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Robust Optimal Coordinated Charging Bidding of Ancillary Services for the Vehicle to Grid in Regulation and Spinning Reserve Markets

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Abstract— *Vehicle to grid (V2G) is one the most important ways to effectively integrate electric vehicles (EVs) with electric power systems. The important benefits can be made by V2G such as reducing/increasing the cost/revenue of EV owners and technically sup-porting electric power systems. Concerning technical and regulatory constraints, EV owners must participate in electricity mar-kets via aggregators. This paper proposes a robust optimal coordinated charging (OCC) model including bidding ancillary ser-vices for regulation and spinning reserve markets. The presented work handles the uncertain behavior of the electricity market that are ancillary service prices and their deployment signals by the robust optimization approach. The aim of optimization is the maximization of the aggregator's profits from V2G by joining the ancillary services markets. The recommended robust OCC model which is a robust linear problem (RLP) model is simulated by the CPLEX solver in GAMS software. An assumed set of 10000 EVs in the electric reliability council of Texas (ERCOT) electricity markets is considered for doing simulations. Employ-ing the presented model in this test system shows the efficacy of the proposed model in comparison to other deterministic and stochastic models.*

Keywords—Electric vehicles (EVs), electricity market, optimal coordinated charging (OCC), regulation service, robust optimization, vehicle to grid (V2G)

NOMENCLATURE

Abbreviations

EV	Electric Vehicle
GAMS	General Algebraic Modelling System
LP	Linear Programing
OCC	Optimal coordinated charging
PDF	Probability Density Function
POP	Preferred Operating Point
RER	Renewable Energy Resource
RLP	Robust Linear Programing
SOC	State of Charge
V2G	Vehicle to Grid

Indices

i	Indices of the EVs
m	Indices of the objective function and constraints
n	Indices of the decision variables
t	Index of the time (in this study it is one hour)

Parameters

$\beta(m)$	Amount of the preservation level for either fitness function ($m = 0$) or restriction m
δ	Fix price of selling electrical power to EVs owner ($/MWh)
$\hat{d}\,(n)$	Amount of the deviance of the indeterminate element of the control variable n
$\hat{e}\,(m,n)$	Amount of the deviance of the indeterminate element of among the control variable n and restriction m
$\overline{d}\,(n)$	Nominal amount of the indeterminate element of the control variable n
$\overline{e}\,(m,n)$	Nominal amount of the indeterminate element of among the control variable n and restriction m
$AV(i)$	Availability of EV i for contribution in V2G (1 if EV is available, otherwise, 0)
$C_{mar}^{real}\,(t)$	Real time price of the energy market at hour t ($/MWh)
$C_{reg}^{up}\,(t)$	Market price of regulation up at hour t ($/MWh)
$C_{reg}^{dw}(t)$	Market price of regulation down at hour t ($/MWh).
$C_{sr}\,(t)$	Market price of regulation down at hour t ($/MWh)
$d(n)$	Indeterminate element of the control variable n
$D\,(t,i)$	Percentage of unscheduled departure of EV i at hour t
$E(.)$	Operator of expected value
$e(m,n)$	Indeterminate element of among the control variable n and restriction m
E_{reg}^{dw}	Percentage of EV's deployment for contribution in regulation down
E_{red}^{sr}	Percentage of EV's deployment for contribution in spinning reserve
E_{reg}^{up}	Percentage of EV's deployment for contribution in regulation up
$lx(n)$	Inferior bound of the control variable n
$P^{\max}(i)$	Maximum electrical power charging of EV i (MW)
$T_{trip}(i)$	Trip time of EV i (h)
$ux(n)$	Higher bound of the control variable n
$z,\ p,\ \theta$	Supplementary variables of the robust optimization modelling

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$\beta^{com}(t,i)$	Compensation factor for unscheduled departure of EV i at hour t
$\eta^{ch}(i)$	Charging efficiency of EV i
$\rho_{EV}^{st}(t)$	Expected percentage of staying EVs to do charge at hour t
$SoC^{dfin}(i)$	Desired final SoC of EV i (MWh)
$SoC^{ini}(i)$	Initial SoC of EV i (MWh)
$SoC^{max}(i)$	Maximum SoC of EV i (MWh)
Sets	
Ψ (m)	Set of indeterminate parts of the fitness function ($m = 0$) and limitation m picking up values from vagueness interval
$\Theta(m)$	Indeterminate parts of the fitness function ($m = 0$) and limitation m picking up values from the shortened vagueness interval
$J(m)$	Set of indeterminate parts of the fitness function ($m = 0$) and limitation m
M	Set of the fitness function and the restrictions
N_{EV}	Set of EVs
T	Set of hours
Variables	
$P_{dif}^{\max}(t,i)$	Maximum differential electrical power drawn by EV i at hour t (MW)
$P_{inc}^{\max}(t,i)$	Maximum incremental electrical power drawn by EV i at hour t (MW)
$P_{reg}^{dw}(t)$	Electrical power of regulation down at hour t (MW)
$P_{red}^{sr}(t,i)$	Reduction in electrical power
$P_{reg}^{up}(t)$	Electrical power of regulation up at hour t (MW)
$P_{EV}(i,t)$	Charging power of EV i at hour t (MW)
$P_{sr}(t)$	Electrical power of spinning reserve at hour t (MW)
$POP(t,i)$	Preferred operating point EV i at hour t (MW).
$Revenue$	Revenues achieved by EVs aggregator in day ahead
$SoC^{fin}(i)$	Final SoC of EV i (MWh)
$SoC_{red}^{Trip}(i)$	SoC reduction initiated by trip EV i (MWh)
x_n	Decision variable n

1. INTRODUCTION

1.1. Motivation

EVs can integrate with electric power systems via V2G in a reliable, cost-effective, and beneficial way [1, 2]. If the V2G mechanism is properly implemented, the negative impact of uncontrollable RERs will be reduced, and also the aging electric power system will be delayed [3, 4]. They also can play a vital role to support energy and ancillary services and make bilateral benefits for both electric power systems and EVs owners [5]. Furthermore, EVs can make positive environmental impacts on world decarbonization and can offer several financial benefits for various market players [6–8].

Aggregation of EVs is essential to contribute to ancillary service and electrical energy markets as OCC [9]. This is due to the fact that the least bid capacities in the range of MW are required by current electric market regulations, while an EV individually doesn't have this size [10]. On the other hand, each player in the ancillary service market should have an essential level of availability and reliability, while an EV cannot individually make these levels without creating troublesomeness for EV's owner [11].

The V2G can be unidirectional or bidirectional [12, 13]. The latter is more effective for regulation and supporting spinning reserve [14], while the former has simplicity for implementation and makes fewer challenges for both aggregator and the EV owner [15]. From the point of view of the aggregator, there are several papers on the topic of participating in ancillary service markets in the day-ahead including the regulation market and spinning reserve market [16]. Nevertheless, the majority of them deal with deterministic modeling and don't consider the uncertainties in aggregated bidding [17, 18]. Therefore, this paper wants to include the uncertainties pertaining to the electricity market that are ancillary service prices and the deployment signals as well as EVs aggregators as a robust OCC model.

1.2. Literature review

Recently, various optimization models have been proposed to deal with uncertainties related to electricity markets in presence of EVs aggregators as OCC. For example, Ref. [19] presents a comparative study of power management strategies for secondary frequency regulation (SFR) employing a fleet of EVs is presented. A hierarchical control scheme is employed to compare two cases, namely control at the charging station level and control at the EVs level. Ref. [20] proposes optimal scheduling of ancillary services provided by an electric vehicle aggregator. It suggests an optimization approach for EVs aggregators that jointly considers the most important aspects influencing EVs profitability, such as uncertainty, drivers' patterns, capacity constraints, state of charge constraints, regulation demand constraints, regulation offer constraints, regulation bounds constraints, and power-system security constraints. Ref. [21] introduces a stochastic programming model to formulate a unit commitment problem subjected to security-based constraints in a power system equipped with a high penetration level of EVs. However, it doesn't consider the electricity market. Sequential linear programming is proposed by [22, 23] to optimize EV charging. However, they don't take into EVs aggregator revenues consideration. Ref. [24] proposes a stochastic offering regulation service mechanism for EV aggregators in the electricity market. It considers regulation capacity and price in a deterministic way while it uses Monte Carlo simulations to model the uncertainties related to the EV driving patterns, energy market prices, and regulation energy requirements. It divides the total problem into multiple reduced sub-problems and consequently may cause a sub-optimal solution. Ref. [25] presents coordinated bidding of EVs aggregators in the electricity market considering uncertainties using fuzzy optimization. It uses the autoregressive integrated moving average model to predict electricity market parameters. Ref. [5] briefly reviews the interrelation of ancillary services and EVs aggregators which can increase the flexibility of power system operation. In Ref. [11], regarding the pattern of EVs' charging and power system's regulation signal, a data-driven method is presented to optimize EV's contribution to the ancillary service market. Ref. [26] presents an EV aggregator that is an EVs charging station equipped with a photovoltaic installation. The aggregator interacts with the power system such that optimizes the contribution of this solar powered EVs aggregators in electrical energy and ancillary services markets. In Ref. [27] an ancillary service bidding is proposed based on fuzzy linear programming such that the uncertain operation of bidirectional V2G of EVs aggregator is optimized. Ref. [28] presents a stochastic model to use EVs aggregator for the provision of ancillary services. This model uses stochastic pro-gramming considering the optimal bidding and deterministic EV's behavior. Some references evaluate the contribution of the bidirectional V2G on ancillary services based on EVs aggregator framework in numerous real word power systems [2, 29–32]. In Ref. [33] a decision support tool is presented for EVs aggregators that can specify the optimal bidding strategy to contribute to the energy and ancillary service markets. It models the stochastic behavior of EVs as a stochastic programming model, where risk aversion is demonstrated by the conditional value-at-risk.

It can be noted that most above mentioned references model the behavior of EV owners in different ways such as deterministic, stochastic scenario-based, and stochastic fuzzy based. The scenario-based approach needs rich data about the PDF of the un-certain parameters. Consequently, if there is no adequate information about the PDF of indeterminate parameters, the proposed model will fail to obtain optimal results. Also, the nature of scenario-based stochastic optimization is multi-stage stochastic optimization and the combinatorial growth of computation burden. On the other hand, fuzzy optimization needs a membership function and solving the problem for multiple values of cuts and is computationally expensive. Therefore, in this paper, the pro-posed model is solved by robust optimization which shows its capability in other applications.

1.3. Contributions and organization

This paper models the uncertainties of bidding EV aggregators into energy and ancillary service markets by robust OCC model, which has less been previously paid attention to them. The proposed EV aggregator model is based on RLP that coordinates the provision of ancillary services of electricity markets that are regulation and spinning reserves using unidirectional V2G. It also considers numerous electricity market uncertainties that are the ancillary service prices and the ancillary service deployment signals. One of the most important features of the robust OCC proposed model is to capably include uncertainties while keeping the manageability of the problem size. This is due to the fact that unlike the work done in Ref. [24], robust optimization doesn't want to denote each indeterministic parameter by a number of scenarios. Also, unlike Ref. [25], RLP doesn't need a membership function and working out the problem for multiple values of cuts. Therefore, it can optimize the charging of all EVs at the same time. It also treats market aspects that were omitted in [21], and it maximizes EVs aggregator revenues, which is not treated by [22, 23].

The aims of the presented work are as follows:

- Scrutinizing a robust OCC model to assess uncertainties of bidding EV aggregators into energy and ancillary service mar-kets,
- Coordinating the provision of ancillary services of electricity markets that are regulation and spinning reserves, and
- Modelling uncertainties that are behaviour of the EVs owner, ancillary service prices, and the ancillary service deployment signals.

The paper is continued as follows: Section 2 states the problem formulation for the proposed model. At that time, Section 3 re-develops the anticipated model handling the robust optimization vagueness modeling. Next, the solution algorithm and flowchart are stated in Section 4. Later, Section 5 precisely discusses simulation outcomes and results. Last, Section 6 depicts the paper's conclusion.

2. PROBLEM FORMULATION FOR PROPOSED OCC

This section elucidates the definition of the OCC model, assumptions, objective function, and the problem's restrictions as follows:

2.1. Proposed OCC

It is clear that in unidirectional V2G, EVs are not capable of discharging into the power systems. Thereby, the EVs aggregator offers its ancillary service capacities regarding POP which is the amount of difference between the actual and scheduled charging rate of each EV. The EVs aggregator has to optimize its POP and consequently its ancillary service capacities such that makes the most of income. It is assumed that the EVs aggregator has to submit its bids for the day ahead. Consequently, it faces numerous uncertainties related to the electricity market that they should be considered for the day ahead bidding. The main goal of the EVs aggregator is to harvest maximum revenues via contributing to ancillary service markets. This paper assumes that the EVs owners charge their EVs with a fixed energy price so that they don't face the variation in the real-time energy price in the market [13]. Indeed, the benefits of EVs aggregator are originated by both contributing to ancillary service markets and the price differences among the fixed electrical energy rate for charging EVs and the market energy price.

2.2. Assumptions for the optimization model

Numerous assumptions are considered for the suggested optimization model as follows:

- The mechanism of the V2G is unidirectional, therefore, EVs aggregator cannot sell electrical energy to the market.
- The bids are announced by EVs aggregator to the energy market for the day ahead.
- The EVs aggregator sells electrical energy to EVS owners at a fixed energy price while it purchases electrical energy from the electricity market at real-time prices.
- The assumed fixed energy price is lower than the average real-time energy price in market until it makes motivation for EV owners that give their charging control to EVs aggregator and contribute to the V2G scheme.

2.3. Objective function

The proposed OCC has an objective function as (1) that is revenue of EVs aggregator within day ahead. The objective function includes two parts. The first part is the aggregator's income including contribution to regulation and spinning reserve market and selling electrical energy to EVs owner with a fixed price, while the second part is the aggregator's cost related to purchasing elec-trical energy from the electricity market in real-time price. It can be noted that other costs of EVs aggregator comprising infra-structure cost of charging station, communication costs, and personal costs are taken fixed into consideration notwithstanding variation of the amount of the daily bids [25].

$$\max\{Revenue\} = \max\Bigg\{\Bigg[\sum_{t\in T}\Big[C_{reg}^{up}(t)\times P_{reg}^{up}(t)+C_{reg}^{dw}(t)\times P_{reg}^{dw}(t)+C_{sr}(t)\times P_{sr}(t)+\delta\times\sum_{i\in N_{EV}}E(P_{EV}(i,t))\Big]\times\rho_{EV}^{st}(t)\Bigg]$$
$$-\Bigg[\sum_{t\epsilon T}\Bigg[\sum_{i\epsilon N_{EV}}E(P_{EV}(i,t))\times C_{\max}^{real}(t)\Bigg]\times\rho_{EV}^{st}(t)\Bigg]\Bigg\} \tag{1-a}$$

$$P_{reg}^{up}(t)=\sum_{i\epsilon N_{EV}}P_{inc}^{\max}(t,i)\qquad\forall\, t\in T \tag{1-b}$$

$$P_{reg}^{down}(t)=\sum_{i\in N_{EV}}P_{dif}^{\max}(t,i)\qquad\forall\, t\in T \tag{1-c}$$

$$P_{sr}(t)=\sum_{i\epsilon N_{EV}}P_{red}^{sr}(t,i)\qquad\forall\, t\in T \tag{1-d}$$

$$E(P_{EV}(i,t))=P_{inc}^{\max}(t,i)\times E_{reg}^{up}+POP(t,i)-P_{dif}^{\max}(t,i)\times E_{reg}^{down}-P_{red}^{sr}(t,i)\times E_{red}^{sr}\qquad\forall t\in T,\forall\, i\in N_{EV} \tag{1-e}$$

$$\rho_{EV}^{st}(t)=\begin{cases}1-\sum_{tt=1}^{t}\sum_{i\epsilon N_{EV}}D(tt,i) & t<T_{trip}(i)\\ 1-\sum_{tt=T_{trip}(i)}^{t}\sum_{i\epsilon N_{EV}}D(tt,i) & t\geq T_{trip}(i)\end{cases}\qquad\forall\, t\in T \tag{1-f}$$

2.4. Constraints

The constraints formulated for the proposed OCC problem are outlined as follows [25]:

$$\sum_{t=1}^{T_{trip}(i)}E(P_{EV}(i,t))\times\beta^{com}(t,i)\times\eta^{ch}(i)+SoC^{ini}(i)\leq SoC^{\max}(i)\qquad\forall\, i\in N_{EV} \tag{2-a}$$

$$\sum_{t\in T}E(P_{EV}(i,t))\times\beta^{com}(t,i)\times\eta^{ch}(i)+SoC^{ini}(i)-SoC_{red}^{Trip}(i)\leq SoC^{max}(i)\qquad\forall\, i\in N_{EV} \tag{2-b}$$

$$\beta^{com}(t,i)=1+\frac{D(t,i)}{1-D(t,i)}\qquad\forall\, t\in T,\forall\, i\in N_{EV} \tag{2-c}$$

$$\left[P_{inc}^{max}(t,i)+POP(t,i)\right]\times\beta^{com}(t,i)\times\eta^{ch}(i)+SoC^{ini}(i)\leq SoC^{max}(i)\qquad\forall\, t\in T,\forall\, i\in N_{EV} \tag{2-d}$$

$$P_{red}^{sr}(t,i) \le POP(t,i) - P_{dif}^{max}(t,i) \qquad \forall\, t \in T, \forall\, i \in N_{EV} \quad \text{(2-e)}$$

$$\left[P_{inc}^{max}(t,i) + POP(t,i)\right] \times \beta^{com}(t,i) \le P^{max}(i) \times AV(i) \qquad \forall\, t \in T, \forall\, i \in N_{EV} \quad \text{(2-f)}$$

$$SoC^{fin}(i) \ge SoC^{dfin}(i) \qquad \forall\, i \in N_{EV} \quad \text{(2-g)}$$

$$SoC^{fin}(i) = SoC^{ini}(i) \qquad \forall\, i \in N_{EV} \quad \text{(2-h)}$$

$$P_{inc}^{max}(t,i) \ge 0, \quad POP(t,i) \ge 0, \quad P_{dif}^{max}(t,i) \ge 0, \quad P_{red}^{sr}(t,i) \ge 0 \qquad \forall\, t \in T, \forall\, i \in N_{EV} \quad \text{(2-i)}$$

The constraints (2-a)-(2-h) show some restrictions for batteries of EVs. Restrictions (2-a), (2-b), and (2-d) guarantee that EV's battery will not overcharge earlier than the initial travel trip, during the daily trip, and throughout the mid-scheduling period, respectively. The rate restrictions of the EV's battery are expressed by (2-e) and (2-f). $\boldsymbol{AV(i)}$ in (2-f) shows the availability of EVs in the day ahead. If EVs are available and contribute to the electricity market, $\boldsymbol{AV(i)=1}$ otherwise, 0. Departure availability that is $\boldsymbol{D(t,i)}$ in (2-c), models the probability that the EVs cannot connect to the grid for that whole hour. It helps the aggregator to model and to schedule EVs regarding the behavior of EV's owner. Eq. (2-g) guarantees that the charging amount of the EV's battery will be reached to the anticipated level at the end of the day ahead. Indeed, this restriction leads to announcing the needed minimum SoC by EV's owner to the aggregator. This needed amount can change for each weekday. Constraint (2-h) expresses that final and initial SoC of EVs are same on the simulation. Regarding unidirectional bidding, (2-i) represents the EV's battery variables and restrictions should be positive.

3. Robust Optimization Method

Different optimization methods can handle uncertainties. For example, probabilistic optimization, stochastic programming, interval optimization, and robust optimization [34]. It can be noted that the latter is very well-known to scholars and planners because of its prevailing risk management, high robustness, and low computational load [34]. It can be noted that the most important advantage of robust optimization in comparison with other approaches is the lack of need for PDF or membership functions of the uncertain inputs [35].

The succeeding equations depict a typical LP optimization model as [35]:

$$Min \sum_{n\in N} d(n) \times x(n) \qquad (3)$$

Subject to

$$\sum_{n\in N} e(m,n) \times x(n) \le f(m) \qquad \forall\, m \in M \quad \text{(4-a)}$$

$$lx(n) \le x(n) \le ux(n) \qquad \forall\, n \in N \quad \text{(4-b)}$$

$$x(n) \in Z; \quad \forall n = 1,\ 2,\ \ldots,\ k \quad and$$
$$x(n) \in R; \quad \forall n = k+1, k+2, \ldots \quad \text{(4-c)}$$

This approach considers limited intervals to model the input uncertainties. These intervals are determined concerning sets of uncertainties. Thereby, $d(n)$ and $e(m,n)$ as the uncertain elements are written as follows [35]:

$$d(n) = \left[\overline{d}(n) - \hat{d}(n),\ \overline{d}(n) + \hat{d}(n)\right] \qquad \forall n \in N \quad \text{(5-a)}$$

$$e(m,n) = \left[\overline{e}(m,n) - \hat{e}(m,n),\ \overline{e}(m,n) + \hat{e}(m,n)\right] \qquad \forall n \in N, \forall m \in M \quad \text{(5-b)}$$

The proposed RLP problem is formulated by introducing an integer parameter $\beta(m)$ which controls the conservation level and it belongs to the interval $[0, |J(m)|]$. Surely, $J(m)$ is a set of uncertain elements of not only the objective function $(m=0)$ that is $J(0) = \{n\,|d(n) > 0\}$ but also the restriction m that is $J(m) = \{n\,|e(m,n) > 0\}$ [36]. Considering that all the uncertain elements cannot deviate from their nominal values at the same time, this paper assumes that up to $\beta(m)$ of these variables can change within specified intervals defined by (5), although the deviation of one of them is circumscribed by subsequently reduced intervals [36]:

$$dt(0) = \left[\overline{dt}(0) - (\beta(0) - \beta(0)) \times \widehat{dt}(0), \overline{dt}(0) + (\beta(0) - \beta(0)) \times \widehat{dt}(0)\right] \qquad \forall dt(0) \in J(0), m = 0 \quad \text{(6-a)}$$

$$et(m,n) = \left[\overline{et}(m,n) - (\beta(m) - \beta(m)) \times \widehat{et}(m,n),\ \overline{et}(m,n) + \left(\beta(m) - \beta(m)\right) \times \widehat{et}(m,n)\right] \qquad \forall\, et(m,n) \in J(m), \forall\, m \in M \quad \text{(6-b)}$$

where $\beta(m)$ is a real number. For instance, if $\beta(m)$ is equal to 2.5, it can be deduced that uncertain elements of two restrictions can change inside the complete range of the defined limits, although, uncertain elements of one of the restrictions have a disparity inside half range.

The RLP model of the suggested LP expressed as (1) is assumed as [35]:

$$Max \sum_{n\in N} \overline{d}(n) \times x(n) + \max_{\{\Psi(0)\cup\{\Theta(0)\}|\Psi(0)\subseteq \mathrm{J}(0), \Psi(0)=\Upsilon(0), \Theta(0)\in J(0)/\Psi(0)\}} \left\{ \sum_{n\in\Psi(0)} \hat{d}(n) \times |x(n)| + (\Upsilon(0) - \Upsilon(0)) \times \widehat{dt}(0) \times |xt(0)| \right\} \qquad (7)$$

Subjected to

$$\sum_{n\in N} \overline{e}(m,n) \times x(n) + \max_{\{\Psi(\mathrm{m})\cup\{\Theta(m)\}|\Psi(\mathrm{m})\subseteq \mathrm{J}(\mathrm{m}),\ \Psi(\mathrm{m})=\Upsilon(\mathrm{m}), \Theta(m)\in J(m)/\Psi(\mathrm{m})\}} \left\{ \sum_{n\in\Psi(0)} \hat{e}(m,n) \times |x(n)| + (\Upsilon(0) - \Upsilon(0)) \times \widehat{et}(m,n) \times |xt(m)| \right\} \le f(m) \qquad \forall m \in M \quad (8)$$

Moreover, (4-b) and (4-c).

Eqs. (7)-(8) and (4-b)-(4-c) represent a robust nonlinear problem that is linearized by duality theory [35], and thereby, the final RLP is specified as [35]:

$$Min \sum_{n\in N} \overline{d}(n) \times x(n) + z(0) \times \beta(0) + \sum_{n\in J(0)} p(0,n) \qquad (9)$$

Subjected to

$$\sum_{n\in N} \overline{e}(m,n) \times x(n) + z(m) \times \beta(m) + \sum_{n\in J(m)} p(m,n) \le f(m) \qquad \forall m \in M \quad \text{(10-a)}$$

$$z(0) + p(0,n) \ge \hat{d}(n) \times \theta(n) \qquad \forall n \in J(0) \quad \text{(10-b)}$$

$$z(m) + p(m,n) \ge \hat{e}(m,n) \times \theta(n) \qquad \forall n \in J(m), \forall m \in M \quad \text{(10-c)}$$

$$-\theta(n) \le x(n) \le \theta(n) \qquad \forall n \in N \quad \text{(10-d)}$$

$$lx(n) \le x(n) \le ux(n) \qquad \forall n \in N \quad \text{(10-e)}$$

$$p(m,n) \geq 0, \qquad \forall n \in J(m), \ \forall m \in M \quad (10\text{-f})$$
$$\theta(n) \geq 0 \qquad \forall n \in N \quad (10\text{-g})$$
$$z(m) \geq 0 \qquad \forall m \in M \quad (10\text{-h})$$
$$x(n) \in Z; \quad \forall n = 1, 2, \ldots, k \quad and$$
$$x(n) \in R; \quad \forall n = k+1, k+2, \ldots \quad (10\text{-i})$$

Thereby, Eqs. (1)-(2) in deterministic form can be reformulated by (9)-(10) as follows:

$$\max Revenue = \max \Bigg\{ \Bigg[\sum_{t \in T} [\overline{C}^{up}_{reg}(t) \times P^{up}_{reg}(t) + \overline{C}^{dw}_{reg}(t) \times P^{dw}_{reg}(t)$$
$$\overline{C}_{sr}(t) \times P_{sr}(t) + \delta \times \sum_{i \in N_{EV}} E(P_{EV}(i,t))] \times \rho^{st}_{EV}(t) \Bigg] - \Bigg[\sum_{t \in T} [$$
$$\sum_{i \in N_{EV}} E(P_{EV}(i,t)) \times C^{real}_{mar}(t)] \times \rho^{st}_{EV}(t) \Bigg] \Bigg\} + z_0^{C^{up}_{reg}} \times \beta_0^{C^{up}_{reg}} +$$
$$z_0^{C^{dw}_{reg}} \times \beta_0^{C^{dw}_{reg}} + z_0^{C_{sr}} \times \beta_0^{C_{sr}} + \sum_{t \in T} \left[p_0^{C^{up}_{reg}}(t) + p_0^{C^{dw}_{reg}}(t) + p_0^{C_{sr}}(t) \right] \quad (11\text{-a})$$

Also, (1-b) − (1-d), **and** (1-f) (11-b)

$$E(P_{EV}(i,t)) = \Big[P^{\max}_{inc}(t,i) \times \overline{E}^{up}_{reg} + POP(t,i) - P^{\max}_{dif}(t,i) \times$$
$$\overline{E}^{dw}_{reg} - P^{sr}_{red}(t,i) \times \overline{E}^{sr}_{red} \Big] + z_0^{E^{up}_{reg}} \times \beta_0^{E^{up}_{reg}} + z_0^{E^{dw}_{reg}} \times \beta_0^{E^{dw}_{reg}} +$$
$$z_0^{E^{sr}_{red}} \times \beta_0^{E^{sr}_{red}} \sum_{t \in T} \left[p_0^{E^{up}_{reg}}(t) + p_0^{E^{dw}_{reg}}(t) + p_0^{E^{sr}_{red}}(t) \right] \ \forall t \in T, \forall i \in N_{EV} \quad (11\text{-c})$$

Subjected to

(2) (12-a)

$$z_0^{C^{up}_{reg}} + p_0^{C^{up}_{reg}}(t) \geq \hat{C}^{up}_{reg}(t) \times \theta^{C^{up}_{reg}}(t) \qquad \forall t \in T \quad (12\text{-b})$$
$$z_0^{C^{dw}_{reg}} + p_0^{C^{dw}_{reg}}(t) \geq \hat{C}^{dw}_{reg}(t) \times \theta^{C^{dw}_{reg}}(t) \qquad \forall t \in T \quad (12\text{-c})$$
$$z_0^{C_{sr}} + p_0^{C_{sr}}(t) \geq \hat{C}_{sr}(t) \times \theta^{C_{sr}}(t) \qquad \forall t \in T \quad (12\text{-d})$$
$$z_0^{E^{up}_{reg}} + p_0^{E^{up}_{reg}}(t) \geq \hat{E}^{up}_{reg}(t) \times \theta^{E^{up}_{reg}}(t) \qquad \forall t \in T \quad (12\text{-e})$$
$$z_0^{E^{dw}_{reg}} + p_0^{E^{dw}_{reg}}(t) \geq \hat{E}^{dw}_{reg}(t) \times \theta^{E^{dw}_{reg}}(t) \qquad \forall t \in T \quad (12\text{-f})$$
$$z_0^{E^{sr}_{red}} + p_0^{E^{sr}_{red}}(t) \geq \hat{E}^{sr}_{red}(t) \times \theta^{E^{sr}_{red}}(t) \qquad \forall t \in T \quad (12\text{-g})$$
$$P^{up}_{reg}(t) \leq \theta^{C^{up}_{reg}}(t); \ z_0^{C^{up}_{reg}} \geq 0; \ p_0^{C^{up}_{reg}}(t) \geq 0; \quad \forall t \in T \quad (12\text{-h})$$
$$P^{dw}_{reg}(t) \leq \theta^{C^{dw}_{reg}}(t); \ z_0^{C^{dw}_{reg}} \geq 0; \ p_0^{C^{dw}_{reg}}(t) \geq 0; \quad \forall t \in T \quad (12\text{-i})$$
$$P_{sr}(t) \leq \theta^{C_{sr}}(t); \quad z_0^{C_{sr}} \geq 0; \quad p_0^{C_{sr}}(t) \geq 0; \quad \forall t \in T \quad (12\text{-j})$$
$$P^{max}_{inc}(t,i) \leq \theta^{E^{up}_{reg}}(t); \ z_0^{E^{up}_{reg}} \geq 0; \ p_0^{E^{up}_{reg}}(t,i) \geq 0; \ \forall t \in T, \forall i \in N_{EV} \quad (12\text{-k})$$
$$P^{max}_{dif}(t,i) \leq \theta^{E^{dw}_{reg}}(t); \ z_0^{E^{dw}_{reg}} \geq 0; \ p_0^{E^{dw}_{reg}}(t,i) \geq 0; \ \forall t \in T, \forall i \in N_{EV} \quad (12\text{-l})$$
$$P^{sr}_{red}(t,i) \leq \theta^{E^{sr}_{red}}(t); \ z_0^{E^{sr}_{red}} \geq 0; \ p_0^{E^{sr}_{red}}(t,i) \geq 0; \ \forall t \in T, \forall i \in N_{EV} \quad (12\text{-m})$$

It can be noted that the non-linear terms in (12) will be linear by the duality theory. The indeterminate inputs i.e. market price and percentage of EV's deployment for contribution in regulation up, regulation down, and spinning reserve are demonstrated by symmetric limited intervals as follows:

$$C^{up}_{reg}(t) = \left[\overline{C}^{up}_{reg}(t) - \hat{C}^{up}_{reg}(t), \overline{C}^{up}_{reg}(t) + \hat{C}^{up}_{reg}(t) \right] \qquad \forall t \in T \quad (13\text{-a})$$
$$C^{dw}_{reg}(t) = \left[\overline{C}^{dw}_{reg}(t) - \hat{C}^{dw}_{reg}(t), \overline{C}^{dw}_{reg}(t) + \hat{C}^{dw}_{reg}(t) \right] \qquad \forall t \in T \quad (13\text{-b})$$
$$C_{sr}(t) = \left[\overline{C}_{sr}(t) - \hat{C}_{sr}(t), \ \overline{C}_{sr}(t) + \hat{C}_{sr}(t) \right] \qquad \forall t \in T \quad (13\text{-c})$$
$$E^{up}_{reg}(t) = \left[\overline{E}^{up}_{reg}(t) - \hat{E}^{up}_{reg}(t), \overline{E}^{up}_{reg}(t) + \hat{E}^{up}_{reg}(t) \right] \qquad \forall t \in T \quad (13\text{-d})$$
$$E^{dw}_{reg}(t) = \left[\overline{E}^{dw}_{reg}(t) - \hat{E}^{dw}_{reg}(t), \overline{E}^{dw}_{reg}(t) + \hat{E}^{dw}_{reg}(t) \right] \qquad \forall t \in T \quad (13\text{-e})$$
$$E^{sr}_{red}(t) = \left[\overline{E}^{sr}_{red}(t) - \hat{E}^{sr}_{red}(t), \overline{E}^{sr}_{red}(t) + \hat{E}^{sr}_{red}(t) \right] \qquad \forall t \in T \quad (13\text{-f})$$

The (11)-(13) denote the proposed RLP.

4. The Application of the Solution Algorithm to the OCC Model

With increasing the historical data about EV behavior, some uncertain parameters tend to be deterministic. As an illustration, Ref. [37] represents that when the number of EVs succeeds from 10000, the EV's aggregator can deterministically operate such as a conventional power plant in the electricity market. Therefore, this paper considers some parameters related to EVs as deterministic parameters instead of stochastic. This paper assumes the EV's aggregator is one of the numerous participants in the robust ancillary service market. The variables of the suggested optimal operation model are continuous variables that are electrical power of regulation up and regulation down as well as electrical power of spinning reserve and POP at each hour. Deci-sion variables are as follows:

$$Y(t) = \left[P^{up}_{reg}(t), P^{dw}_{reg}(t), P_{sr}(t), POP(t,i) \right] \qquad \forall t \in T, \forall i \in N_{EV} \quad (14)$$

The suggested model is solved by a GAMS-based solver that is CPLEX 12.1 with a MIP gap of 0.1%. this solver has an appropriate efficacy to solve LP problems [37]. PC utilized for running simulations has appropriate structures including Intel Core i7, 2.5GHz CPU with 12 GB of RAM. Fig. 1 illustrates the performance flow diagram of the suggested model. There are three stages in this method. First of all, $\beta(m)$, which is the robustness monitoring parameter, is set to zero. Then, $\beta(m)$ is augmented by a step $\xi = 0.1$ through a loop, which is ended every time the robustness monitoring parameter surpasses its superior boundary. Lastly, the results relating to $\beta(m) = 0$ are called deterministic results and $\beta(m) \neq 0$ makes robust results.

5. Simulation Results

This section presents simulation results of proposed OCC model on the ERCOT electricity market considering 10000 EVs [25, 39].

5.1. The under-study electricity market

The ERCOT electricity market is treated as a market that evaluates the efficacy of the advised OCC model. The database of ERCOT is used to harvesting the needed data for simulations [25, 39]. This data is electrical demand data, ancillary services signals, and electrical energy prices. The resolution of ancillary service deployment signals are 5 minutes. However, an EV can follow the signals with much higher resolution [40]. The electrical demand data of ERCOT is generated based on the procedure described by [41, 42]. The proposed OCC model doesn't need demand profile during optimization. Nevertheless, this data is used to evaluate effects of the proposed OCC on the electrical demand of the under-study market. Figs. 2 and 3 illustrate averaged ancillary service prices and deployment signals for ERCOT, respectively [25, 43, 44]. The availability of EVs is shown in Fig. 4. This figure is obtained regarding driving profiles made by the 2009 National Household Travel Survey (NHTS) data [25]. The NHTS data is cleaned for vehicle trips in urban Texas. Fig. 5 shows the predicted electrical demand of ERCOT. This study considers three brands of EVs that are Mitsubishi i-MiEV, Nissan Leaf, and Tesla Model S. The specifications of EV's battery are gotten

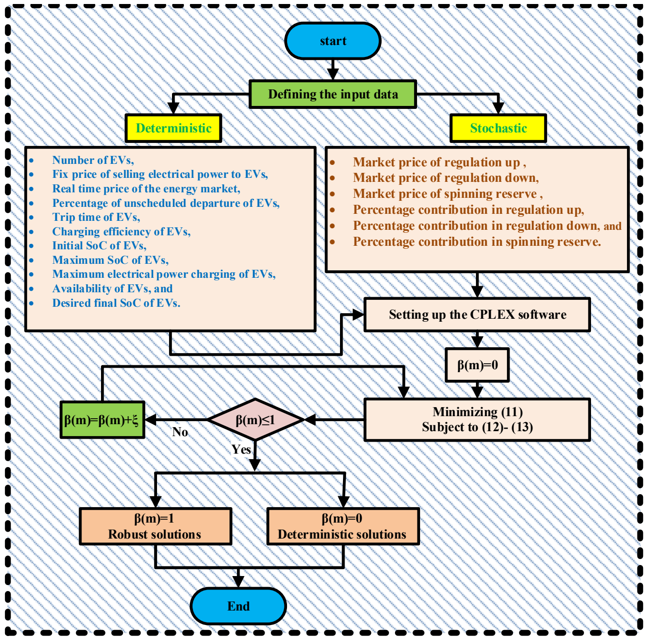

Fig. 1. . Flow diagram for employing the suggested model

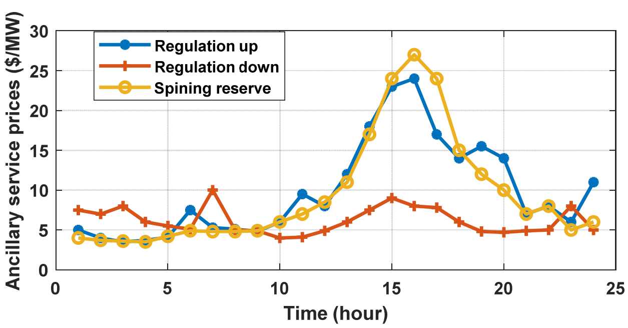

Fig. 2. Averaged ancillary service prices of ERCOT in the day ahead [25, 43, 44].

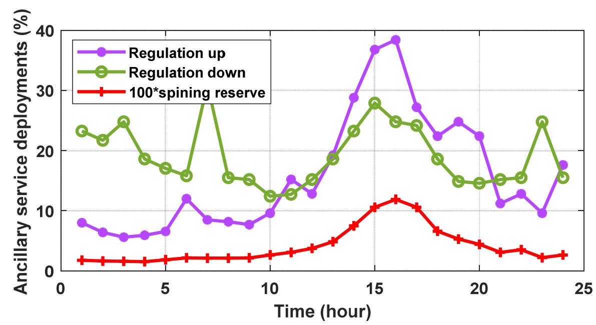

Fig. 3. Averaged ancillary service deployments of ERCOT in the day ahead [25, 43, 44].

from [25]. This paper assumes that 50% of EVs are Nissan Leaf, 30% are Tesla Model S, and 20% are Mitsubishi i-MiEV [25]. It also undertakes that $\eta^{ch}(i)$ is 90%, and $SoC^{dfin}(i)$ is 99% [25]. The paper assumes that δ equals 0.05 $/kWh [25].

To assure that when the electricity market clears, the bids of EV's aggregator will be accepted, the bid price of EV's aggregator submitted to electricity market is assumed by 0 $/MWh [25].

5.2. Sensitivity analysis

The sensitivity of the objective functions to the amount of uncertainty of input parameters is analyzed in this subsection. These studies have been illustrated in Fig. 6. To better evaluate, two studies are treated as:

- **Study 1:** handling uncertainty of ancillary service prices.
- **Study 2:** handling uncertainty of ancillary service deployments.

The horizontal axis of Fig. 6 reflects the variation of the control parameter of the uncertainty. It is seen, this

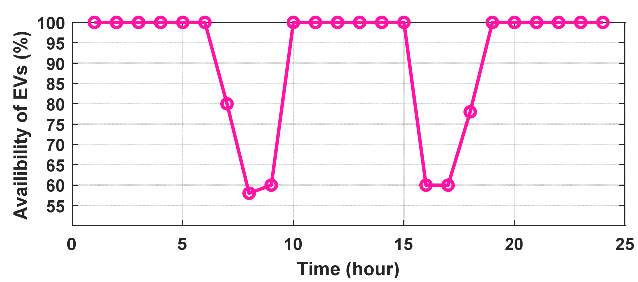

Fig. 4. Availability of EVs [25].

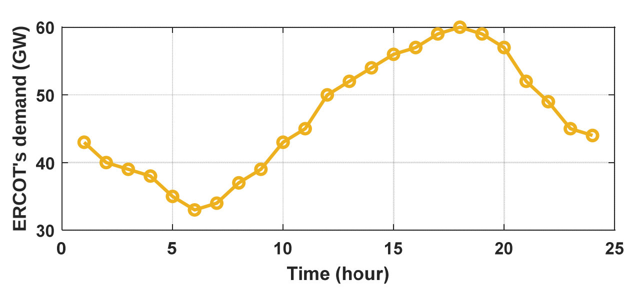

Fig. 5. Predicted electrical demand of ERCOT [42].

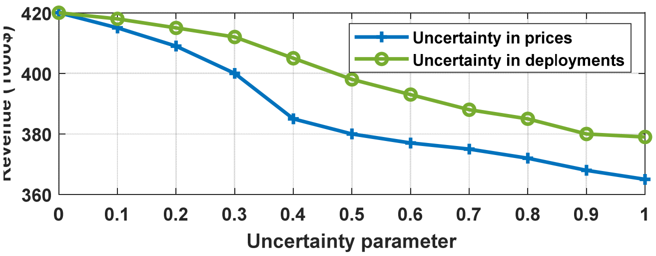

Fig. 6. Effect of uncertainty on the aggregator's revenue.

parameter changes in the range zero up to one by steps 0.1. The uncertainty parameter is zero when the decisions are made without consid-ering risk i.e., risk-neutral and it is one when the decisions are made based on risk-averse. Fig. 6 says to us, that if decisions of MGOs make based on high risk-averse, the revenue of EV's aggregator will decrease for two studies. To put it more simply, the more the uncertainty of parameters, the less the aggregator' revenue is. It can be noted that increasing uncertainty of prices is to increase prices from the forecasted values and increasing uncertainty of deployment signals is to decrease these signals from the forecasted amounts. With rising the uncertainty parameter from 0 to 1 in Study 1 and 2, the revenue is decreased by 13.09%, and 9.76%, respectively. As well, Fig. 6 signifies that the effect of uncertainty in prices is more than uncertainty in deployment signals on reducing revenue.

5.3. Numerical results

To assess the capability of the proposed model, the two following simulation results are reported. The stochastic behavior of prices and deployments are modeled considering a moderate value for the uncertainty parameter that is 0.5.

A. Results of charging profiles

This subsection evaluates the results of charging profiles and ancillary services provided by EV's aggregator. These results for proposed and deterministic models are shown in Figs. 7-11. Fig. 7 shows the results of POP. It is seen that both models have same pattern in the all hours of day. The models preserve the POP in a low value from early hours of the morning until before noon. The POP has the higher values in the middle of the day due to the regulation up prices are high. For the similar reasons, the average of POP during the day ahead is relatively high. The both models obtain the maximum POP in 4 am, because if EV's aggregator charges the EVs later, they cannot effectively collaborate in providing the ancillary services. The regulation up and down resulted by both models are illustrated by Figs. 8, and 9. Both figures show that the ancillary services amounts have the patterns that are proportional with the regulation up and down prices. On the other words, capacities are adjusted by prices. In addition, it can be noted that the average of regulation down capacities is higher than regulation up, because that regulation down can be offered with the POP at zero price which adds

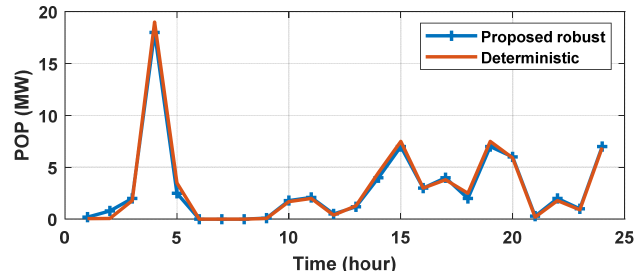

Fig. 7. The results of the POP in the day ahead.

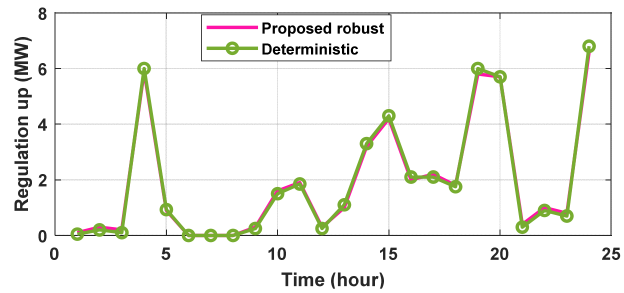

Fig. 8. The results of the regulation up in the day ahead.

less electrical energy to the EV's battery than regulation up as illus-trated in Fig. 10. Regarding Figs. 9, and 10, at the morning earlier 8 am, the lack of rest EV's battery capacities cause regulation down bids are nearly zero.

Fig. 11 exemplifies the spinning reserve capacity. Regarding this figure, the higher spinning reserve prices in the afternoon leads to more responsive reserve capacity is bided by aggregator. Nonetheless, this bided capacity is low due to limitations of the scheduling POP and the regulation up capacity bid in this period. The maximum spinning reserve capacity is bided at 4 am due to being high POP

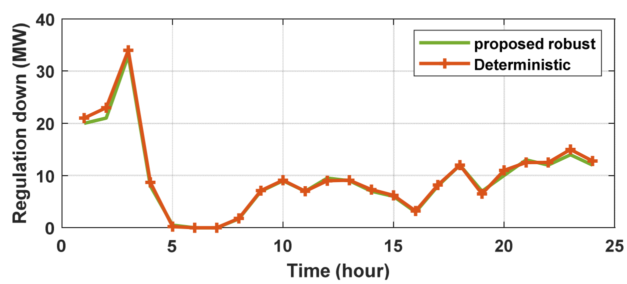

Fig. 9. The results of the regulation down in the day ahead.

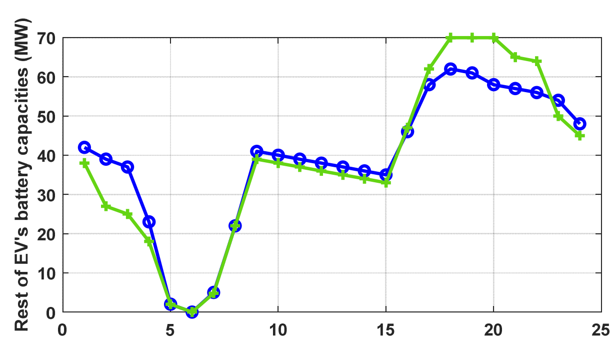

Fig. 10. Available EV's battery capacities in day ahead.

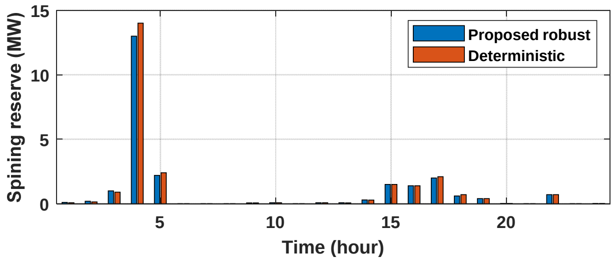

Fig. 11. The results of the spinning reserve in the day ahead.

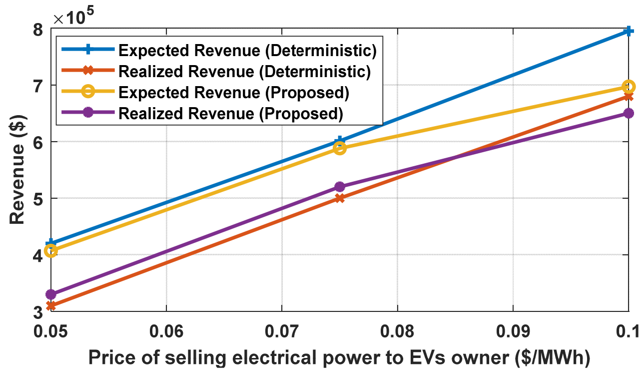

Fig. 12. The variation of the total expected and actual revenues with respect to variations of δ.

planned at this hour. Considering constraint (2-g) in the simulation shows that the models schedule the maximum POP at 4 am, until reduce probability of the failure to meet desired final SoC. It can be noted that given this is shifted to the last hour, i.e., 5 am and consequently, the spinning reserves are called upon, the majority of the EV's battery will be taken risk of the lack to satisfy desired final SoC constraint, i.e. (2-g).

B. Comparative studies

This subsection compares the result of the proposed robust model and deterministic model from the point of view all stockholders that are power system operator, EV's aggregator, and EV's owners. Fig. 12 shows the sensitivity of total expected and actual revenues with respect to variations of δ for deterministic and robust proposed models. It is seen that for $\delta = 0.05$ \$/kWh, the revenue of EV's aggregator obtained by robust proposed model is 407,000\$ which is 2.45% lower than deterministic ones. Nonetheless, it can be noted that the realized revenues harvested by proposed model are 6.34% more than deterministic those. As a result, the proposed model has the better performance in comparison to deterministic models for an actual day. It shows the necessities of including the uncertain behavior of some parameters in the electricity market. Furthermore, it is observed that revenue of the EV's aggregator increases if the EVs are charged at higher electrical energy rates.

From the point of view of power system operator, it is better that the charging of EVs doesn't add the extra burden on power system. Table 1 shows the statistics of increasing load in all hours of the day ahead and increasing load within peak hours. It is seen that the amount of the load increase

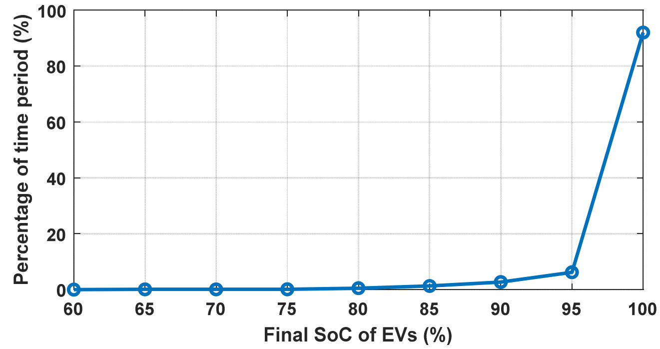

Fig. 13. Statics of the final SoC of EVs.

during peak hours is less than load increase within all hours for both models. In the other word, both models try to shift the EV's charging from peak hours to off peak hours. Also, it is observed that maximum load increase during peak hours are 10.56 MW and 11.02 MW deterministic and proposed model, respectively. These amounts are very smaller than 60 MW and 45.67 MW that are peal load and average load in the ERCOT system in this simulation.

It is necessary that EVs are charged to SoC^{dfin} in the end of duration of charging. Fig. 13 depicts the realized final SoC of EVs within simulation period. Regarding this figure, the final SoC of EVs for 5% of time is less than 90% of batterie's capacity and for a little bit of time that is 0.8% of time simulation is less than 80%. Table 2 represents average of final SoC of EVs for deterministic case in comparison to proposed robust ones. The results shown by Table 2 and Fig. 13 are hopeful, however, these can be improved by prioritizing EV's charging from low SoC to high SoC. While this ranking for EV's charging doesn't disturb electricity market bidding process or the benefits, however, it might support to remove the minor percentage of incidences at which final SoC of EVs that cannot approach to 99%.

6. Conclusions

This paper proposes a robust OCC model for bidding EV aggregators into energy and ancillary service markets considering uncertainties. The present work introduces a RLP for modelling EV aggregator based on unidirectional V2G and also coordinates the provision of ancillary services of electricity markets that are regulation and spinning reserves. It correspondingly deliberates several electricity market uncertainties that are the ancillary service prices and the ancillary service deployment signals. Considering diverse parameters pertaining to EVs behavior that are EV availability, trip durations, and time of trips make results of this paper more realistic than similar other papers. Simulation results including sensitivity analyses display that the robust modelling rises the aggregator's revenues and declines the deviation between expected and realized revenues. It is observed that for δ=0.05 \$/kWh, the income of EV's aggregator gotten by robust proposed model is 407,000\$ which is 2.45% lower than deterministic ones. However, it is worthwhile to mention that the realized

Table 1. The statistics of load increase.

Load increase	Statistics	Deterministic model	Proposed model
Average load increase in all hours (MW)	Average	4.45	4.39
	Standard deviation	6.56	6.21
Average load increase in peak hours (MW)	Average	2.34	2.21
	Standard deviation	2.89	2.45
	Maximum	10.56	11.02

Table 2. The statistics of final SoC of EVs.

Final SoC of EVs	Statistics	Deterministic model	Proposed model
Expected (%)	Average	97.67	98.22
	Standard deviation	1.89	2.01
Realized (%)	Average	96.37	97.45
	Standard deviation	2.77	2.13

incomes picked by proposed model are 6.34% more than deterministic those. It is seen that the quantity of the load increase within all hours is more than load increase during peak hours for deterministic and proposed models. Indeed, two models attempt to move the EV's charging from peak hours to off peak hours. The proposed model shows the acceptable results related to final SoC of EVs. On the other words, the proposed model somewhat enhances final SoC of the EVs and somewhat reduces the average peak load initiated by EV's charging in comparison to deterministic ones.

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