Energy Management of Electric Vehicles Parking in a Power Distribution Network Using Robust Optimization Method

MEHRDAD GHAHREMANI[1], **MORTEZA NAZARI- HERIS**[2], **KAZEM ZARE**[3], **AND BEHNAM MOHAMMADI-IVATLOO**[4]

[1,2,3,4] *Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran*
[*] *Corresponding author: mehrdad.ghahramani@yahoo.com*

Manuscript received 25 May, 2018;Revised 05 August, 2018, accepted 05 August,2018. Paper no. JEMT-1804-1079.

Optimal, safe and robust scheduling, and planning of electric energy distribution networks are very important considering such networks as one of the most important components of electrical networks. Electric vehicles are one of the major elements of the future electricity distribution systems. In this study, an optimal robust model is presented for short-term operational scheduling of distribution network in presence of uncertainties to minimize the cost of network operation. The robust optimization (RO) concept is employed in this research to address the uncertainty of power market price. To investigate the proposed method, a 33-bus IEEE-standard system has been applied, which contains distributed renewable generation units and non-renewable energy sources. The obtained results indicate the effectiveness of the presented model in network scheduling in the presence of uncertainties. Also, the impact of electric vehicle parking as an energy storage technology on the functional cost of the distribution system is discussed, which shows high performance and convenient operation of the proposed model on scheduling of electric distribution networks.

keywords: *Distribution network, robust optimization, uncertainty, wind turbine, electric vehicles, load accountability.*

http://dx.doi.org/10.22109/jemt.2018.133242.1094

1. INTRODUCTION

A. Problem definition and literature review

In recent years, the movement towards the use of less polluting technologies has increased at all levels of production and energy consumption. Many countries have put their policies on the utilizing renewable energy resources such as wind units and solar units. Also, electric vehicles will be the best alternative for gasoline cars, which will be able to participate as energy storage system in distribution systems. In addition, load response programs have attracted a lot of attention as one of the ways to reduce energy consumption and enable consumers to participate in providing the required network power [1]. Demand response (DR) programs are a set of programs that are introduced by the network operator to reduce energy consumption or transfer of consumption to other hours. The basis of the process of these programs is to encourage consumers to cooperate in these programs by increasing the price of electricity during hours of high consumption or rewarding for the consumption of low-consumption hours. At the same time, the simultaneous presence of renewable and non-renewable energy sources along with the participation of consumers in DR programs complicates the distribution network scheduling [2]. Also, the uncertainty in power distribution networks, including the uncertainty associated with renewable resources and the upstream price, will double the complexity of network scheduling.

Remarkable efforts have been made in the operation of electric energy distribution networks using various methods for network scheduling in the presence of uncertainties. In this case, various concepts including Monte Carlo simulation concept [3], point estimate approach [4, 5], fuzzy method [6, 7], robust optimization (RO) method [8], scenario-based modeling approach [9] and possibilistic–probabilistic-based method [10] are utilized for handling the uncertainties of distribution networks. Deterministic methods take only one particular mode, which obtains the optimal scheduling for that state, and cannot be accepted in general and in other possible conditions of the network. Probabilistic methods also depend on the amount, accuracy and quality of available information. Accordingly, in the absence or inaccuracy of sufficient information, probabilistic scheduling will not be correct. Studies on distribution network scheduling have addressed this issue in some ways. For example, a study is conducted in [11] exploring the impact of the presence of energy storage sources on energy distribution networks. The authors explored the optimal design of various energy sources in the presence of cooling and heating systems connected to power distribution networks in [12]. A linear scheduling framework is presented in the presence of scattered energy resources and flexible loads in [13]. In [14], multi-purpose short-term scheduling is presented through the contribution of price responsive loads, which seeks to find out how best to propose load response programs. The authors of [15] have created an energy storage system for optimizing the distribution network, where the fuel cell is intended. In this paper, the loss and air pollution are also considered in the objective function. In [16], a multi-objective environmental economic scheduling is proposed to optimize the distribution network in the presence of wind turbines. In [17], the effect of load response programs on the performance of distribution networks has been studied. In this paper, two types of load response programs, called real-time schedules and emergency loading plans, have been investigated. In [18], a multi-objective operational scheduling based on augmented e-constraint concept is presented for charging and discharging of EVs in a distribution network, aims at minimizing the total operational costs and emissions. In addition, EVs participated in supplying the required energy of distribution networks in [19], where their effectiveness in short-term operational costs is analyzed. In [20], a novel method based on RO concept is utilized to address the uncertainties of demand and wind units production. In [21], an optimal day-ahead management of distribution network is analyzed considering fuel cell and as storage technology, where the emission function and power transmission loss are considered. A stochastic-based method which studied the optimal scheduling of distribution networks include scenario-based modeling is presented in [22]. A risk based optimization model is introduced in [23] taking into consideration risk level for distribution systems operation considering wind power.

B. Innovations of study

According to the authors' information, the impact of electric vehicle parking as an energy storage system has not been considered through the day-ahead optimization of distribution network considering the uncertainties related to power market price using the RO method. So far, this system has not been utilized to modify the performance of distribution systems and reduce the operation cost of such networks. This study proposed an optimization framework based on the RO method that can address the problems of both deterministic and random methods. So, this method models random variables with uncertain distribution and free of limitations, which can find optimal solutions against the worst conditions of safe uncertainty. Compared to stochastic optimization, the proposed model has various advantages. First, this method only needs the predicted values of the upper limit and the lower limit of random variables that are easier to obtain from historical data. Second, unlike random methods that use probabilistic guarantees to satisfy the constraints, the proposed method is followed by optimal solutions that are safe for all variables in the random variables. In this paper, the scheduling of distribution network in the presence of renewable energy sources is based on a mixed integer optimization. The proposed model defines the short-term operation of the network, including the amount of exchange with the upstream network and the generation of distributed resources in a way that minimizes the cost of network operation. In order to provide a model for future distribution networks, the presence of diesel generators and renewable sources including wind turbines and parking of electric vehicles as an energy storage system as well as responsive loads have been considered. The aim of the proposed model is to minimize the overall cost of the smart distribution network with respect to the predicted values of wind power generation and consumption while ensuring that the scheduled energy and reserve of the next day remain reliable through changing the uncertain variables of the distribution network. Also, in order to demonstrate the effect of the presence of electric vehicle parking as an energy storage system, two different case studies for the network are considered in this paper. These two case studies are as follows:

Case 1: In this case, the next day scheduling of the distribution network takes place without the presence of electric vehicles parking as an energy storage system, and the cost of system operation is reported.

Case 2: In this case, the next day scheduling of the distribution network takes place in the presence of electric vehicle parking as an energy storage system, and the cost of system operation is reported.

C. Paper structure

The organization of the article is as follows. In Section 2, mathematical modeling including target function and problem constraints are presented. The RO method for the uncertainty modeling is described in section 3. Information about the test network is provided in Section 4. The statistical results and charts related to the achievements of this study are presented in Section 5. A summary of the work is presented at the end of the article.

2. MATHEMATICAL MODELING

A complete mathematical model for day-ahead optimal energy management of the smart distribution network, containing objective function and problem constraints, is presented in this section. Also, modeling for renewable energy sources including wind turbines, load response programs, electric vehicle parking and distribution network is provided in this section.

A. The objective function

Scheduling the power of distribution networks by the independent operator of the system takes place with the goal of minimizing the costs of the network over a 24-hour period.

$$Min \sum_{t=1}^{24} \{P_{grid}(t) \times p_g^E(t)\} + \sum_{j=1}^{N_{DG}} \{CE_{DG}(j,t) + CS_{DG}(j,t)\} + \sum_{d=1}^{N_{DRP}} \{CE_{DRP}(d,t)\} \tag{1}$$

The proposed objective function includes two parts. The first part is the cost of providing power and exchange with the upstream network, which is the product of the hourly power purchased from the upstream network (P_{grid}) at the hourly price of the upstream power supply (p_g^E). The second part relates to the costs of the DGs, including the cost of performance (CE_{DG}) and the start-up cost (CS_{DG}), which are subsequently introduced by (5) and (6) respectively. The third part relates to the costs associated with the suppliers of DR programs, including energy costs (CE_{DRP}). The index $t = 1, ..., N_T$ denotes the time, the index $j = 1, ..., N_{DG}$ represents the DG units, the index $d = 1, ..., N_{DRP}$ is related to DR programs.

B. Constraints

The constraints of day-ahead scheduling including equal and unequal constraints, are presented in this section.

B.1. Distribution Network Constraints

In order to ensure safe and correct operation of the distribution network, constraints (2) and (3) is considered. Equation (2) ensures that the voltage remains within an acceptable range. The feeder current range is also considered by Equation (3) [24].

$$V_{\min}(n) \leq v(n,t) \leq V_{\max}(n) \quad \forall n,t \tag{2}$$

$$I(m,n,t) \leq I_{\max}(m,n) \quad \forall m,n,t \tag{3}$$

where, $V_{\min}$, $V_{\max}$ and v are the minimum, maximum and hourly values of the bus voltages, respectively. Also, $I_{\max}$ and I are the maximum flow capacity and the hourly flow rate of the feeder between the m and n buses, respectively.

B.2. Power balance constraints

The reliable performance of distribution networks requires a constant balance between power generation and load demand. For this purpose, constraint (4) is intended to establish a balance between the distribution network power with the demanded network load in each bus n and at each hour t [25].

$$\begin{aligned} &P_{grid}(t) + \sum_{j \in n} P_{DG}(j,t) + \sum_{w \in n} P_{Wind}(w,t) - \sum_{v} P_{ch}(t,v) + \sum_{v} P_{dis}(t,v) \\ &+ \sum_{d \in n} (1-DR).load^0(d,t) + ldr(d,t) - P_{load}(n,t) \\ &= V_{i,h} \sum_{j} V_{j,h}(G_{ij}\cos\delta_{i,h} + B_{ij}\sin\delta_{j,h}) \end{aligned} \tag{4}$$

P_{Load} is the load power of each bus, P_{DG} is the hourly power of each DG unit, P_{Wind} is the production capacity of each wind turbine, P_{ch} and P_{dis} are the active power charged and discharged by electric vehicle parking as an energy storage system and P_{grid} is the power input from the upstream network.

B.3. Constraints of DG Units

In this section, the constraints relating to the operation of the DGs have been fully incorporated [26]. The cost of performance of non-renewable DG units is modeled in function of its power production according to Equation (5). The start-up cost of the DG is modeled by Equation (6).

$$CE_{DG}(j,t) = a_j \times u(j,t) + b_j \times P_{DG}(j,t) + C_j \times {P_{DG}}^2(j,t); \forall j,t \tag{5}$$

$$CS_{DG}(j,t) = SUC(j) \times (u(j,t) - u(j,t-1)); \forall j,t \tag{6}$$

Constraint (7) ensures that the DG unit's point of view considers technical constraints including the minimum and maximum production capacity.

$${P_{DG}}^{\min}(j) \times u(j,t) \leq P_{DG}(j,t) \leq {P_{DG}}^{\max}(j) \times u(j,t) \quad \forall j,t \tag{7}$$

The amount of increase or decrease in generation capacity by DG units cannot exceed the specified value at any time. Equations (8) and (9) limit the rate of increase and decrease in DG unit production.

$$P_{DG}(j,t) - P_{DG}(j,t-1) \leq UR(j) \times (1 - y(j,t)) + {P_{DG}}^{\min}(j) \times y(j,t) \quad \forall j,t \tag{8}$$

$$P_{DG}(j,t-1) - P_{DG}(j,t) \leq DR(j) \times (1 - z(j,t)) + {P_{DG}}^{\min}(j) \times z(j,t) \quad \forall j,t \tag{9}$$

Each DG unit should remain on for a few hours after it is turned on. Also, each DG unit must remain off after shutdown. The constraints (10) and (11) refer to the minimum up-time and minimum down-time.

$$\sum_{h=t}^{t+UT(j)-1} u(j,h) \geq UT(j) \times y(j,t) \quad \forall j,t \tag{10}$$

$$\sum_{h=t}^{t+DT(j)-1} (1 - u(j,h) \geq DT(j) \times z(j,t) \quad \forall j,t \tag{11}$$

B.4. Wind turbine modeling

Recent technological advances have led to a reduction in the cost of energy produced by wind turbines, and this technology has been able to compete with other energies. Equation (12) calculates the amount of power produces by the wind turbine depending on the wind speeds.

$$P_w(v) = \begin{cases} P_r \times \frac{(v - v_{ci})}{(v_r - v_{ci})} & v_{ci} \leq v \leq v \\ P_r & v_r \leq v \leq v_{co} \\ 0 & otherwise \end{cases} \tag{12}$$

In this equation, v is the instantaneous wind speed, v_{ci} is the cut-in speed, v_{co} is cut-out speed and v_r is the rated wind turbine rated. Cut-in speed is the minimum wind speed after which the wind turbine begins to produce electrical energy. In addition, cut-out speed is the maximum speed that after it turbine will be stopped to protect the turbine safety and prevent its reversal. Nominal speed is the average wind speed, if wind turbine winds up, the power output will be the nominal power of turbine.

B.5. Modeling electric vehicles parking lot as an energy storage system

The electric vehicle has three charging, discharging and idle modes. The electric vehicles parking scheduling is modeled by equations (13) to (18) [27]. Equation (13) determines the charge of an electric vehicle that depends on its initial charge. Equation (14) defines the range of electric vehicle charging. Equation (15) calculates the energy required to travel after leaving the parking lot. By equations (16) and (17), the charging and discharge rates are limited to the maximum and minimum values. Equation (18) ensures parking at any time in only one of the states of charge or discharge.

$$SOC(t,v) = SOC(t-1,v) + \eta_v^{ch} P_{ch}(t,v) - \frac{P_{dis}(t,v)}{\eta_v^{dis}} - P_{tra}(t,v) \tag{13}$$

$$SOC_{\min}^{v} \leq SOC(t,v) \leq SOC_{\max}^{v} \tag{14}$$

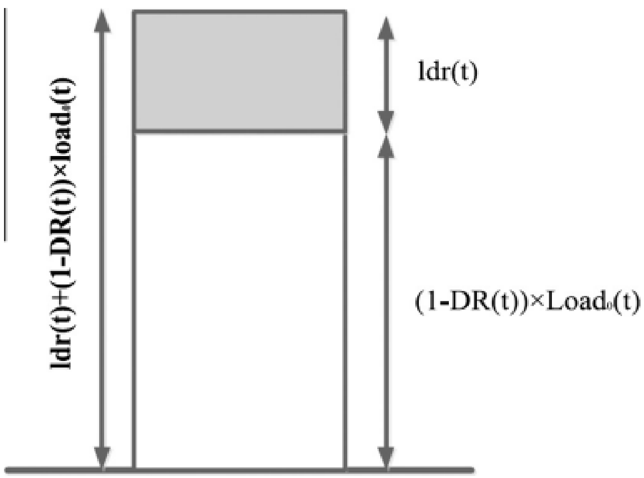

Fig. 1. Load modeling with DR programs

$$P_{tra}(t,v) = \Delta D(t,v) \times \Omega_v \tag{15}$$

$$\underline{P_{ch}} \times Uch(t,v) \le P_{ch}(t,v) \le \overline{P_{ch}} \times Uch(t,v) \tag{16}$$

$$\underline{P_{dis}} \times Udis(t,v) \le P_{dis}(t,v) \le \overline{P_{dis}} \times Udis(t,v) \tag{17}$$

$$Uch(t,v) + Udis(t,v) \le 1 \tag{18}$$

B.6. Modeling DR programs

DR programs as defined by American Federal Energy Regulatory Committee (FERC) are programs that change energy prices to change the amount of consumption of subscribers or transfer this consumption from on-peak hours (i.e., high prices) to off-peak hours (i.e., low prices). In electricity markets, DR programs have been used to reduce market prices and operating costs. Therefore, considering DR programs, the distribution network can shift its load from peak times to other times to reduce its supply costs. It should be noted that according to [28] consumers participate in TOU DR programs. It is worth noting that the maximum transfer capacity is limited. Therefore, in this article, this amount is about 15% of the courier's intake. The TOU DR program can be modeled as shown in Fig. 1. As shown in Fig. 1, the hatched part does not participate in DR programs, but the other part is able to move from one time to another. In addition the amount of transferred load is dependent on the market price. Therefore, Fig. 1 is mathematically modeled as follows:

$$P_{load}^{DR}(n,t) = P_{load}(n,t) + ldr(n,t) \tag{19}$$

$$ldr(n,t) = DR(n,t) \times P_{load}(n,t) \tag{20}$$

$$\sum_{t=1}^{T} ldr(n,t) = 0 \tag{21}$$

$$DR_{\min}(n,t) \le DR(n,t) \le DR_{\max}(n,t) \tag{22}$$

3. THE PROPOSED METHOD

RO method is a novel method for problems that are faced with the uncertainty of input parameters. This method is especially suitable for issues that do not provide complete information about the nature of uncertain parameters. The initial idea of RO is to consider the worst possible scenario and optimization based on the worst-case scenario [29]. In RO, the worst case that may occur for that constraint due to the change in the coefficients is considered and the optimization is based on that state [30].

A. RO method

Assume a function as $z = f(X,y)$ non-linear in y and linear in X. The values of X are uncertain and the values of y are known. It is assumed in RO that the probability distribution function of the variable X is not available. The uncertainty of X is modeled by an interval that X takes its values from interval $U(X)$. Minimizing $z = f(X,y)$ is formulated as:

$$\max_{y} \; z{=}f(X{,}y) \quad ; \; X{\in}U(X) \tag{23}$$

Given the linearity of z relative to X, the equation is rewritten as follows:

$$\max_{y} \; z \quad s.t \begin{Bmatrix} z \le f(\hat{X},y) \\ h(\hat{X},y) = A(y) * \hat{X} + g(y) \\ \hat{X} \in U(X) = \{X \,|\, |X - \overline{X}| \le \hat{X}\} \end{Bmatrix} \tag{24}$$

That $\hat{X}, \bar{X}, \tilde{X}$ is the non-deterministic value, the forecasted amount, and the maximum value of the variation X from $\bar{X}$. A RO method not only searches for a solution to the objective function of the problem, but also ensures that in the event of an error in the predicted values of the variable X, with an extremely high probability, the objective function remains optimal. For this purpose, a robust counterpart of the problem has been created and solved, which can be written as:

$$\begin{gathered} \max_{y} \; z \\ z \le f(\hat{X},y) \\ \begin{Bmatrix} \sum_i W_i \;\le\; \Gamma \\ 0 \;\le\; W_i \;\le 1 \\ f(X,y) \;=\; A(y) * \bar{X} + g(y) - \max_{w_i} \sum_i a_i(y) * \bar{X}_i * W_i \end{Bmatrix} \end{gathered} \tag{25}$$

Based on (24), two nesting problems should be studied. Based on W_i, (25) is linear and its dual form is as:

$$\begin{gathered} \min \left[\Gamma\beta + \sum_i \xi_i\right] \\ \beta + \xi_i \ge a_i(y) * \hat{x}_i \end{gathered} \tag{26}$$

By placing (26) in (25) we have:

$$\begin{gathered} \max_{y,\beta,\xi_i} z \\ z \le f(X,y) \\ \begin{Bmatrix} f(X,y) \;=\; A(y) * \bar{X} + g(y) - \Gamma\beta - \sum_i \xi_i \\ \beta + \xi_i \ge A(y) * \bar{X}_i \end{Bmatrix} \end{gathered} \tag{27}$$

B. The presented RO-based scheduling model

After providing the definition of the RO method, the presented model for optimal robust management of distribution networks considering uncertainties related to up-grid market price is stated in the following [29]:

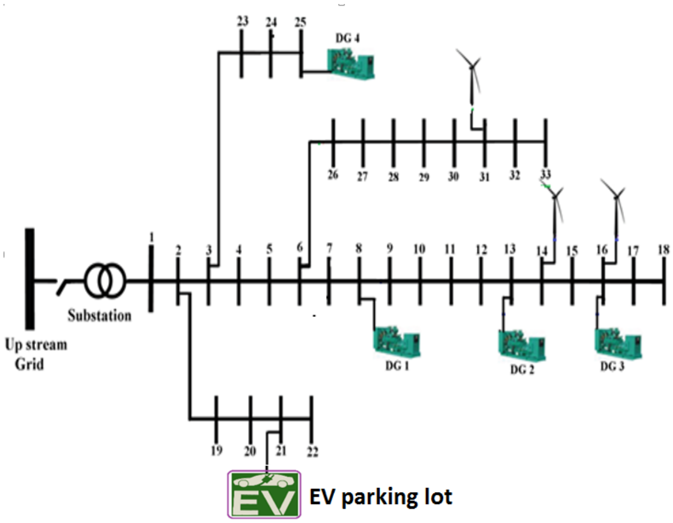

Fig. 2. The studied IEEE 33-bus network

$$
\begin{aligned}
& Min \sum_{t=1}^{24} \{P_{grid}(t) \times p_g^E(t)\} + \sum_{j=1}^{N_{DG}} \{CE_{DG}(j,t) + CS_{DG}(j,t)\} + \\
& \sum_{d=1}^{N_{DRP}} \{CE_{DRP}(d,t)\} + \sum_{t=1}^{24} \xi_1^t + \Gamma\beta \\
& subjectto: (2)-(22) \\
& \xi_1^t + \beta \geq dev. \times p_g^E(t) \times P_{grid}(t) \\
& \xi_1^t \geq 0 \\
& \beta \geq 0
\end{aligned} \tag{28}
$$

where, Γ is robust budget related to the proposed robust scheduling model. $dev.$ Is variation of up-grid price from the predicted values during the scheduling time horizon. ξ_1^t and β are dual variables of the proposed robust model.

4. CASE STUDY

The IEEE 33-bus distribution network has been adopted for evaluating the performance of the introduced model [30]. The studied system in shown in Fig. 2. The studied system contains three wind turbines connected to buses 14, 16 and 31, which are adopted from [31]. The nominal power of the wind units is 3 MW and the cut-in, cut-out and rated speed of the turbines are 3, 25 and 13 m/s, respectively. The forecasted wind speed for the 24-hours scheduling time horizon are demonstrated in Fig. 3 [32].

Four diesel generators are installed in the studied test system, which are installed to buses 8, 13, 16 and 25. Table 1 provides the cost coefficients of diesel generators. Also, the minimum and maximum power production, increase/decrease power rates and minimum up-time and minimum down-time of the plants are prepared in Table 2, which are adopted from [33]. The forecasted load demand during 24-hours time interval is depicted in Fig. 4 [34]. Table 3 reported the pattern of five EV parked at the parking.

The forecasted up-grid market price during the 24-hours interval is shown in Fig. 5 [28].

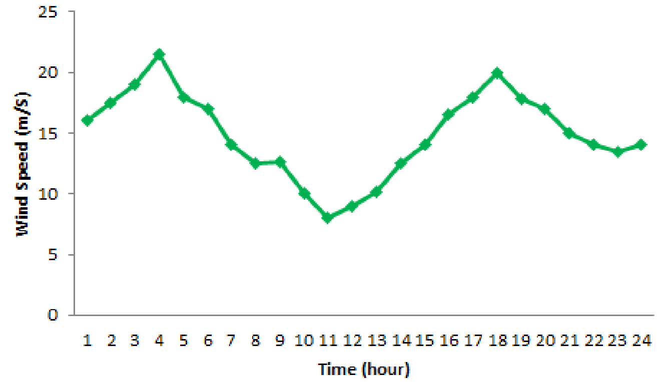

Fig. 3. Forecasted wind speed for the 24-hours scheduling time horizon

Table 1. Cost coefficients of diesel generators

Plant	$a_i(\$)$	$b_i(\$/MWh)$	$c_i(\$/MWh^2)$
DG 1	26	81	0.184
DG 2	27	87	0.0025
DG 3	28	92	0.0035
DG 4	25	87	0.0035

Table 2. Characteristics of diesel generators

Plant	SUT ($)	MUT/MDT (h)	RU/ RD (MW/h)	P_{max}(MW)	P_{min}(MW)
DG 1	26	2	1.8	4.1	1
DG 2	28	1	1.5	3	0.75
DG 3	25	1	1.5	3	0.75
DG 4	15	2	1.8	3.5	1

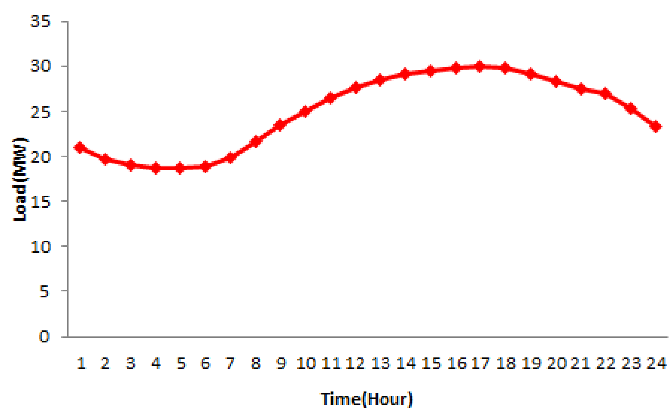

Fig. 4. Forecasted load demand for the 24-hours scheduling time horizon

5. SIMULATION RESULTS

The proposed model obtains an optimal energy management of the distribution network in presence of DR programs and EVs considering a 15% variation of up-grid market price with the forecasted values and a robust budget of 7.

Table 3. The pattern of five EV parked at the parking

Time (h)	V1	V2	V3	V4	V5	Time (h)	V1	V2	V3	V4	V5
T1	0	0	0	4.6	0	T13	0	0	0	0	2
T2	0	3.6	0	1.8	0	T14	0	0	0	0	3
T3	0	5	0	0	0	T15	0	0	0	0	0
T4	0	0	0	0	3.6	T16	3.6	0	0	4.6	0
T5	2.4	0	0	0	1.8	T17	0	0	3.6	0	1.6
T6	0	4.8	0	0	1.4	T18	0	0	0	4	0
T7	0	0	0	0	1.6	T19	0	0	4	0	2.2
T8	4.8	0	1	2	0	T20	0	0	0	0	3
T9	0	0	0	0	1.2	T21	0	0	4.8	3.8	0
T10	0	2.4	0	4	0	T22	0	0	0	0	3.8
T11	0	0	0	4.6	2.4	T23	0	4.8	0	0	0
T12	4	0	0	0	4.2	T24	0	0	0	0	2.2

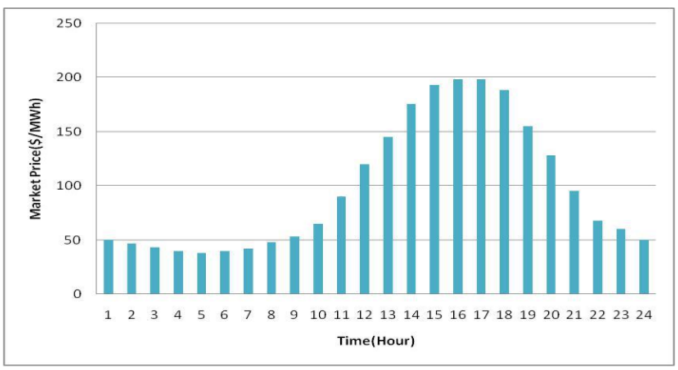

Fig. 5. The forecasted power market price

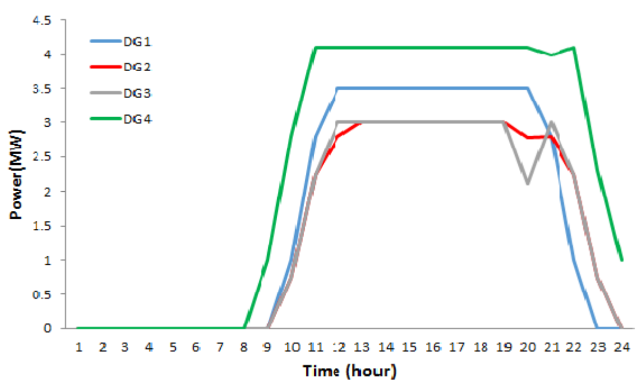

Fig. 6. Power generation scheduling of DGs

A. Case study 1: Non-presence of EV parking as storage unit

The optimal scheduling of DGs are demonstrated in Fig. 6 for this case study. Considering the obtained solution for this case study, DG units have participated in power generation when the power market price is higher than operation cost of DG units. Accordingly, the power purchased form the upper network is decreased in this time interval. In addition, wind turbines have provided power in their maximum capacity considering ignorable power production of such units. Moreover, the DRP has been effective in time intervals with on-peak condition and high market price, where the load has been shifted to off-peak hours. In addition, the required reserve for this case has been provided by DRP, which is shown in Fig. 7.

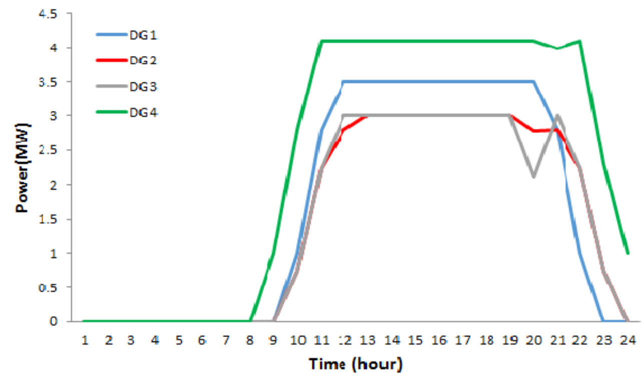

Fig. 7. Power provided by employing DRP

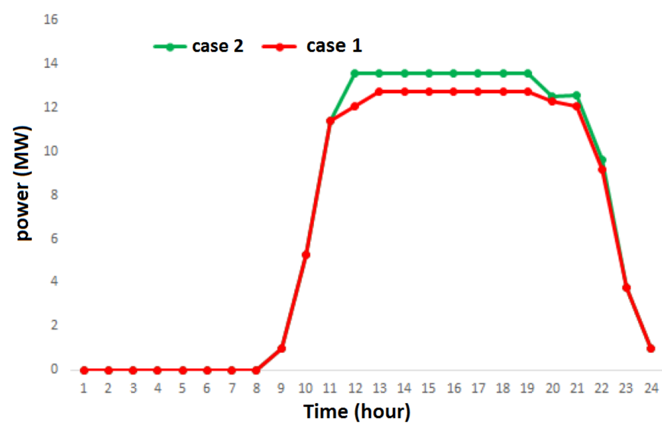

Fig. 8. Total generation of DGs in two studied cases

B. Case study 2: Presence of EV parking as storage unit

In this case study, the application of EVs has been studied in optimal operation of distribution networks. In this condition, the parking will charge the EVs in time intervals with lower market prices. On the other hand, the parking will transfer the power to the distribution network in time on-peak hours with high power market price to minimize its operation cost. In addition, the presence of such units in supplying the required reserve will be effective to attain free capacity of DGs and accordingly their participation in providing the nergy of the network. The result of such situation is decreasing the operation cost of the distribution network. The generated power of DGs in two case studies are shown in Fig. 8, which shows that the capacity of DGs is free and such units have generated more power with respect to case 1.

In addition, it is obvious from Fig. 9 that in presence of EVs as storage units, they have been charged in t=3, 4 and 5, where the market price is low. Accordingly, the power purchase from the main grid has been increased as shown in Fig. 10. On the other hand, at t=7, 8 and 9, when the EVs are operated, the power discharge has been increased. Such pattern has been repeated during the day.

As mentioned before, considering the ignorable power generation cost of wind turbine, such units have produced power in their maximum capacity as shown in Fig. 11. The scheduling for day-ahead energy providing of distribution network is presented in Figure 12. In this figure, the amount of hourly contribution of each resource is shown.

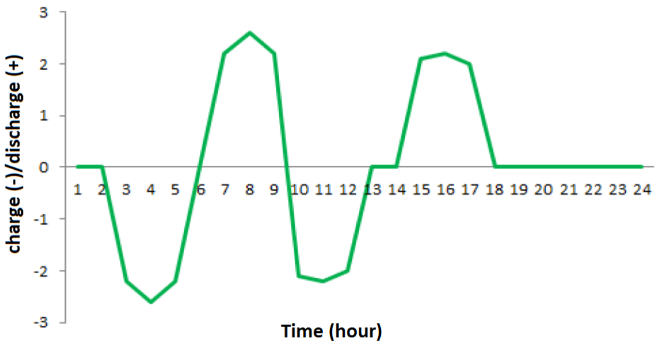

Fig. 9. Charge/discharge of the EVs during scheduling time interval

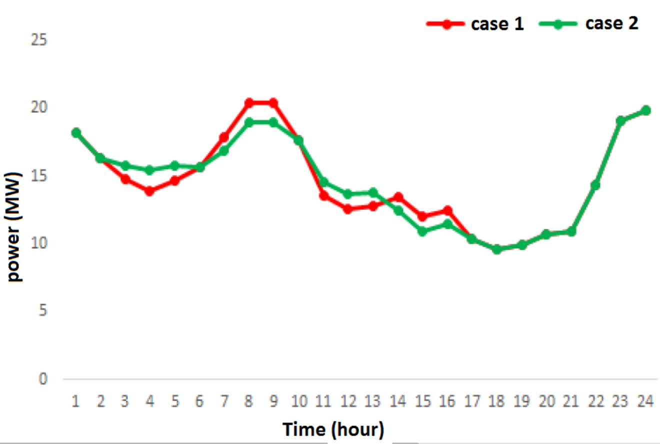

Fig. 10. Power purchased from the up-stream network

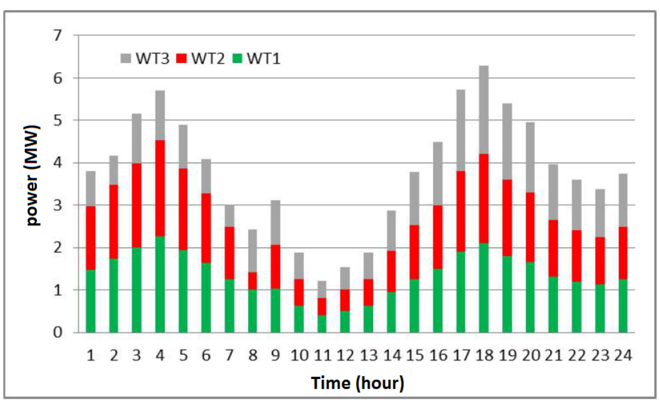

Fig. 11. Energy production of wind turbines

The operation cost of the network has been reported in Table 4, which proves the cost has been decreased employing the parking of EVs as energy storage unit for the distribution network.

The sensitivity analysis of the operation cost considering different values for robust budget and variations of the up-grid market price from the predicted values is accomplished. Figure 13 shows the operation cost considering the impact of different robust budgets and deviations of the up-grid market price. As seen in this figure, for same robust budget, the operation cost

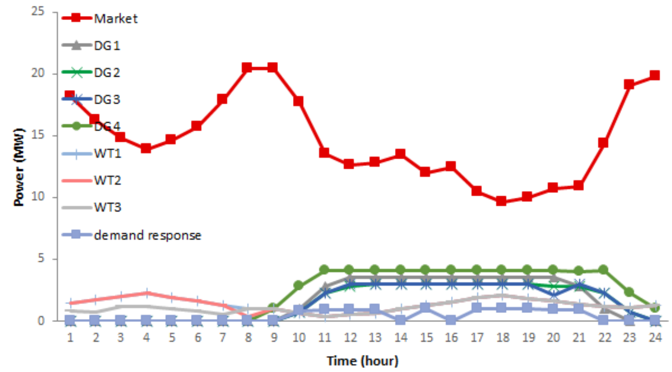

Fig. 12. Scheduling for day-ahead energy providing of distribution network

Table 4. Operation cost of the network

Case study	Operation cost ($)	Run time (S)
Non-presence of EVs	65478	36.2
Presence of EVs	58745	68.7

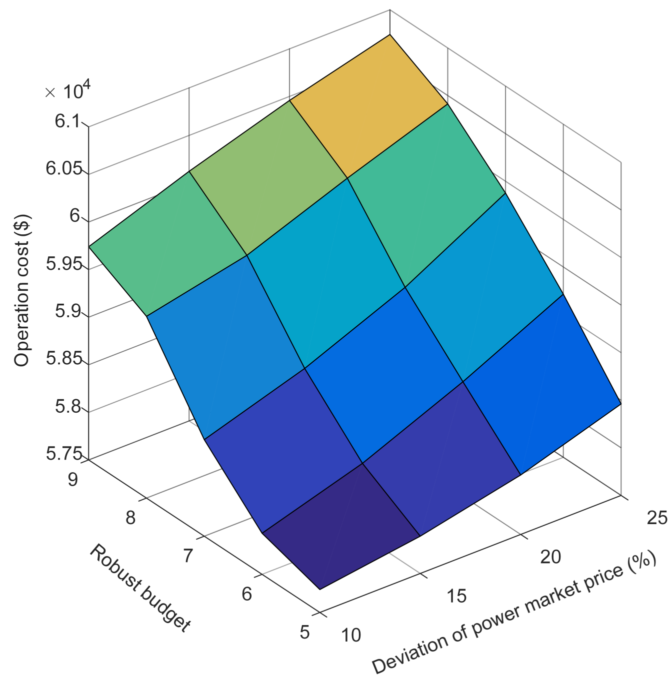

Fig. 13. Sensitivity analysis of robust budget and deviation of the power market price

is increased by growth in the variation of up-grid market price. In addition, for the same deviation of up-grid market price, the costs of distribution network operation is increased by growth the robust budget.

6. CONCLUSION

Recently, considerable efforts have been accomplished on optimal energy management of distribution networks in presence of price responsive loads and renewable based sources. In this article, the effect of uncertainties associated with power market prices is investigated in optimal scheduling of distribution networks considering electric vehicles parking as storage unit, renewable sources and DR programs. The introduced model has been employed on IEEE 33-bus network to assess the operation of the model, and RO method is utilized to model the uncertain parameter. The obtained solution proved that the electric vehicles parking has charged the electrical energy during of-peak hours, where the price of power market is low. On the other hand, the parking has discharged power during the on-peak hours to supply the load demand of the network. A 15% deviation of grid market price with the forecasted values and a robust budget of 7 to optimize the proposed robust scheduling model in the worst-case condition. The obtained results of day-ahead scheduling of the distribution system can be address the worst conditions of safe uncertainty, which only requires the predicted values of the minimum and maximum power market price. In addition, the proposed model provides the optimal solutions safe for all variables in the random variables. The operation cost of the studied network without considering electric vehicles parking was $65478, which decreased to $58745 in the presence of electric vehicles parking. Future works will pay attention on the uncertainty modeling related to behaviors of drivers of EVs in smart distribution networks and proposing a hybrid stochastic robust model to cover the uncertainties associated with other parameters.

REFERENCES

1. Nazari-Heris, M., Mohammadi-Ivatloo, B., & Gharehpetian, G. B. (2017). A comprehensive review of heuristic optimization algorithms for optimal combined heat and power dispatch from economic and environmental perspectives. Renewable and Sustainable Energy Reviews.

2. Majidi, M., and S. Nojavan. "Optimal Sizing of Energy Storage System in A Renewable-Based Microgrid Under Flexible Demand Side Management Considering Reliability and Uncertainties." Journal of Operation and Automation in Power Engineering 5.2 (2017): 205-214

3. Zio, Enrico, et al. "Monte Carlo simulation-based probabilistic assessment of DG penetration in medium voltage distribution networks." International Journal of Electrical Power & Energy Systems 64 (2015): 852-860.

4. Su, Chun-Lien. "Stochastic evaluation of voltages in distribution networks with distributed generation using detailed distribution operation models." IEEE Transactions on Power Systems 25.2 (2010): 786-795.

5. Alavi, Seyed Arash, Ali Ahmadian, and Masoud Aliakbar-Golkar. "Optimal probabilistic energy management in a typical micro-grid based-on robust optimization and point estimate method." Energy Conversion and Management 95 (2015): 314-325

6. Ramírez-Rosado, Ignacio J., and J. Antonio Domínguez-Navarro. "Possibilistic model based on fuzzy sets for the multiobjective optimal planning of electric power distribution networks." IEEE Transactions on Power Systems 19.4 (2004): 1801-1810.

7. Soroudi, Alireza, et al. "Possibilistic evaluation of distributed generations impacts on distribution networks." IEEE Transactions on power systems 26.4 (2011): 2293-2301

8. Nazari-Heris, M., Madadi, S., & Mohammadi-Ivatloo, B. (2018). Optimal Management of Hydrothermal-Based Micro-Grids Employing Robust Optimization Method. In Classical and Recent Aspects of Power System Optimization (pp. 407-420).

9. Carvalho, Pedro MS, et al. "Distribution network expansion planning under uncertainty: a hedging algorithm in an evolutionary approach." Power Industry Computer Applications., 1997. 20th International Conference on. IEEE, 1997.

10. Ahmadian, Ali, et al. "Optimal WDG planning in active distribution networks based on possibilistic–probabilistic PEVS load modelling." IET Generation, Transmission & Distribution11.4 (2017): 865-875

11. Farrokhifar, M. "Optimal operation of energy storage devices with RESs to improve efficiency of distribution grids; technical and economical assessment." International Journal of Electrical Power & Energy Systems 74 (2016): 153-161

12. Yang, Yun, Shijie Zhang, and Yunhan Xiao. "Optimal design of distributed energy resource systems coupled with energy distribution networks." Energy 85 (2015): 433-448

13. Babonneau, Frédéric, Michael Caramanis, and Alain Haurie. "A linear programming model for power distribution with demand response and variable renewable energy." Applied Energy 181 (2016): 83-95

14. Ghazvini, Mohammad Ali Fotouhi, et al. "A multi-objective model for scheduling of short-term incentive-based demand response programs offered by electricity retailers." Applied Energy 151 (2015): 102-118

15. Niknam, Taher, Hamed Zeinoddini Meymand, and Majid Nayeripour. "A practical algorithm for optimal operation management of distribution network including fuel cell power plants." Renewable Energy 35.8 (2010): 1696-1714

16. Zakariazadeh, Alireza, Shahram Jadid, and Pierluigi Siano. "Economic-environmental energy and reserve scheduling of smart distribution systems: A multiobjective mathematical programming approach." Energy Conversion and Management 78 (2014): 151-164

17. Gutiérrez-Alcaraz, G., J. H. Tovar-Hernández, and Chan-Nan Lu. "Effects of demand response programs on distribution system operation." International Journal of Electrical Power & Energy Systems 74 (2016): 230-237

18. Zakariazadeh A, Jadid S, Siano P. Multi-objective scheduling of electric vehicles in smart distribution system. Energy Conversion and Management. 2014 Mar 1;79:43-53.

19. Ghahramani M, Nojavan S, Zare K, Mohammadi-ivatloo B. Short-term Scheduling of Future Distribution Network in High Penetration of Electric Vehicles in Deregulated Energy Market. Operation of Distributed Energy Resources in Smart Distribution Networks. 2018 Jun 5:139.

20. Mazidi M, Monsef H, Siano P. Robust day-ahead scheduling of smart distribution networks considering demand response programs. Applied Energy. 2016 Sep 15;178:929-42.

21. Niknam, Taher, Hamed Zeinoddini Meymand, and Majid Nayeripour. "A practical algorithm for optimal operation management of distribution network including fuel cell power plants." Renewable Energy 35.8 (2010): 1696-1714.

22. Zakariazadeh, Alireza, Shahram Jadid, and Pierluigi Siano. "Stochastic operational scheduling of smart distribution system considering wind generation and demand response programs." International Journal of Electrical Power & Energy Systems 63 (2014): 218-225.

23. Tan, Yi, Yijia Cao, Canbing Li, Yong Li, Jinju Zhou, and Yan Song. "A two-stage stochastic programming approach considering risk level for distribution networks operation with wind power." IEEE Systems Journal 10, no. 1 (2016): 117-126.

24. Ross, Stephanie C., Gabrielle Vuylsteke, and Johanna L. Mathieu. "Effects of load control for real-time energy balancing on distribution network constraints." PowerTech, 2017 IEEE Manchester. IEEE, 2017

25. Asensio, Miguel, Gregorio Munoz-Delgado, and Javier Contreras. "A bi-level approach to distribution network and renewable energy expansion planning considering demand response." IEEE Transactions on Power Systems (2017).

26. Coster, Edward J., et al. "Integration issues of distributed generation in distribution grids." Proceedings of the IEEE 99.1 (2011): 28-39

27. Ortega-Vazquez, Miguel A. "Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty." IET Generation, Transmission Distribution 8, no. 6 (2014): 1007-1016.

28. Nojavan, Sayyad, et al. "A cost-emission model for fuel cell/PV/battery hybrid energy system in the presence of demand response program: -constraint method and fuzzy satisfying approach." Energy Conversion and Management 138 (2017): 383-392

29. Nazari-Heris, M., Mohammadi-Ivatloo, B., Gharehpetian, G. B., & Shahidehpour, M. (2018). Robust Short-Term Scheduling of Integrated Heat and Power Microgrids. IEEE Systems Journal, (99), 1-9.

30. Nazari-Heris, M., & Mohammadi-Ivatloo, B. (2018). Application of Robust Optimization Method to Power System Problems. In Classical and Recent Aspects of Power System Optimization(pp. 19-32).

31. Ghahramani, Mehrdad, et al. "Incorporation of demand response programs and wind turbines in optimal scheduling of smart distribution networks: A case study." Electrical Power Distribution Networks Conference (EPDC), 2017 Conference on. IEEE, 2017

32. Atwa, Y. M., et al. "Optimal renewable resources mix for distribution system energy loss minimization." IEEE Transactions on Power Systems 25.1 (2010): 360-370.

33. Willy Online Pty Ltd, online available at: http://wind.willyweather.com.au/.

34. Diesel generators specification sheets, Kohler Power Systems Company, online available at: http://www.yestramski.com/industrial/generatorsdiesel/industrial-diesel-generators-all.htm.

35. (2013, July. 18). New York Independent System Operator, online available at: http://www.nyiso.com/public/markets_operations/index.jsp.