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Traffic Uncertainty Modeling and Energy Management of Smart Distribution Networks with the Presence of Parking Lots

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Abstract— *Energy management (EM) in smart distribution networks (SDN) is to schedule the power transaction between the SDN and the existing distributed energy resources (DERs) e.g., distributed generations, especially renewable resources and electrical vehicles, from an eco-technical viewpoint. Due to the dual role of electric vehicles (EVs) acting as a power source and load, they presented both challenges and opportunities in EM. The complexity of EM increases as DERs become more prevalent in SDN. Moreover, the uncertainties of renewable resources, price, and load besides the uncertainties related to the place, amount, and time of EV's charging makes EM a more intricate field. This supports the necessity of extensive tools and approaches to manage EM in SDNs. In this respect, this paper proposes an optimum scenario-based stochastic energy management scheme for intelligent distribution networks. The proposed approach is modeled as a MINLP problem and solved in GAMS software under the DICOPT solver. The test is conducted on a 33-bus SDN with and without factoring in uncertainties.*

Keywords—Energy management, distribution network, electrical vehicle, parking lot, traffic, uncertainty.

NOMENCLATURE

Binary Variables

$b_{v,t}^{ch}$ Decision variable for v-th EVs charging at t-th hour
$b_{v,t}^{disc}$ Decision variable for v-th EVs discharging at t-th hour

Sets and Indices

i DGs index
n, m Buses index
s Uncertainty scenarios index
t Time index (hour)
v EVs index
w Wind-Turbins index

Parameters

β Constant price coefficient for EVs charge/discharge
η_v^{ch} Charge efficiency
η_v^{disc} Discharge efficiency
γ Repair and maintenance cost of wind turbine
λ_t^{Price} Electricity price at t-th hour
A, B, C Wind-Turbine characteristic's curve parameters
a, b, c DG's characteristic curve's parameters
$E^{\max}$ EVs maximum energy
$E^{\min}$ EVs minimum energy
$P_v^{ch,\max}$ Maximum charging power of v-the vehicle
$P_v^{disc,\max}$ Maximum discharging power of v-the vehicle
P_w^r Nominal power of wind-turbine
$P^{DG,\max}$ Active power generation of DG
$P^{Sub,\max}$ Maximum active power purchased from the distribution substation
$Q^{DG,\max}$ Maximum reactive power generation of DG
$Q^{Sub,\max}$ Maximum reactive power purchased from distribution substation
$V_n^{\max}$ Maximum voltage of n–th bus
$V_n^{\min}$ Minimum voltage of n–th bus
v_{in}^c Cut-in speed of wind-turbine
v_{out}^c Cut-out speed of wind-turbine
v_r Rated speed of wind-turbine

Variables

P_t^{Loss} Active power loss at t-th hour
P_t^{sub} Purchased power from distribution substation at t-th hour
$P_{n,t}^{Demand}$ n-th bus active load at t-th hour
$P_{p,t}^{ch}$ Total charging power of parking lots at t-th hour
$P_{p,t}^{disc}$ Total discharging power of parking lots at t-th hour
$P_{t,i}^{DG}$ Generated power of i-th DG at t-th hour
$P_{t,v}^{ch}$ Charging power of v-th vehicle at t-th hour
$P_{t,v}^{dch}$ Discharging power of v-th vehicle at t-th hour
$P_{t,w}^{Wind}$ Generated power of w-th wind-turbine at t-th hour
Q_t^{Loss} Distribution network power loss
Q_t^{Sub} Reactive power purchased from the distribution substation at t-th hour
$Q_{i,t}^{DG}$ Reactive power generation of i-th DG at t-th hour
$Q_{n,t}^{Demand}$ n-th bus reactive load at t-th hour
$V_{n,t}^{net}$ Network voltage at t-th hour
δ_n Voltage angle of n-th bus
Cost^{EV} EVs degradation cost
Cost^{Total} Total operation cost
Cost^{Wind} Wind-turbine power generation cost
$\theta_{n,m}$ Voltage angle between n-th and m-th buses
P_w The output power of wind-turbine
t^{arr} Arrival time of EVs to parking lot
t^{dep} Departure time of EVs from parking lot
v_t Wind-turbine speed at t-th hour
$V_{n,t}$ Voltage of n–th bus at t-th hour
$Y_{n,m}$ Admittance between n-th and m-th buses

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1. INTRODUCTION

1.1. Motivation and background

Energy management (EM) system (EMS) is a tool to select suitable energy sources and develop the power consumption pattern and energy efficiency. Implementing the EMS minimizes energy costs, optimizes energy consumption, diminishes environmental pollutants, and can supply the demanded energy at higher quality and lowest possible costs. EM in the smart distribution network (SDN) has attracted great attention, since SDN as the final stage of power delivery to the end-user consumers substantially affects the economics and power quality. The emergence of power market added to the importance of the SDN and now its significance is ever-increasing with the development of distributed energy sources (DERs) e.g., distributed generations (DGs) and electrical vehicles (EVs). In this regard, EMS tries to find the best-suited energy resources and also schedule them to economically supply the demanded load in the highest possible quality.

1.2. Literature review

As known, limited fossil fuel resources and high emissions have led to the growing penetration of electric vehicles (EVs) in transport fleets. The dual role of EVs acting as a power source and load has introduced both challenges and opportunities in the way of EM at SDN[1].

In addition, the connection of DGs at the distribution level, if properly planned and operated, has positive effects on all economic, technical, and environmental parameters. Anyway, as the penetration of DERs in SDN increases, so does the complexity of EM.

Combatively to the combustion engines, the fuel cost of EVs is lower[2–4]. On average, the cost of traveling a certain distance with an EV is less than half that of a traditional vehicle. Also, the environmental pollutant and the maintenance cost of EVs are lower. Therefore, nowadays, EVs play a vital role in EM[5].

However, if a large number of EVs are being charged simultaneously in a small geographical area, especially at peak load periods, the increment in demand for electricity will jeopardize the reliability of the power supply. To overcome the mentioned problem, there is a need for substantial investments in installing new power generation sources. Moreover, DN must adapt to the high penetration of EVs[6].

On the other hand, EVs with vehicle-to-grid capability can supply their extra power, stored in their batteries, to the grid. This technology helps to increase the flexibility of DN, improving technical parameters of DN, providing auxiliary services, etc. [7–12]. Traveling patterns and EV characteristics have a substantial effect on the charging profile of the EV[3].

The primary aim of [4] is to study the main parameters that EV owner considers when buying an EV. The proposed coordinated approach optimizes the number of EVs that can be charged simultaneously, without any reinforcement/expansion on DN. Moreover, it determines the optimal charging profile of EVs to flatten the voltage profile. In [13] a smart management model is proposed for the optimal operation of the parking lot considering the charging cost and the operational constraints e.g., battery characteristics and aging. The proposed approach can guarantee financial benefits for EV owners. Investigating the preferences of EV owners in charging their vehicles can provide an accurate estimation of Evs' effects on DN's technical parameters and also provides a roadmap for future energy policy. Therefore, the effects of consumers charging patterns and different EVs characteristics are studied in [14]. It depicts that most of the EVs are charged in the evenings. The flexibility of battery electric vehicles (BEVs) as a DER is limited by their traveling patterns, their usage in transportation fleets, and also the possibility of charging them at a certain time/place. Accordingly, the availability of the BEVs as a modern storage device is studied in [15]. In addition to the environmentally friendly nature of EVs, they affect the reliability of DNs. In [16] the reliability of DN is evaluated at different levels of EV penetration. In modern DNs, EVs with V2G capability are assumed as a reliable and flexible source to provide a load-generation balance. In this evolving paradigm, designing EM strategies for the economical and cost-effective use of V2G is one of the several challenges faced by DN operators and regulators. In this regard, an EM strategy to utilize the V2G potential of EVs is proposed to overcome the energy imbalance in a connected microgrid [17]. The proposed approaches can support the economical use of V2G in a competitive power market when the price variation is high. In [18] a practical approach is proposed to overcome the challenges caused by higher integration of renewable energies and EVs in DN considering the high variations in generation side and inconsistency in energy consumption. A multi-carrier energy system model by considering the traffic patterns of EVs is proposed in [19]. Moreover, two kinds of charging infrastructures e.g., household and parking lots have been studied. Ever-increasing penetration of EVs in transportation fleets connecting to the DN requires efficient and powerful tools and approaches to manage the parking lots. Reference [20] proposed a coordinated scheduling strategy for EV parking lots considering the dependency of DNs and traffic. The challenges encountered when charging EVs in a DN in the presence of renewable energies and local storage devices are investigated in [21].

A review of the optimization of EV charging in the residual section is provided in [22] to minimize the EV owners' costs. In [23] a fuzzy set theory-based cost-effective approach related to EM in an AC microgrid connected to a residual network is proposed. In [24] optimization of EV charging to minimize the battery degradation costs by considering the battery characteristics is studied. In [25], the effects of time of use-based (TOU) demand response program and direct load control (DLC) demand response program to reduce the operating costs of the microgrid including intelligent parking lots and renewable energy resources were studied. An optimal framework for the operation of integrated energy systems using demand response programs is presented in [26]. In [27], a new hybrid decomposition-based multi-objective evolutionary algorithm (MOEA) is proposed for the optimal power flow (OPF) problem including Wind, PV, and PEVs uncertainty with four conflicting objectives. Monte Carlo simulations were used to assess the uncertainty of Wind, PV, and PEV power.

1.3. Contributions

A review shows that there is a lot of research regarding EM in DN in the presence of EVs. However, from the author's knowledge, in most of the reported works of literature, the traffic pattern of EVs due to its complexity is neglected from the modeling, while the amount of required charge and also the time of charging are directly dependent on the traffic pattern.

Therefore, there is a substantial gap that the proposed approach in this paper tries to fill.

The main novelties of this paper can be summarized as follows:

- Proposing a MINLP mathematical model for day-ahead scheduling of EV parking lots in a Distribution Network.
- Considering the uncertainties of traffic patterns.
- Applying the uncertainties of renewable energies, load, and price into the modeling.

1.4. Paper organization

The remainder of the paper is organized as follows: Mathematical Model is provided in section 2. Section 3 is assigned to Simulations and Results. Case Studies are explained in Section 4. And finally, the Conclusion is provided in section 5.

2. Mathematical Model

As discussed earlier, the proposed approach aims to optimize the day-ahead EM of DN in the presence of parking lots and renewable energies considering the operational constraints of DN and battery characteristics of different EV models from the distribution system operator (DSO) viewpoints. The mathematical formulations of the proposed approach and the considered constraints are detailed in the following.

The proposed cost-based objective function is as follows:

$$\mathrm{Cost}^{Total} = \mathrm{Cost}^{sub} + \mathrm{Cost}^{DG} + \mathrm{Cost}^{EV} + \mathrm{Cost}^{Wind} \quad (1)$$

As seen, the first term of the proposed objective function (Cost^{sub}) is related to the cost of purchased power from the upstream network, Cost^{DG} and Cost^{Wind} are the cost of purchased power from the installed dispatchable DGs and wind turbines at DN, respectively, and Cost^{EV} is the degradation cost of EVs which DSO pays to EV owners, since battery degradation is the result of charging/discharging procedure. The aforementioned terms in the cost function are calculated using the following equations. The amount of constraint parameters used in these formulas are borrowed from [28].

$$\mathrm{Cost}^{sub} = \sum_s \rho_s \times \sum_t P_{t,s}^{sub} \times \lambda_{t,s}^{\mathrm{Price}} \quad (2)$$

$$\mathrm{Cost}^{DG} = \sum_s \rho_s \times \sum_t \sum_i a \times P_{t,i,s}^{DG^2} + b \times P_{t,i,s}^{DG} + c \quad (3)$$

$$\mathrm{Cost}^{EV} = \sum_s \rho_s \times \sum_t \sum_v \beta \times \left(P_{t,v,s}^{ch} + P_{t,v,s}^{dch}\right) \quad (4)$$

$$\mathrm{Cost}^{Wind} = \sum_s \rho_s \times \sum_t \sum_w \gamma \times P_{t,w,s}^{Wind} \quad (5)$$

In Eq. (2) $P_{t,s}^{sub}$ is the purchased power from distribution substation and $\lambda_{t,s}^{\mathrm{Price}}$ is the electricity price at t-th hour. As seen in Eq. (3), DG's operation cost is a quadratic function with a, b and c constants whose values are different for diverse DGs. $P_{t,i,s}^{DG}$ is the active power generated by i-th DG at t-th hour. In Eq. (4), β is the constant value and $P_{t,v,s}^{ch}$ and $P_{t,v,s}^{dch}$ are the amount of active power charge/discharge of v-th EV at t-th hour, respectively. In Eq. (5), γ is a constant value and $P_{t,w,s}^{Wind}$ is the active power generated by w-th wind turbine at t-th hour.

In the above-mentioned objective function, DSO tries to minimize the cost of purchased energy from the upstream network and all types of installed DGs at DN. Since the amount of purchased power is the summation of the loads and power loss and is calculated using AC power flow, there is no necessity to add power loss cost to the objective function. As a notable point, DSO is the owner of the parking lots, and charging/discharging of the EVs has considerable effect on their financial statements, so the charge/discharge cost is applied to the mentioned cost function.

As discussed previously, the proposed approach is to optimally execute EM with considering the technical and operational constraints. The considered constraints are detailed in the following:

2.1. AC power flow

The modeling and mathematical formulation of the executed load flow are borrowed from [29, 30]. Load flow analysis is based on active and reactive power balance in any node at any hour. This principle is summarized in Eqs. (6)-(7).

$$\begin{aligned}&\sum_g^G P_{n,g,t,s}^{Sub} + \sum_i^I P_{n,i,t,s}^{DG} + \sum_w^W P_{n,w,t,s}^{wind} \\ &-P_{n,t,s}^{Demand} + \sum_{v=1}^{V} \left(P_{v,t,s}^{disc} - P_{v,t,s}^{ch}\right) = \\ &V_{n,t,s} \sum_m V_{m,t,s} Y_{n,m} \cos\left(\theta_{n,m,t} - \delta_{n,t,s} - \delta_{m,t,s}\right) \quad \forall n, s\end{aligned} \quad (6)$$

$$\begin{aligned}&\sum_g^G Q_{n,g,t,s}^{Sub} + \sum_i^I Q_{n,i,t,s}^{DG} - Q_{n,t,s}^{Demand} = \\ &V_{n,t,s} \sum_m V_{m,t,s} Y_{n,m} \sin\left(\theta_{n,m,t} - \delta_{n,t,s} - \delta_{m,t,s}\right) \quad \forall n, s\end{aligned} \quad (7)$$

where $P_{n,t,s}^{Demand}$ and $Q_{n,t,s}^{Demand}$ are the active and reactive power of n-th node at t-th hour in s-th scenario, respectively. $V_{n,t,s}$ is the voltage amplitude of n-th bus at t-th hour and $Y_{n,m}$ is the admittance between n–th and m–th nodes. Finally, $\theta_{n,m,t}$ is the admittance angle between n–th and m–th nodes and $\delta_{n,t,s}$ is the voltage angle of n-th node, at t-th hour in s-th scenario.

Regarding Eq. (8), the safe operation of DN needs voltage amplitude to be preserved in a predefined standard range.

$$V_n^{\min} \le V_{n,t,s}^{net} \le V_n^{\max} \qquad \forall n, t, s \quad (8)$$

where $V_n^{\min}$ and $Q^{Sub,\max}$ are the minimum and maximum allowable voltage amplitude and the is voltage amplitude of n-th node at t-th hour in s-th scenario.

Moreover, the amount of active and reactive powers purchased from the distribution substation must be preserved in the allowable range, which is considered in Eqs. (9)-(10), respectively.

$$0 \le P_{n,g,t,s}^{Sub} \le P^{Sub,\max} \qquad \forall n, g, t, s \quad (9)$$

$$0 \le Q_{n,g,t,s}^{Sub} \le Q^{Sub,\max} \qquad \forall n, g, t, s \quad (10)$$

where $P^{Sub,\max}$ and $Q^{DG,\max}$ are the maximum active and reactive power that can be purchased from the distribution substation.

2.2. Dispatchable DG

The active and reactive power generation of DGs is limited by their nominal capacity[28], which are represented by Eqs. (11)-(12), respectively.

$$0 \le P_{i,t,s}^{DG} \le P^{DG,\max} \qquad \forall i, t, s \quad (11)$$

$$0 \le Q_{i,t,s}^{DG} \le Q^{DG,\max} \qquad \forall i, t, s \quad (12)$$

where $P^{DG,\max}$ and $Q^{DG,\max}$ are the nominal capacity of i-th DG.

2.3. Power loss

Power loss in DN is calculated using the following equations.

$$\begin{aligned}P_{t,s}^{Loss} &= \sum_g^G P_{n,g,t,s}^{Sub} + \sum_i^I P_{i,t,s}^{DG} + \sum_w^W P_{w,t,s}^{wind} - \sum_n^N P_{n,t,s}^{Demand} \\ &+ \sum_v^V \left(P_{v,t,s}^{disc} - P_{v,t,s}^{ch}\right) \qquad \forall t, s\end{aligned} \quad (13)$$

$$\begin{aligned}Q_{t,s}^{Loss} &= \sum_g^G Q_{n,g,t,s}^{Sub} + \sum_i^I Q_{i,t,s}^{DG} \\ &- \sum_n^N Q_{n,t,s}^{Demand} \qquad \forall t, s\end{aligned} \quad (14)$$

It is evident that $P_{n,g,t,s}^{Sub}$, $P_{i,t,s}^{DG}$, $P_{w,t,s}^{wind}$ and $P_{v,t,s}^{disc}$ are considered to be positive since they produce power, whilst $P_{n,t,s}^{Demand}$ and $P_{v,t,s}^{ch}$ consume power. Hence, they are in negative form.

2.4. Electrical vehicle

Charging and discharging of EVs are done considering the technical constraints related to the battery characteristics [27]. Charging/Discharging power is limited by their maximum allowable values, as Eq. (15).

$$\begin{cases} 0 \le P_{v,t,s}^{ch} \le b_{v,t,s}^{ch} P_v^{ch,\max} & \forall v,t,s \quad ,t^{arr} \le t \le t^{dep} \\ 0 \le P_{v,t,s}^{disc} \le b_{v,t,s}^{disc} P_v^{disc,\max} & \forall v,t,s \quad ,t^{arr} \le t \le t^{dep} \end{cases} \tag{15}$$

where t^{arr} and t^{dep} are the arrival/departure time of the EVs to/from parking lots, respectively. As known, an EV must be in one of these modes, charging, discharging and idle. Therefore, the following equation is used to determine the EV's mode.

$$\begin{cases} b_{v,t,s}^{ch} + b_{v,t,s}^{disc} \le 1 & \forall v,t,s \quad ,t^{arr} \le t \le t^{dep} \\ b_{v,t,s}^{ch}, b_{v,t,s}^{disc} \in \{1,0\} & \forall v,t,s \quad ,t^{arr} \le t \le t^{dep} \end{cases} \tag{16}$$

For this purpose, binary variables are needed to be defined, $b_{v,t,s}^{ch}$ and $b_{v,t,s}^{disc}$. The amount of stored energy at EV battery is calculated using the following equations.

$$E_{v,t,s} = E_{v,s}^{ini} + \left(\eta_v^{ch}.P_{v,t,s}^{ch} - \frac{P_{v,t,s}^{disc}}{\eta_v^{disc}} \right) \quad \forall v,s \quad ,t = t^{arr} \tag{17}$$

$$\begin{aligned} &E_{v,t,s} = E_{v,t-1,s} + \\ &\left(\eta_v^{ch}.P_{v,t,s}^{ch} - \tfrac{P_{v,t,s}^{disc}}{\eta_v^{disc}} \right) \quad \forall v,t,s \quad ,t^{arr} \le t < t^{dep} \end{aligned} \tag{18}$$

where $E_{v,s}^{ini}$ is the initial stored energy of an EV when it arrives at the parking lot. The efficiency of the charging/discharging of EVs is shown by η_v^{ch} and η_v^{disc}, respectively.

It is assumed that the stored energy of the EVs at departure time must be above the predefined value, as represented in Eq. (19).

$$0.8E^{\max} \le E_{v,t,s} \quad \forall v,s \quad ,t = t^{dep} \tag{19}$$

The amount of stored energy at EVs battery at any hour must be preserved within the minimum ($E^{\min}$) and maximum ($E^{\max}$) values.

$$E^{\min} \le E_{v,t,s} \le E^{\max} \quad \forall v,t,s \quad ,t^{arr} \le t \quad ,t = t^{dep} \tag{20}$$

The total amount of charging/discharging power of all EVs parked in a parking lot can be calculated using Eqs. (21)-(22).

$$P_{p,t,s}^{ch} = \sum_{v}^{V} P_{v,t,s}^{ch} \qquad \forall v,p,t,s \tag{21}$$

$$P_{p,t,s}^{disc} = \sum_{v}^{V} P_{v,t,s}^{disc} \qquad \forall v,p,t,s \tag{22}$$

where $P_{v,t,s}^{ch}$ and $P_{v,t,s}^{disc}$ are the charging and discharging power of v-th EV at t-th hour, respectively.

2.5. Wind turbine

As detailed in Eq. (23), the power generation of wind turbines is dependent on the wind speed.

$$P_{w,t,s} = \begin{cases} 0 & v_{t,s} \le v_{in}^c, v_{t,s} \ge v_{out}^c \\ P_{w,s}^r \left(A + Bv_t + Cv_t^2 \right) & v_{in}^c \le v_{t,s} \le v_r \\ P_{w,s}^r & v_r \le v_{t,s} \le v_{out}^c \end{cases} \tag{23}$$

here v_r, v_{in}^c and v_{out}^c are the nominal, cut-in, and cut-out speed, respectively and $P_{w,s}^r$ is the nominal power of the installed wind turbine. Moreover, the A, B and C are the parameters of the wind turbine characteristic's curve and are constant values.

2.6. Uncertainty model

Scenario-based stochastic modeling is an appropriate tool to model such uncertain parameters as load, price, and renewable energies, all of which are considered in the mentioned problem. Since many uncertainties are impacting the real-life network, it is proper to point out the limitation of assumptions.

Commonly, Weibull distribution or Rayleigh probability distribution function (PDF) are used to model the wind speed uncertainty [31]. Rayleigh PDF is represented in Eq. (24).

$$PDF\left(v\right) = \left(\frac{v}{c^2}\right) \exp\left[-\left(\frac{v^2}{2c^2} \right) \right] \tag{24}$$

Also, normal PDF is used for uncertainty modeling of load and price[31]. Moreover, to model the uncertainty of traffic patterns including the arrival/departure time of EVs to/from the parking lot and the initial stored energy of EVs, the normal PDF is used.

$$PDF\left(d\right) = \frac{1}{\sqrt{2\pi\sigma^2{}_d}} \exp\left[-\frac{\left(d-\mu_d\right)^2}{2\sigma^2{}_d} \right] \tag{25}$$

2.7. Scenario reduction

The number of defined scenarios in scenario-based stochastic problems has a considerable effect on the speed of the optimization process and the accuracy of the attained results. So, the SCENRED algorithm (applied to GAMS software) is used for scenario reduction purposes.

3. Simulations and Results

As noted, the main aim of this paper is to propose a new method for EM in DN in the presence of parking lots and renewable energies considering the uncertainties. The proposed approach is tested on an IEEE 33-bus DN. The complete view of the studied DN besides the sites where wind turbines, dispatchable DGs, and parking lots are installed, is shown in Fig. 1 [32].

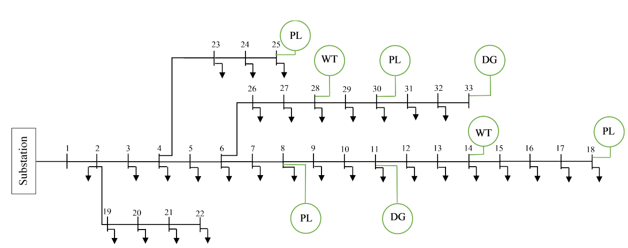

Fig. 1. IEEE 33 bus DN in the presence of DGs and parking lots.

The hourly profiles of the total active and reactive load of DN [36] are represented in Fig. 2.

As seen from Fig. 1, a couple of 1MW Dispatchable DGs are installed at the 11^{th} and 33rd buses of DN. Also, there are four

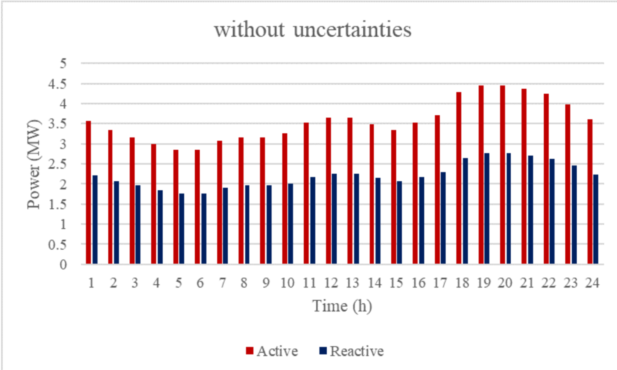

Fig. 2. The hourly active and reactive load profile of DN.

Table 1. Wind turbine characteristics.

Parameter	Unit	Value
P_w^r	kW	300
v_{in}^c	m/s	4
v_{out}^c	m/s	22
v_r	m/s	10
A	-	0.0311
B	-	-0.0776
C	-	0.0174
Cost	$	5

parking lots in DN for buses 8, 18, 25, and 30. Each one has a capacity of 100 EVs. Two 300 kW wind turbines are installed at the 1st and 28th buses of DN. The hourly profile of wind speed [33] is given in Fig. 3. According to the detailed wind turbine characteristics [34], in Table 1, and previously described wind turbine modeling, the hourly profile of wind turbine power generation is depicted in Fig. 4.

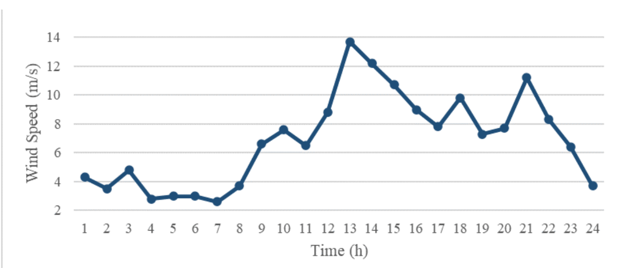

Fig. 3. Hourly profile of wind speed.

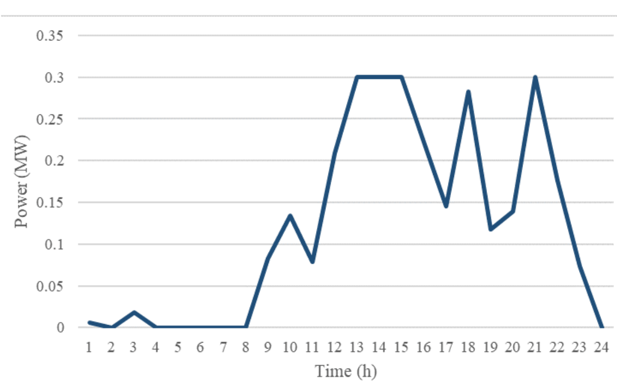

Fig. 4. Hourly profile of wind turbine power generation.

Table 2. The characteristics of dispatchable DGs.

Parameter	Unit	Values	
		DG1	DG2
$P^{DG,\max}$	MW	1	1
$Q^{DG,\max}$	MVAr	0.5	0.5
a	$\frac{\$}{(MWh)^2}$	0.0075	0.0075
b	$\frac{\$}{MW}$	36	40
c	$	28.5	22

Table 3. The characteristics of EVs.

Parameter	**Unit**	**Value**
$E_v^{\max}$	MWh	0.025
$E_v^{\min}$	MWh	0.001
$P_v^{ch,\max}$	MW	0.0125
$P_v^{disc,\max}$	MW	0.0125
η_v^{ch}	-	0.90
η_v^{disc}	-	0.93
Cost	$	5

The values of different parameters used to model dispatchable DGs [28] and EVs [35] can be found in Tables 2 and 3, respectively.

As known, EM in DN is to find the eco-technical solution for the operation of DN and the installed power source in it. Therefore, one of the parameters, considerably affecting the solution is the electricity price, the hourly profile of which [36] is represented in Fig. 5.

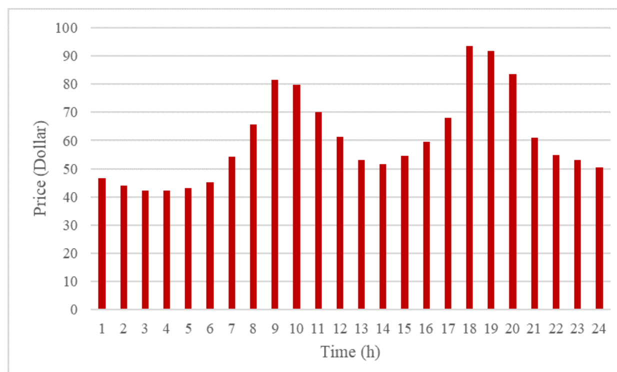

Fig. 5. The hourly price.

3.1. Traffic pattern modeling

The commercial parking lots are studied in this simulation. The arrival and departure times of EVs to/from Parking Lots are summarized in Table 4. It is assumed that when EVs arrive at the Parking Lot, there is a certain amount of stored energy in their batteries. Also, EM must guarantee that the stored energy at EVs battery must be upper than 80% of its capacity at departure time.

4. CASE STUDIES

As noted earlier, the proposed approach is modeled as a MINLP problem and solved using GAMS software under the DICOPT solver.

Table 4. The details related to the arrival and departure times of EVs.

Parking Lot No.	Arrival time	Departure time
1	8	16
3	11	21
4	12	24

The proposed approach is studied in two cases:

1) Optimization of EM in DN in the presence of parking lots without considering the uncertainties of the traffic pattern, price, load, and initial stored energy at EV batteries
2) Optimization of EM in DN in the presence of parking lots with considering the uncertainties of the traffic pattern, price, load, and initial stored energy at EV batteries

The outcomes of each case study and finally the comparison study are given in the following.

4.1. First case study

First Case Study regards the optimization of EM in DN in the presence of Parking Lots without considering the uncertainties of the traffic pattern, price, load, and initial stored energy at EV batteries. The required data for this study are provided in the above sections.

The hourly profile of purchased power from the upstream network is depicted in Fig. 6. Moreover, the power generation of DGs at different hours of the day is represented in Fig. 7.

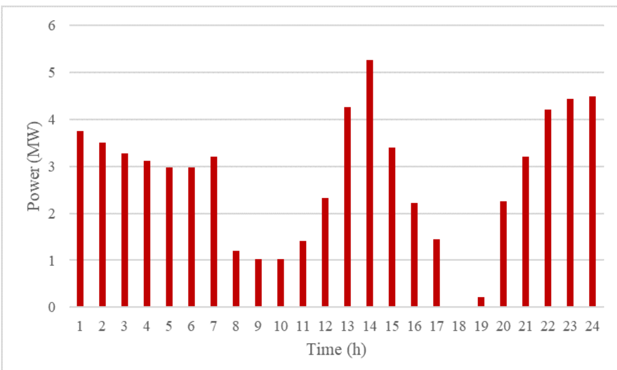

Fig. 6. The hourly profile of purchased power from the upstream network in case 1.

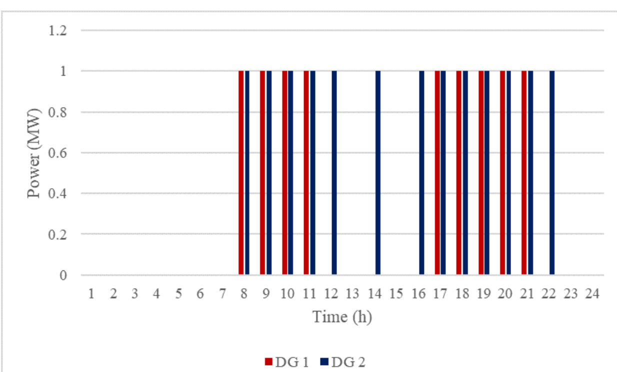

Fig. 7. Hourly profile of DG's power generation in case1.

The amount of purchased power and power generation of DGs varies at different hours of the day both dependent on electricity price. Considering Fig. 1, DN prefers to purchase a higher amount of power at times with lower prices. As seen, the amount of purchased power is lower at 8-12 and 17-22, while they purchase higher amounts of power in low price times, 1-7, 13-15, and 21-24. Also, it is validated that DGs generate higher amounts of power in times when the market price of electricity is higher. Comparing Fig. 6 and 7 signify that when the power purchased from the upstream network lessens due to the higher prices, to provide the load, DGs generate power up to their full capacity. Moreover, when the hourly price profile reaches its peak at 18, the purchased power from the upstream network descends to zero.

The charging/discharging profiles of different parking lots are represented in Figs. 8 and 9, respectively.

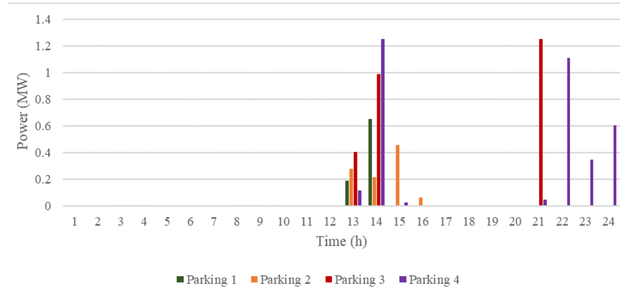

Fig. 8. Charging profile of different parking lots in case 1.

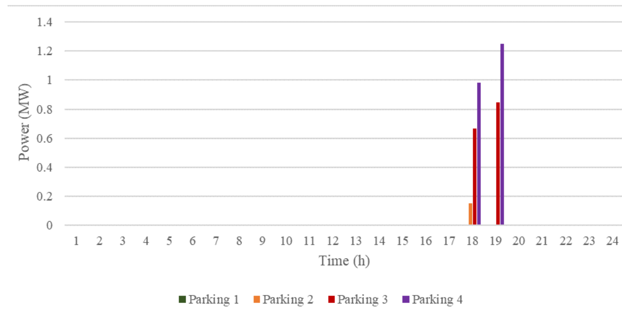

Fig. 9. Discharging profile of different parking lots in case 1.

Charging and discharging of EVs is dependent on the electricity price and technical issues like DN's load and bus voltages. As seen from Fig. 8, at 13-18 and 21-24, EVs are charged on account of lower prices. Also, at times when DN's load is lower than peak, EVs can be charged.

Since there is no EV in parking lots after midnight, there would not be any charging and discharging despite the low electricity price between 2 and 5, which is evident in the given figures. As seen in Fig.1, peak load occurs at 18-19, during which EVs are discharged. The injected power from EVs to DN aids DN in supplying the loads. Therefore, it is concluded that DSO prefers to charge EVs in off-peak periods accompanied by lower prices while discharging them at higher prices.

The hourly profile of power loss is presented in Fig. 10.

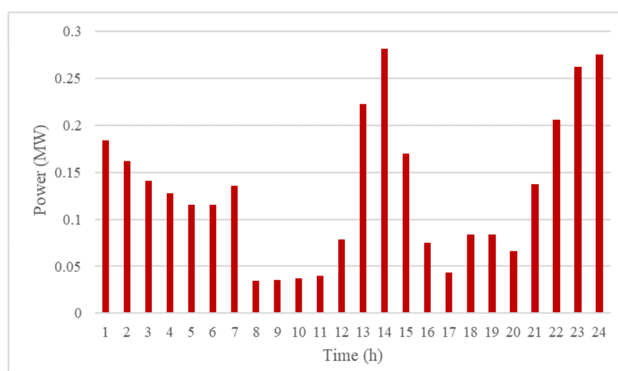

Fig. 10. Hourly profile of power loss.

As it is acknowledged, the imbalance between demand generation leads to power transaction which inevitably is accompanied by power loss. Network optimization should be planned to take the edge off that loss. It is observed that the least power loss occurs when the amount of power proceedings from the upstream network

Table 5. The probability of each scenario.

Scenario No.	Probability (%)
1	0.088
2	0.102
3	0.103
4	0.119
5	0.095
6	0.089
7	0.128
8	0.089
9	0.096
10	0.091

has been scaled down following augmentation of the electricity price. In this regard, by optimizing the performance of DGs, WTs, and smart planning of PLs, EM can moderate the loss.

4.2. Second case study

In Second Case Study, the optimization of EM in DN in the presence of parking lots considering the uncertainties of the traffic pattern, price, load, and initial stored energy at EV batteries is done. The required data are previously provided.

The uncertainties of traffic patterns include the arrival and departure times of EVs to/from Parking Lots. As said before, several scenarios are used to model the uncertainties of the mentioned parameters. Each scenario is a set of values for uncertain parameters and the probability of each scenario is given (Table 5).

The hourly profile of load and price in different scenarios are detailed in Figs. 11 and 12, respectively.

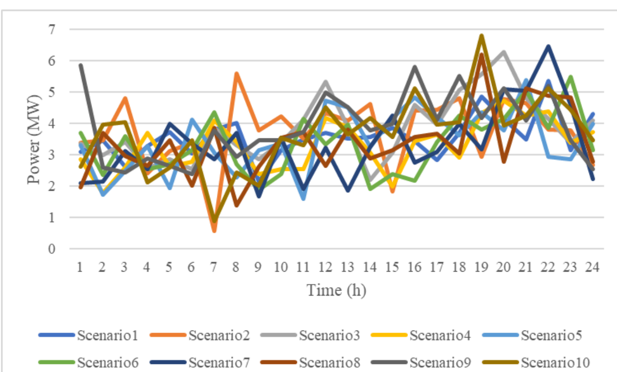

Fig. 11. Hourly profile of active load in defined scenarios.

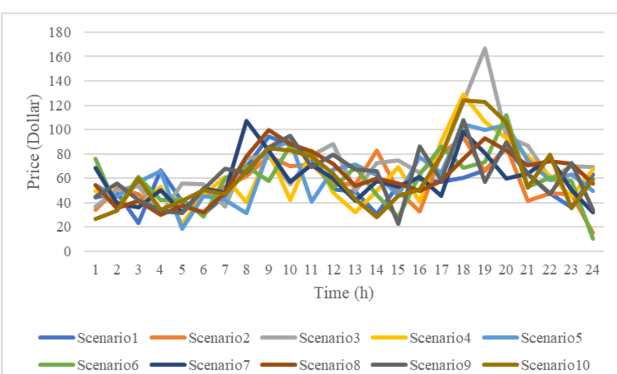

Fig. 12. Hourly profile of electricity price in defined scenarios.

Moreover, the arrival time, departure time, and the initial stored energy of EVs at arrival time in different scenarios are represented in Figs. 13, 14, and 15.

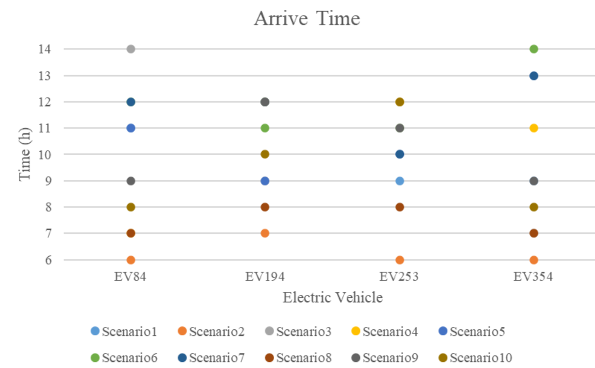

Fig. 13. Arrival time of EVs to parking lots in different scenarios.

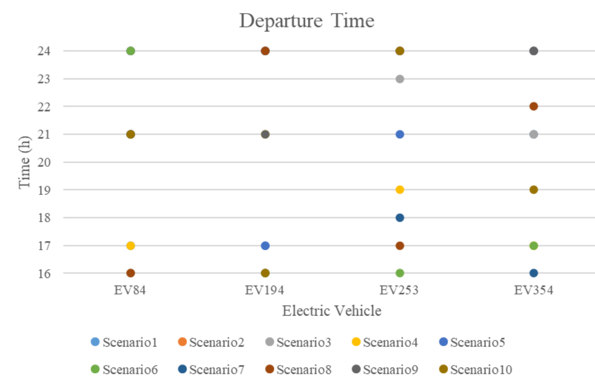

Fig. 14. Departure time of EVs from parking lots in different scenarios.

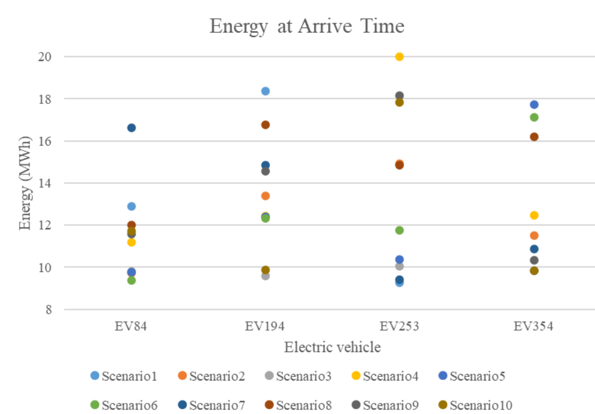

Fig. 15. The initial stored energy of EVs at arrival time to parking lots in different scenarios.

Comparing the attained solution of executing the proposed approach to the defined EM problem in case 2, with the obtained solution from case 1, shows substantial differences. It is seen from Table 6; the total cost of DSO is higher when considering the uncertainties.

For more details, the share of each scenario in total cost is provided in Table 7.

Table 6. A comparison study on total costs in both cases.

Total Cost Case 1	Total Cost Case 2
5003.639	5169.511

Table 7. Cost of each scenario in case 2.

Scenario No.	Total Cost
1	4921.2501
2	5157.0511
3	6128.6772
4	4748.9307
5	5178.6345
6	4751.438
7	4780.6879
8	5084.0721
9	5717.4444
10	5339.6938

According to this table, executing EM based on Scenario 4 has the lowest cost for DSO, while Scenario 3 will cost them the highest.

The following figures demonstrate the energy level of the EV during its stay at the PL and charged and discharged power by EV in case 2. Data from Scenario 10 for EV 4 in PL1 is represented in Fig. 16. This EV has a realistic behavior in the mentioned scenario, arriving at PL at 8 and departing at 16.

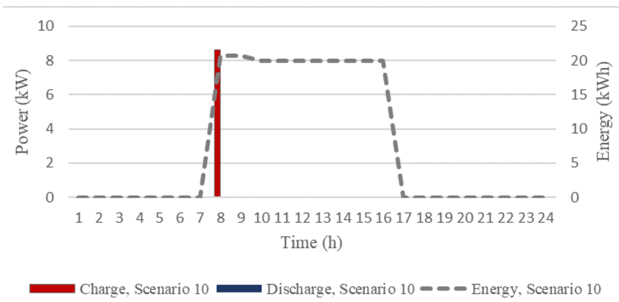

Fig. 16. Energy, charging, and discharging power by EV 4 in PL1 in Scenario 10, viewpoints.

Moreover, the behavior of EV354 in PL4, data from Scenario 2 is studied in Fig. 17. This EV has a nonrealistic behavior in this scenario, arriving at PL at 6 and departing at 24.

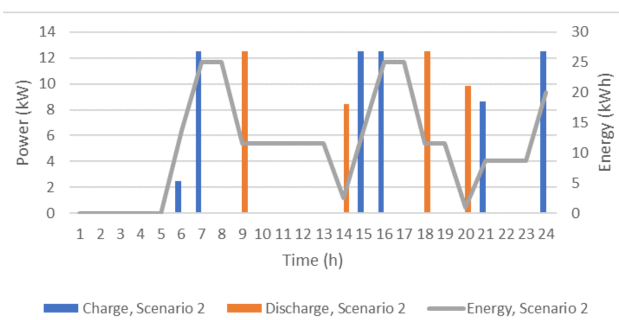

Fig. 17. Energy, charging, and discharging power by EV 354 in PL4 in Scenario 2, viewpoints.

The energy status of the EV from Arrival time to Departure Time is represented by dashed lines. It is evident that the energy level of the EV changes each time charge and discharge happens. According to Fig. 17, charging EVs at 6 and 7 in the morning, results in a boost in EV's energy reaching 25 kWh (Defined E-max). The energy remains constant at this value until it drops to 11.55 kWh and then to 2.5kWh when the EV is discharged consecutively at 9 and 14. Then, by charging the EV at 15 and 16, it shifts back to 25 kWh. Fulfilling the energy capacity of the EV means that it can participate in the electricity market and power the grid, again. So, at 18 and 20, the EV discharges fully and the energy level descends to 1 kWh (Defined E-min). By recharging at 21, part of that energy is compensated. Until it charges again and leaves the PL at 24, with an estimated energy of 20 kWh. The amount of power charged and discharged at each step is limited by the minimum and maximum of both charging and discharging power. In the course of the procedure, the energy remained in its defined range between minimum and maximum value, evincing that all constraints are satisfied.

The depiction below attests to hourly price, data from Scenario 2.

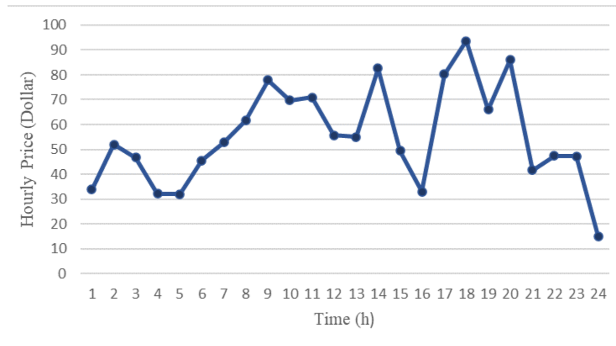

Fig. 18. Hourly Price in Scenario 2, viewpoints.

Comparing Fig.17 and 18, all discharges took place immediately upon the peak price; At 9, 14, 18 and 20. The charging process was carried out at low prices; Notably at 16, 21, and 24. These numerical results are corroboration that the simulation was implemented to satisfy all constraints designated in the Mathematical Modeling.

4.3. Comparison study

In this section, a comprehensive comparison is provided between different scenarios of case 2 and the final solution obtained from case 1. Different scenarios are appointed to manifest the feasibility of the proposed approach dealing with the uncertainty and also the accuracy of the attained results. As defined in the objective function, the cost of purchased power from the upstream network, DG's power generation, and charging/discharging of EVs have a vital effect on DSO's final costs.

A comparison study is delivered between case 1 and 3^{rd} scenario of case 2 from the purchased power from upstream network, viewpoints.

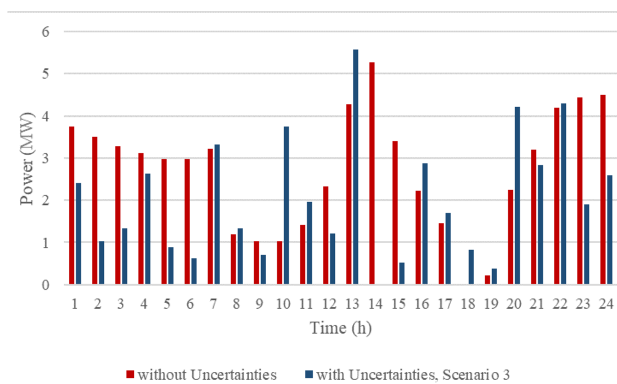

Fig. 19. A comparison study between case 1, and 3^{rd} scenario of case 2, from the purchased power from the upstream network, viewpoints.

Obtained from this collation, appealing the uncertainties to the modeling has revamped the purchase.

In Fig. 20 and 21, the hourly profile of installed DGs' power generation is compared.

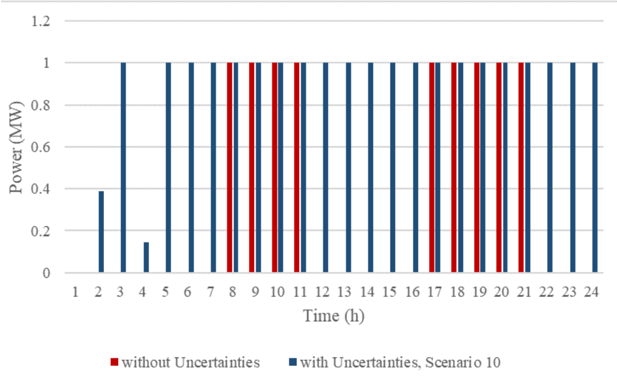

Fig. 20. A comparison study between case 1 and the 10th scenario of case 2 from the installed DG1 power generation, viewpoints.

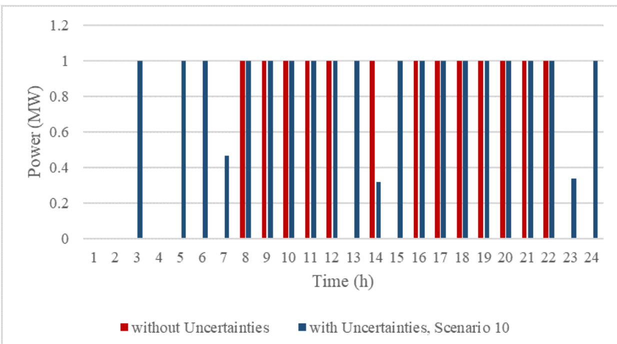

Fig. 21. A comparison study between case 1 and the 10th scenario of case 2 from the installed DG2 power generation, viewpoints.

The comparison shows that the duration of power generation by dispatchable DGs is higher in case 2, stating an improvement in the DG function in DN after considering the Uncertainties.

Moreover, the two identical wind turbines were placed in the respective distribution network to upgrade the performance of the network, meet the demand and thus reduce the total cost of the operation. The power generation of the wind turbine at different hours of the day is investigated in both defined cases.

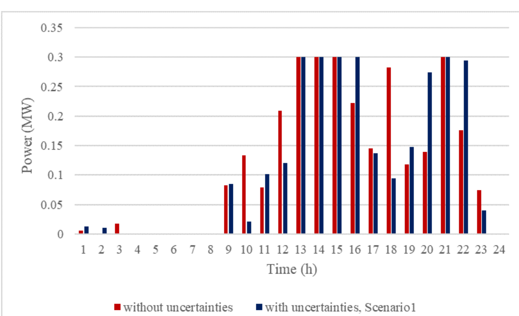

Fig. 22. A comparison study between case 1 and 1st scenario of case 2 from the installed Wind turbine1 power generation, viewpoints.

As it is evident from Fig. 22, the power generation of Wind turbines slightly changes after applying the uncertainties to the modeling. Two critical variables that play a role in the quantity of the generated power, are demonstrated in Fig. 23. While high electricity prices would require more generation from the WT, Wind speed can limit it at any time.

In Figs. 24 and 25 the charging and discharging profiles of different parking lots are provided and a comparison study is done between the defined cases.

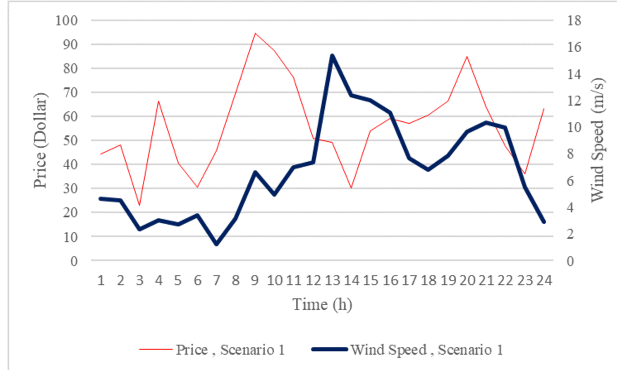

Fig. 23. Electricity price and wind speed in scenario 1, viewpoints.

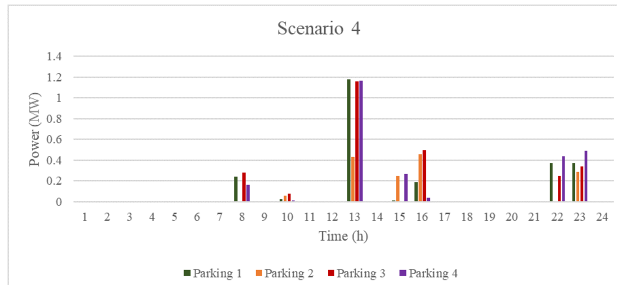

Fig. 24. Charging profile of parking lots in 4th scenario of case 2.

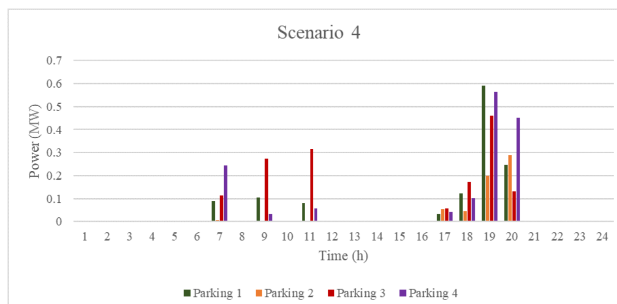

Fig. 25. Discharging profile of parking lots in 4th scenario of case 2.

As it was stated earlier in case 1, charging and discharging of EVs are dependent on the electricity price and technical issues; Applying uncertainties does not alter its nature. Moreover, as load, price, arrival and departure time, and EV initial energy change in case 2 (Figs. 11, 12), so does the charge/discharge profile.

As known, EM in DN is an optimization problem considering the technical and economic issues. Voltage amplitude is the main operational parameter of DN which affects power loss, etc. In this regard, voltage amplitude is considered a constraint that must be preserved in a suitable range. To validate the fact that the proposed approach can maintain the voltage in the preferable limit, the voltage of DN nodes with installed parking lots is represented. In this regard, Figs. 26-29 are provided.

It is concluded that the Voltage profile of buses is escalated up to the defined maximum value which prevents voltage drop. Voltage drop can become a safety concern as it results in harmful consequences. Therefore, the technical parameters of the DN are enhanced in case 2.

A comparison study between case 1 and the 7th scenario of case 2 from the power loss, viewpoints, is represented in Fig. 30, indicating a high-profile diminution in power loss comparatively in case 2.

As discussed before, considering uncertainties results in a rise in

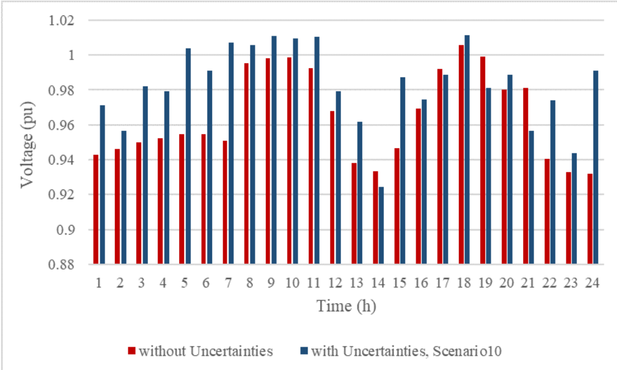

Fig. 26. A comparison study between case 1 and the 10th scenario of case 2 from the voltage profile of the 8_{th} bus connected to PL1, viewpoints.

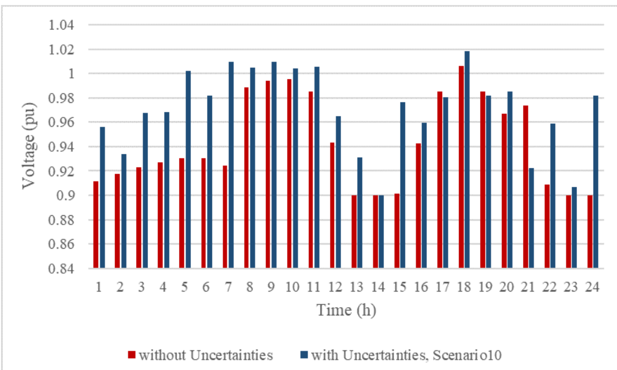

Fig. 27. A comparison study between case 1 and the 10th scenario of case 2 from the voltage profile of the 18_{th} bus connected to PL2, viewpoints.

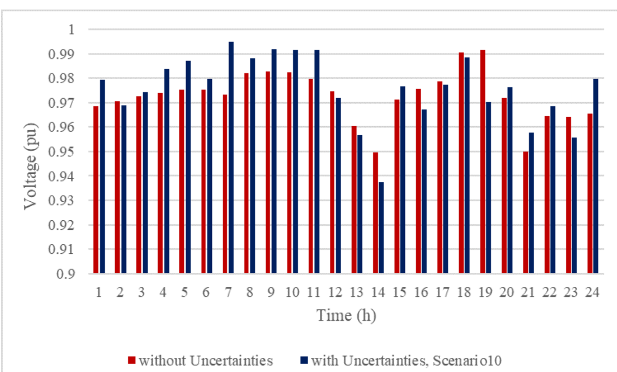

Fig. 28. A comparison study between case 1 and the 10th scenario of case 2 from the voltage profile of the 25_{th} bus connected to PL3, viewpoints.

cost, however, evidently, the general circumstances are ameliorated in case 2 when DGs and WTs are manipulated smartly, and Parking Lots are wielded to subdue the hindrance of the uncertainties in their charging/discharging planning caused by traffic, the network beholds momentous changes in power loss.

5. Conclusions

In this study, a new eco-technical scheme for energy management in modern distribution networks in the presence of parking lots considering the uncertainties of load, price, renewable energies, and traffic patterns is proposed. This method is employed to model the uncertainties mentioned earlier using the scenario-based stochastic approach. Notably, the uncertainties related to traffic patterns lead to different scenarios in which the arrival/departure time of

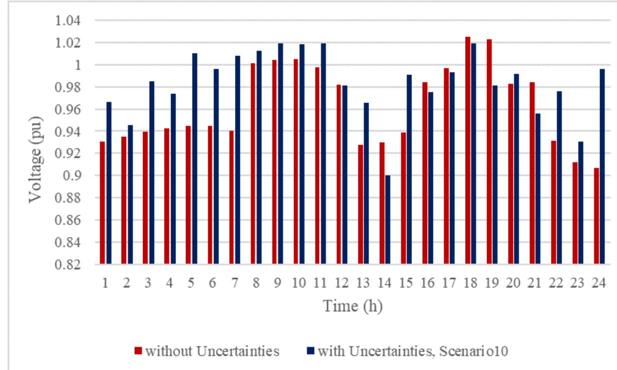

Fig. 29. A comparison study between case 1 and the 10th scenario of case 2 from the voltage profile of the 30_{th} bus connected to PL4, viewpoints.

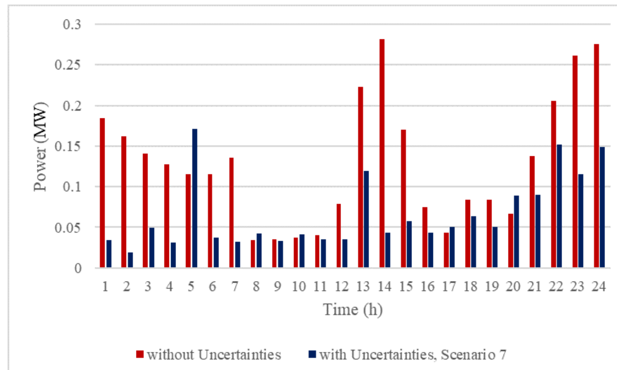

Fig. 30. A comparison study between case 1 and the 7th scenario of case 2 from the power loss, viewpoints.

EVs to/from parking lots and EVs' initial stored energy in their batteries would be different. The mentioned problem is modeled as a MINLP problem and is solved using the DICOPT solver in GAMS software. Two different cases are defined to validate the feasibility of the proposed approach and the accuracy of the attained results. Uncertain parameters are treated as deterministic ones in case 1, whereas in case 2 the uncertainties are applied to the modeling.

In both cases, the number of different parameters including purchased power from the upstream network, power generation of DGs, and charging/discharging of parking lots are dependent mainly on the electricity price and also the load demand of the network. In off-peak periods with lower prices, distribution system operators often opt to purchase a larger amount of power from the upstream network, while at peak periods, DGs work near their nominal capacity and generate a higher amount of power.

In the parking lots, charging is mainly done at lower prices, and discharging happens at peak loads. The discharge allows the distribution system to provide the required loads. It must be mentioned that each parking lot has its own charging/discharging profile on account of the price of electricity, demand, hours of electric vehicle presence in the parking lot, the EVs characteristics, and also due to the technical issues of the node where the parking lot is installed.

A comparison of the two cases reveals that the total cost of a distribution system operator increases in case 2 where the uncertainties are accounted for in EM in the distribution system.

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