1)\Delta S_{t,b,b'} \Delta Q_{t,b,b'} \quad \forall t, \forall b. \tag{37}$$

$$P^{+}_{t,b,b'} + P^{-}_{t,b,b'} = \sum_{\tau} \Delta P_{t,b,b'}(\tau) \qquad \forall t, \forall b. \tag{38}$$

$$Q^{+}_{t,b,b'} + Q^{-}_{t,b,b'} = \sum_{\tau} \Delta Q_{t,b,b'}(\tau) \qquad \forall t, \forall b. \tag{39}$$

$$\Delta P_{t,b,b'}(\tau) \le \Delta S_{t,b,b'}, \Delta Q_{t,b,b'}(\tau) \le \Delta S_{t,b,b'} \qquad \forall t, \forall b. \tag{40}$$

$$I2_{t,b,b'} \le (I^{Max}_{b,b'})^{2} \qquad \forall t, \forall b. \tag{41}$$

$$V^{2}_{Min} \le V2 \le V^{2}_{Max} \qquad \forall t, \forall b. \tag{42}$$

$$V2^{Nom}_{t,b} = (V^{Nom})^{2} \qquad \forall t, \forall b. \tag{43}$$

$$\Delta S_{t,b,b'} = \frac{V^{Nom} I^{Max}_{b,b'}}{\tau} \qquad \forall t, \forall b. \tag{44}$$

$$P^{\bar{U}}_{t,b} \tan(\cos^{-1}(-\theta)) \le Q^{\bar{U}}_{t,b} \le P^{\bar{U}}_{t,b} \tan(\cos^{-1}(\theta)) \qquad \forall t, \forall b. \tag{45}$$

3.2.4 Line Capacity and Bus Voltage

Due to the thermal capacity of line, the power flow of branch should not be more than the maximum permissible power of branch. Besides, the voltage of each bus must not be greater than its maximum range of voltage and also not be lower than its minimum value. To this end, inequalities (46) – (47) are used.

$$S_{b,t,Sc} \le S^{Max}_{b,t} \tag{46}$$

$$V_{\min} = 0.95 \le V_{b,t,Sc} \le V_{\max} = 1.05 \tag{47}$$

3.2.5 Thermal Balance

Based on the thermal energy balance, the total heat rate generated is equal to the heat rate demand that is indicated in (48).

$$H^{CHP}_{t} + H^{Boil}_{t} + H^{Dis,TES}_{t} = H^{L}_{t} + H^{Ch,TES}_{t}, '' t \tag{48}$$

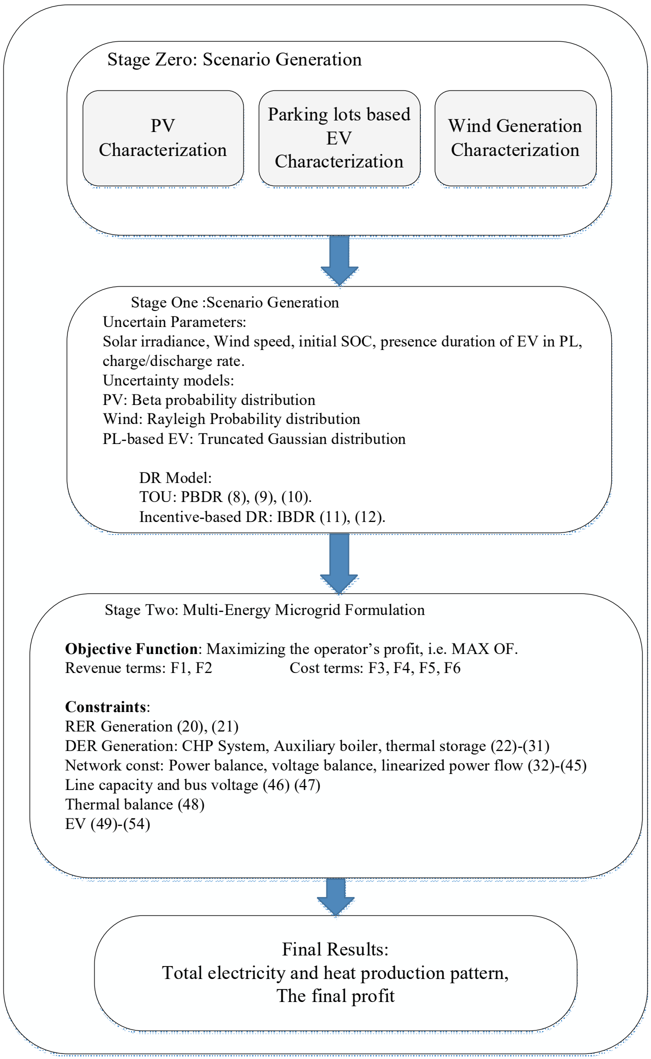


Fig. 2. *Framework of the proposed model*

3.2.6 EV Constraints

In this work, the EV are considered at it cannot be charged and discharged at the same time. This can be achieved through (49). Based on (50), the total SOC of the EV cannot surpass the range of SOC of each EV. As well, with reference to Eq. (51) the EVs' SOC at each time related to lots of factors such as leftover amount of SOC of the EV from the previous hour, the volume of the exchanged power with the system and PL, the efficiency of charging and discharging and initial SOC of EV [17,24]. The constraint (52) states the volume of energy that is purchased of every EV from PL cannot exceed its maximum value. Likely, the constraint (53) shows the volume of energy that each EV sold to PL cannot exceed its maximum. Finally, according to (54) the operation of charge and discharge of each EV must be perfectly valid in which in departure time of PL, the SOC of EV comes to the desired SOC.

$$X^{Ch,EV}_{n,t,sc} + X^{Dch,EV}_{n,t,sc} \le 1 \qquad \forall n,t,sc \tag{49}$$

$$SOC^{\min}_{n,t,sc} \le SOC^{EV}_{n,t,sc} \le SOC^{\max}_{n,t,sc} \qquad \forall\ n, t, sc \tag{50}$$

$$SOC^{EV}_{n,t,sc} = SOC^{EV}_{n,t-1,sc} + \left(P^{Ch,EV}_{n,t,sc}\,\Delta t\,\eta_{ch}\right) - \left(\frac{P^{Dch,EV}_{n,t,sc}\,\Delta t}{\eta_{Dch}}\right) + \mathrm{SOC}^{\mathrm{EV,Arv}}_{\mathrm{n,t,sc}} \qquad \forall\ \mathrm{n,t,sc} \tag{51}$$

$$0 \le P^{Ch,EV}_{n,t,sc} \le X^{ch,EV}_{n,t,sc}\,P^{\max}_{n} \qquad \forall\ \mathrm{n,t,sc} \tag{52}$$

$$0 \le P^{Dch,EV}_{n,t,sc} \le X^{Dch,EV}_{n,t,sc}\,P^{\max}_{n} \qquad \forall\ \mathrm{n,t,sc} \tag{53}$$

$$SOC^{EV}_{n,t,sc} = \mathrm{SOC}^{\mathrm{EV,dep}}_{\mathrm{n,t,sc}} \qquad \forall\ \mathrm{n},\ \mathrm{t}_{\mathrm{dep}},\ \mathrm{sc} \tag{54}$$

The proposed framework of this model is depicted in Fig. 2. In the stage zero, the scenarios for different considered items are characterized. In the next stage, the uncertain parameters and scenario generation functions are taken into account. Moreover, the utilized DR programs are also considered, i.e. PBDR and IBDR. Then, in stage two, the multi-energy microgrid total model is formulated from the microgrid operator's viewpoint. Thus, the objective function which are procured from gas and/or electricity power resources. Besides that, the constraints such as RER generation, DER generation, and the network constraints are taken into account, line capacity and bus voltage and thermal balance. Finally, the results including final objective function, total electricity and heat production pattern are indicated.

4. Simulation Results and Discussion

This model is studied by considering different kind of customers that are represented as follows: hospital, supermarket, strip mall, hotel and small office.

This program is implemented on the standard IEEE 15-bus distribution system for a whole day, i.e. 24 hours. The proposed model is simulated using a PC System with 6GB RAM and 2.43GHz CPU speed. The solution takes about 140 seconds. The data of this test system which is shown in Fig. 3 are taken from [45]. One wind turbine and PV systems are installed on bus 12 with specifications power rated of 200 *kW*, cut-in speed of 4 *m/s*, nominal speed of 14 *m/s*, and cut-out speed of 25 *m/s*. 200 kW PV systems are installed in the test system that each of them is composed of 10 × 10 kW solar panels with efficiency 18.6 percent and $S_{PV} = 40\ m^2$.

Also, the PL is installed on bus 11, assumed that 300 EVs is parked in PL. The load profile of the test system is demonstrated in Fig. 4 and the share of each bus of hourly demand is given in Table 1.

The loads' power factor assumed to be 0.95 lagging. As well, fixed power factor, i.e. 1, is considered for the wind and PV units. A 24 hours day is divided in three time intervals as follows: off peak (1-6 and 22-24), mid peak (7-10 and 16-18), and on peak (11-15 and 19-21).

In the following, the main required data and their values for the optimal operation of the system are given. Charge and discharge efficiency of EVs' batteries are assumed 90% and 95%, respectively. The battery capacity is assumed to be 50 kWh and batteries of EV are charged and discharged with a constant power of 10 kW per hour. Up to 85% of the rated battery capacity is considered as the depletion of EV battery for optimization of the EV battery life [33-34].

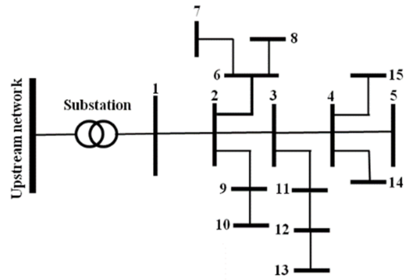


Fig. 3. IEEE 15-bus distribution system

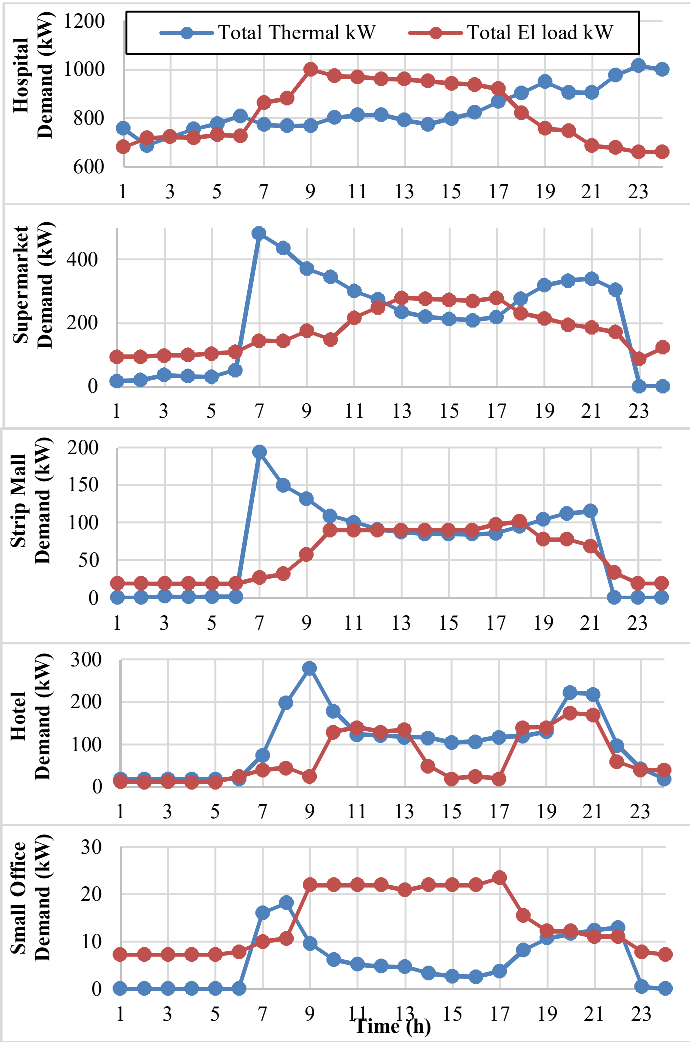


Fig. 4. The load profiles of the test system for different customers

Table 1 Self and cross elasticity

	On peak	Mid peak	Off peak
On peak	-0.1	0.016	0.012
Mid peak	0.016	-0.1	0.01
Off peak	0.012	0.01	-0.1

The price elasticity of the demand is considered as listed in Table 1. Furthermore, the wholesale electricity prices are shown in Fig. 5. To evaluate the proposed model, three scenarios are introduced. The first scenario is solving the objective function while no DR and no EV are taking into account. However, in the second scenario, the results are obtained based on considering DR and EV models. In the third scenario, the impact of different number of EVs is discovered on the network.

Three scenarios are considered to investigate the effectiveness and advantages of the proposed problem.

• *Scenario 1: The absence of DR resources and EVs.*

The first scenario aims to evaluate the operational costs of the selected network. As it is shown in Table II, the objective function has a negative value that expresses the additional cost to operate the system and satisfy the existing constraints. The share of different electrical and thermal resources to provide the required electricity and heat values are illustrated by Fig. 6.

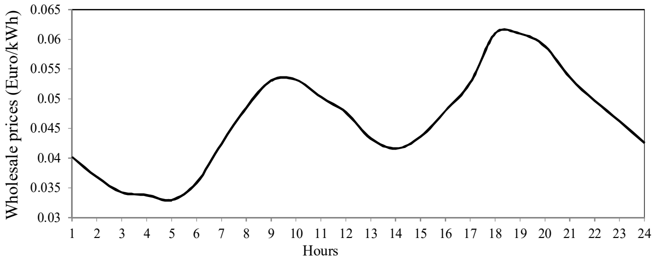


Fig. 5. *The wholesale electricity prices*

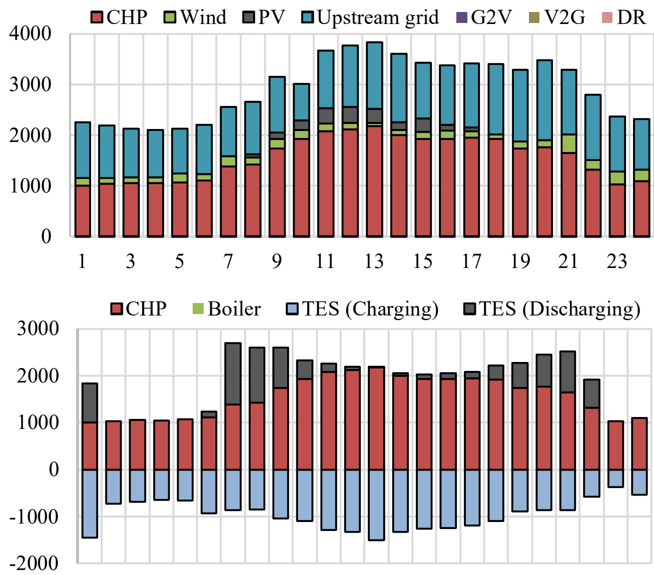


Fig. 6. *The total electricity (1st chart) and heat (2nd chart) production pattern in Scenario 1 (kW)*

Table 2 The value and terms of the objective function in scenario 1

Total OF	F1	F2	F3	F4	F5	F6
-323.343	-	3652.914	3982.90	-	-	-

Table 3 The value and terms of the objective function in scenario 2

Total OF	F1	F2	F3	F4	F5	F6
417.46	3053.4	2530.7	4127.7	746.9	242.03	50.01

• *Scenario 2: The presence of DR resources and EVs;*

In this scenario, 300 EVs have been considered besides the presence of DR resources. The positive value of objective function denotes an income in this scenario. Fig. 7 shows the electricity production patterns.

In this figure, DR potentials are shown as some virtual resources to overcome the electricity demand. In the peak period of time like 12-15 and 19-21, DR is scheduled to reduce the load and decrease the operation cost which lead to increase the income. Meanwhile, the reduced loads are shifted to some off-peak hours like 1-6 and 22-24. Moreover, the EVs are discharging when the wholesale electricity prices are high, while they are decided to be charged when the wholesale process are low. Therefore, in comparison to the previous scenario, the advantages of EVs and DR programs are utilized. Hence, an income is achieved in this scenario. The total load in the figure demonstrates the summation of various commercial customers and loss of the network. Accordingly, utilizing DR and EV aids not only to increase the income but also to fulfill the requirements of load side. Moreover, the strategies of different thermal resources are also illustrated in Fig. 7.

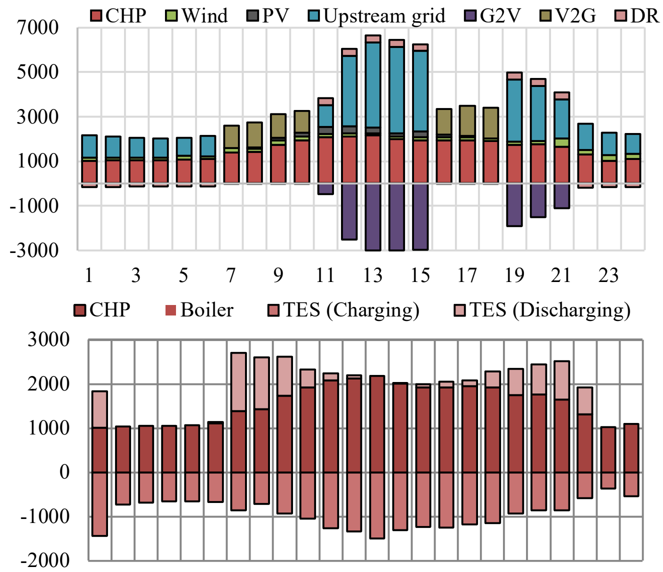
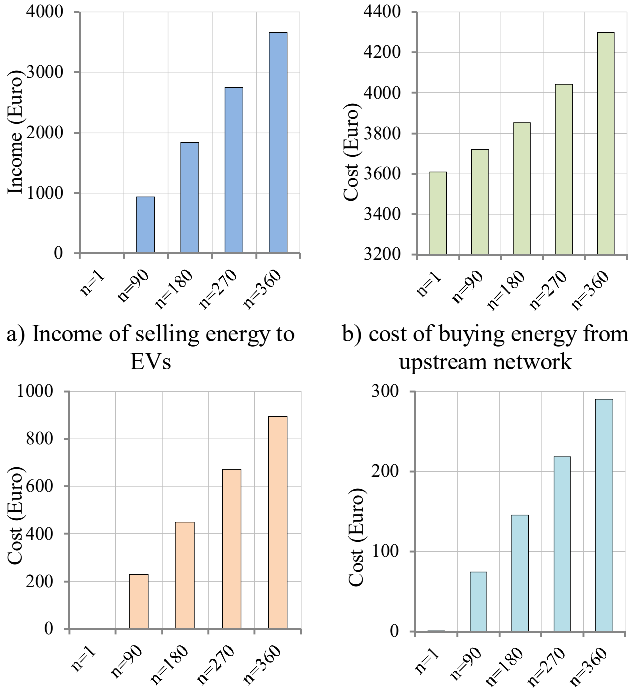


Fig. 7. *The total electricity (1st chart) and heat (2nd chart) production pattern in Scenario 2 (kW)*

• *Scenario 3: Sensitivity analysis of EV numbers*

The impact of number of EVs on different terms of income and cost of the operator is presented in Fig. 8. As can be seen from Fig. 8.a and Fig. 8.b, with increasing the number of EVs, although the microgrid operator gains more income of selling energy to EVs, it has to buy more energy from the upstream network to charge them. Moreover, although the microgrid can benefit from using the charged energy in the EVs at peak hours, the degradation cost of the batteries increases as illustrated in Fig. 8.d.

In order to show the effect of EV potential in the operation of the system, the objective function is calculated to different numbers of EVs. As it is shown in Fig. 9, when the number of EVs is less than 300, additional costs are needed for the operation of the system. However, if the penetration level of EVs in the system raised to be more than 210, the system operator could achieve some income. Indeed, the higher EV potential in the system could provide more income, since the operation of the system can be better managed to overcome the system constraints and satisfy the electricity and heat demand.



a) Income of selling energy to EVs

b) cost of buying energy from upstream network

c) Cost of buying energy from EVs

d) Degradation cost of batteries paid to EV owners

Fig. 8. *Impact of number of EVs on the income and cost of the operator*

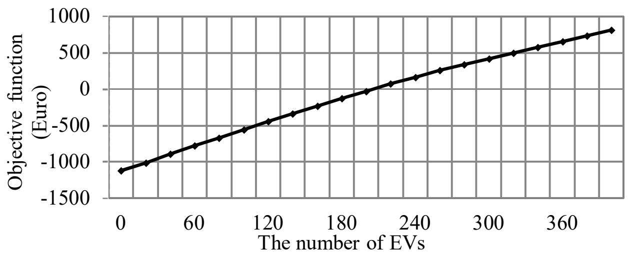


Fig. 9. *The values of objective functions with different numbers of EVs in the system*

5. Conclusion

This paper proposed an operational scheduling of a multi-energy microgrid considering the uncertain nature of renewable energy resources and EV parking lots. The multi-energy system included CHP generation, thermal energy storage, and auxiliary boilers. In addition, price-based and incentive-based DR programs were modeled in the proposed multi-energy microgrid to manage a commercial complex, and a linearized AC power flow was utilized to model the distribution system including EVs. Utilizing DR and EVs could increase the income of the microgrid and fulfill the requirements of load side. Based on the obtained results, when the number of EVs increased, the system operator could achieve some income, since the operation of the system could be better managed to meet the system constraints and supply the electricity and heat demand. The numerical studies proved that well-management of EVs could make them an appropriate match for thermal energy systems in renewable-based microgrids. In future work, thermal energy network will be considered and implementation of demand response programs on the thermal loads will be modeled.

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