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Optimal energy and reserve management of a smart microgrid incorporating parking lot of electric vehicles/renewable sources/ responsive-loads considering uncertain parameters

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ABSTRACT

Due to the increasing presence of electric vehicles (EVs) in urban electricity distribution networks, distribution network operators face the challenge of energy management. A smart parking lot (SPL), renewable energy sources (RESs) such as photovoltaic systems (PV) and wind turbines (WT), and local dispatchable generators (LDG) such as microturbines (MT) and fuel cells (FC) are integrated as a microgrid (MG) while an energy management system is presented in this study which considers the uncertainties of wind speed, solar irradiation, and load consumption. The optimal operation of the SPL, which serves as a load and energy generation source for the distribution network, is done in this article with the goal of lowering costs. To cut costs, demand response program (DRP) based on a time of use (TOU) tariff is utilized, which moves a part of load from on-peak to off-peak time intervals, flattening the load curve. The goal is to reduce the operational expenses of the upstream grid (UG), LDGs, and SPL while taking into account the technical and physical limits of the units. Furthermore, for dealing with the uncertainties of load consumption and wind generation, this research employs a new uncertainty modeling method based on Hong's two-point estimate method. The suggested model is investigated by applying the General Algebraic Modeling System (GAMS) software and is formulated as mixed linear programming (MIP). The suggested model includes both a spinning reserve of LDG and a SPL, and the simulation results verified that the DRP has a good impact on lowering operation costs.

1. Introduction

Governments and international organizations all around the world are increasingly working on instructions to protect the environment for human health. The transportation fleet, which accounts for a major share of global pollutant gas emissions, is a critical contributor to rising greenhouse gas emissions [1]. Challenges of energy security and climate change are motivating a transition away from fossil fuels and toward alternative fuels and electric vehicle (EV) technologies that can guarantee long-term sustainability [2]. Moreover, transportation accounts for one-third of total energy use in the United States, with fossil fuels accounting for 97 % [3]. EVs have been advocated as a potential option for lowering fossil fuel consumption while also addressing environmental challenges including climate change.

1.1. Problem and procedure definition

Increases in the penetration of EVs and renewable sources may cause challenges for power systems that result to significant increment in peak load, renewable energy overproduction within low-load time intervals, and increased ramping need. The transportation sector's energy consumption is predicted to climb in the next years as a result of the massive increase in electric car use [4]. Global penetration of EVs into the transportation industry of 135 million by 2030 is anticipated by the International Energy Agency in its Energy Outlook report [6,7].

Because most electricity consumers do not benefit from the advantages and benefits of the power market and lack the skills to contribute to the electricity market, power production and transmission entities were the legislators of the power industry in the conventional structure of the power grid. The advent of certain issues, such as higher servicing costs, lower efficiency and system performance, and voltage drops during peak hours, caused several power markets to collapse and impose blackouts. As a result, power costumers tended to receive power at fixed

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Nomenclature

Indices

t	Time indicator
j	LDG indicator
i	EV indicator
k	WT indicator
p	PV cell indicator
f	Auxiliary variable

Parameters

P_R^k	WT rated power
$P_W^{k,t}$	WT output power
V_c^k	WT lower bound speed
V_R^k	WT nominal speed
V_F^k	WT upper bound speed
V^t	WT forecasted peed
$P_{PV}^{p,t}$	PV output power
η^p	PV conversion efficiency
s^p	PV area
T_a	PV ambient temperature
G^t	PV solar radiation
a^j b^j	LDG power cost coefficients
$P_{LDG,\max}^j$	LDG maximum power
$P_{LDG,\min}^j$	LDG minimum power
MUT_j	LDG minimum up-time
MDT_j	LDG minimum down-time
$t_{ON}^{j,t}$, $t_{OFF}^{j,t}$	LDG duration of continuous on/off status
UDC^j	LDG startup cost
RD^j,RU^j	LDG ramp-down/up rates
$\psi_{LDG}^{j,t}$	Reservation fee of LDG
$\psi_{EV}^{i,t}$	Reservation fee of EV
$TU^{j,n}$	LDG minimum up time
$TD^{j,n}$	LDG minimum down time
π_{UG}^t	Power market price
N_{Ev}	EVs number parked in SPL
$P_{UG}^{\max}$	Upper bound of exchangeable power between MG and UG
Δt	Sampling time for counting available EVs in SPL
$P_{Ch,\max}^i$	Charger maximum power when charging EV
$P_{Dch,\max}^i$	Charger maximum power when discharging EV
$SOC_{\max}^i$	EV maximum SOC
$SOC_{\min}^i$	EV minimum SOC
$\Delta SOC_{\max}^i$	EV maximum possible charge/discharge rate
T_p^i	Approximated EV presence time in the SPL
$\pi_{Ch,Ev}^i$	Optimal EV charging price in the SPL
$\pi_{Dch,Ev}^i$	Optimal EV discharging price in the SPL
η_{V2G}	EV battery efficiency in V2G mode
η_{G2V}	EV battery efficiency in G2V mode
$SOC_{Arrival}^{i,t}$	EV initial SOC at departure time from SPL
$N_{\max}$	Maximum permitted switching times between charge and discharge
ω_W	Predicted wind speed error
ω_{Pv}	Predicted solar radiation error
$load_0^t$	Base load
$DR\max$	Maximum load size contributing to DRP
$inc\max$	Maximum increase load size
$M^{i,t}$	Auxiliary variable for EVs presence status in the SPL
α	Percentage of EV discharged power for contributing to spinning reserve
t_a^i	Estimated EV entrance time to the SPL
t_d^i	Estimated EV departure time from the SPL

Variables

P_{UG}^t	MG and UG power exchange
$C_{LDG}^{j,t}$	LDG scheduled power cost
$SC_{LDG}^{j,t}$	LDG startup cost
$SR_{LDG}^{j,t}$	LDG scheduled spinning reserve
$P_{Ch,Ev}^{i,t}$	EV charged power
$P_{Dch,Ev}^{i,t}$	EV discharged power
$SR_{Ev}^{i,t}$	Spinning reserve scheduled for EV
$P_{LDG}^{j,t}$	LDG scheduled power
$SOC^{i,t}$	EV SOC
$\Delta SOC^{i,t}$	Energy changes amount in two continuous time intervals
$SOC_{Departure}^{i,t}$	Conclusive SOC of EV when departing SPL
$\mathrm{Up}_{j,f}$	Auxiliary variables used in minimum up-time model of LDG
$Dn_{j,f}$	Auxiliary variables used in minimum down-time model of LDG
$load^t$	Load considering the application of DRP
DR^t	DRP participation amount
idr^t	Load transferred between two time intervals
$load_{inc}^t$	Increased load amount
inc^t	Increased load size
$U^{j,t}$	Binary variable used for defining the on/off status of LDG in the SPL
$W_{ch}^{i,t}$	Binary variable used for defining the charge status of EV in the SPL
$W_{Dch}^{i,t}$	Binary variable used for defining the discharge status of EV in the SPL
$SRS^{i,t}$	Binary variable used for defining the participation of EV in spinning reserve

prices without considering the volatility of the electricity market. Other issues include reduced fossil fuel resources, increased environmental pollution and greenhouse gas emissions [8]. Accordingly, decision-makers and the electrical business policymakers are being pressed to make decisions about electrical industry restructuring [9]. Application of demand response programs (DRPs), making smart microgrids (MGs), and developing smart electric vehicle (EV) parking lots are some of the methods that have been used in the field of restructuring the electrical sector to increase system efficiency and performance while reducing pollution [10]. The energy sector is currently studying a unique solution known as the EVs smart parking lot (SPL) to manage the charging and discharging of electricity as well as energy supply challenges [11].

According to Fig. 1 there is a central controller which gathers all the required information from the various sources and the market operator, upstream grid and parking lot and optimizes the problem and specifies the optimal production of all sources and the hourly charge and discharge schedule of the parking lot.

In addition, microgrid central controller utilizes point estimate method during optimization to address the uncertainties of wind and load. This process helps the operator to consider uncertain situations and utilize the information which is more reliable.

Some challenges, such as rising electrical energy demand, diminishing fossil fuel resources, and rising greenhouse gas emissions, are prompting increased investment in the field of renewable resources [12]. Smart grids will play an essential role in supplying electrical energy demand by changing the structure of power networks and moving to make power systems smart [13]. LDGs in the MG will have major advantages such as increased efficiency, reduced losses, and reduced environmental effects, and distributed generation power will be achievable with the utilization of renewable energy sources such as photovoltaic (PV) cells and wind turbine (WT) [14], as well as fuel cell (FC) [15]. DRP has given active consumer participation to improve the

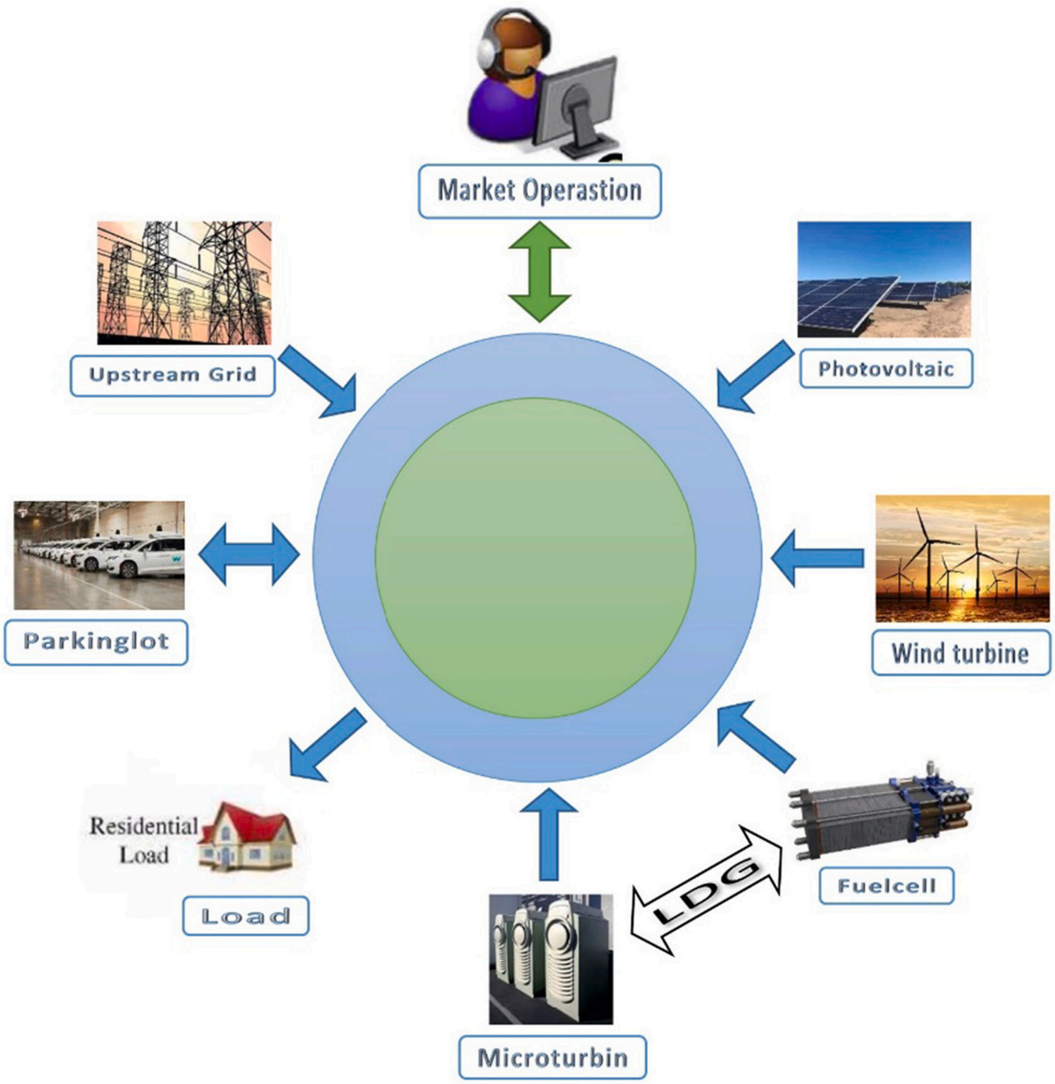

Fig. 1. A graphic explainer of the microgrid optimization process.

power system operation, and DRP in a critical state can lower system demand in a short period [16]. This program moves the load from peak to off-peak time intervals, resulting in a smoother load curve and lower operational expenses. The time of use (TOU) DRP was utilized in this study [17]. This program will benefit consumers, society, and the electrical firm by lowering electricity prices, improving service levels, and reducing harmful environmental effects. It is believed that the optimal scheduling of renewable energy systems and DRP will increase the reliability and security of the MG. However, renewable generation and load fluctuations are non-dispatchable and their participation in MG increases the uncertainties of scheduling. To achieve optimal production of various sources and reduce operating costs, proper day-ahead scheduling and correct financial decisions are required in MG. Therefore, the uncertainties of scheduling pose challenges for the operator in achieving an optimal simulation for the MG.

1.2. Literature review

Researchers have studied several SPL energy management approaches in recent studies to charge and discharge EVs in a smart parking lot. For example, while parking lots connect grid and EV for exchanging electrical energy between them, some suggestions are presented in [18], such as using vehicle-to-parking (V2P) and parking-to-vehicle (P2V) instead of vehicle-to-grid (V2G) and grid-to-vehicle (G2V), and a random approach is presented based on statistical data and general instructions on charging EVs for estimating the daily impact of having EVs. In [19], the problem of charging an electric vehicle in a parking lot is solved by applying the game theory. In [20], two studies were provided that were compared in an attempt to establish the best charging strategy, one of which related to parking lot service during the day and outside of commercial areas, and the other to parking lot service at night and outside of residential areas. The authors in [21] presented a discharge scheduling system for EVs in parking lots based on the real-time movement and park pattern of the EV, with a concentration on the personal parking lot. The authors in [22] presented the ideal behavior of electric vehicles in the energy market and reserve, considering DRP and EV owner satisfaction.

The authors in [23] provided a probabilistic strategy for determining the ideal allocation of an EV parking lot in the distribution network and determining the optimal capacity while considering EV's variable driving behaviors. The authors in [24] established an online smart demand coordination amongst EV in dispersed systems based on the fuzzy system distributing points for EVs. For molding the participation of EV SPLs with PV cells in reserve market and in ancillary services provision, a Mixed Integer Linear Program (MILP) is presented in [25]. In [26], EVs battery in the SPL is studied as an energy storage source in multifunctional systems, and to reach this goal, the authors have modified energy hub approach for considering reservation sources as ancillary services and power generation participation, based on the profitable role of smart parking lot. The optimal placement of the SPL in distribution networks is done in [27] with the goal of dealing with voltage drop and power loss in distribution network considering renewable energy sources such as PV and WT. The authors in [28] have investigated the conversion of a traditional parking lot to an SPL in Tehran, Iran, allowing for large-scale charging and discharging of electric vehicles.

The authors in [29] proposed a model of MG management's energy resources, taking into account some constraints related to optimal probabilistic operation of the SPL and renewable sources in MG. In [30], a scheduling model is proposed for a large number of EVs in the urban SPL, taking into account various constraints connected to the EV battery and its capacity. In [31], a stochastic scheduling model is introduced for charging and discharging EVs in the SPL, which includes PV and LDG. The authors in [32], performed two optimizations, the first of which studies optimal size and location of installed distributed generators in the MG with the goal of lowering costs and losses, and the second of which studies the optimal size of combined renewable energy systems with the goal of lowering costs and determining the appropriate number of decision variables. A multi-objective strategy is described in [33] to find the ideal size and location of the SPL in urban areas that serve as an assistant for drivers in reaching a station from anywhere in a city considering an appropriate distance. In [34], a multi-objective approach is presented for determining the optimal number, location, and size of SPL in distribution systems, as well as the generated power by each energy source in the system. Table 1 is provided in the following to summarize the literature with a focus on operation optimization of microgrids with RESs and EVs/EV parking lots with RESs.

1.3. Procedure and contributions

The evaluated studies looked at some of the most relevant consequences; nevertheless, further research is needed to address the uncertainties of renewable resources and load consumption in optimal energy and reserve scheduling of MG with DRP. Comparing alternative methods to model uncertainties when reaching optimal values, on the other hand, is a research gap around this topic, according to the authors' best knowledge.

The energy management of the SPL in the MG is discussed in this study, which takes into account the SPL's participation in the energy market and reserve, as well as the use of DRP to lower operation costs. The amount of charge and discharge of an EV, as well as the dispatched power of an LDG containing MT and FC, were compared, and solved in four distinct situations to demonstrate the effects of SPL participation in the reserve market and the use of DRP in cost reduction.

Furthermore, a novel optimization model based on the concepts of a stochastic method called two-point estimated method (2-PEM) has been proposed in this study for addressing the uncertainties of renewable generation and load consumption in order to approach optimal results for short-term MG scheduling. To put it another way, a risk management model based on the 2-PEM is offered to protect the operator from financial losses resulting from MG uncertainty. This research aims to reduce an MG's operating costs while taking into account the unpredictability of load use and renewable energy supply. As a result, by varying wind and solar production and load consumption, the 2-PEM approach is employed to ensure that the schedule remains optimal. This method has several advantages over other methods for modeling uncertainty. To begin with, this method does not necessitate a large amount of data and instead models using only a few initial moments derived from the incoming data. Second, this method employs deterministic methods like the Monte Carlo method, with the exception that it requires a significantly fewer number of executions, resulting in a very quick simulation time and entirely reliable and useable results. As a result, the GAMS software was used to optimize the problem under investigation.

Table 1
Summary of the literature around EV SPLs.

Reference	Main objective	Optimization procedure	Considerations	Published year
[35]	Analyzing the influence of EV PLs with rooftop PVs on distribution systems	Electrical Power System Analysis Software (ETAP) environment	Studying the impact of changes in seasonal weather	2019
[11]	Optimal management of EV PLs with renewable energy sources	CPLEX solver of GAMS	Studying uncertain parameters by proposing a robust-stochastic model	2021
[36]	Energy management of EV PLs	Genetic optimization algorithm	Investigating encouragement and punishment policies for EV drivers in PLs	2021
[37]	Operation optimization of smart distribution systems with EV PLs	CPLEX solver of GAMS	Studying DR programs and vehicle to grid (V2G)	2018
[38]	Satisfaction of charging demand and in minimizing the energy cost of the EV PL	Fuzzy particle swarm optimization algorithm	Investigating allocation of resources to EV PLs	2018
[39]	Optimization and management of EV SPLs	MATLAB software environment	Considering the satisfaction of EV drivers and a real-time model	2019
[40]	Dynamic planning of EV PLs	Backward/forward sweep load flow approach	Studying uncertainty of SPL investment	2020
[41]	Maximizing profit of smart distribution companies and EV PLs	CPLEX solver of GAMS	Investigating the uncertainty of RERs and EVs	2017
[42]	Energy management of EV PLs considering uncertainty	MIP in GAMS software environment	Modeling price uncertainty by application of robust optimization model	2020

1.4. Highlights

In order to specify the contributions and highlights of the paper this subsection is added to introduction. The important contributions of this paper are highlighted as follows:

- Integrated schedule and management of LDG and SLP of the EVs in the MG.
- Using the SPL to make it easier for EV owners and MG operators to interact and communicate.
- Using demand side management programs to decrease the operating costs, smoothen demand profile and facilitate the load participation in power demand decrement.
- SPL participation in the energy market and reserve, as well as consideration of DRP at the same time.
- For dealing with the unpredictable nature of wind and solar generation and load consumption, a novel uncertainty modeling algorithm

based on 2-PEM concepts is being used, which uses deterministic approaches in solving stochastic situations.

- The competence of the used 2-PEM in addressing the unknown parameters was evaluated using the MC approach.

1.5. Paper organization

The following is a breakdown of the structure of this paper: In Section 2, mathematical modeling is presented that relates to the best use of the SPL and lowering the cost of the MG in the presence of DRP. Section 3 discusses the 2-PEM approach for modeling uncertainty. The suggested model was tested in a test environment, and the results were compared to examine how the SPL affected participation in the spinning reserve market and how the DRP affected participation in Section 4. Finally, conclusions based on the acquired results are offered in Section 5.

2. Formulation

Various distributed sources such as PVs, WTs and SPL are considered in the studied MG. In addition, the UG has been considered to maintain the stability and reliability of the MG. EVs can play both the role of load with charging and an energy source with discharging which can reduce system operation costs. When the EV enters the SPL, some information is received from the owner by SPL. This information includes the current SOC of the EV, departure time, the amount of charge required at the time of departure, battery life and the price of charge and discharge of the battery. The information received by the SPL is sent to the MG operator to be used in the optimization process. There is also an interface between the MG and the upstream network that seeks the optimal MG performance.

2.1. Objective function

The objective function of this study is to minimize the operating costs of MG. The objective function of the problem is formulated as follows:

$$OBJ=\sum_{t=1}^{T}\left[\left(\begin{array}{l}P_{UG}^{t}\times\pi_{UG}^{t}+\\ \sum_{j=1}^{G}\left(C_{LDG}^{j,t}+SC_{LDG}^{j,t}+\left(SR_{LDG}^{j,t}\times\psi_{LDG}^{j,t}\right)\right)+\\ \sum_{i=1}^{N}\left(-W_{Ch}^{i,t}\times P_{Ch,EV}^{i,t}\times\pi_{Ch,EV}^{i}+W_{Dch}^{i,t}\times P_{Dch,EV}^{i,t}\times\pi_{Dch,EV}^{i}+SRS^{i,t}\times SR_{EV}^{i,t}\times\psi_{EV}^{i,t}\right)\end{array}\right)\times\Delta t\right] \tag{1}$$

The objective function of the problem includes three segments. The first segment deals with the costs of exchanging power with the upstream network. The second part includes the costs of starting up and generating power by LDGs and the third part considers the costs of power exchange between MG and SPL and the costs of charging and discharging of EVs.

2.2. Wind turbine

A big part of the microgrid's required power can be supplied by WT units. The equation of power generation by WT is related to wind speed as below [43].

$$P_{W}^{k,t}=\begin{cases}0 & V^{t}<V_{c}^{k}\,or\,V^{t}\geq V_{F}^{k}\\ \dfrac{V^{t}-V_{c}^{k}}{V_{R}^{k}-V_{c}^{k}}\times P_{R}^{k} & V_{c}^{k}\leq V^{t}<V_{R}^{k}\\ P_{R}^{k} & V_{R}^{k}\leq V^{t}<V_{F}^{k}\end{cases} \tag{2}$$

2.3. Photovoltaic system

The power produced by a PV unit depends on solar radiation and temperature change, which is modeled as the following equation [44].

$$P_{PV}^{p,t}=\eta^{p}\times s^{p}\times G^{t}\times(1-0.005\times(T_{a}-25)) \tag{3}$$

2.4. LDG

Local distributed generation sources include MT and FC. Eqs. (4) to (6) are related to power generation cost and start-up cost of LDGs [45].

$$C_{LDG}^{j,t}=a^{j}\times U^{j,t}+b^{j}\times P_{LDG}^{j,t} \tag{4}$$

$$SC_{LDG}^{j,t}\geq\left(U^{j,t}-U^{j,t-1}\right)\times UDC^{j} \tag{5}$$

$$SC_{LDG}^{j,t}\geq 0 \tag{6}$$

Constraints (7)–(12) are related to LDG units and they can be presented as below:

$$P_{LDG}^{j,t}+SR_{LDG}^{j,t}\leq P_{LDG,max}^{j}\times U^{j,t} \tag{7}$$

$$P_{LDG}^{j,t}\geq P_{LDG,min}^{j}\times U^{j,t} \tag{8}$$

$$P_{LDG}^{j,t}-P_{LDG}^{j,t-1}\leq RU^{j}\times U^{j,t} \tag{9}$$

$$P_{LDG}^{j,t-1}-P_{LDG}^{j,t}\leq RD^{j}\times U^{j,t-1} \tag{10}$$

$$U^{j,t}-U^{j,t-1}\leq U^{j,t+Up_{j,f}} \tag{11}$$

$$U^{j,t-1}-U^{j,t}\leq 1-U^{j,t+Dn_{j,f}} \tag{12}$$

$$\mathrm{Up_{j,f}}=\left\{\begin{array}{ll}f & f\leq \mathrm{MUT_j}\\ 0 & f>\mathrm{MUT_j}\end{array}\right\} \tag{13}$$

$$\mathrm{Dn_{j,f}}=\left\{\begin{array}{ll}f & f\leq \mathrm{MDT_j}\\ 0 & f>\mathrm{MDT_j}\end{array}\right\} \tag{14}$$

Eqs. (7) and (8) limit the maximum and minimum power output by these units. The increase and decrease rate of power produced by LDGs cannot be more or less than certain values modeled by Eqs. (9) and (10). Eqs. (11) and (12) restricts the minimum up and down times which each unit should deal with it.

2.5. Upstream grid

Due to the limitations of transmission lines and feeders, the power received from the upstream network must be less than the specified values modeled by the following equation [46].

$$|P_{UG}^{t}| \le P_{UG}^{\max} \tag{15}$$

2.6. SPL of the EVs

EVs in the SPL in order to charge and discharge and participate in providing the required power of the MG with the SPL should respect the following constraints [47]:

2.6.1. Charging and discharging constraints

The amount of charge and discharge power in each time interval should be less than a maximum value modeled by Eqs. (16) and (17).

$$P_{Ch,EV}^{i,t} \le P_{Ch,max}^{i} \times W_{ch}^{i,t} \times M^{i,t} \tag{16}$$

$$P_{Dch,EV}^{i,t} + SR_{EV}^{i,t} \le P_{Dch,max}^{i} \times W_{Dch}^{i,t} \times M^{i,t} \tag{17}$$

2.6.2. Synchronization constraint

EVs cannot be in both charge and discharge mode at the same time, which is applied by Eq. (18).

$$W_{ch}^{i,t} + W_{Dch}^{i,t} \le 1 \times M^{i,t} \tag{18}$$

2.6.3. Switching constraint

Constantly switching the battery between charge and discharge modes can reduce battery life, so it is limited by Eq. (19).

$$\sum_{t=t_a^i}^{t_d^i} W_{ch}^{i,t} + W_{Dch}^{i,t} \le N_{\max} \tag{19}$$

2.6.4. EV spinning reserve constraints

Constraints of the spinning reserve related to the EVs of the ILP are presented in Eqs. (20) and (21).

$$SR_{ev}^{i,t} \le \alpha \times P_{Dch,max}^{i} \times SRS^{i,t} \times M^{i,t} \tag{20}$$

$$SR_{Ev}^{i,t} \le \alpha \times P_{Dch,max}^{i} \times W_{Dch}^{i,t} \times M^{i,t} \tag{21}$$

2.6.5. EVs SOC

Eq. (22) determines the hourly SOC of each EV in each time interval, which also depends on the charging and discharging efficiency of each EV.

$$SOC^{i,t} = SOC^{i,t-1} + P_{Ch,EV}^{i,t} \times \eta_{G2V} - P_{Dch,EV}^{i,t} \Big/ \eta_{V2G} \tag{22}$$

2.6.6. EV SOC restrictions

Eq. (23) limits the hourly SOC level of each EV to its maximum and minimum values. This constraint is modeled as follows:

$$SOC_{\min}^{i} \le SOC^{i,t} \le SOC_{\max}^{i} \tag{23}$$

2.6.7. Charge and discharge rate constraints

The difference between the charge and discharge rates of EVs must be taken into account. For this purpose, constraint (24) has limited the change of SOC level of EVs to maximum and minimum values.

$$-\Delta SOC_{\max}^{i} \le SOC^{i,t} - SOC^{i,t-1} \le \Delta SOC_{\max}^{i} \tag{24}$$

2.6.8. Departure SOC of the EVs

For the convenience of the owner of EVs, constraint (25) guarantees that the EV has maximum power when leaving the SPL. Constraint (26) also ensures that the SOC level is higher than the arrival charge throughout the EVs presence in the SPL.

$$SOC_{\mathrm{Departure}}^{\mathrm{i,t}} = SOC_{\max}^{i} \tag{25}$$

$$SOC^{i,t} \ge SOC_{Arrival}^{i,t} \tag{26}$$

2.7. Demand response program

In this paper, the TOU program has been utilized which shifts the loads from peak periods to off-peak periods and smoothen the load profile which can decrease costs [48]. It should be mentioned that DRP is only able to shift the percentage of the loads which in this paper, only 20 % is allowed to shift. The utilized DRP has been formulated by Eqs. (27) and (28).

$$load^{t} = (1 - DR^{t}) \times load_{0}^{t} + idr^{t} \tag{27}$$

$$load_{0}^{t} - load^{t} = DR^{t} \times load_{0}^{t} - idr^{t} \tag{28}$$

Eqs. (29)–(32) propose the practical constraints related to TOU program.

$$\sum_{t=1}^{T} idr^{t} = \sum_{t=1}^{T} DR^{t} \times load_{0}^{t} \tag{29}$$

$$load_{inc}^{t} \le inc^{t} \times load_{0}^{t} \tag{30}$$

$$DR^{t} \le DRmax \tag{31}$$

$$inc^{t} \le inc\,max \tag{32}$$

The amount of load transmitted by DRP depends on the hourly price of power in the network. Therefore, the shifted load in each time interval can have different values and amounts. However, the sum of the loads transmitted per hour must be equal to the sum of the contributions to the DRP. This rule has been modeled by Eq. (29). Eq. 30 states that the amount of load increase due to DRP in each time interval cannot be more than a certain value. The percentage of transferable load by DRP in each time interval cannot be more than a certain value (20 % in this study) that is limited by Eqs. (31) and (32).

2.8. Spinning reserve of MG

If any problem occurs and RES are not able to inject power to the MG, LDGs and SPL should inject power to the MG and cause balance between produced power and consumption, Eq. (33) is expressed for this reason [49].

$$\sum_{j=1}^{G} SR_{LDG}^{j,t} + \sum_{i=1}^{N} SR_{EV}^{i,t} \ge \left(\omega_{w} \times P_{W}^{k,t} + \omega_{PV} \times P_{PV}^{p,t}\right) \tag{33}$$

2.9. Power balance constraint

In order for the microgrid to operate reliably, a balance must be struck between the output power and the demand load, which is modeled by Eq. (34) [50]. On the demand side, the new load has been replaced which is changed by DRPs.

$$P_{UG}^{t} + \sum_{k=1}^{K} P_{W}^{k,t} + \sum_{p=1}^{P} P_{PV}^{p,t} + \sum_{j=1}^{G} P_{LDG}^{j,t} + \sum_{i=1}^{N} P_{Dch,EV}^{i,t} = load^{t} + \sum_{i=1}^{N} P_{Ch,EV}^{i,t} \tag{34}$$

3. Uncertainty modeling

To formulate the energy systems, several methodologies such as analytical, approximation, and simulation approaches can be used to solve various optimization issues depending on their application.

3.1. Point estimate method

The point estimation method (PEM) formulation is a popular approximate method because of its excellent accuracy and short processing time [51]. As a result, a strategy based on PEM is provided in this study to address wind, solar and load uncertainty. The disparity between projected and actual values is characterized as uncertainty. The executive costs will be greatly reduced by using a more accurate way to deal with uncertainty. Depending on the type of problem and the factors that are unknown, several modeling strategies are employed. 2-PEM can be used by system operators to handle uncertainties because it is accurate and has a short processing time [52].

According to the authors' best understanding, Hong's 2-PEM is a useful method for dealing with uncertain issues, including random variables and statistical data. The whole information of the density functions of probabilistic parameters is not required by Hong's 2-PEM. Such a strategy operates based on the approach of unknown input parameter moments. The raw moments of output variables, such as the average and variance of the variables, are approximated using PEM. Using statistical data from random input variables, many moments can be generated in this manner [53]. The authors will calculate two typical points known as concentrations using central moments. These concentration locations will be used to locate statistical data that will aid in the discovery of random output variables. The concentrations of each variable come from a combination of a location and a weight if we assume as uncertain input variables with a particular mean and a definite standard deviation. The following equation yields the location:

$$x_{l,s} = \mu_{x_l} + \xi_{l,s}\cdot\sigma_{x_l} \tag{35}$$

where, $\xi_{l,\ s}$ is the standard position of the uncertain variable x_1, as determined by the equation below:

$$\xi_{l,1} = \frac{\lambda_{l,3}}{2} + \sqrt{m + \left(\frac{\lambda_{l,3}}{2}\right)^2}, \xi_{l,2} = \frac{\lambda_{l,3}}{2} - \sqrt{m + \left(\frac{\lambda_{l,3}}{2}\right)^2} \tag{36}$$

The following equations were used to compute the weights of the uncertain input variable x_1.

$$w_{l,1} = -\frac{\xi_{l,2}}{m(\xi_{l,1} - \xi_{l,2})}, \quad w_{l,2} = \frac{\xi_{l,1}}{m(\xi_{l,1} - \xi_{l,2})} \tag{37}$$

where, $\lambda_{l,\ 3}$ denotes the skewness of the uncertain input variable x_1.

$$\lambda_{l,3} = \frac{E\left[(x_l - \mu_{x_l})^3\right]}{(\sigma_{x_l})^3} \tag{38}$$

Following the computation of concentration points, a deterministic optimization will be performed, with the results displayed as $Z_{l,\ s} = F(x_{l,\ 1}, x_{l,\ 2}, \ldots, x_{l,\ s}, \ldots x_{m,\ s})$. Where, $Z_{l,\ s}$ is a function that acts as a vector between uncertain input variables, approximating their output quantities. The raw moments of output variables are represented as follows:

$$\begin{aligned} E(Z) &\cong E(Z) + w_{l,s}Z_{l,s} \\ E(Z^j) &\cong E(Z^j) + w_{l,k}Z^j_{l,s} \end{aligned} \tag{39}$$

where, Z is a function of uncertain input variables and can be defined as $Z = f(x_1, x_2, \ldots, x_m)$. For each unknown input variable x_1, the function F calculates just twice, utilizing the estimated locations and the mean value μ_{x_l} of the other input variables. To put it another way, $2 \times m$ yields the total number of calculations.

Table 2
WT and PV parameters.

Photovoltaic system			Wind turbine		
Parameter	Value	Unit	Parameter	Value	Unit
T_a	25	°C	V_R	12	m/s
η	15.7	%	P_R	500	kW
s	1500	m^2	V_C	3	m/s
ω_W/ω_{PV}	20	%	V_F	30	m/s

4. Numerical optimization

In this study, the effect of DRP, spinning reserve of the LDG and spinning reserve of the SPL on network performance has been studied and the objective function has been analyzed in four different cases. The objective function of the paper seeks to minimize the cost of MG operation so that the technical constraints of LDGs, SPL, and UG are taken into account. The proposed objective function is modeled as a mixed integer linear programming (MILP) formulation and optimization is performed by General Algebraic Modeling System (GAMS) package.

4.1. Input parameters

Data on WTs and PVs are presented in Table 2 [54]. The information about the parameters of the LDGs which contains MT and FC are provided in Table 3. The predicted day-ahead demand and the day-ahead power cost of UG are shown in Figs. 2 and 3. Predictions of wind speed and solar radiation for the next 24 h are provided in Figs. 4 and 5 [55]. EVs batteries have different capacities [56] from 8 to 48 kWh, and in this article, it is assumed that EVs in the SPL have a capacity of 10 to 20 kWh. The spinning reservation fee for ith-EV is determined 10 % of the expected discharge cost of the ith-EV. In addition, the spinning reservation fee for the jth-LDG is determined 10 % of the UG power price at that period of time. The parking capacity is equivalent to 230 EVs and the SOC amount of ith-EV at the time of departure from the SPL is a random number between 0.1 and 0.7. The optimal charge price of EVs is considered a random number between 0.15 and 0.3 and the optimal discharge price of these EVs is considered a random number between 0.25 and 0.4. Other information on EVs parameters is provided in Table 4 [57]. The amount of power that can be exchanged with the UG is limited to a maximum of 1000 kW. It is worth noting that the transferable power by DRP is equal to 20 % of the demand.

4.2. Optimization results

In order to investigate the presence of SPL in the energy and reservation market and the effect of DRPs on the demand curve, the objective function of the problem has been investigated in 4 different cases:

- Case one: The objective function has been analyzed considering the UG, LDGs and EVs constraints and without consideration of effect of the DRP and spinning reserve.
- Case two: To observe the impact of DRP on demand side and operating costs, the objective function has been investigated with consideration of the impact of the DRP and without consideration of the spinning reserve constraints.
- Case three: The SPL participates in the spinning reserve market but do not participate in DRP thus constraints of the spinning reserve are considered but constraints of the DRP are neglected.
- Case four: The presented objective function has been formulated with consideration of the effect of the DRP and participation in the Spinning reserve market, therefore the effects of DRP on the load curve and operation costs of the MG is studied in this case.

The output power of WT and PV according to the input data related to 24-hour forecasting wind speed and solar radiation is shown in Figs. 6 and 7.

Table. 5 shows the cost of MG operation in 4 different cases. According to the results of Table 5, in case one, which SPL only participated in the energy market and has not participated in the reserve market and DRP has not been considered, operation cost is $1782.4. In case two, objective function has been investigated in order to observe the positive effect of the DRP on the demand profile and decrease the operation cost of the MG. The difference between cases 1 and 2 shows that DRP Cause 40 percent reduction in costs. It should be mentioned that DRP with smoothen the demand profile and shift the demand from

Table 3
Parameters of the LDGs.

Source	Type	a	b	P^{min}	P^{max}	MDT	MUT	t_{on}/t_{off}	UDC	RD	RU
		$	$/kW	kW	kW	h	h	h	$		
1	MT	0.02	0.15	150	700	3	3	4	0.1	350	350
2	MT	0.04	0.25	100	450	2	2	−6	0.02	200	200
3	FC	0.09	0.45	50	300	1	1	−8	0.02	150	150

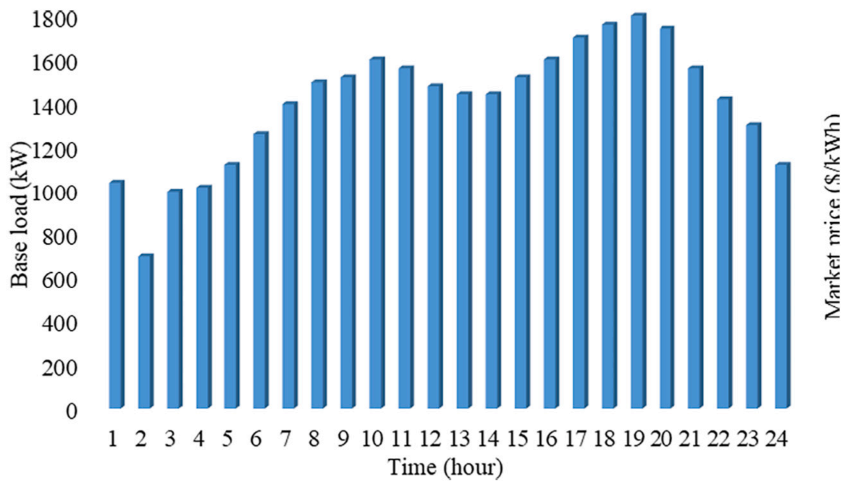

Fig. 2. Forecasted base load.

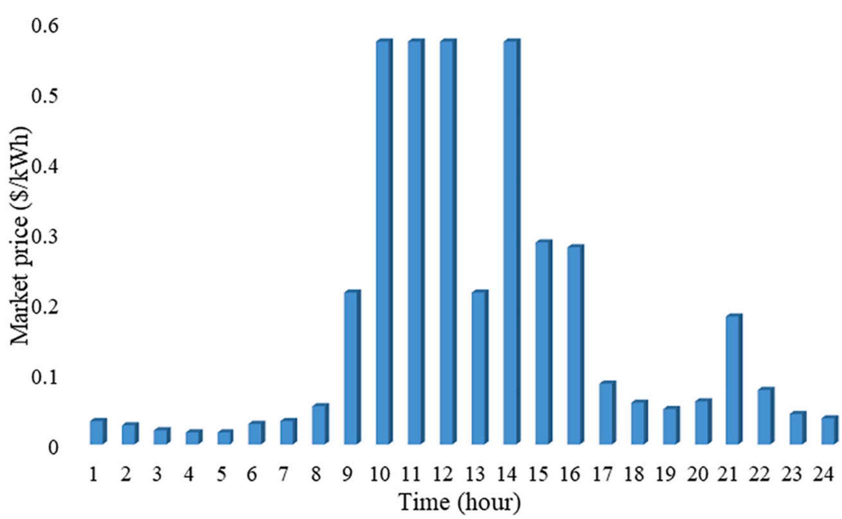

Fig. 3. Forecasted price of the UG.

peak hours to off-peak hours cause the reduction in costs.

Also, SOC is getting lower in comparison with the case one and therefore, less charging and more discharging cause reduction in operational cost. Second MT has a higher operating cost than first MT, and as a result, reducing the use of second MT and replacing it with first MT reduces operating cost. In the third case, the proposed objective function is studied without considering the DRP in order to observe the participation effect in the reserve market on the operating costs of the MG. With comparing cases 1 and 3, we see that spinning reserve increased the 27.7 % of the operation costs. This increase of the operations cost due to considering the 20 percent error of the weather condition and the probability of reducing the produced power by the WT and PV. Finally, in case four, in order to see the effect of the DRP on the load curve and operation costs of the MG and considering the participation of the SPL in the reserve market, constraints related to the DRP and spinning reserve have been added to the objective function. With comparing cases 1 and 4 we see that operation costs reduced 36.7 % and 3.31 % of the difference between case 2 and 4 is the result of the participation in the reserve market which increases the operation costs. In general, as we have seen DRP had been reduced the operation costs of the MG and spinning reserve. In addition to its advantages, it has been increased the operation costs of the MG.

Fig. 8 shows the load curve with considering the DRP in four cases. It should be mentioned that, only in cases 2 and 4 DRP have been affected and in case 3 DRP have not been affected for this reason demand profile of case 3 is the same as case 1. With observing this figure, we realize that DRP smoothen the demand profile in the second case more than other cases. Whatsoever the demand profile smoothens more, operation costs

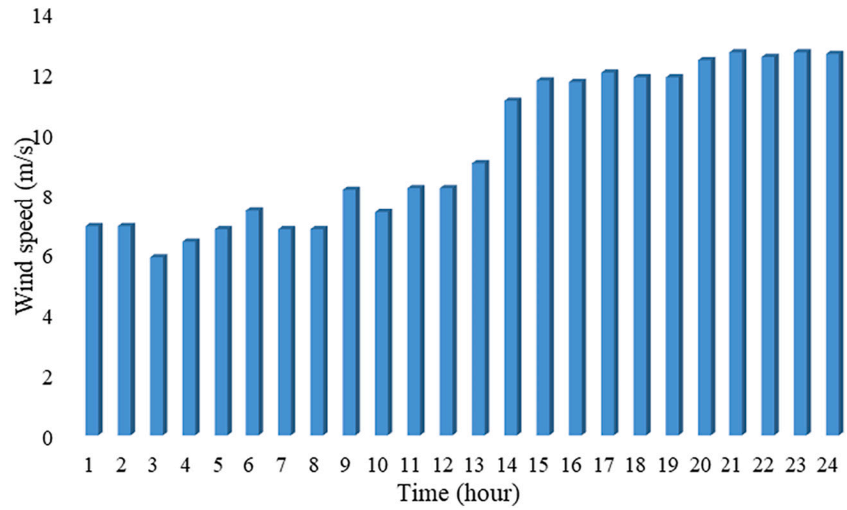

Fig. 4. Forecasted wind speed.

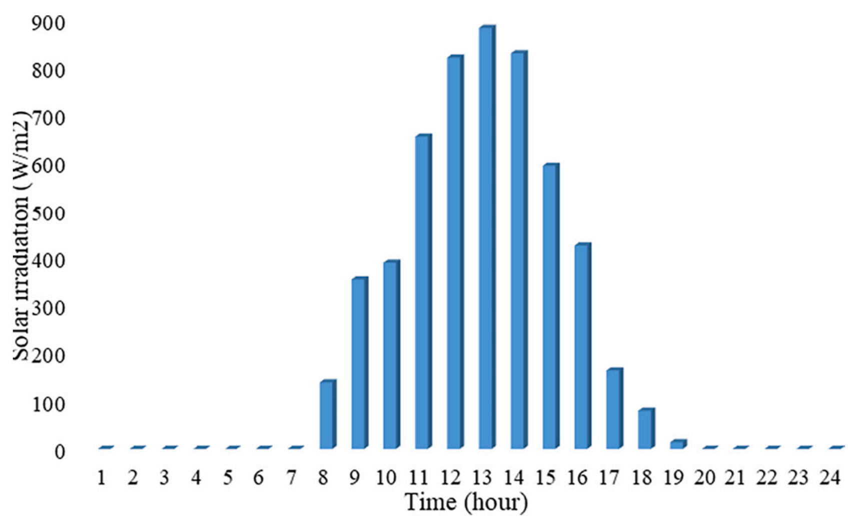

Fig. 5. Forecasted solar radiation.

Table 4
Parameters of the EVs.

α	T_P^i	$P_{Ch,\max}^i$	$P_{Dch,\max}^i$	$SOC_{\max}^i$	$SOC_{\min}^i$	$\Delta SOC_{\max}^i$	η_{G2V}	η_{V2G}	$N_{\max}$
0.2	2–8	5–10	5–10	10–20	0	5–10	0.9	0.8	10

reduced more.

Fig. 9 illustrates the charging/discharging of EVs in SPL and Fig. 10 illustrates the SOC of the EVs in the SPL. As we can see, SOC of the EVs in the second case in some periods of time is less than other cases and this mean more discharging occurred in these periods. In fact, in peak hours, SPL acts as a source and provides the required power to the MG to buy less power from UG, and in non-peak hours, when the price of UG power is lower, SPL operates such as a load and recharges EVs.

The power exchanged between the MG and the UG is shown in Fig. 11. In case two, DRP selling the power to the UG during peak periods and cause reduction in the operation costs of the MG. In the third case, MG exchanged power with spinning reserve instead of exchange power with the UG in peak periods and this caused the reduction of the operation costs of the MG.

Figs. 12–14 illustrate the output power of MT 1, MT 2 and FC which are the LDGs of the studied MG. Furthermore, in Table 6 the hourly spinning reserve of the LDG and SPL is presented. As we can see in Figs. 12–14 and Table 6, due to the fact that first MT has a lower cost, in cases 2 and 4, where DRPs cover part of the power, the capacity of first MT is released and more power is provided for the MG. As a result, it reduces operating costs by reducing power purchases from the UG. It can also be seen in Fig. 13 that due to the fact that second MT has a high cost for power supply, in case 2 of DRPs, the production of second MT is reduced and the cost of MG is reduced.

Also, in order to have a better understanding of the study, we compared the results of this study with Monte Carlo simulation and the results of [54]. In order to address the uncertainties of wind, solar irradiation and load, 2-PEM and MC simulation as uncertainty modeling methods have been utilized in 4 cases, and the results of operational costs are illustrated in Tables 7 and 8. In the first step of the MC method, 10,000 scenarios for wind speed, solar irradiation and load consumption are randomly produced which due the number of scenarios, the accuracy

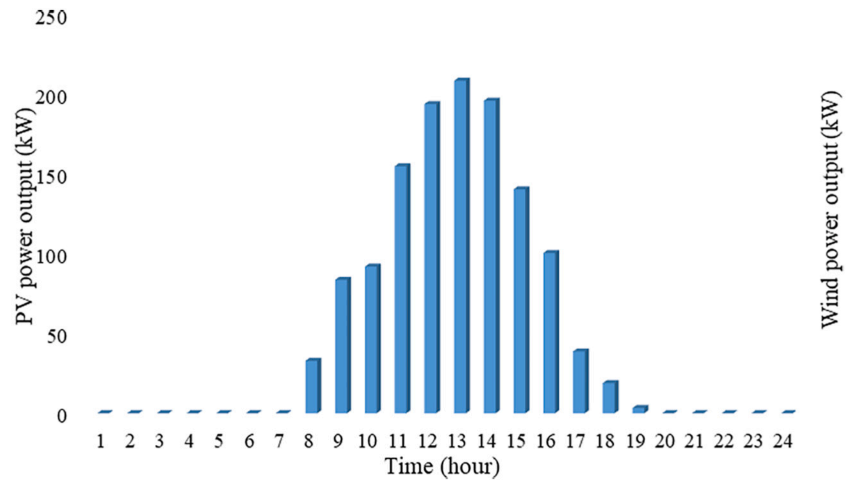

Fig. 6. PV power output.

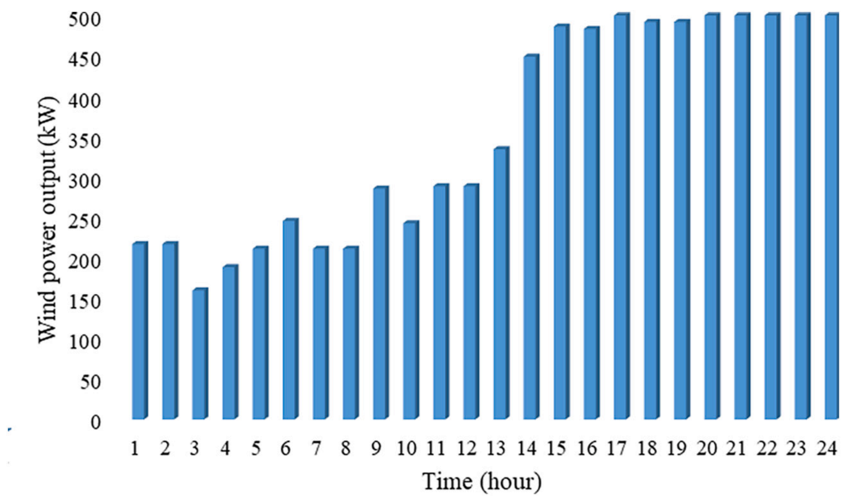

Fig. 7. WT power output.

Table 5
Cost of MG performance studied in 4 cases.

	Case 1	Case 2	Case 3	Case 4
Operation costs	1782.5	1068	1912.1	1127.71
Decrease cost compared to case 1		40 %	−7.27 %	36.7 %

of the utilized MC method are guaranteed and the variation coefficient of this method will be under 1 %. In the next step, the produced scenarios are utilized in the optimization process of the problem through MC simulation.

It can be seen that the operating cost of the microgrid in [52] is equal to 1029 in deterministic mode, which is equal to case two of this study. Also, in the case of applying the robust optimization method, this value has been reduced to 995. As the results of Table 9, the results of the simulation in the presence of demand response programs in both studies are very close to each other and these results are correct and reliable.

Tables 7 and 8 illustrate the closeness of the results achieved from the MC and 2-PEM which shows the accuracy of the 2-PEM in addressing the uncertainties of input parameters. Comparing the results, it can be seen that the point estimation method has the capability of short-term MG programming in terms of uncertainty. However, this method requires much less repetition than the MC method, which reduces the simulation time.

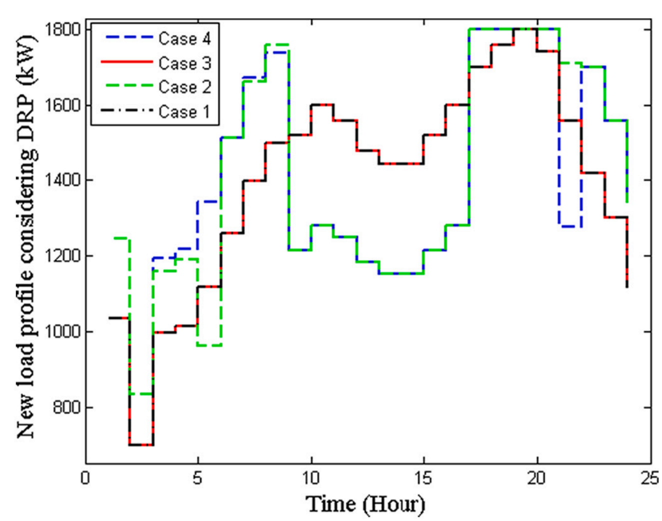

Fig. 8. Demand profile considering DRP.

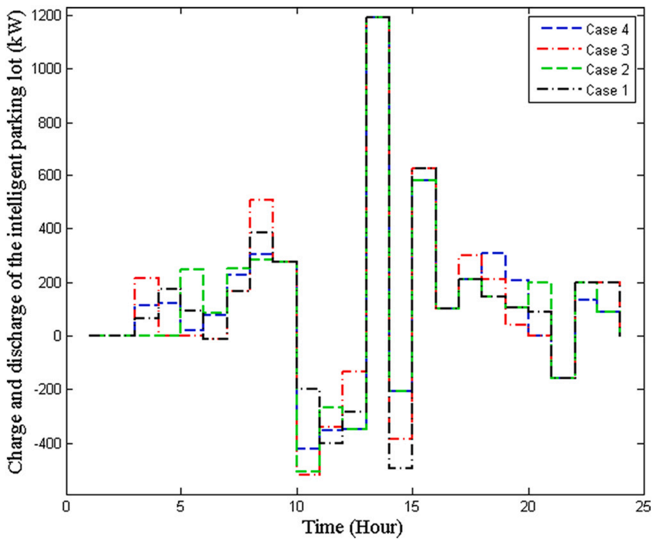

Fig. 9. Charging/discharging of the EVs.

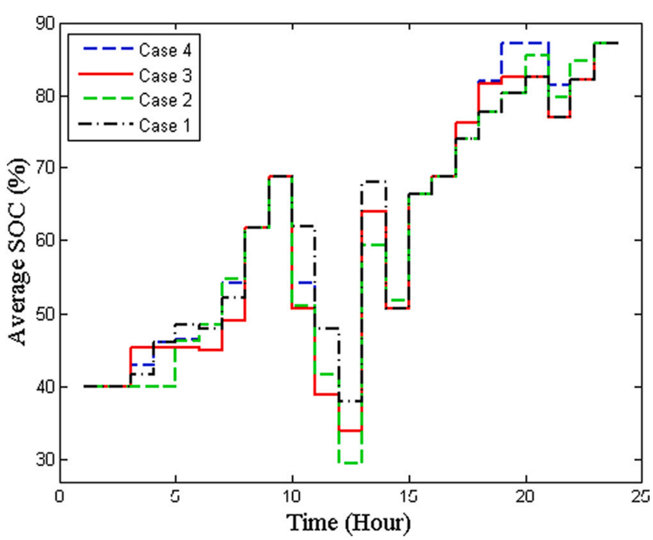

Fig. 10. Hourly SOC of the EVs.

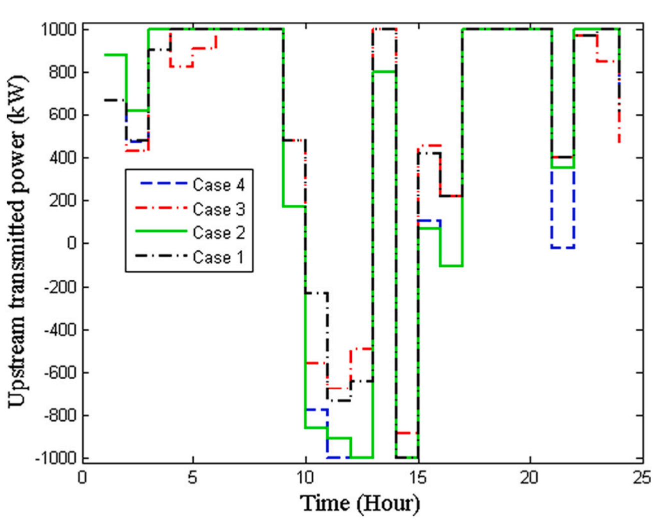

Fig. 11. Power exchanged between the MG and the UG.

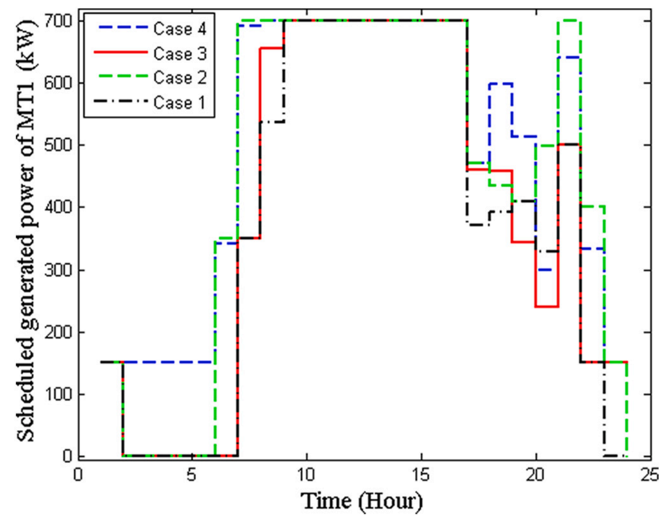

Fig. 12. The hourly output production by MT1.

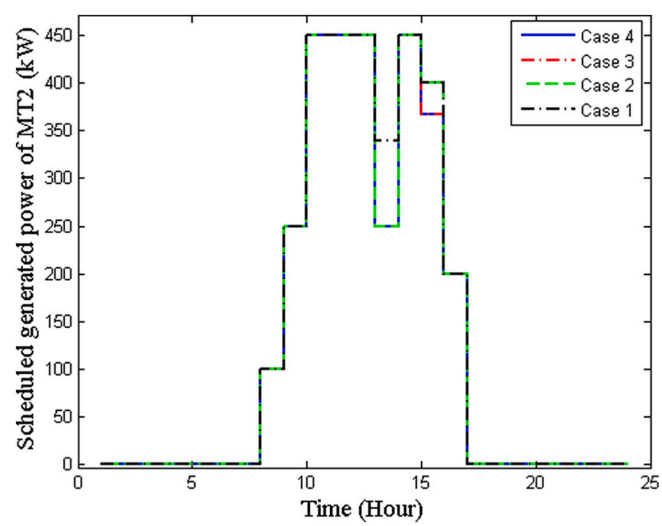

Fig. 13. The hourly output production by MT2.

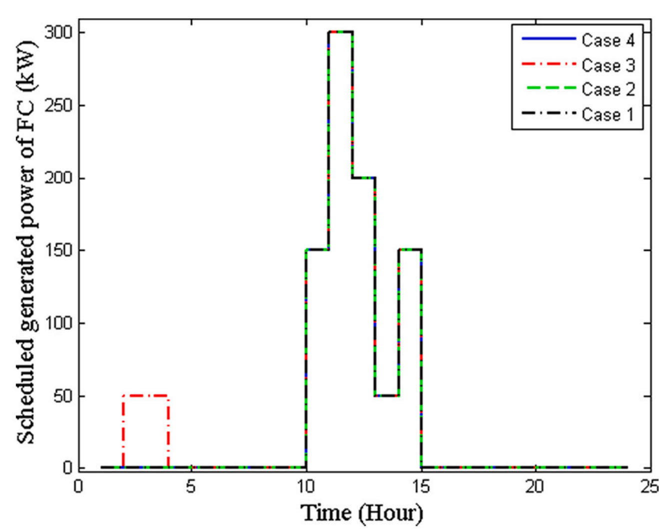

Fig. 14. The hourly output production by FC.

Table 6
Spinning reserve of the LDG and smart parking lot.

Time	MT1				MT2				FC				Smart parking lot			
	Case				Case				Case				Case			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	–	–	43.4	43.4	–	–	–	–	–	–	–	–	–	–	–	–
2	–	–	–	43.4	–	–	–	–	–	–	43.4	–	–	–	–	–
3	–	–	–	32	–	–	–	–	–	–	32	–	–	–	–	–
4	–	–	–	37.7	–	–	–	–	–	–	–	–	–	–	37.7	–
5	–	–	–	42.3	–	–	–	–	–	–	–	–	–	–	42.3	–
6	–	–	–	49.1	–	–	–	–	–	–	–	–	–	–	49.1	–
7	–	–	42.3	8.3	–	–	–	–	–	–	–	–	–	–	–	34
8	–	–	43.6	–	–	–	5.2	48.8	–	–	–	–	–	–	–	–
9	–	–	–	–	–	–	73.8	73.8	–	–	–	–	–	–	–	–
10	–	–	–	–	–	–	–	–	–	–	–	–	–	–	66.9	66.9
11	–	–	–	–	–	–	–	–	–	–	–	–	–	–	88.6	88.6
12	–	–	–	–	–	–	–	–	–	–	–	–	–	–	96.4	96.4
13	–	–	–	–	–	–	–	–	–	–	108.4	108.4	–	–	–	–
14	–	–	–	–	–	–	–	–	–	–	–	–	–	–	128.8	128.8
15	–	–	–	–	–	–	83.2	83.2	–	–	–	–	–	–	42	42
16	–	–	–	–	–	–	116.7	116.7	–	–	–	–	–	–	–	–
17	–	–	107.7	107.7	–	–	–	–	–	–	–	–	–	–	–	–
18	–	–	102.2	102.2	–	–	–	–	–	–	–	–	–	–	–	–
19	–	–	99.1	99.1	–	–	–	–	–	–	–	–	–	–	–	–
20	–	–	100	100	–	–	–	–	–	–	–	–	–	–	–	–
21	–	–	100	60	–	–	–	–	–	–	–	–	–	–	–	40
22	–	–	100	100	–	–	–	–	–	–	–	–	–	–	–	–
23	–	–	100	100	–	–	–	–	–	–	–	–	–	–	–	–
24	–	–	100	100	–	–	–	–	–	–	–	–	–	–	–	–

Table 7
Cost of MG performance in 4 cases using point estimation method.

	Min	Mean	Max	Standard deviation
Case one	1732	1798	1851	403
Case two	1025	1076	1103	265
Case three	1843	1929	2034	472
Case four	1076	1133	1189	277

Table 8
Cost of MG performance in 4 cases using MC method.

	Min	Mean	Max	Standard deviation
Case one	1743	1801	1869	409
Case two	1032	1084	1113	278
Case three	1842	1925	2038	467
Case four	1089	1145	1195	258

Table 9
Cost of MG performance in various methods.

Utilized method	Cost ($)
Deterministic	1743
2-PEM	1032
Robust optimization method	1842

5. Conclusion

In this paper, an optimal scheduling was performed to determine the participation of different energy production units in supplying the required demand of a MG, which aimed to minimize the operating costs. The effect of DRPs and spinning reserve of LDGs and SPL on the cost of MG performance was also investigated. Comparison of the results shows that the DRP has had a positive effect on reducing costs, but spinning reserve has increased costs. It was also observed that SPL also has a beneficial effect on MG performance by reducing electricity costs for the MG owner and smoothing overall demand profile. The results showed that the 2-PEM has the ability to manage the studied MG in the presence of wind, load and solar uncertainties and the results obtained from this method are completely reliable. Also, in this paper, the results related to the operating cost of MG by MC method and 2-PEM were compared in four case studies of presence and absence of DRPs and spinning reserve. The cost analysis of the operation of the studied EV PL shows that the scenario where the robust optimization method has been used has decreased the operation cost of the PL by 3.31 % with respect to the deterministic model. Analyzing the load curve while taking the DRP into account in the four cases reveals that only the DRP in cases 2 and 4 has been impacted, while the DRP in case 3 has not been, and as a result, the demand profile of case 3 is the same as case 1. With this realization, we can see that DRP more thoroughly smooths the demand profile in the second case than in the other circumstances. The smoother the demand profile, the more the operation costs are lowered.

CRediT authorship contribution statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the Journal of Energy Storage.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We understand that the corresponding author is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jamal Beiza reports funding was provided by Islamic Azad University,

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Data availability

The authors do not have permission to share data.

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