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Optimal Operation of Multi-microgrid System Considering Uncertainty of Electric Vehicles

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Integration of electric vehicles (EVs) into the power systems has been a concern for distribution system operators due to their impacts on several aspects of power system operation, such as congestion management, power quality, voltage regulation, and peak time changing. In this paper uncertainty parameters such as charging time, traveled distance, and plug-in location of EVs are considered and their effects on the optimal daily operation of microgrids (MG) are discussed. A power system, including geographically-adjacent quasi-independently controlled MGs, each of which has a different operation objective function (OF) is modeled in this paper. A set of socioeconomic OFs i.e. minimum purchase power from the main grid, maximum usage of green power, and minimum Expected Energy Not Supplied (EENS) are considered for each MG which appear in the optimization process with different weights based on the MG policy. The effect of EV integration into the Multi Microgrid System (MMS) is also investigated in this paper and the performance effectiveness of different operation management policies against EV integration is discussed.

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NOMENCLATURE

Acronyms	
DG	Distributed generation
MG	Microgrid
MMS	Multi microgrid system
EV	Electric vehicles
PV	Photovoltaic
D-IPFC	Distribution Interline Power Flow Controller
GA	Genetic Algorithm
S3P	Small power generation
V2G	Vehicle to grid
MCS	Monte-Carlo simulation
SOC	state of charging
PDF	probabilistic distribution function
OF	Objective function
ESS	Energy Storage Systems
Variables	
n_m	Number of batteries in *m*-th microgrid
e_m	Number of electrical vehicles in *m*-th microgrid
h	Time horizon (hour)
C_h	Cost of energy at time *h* ($)
P_h	Purchased energy from the main grid at time *h* (kWh)
E^h_j	Greenhouse emission of *j*-th DG at time *h* (ton/h)
P^h_j	Generation power of *j*-th DG at time *h* (kW)
α_j	Greenhouse emission rate of *j*-th DG (ton/kWh)
τ_i	Interruption time of *i*-th bus (h)
$P_{i,h}{}^D$	Load on the *i*-th bus at time h (kWh)
SOC(h)	Battery state of charge at time *h* (kWh)
$SOC_{n_m}^{k_m}$	State of charge in n_m-th battery in k_m-th microgrid (kWh)
$SEV_{n_m}^{k_m}$	Start time of e_m-th EV charging in k_m-th microgrid (h)
η_{bat}	ESS charging/discharge efficiency (%)
$P_{PV,h}$	PV generated power at time *h* (kWh)
$P_{bat,h}$	Battery charge/discharge power at time *h* (kWh)
$P_{l,h}^i$	Power demand at time h in bus i (kWh)
$P_{ev,h}^i$	EVs charging power at time *h* in bus i (kWh)
P_{loss}	Active power loss (kWh)
ROC	Rate of Charge (kWh/h)
ROD	Rate of Discharge (kWh/h)
SOC_{min}	Minimum charge level of battery (kWh)
SOC_{max}	Maximum charge level of battery (kWh)
P_{move}	EV energy consumption rate (kWh/km)
ΔL	Distance traveled by the EV (km)
L	Distance between different zones (MGs) (km)
Subscripts	
i	Index of buses
l	Index of loads
m	Index of microgrid
j	Index of power source

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1. INTRODUCTION

High penetration of distributed generation (DG) units and storage systems along with emerging the concept of microgrid (MG) [1, 2] have enhanced the reliability of electrical energy supply [3]. Another technology significantly changed the paradigm of power system operation is EV, which has gained considerable attention in the last years [4-6] because they have negligible CO_2 emission, which has a significant influence in decreasing greenhouse gases. However, strategies for their charging and discharging cycles are the primary concern of distribution and MGs operators [7].

Management of energy in such systems has several concerns, such as optimal management of DGs [8, 9]. Wouters et al. [10] addressed the necessity of designing a local energy system via the integrity of DG and microgrids. A mixed-integer linear programming model was introduced to optimize local energy systems. Based on the proposed model by Wouters et al. [10], DGs, heating units, and storage systems can supply the electrical, and cooling/heating energy of a small residential neighborhood. A central controller was considered in the proposed model. The system's annual cost was considered as the OF and GAMS software was used for solving the problem. The concept of multiagent systems was used for the optimal operation of microgrids [11]. Genetic Algorithm (GA) [12] was used as a meta-heuristic algorithm for the optimal operation of microgrids. The concept of multi-microgrid has been introduced in this paper for clustering the available houses. This concept was introduced by Arefifar et al. [13] and it has been modified in this paper. A distribution interline power flow controller (D-IPFC) was introduced as a new device by Kargarian and Rahmani [14]. By presenting a model for injection power by D-IPFC, Kargarian and Rahmani [14] showed that it can improve the operational capability of the distribution system. The D-IPFC was used to connect several MGs to form a MMS. The nonlinear loads have been modeled in the optimal operation of the standalone microgrid [15]. Energy management based on contingency analysis for a MMS has been presented by Aghdam et al. [16]. The economic comparison between the microgrid development versus the conventional distribution system has been discussed by Parag and Ainspan [17].

Moreover, the uncertain parameters make the decision-making process more complicated. Niknam et al. [18] presented a stochastic model for optimal management of energy in a microgrid, in which the operating cost and greenhouse gas emission were minimized. Uncertain parameters such as load, wind turbine, and photovoltaic power output as well as the tariff of purchasing electricity from the main grid were considered. A scenario-based method, i.e. roulette wheel mechanism, was used for uncertainty modeling considering the normal distribution function for input parameters. Some new devices have been introduced for improving the distribution system capability. Khodaei et al. [19] investigated the MG planning problem and its economic viability deployment. The optimal generation mix of distributed energy resources (DERs) for installation were determined considering uncertainties. A robust optimization approach was adopted for considering uncertainty in load forecast error, variable renewable generation, market prices, and microgrid islanding. Xiang et al. [20] developed a scenario-based robust energy management method accounting for the worst-case amount of renewable generation and load. The economic and robust model was formulated to maximize the total exchange cost while getting the minimum social benefits cost at the same time. The uncertainty of renewable generation and load demand was described as an uncertain set produced by interval prediction. Then, Taguchi's orthogonal array testing method was used to provide possible testing scenarios.

The storage system has incrementally grown in the networks in the last several years [21, 22], due to the high penetration of distributed energy resources such as wind turbines and photovoltaics [23] and the intermittency nature of renewable energies [24]. ESSs have brought many benefits to the power system such as short-term power supply, improving the power quality, and ancillary services in microgrids. A cost-based formulation was presented for the optimum sizing of storage units in the microgrid [25, 26]. Xiao [27] proposed the hierarchical control of ESS, composed of both centralized and distributed control to enhance system reliability. Xu et al. [28] used ESSs to support the frequency control in microgrid systems, due to the intermittency of the renewable generation and constantly changing load demand. A distributed cooperative control strategy was proposed for coordinating the ESSs to maintain the supply-demand balance and minimize the total power loss associated with charging/discharging inefficiency. A review of hybrid energy storage system usage in standalone microgrids has been proposed by Jing et al. [29]. In fact, different control strategies have been compared by Jing et al. [29].

The electric vehicles can perform as a storage system in the distribution networks and at the same time act as a distributed load for the distribution operator [30]. The EV was defined as a small power generation (S3P) for improving the security and reliability of the power system [31]. Vehicle-to-grid (V2G) technology can significantly affect power grids, but there should be a smart program for electrical parking lots. Zhang et al. [32] redefined the unit commitment problem by considering demand response and EVs. These technologies can reform the demand curve of the grid and can be used as a reserve source as well. Lin et al. [33] presented the distribution system planning by considering charging stations of EVs. The costs regarding the investment, operation, and maintenance were considered as OFs. Rana et al. [34] introduced a modified droop control for frequency support of microgrids based on EVs. Derakhshandeh et al. [35] used EVs for the coordination of generation scheduling in an industrial microgrid manner.

In this paper, a new model for the optimal daily operation of geographically-adjacent MGs, including PV integration is presented. In the proposed model, the uncertain parameters related to EVs are considered for the hour-ahead scheduling process. The uncertainties of the daily traveled distance of EVs inside a MG and among MGs are considered in the modeling. There are different uncertain parameters such as charging time, traveled distance, and number of EVs in the network, which are considered in this paper with Monte-Carlo simulation (MCS) [1]. MMS consists of several quasi-independent MGs, each of which has different OFs, i.e. minimum energy cost, minimum greenhouse gas emission, and maximum reliability.

The contributions of this paper are as follows:

- Behavior of MMS with different OFs is analyzed and its optimal operation with the presence of daily travelled distance of EVs as an uncertain parameter is investigated.
- A new model for the daily optimal operation of geographically-adjacent MGs, including PV integration is proposed.
- A comparison is made to assess the effect of weighting factors on the optimal operation of MMS.

The rest of the paper is organized as follows. System modeling is introduced in section 2, in which the mathematical models of all elements of the microgrid are presented. In section 3, the objective function, constraints, decision variable, and pseudo code of the optimal operation optimization of the MMS system are proposed. This optimization is the main function of the central controller in each microgrid in connected mode. In section 4, the proposed method is implemented on a MMS system and the results are discussed. Finally, section 5 concludes the paper.

2. MULTI-MICROGRID POWER SYSTEM MODELING

2. 1. System Description and Modeling In this section, a MMS, which is composed of some adjacent MGs is modeled, each of which includes several EVs whose charging time intervals are controlled by a central controller. As shown in Figure 1, the EVs' batteries can be charged by connecting to the local distribution system. As mentioned earlier, the starting time of charging the EVs is managed by the microgrid central controller while the EV's owners set the allowed timespan for this purpose.

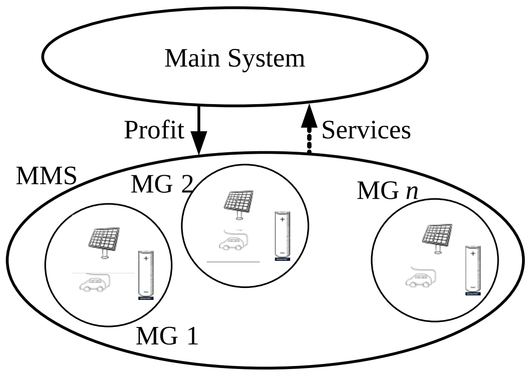

Figure 1. MMS layout

As shown in Figure 1, each MG has at least a PV source and a battery to store the excess energy of photovoltaic sources in the case that surplus energy generation exists. The daily charging and discharging plan of the batteries is controlled by the microgrid operator.

The MMS can have two types of controllers [13]. In one type a central controller is considered for all microgrids, as studied in this paper while in the other type, each microgrid has a dedicated controller. The former version has lower implementation costs.

The distribution lines are parameterized based on pi-section modeling. As the length of the lines in the distribution systems and microgrids is short, this model is reasonably accurate. The shunt admittance should be considered because there are underground cables in the distribution network; therefore, a simplified short-line model without shunt admittance modeling will lead to inaccurate results.

Power output by the PV system is considered in the power system analysis as a deterministic variable as the main objective of this paper is about the effect of uncertainty of EVs on MMS operation.

EVs are modeled based on their charging rate, which is assumed to be a constant value. This charging is added to the load profiles of each home in load flow studies.

$$\sum_i P^D_{i,h} = P^i_{l,h} + P^i_{ev,h} \quad (1)$$

The cost of energy is assumed to be based on the market price, which is variable over the day. The time horizon for each time interval for price change is considered one hour.

$$Energy\,Cost = \sum_h C_h P_h \quad (2)$$

The upstream network is modeled as an all-the-time available infinite bus. Although it can be considered that the upstream network has limited availability, but this assumption does not affect the presented method.

2. 2. Uncertainty Modeling– Monte Carlo Simulation The following steps are presented for scheduling the proposed multi-microgrid structure.

Step 1: Collect the customers' load data and PV power generation. Real data sets are used in this step. The customer loads and photovoltaic generations are based on the real data of residential loads in Tehran.

Step 2: Random number generation. As it is concerned before, MCS is used to model the uncertainty. So, random numbers are generated for every single EV in each MG, the distance moved in each day, and the charging hour of each EV. Normal probability distribution function (PDF) is used for the number of EVs and uniform PDF is used for the distance covered and charging hour. Each random number set is concerned with a scenario.

Step 3: Solving the optimization problem. The optimization problem of each microgrid based on its own OFs and different scenarios is solved. The number of optimization problems is equal to the number of microgrids. Each MG has its own OF. Different objectives and constraints are presented in the next section. The decision variables in these problems are the daily charging and discharging plan of batteries and the charging time of EVs.

Step 4: Data Analysis. The results of optimization problems are analyzed and the exchanging power between the microgrids and main grids is stored.

3. MMS OPTIMAL OPERATION

In this section, the OFs and constraints of the MMS optimal operation problem are explained. Three OFs are considered, i.e. the cost of energy, gas emission, and reliability. It is assumed that the MGs are connected to the main grid from which the required energy is supplied.

3. 1. Objective Functions MGs are running with different OFs, i.e. minimization of cost of energy, minimization of green gas emission, and minimization of expected not-supplied energy. The weighted sum of the mentioned OFs results in the proposed OF in this paper. The weight factors can be tuned based on the global and upstream rules and/or objectives of the microgrid operators, which can be changed from time to time, based on the nature of the grid and special events of the year. The OFs are stated in Equations (3), (4), and (6).

1) Cost of the Energy

$$OF_1 = \sum_h C_h P_h \tag{3}$$

In this paper, the time horizon for each time interval for price charging is considered one hour. Ph is considered negative if the generated power in the microgrid is more than the demand in each hour and positive when there is a power surplus in MG. It is assumed that the excess energy of the microgrid can deliver to the main grid. In other words, the connection between the main grid and microgrids is bi-direction.

2) Greenhouse Gas Emission

$$OF_2 = \sum_j \sum_h E_h^j \tag{4}$$

E_h^j can be considered as a coefficient of Phj based on Equation (5). The available source of energy in the microgrids is PV systems which are emission-free. However, the excess energy which is purchased from the main grid causes greenhouse gas emissions. This explains why the greenhouse gas emission rate shows a straight relation with the delivered energy from the upstream grid to the MG.

$$E_h^j = \alpha_j P_h^j \tag{5}$$

3) Expected Energy not Supplied

$$OF_3 = EENS = \sum_i \tau_i P_i^D \tag{6}$$

Values of τi, denoting the average yearly interruption time for each bus are calculated based on historical data, i.e. yearly unavailable periods.

The decision variables in this problem are the set of SOC of batteries in each microgrid and the time of EV charging. Based on the SOC the amount of charging/discharging of the battery is calculated as follows:

$$P_{bat}(h) = \eta_{bat}\left(SOC(h) - SOC(h-1)\right) \tag{7}$$

where Pbat is the amount of charging (positive value) and/or discharging (negative value) of the battery and SOC(h) is the SOC of the battery in hour, h.

3. 2. Constraints The constraints are as follows:

1) Power Balance

The generation and demand values of active power should be equal at all times to prevent frequency deviation in the system.

$$P_h + P_{PV,h} = \sum_L P_{l,h} + P_{ev,h} + P_{bat,h} + P_{loss} \tag{8}$$

2) Battery SOC limitation

The SOC of the battery has limitations to guarantee that it works in safe operating conditions.

$$SOC_{\min} \leq SOC(h) \leq SOC_{\max} \tag{9}$$

The upper and lower limits are designed based on the battery structure, type, and usage. In some cases, SOCmin can be zero, but in other ones always there should be some minimum charge.

3) Intraday energy transfer

The SOC of the battery on the first and the last time interval of a day are considered equal. This assumption makes the proposed algorithm comparable with the others without dependency on the initial condition of the battery.

$$SOC(h=1)=SOC(h=24) \tag{10}$$

4) EVs charging Power

The available charge of EVs is calculated by knowing the SOC at the last time interval and traveled distance by the EV, the latter is reflected in Pmove.

$$SOC(h)=SOC(h-1)-P_{move}\times\Delta L \tag{11}$$

Based on the distance which is covered by an EV, the discharging amount of the EV is calculated. The discharging rate of the EVs is considered constant and by multiplying the distance in the discharging rate, the amount of reduction in SOC is calculated.

5) EV Charging Time

In this paper, it is considered that the charging time of EVs is 2 hours continuously because the discontinuous charging of batteries will reduce their lifetime.

6) Battery charge/discharge rate limitation

In this paper, the charge and discharge rates have been limited as follows:

$$\begin{cases} SOC(h)-SOC(h-1)<ROC & if \quad SOC(h)>SOC(h-1) \\ SOC(h)-SOC(h-1)<ROD & if \quad SOC(h-1)>SOC(h) \end{cases} \tag{12}$$

3. 3. Decision Variables The decision variables in this problem are the SOC of batteries in each hour and the time of EV charging. While the EV owners set the desired interval for charging, the starting time is optimally decided by the central control. In other words, the following set of decision variables is determined optimally by the central controller of MMS.

$$\begin{aligned} U=[&SOC_1^{k_1},...,SOC_{n_1}^{k_1},...,SOC_1^{k_m},...,SOC_{n_m}^{k_m}, \\ &SEV_1^{k_1},...,SEV_{e_1}^{k_1},...,SEV_1^{k_m},...,SEV_{e_m}^{k_m}] \end{aligned} \tag{13}$$

3. 4. Optimization Procedure As one of the best optimization algorithms in discrete variables, GA is adopted for MMS optimal operation in this paper. As mentioned in step 3 of section 2.B, MCS is used in this paper.

Two sets of input data are provided for the GA. The first set includes deterministic data such as the load profiles of customers and generated power by PV systems, while the second set consists of probabilistic data such as the number of EVs in each MG, the daily traveled distance by EVs, and the charging hour of each EV. The output of the GA is the power system control parameters, i.e. decision variables defined in Equation (12). SOC variables address the optimal charge/discharge of the battery and SEV shows the optimal starting time of EV charging.

The parameters of optimization are selected based on the knowledge of the authors and the GA toolbox of MATLAB is employed for this purpose. The selected GA parameters are presented in Table 1.

The following pseudo-code summarizes the procedure that is implemented on MMS optimal operation problem.

Loop (for all the scenarios)

Collect Real Data for Loads

Collect Real Data for PV Generation

Generate Random Data for the Number of EVs in each MG

Generate Random Data for Distance Moved by each EV

Generate Random Data for the charging hour of each EV

[SOC, SEV]← **GA Optimization**

Save the Output of GA

The flowchart of the optimization process is shown in Figure 2.

4. SIMULATION RESULTS AND DISCUSSION

4. 1. System Description and Assumptions As shown in Figure 3 a system consisting of three microgrids connected to the main grid is considered in this paper. These microgrids are geographically close to each other. The distance between the two parts of MMS is shown by L in Figure 3.

It is assumed that the scheduling horizon is one day (24 hours). The time step is 1 hour, and it is assumed that the load and distributed generation are constant in each step.

It is assumed that the EVs travel some round trips and the charging place of the EV is on its parking. It is assumed that the SOC values of the batteries are equal in the first and last hour of the scheduling horizon. It is assumed that each microgrid has one ESS with a capacity of 600 kWh. The ESS can discharge to 15% of its capacity. The charging/discharging rate of the ESS is considered 100 kWh/hour. ESS usage has two main reasons:

1. The maximum generation of PV and maximum consumptions of loads are different and also take place in

TABLE 1. GA parameters

Parameter	Value
Number of Iteration	200
Population Type	Double vector
Selection Operators	Stochastic uniform
Mutation Operators	Gaussian
Percent of Mutation	20%

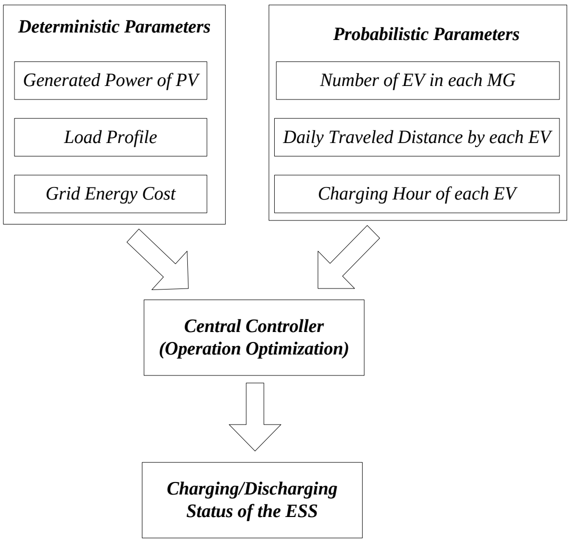

Figure 2. Optimization process flowchart

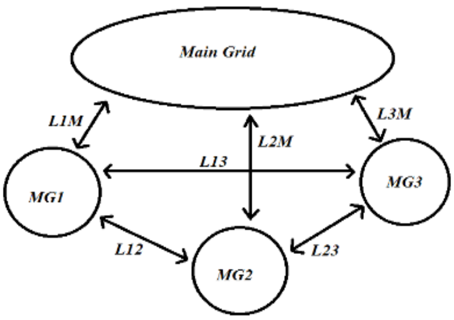

Figure 3. A 3-MG system

different time intervals. The ESS can solve this problem by charging in maximum PV generation time and discharge in the load maximum consumption times.

2. The main grid electricity price varies during the day. The ESS can be charged during low-price hours and can be discharged during peak-price hours.

The ESS has two operating modes with different objectives, i.e. energy management in the connected mode and frequency/voltage control in the islanded mode of the microgrid. In this paper, it is assumed that the energy management function of the ESS is investigated. It is considered that there are some photovoltaic, EVs and loads in each microgrid, which are presented in Table 2.

Load profiles of each MG are presented in Figure 4, which are based on real data which are collected from some residential loads in the city of Tehran, Iran. It is assumed that there are 4, 3, and 5 load centers in microgrids 1, 2, and 3, respectively. So, there are 4, 3, and 5 load profile curves in each part of Figure 4.

The PVs generation profiles are presented in Figure 5. These values are collected based on real data for the city of Tehran, Iran.

TABLE 2. Number of PV Sources and Loads in Each Microgrid

Microgrid	Installed PV capacity (kW)	Maximum Loads (kWh)
1	1400	1705
2	540	577
3	900	915

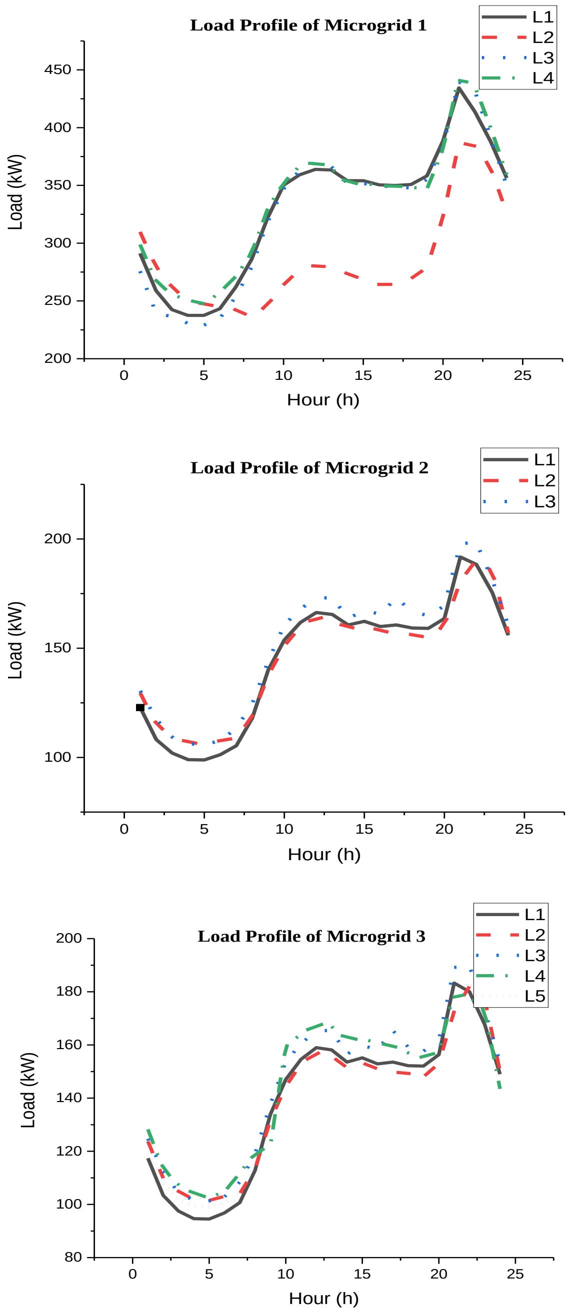

Figure 4. Load Profile of Microgrid

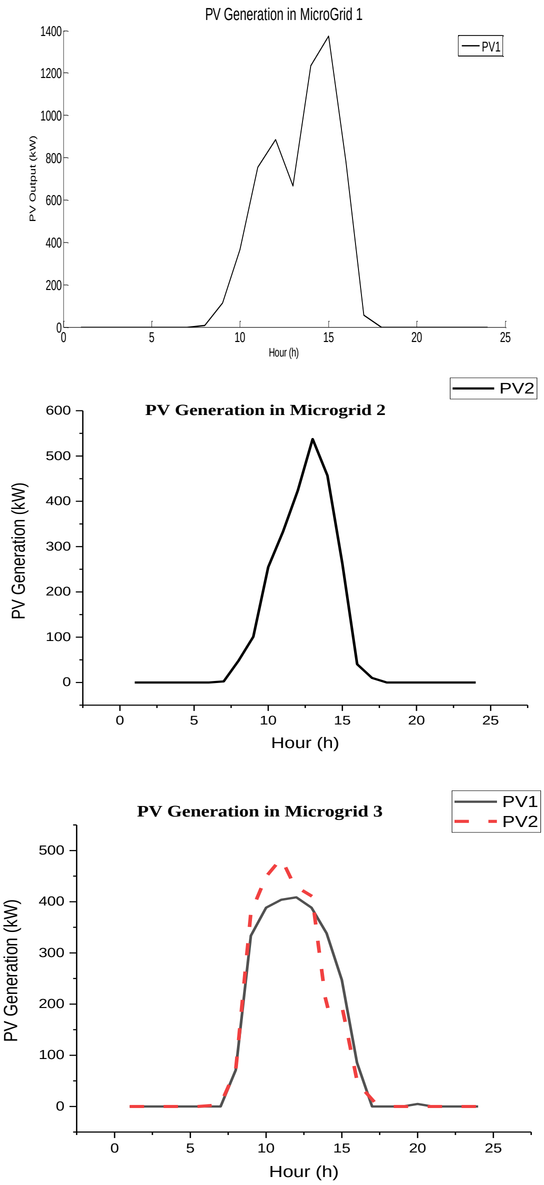

Figure 5. PV power generation

The average yearly interruption time is considered equal for all customers of each microgrid. The average yearly interruption time of microgrids 1, 2 and 3 are considered 21, 12 and 9 hours per year, respectively. These values are collected from literature [36].

4. 2. Monte Carlo Simulation The uncertain parameters are modeled with MCS in this paper with 1000 scenarios generated based on the random generation of uncertain parameters based on which the optimization problems are solved. The uncertain parameters are as follows:

- The number of EVs in each microgrid. The PDF of this parameter is considered a normal distribution function, with a mean value of 50 and a standard deviation of 20 [37].
- The distance travelled by EVs. The uniform distribution is considered for this parameter. It is considered that the EVs can travel between the microgrids and between their microgrid and the main grid. It is considered that travel is a round trip. The number of EVs which travel from each microgrid through other microgrids and the main grid is generated based on the random number generation process.
- Time of charging commencement of EVs. The uniform distribution addresses the statistical distribution of this parameter.

The dispersion of the number of EVs in each MG is shown in Figure 6.

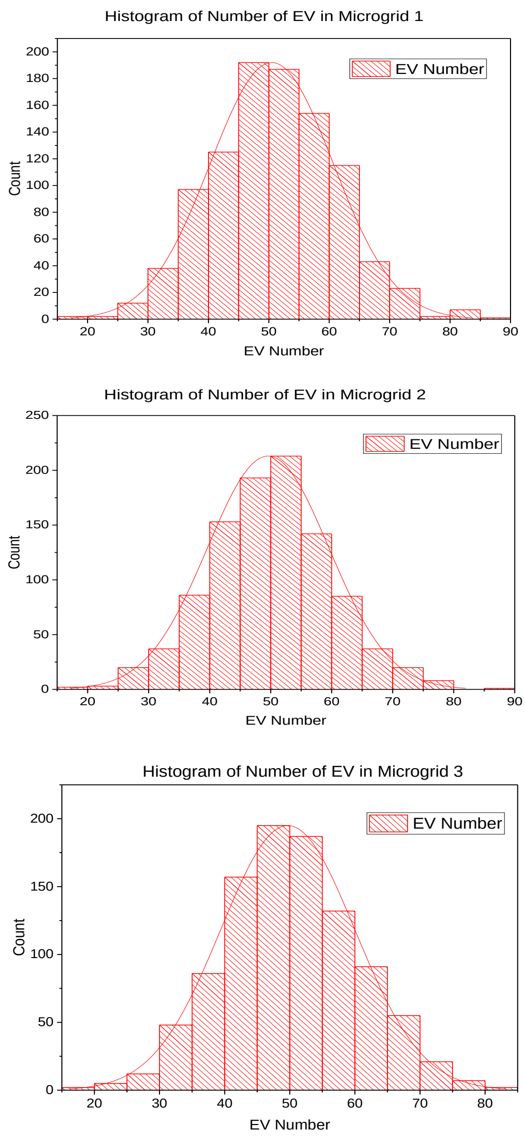

Figure 6. Dispersion of EV Numbers

The charging of EV batteries is reduced based on the traveled distance. The energy reduction of EV batteries based on each trip between the grids is presented in Table 3.

The weighting coefficients of OFs for microgrids are different. So, the cost of energy, emission, and reliability of microgrids are different. The selected weighting coefficients are presented in Table 4.

The results in this section are categorized into two parts: scenario 1, which shows the base case results of MMS, and scenario 2, which discusses the optimal results.

4. 3. Scenario 1: Base Case For a better presentation of the effect of the quality of the optimization problem, at first, the MG is planned without the optimization problem. The results of this case are presented in Table 5.

TABLE 3. Energy Deployment of EV Batteries for Travel among MGs (kWh)

Grid	Microgrid1	Microgrid2	Microgrid3	Main Grid
MG 1	-	5	4	3
MG 2	5	-	7	5
MG 3	4	7	-	7
Main Grid	3	5	7	-

TABLE 4. Weighting Coefficients for different OF in MGs

MG number	OF1: Cost of Energy	OF2: Emission Cost	OF3: EENS
MG 1	0.7	0.2	0.1
MG 2	0.1	0.7	0.2
MG 3	0.2	0.1	0.7

TABLE 5. Average and Standard Deviation of Energy Cost for Each MG Before Optimization

Objective Function	MG number	Average ($)	Standard Deviation ($)	Max ($)	Min ($)
Cost of Energy	MG 1	6538.1	627.29	8927.3	4653.3
	MG 2	4609.4	699.94	6877.8	2710.3
	MG 3	5458.1	767.31	7760.9	3472.7
Emission	MG 1	524.23	11.62	558.78	493.55
	MG 2	350.39	8.40	375.33	331.50
	MG 3	467	9.09	487.94	440.90
EENS	MG 1	2425.2	13.6	2461.4	2392.6
	MG 2	1106.3	10.3	1134.8	1074.6
	MG 3	60.4	2.1	66.8	54.1

4. 4. Scenario 2: Optimal Operation of MMS The weighting coefficients of OFs for microgrids are different. So, the cost of energy, emission and reliability of microgrids are different. The higher coefficient for the cost of energy causes a lower cost and a higher coefficient for the EENS leads to a higher cost of energy and hence higher reliability. The summary of the result is presented in Table 6 and the comparison is presented in Table 7.

As shown in Table 7, the optimization process reduces the cost of energy by 2.4%, 3.4%, and 2.8% in microgrids 1, 2, and 3, respectively. This reduction in cost causes a $474 daily reduction and a $173010 annual saving in energy cost.

TABLE 6. Average and Standard Deviation of Energy Cost for Each MG

OF	MG number	Average ($)	Standard Deviation ($)	Max ($)	Min ($)
Cost of Energy	MG 1	6380.8	627.30	8777.5	4496.3
	MG 2	4451.3	700.59	6719.9	2553
	MG 3	5300.2	767.76	7603.2	3308.9
Emission	MG 1	522.7	10.2	556.7	499.4
	MG 2	330.3	8.9	352.6	308.1
	MG 3	451.7	9.03	478	431.3
EENS	MG 1	2411.2	14.1	2445.2	2376.1
	MG 2	1084.3	8.5	1108.1	1060.2
	MG 3	56.2	2.3	61.8	51.1

TABLE 7. Comparison between scenarios 1 (Base Case) and 2 (Optimal Operation)

OF	MG Number	Average (optimized)	Average (non-optimized)	Percent of Improvement
Cost of Energy	MG 1	6380.8	6538.1	2.4%
	MG 2	4451.3	4609.4	3.4%
	MG 3	5300.2	5458.1	2.8%
Emission	MG 1	522.7	524.23	0.29%
	MG 2	330.3	350.39	5.73%
	MG 3	451.7	467	3.28%
EENS	MG 1	2411.2	2425.2	0.58%
	MG 2	1084.3	1106.3	1.99%
	MG 3	56.2	60.4	6.95%

In other words, the optimization process reduces the emission by 0.29%, 5.73%, and 3.28% in microgrids 1, 2 and 3, respectively and the reduction in EENS is 0.58%, 1.99%, and 6.95% in microgrids 1, 2 and 3, respectively.

As shown in Table 7, the effect of weighting coefficients, listed in Table 4, on the percentage of reduction of each part of OF is interesting. As an example, the reductions in the cost of energy, emission and EENS for the MG1 after applying the optimization process are 2.4%, 0.29%, and 0.58%, respectively. The interesting point is the relation between the reduction percent and the weighting coefficients of these three parts, which are 0.7, 0.2, and 0.1, respectively. As it is shown in Table 7, the higher value of the coefficient resulted in more reduction in OF optimization. This procedure is repeated for both microgrids 2 and 3.

To show the effects of weighting factors on the results, the weighting factors of MG 1 are changed and the microgrid OFs are obtained. Three scenarios are analyzed as follows:

1. The base case, in which 0.7, 0.2, and 0.1 are weighting factors for objective functions of 1, 2, and 3, respectively.
2. Scenario 1, in which 0.1, 0.7, and 0.2 are weighting factors for objective functions of 1, 2, and 3, respectively.
3. Scenario 2, in which 0.2, 0.1, and 0.7 are weighting factors for objective functions of 1, 2, and 3, respectively.

The results listed in Table 8 show the weighting factors' effects on the objective functions. The first column shows the number of scenarios and the second one shows the objective functions considered under that scenario. Being listed in the third column, the weighting factors are shown and the fourth and fifth columns show the average OF value considering all the random numbers generated by MCS, after and before the optimization process, respectively. The average value is selected as a descriptive index to show the performance of the optimization process. The last column shows the improvement percentage in the objective function value due to the optimization process.

As an example, the convergence process of one of the 1000 scenarios is shown in Figure 7.

Figures 8 and 9 depict the effect of changing the weighting factors on the value of the OFs., in which the changes of OF 1 and 2 versus the weighting factors variations are drawn. It is assumed that the weighting factor of OF 1 is fixed to 1.0 and that of the other OFs is changed from 0.1 to 4.0. The changes of OF 1 and 2 are shown in Figures 8 and 9, respectively. Each curve in these figures shows a fixed amount of objective function.

TABLE 8. Average and Standard Deviation of Energy Cost for MG1

Scenario	OF Number	W	Average (optimized)	Average (non-optimized)	Percent of Improvement
	OF1	0.7	6380.8	6538.1	2.40%
Base Case	OF2	0.2	522.7	524.23	0.29%
	OF3	0.1	2411.2	2425.2	0.58%
	OF1	0.1	6501.5	6538.1	0.56%
Scenario 1	OF2	0.7	516.52	524.23	1.47%
	OF3	0.2	2399.8	2425.2	1.05%
	OF1	0.2	6421.5	6538.1	1.78%
Scenario 2	OF2	0.1	523.41	524.23	0.16%
	OF3	0.7	2374.9	2425.2	2.07%

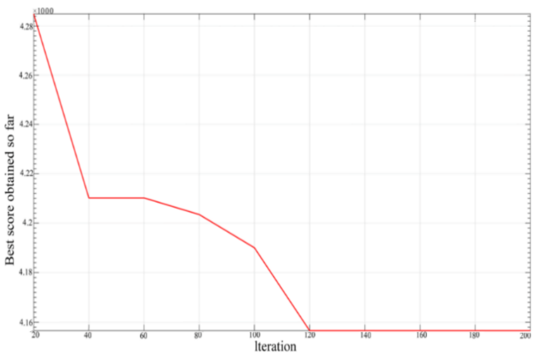

Figure 7. The convergence process of optimization algorithm

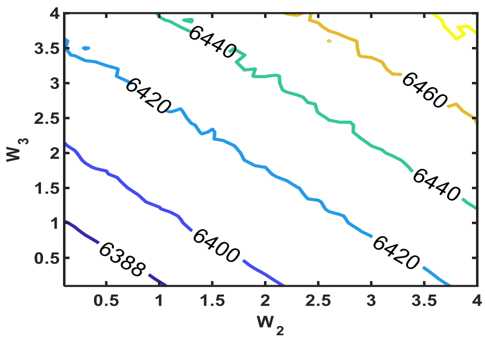

Figure 8. Changes of OF1 based on changing weighting factors

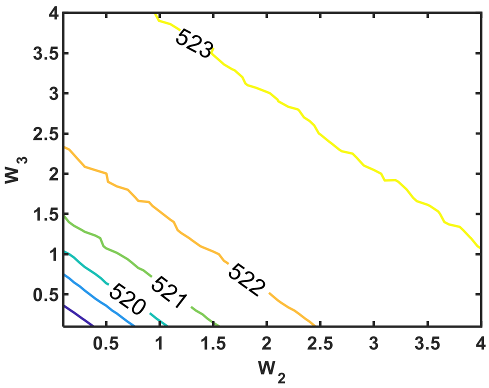

Figure 9. Changes of OF2 based on changing weighting factors

5. CONCLUSION

In this paper, an MMS, including three MGs with different operation objectives, was modeled and its operation was investigated. Three OFs considered for the microgrids are the cost of energy, greenhouse gas emission, and expected not-supplied energy. The number of EVs in each microgrid was considered by appropriately-shaped normal PDF and uniform density functions were adopted to consider the EVs traveled distance and their charging time. MCS was used to generate scenarios of uncertain parameters and the effect of uncertainty of EV numbers on the energy cost, EENS and gas emission cost was discussed. It was shown that the objective functions were decreased according to their weights, set by the MG operator. The optimal operation of MMS was also determined by adopting GA to the multi-objective MMS operation problem. Comparing two cases, i.e. base case and optimal operation showed that the optimization process led to a decrease in the cost of energy in MMS, enhancing the reliability index of the MG and greenhouse gas emission reduction.

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Persian Abstract

چکیده

ادغام وسایل نقلیه الکتریکی در سیستم های قدرت به دلیل تأثیرات آنها بر چندین جنبه از عملکرد سیستم قدرت، مانند مدیریت ازدحام، کیفیت توان، تنظیم ولتاژ و تغییر زمان پیک، یک نگرانی برای اپراتورهای سیستم توزیع بوده است. در این مقاله پارامترهای عدم قطعیت مانند زمان شارژ، مسافت طی شده و محل اتصال EV ها در نظر گرفته شده و اثرات آنها بر عملکرد روزانه بهینه ریزشبکه ها مورد بحث قرار گرفته است. یک سیستم قدرت، شامل MGهای شبه مستقل کنترل شده از نظر جغرافیایی مجاور، که هر کدام تابع هدف عملیاتی متفاوتی دارند، در این مقاله مدل‌سازی شده‌اند. مجموعه ای از OF های اجتماعی-اقتصادی یعنی حداقل توان خرید از شبکه اصلی، حداکثر استفاده از توان سبز و حداقل انرژی مورد انتظار تامین نشده برای هر MG در نظر گرفته می شود که در فرآیند بهینه سازی با وزن های مختلف بر اساس خط مشی MG ظاهر می شود. اثر ادغام EV در سیستم چند ریزشبکه نیز در این مقاله بررسی شده و اثربخشی عملکرد سیاست‌های مدیریت عملیات مختلف در برابر یکپارچه‌سازی EV مورد بحث قرار گرفته است.