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A Two-Point Estimate Method for Optimal Dispatching of Large-Scale Electric vehicles into Distribution Networks under Uncertainty

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Abstract— Electric vehicle (EV) charging irregularities have a massive effect on the distribution system. In recent years, research has focused on how to address the issue of large-scale charging and discharging of EVs while ensuring the grid's security. Distribution network operators should choose places where EV charging is practicable in terms of environmental and financial benefits. To establish how to best charge and discharge EVs in the distribution network, first comprehend and then determine the optimal position of EV parking lots in the distribution network. In this article, to solve this optimization problem, first the mathematical model of the problem is built, and then - according to the nonlinear features of the proposed optimization model - the second-order cone method is used to find the optimal solution with high accuracy and speed. The objective functions can accomplish more realistic objectives like lowering losses and minimizing voltage deviation changes with the charging and discharging time control technique, in addition to optimizing the technical requirements of the distribution network. The two-point estimation method of Hang is used to describe the uncertainty in the loads and capacities of solar sources in the random state, and optimization is applied to the IEEE 33-bus distribution system. The obtained results reveal that the proposed method not only meets the charging and discharging requirements of large-scale EVs, but also ensures the stability of the power grid, demonstrating the effectiveness of the proposed method in the optimal planning of EVs.

Keywords— Distribution network; Electric vehicles; Uncertainty; Hong's two-point estimation method.

1. INTRODUCTION

With the improvement of people's awareness of environmental protection and energy security, people have gradually realized the inherent shortcomings of the traditional power grid [1]. In the future, increasing demand for oil is expected to become an important issue in terms of cost and availability [2] In order to save energy and reduce greenhouse gas emissions and environmental pollution, the electric vehicle market has grown rapidly in recent years [3].

Electric vehicles act as an energy storage system to transfer load from peak hours to off-peak times [4]. From the point of view of the electric grid, electric vehicles are additional loads that are connected to the grid to receive charging and increase the cost of the system and losses due to electricity consumption. However, this situation can be changed by EV charging management, and with the rapid growth of infrastructure, electric vehicles are presented as a promising option to stabilize the power grid [5]. Because electric vehicles are clean, comfortable, network-capable, smart, and cost-effective [6]. Unlike a typical load, the spatial and temporal

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distribution of an electric vehicle (EV) is random. Access to large-scale electric vehicles has become a trend, and the charging technology of electric vehicles should also widely respond to the use of this type of vehicle [7]. The main finding of many studies states that EVs' charging significantly reduces the stability of the power grid [8, 9]. Uncertainty in the charging of electric vehicles on a large scale has a negative effect on the grid [10], and their existence can lead to a series of problems such as a large difference between peak and valley loads, overload distribution network lines, and increase the distribution network losses [11]. It is necessary to understand how to reduce the impact of electric vehicles on the distribution network, and implementing some optimal dispatching measures can improve its performance indicators [12], [13]. For example, if the charging and discharging behavior of electric vehicles is regulated and controlled, a sudden increase in load caused by uncontrolled charging is prevented, and the goal of "shaving the peak and filling the valley" is also possible [14].

In controlled EV charging, the system cost will be significantly saved [15], which is greatly improved by the integration of renewable energy sources into the power grid. Besides these issues, since EV charging time is still high, the deployment of this work requires comprehensive studies to optimally plan the location of charging stations (CS) that ensure EV charging demand is met [16]. Many factors are considered when establishing this goal, such as EV losses, grid stability, development costs, and grid constraints. Of course, it is important to note that the use of coordinated charging strategies leads to greater complexity and cost, but they perform better than uncoordinated charging and discharging strategies. Uncoordinated strategies do not have a positive effect on the network, even if EVs are introduced in small amounts [17, 18].

The planning of large-scale electric vehicles changes the distribution of the total load in each period, so it is necessary to determine the total load information of each period, and for a large scale of electric vehicles that can be dispatched, the relevant dispatching plan should be formulated in the next day [19]. In the optimal planning process for electric vehicles, probabilistic methods such as analytical methods, simulation methods, and approximate methods are used to model the uncertainty in the loads and capacities of electric vehicles. These methods lead to single-level optimization problems and can control the strength of the constraints by changing the tolerance factors to avoid overly conservative solutions [20].

The study of the integration of electric vehicles in the distribution system dates back to the 1980s, when coordinated charging of electric vehicles was investigated and papers such as [21] were published. The main approaches in these papers included aspects related to economics, impacts on distribution systems, and EV mobility [22]. After that, researchers began to study how to charge EVs to minimize the negative impact of their charging on the distribution network [23].

In [24], the simulation of a time-varying electric vehicle load model that was placed in different buses of a system was performed, and the number of electric vehicles that could be connected to one bus was determined based on the simulation results until the voltage level reached standard values.

Most papers consider static analyses, which always start and stop EV charging processes during the day [25]. In the study conducted by Source [26], the authors showed the increase in losses as one of the main concerns in the widespread use of these types of cars and stated the reason for the high investment costs for distribution networks is the coincidence between the daily peak load and the start time of charging, which they described as the worst-case scenario. They have shown a desire to solve the excessive impact of EVs in the paper.

Other studies use probabilistic models that may represent the charge-load profile in a better way compared to using deterministic charge patterns. In sources [27, 28], the presence of electric vehicles in the network has led to a significant increase in system losses. Since accurate household load forecasting is not available, this study introduces stochastic scheduling to obtain the optimal coordinated charging load profile with minimum system losses. A three-layer distributed multi-agent framework for optimal EV charging scheduling is proposed in [29]. This framework reduces the negative effects of EV charging demand on electrical networks [30].

Authors in [31] proposed a probabilistic modelling approach that uses statistical analysis, stochastic simulation, and queuing theory to generate charging load distributions for electric vehicles. On the other hand, the simulation model presented in [32] shows the random nature of charging location and time, adds its effects on the distribution system, and evaluates the reliability performance of the distribution system using Monte Carlo simulation.

In [33], the effect of electric vehicle charging station load on the voltage level, reliability indicators, power, and economic losses of the distribution network have been analysed for the steady state of the system. In [34], the establishment of parking lots is planned, considering the simultaneous benefits of the network and electric vehicle owners in the long term. This paper uses a multi-objective genetic algorithm to find the optimal location and capacity of EV parking lots, along with a distribution network enhancement plan. However, the joint planning of fast charging stations and DGs on a 33-bus system is also described in [35].

In [36], a management algorithm is developed for electric vehicle charging in real time, considering the operation conditions of the distribution system. In addition, in [37], it deals with electric vehicle charging management, considering wind power and tariff uncertainty, and uses a robust optimization approach in a model prediction framework.

In Table 1, some examples of studies conducted in recent years are shown. In these studies, an overview of the proposed models used with the innovations made is briefly presented, the obtained results are expressed, and the research gaps of the studies are presented and based on this, the idea of starting research in this article is provided.

In this paper, according to the scientific gaps raised in the previous literature review section, the model of load and solar resources as one of the sources of distributed generation is proposed, and they are defined in a definite and possible way during 24 hours in order to evaluate the economic effects, losses, and costs of investment and operation resulting from the integration of the theme. Also, a case study has been presented to the MILP model to determine the optimal size and placement of EV charging stations and PV units, taking into account deterministic quantification and uncertainty using the two-point estimation method (PEM). It has a more accurate and correct answer than the method based on repetition or meta-heuristic, with the lowest difference error. To ensure efficiency and acceptability, this paper has investigated and analyzed the success of electric vehicles in achieving technical and economic performance with network safety constraints and in the presence of solar sources in different scenarios.

Table 1. Overview of the recently published works on the scheduling of EV parking lots.

Ref.	PV	Uncertainty	Disch.	Novelty	Objective function	Research gap	Conclusion
[38]	✓	×	✓	The economic dispatch strategy (charge-discharge balance).	Optimizing the energy storage system's output power as well as the arbitrage revenue and network loss income from operation.	It is not realistic to rely solely on energy storage control strategies to make a profit.	Improve the investment cost and losses.
[39]	✓	×	✓	The economic multi-objective model for microgrids.	The costs, efficiency and security of MG system.	The PV output and the MG's initial load are calculated without taking uncertainty into account.	Obtain the optimal effects in economic costs, efficiency, and security.
[40]	✓	✓	✓	A stochastic multi-objective model.	VSI, operating costs, power loss, and pollution.	A tree method is used to construct the situations, which are then condensed using the GA and reduction theorem.	Improve all of the objective functions, such as operation cost and emissions.
[41]	✓	×	×	Links high-resolution mobility and grid dispatch models.	Operating costs.	PEV energy consumption in BEAM is derived from a simple calculation based on the average fuel economy of the vehicle, and BEAM does not consider other forms of mobility.	Improve the models through more robust and realistic simulation and represent the hourly impacts with large-scale PEV and RE adoption.
[42]	×	×	✓	EV's SPL model with hybrid robust-stochastic programming.	maximize the profit of an EV.	Charge and discharge management, as well as the effects of photovoltaic sources, are not illustrated. SPL met its power needs for recharging EV batteries and sold any excess energy to the power market.	Hybrid robust-stochastic programming is used in a case study to demonstrate how it can be used to control wind power output and determine optimal power prices.
[43]	✓	✓	×	The proposed methodology consists of scenario-based analysis.	Voltage regulation while reducing line losses.	Uncertainty, optimizing network purchase costs, photovoltaic costs, and the charging and discharging processes of electrical vehicles are not taken into account.	Evaluating the optimal operation of EV PLs equipped with PVs.
[44]	✓	×	✓	nonlinear stochastic programming, including uncertainty in solar energy.	Energy's annualized cost.	EVs in small-scale charging stations. Not examining the effects of the V2G system on network flexibility and self-healing.	Proposing a model for obtaining an optimal charge and discharge schedule considering the uncertainty of the electrical energy load.

2. OPTIMAL MODELLING

2.1. Optimization Objectives

Fig. 1 shows the general structure of the network under investigation. As can be seen, the network has power exchanges with electric vehicles and solar production sources. The study of electric vehicles as a type of load that is different from traditional examples and has random charging behaviour is essential. When electric vehicle owners get home from work, they charge their vehicles. This process adds to the existing peak load and results in a larger peak that puts a lot of pressure on the network. In this regard, in order to access electric vehicles on a large scale, the charging and discharging of these vehicles must be connected to the most suitable nodes in the distribution network.

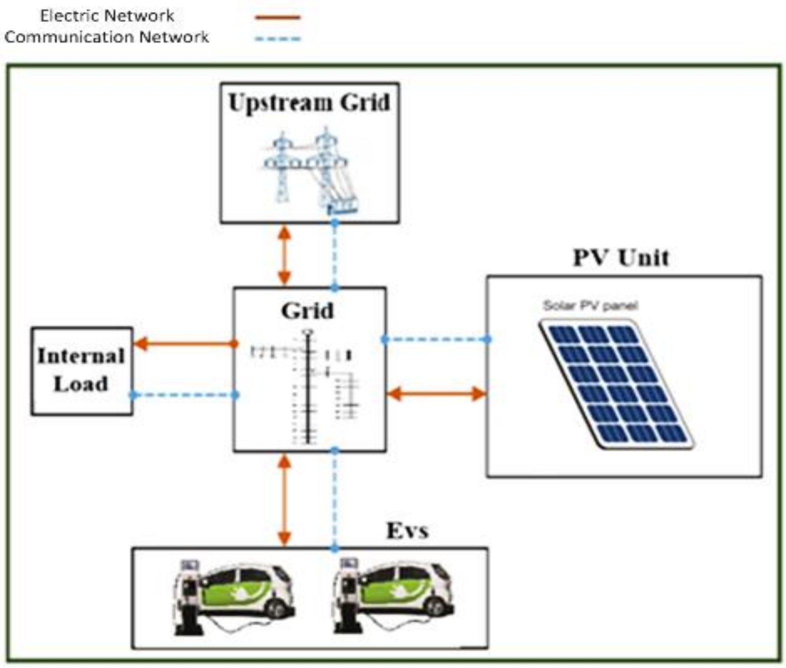

Fig. 1. General structure of the network.

In this distribution network with high penetration of PV sources, the objectives of the operation include minimizing the cost of purchasing network energy, power losses, and costs related to investment and operation, along with meeting the limitations of the studied system. Therefore, by optimizing the objective function, the losses of the distribution network, taking into account the hourly load changes in the cycle of a day and night and the changes of solar radiation, are reduced to a minimum value, and with this process, not only can power losses be reduced but also the network load flow of the distribution system be optimized.

The expression of the objective function for the optimal scheduling of the distribution network is expressed as follows: the objective function includes power loss (F_{loss}), the cost of purchasing electricity from the grid (F_{Grid}), the cost of a photovoltaic unit (F_{PV}), and the cost of maintaining electric vehicles (F_{PEV}), which are shown as Eqs. (1) to (5).

$$\min(F_t) = \min(F_{loss} + F_{Grid} + F_{Ev} + F_{Pv}) \tag{1}$$

$$F_{loss}=\sum_{t=1}^{T}\sum_{i,j\in\Omega}(I_{ij,t}^{2}R_{ij})\Delta t) \tag{2}$$

$$F_{Grid}=C_{Grid}\times\sum_{t=1}^{T}\sum_{i\in\Omega}P_{Grid}(i,h) \tag{3}$$

$$\begin{aligned}
&F_{pv}=F_{pv}^{Fixed}+F_{pv}^{Variable}\\
&F_{pv}^{Fixed}=CRF_{Pv}\times C_{Pv}\times P_{sr}\\
&F_{pv}^{Variable}=C_{O\&M}\times\sum_{t=1}^{T}\sum_{i\in N}P_{pv}(t,i)\\
&CRF=\frac{\gamma(1+\gamma)^{s}}{(1+\gamma)^{s}-1}\\
&P_{pv}=\begin{cases}P_{sr}\left(\dfrac{G_s^2}{G_{std}\times X_c}\right):0\le G_s\le X_c\\ P_{sr}\left(\dfrac{G_s}{G_{std}}\right):X_c\le G_s\le G_{std}\\ P_{sr}:G_s\le G_{std}\end{cases}
\end{aligned} \tag{4}$$

$$F_{Ev}=CRF_{Battery}\times C_{Battery}\times P_{Battery}+\sum_{t=1}^{T}\sum_{Ev\in P}(C_{M\&O}\times(P_{ch}-P_{dc})) \tag{5}$$

where C_{Grid} , CRF_{Pv} , $CRF_{Battery}$, C_{Pv} , $C_{Battery}$ and $C_{O\&M}$ are the purchase cost per network capacity, the capital recovery factor of photovoltaic, the capital recovery factor of the EVs, capital expenditure of photovoltaic, capital expenditure of the EVs and the operation and maintenance cost of the PV in \$/kWh, respectively, and P_{Grid} is the imported power from the grid, P_{sr} is the rated power of the PV unit, and P_{pv} is the generated power by the PV unit. Among them, S is the lifetime of PV in years, γ is the rate of interest on the capital investment of the installed PV, G_s is the solar irradiance at the determined location, and G_{std} is the solar irradiance in a standard environment (1000 W/m^2).

2.2. Constraints

2.2.1. Load Flow in the Radial Distribution Network Constraint

Due to the complexity and interconnectedness of the network, the load flow model based on the voltage (V_i , V_j) and power values of each node has a non-linear structure. This model is generally used by users and analysts, but in this paper, it is used for easy analysis and non-neglect. Based on the values of each branch (dist Bfm), the equations of the nonlinear load flow model have been transformed into an alternating model using the power losses. The errors in this method are smaller, so the performance of the proposed method is much better than the conventional methods. An intuitive explanation for the topology of the proposed model in a 2-bus radial network is shown in [10], where nodes *i* and *j* are examples of connections in a multi-bus network, where *i* is the transmitting power bus and *j* is the receiving power bus. In the proposed model, active and reactive power (S_{ij}) are used instead of currents (I_{ij}) or impedances (Z_{ij}) for calculations. The voltage drop between the buses($V_i - V_j$) is proportional to the current of the communication line, and based on this, the power of the line is calculated according to the following equations: These equations are the constraints of line *ij* and can be referred to as the voltage and current equations of branch load distribution and the power balance equation.

$$V_i - V_j = Z_{ij} I_{ij} \tag{6}$$

$$S_{ij} = V_i I_{ij}^* \tag{7}$$

$$S_j = \sum_{k:j\to k} S_{jk} - \sum_{i:i\to j} (S_{ij} - Z_{ij} \left|I_{ij}\right|^2) \tag{8}$$

By replacing Eq. (7) with Eq. (8), we will take:

$$V_i - V_j = Z_{ij} \frac{S_{ij}^*}{V_i^*} \tag{9}$$

We will take the sides of Eq. (9) to the power of two to get the final Eq. (10).

$$V_j^2 = V_i^2 - 2V_i Z_{ij} \frac{S_{ij}^*}{V_i^*} - Z_{ij}^2 (\frac{S_{ij}^*}{V_i^*})^2 \tag{10}$$

After separating the active and reactive power (P_{ij} , Q_{ij})in order to analyze the load distribution, the limitations are stated as follows:

$$P_{ij} = P_j + R_{ij} I_{ij}^2 + \sum_{k\in w(j)} P_{jk} \tag{11}$$

$$Q_{ij} = Q_j + X_{ij} I_{ij}^2 + \sum_{k\in w(j)} Q_{jk} \tag{12}$$

$$V_j^2 = V_i^2 - 2(R_{ij} P_{ij} + X_{ij} Q_{ij}) - (R_{ij} + X_{ij})^2 I_{ij}^2 \tag{13}$$

$$I_{ij}^2 = \frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \tag{14}$$

Eqs. (11) and (12) express the balance of active and reactive power, Eq. (13), the equation of voltage balance or the constraints of applying Kirschoff's laws and guaranteeing the radial performance of the distribution system, and Eq. (14), the power equation.

2.2.2. Distribution Network Constraint

When the electric vehicle is connected to the power grid, the operating limits of the distribution network, such as power limits, voltage range, and current limits, must be established. The power limits include active and reactive power, and for each node, the Eqs. (15) and (16) must be satisfied:

$$P_{Gn,t} + P_{dc} = P_{i,t} + P_{ch} + P_{n,t} \tag{15}$$

$$Q_{Gn,t} = Q_{i,t} + Q_{n,t} \tag{16}$$

Eqs. (15) and (16) show the limitations of active and reactive power balance, where $P_{Gn,t}$, $P_{i,t}$ and $P_{n,t}$ represent active power, and $Q_{Gn,t}$, $Q_{i,t}$, and $Q_{n,t}$ represent the reactive power of sources, loads, and nodes n at time t. P_{ch} is the charging power of the electric vehicle, and P_{dc} is the discharging power of it.

In order to ensure the safety of node voltage values and network performance, node voltage and current in the distribution network must meet the following operational constraints:

$$V_{\min} \leq V_{j,t} \leq V_{\max} \tag{17}$$

$$I_{\min} \leq I_{j,t} \leq I_{\max} \tag{18}$$

In Eq. (17), V_{min} and V_{max} show the minimum and maximum voltage range of the bus in period t, and in Eq. (18), the allowable range will be the critical value of branch load current. $I_{\min}$ is the minimum current, and $I_{\max}$ is the overload current of the branch.

2.2.3. *Photovoltaic Production Capacity Constraint*

The injected power penetration from photovoltaic sources is determined by the countries' renewable energy policies. In this paper, it is assumed that the total active power injected by PV varies with the percentage factor of active load demand and is expressed as follows:

$$\sum_{i=1} P_{pv} \leq \rho \times \sum_{i=1} P_i \tag{19}$$

where ρ is the percentage penetration level of the PV unit.

3. SECOND-ORDER CONE METHOD

SOCP (second-order cone programming) is a very special large-scale convex optimization with a very efficient solution algorithm that deals with a class of optimization problems with conic structures that can be efficiently solved by interior point methods [45].To solve the distribution load flow optimization model, it is necessary to use the standard second-order cone technology to transform the nonlinear load distribution model; The intermediate variables L_{ij} and U_i are a new series of current variables that are expressed by the square of current and voltage as follows:

$$L_{ij} = I_{ij}^2 \tag{20}$$

$$U_i = V_i^2 \tag{21}$$

By using Eqs. (20) and (21) resulting from the second order cone and rewriting the power balance constraints mentioned in the previous section, we will take the new equivalent equations:

$$P_{ij} = P_j + L_{ij}R_{ij} + \sum_{k \in w(j)} P_{jk} \tag{22}$$

$$Q_{ij} = Q_j + L_{ij}X_{ij} + \sum_{k \in w(j)} Q_{jk} \tag{23}$$

$$U_j = U_i - 2(R_{ij}P_{ij} + X_{ij}Q_{ij}) - (R_{ij}^2 + X_{ij}^2)L_{ij} \tag{24}$$

$$L_{ij} = \frac{P_{ij}^2 + Q_{ij}^2}{U_i^2} \tag{25}$$

In order to convert Eq. (25) into a linear convex constraint, define the auxiliary variable of the conical constraint:

$$L_{ij} \geq \frac{P_{ij}^2 + Q_{ij}^2}{U_i^2} \tag{26}$$

The new inequality constraint introduced in Eq. (26) can be shown through the equivalent transformation into a standard second-order cone according to Eq. (27):

$$\left\| \begin{matrix} P_{ij} \\ \dfrac{L_{ij} - U_i}{2} \\ Q_{ij} \end{matrix} \right\|_2 \leq \frac{L_{ij} + U_i}{2} \tag{27}$$

The objective function Eq. (2) and safety constraint Eqs. (17) and (18), which are cone optimization variables, are converted into Eqs. (28) to (30).

$$F_{loss} = \sum_{t=1}^{T} \sum_{i,j \in \Omega} (L_{ij,t}R_{ij})\Delta t) \tag{28}$$

$$V_{\min}^2 \leq U_{j,t} \leq V_{\max}^2 \tag{29}$$

$$I_{\min}^2 \leq L_{ij,t} \leq I_{\max}^2 \tag{30}$$

After the above transformation, the nonlinear part of the original model is transformed into a quadratic cone model, which is quickly obtained by the corresponding solver in each iteration of the optimal solution.

3.1. Hong's point estimation method

The presence of uncertainty in the input of a probabilistic problem causes the output to be uncertain. Predicting output is very difficult due to its probabilistic nature. Accordingly, the point estimation method based on the estimation of statistical information was proposed in 1975 to solve possible problems [46], but this method was ineffective due to the need for a high number of simulations and caused the PEM method to prevail in 1989 developed on the problems that arose, and this development finally led to the introduction of the effective point estimation method by Hong for symmetric and asymmetric variables [47, 48].

In this method, the information provided by the central moments is used to find some representative points (points for each variable) called "focus." These representative points are used to solve the model, and the statistical information of the random output variable is calculated using the obtained solutions [49]. They focus the problem's input random variable on k points for each variable, and using these estimated points, or the central moments, and the F function that relates the input and output variables, it is possible to obtain information about the uncertainty associated with the random variables of the output of the problem [50]. Mathematically, the function F can be defined as follows:

$$U = F(I) \tag{31}$$

Considering m cases of the input random variable, (8) can be written as follows:

$$U = F(c, X) \tag{32}$$

It is assumed that a random variable with a mean value and standard deviation is the coefficient of skewness. Moreover, U is a stochastic function of X, and c is a set of certain variables under uncertainty with a probability function. Each random input variable (X_l) can be defined as a pair consisting of a location $X_{l,s}$ and a weight. For X_l the function F must be evaluated s times.

As seen in Fig. 2, in general, the point estimation method can be implemented for 2 m points. In the implementation of the point estimation method, the steps of the work are as follows:

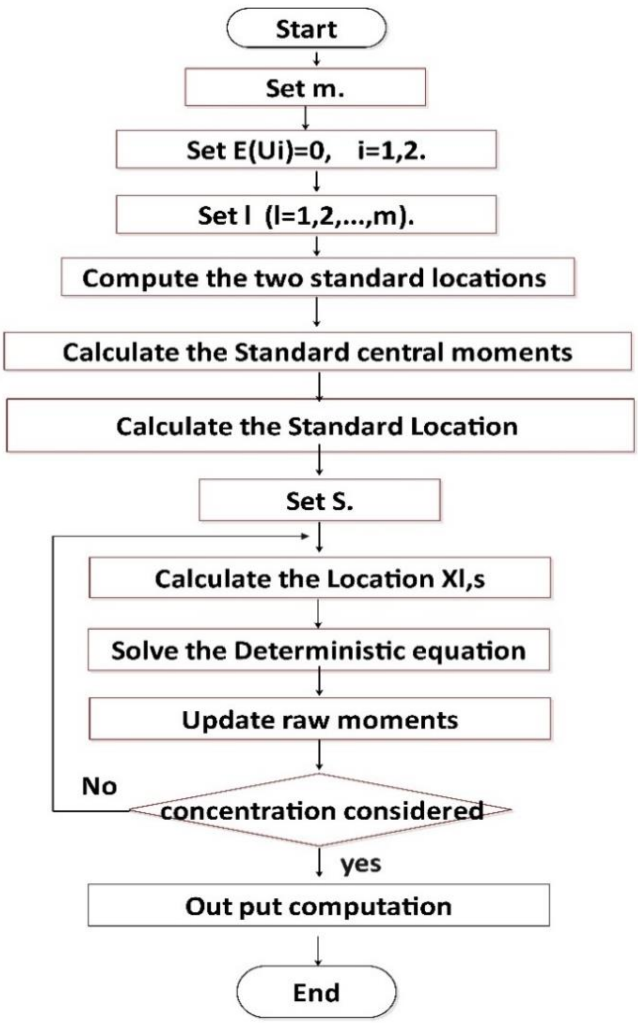

Fig. 2. Flowchart of the proposed algorithm.

Step 1: Determining the value of m

Step 2: Determining the value of E(Ui) = 0 for i = 1, 2, and 3.

Step 3: Determining the value of l, which can be from 1 to m.

Step 2: Determining the two primary locations of the standard random variable (X_l).

Step 3: Determining the skewness coefficient and the standard position of the random variable based on Eqs. (33) and (34).

$$\lambda_{l,3}=\frac{E\left[(X_l-\mu_{x,l})^3\right]}{(\sigma_{x,l})^3} \tag{33}$$

$$E\left[(X_l-\mu_{x,l})^3\right]=\sum_{p=1}^{N}(X_{l,p}-\mu_{x,l})^3\times prob(X_{l,p}) \tag{34}$$

In Eqs. (33) and (34), N is the number of X_l observations, and $Prob(X_{l,p})$ is the probability of each $X_{l,p}$ observation determined by the system operator. $\lambda_{l,3}$ is skewness, μ_{x_l} is mean value, and σ_{x_l} is standard deviation.

$$\xi_{l,j}=\frac{\lambda_{l,3}}{2}+(-1)^{3-j}\sqrt{m+\left(\frac{\lambda_{l,3}}{2}\right)^2}\quad j=1,2 \tag{35}$$

where $\xi_{l,j}$ represents the standard location of the random variable.

Step 4: Determining the position value of $X_{l,s}$

$$X_{l,s}=\mu_{x,l}+\xi_{l,s}.\sigma_{x,l} \tag{36}$$

Step 5: Determining the definitive value of U for two locations $X_{l,s}$ calculated from the previous step:

$$U_{l,s}=F(\mu_{z_1},\mu_{z_1},.....,X_{l,s},....,\mu_{z_m}) \tag{37}$$

Step 6: Determination of weight coefficients

$$g_{l,s}=\frac{(-1)^j\xi_{l,(3-j)}}{m(\xi_{l,1}-\xi_{l,2})} \tag{38}$$

where $g_{l,s}$ is the weight of the random variable.

Step 7: Update $E(U^i)$:

$$E(U^i)=E(U^i)+\sum_{i=1}^{2}g_{l,s}(U_{l,s})^i \tag{39}$$

Step 8: Repeat steps 2 to 7 until all input random variables are calculated.

Step 9: Calculate and use statistical torques of the output random variable:

$$\mu_U=E(U),\delta_U=\sqrt{e(U^2)-\mu_U^2} \tag{40}$$

where μ_U, δ_U are the mean and standard deviation of the deterministic output calculated for the uncertain variable.

4. SIMULATION AND RESULTS

The single-line structure of the 33-bus IEEE network has been considered for implementing the proposed model and analyzing the obtained results in order to select the type and size of photovoltaic sources, parking lots, charging positions, and the condition of the load profile and network voltage. The network buses are connected through 32 lines with a rated power of 1000 kVA at a voltage level of 12.66 kV, and for them it is possible to connect 8 types of photovoltaic sources to check the effects of renewable sources and 4 battery models to provide the energy needed to charge electric vehicles with 70–85% efficiency, according to the information listed in Tables 2 and 3.

Table 2. Parameters of PV systems [51].

PV types	Rate of return (ROR) [%]	Life time (LT) [year]	Energy cost (O&M) [$/kWh]	Investment cost INV [$/kw]	Power rating Pr [kw]
PV1	10	20	0	0	0
PV2	10	20	0.01	770	100
PV3	10	20	0.01	770	500
PV4	10	20	0.01	770	800
PV5	10	20	0.01	770	1000
PV6	10	20	0.01	770	1300
PV7	10	20	0.01	770	1500
PV8	10	20	0.01	770	2000

Table 3. Parameters of the parking lot [52].

Battery types	Rate of return (ROR) [%]	Efficiency [%]	DOD Depth of discharge (DOD) [%]	Life time (LT) [year]	Life time (LT) [cycle]	Res. time (RT) [sec]	Energy cost (O&M) [$/kWh]	Investment power cost (Inv) [$/kW]	Cap. rating [kWh]	Power rating P_r [kW]
Le-Ac	10	85	50	10	3000	10	300	200	2500	1000
Li-On	10	75	80	15	2500	15	1200	600	2000	700
Ni-Cd	10	80	50	16	3000	20	500	800	1500	500
Zn-Br	10	70	80	8	1000	6	700	150	1000	400

It is assumed that the bus voltage should be within the allowed range. For this purpose, the effectiveness of the proposed methods in the network under study is evaluated by comparing two scenarios: deterministic optimization (regardless of the uncertainty in the input parameters) and the characteristics of uncertainty using TPEM. The base load definitive data for the distribution system under study is shown in Table 4, based on which the values of hourly load and source profiles are determined in Figs. 3 and 4. The possible data for the system was also obtained in [39].

These data were expressed annually and in the form of four seasons, through which the daily load and production of cars and production resources were calculated. The charging and discharging conditions of cars all follow the same timing order, and when the battery capacity is less than 10%, electric vehicles need to be charged, and the charging process is complete every time. The cost of energy includes the cost purchased from the substation and the cost provided from renewable sources, which are equal to 0.06 and 0.96 with the capital recovery factor for the solar source of 0.1175.

Table 4. Parameters of the basic load of the distribution grid under study.

Time [h]	Base load [MW]	Time [h]	Base load [MW]	Time [h]	Base load [MW]
1	1.73	9	3.22	17	2.48
2	1.86	10	3.46	18	2.72
3	2.11	11	3.59	19	2.97
4	2.35	12	3.71	20	3.47
5	2.48	13	3.47	21	3.21
6	2.72	14	3.22	22	2.72
7	2.84	15	2.97	23	2.23
8	2.97	16	2.6	24	1.98

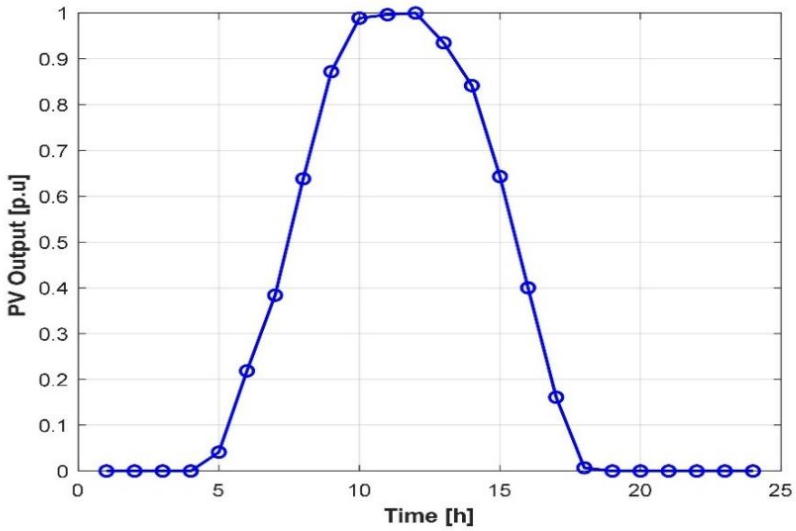

Fig. 3. Photovoltaic profile.

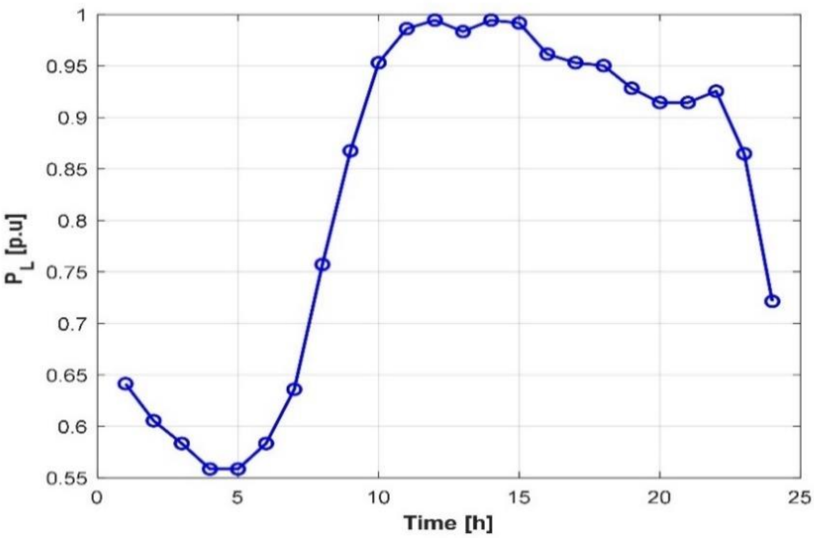

Fig. 4. Daily load profile.

4.1. First Scenario

In this case, all production values of photovoltaic sources and loads connected to the network are considered definitively, and according to the activity of electric vehicles and the implementation of their charging and discharging processes, first the size, type, and optimal location of connecting sources and car chargers are determined, and then the amount of change in the critical values of the network is analyzed. The values of the objective function as 4 separate objectives (F1 to F4) and the losses for this scenario are shown in Table 5, according to which the total costs are 2464003.997 and the costs of electric vehicles and casualties respectively have the lowest and highest share in the function. They will have a total cost.

Table 5. Cost and amount of losses in the first scenario.

	F_1. Cost of losses	F_2. Cost of purchasing from the network	F_3. Cost of renewable resource	F_4. Cost of electric vehicle	Grid losses(kWh)
Scenario1	58944.598	2251600.134	135834.99	17625.000	2691.534

In Table 6, according to the network topology and the possibility of installing various types of batteries in the parking lots and solar production sources, Bus 10 is proposed as a place to install a type 7 solar source with a capacity of 1500 kw and Bus 11 as a connection point for charging and discharging electric vehicles with a capacity of 1000 kwh.

Table 6. Capacity and installation location of the photovoltaic source and parking lots in the first scenario.

EV		PV	
BAT4,1000kWh	Bus11	PV7,1500kW	Bus10

Fig. 5 shows the connection point of the photovoltaic source and the electric vehicle parking lot in the single-line diagram of the 33-bus IEEE network. As shown in the figure, an optimal value for the battery and photovoltaic source has been selected from the standard values of Tables 2 and 3, and to ensure the stability of the distribution network and the voltage profile, it is suggested. Fig. 6 shows the changes in the voltage profile before connecting the photovoltaic source and the battery.

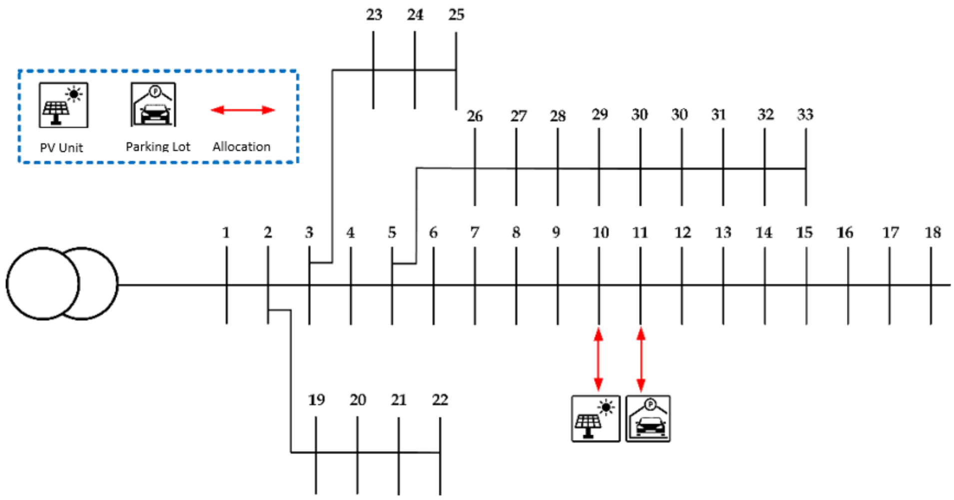

Fig. 5. Single-line diagram of the 33-bus IEEE network.

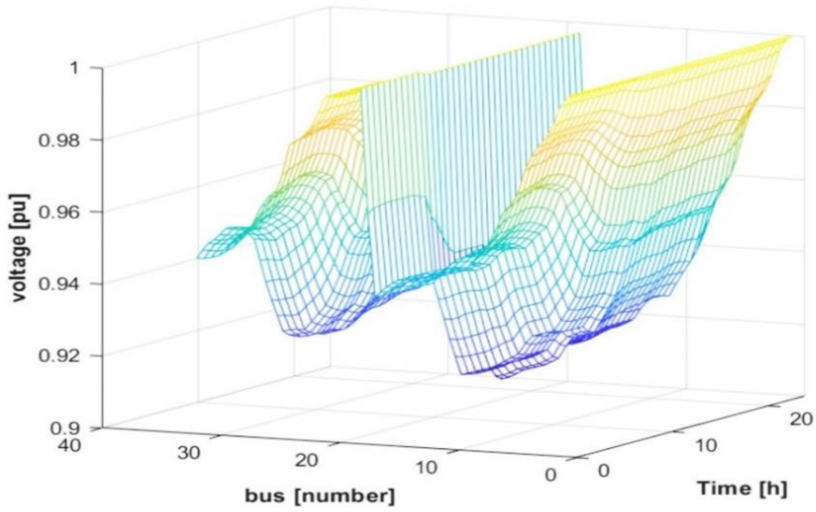

Fig. 6. Voltage variation without EVs and PVs.

Has been assuming the above placement, network utilization values are evaluated according to Figs. 7 to 14. Fig. 7 shows the diagram of the voltage changes of the network buses under study for every hour and when the electric vehicle is involved in charging and discharging. According to the Fig. 7, it can be seen that the amount of daily change in the voltage of all network buses is within the permissible range.

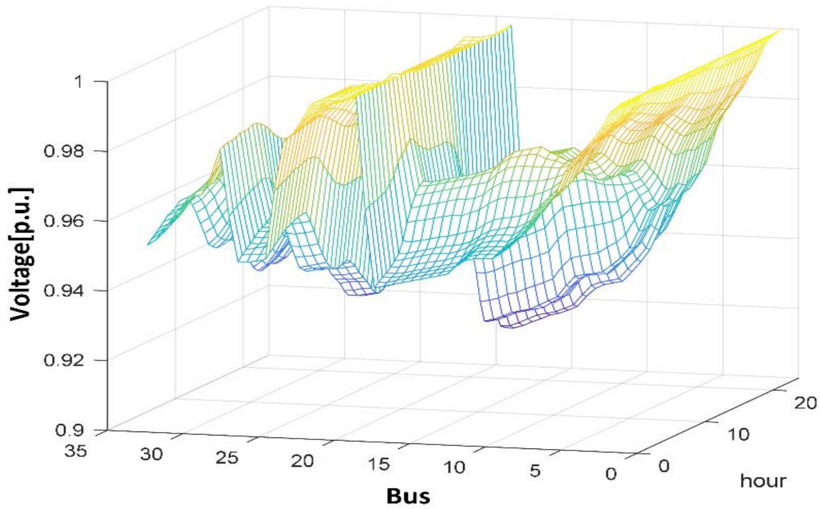

Fig. 7. Voltage variation with EVs and PVs.

The total grid losses in the basic state without the presence of PVs and processes of charging and discharging EVs is 3522.793 kWh, and with the presence of renewable production and the connection of electric vehicles to the network, this value is equal to 2691.534 kWh. As can be seen from Fig. 8, the grid losses are displayed hourly, and the loss curve is a function of changes in load consumption and purchases from the network. With the increase in load resulting from the charging of electric vehicles and the decrease in impact of the photovoltaic source, the losses have increased in the early hours of the day. In this way, the losses for the network in this hour are very close to each other. Although in the peak hour, with the discharge of electric vehicles and the injection of power into the network with the integration of the power of photovoltaic sources, the amount of losses has been significantly reduced. This network has lost 831 kw in 24 hours. The important point is that the target index has been effectively improved, and we are witnessing a decrease in the amount of loss difference in peak and non-peak hours, unlike the load changes in the base state. From the point of view of the optimization effect, the high peak is optimized, the peak-to-valley difference and the total network losses are reduced; This issue shows the ability of integration sources and vehicles in flattening the loss graph and transferring the time of occurrence of the maximum amount of losses from the peak hour to other hours of the day and night.

Figs. 9 and 10 show, respectively, the time distribution and quantity of charging and discharging status of parking lots along with the amount of charging and discharging power of electric vehicles.

In Fig. 9, it can be seen that the position of charging and discharging the batteries in the parking lots is changing. These parking lots are placed in the charge position in the early hours of the day based on the optimal timing strategy and are responsible for providing the power needed by the electric vehicles in the distribution network to be charged in a regular manner at the right time and with the optimal amount.

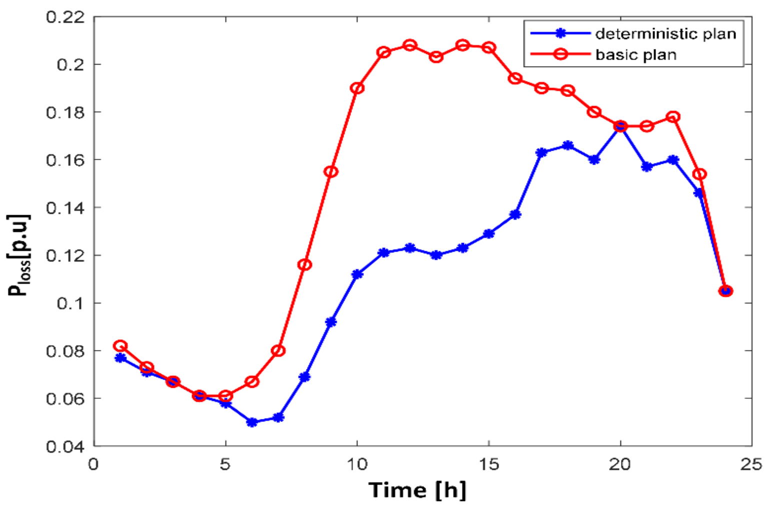

Fig. 8. Losses of the network under study for deterministic and basic condition.

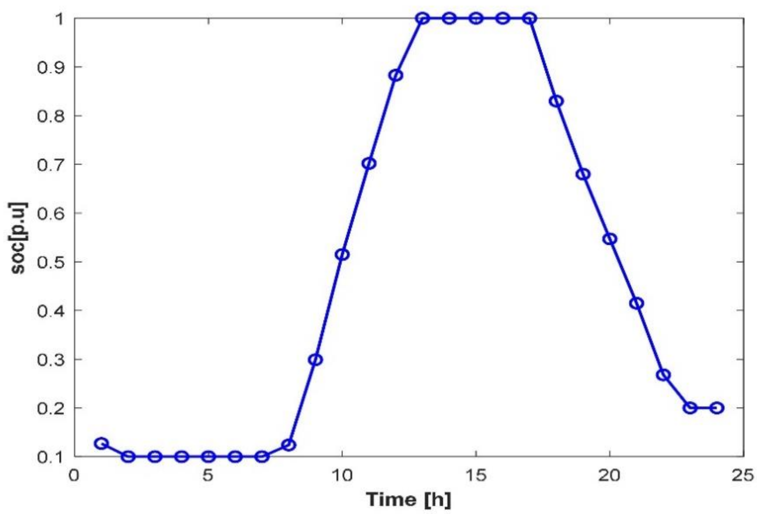

Fig. 9. SOC values of electric vehicle parking lots under certain conditions.

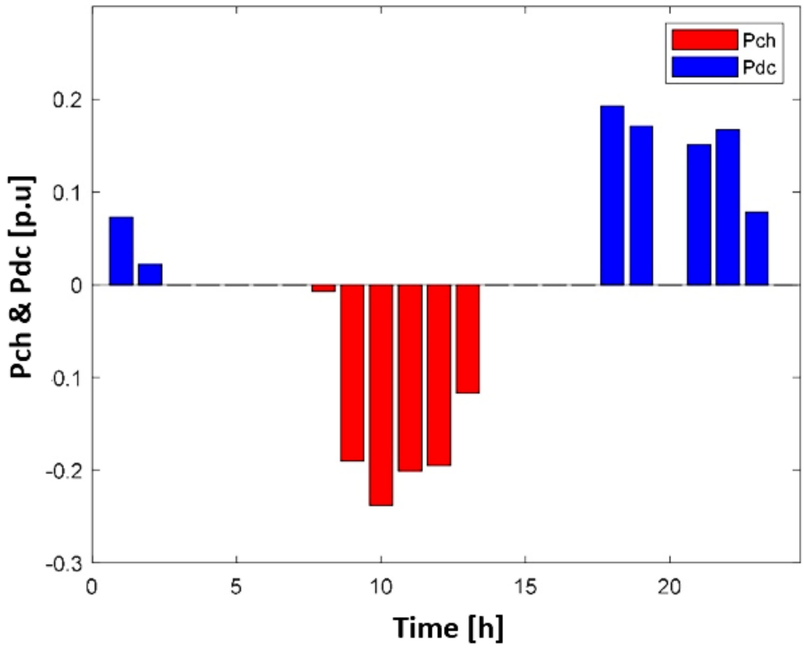

Fig. 10. Charging and discharging power of parking lots to the grid under nominal conditions with forecasted data.

Also, they are fully charged at peak times through the supply of power from the PV units and electric vehicles and are placed in charging position 1. This has made it possible to ensure that the changing needs of electric vehicle users are met. In Fig. 9, "discharge power" means the power injected into the network through electric vehicles, and as can be seen from the Fig. 10 it can be understood that the optimal timing strategy effectively prevents the phenomenon of charging peaks in the distribution network, and this process with the integration of production ensures the supply of the required load during peak consumption. Of course, in non-peak hours, the energy needed by cars is provided through the parking lots, and this makes it possible to connect cars during peak hours and can minimize the limits of operation in the network and ensure the safe and economical operation of the electricity network.

4.2. Second Scenario

A In the configuration of the second scenario, the policy introduced in Section 3 for the internal skewness and elasticity considered as 0.5 and 2, respectively, for the random generation of solar sources and load becomes the curves of Figs. 11 and 12. Table 7 examines the losses and non-comparable objective functions with non-comparable actions and standard deviation. In the two-point estimation method, two points at the top and bottom of the value are used. According to this issue, in Figs. 11 and 12, there are three random values for weight determination and estimation of load and production. Corresponding to sc1 in Table 7 as the upper limit of the loss with the higher cost value, sc2 is the lower limit with the minimum value, and sc3 is the middle one, which is equal to the value of the limit obtained from the first scenario.

By using random load and production values and implementing the two-point estimation method, the results are shown in Table 8 and Figs. 13 and 14.

Table 7. Cost and amount of losses in the uncertainty scenario.

Scenario	F_1. Cost of losses	F_2. Cost of purchasing from the network	F_3. Cost of renewable resource	F_4. Cost of electric vehicle	Grid Losses [kWh]
Sc1	80766.493	2596453.593	135863.589	17625.0	3687.968
Sc2	46153.097	2018385.268	135814.354	17625.0	2107.447
Sc3	58944.598	2251600.134	135834.399	17625.0	2691.534

In the proposed method, the values of the load and production of the source are expressed as a scale in units of 24 hours. By using the input variables in the implementation of the two-point estimation method for the studied network, it is possible to display the average value and the deviation, and these results are shown in Table 8.

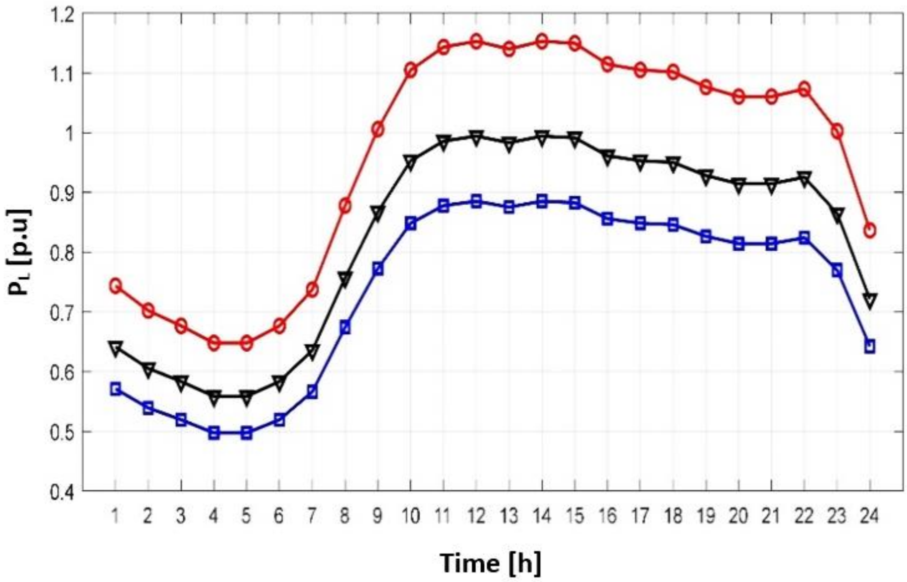

Fig. 11. Uncertainty load profile.

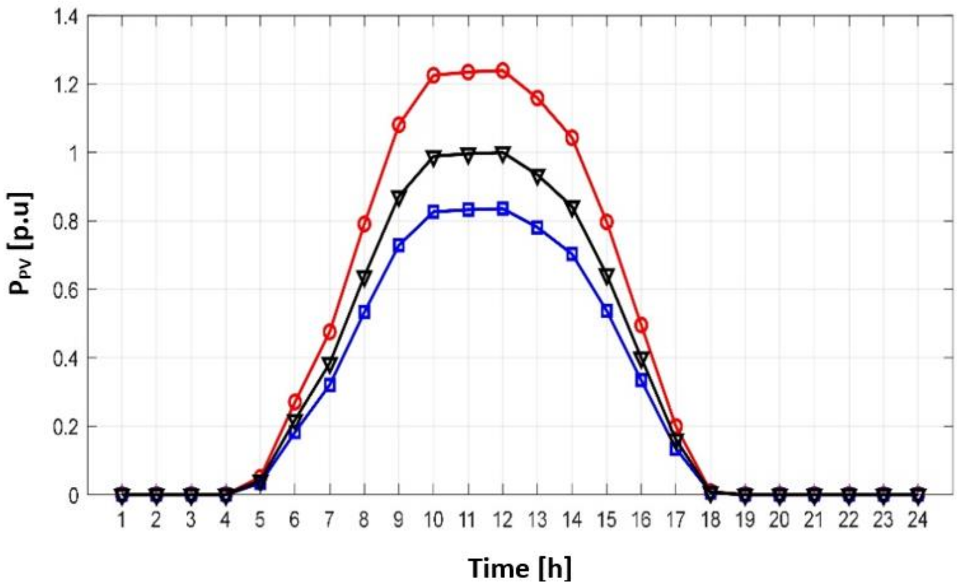

Fig. 12. Uncertainty production profile of photovoltaic sources.

Table 8. Cost and amount of losses in the second scenario.

		E(y)	μ	σ
Grid losses [kw]		2.7255	7.7749	0.58873
O.F	F_1. Cost of losses	58694.68688	3728791465.053688	12858.29781
	F_2. Cost of purchasing from the network	2253059.4973	51218686439.73	213521.7681
	F_3. Cost of renewable resource	135847.98371	18452829728.69472	1358.288826
	F_4. Cost of electric vehicle	17626.7625	31067689.0625	176.2588123

In Figs. 13 and 14, soc parking lot charges and loss values are compared in two definite states with blue color and random with the criteria of the two-point estimation method with red color. The values obtained in the optimization using the two-point estimation method have a curve very close to the deterministic state, which shows that the proposed method implemented on the network has an acceptable performance and the slight difference in the graph can be ignored. It proceeded on the assumption of sacrificing some indicators. This means that if the results of the deterministic approach are considered, the operating cost and the number of violations will not be acceptable in practice, so it is necessary to consider the probabilistic approach instead of the deterministic approach to deal with the real conditions because the real conditions of the system should be ignored in the deterministic analysis.

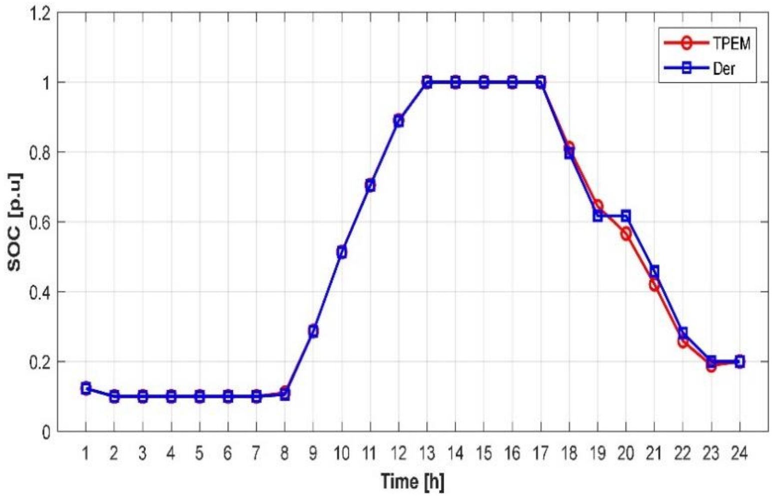

Fig. 13. SOC of deterministic and random charging.

Table 9 compares the costs of the objective functions and the amount of losses in three cases without resources and without the presence of electric vehicles and after using them with the production and load values in a deterministic and random manner. The first column shows that the total objective function is caused by the costs of losses and purchases from the network, and renewable sources and electric cars have no effect.

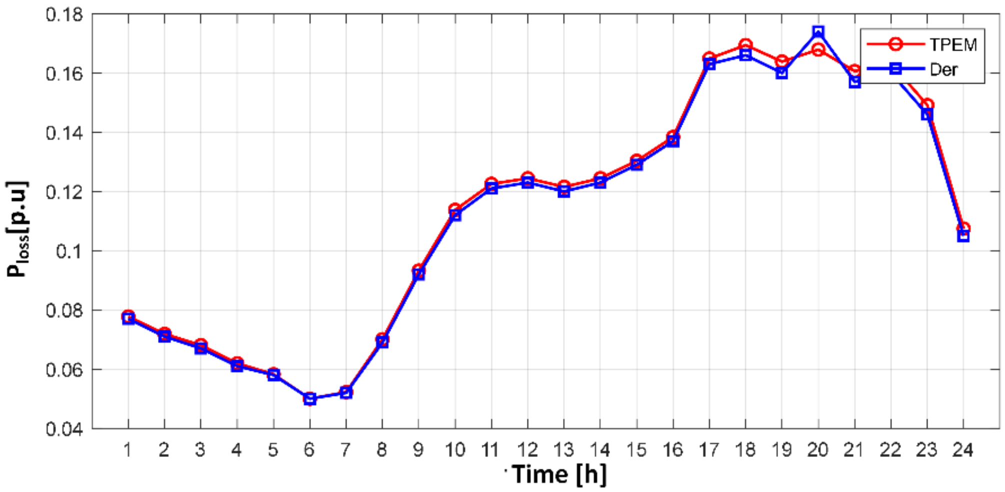

Fig. 14. Losses of deterministic and random state.

Table 9. Cost and amount of losses in the uncertainty scenario.

	Basic case	Deterministic case	Uncertainty case
F_1. Cost of losses	77149.161	58944.598	59694.686888
F_2. Cost of purchasing from the network	2704624.936	2251600.134	2253059.4973
F_3. Cost of renewable resource	0	135834.399	135847.98371
F_4. Cost of electric vehicle	0	17625.00	17626.7625
Grid losses(kWh)	3522.793	2691.534	2725.5

However, after their optimal placement, the total objective function consists of four parts, in which the values of the loss objective functions decreased from 77149.161 to 58944.598, purchase from the network decreased from 2704624.936 to 2251600.134, and the amount of expenses related to electric cars and renewable resources increased from zero to 135834.399, 17626.7625, and 17625.000, respectively, and these changes caused an 11% decrease in the function. The goal has been achieved. The most important point in comparing the values in Table 9 is the small difference between the deterministic and random values, which has been shown using the two-point estimation method, this confirms the power of the proposed method in optimising the processes of reducing losses and costs compared to the deterministic state and it shows the possibility that in the case of uncertainty of resources and load, the calculations can be converged by relying on this method so that no significant change in the results is achieved. Therefore, according to the obtained results, with optimal integration of PV units to minimise grid losses along with other costs by considering hourly variations of solar radiation and load characteristics, a two-point estimation method for a large-scale electric vehicle network planning model, and optimal allocation of solar units and parking Electric vehicle charging methods have been proposed considering the uncertainty of the load and power of the solar source and have been determined in order to reduce the negative impact of charging electric vehicles connected to the power grid on the distribution network.

5. CONCLUSIONS

This paper compared the costs of objective functions and the amount of losses - in a deterministic and uncertain manner - in three cases with and without the presence of resources and electric vehicles, as well as their presence with production and load values. The parking lot was considered as a large storage facility that can be charged and discharged, and the number of cars in it cannot be less or more than a certain limit. So according to the charge and discharge profile, the parking lot starts to discharge at peak hours, and when the photovoltaic source starts producing power, the cars also start charging in the parking lot, which balances - economically and technically - the distribution network in the presence of renewable sources. As can be seen, the losses and costs associated with them are highest in the absence of renewable resources and without managing the charging and discharging of electric vehicles. After the optimal location of PV and EV buses and the application of definite values, the amount of cost due to losses decreased by 23%, which was achieved using the proposed method with a difference of less than 1%.

Pertaining to the objective function of purchasing from the network, the presence of renewable production sources and the managed capacity of charging and discharging resulting from the connection of cars to the network resulted in 16% saving. However, this cost reduction was accompanied by a 100% increase in the costs of resources, and electric cars had caused the total cost savings to be reduced to 11%. Nonetheless, this indicated the acceptable performance of the second-order cone model and the implementation of the two-point estimation method on the IEEE-33 bus network for optimizing the charging and discharging of electric vehicles in the power grid.

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