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Evaluating the Robust Economic Operation Capabilities of Stationary and Mobile storage and Sources Management in the Smart Distribution network

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ABSTRACT

In this article, the robust scheduling of the distribution network is presented considering electric vehicles, distributed generation, and energy storage, in which the energy management of the mentioned elements is considered, and also only one scenario is needed. The proposed deterministic problem is an optimization problem whose objective function is equal to minimizing energy cost. Also, the limitations of the problem are equal to the power flow equations of the network, the limitations of the technical indicators of the network such as the voltage of the buses and the passing power of the lines, the operation equations of electric vehicles, energy storages, and distributed generation. It is worth mentioning that the mentioned problem is non-linear. In the following, to achieve the global optimal point with a high solution speed, the linear model of the mentioned problem is presented with a very low calculation error. In this research, the uncertainty parameters of the problem are equal to active and reactive loads, energy prices, parameters of electric vehicles, and renewable productions. Finally, to simplify the decision-making of the distribution network operator, a robust model of the mentioned problem was presented. Finally, the proposed problem is applied to the IEEE standard 33-bus radial distribution network using GAMS optimization software, and then the capabilities of the proposed design are evaluated.

Nomenclature

E^u	Uncertainty variable for energy consumption of electric vehicles (EVs) in per-unit (p.u.)	ES	Stored energy in storage (p.u.)
P^u, Q^u	Uncertainty variable for active and reactive load (p.u.)	V	Voltage magnitude (p.u.)
PB	Active power of EVs battery (p.u.)	ΔV, θ	Voltage deviation (p.u.) and voltage angle (rad)
PB^u, SE^u	Uncertainty variable for charge rate of EVs battery and capacity of EVs charger (p.u.)		Dual variables
PE, QE	Active and reactive power of EVs (p.u.)	ρ^{up}	Uncertainty variable for energy price ($/MWh)
PG, QG	Active and reactive power of distribution station (p.u.)	PD, QD	Active and reactive load (p.u.)
PL, QL	Active and reactive power of distribution line (p.u.)	BC, SOC	(%) Battery capacity (kWh) and state of charge
PLC, QLC	Active and reactive power losses of EVs chargers (p.u.)	PF^{min}	Minimum power factor
PDG, PS	Active power of distributed generation (DG) and storage	SE^{max}	Capacity of EVs charger (p.u.)
QC	Reactive power of EVs charger (p.u.)	SG^{max}	Station capacity (p.u.)
QDG, QS	Reactive power of distributed generation (DG) and storage (p.u.)	SL^{max}	Distribution line capacity (p.u.)
		SDG^{max}	DG capacity (p.u.)
		SS^{max}	Storage capacity (p.u.)
		TPF	Tangent value for minimum power factor
		T_{step}, $\Delta\alpha$	Time step (hour) and angle deviation (rad)
		V^{max}	Maximum value of voltage magnitude (p.u.)
		V^{min}	Minimum value of voltage magnitude (p.u.)

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I. Introduction

Due to the pollution caused by the uncontrolled consumption of fossil fuels as well as the depletion of this fuel in recent years, organizations and governments have decided to use new technologies such as electric vehicles (EVs), distributed generations (DGs), and energy storage systems (ESSs) that has very low environmental pollution [1]. Therefore, according to various researches, it is predicted that the use of EVs, DGs, and ESSs will grow significantly in the next few years. In other words, it should be noted that to reduce environmental concerns, one way is to replace EVs instead of cars with fossil fuel consumption. Therefore, it is predicted that the number of EVs will increase worldwide [2]. Since EVs perform this process by connecting to the electrical network, especially the distribution network, to supply energy to their batteries, it is expected that the amount of energy demand in the distribution network will noticeably increase [3]. In addition, to reduce pollution, another solution is to use renewable energy sources (RESs). Therefore, these types of sources will grow significantly in the coming years, as they are generally connected to the distribution network. To establish flexibility in the distribution network, ESSs will have a high number in the distribution network in the coming years [4]. Since these elements are placed in the distribution network, increasing their number will cover a large volume of the distribution network. It is worth mentioning that the increase of the mentioned elements in the distribution network and their lack of energy management will cause challenges in the distribution network. In other words, the voltage profile goes out of the uniform and smooth state, and also network losses increase, and other cases will occur [5]. In addition to this, the behavior of EVs depends on the decision-making of their owners, and the output of RESs also depends on natural phenomena. Since the decisions of EV owners and natural phenomena are not certain, therefore the number of uncertainty parameters in the network has increased and therefore the decision-making of the distribution network operator will be very complicated. Therefore, there is a need to plan the schedule of the distribution network by considering EVs, DGs, and ESSs including the uncertainty model.

Various researches have been done in the field of distribution network operation. In [6], a Stackelberg game approach is proposed for the energy sharing management of a microgrid including prosumers and plug-in electric vehicle (PEV) charging stations (CSs), and a proper billing scheme is designed to increase the robustness of the approach on real-time applications. In the hereby game-theoretic approach, the energy demands of PEV CSs are determined as variable demands considering the operational characteristics of CSs. The purpose of [7] is to assess the impact of emergencies on smart grids through a novel optimization algorithm. The algorithm comprises an optimizer, which maximizes the autonomy of the smart grid, prioritizing its Renewable Energy Sources (RES), and Artificial Neural Networks (ANN), which provide forecasts related to the intermittent RES production. Ref. [8] presents an optimal and simultaneous allocation of the photovoltaic panel (PV) and wind turbine (WT) with the reconfiguration of radial distribution networks to reduce power losses and improve reliability. Determining the optimal optimization variables is very important to obtain the maximum benefits of renewable resource allocation and network reconfiguration, i.e. achieving the lowest losses and reliability cost. In [9], it investigates the optimal operation of a multi-carrier virtual energy storage system (VESS), including batteries, thermal energy storage (TES) systems, power to hydrogen (P2H), and hydrogen to power (H2P) technologies in hydrogen storage systems (HSS), and EVs in dynamic energy storage system (ESS). Further, the demand response program (DRP) for electrical and thermal loads has been considered as a tool of VESS due to the similar behavior of physical ESS. Changes in the climate, environmental pollution, and lack of classical energy sources forced many countries to address renewables. In [10], the smart distribution network reconfiguration is considered to minimize power losses and economic costs. Also, capacitor switching (placement of shunt capacitors) and the presence of distribution generation are always incorporated in modern networks. Further, the On Load Tap Changer in the supplying substation has to be used. Simulated Annealing and Minimum spanning tree algorithms work separately to find the best appropriate solution. The main goals of [10] are minimization of power losses and costs. A distributed operation optimization model incorporating peer-to-peer (P2P) electricity trading in a blockchain environment is proposed in [11], where network usage fees considering electrical distance are specially addressed. Meanwhile, the private information security of prosumers is ensured by the Proof-of-Authority (PoA) consensus blockchain during P2P electricity trading. The trading information of adjustable prosumers should be sent to the proxy entity authorized by the distribution network using the blockchain platform. The contribution of [12] includes the presentation of a model for managing the coordinated and uncoordinated charging system of grid-connected EVs with wind power and photovoltaic power units as dispersed generation sources and dividing the EVs into 4 classes by considering the share of each in the grid and considering a random number of vehicles per class using the normal distribution function and implementing the incoordination in wind speed and solar irradiation. In [13], a probability-solving model for a three-phase unbalanced modern power electronic distribution network with distributed generation (DG) integration is developed, and the probability model is solved using Point Estimation Method (PEM) combined with Gram–Charlier expansion and Monte Carlo Simulation (MCS). Besides, this paper presents a detailed analysis comparing the results of PEM and MCS solutions from the perspective of voltage and line loss. Based on the deep learning and mechanism models, a novel probabilistic power flow (PPF) method is proposed in [14] for multi-microgrid distribution systems considering incomplete network information. Firstly, accessible power exchange data as well as public and independent information are utilized to realize equivalent modeling for microgrid areas with incomplete parameters, based on a novel Kriging surrogate enhanced Gate Recurrent Unit-Temporal Convolutional Network (GRU-TCN). Ref. [15] presents a new management methodology to find the optimum operation of a grid-connected MG, which is modeled as an optimization approach and aims to minimize total cost. The uncertainties in renewable energy-based DG units, including WT and PV, are also considered in this study. The balance between total electricity generation and required demand in the system is determined based on the power interchange between the MG and the distribution system. Ref. [16] presents the optimal scheduling model of the active distribution network (ADN) containing RESs and flexible sources (FSs) such as non-RESs (NRESs) and EVs parking lot based on adaptive robust optimization (ARO). In the deterministic programming, a two-objective optimization model is expressed. It minimizes the difference between the network and NRES operation cost and the revenue of the RES, NRES, and FS due to the sale of active and reactive power in the first objective function, and the second objective function considers the minimizing of the voltage deviation. Ref. [17] develops a robust bundled active and reactive power management of EV-integrated smart distribution networks. To model the problem, at first, the deterministic formulation of the problem is expressed as a non-linear programing (NLP), which minimizes the difference between the energy cost and the revenue of EVs' (parking lot's) reactive power exchange with the network as the objective function, subject to the AC power flow equations, system operation limits and EVs' characteristics as the problem constraints. Ref. [18] presents a two-level optimization model for the optimal scheduling of an active distribution system in day-ahead and real-time market horizons. The distribution system operator transacts energy and ancillary services with the electricity market, plug-in hybrid electric vehicle parking lot aggregators, and demand response aggregators. Ref. [19] presents a two-level optimization problem for optimal day-ahead scheduling of an active distribution system that utilizes renewable energy sources, distributed generation units, electric vehicles, and energy storage units and sells its surplus electricity to the upward electricity market. Ref. [20] proposes an optimal scheduling of the distribution network considering the uncertainty of wind and solar output. This scheme takes the minimum expected value of electricity purchase cost from the main network as the objective function in several scenarios and uses the improved whale algorithm to solve the problem. As the influence of time-varying temperature and driving speed on electric vehicle charging load is not considered in the process of distribution network scheduling, a multi-objective optimal scheduling model for distribution networks, which considers electric vehicle charging load, is proposed in [21]. In [22], stochastic scheduling of a hybrid system (HS) composed of a photovoltaic (PV) array and wind turbines incorporated with a battery storage (HPV/WT/Batt) system in the distribution network was proposed to minimize energy losses, the voltage profile, and the HS cost, and to improve reliability in shape of the energy-not-supplied (ENS) index, considering energy-source generation and network demand uncertainties through the unscented transformation (UT). To improve the operating dependability of a generalized power active distribution network, a multi-objective optimal scheduling approach based on game theory is proposed in [23]. The active distribution network's multistakeholder coordinated and optimal dispatching mode is then established, and the game interaction between various stakeholders in the generalized power active distribution network is evaluated. Finally, a summary of the works is presented in Table 1.

TABLE 1
TAXONOMY OF RECENT ACADEMIC PUBLICATIONS

Ref.	**Reactive power management by**			**Uncertainty model**	**Optimal power flow (OPF) model**
	DG	**EV**	**ESS**		
[6]	×	×	×	Stochastic optimization	Non-linear OPF
[7]	×	×	×		
[8]	×	×	×		
[9]	×	×	×		
[10]	✓	×	×		
[11]	×	×	×		
[12]	×	×	×	-	
[13]	×	×	×	Probabilistic optimization	
[14]	×	×	×	Stochastic optimization	
[15]	×	×	×		
[16]	✓	✓	×	ARO	Linearized OPF
[17]	×	✓	×	ARO	
[18-23]	×	×	×	Stochastic optimization	Non-linear OPF
Current paper	✓	✓	✓	**ARO**	**Linearized OPF**

Based on the research background and Table 1, there are major research gaps in the field of distribution network exploitation. As a research gap, in most researches, only the control and management of the active power of resources and storage devices has been considered. However, it should be noted that some of the technical and economic indicators of the network are improved by reactive power management. Like the voltage profile, the control of the reactive power leads to the regulation of the voltage. Even reactive power control can be effective in reducing energy losses and network power factors, which can play a significant role in reducing the cost of network operation. However, this issue has been considered in less research. Of course, in various researches such as [10], reactive power control with capacitors has been considered. However, it should be said that to reduce environmental pollution, the use of renewable resources and storage devices in the distribution network increases. These elements generally have electronic power converters, which can play a role in reactive power control. This issue has been considered in less researches such as [16-17]. As another research gap, it should be noted that network energy management is a power system operation problem. In these problems, the implementation step is low, so that in some applications it is less than 1 hour. Therefore, low computing time is of particular importance in these problems. To access this topic, it is necessary that the volume of the problem is low and the equations are simplified. However, it should be noted that in most researches such as [6-15], stochastic optimization has been used to model uncertainties. This method extracts a significant number of scenarios to reach a reliable solution, which leads to an increase in the volume of the problem. To compensate for this issue, methods with a low number of scenarios are needed. This issue is accessible in robust optimization, but it has been included in less researches such as [16-17]. In most researches, the nonlinear optimal power flow (OPF) model has been used. The solution to this problem is based on methods according to repetition. Therefore, this method leads to an increase in computing time. To compensate for this issue, linearization of the equations is effective, but it is included in less researches such as [16-17].

In this article, to compensate for the research gaps, the simultaneous management of active and reactive power in the smart distribution network using DGs, EVs, and ESSs is used. The proposed plan minimizes the cost of purchasing energy from the distribution network from the upstream network. It is bound to the equations of AC optimal power low and the operation model of resources and storage devices. The proposed design has a non-linear model, where a linear approximation model for OPF is used to compensate for the last research gap. This plan has uncertainties regarding load, renewable power, energy price, and parameters of EVs. In this article, to reach the optimal solution resistant to the prediction error of uncertainties in low computing time, adaptive robust optimization (ARO) is used to model the aforementioned uncertainties. This method has only one scenario which has the worst case of uncertainties. Finally, the innovations of this article are as follows:

- Simultaneous management of active and reactive power of the distribution network using electric vehicles, distributed generations, and stationary storage devices.
- Simultaneous improvement of the economic and operational indicators of the distribution network with the addition of the ability to control reactive power to sources and storage devices.
- Access to a suitable linear approximation model with low calculation error for the AC optimal power distribution problem, and
- Simultaneous modeling of uncertainties of load, parameters of electric vehicles, energy price, and renewable power using adaptive robust optimization.

Next, the power management modeling of the distribution network is presented in the second section, and then the uncertainty modeling based on ARO is described in the third section. Numerical results obtained from different study cases are reported in the fourth section. Finally, the conclusions are presented in the fifth section.

II. Optimal scheduling of distribution network

2.1. Original model

This section outlines the non-linear deterministic model proposed for the design. This technique minimizes energy costs to satisfy network, resource, and storage device requirements [16]. Therefore, the problem model is as follows:

A. Objective function:

The objective function of the proposed plan is stated in Equation (1), which represents the minimization of the cost of energy received from the upstream network [17].

$$min_{PG} \ \sum_{t\varepsilon\varphi_t}\sum_{b\varepsilon\varphi_b} T_{stop} F_b^{sub} \rho_{b,t}^{p} PG_{b,t} \tag{1}$$

B. Power flow equations:

Constraints (2) to (6) express the power distribution equations, which are equal to active power balance, reactive power balance, active power passing through the lines, reactive power passing through the lines, and the reference bus voltage angle, respectively. Slack) are It should be noted that in these equations, the terms PG and QG are non-zero only for slack bass, and they are equal to zero in other basses [16-17].

$$PG_{b,t} + PDG_{b,t} + PS_{b,t} - PE_{b,t} - \sum_{j\varepsilon\varphi_b} A_{b,j} PL_{b,j,t} = PD_{b,t} \quad \forall b,t \tag{2}$$

$$QG_{b,t} + QDG_{b,t} + QS_{b,t} - QE_{b,t} - \sum_{j\varepsilon\varphi_b} A_{b,j} QL_{b,j,t} = QD_{b,t} \quad \forall b,t \tag{3}$$

$$PL_{b,j,t} = g_{b,t}\left(V_{b,t}\right)^2 - V_{b,t}V_{j,t}\left\{g_{b,j}cos\left(\theta_{b,t}-\theta_{j,t}\right) + b_{b,j}sin\left(\theta_{b,t}-\theta_{j,t}\right)\right\} \quad \forall b,j,t \tag{4}$$

$$QL_{b,j,t} = -b_{b,t}\left(V_{b,t}\right)^2 + V_{b,t}V_{j,t}\left\{b_{b,j}cos\left(\theta_{b,t}-\theta_{j,t}\right) - g_{b,j}sin\left(\theta_{b,t}-\theta_{j,t}\right)\right\} \quad \forall b,j,t \tag{5}$$

$$\theta_{b,t} = 0 \quad \forall b = ref, t \tag{6}$$

C. Technical limitations of the distribution network

The voltage limitation of the buses, the capacity of the lines and the upstream network, and the power factor of the upstream network are shown in relations (7) to (10) respectively. It should be noted that in (10), the equivalent relationship with the power factor limit is presented, in which TPF is equal to tan(cos-1(PFmin)), and the minimum power factor is considered to be 0.9 [2-3, 17].

$$V^{min_{b,t}{}^{max}} \tag{7}$$

$$\left(PL_{b,j,t}\right)^2 + \left(QL_{b,j,t}\right)^2 \le \left(SL_{b,j}^{max}\right)^2 \quad \forall b,j,t \tag{8}$$

$$\left(PG_{b,t}\right)^2 + \left(QG_{b,t}\right)^2 \le F_b^{sub}(SG_b^{max})^2 \quad \forall b,t \tag{9}$$

$$-F_b^{sub}TPF \times PG_{b,t} \le QG_{b,t} \le F_b^{sub}TPF \times PG_{b,t} \quad \forall b,t \tag{10}$$

D. EV aggregation restrictions:

The constraints on electric vehicles (EVs) are demonstrated in relationships (11) to (17), which indicate the necessary energy consumption of EVs in the parking area, the power balance between the EV battery and the grid, the power balance between the EV charger and the grid, the losses from the EV charger, the charging rate for all EV batteries, and the limitation of EV chargers [2, 16].

$$PE_{b,t} = PB_{b,t} + PLC_{b,t} \quad \forall b,t \tag{11}$$

$$QE_{b,t} = QB_{b,t} + QLC_{b,t} \quad \forall b,t \tag{12}$$

$$PLC_{b,t} = a_r\left|PE_{b,t}\right| + a_{im}\left|QE_{b,t}\right| \quad \forall b,t \tag{13}$$

$$QLC_{b,t} = b_r\left|PE_{b,t}\right| + b_{im}\left|QE_{b,t}\right| \quad \forall b,t \tag{14}$$

$$0 \le PB_{b,t} \le PB_{b,j}^{max} \quad \forall b,t \tag{15}$$

$$\left(PE_{b,t}\right)^2 + \left(QE_{b,t}\right)^2 \le (SE_b^{max})^2 \quad \forall b,t \tag{16}$$

$$\sum_{t\varepsilon\varphi_t} T_{stop}PE_{b,t} = EC_b \quad \forall b \tag{17}$$

According to [3], EVs can work in the charging and discharging mode of their batteries, but the discharging mode will reduce the useful life of the battery, so the owners of EVs do not want to inject active power into the network. Also, based on [17], it is assumed in this article that EVs connect to the grid after their last trip during the day and night and receive the electrical energy they need from the grid. Therefore, in relation (17), the term EC is equal to the total energy consumption required by EVs in the parking lot. Also, the required energy consumption of an EV is calculated from the equation (1-SOC)*BC, where SOC is equal to the state of charge and BC is equal to the battery capacity of the EV. SOC is like the fuel gauge of gasoline cars that displays the amount of remaining fuel. In addition, SOC is also calculated from the relationship (1-L/AER) where L is equal to the distance traveled by EV in electric mode and AER is the total distance traveled by EV in electric mode proportional to the battery capacity [17].

E) *Operation model of DGs*: Condition (18) is related to distributed generation, which indicates their apparent power control capacity. This condition expresses the capability curve of DGs, and it includes the limitation of active power generation and the limitation of reactive power control of DGs. In addition, it should be noted that this relationship is also true for renewable DGs, with the difference that the term PDG is considered a parameter for them. But this expression is a variable in non-renewable DGs [3]

$$\left(PDG_{b,t}\right)^2 + \left(QDG_{b,t}\right)^2 \le (SDG_b^{max})^2 \quad \forall b,t \tag{18}$$

F) *The operation model of the stationary storage device*: the limitations of the energy storage device are stated in relations (19) to (21), which respectively indicate the limitation of the apparent power generation capacity of its charger, the calculation of the stored energy and the limitation of the stored energy. It is noteworthy that the difference between two efficiency of charging and discharging in storage devices has a low value [3], therefore the equation (21) can be written according to the hypothesis of equality of charging and discharging efficiency.

$$\left(PS_{b,t}\right)^2 + \left(QS_{b,t}\right)^2 \le (SS_b^{max})^2 \quad \forall b,t \tag{19}$$

$$ES_{b,t} = ES_{b,t-1} - \eta * PS_{b,t} \quad \forall b,t \tag{20}$$

$$E^{min} \le ES_{b,t} \le E^{max} \quad \forall b,t \tag{21}$$

This problem is for the distribution network. The model of the network is based on optimal power flow constraints, i.e. (2)-(10). Also, this paper considers the capabilities of ESS, DG, and EVs. Hence, the problem includes the formulation of ESS, DG, and EVs according to constraints (11)-(21).

2.2. Linear approximation model of the problem

In formulation (1)-(21), constraints (4), (5), (8), (9), (13), (14), (16), (18) and (19) have the format It is non-linear. Also, constraints (4) and (5) are non-convex. Therefore, the model (1)-(21) is non-convex in a non-linear way [16]. Algorithms for solving this problem are generally based on numerical methods based on repetition, so their computing time is expected to be high for solving complex engineering problems like model (1)-(21). Also, due to the non-convexity of the problem, different solvers do not extract a unique solution [16]. However one of the goals of this article, based on part 1, is to derive a stable model of uncertainties. This modeling requires the convexity of the basic problem. For this purpose, a linear approximation model is obtained in this section for the proposed design. One of the characteristics of the linear model is its convexity, its different solvers can extract a unique solution, and the computing time of the solvers of this problem is lower than the nonlinear model [17].

CPLEX solver is a strong algorithm to obtain the optimal solution. This solver is for linear problems, hence, the linear model of the scheme is obtained in this paper. Also, this paper needs robust optimization. The robust formulation is for linear programming. Hence, the linear model was obtained for the scheme.

According to [2], in a distribution network, generally, the voltage angle difference between two ends of a line is less than 6 degrees or 0.105 radians. Therefore, the terms sin(θ) and cos(θ) in relations (4) and (5) can be approximated to and 1, respectively. Bus voltage based on the piecewise linearization technique [17] can be expressed as$V^{min\sum_{l\varepsilon\phi_l}\Delta V_l}$. ΔV represents the voltage deviation and has a value much less than one per-unit. According to the piecewise linear method, the expressions V2 and VbVj are equal to and $\left(V^{min}()^{2^{min\sum_{l\varepsilon\phi_l}\Delta V_{b,l}}}{}^{min\sum_{l\varepsilon\phi_l}\Delta V_{j,l}}\right)$, respectively. *m* represents the slope of the line segments. The variables θ and ΔV have a low value, so their product and their power are very small and can be neglected. With these conditions, the linear approximation model of relations (3) and (4) is the same as relations (22) and (23) respectively:

$$\begin{aligned} PL_{b,j,t} = g_{b,j} &\left(\sum_{l\varepsilon\varphi_l}(m_l - V^{min})\,\Delta V_{b,t,l} \right. \\ &\left. - V^{min}\Delta V_{b,t,l}\right) \\ &- (V^{min})^2 b_{b,j}\big(\theta_{b,t} - \theta_{j,t}\big) \\ &: \lambda_{j,t}^{pl} \quad \forall b,j,t \end{aligned} \tag{22}$$

$$\begin{aligned} QL_{b,j,t} = -b_{b,j} &\left(\sum_{l\varepsilon\varphi_l}(m_l - V^{min})\,\Delta V_{b,t,l} \right. \\ &\left. - V^{min}\Delta V_{j,t,l}\right) \\ &- (V^{min})^2 g_{b,j}\big(\theta_{b,t} - \theta_{j,t}\big) \\ &: \lambda_{j,t}^{ql} \quad \forall b,j,t \end{aligned} \tag{23}$$

Since the voltage deviation variable is used in the linear approximation model of relations (4) and (5), therefore, since the voltage deviation variable is used in the linear approximation model of relations (4) and (5), therefore, the following limit replaces the limit The voltage (7) becomes: the following constraint replaces the voltage constraint (7):

$$0 \le \Delta V_{b,t,l} \le \Delta V^{max} : \bar{\mu}_{b,t,l}^{v} \quad \forall b,j,t \tag{24}$$

Constraints (8), (9), (16), (18) and (19) are circular inequalities that can be linearized using the regular polygon method. In this method, the circular plane, $(P)^2 + (Q)^2 \le (S)^2$, is approximated to a regular polygonal plane. The equation of each side (*k*) of this plane is linear, which can be expressed as (24):

$$\cos(k\Delta\alpha)\,P + \sin(k\Delta\alpha)\,Q = S \tag{25}$$

In this regard, Δα represents the angular deviation, and its value is equal to 360/*nk*. *nk* represents the number of regular polygon sides. The square plane resulting from the linear equation (25) is as (26):

$$\cos(k\Delta\alpha)\,P + \sin(k\Delta\alpha)\,Q \le S \tag{26}$$

Repetition of equation (26) for all values of *k* leads to extraction of the plane in the form of regular polygons. Therefore, constraints (8), (9), (16), (18) and (19) can be expressed as relations (27)-(31) respectively:

$$\begin{aligned} the\ \cos(\mathrm{k}\Delta\alpha)\,PL_{b,\mathrm{j},t} + \sin(\mathrm{k}\Delta\alpha)\,QL_{b,\mathrm{j},t} \le SL_{b,j}^{max} \\ : \bar{\mu}_{b,j,t,k}^{sl} \quad \forall b,j,t,k \end{aligned} \tag{27}$$

$$\begin{aligned} \cos(\mathrm{k}\Delta\alpha)\,PG_{b,t} + \sin(\mathrm{k}\Delta\alpha)\,QG_{b,t} \le F_b^{sub} SG_b^{max} \\ : \bar{\mu}_{b,t,k}^{sg} \quad \forall b,t,k \end{aligned} \tag{28}$$

$$\begin{aligned} \cos(\mathrm{k}\Delta\alpha)\,PE_{b,t} + \sin(\mathrm{k}\Delta\alpha)\,QE_{b,t} \le SE_{b,j}^{max} \\ : \bar{\mu}_{b,t,k}^{se} \quad \forall b,t,k \end{aligned} \tag{29}$$

$$\begin{aligned} \cos(\mathrm{k}\Delta\alpha)\,PDG_{b,t} + \sin(\mathrm{k}\Delta\alpha)\,QDG_{b,t} \le SDG_{b,j}^{max} \\ : \bar{\mu}_{b,t,k}^{dg} \quad \forall b,t,k \end{aligned} \tag{30}$$

$$\begin{aligned} \cos(\mathrm{k}\Delta\alpha)\,PS_{b,t} + \sin(\mathrm{k}\Delta\alpha)\,QS_{b,t} \le SS_{b,j}^{max} \\ : \bar{\mu}_{b,t,k}^{ss} \quad \forall b,t,k \end{aligned} \tag{31}$$

Based on relations (11) and (15), the variable PE always has a positive value, so the expression |PE| In relations (13) and (14), it can be written as PE. In addition, it should be noted that generally the consumers of the distribution network are ohmic-selfish. Therefore, reactive power control devices such as EVs will work in a capacitive mode to compensate for reactive power consumption. Therefore, the term QE will always have a negative value, following this, |QE| can be written as -QE. Therefore, relations (13) and (14) can be written as (32) and (33), respectively:

$$PLC_{b,t} = a_r PE_{b,t} - a_{im} QE_{b,t} \ : \lambda_{b,t}^{plc} \quad \forall b,t \tag{32}$$

$$QLC_{b,t} = b_r PE_{b,t} - b_{im} QE_{b,t} \ : \lambda_{b,t}^{qlc} \quad \forall b,t \tag{33}$$

Finally, the linear approximation model for the proposed design can be written as follows:

$$min_{PG} \sum_{t\varepsilon\varphi_t}\sum_{b\varepsilon\varphi_b} T_{stop} F_b^{sub} \rho_{b,t}^{p} PG_{b,t} \tag{34}$$

Subject to:

Constraints (2), (3), (6), (10)-(12), (15), (17), (20)-(21) with dual variables as $\lambda_{b,t}^{p}$, $\lambda_{b,t}^{q}$, λ_{t}^{θ} , $\mu_{b,t}^{pf}$ and $\bar{\mu}_{b,t}^{pf}$, $\lambda_{b,t}^{pc}$, $\lambda_{b,t}^{qc}$, $\bar{\mu}_{b,t}^{pb}$, λ_{b}^{cc} , λ_{b}^{es}, $\mu_{b,t}^{es}$ and $\bar{\mu}_{b,t}^{es}$ respectively. (35)

Constraints (22)-(24), (27)-(33) (36)

The expressions λ and μ in each relationship represent binary variables related to this relationship.

III. ROBUST OPTIMIZATION

A. Uncertainty parameters

The issue model includes characteristics with uncertainties such as active and reactive loads, PD and QD, energy price, , charging rate of EV battery aggregation (PB), EV charger aggregation capacity (SEmax), needed energy consumption of EV aggregation (EC), and active power Renewable DGs (PDGs). The matrix representing the uncertainty parameter is as follows:

$$\bar{u}=\left[PD_{b,t}QD_{b,t}PB_{b,t}^{max_{b,t}}{}^{max_{b_{b,t}b,t}^{p}}\right] \qquad (37)$$

The uncertainty parameter matrix has nb rows and (6nt + 1) columns. Nb represents the number of network buses and nt represents the operating hours. Uncertainty is a reliable indicator of the expected value of variables, as stated in reference [18]. Another way to define the uncertainty variable matrix is as follows:

$$u=\left[P_{b,t}^{u}Q_{b,t}^{u}PB_{b,t}^{u}SE_{b,t}^{u}E_{b}^{u}\rho_{b,t}^{up}PDG_{b,t}^{u}\right] \qquad (38)$$

B. ARO formulation

This part uses the ARO formulation to represent the uncertainty in (38), making up for the remaining research gap in section 1. In ARO, a scenario that results in the worst possible circumstance for the issue in terms of the objective function is retrieved for the uncertainty variables [17]. We refer to this situation as the worst-case scenario. ARO finds both the worst-case situation and the ideal quantity of the problem's primary variables at the same time. As a result, the problem's objective function in ARO is given by the expression max min, where the term max is used to extract the number of uncertainty variables, u, in the worst scenario, and the term min (corresponding to relation (1)) is used to find the main problem's optimal variable value. It is the scenario's case. The same specific issue, (34)– (36), is included in the internal formulation of the ARO problem (min expression). The u matrix in relation (38) takes the place of the matrix in this issue. The collection of uncertainties yields the u matrix's range of changes, which may be expressed as the following relationship for row b of the u matrix [18]:

$$U^{b}(\bar{u}^{b},\tilde{u}^{b},\triangle^{b})=\begin{Bmatrix}u^{b}\varepsilon R^{6n_t+1}:\frac{1}{6n_t+1}\sum_{i=1}^{6n_t+1}\frac{\left|u_i^b-\tilde{u}_i^b\right|}{\tilde{u}_i^b}\leq\triangle^{b},\\ \tilde{u}_i^b\,\varepsilon[\bar{u}_i^b-\tilde{u}_i^b,\bar{u}_i^b+\tilde{u}_i^b]\end{Bmatrix}$$

(39)

In this regard, , and respectively show the i-th variable of uncertainty, the amount of deviation of uncertainty, and the normal value (prediction) of uncertainty in bus b. represents the uncertainty budget, which is between zero and one. If is equal to zero, the deterministic model is established, and if the uncertainty budget is greater than zero, the stable model is established. Moreover, the interval is equal to the interval of variation of the uncertainty variable. Then the uncertainty set is defined as [18]. In the following phase of ARO, the term max min must be modified to max or min so that the issue may be solved using traditional solvers. In these circumstances, the dual model of the internal issue (i.e. the problem involving the word min) is retrieved. In these circumstances, the term max max is retrieved for the ARO issue, which corresponds to an objective function problem with max. As a result, the ARO model for the proposed plan includes a dual objective function for problems (34)-(36). It has two constraints: issue (34)-(36) and constraint [18]. Thus, the suggested ARO model is as follows:

$$max_{u,\lambda,\mu}\sum_{b\in\varphi_b}\{E_b^u\lambda_b^{ec}+\sum_{t\in\varphi_t}\{P_{b,t}^u\lambda_{b,t}^p+Q_{b,t}^u\lambda_{b,t}^q+PB_{b,t}^u\bar{\mu}_{b,t}^{pb} \qquad (40)$$

$$+\left(\sum_{l\in\varphi_l}^{\bar{\Sigma}_{b,t,l}^{v}}\Delta V_b^{max}\,()\right)$$

$$\sum_{\substack{k\in\varphi_k\\ b\,\text{with renewable DG}}}\left\{cos(k\Delta\alpha)PDG_{b,t}^u\bar{\mu}_{b,t,k}^{se}\right\}+E$$

$$\Sigma\Sigma_{k\in\varphi_k}^{\Sigma}\begin{Bmatrix}SDG_{b,t}\mu_{b,t,k}^{dg}+SS_{b,t}\mu_{b,t,k}^{ss}\\ +SE_{b,t}^u\bar{\mu}_{b,t,k}^{se}+F_b^{sub}SG_b^{ma\bar{x}_{b,t,k}^{sg}}\end{Bmatrix}\}\}\}\}$$

$$ma\bar{x}_{b,t}^{es}{}^{min_{b,t}^{es}}\sum_{j\in\varphi_b}\quad\sum_{k\in\varphi_k}^{\Sigma}\left\{SL_{b,j}^{ma\bar{x}_{b,j,t,k}^{sl}}\{\}\right\}$$

Subject to:

$$\lambda_{b,t}^{p}+\sum_{k\in\varphi_k}cos(k\Delta\alpha)\overline{\mu}_{b,t,k}^{sg}+F_b^{sub}TPF(\mu_{b,t}^{pf}-\overline{\mu}_{b,t}^{pf}) \qquad (41)$$
$$=T_{stop}F_b^{sub}\rho_{b,t}^{p}:PG_{b,t}\quad\forall b$$
$$=ref,t$$

$$\lambda_{b,t}^{q}+\mu_{b,t}^{pf}+\overline{\mu}_{b,t}^{pf}+\sum_{k\in\varphi_k}sin(k\Delta\alpha)\overline{\mu}_{b,t,k}^{sg} \qquad (42)$$
$$=0:QG_{b,t}\quad\forall b=ref,t$$

$$-\lambda_{b,t}^{p}+\lambda_{b,t}^{pe}-a_r\lambda_{b,t}^{plc}-b_r\lambda_{b,t}^{qlc} \qquad (43)$$
$$+\sum_{k\in\varphi_k}cos(k\triangle\alpha)\overline{\mu}_{b,t,k}^{se}\leq 0$$
$$:\;PE_{b,t}\;\forall b,t$$

$$-\lambda_{b,t}^{q}+\lambda_{b,t}^{qe}+\sum_{k\in\varphi_k} sin(\,k \bigtriangleup \alpha)\overline{\mu}_{b,t,k}^{se} \geq 0 \quad : \; QE_{b,t} \; \forall b,t \tag{44}$$

$$-\lambda_{b,t}^{pe}+T_{stop}\lambda_{b}^{ec}+\overline{\mu}_{b,t}^{pb} \leq 0 : \; PB_{b,t} \; \forall b,t \tag{45}$$

$$-\lambda_{b,t}^{qe}=0 : \; QC_{b,t} \; \forall b,t \tag{46}$$

$$-\lambda_{b,t}^{pe}+\lambda_{b,t}^{plc} \leq 0 : \; PLC_{b,t} \; \forall b,t \tag{47}$$

$$-\lambda_{b,t}^{qe}+\lambda_{b,t}^{qlc} \leq 0 : \; QLC_{b,t} \; \forall b,t \tag{48}$$

$$-A_{b,j}\lambda_{b,t}^{p}+\lambda_{b,j,t}^{pl}+\sum_{k\in\varphi_k} cos(\,k \bigtriangleup \alpha)\overline{\mu}_{b,j,t,k}^{sl}=0 \quad : \; PL_{b,j,t} \; \forall b,j,t \tag{49}$$

$$-A_{b,j}\lambda_{b,t}^{q}+\lambda_{b,j,t}^{ql}+\sum_{k\in\varphi_k} sin(\,k \bigtriangleup \alpha)\overline{\mu}_{b,j,t,k}^{sl}=0 \quad : \; QL_{b,j,t} \; \forall b,j,t \tag{50}$$

$$\lambda_{b,t}^{p}+\sum_{k\in\varphi_k} cos(k\Delta\alpha)\, \mu_{b,t,k}^{dg} \leq 0 : PDG_{b,t} \; \forall b,t if \text{DGisnotrewnable} \tag{51}$$

$$\lambda_{b,t}^{q}+\sum_{k\in\varphi_k} sin(k\Delta\alpha)\, \mu_{b,t,k}^{dg}=0 : QDG_{b,t} \; \forall b,t \tag{52}$$

$$\lambda_{b,t}^{p}+\eta\lambda_{b,t}^{es}+\sum_{k\in\varphi_k} cos(k\Delta\alpha)\, \mu_{b,t,k}^{ss}=0 : PS_{b,t} \; \forall b,t \tag{53}$$

$$\lambda_{b,t}^{q}+\sum_{k\in\varphi_k} sin(k\Delta\alpha)\, \mu_{b,t,k}^{ss}=0 : QS_{b,t} \; \forall b,t \tag{54}$$

$$\lambda_{b,t}^{es}-\lambda_{b,t+1}^{es}+\mu_{b,t}^{es}+\bar{\mu}_{b,t}^{es} \leq 0 : ES_{b,t} \; \forall b,t \tag{55}$$

$$\left(V^{min}()^{2}\sum_{j\in\varphi_b}\left(b_{b,j}(\lambda_{b,j,t}^{pl}-\lambda_{j,b,t}^{pl}) + g_{b,j}(\lambda_{b,j,t}^{ql}-\lambda_{j,b,t}^{ql})\right)_{b_{t}\;b,t}^{\theta} \right) \quad \forall b,t \& z_b=1 \; \forall b \; = \; ref \tag{56}$$

$$\bar{\mu}_{b,t,l}^{v}-\sum_{j\in\varphi_b}\left\{g_{b,j}\left(\left(m_l-V^{\min}\right)\lambda_{b,j,t}^{pl}-V^{\min}\lambda_{b,j,t}^{pl}\right)+b_{b,j}\left(\left(m_l-V^{\min}\right)\lambda_{b,j,t}^{ql}-V^{\min}\lambda_{b,j,t}^{ql}\right)\right\} \leq 0 : \Delta V_{b,t,l} \quad \forall b,j,t,l \tag{57}$$

$$\lambda=free, \;\; \mu \leq 0, \; \bar{\mu} \geq 0 \tag{58}$$

$$u \in U \tag{59}$$

The relations (40)-(58) represent the duals of the problem (34)-(36), in case the variable u is parameterized instead $\bar{u}$. Constraint (59) represents the limitation of uncertainties or the worst-case scenario. In addition, it should be noted that relation (40) has non-linear expressions $E_{b}^{u}\lambda_{b}^{ec}$, $P_{b,t}^{u}\lambda_{b,t}^{p}$, $Q_{b,t}^{u}\lambda_{b,t}^{q}$, $PB_{b,t}^{u}\bar{\mu}_{b,t}^{pb}$, and $PDG_{b,t}^{u}\bar{\mu}_{b,t,k}^{se}$. But these expressions are in the objective function and the objective function is of the second degree. This type of problem is due to having convex linear constraints, and it can be solved by powerful solvers such as CPLEX in optimization software such as GAMS [25]. Finally, the flowchart of the scheme is shown in Fig. 1.

The scheme includes the mathematical formulation [26-29]. This formulation is based on the optimization model [30-31]. The optimization problem contains an objective function [32-34]. This function includes min or max term [35-36]. It is a single of multi-objective model [37]. There are different constraints in the optimization problem [38-39]. Constraint contains equality or inequality formulations [40]. To apply the optimization model on the network, the network needs smart devices [41-43]. The smart devices are based on Telecommunication tools and smart algorithms [44-46].

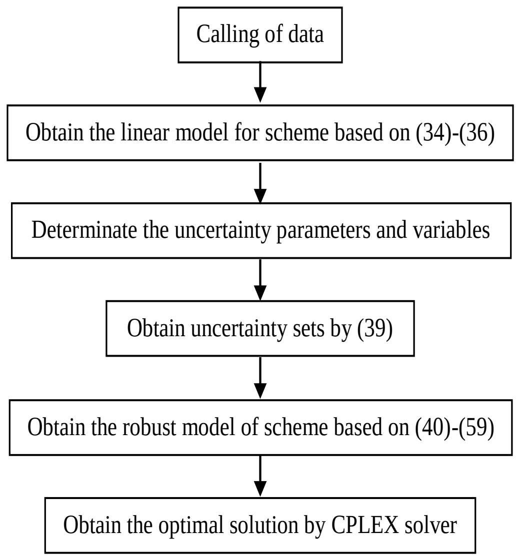


Fig. 1. Single-line Flowchart of scheme

IV. Numerical results

A. Case study

The proposed scheme in this section is implemented on the IEEE standard 33-bus radial distribution network, whose single-line circuit is shown in Figure (2) [47]. This network has a basic voltage and power of 12.66 kV and one megawatt, and its minimum and maximum allowed voltage range is equal to 0.9 to 1.05 per-unit [48-53]. The characteristics of distribution lines and substations are reported in [47]. Reference [47] also includes peak load data. The amount of load in other hours is calculated by multiplying the load of the peak hour and the load factor curve [54-59]. This curve is presented in [17]. The price of energy for hours 1:00-7:00 is equal to \$16/MWh, it is equal to \$30/MWh in hours 17:00-22:00. In other hours, the energy price is equal to \$24/MWh [17]. It has been assumed that there is parking for EVs in all buses except the slack bus. Their number in the parking lot is 21, 30 or 60. Buses whose active peak load is between zero and 0.1 (0.2-0.1) per-unit, the number of EVs in that bus is equal to 21 (30). But if the reactive peak load is more than 0.2, the number of EVs in that bus is equal to 60. Other characteristics of EVs such as battery capacity, SOC, charger capacity, and charging rate are stated in [16-17]. The loss coefficients , and are assumed to be the same for all EVs, which are assumed to be 0.09, 0.0475, 0.02, and 0.02, respectively. The number of EVs per hour is equal to the product of the total number of EVs in the park and the daily EV penetration rate curve. This curve is described in [17]. In the mentioned network, two wind system (WS) type DGs with 1.5 and 1.8 per-unit capacities were installed in 16 and 47 buses, respectively. In Bus 31 / 56, there is a photovoltaic (PV) / fuel cell (FC) DG with a capacity of 2.1/1. The active production power of WS and PV is equal to the product of their capacity and the daily curve of their production power rate. These curves are presented in [1]. In buses 18 and 57, two batteries with a capacity of 1 MWh and an efficiency of 92% have been installed, the charger capacity of which is equal to 0.3 per-unit. The minimum energy stored in each of the batteries is equal to 0.1 MWh. The time step is one hour and the starting time of the simulation is 10:00 am due to the continuous energy in terms of time or relation (17).

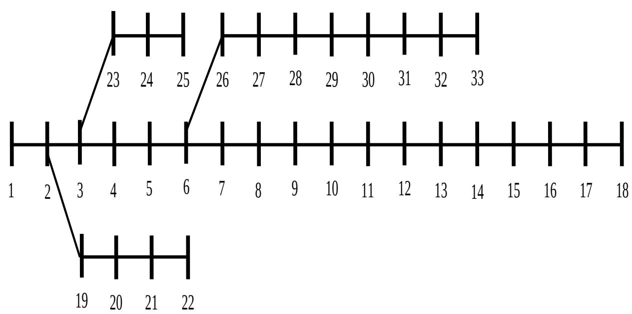


Fig. 2. Single-line circuit of IEEE standard 33 bus radial distribution network [47]

V. Simulation results

The proposed design is coded according to the data of sections 1-4 in the GAMS software environment [25]. 5 linear pieces are used for voltage linearization. A circular plate is rounded to a regular 90-sided plate. The uncertainty deviation, $\tilde{u}$, is equal to the product of the uncertainty budget, Δ, the radius of uncertainty, r, and $\bar{u}$is considered.

A. Comparison of different deterministic models for the proposed plan

The nonlinear model for the requested issue is shown in Table (2) inside the GAMS software [21]. The nonlinear model utilizes mathematical solvers CONOPT, COUENNE, IPOPT, MINOS, PATHNLP, and SNOPT, whilst the linear model employs solvers CPLEX, BDMLP, CBC, CONOPT, and GLPK. These answers rely on mathematical approaches detailed in reference [21]. This table shows that various solvers' solutions to the nonlinear problem model vary, and that their solution times are lengthy. Additionally, the state of the solution is identical to the local optimum for certain solvers. The problem is not with the convergence point. However, in exchange, other linear problem solvers have succeeded in reaching the ultimate optimum point, and their optimal solution yields an answer that is the same for every solver. The computation time and the quantity of problem-solving iterations are the sole distinctions between them. The suggested linear issue is best served by the CPLEX method, whereas the nonlinear problem is best served by the IPOPT algorithm. The CPLEX method is selected due to its very short calculation time, and the IPOPT algorithm is selected because it has been able to reach a low level of the objective function in comparison to other algorithms in the nonlinear problem.

TABLE 2
COMPARISON OF THE RESULTS OBTAINED FROM DIFFERENT SOLVERS AND ALGORITHMS

The deterministic non-linear model				
Solver	Iteration	Calculation time (sec)	Objective function ($)	Model state
CONOPT	390	44	1432.6	**Locally optimal**
IPOPT	34	51.4	1007.3	
MINOS	400	546.5	1268.3	
COUENNE	Infeasible solution			
PATHNLP				
SNOPT				
The deterministic linear model				
Solver	Iteration	Calculation time (sec)	Objective function ($)	Model state
CPLEX	7444	6.6	523.7	**Global optimal**
BDMLP	7787	139.3		
CBC	3788	10.4		
CONOPT	92	57.1		
GLPK	9395	182.2		

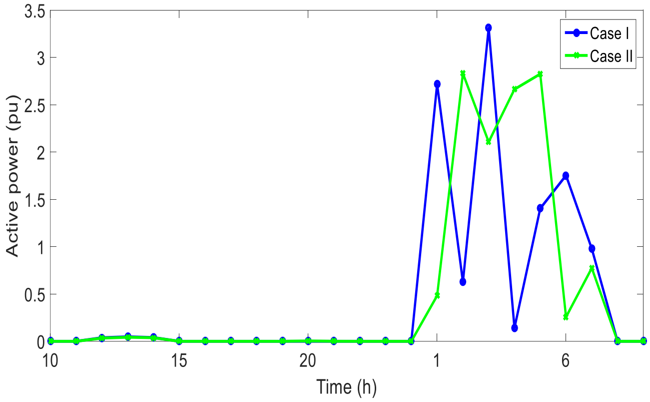
B. Checking the performance of resources and storage devices

In this section, two studies have been carried out, which are:

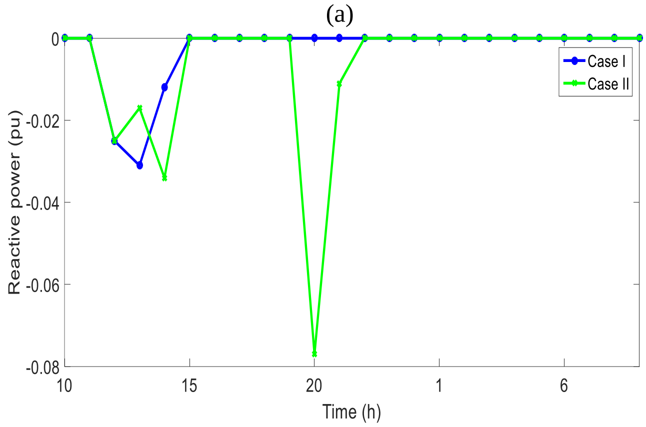
- The first study cases (I): evaluation of the results obtained from the deterministic linear model of the proposed problem
- Second study cases (II): evaluation of the results obtained from the robust linear model of the proposed problem with the assumption of an uncertainty budget equal to 1 and uncertainty radius equal to 0.1

The results of this section are shown in figures (3)-(7), which are equal to the daily curve of active and reactive power of total

EVs, the daily curve of active and reactive power of PVs, the daily curve of active and reactive power of WS, the daily curve of power Active and reactive are the sum of FCs and the daily curve of active and reactive power is the sum of batteries. Based on Figure (3-A), it can be seen that EVs charge during off-peak hours due to low energy prices. Also, their charging level is higher in the stable model than in the deterministic model. Based on Figure (3-b), EVs spend more hours injecting reactive power into the distribution network in the stable model than in the deterministic model.

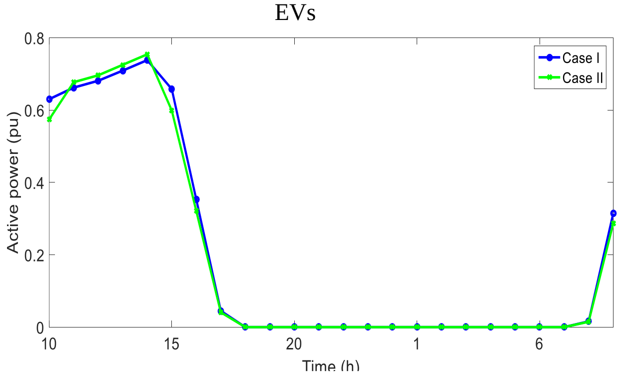


(a)

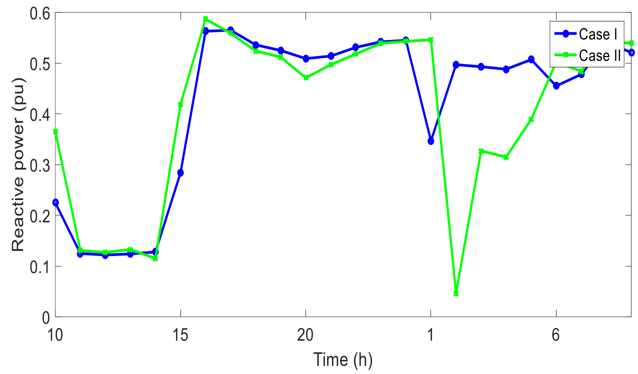


(b)

Fig. 3. Daily curve, (a) active power, (b) reactive power of total EVs



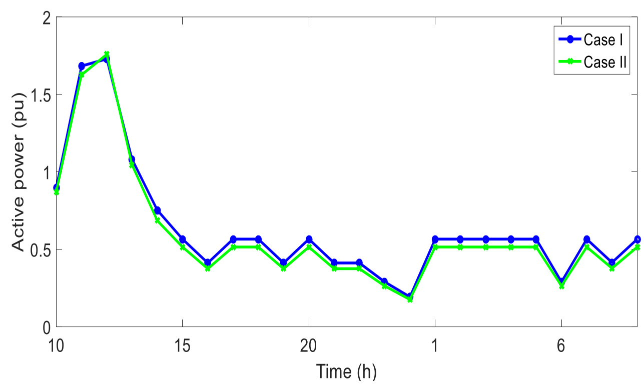
(a)



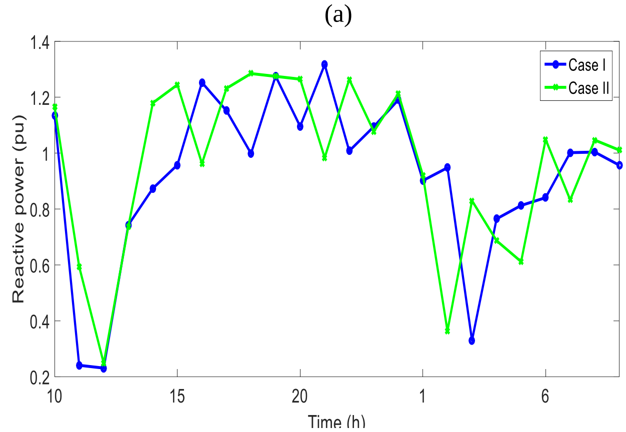
(b)

Fig. 4. Daily curve, (a) active power, (b) reactive power of total solar systems

Based on Figure (4-a) / (5-a), it can be seen that solar/wind systems inject active power into the distribution network when there is solar radiation/wind speed according to [1]. Also, in the stable model compared to the deterministic model, the active power level of renewable sources has decreased. Based on Figure (4-b)/(5-b), high reactive power is injected into the grid by solar and wind systems at most hours, and at most hours, the reactive power in the stable model is more than the reactive power in the deterministic model.



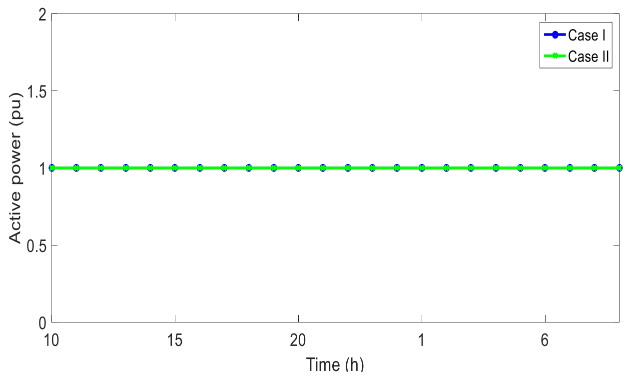
(a)



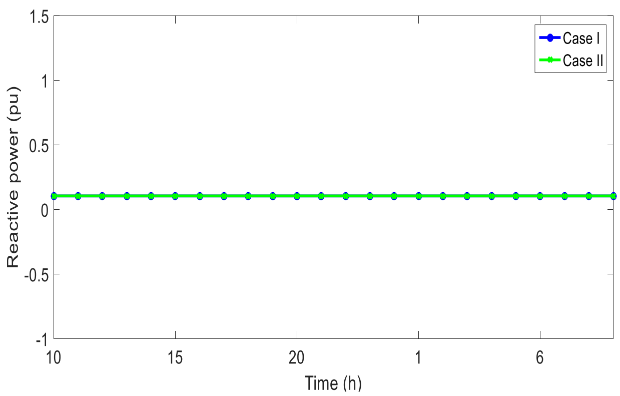
(b)

Fig. 5. Daily curve, (a) active power, (b) reactive power of total wind systems

Based on Figure (6-a), it can be seen that the fuel cell systems inject high active power into the network in all hours of the simulation compared to their capacity. Also, in the stable model and the deterministic model, the active power level of the fuel cell systems is the same. Based on Figure (6-b), low reactive power is injected into the network by fuel cell systems in most hours, and the reactive power of fuel cell systems is the same in two stable and deterministic models.



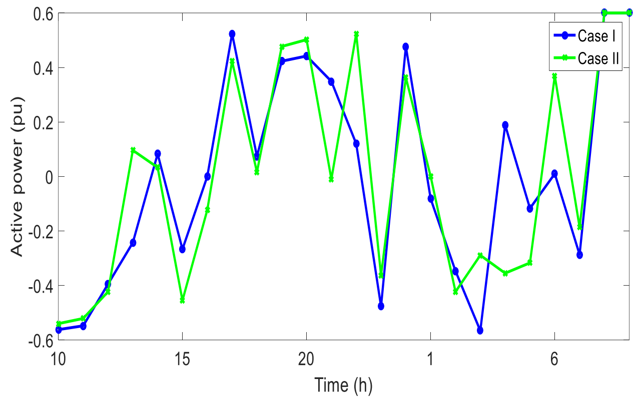
(a)



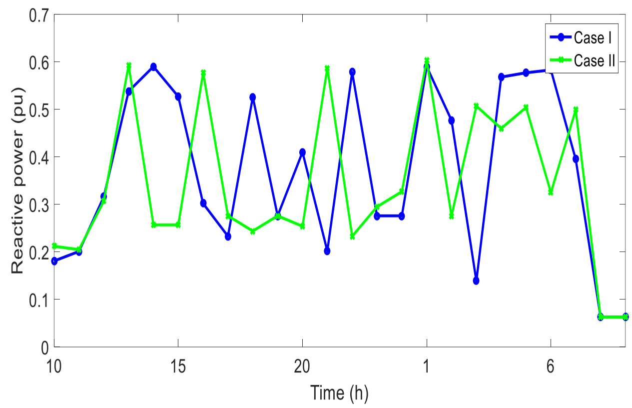
(b)

Fig. 6. Daily curve, (a) active power, (b) reactive power of total fuel cell systems

Based on Figure (7-A), it can be seen that energy storages perform charging operations during off-peak and mid-load hours due to the low price of energy and are discharged during other hours. It can also be said that in the stable model compared to the deterministic model, the power level of the storage generators has increased in most hours. In addition, based on Figure (7-b), it can be seen that the ripple of changes in the reactive power of energy storage is high both in the stable model and the deterministic model.



(a)



(b)

Fig. 7. Daily curve, (a) active power, (b) reactive power of total energy storage

C. *Check network indicators*

In this section, the network indicators, including the transmission power of the distribution post, voltage profile, and network losses due to the study cases of the previous section are evaluated. The results of this section are shown in figures (8) to (10). Based on Figure (8), it can be seen that in the stable model, the apparent power of the distribution substation located in the reference bus (bus 1) increases in most of the simulation hours compared to the deterministic model. This shows that in the worst-case scenario, the amount of active and reactive loads and the amount of demand for electric vehicles have increased compared to the scenario corresponding to the deterministic model. Also, the active power capacity of wind and solar systems and the reactive power capacity of wind and solar systems and electric vehicles have decreased. Therefore, the demand from the upstream network has increased in the stable model.

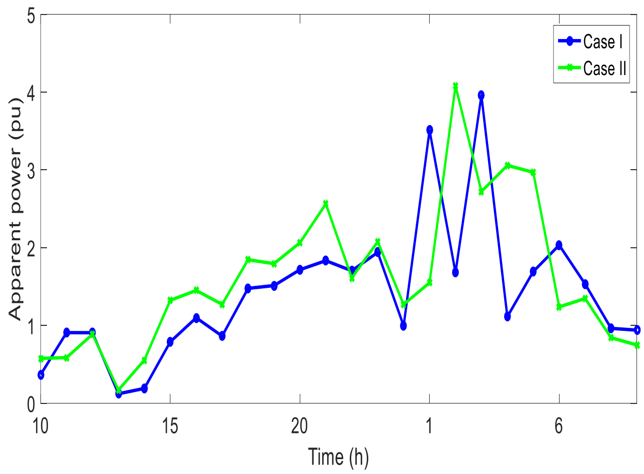


Fig. 8. The daily curve of the apparent power of the distribution substation (Bus 1)

It is worth noting that it can be seen that the voltage of all buses has decreased in the stable model compared to the deterministic model based on Figure (9). Therefore, the network voltage drop in the stable model is more than the voltage drop in the deterministic model. It can also be seen that following the mentioned topic, the active losses of the distribution network have increased in the stable model compared to the deterministic model. Therefore, it can be mentioned that in the stable model, the amount of power demand in the network has increased, but in return, the power generation capacity of scattered productions and electric vehicles has decreased.

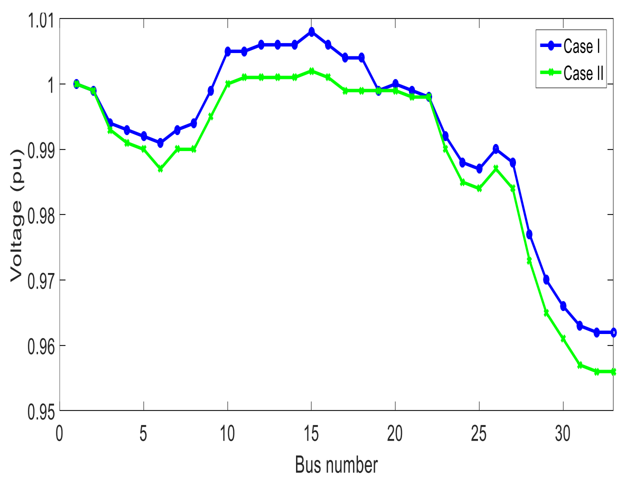


Fig. 9. Voltage profile at peak hour (20:00)

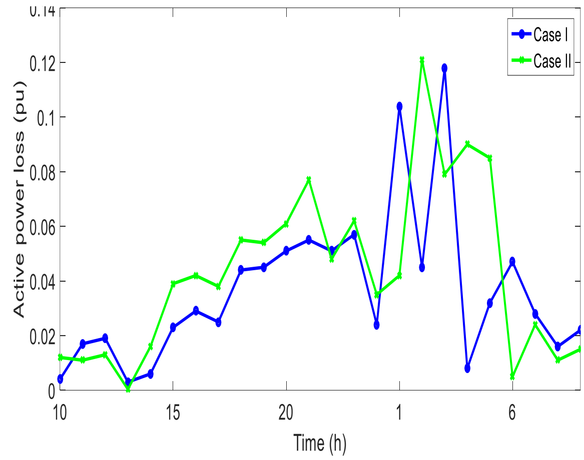


Fig. 10. Time curve of network losses

D. Evaluation of the robust model

Table (3) displays the results of this section, showing the energy cost (objective function), the uncertainty parameters of the robust model for different levels of uncertainty, and the uncertainty budget set at one. According to the statistics, in the worst-case scenario when the stable model is compared to the deterministic model (uncertainty level is zero), the active and reactive demand of network consumption, energy demand of electric vehicles, and energy price all increase. Now, these parameters rise along with these degrees of uncertainty. The level of reactive power production of all electric vehicles, the level of active power production of solar systems, the level of active power production of wind systems, and the charging rate of all electric vehicles in the worst-case scenario are all visible in this table. When comparing the stable model to the deterministic model, they are smaller (the amount of uncertainty is equivalent to zero). Now, these factors also drop as these degrees of uncertainty rise. These directives state that the price of energy will rise as the degree of uncertainty rises.

TABLE 3
THE AMOUNT OF ENERGY COST AND UNCERTAINTY PARAMETERS IN THE STABLE MODEL WITH AN UNCERTAINTY BUDGET EQUAL TO ONE AND VARIOUS LEVELS OF UNCERTAINTY

Parameter	**Unit**	**Uncertainty level**				
		0	**0.02**	**0.04**	**0.06**	**0.08**
Sum of P^u	p.u.	56.592	57.724	58.855	59.987	61.119
Sum of Q^u	p.u.	35.037	35.737	36.438	37.139	37.840
Sum of PW^u	p.u.	18.112	17.750	17.338	17.026	16.663
Sum of PPV^u	p.u.	7.654	7.501	7.348	7.195	7.042
Sum of PB^u	p.u.	48.825	47.849	46.872	45.895	44.919
Sum of S^u	p.u.	74.865	73.368	71.870	70.373	68.876
Sum of E^u	p.u.	241.416	246.244	251.073	255.901	260.729
Sum of ρ^{up}	$/MWh	556	567.12	578.24	589.36	600.48
Energy cost	$	523.751	571.458	621	672.380	725.305

VI. Conclusions

In this article, the operation of the intelligent distribution network in the presence of electric vehicles, stationary sources, and storage devices, taking into account the simultaneous management of their active and reactive power, was described. This plan was responsible for the minimization of the operating cost by taking into account the constraints of the optimal power distribution of the network and the operating model of the mentioned elements. This plan included load uncertainties, energy prices, renewable power, and parameters of electric vehicles, which adaptive robust optimization was used to model them. Also, this design used the linear approximation model of optimal power distribution. Further, based on the numerical results, it was observed that the linearized model of the proposed design can greatly reduce the calculation time compared to the non-linear model. It always has a unique solution. In the worst-case scenario, energy demand increases, while the ability of mobile resources and storage devices in energy production decreases. The performance of sources and storage is such that the apparent power passing through the distribution post is reduced, energy losses are reduced, and a smoother voltage profile is obtained. Effects of DG, EVs, and ESSs size and location not considered in this paper. Also, the simulation results under types of faults are not demonstrated. To cope with this issue, the reliability-based network operation considering the sitting and sizing model of sources and storage is investigated in future works.

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