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Robust Stochastic Blockchain Model for Peer-to-peer Energy Trading Among Charging Stations of Electric Vehicles

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Abstract— *Fossil-fueled vehicles are being replaced by electric vehicles (EVs) around the world due to environmental pollution and high fossil fuel price. On the one hand, the electrical grid is faced with some challenges when too many EVs are improperly integrated. On the other hand, using a massive unexploited capability of the batteries in too many EVs makes these challenges opportunities. This unused capacity can be employed for the grid ancillary services and trading peer-to-peer (P2P) energy. However, the preference of EV users is one of the most important factors, which has to be considered within the scheduling process of EVs. Therefore, this paper proposes a stochastic model for EV bidirectional smart charging taking into account the preferences of EV users, P2P energy trading, and providing ancillary services of the grid. Considering the likings of EV users makes the proposed scheduling model adaptive against changing operating conditions. The presented model is formulated as an optimization problem aiming at optimal managing SOC of EV battery and electrical energy placement of several facilities considering the provision of ancillary services and contributing to P2P transactions. To evaluate the proposed model, real-world data collected from Tehran city are used as input data for simulation. Numerical results demonstrate the ability of the presented model. Simulation results display that considering the preferences of EV users in the proposed model can enhance the total income provided by the EV energy-planning model such that it could balance the charging cost. Moreover, this advanced user-based smart charging model increases P2P energy transactions amongst EVs and raises the ancillary services facility to the grid. Simulation results show that the yearly cost of optimal electrical charging on normal trips, light trips, and heavy trips is reduced by 32.6%, 51.2%, and 34.8% compared to non-optimal ones, respectively.*

Keywords—Ancillary service, Blockchain, Electric vehicle (EV), Peer to peer (P2P), Smart contracts, State of charge (SOC).

NOMENCLATURE

Abbreviations

DN	Distribution Network.
DNO	Distribution Network Operator.
DRP	Demand response program.
ESS	Energy Storage System.
EV	Electric Vehicle.
G2V	Grid to Vehicle.
GAMS	General Algebraic Modelling System.
GUI	Graphical User Interface.
IGDT	Information Gap Decision theory.
PDF	Probability Density Function.
RA	Risk Averse.
ToU	Time of use.
V2G	Vehicle to Grid.
V2V	Vehicle to Vehicle.

Indices

t	Index of time.

Variables

$Revenue$	Total revenue($).
$D^{lev2,S}(t)$	Binary slack variable for managing travelling distance in trip level 2.
$d_{Sch}^{lev2}(t)$	Scheduled distance traveled by EV in Level 2 trip at hour t (km).
$D^{lev3,S}(t)$	Binary slack variable for managing travelling distance in trip level 3.
$d_{Sch}^{lev3}(t)$	Scheduled distance traveled by EV in Level 3 trip at hour t (km).
$E^{dri}(t)$	Energy consumption of EV during trips at hour t (kWh).
$P^{anci,\ddot{S}}(t)$	Slack variable for contribution in ancillary service at hour t (kW).
$P^{anci,\dot{S}}(t)$	Slack variable for contribution in ancillary service at hour t (kW).
$P^{anci}(t)$	Electrical power of ancillary service at hour t (kW).
$P^{Grid}(t)$	EV electrical power imported from DN at hour t (kW).
$P^{P2P,ch,S}(t)$	Slack variable for managing EV electrical power imported from peer at hour t (kW).
$P^{P2P,ch}(t)$	EV electrical power imported from peer at hour t (kW).
$P^{P2P,dis,S}(t)$	Slack variable for managing EV electrical power exported to peer at hour t (kW).
$P^{P2P,dis}(t)$	EV electrical power exported to peer at hour t (kW).
$SOC(t)$	State of charge at hour t (kWh).
$ST(t)$	Status of EV connection (1, if EV connects to DN; otherwise, 0).
$SOC^{dod,S}(t)$	Slack variable for managing depth of discharge at hour t (kWh).
$SOC^{dod}(t)$	SOC level for depth of discharge at hour t (kWh).
$SOC^{sto,S}(t)$	Slack variable for managing stored energy at hour t (kWh).
$SOC^{sto}(t)$	SOC level for storing at hour t (kWh).

Sets

T	Set of hours.

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Parameters

$\mu^{P2P,ch}(t)$	Penalty factor of P2P trading during charging mode at hour t (kWh).
$\mu^{anci}(t)$	Penalty factor of ancillary service at hour t (kWh).
$\mu^{dod}(t)$	Penalty factor for depth of discharge of battery at hour t (kWh).
$\mu^{EST}(t)$	Penalty factor for non-essential trip at hour t (km).
$\mu^{NCT}(t)$	Penalty factor for non-critical trip at hour t (km).
$\mu^{P2P,dis}(t)$	Penalty factor of P2P trading during discharging mode at hour t (kWh).
$\mu^{sto}(t)$	Penalty factor for stored energy of battery at hour t (kWh).
ω	Cycles of operating battery.
$\theta(z)$	Capacity degradation at year z.
ε	Constant coefficient.
$C^{anci}(t)$	Price of contribution in ancillary service at hour t (kWh).
$C^{Bat,ch}(t)$	Cost of battery discharging at hour t (kWh).
$C^{Bat,dis}(t)$	Cost of battery charging at hour t (kWh).
$C^{P2P}(t)$	Price of contribution in P2P energy market at hour t (kWh).
$C^{ToU}(t)$	Price of ToU at hour t (kWh).
$d(t)$	Traveled distance of EV at hour t (km).
$D^{lev1}(t)$	Distance traveled by EV in Level 1 trip at hour t (km).
$D^{lev2}(t)$	Distance traveled by EV in Level 2 trip at hour t (km).
$D^{lev3}(t)$	Distance traveled by EV in Level 3 trip at hour t (km).
LF	Lifetime of battery (year).
P_{ch}^{max}	Maximum charging power of EV (kW).
P_{dis}^{max}	Maximum discharging power of EV (kW).
P_{ch}^{min}	Minimum charging power of EV (kW).
P_{dis}^{min}	Minimum discharging power of EV (kW).
$P^{P2P}(t)$	Amount of electrical power trading as P2P at hour t (kW).
$R^{con}(t)$	Rate of energy consumption by EVs per traveled distance at hour t (kWh/km).
$S^{anci}(t)$	Signal of ancillary service at hour t (kW).
X^{diss}	Dissipation factor of battery.
SOC^{max}	Maximum SOC in the beginning of EV battery lifetime (kWh).
SOC_{z}^{max}	Maximum degraded SOC level (kWh).
SOC^{min}	Minimum SOC of EV battery (kWh).
SOC_{user}^{min}	Minimum SOC controlled by user (kWh).

1. INTRODUCTION

1.1. Motivation

One of the most important reasons to create carbon dioxide emissions and air pollution in the atmosphere is transportation systems [1, 2]. Researchers clear that one of the significant solutions to overcome this problem is to utilize EVs [3, 4]. Nevertheless, increasing the penetration level of EVs in the local DN makes numerous unsolicited effects on the operator of these networks [1, 5]. The complicated problem initiated by EVs in DN is uncoordinated charging which can make a demand peak simultaneously with the traditional load peak in the DN. This situation might lead to more electrical power loss, detraction of voltage profile, and congestion in the DN [6]. Furthermore, employing EVs on a large-scale system result in increasing total demand, which the DN might not effortlessly handle, due to weakness in existing infrastructures [7, 8]. These concerns cause avoiding extensive implementation of EVs in DN and make necessities for the selection of approaches that organize EV charging/discharging mechanisms optimally and encourage EV owners to move their demand outside of the peak hours and offer ancillary services to DN [9, 10]. Therefore, this paper presents a new strategy based on a stochastic model of charging/discharging EVs considering the welfare of EV owners, the P2P energy market, and contributing ancillary services of DN.

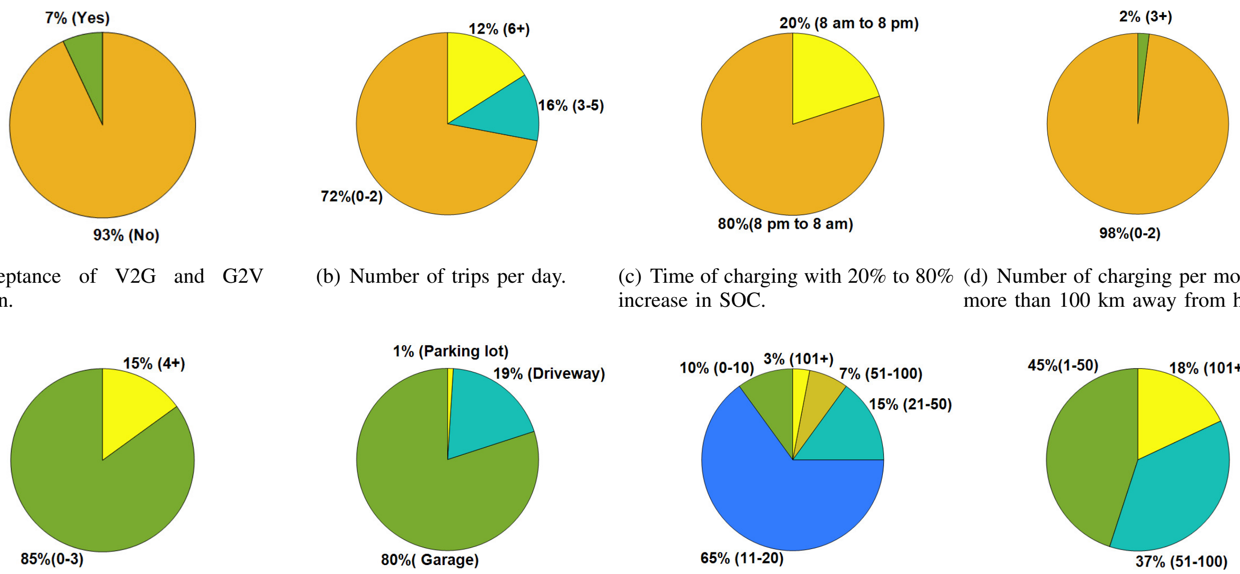
1.2. Literature Review

Researchers' Studies in the literature show that they conventionally have concentrated on studying and evolving EV scheduling methods including coordinated G2V charging [11]. For example, Ref. [11] presents a distributed charging planning algorithm considering the augmented Lagrangian method. Ref. [12] formulates a distributed online/offline charging scheduling model as an optimization problem and the goal of optimization is to maximize the revenue of aggregators. Ref. [13] studies the scheduling model of a large residential EV population considering a two-stage hierarchical optimization algorithm. Ref. [14] formulates the optimal charging scheduling model of a bulky fleet of cooperative EVs as a multi-objective optimization problem considering the limitations of EV owners and the power quality of DN. Ref. [15] determines the day-ahead optimal time for charging/discharging of EVs via solving an optimization problem. The solver is a heuristic algorithm and the goal is to minimize energy cost. In the same way, Ref. [16] proposes an optimal EV charging coordination scheduling. Optimal scheduling aims to minimize charging costs as well as energy losses in an unbalanced DN. Ref. [17] presents an optimal real-time charging scheduling model for EVs to minimize the cost of energy of charging EVs.

Prices of electricity have a vital role in the optimal managing EV charging scheduling and they have been taken into account in numerous literature. For example, Ref. [18] considers dynamic prices and schedules charging times and deadlines for reducing the peak demand for EV charging stations. Ref. [19] develops a day-ahead charging scheduling model using a game theory based on Nash equilibrium considering the electricity prices and interaction among EV demands. Ref. [20] optimally schedules EV aggregators by taking into account the uncertainties of electricity prices.

Although the previously mentioned G2V patterns support coordinate charging of EVs, it is better to use the benefit of EVs' ESS abilities to enhance the DN's resiliency via V2G patterns. Ref. [21] presents an optimal two-level energy management system for the incorporation of EVs into a DN for preventing DN congestion. Ref. [22] proposes a real-time charging scheduling for coordinating the demands of EVs considering dynamic electricity pricing and DRP signals issued by DNO. Ref. [23] formulates an EV charging/discharging schedule for regulating the primary frequency and dynamic grid support. Ref. [24] proposes a charging scheduling strategy based on droop control to lessen frequency uncertainties. Ref. [25] devises a two-level V2G scheduling strategy to provide frequency regulation service. Moreover, Ref. [26] an optimal charging scheduling strategy is presented for supporting the voltage of DN by considering the ability of the EVs to inject electrical reactive power.

Current enterprises in the direction of dispersed solutions as well as improvements in P2P communication links have improved EV charging scheduling patterns to include V2V energy dealing [27, 28]. In Ref. [28], a framework based on EVs is presented for trading electrical energy among EVs, smart, and DN. Ref. [29] introduces a P2P energy marketing system in which the coordination of energy trading among EVs is carried out by an aggregator. In addition, a day-ahead optimal charging scheduling strategy is used by each EV to regulate its surplus or lack of energy. In [30], a V2V scheme is proposed to perform fast charging in parking lots for the duration of the peak demand hours. Ref. [31] presents a centralized cooperative charging system to equal the providing electrical energy and demand of EVs, which are coordinated by max–weight V2V method. This algorithm optimally models demand and generation based on EV in an electrical energy system based on the internet. Furthermore, in Ref. [32] a P2P transaction system based on auction is proposed in an EV's charging station.



(a) Acceptance of V2G and G2V operation.
(b) Number of trips per day.
(c) Time of charging with 20% to 80% increase in SOC.
(d) Number of charging per month for more than 100 km away from home.
(e) Number of days per month for driving more than 200 km.
(f) Location of EV Parking.
(g) Distance driven per day (km).
(h) Distance driven between each charging (km).

Fig. 1. Real–world data gathered from EV users in Tehran city.

The aforesaid researches are conducted considering centrally matched P2P energy interchange plans that are inclined to single point of failure in addition to security and privacy concerns. This requires distributed and direct V2V energy interchange systems, which can be realized by P2P frameworks. Blockchain has recently received attention as the most important P2P platform among other platforms [33]. Direct P2P trading is carried out on the Blockchain platform in a secure, decentralized, and trustful way barring the need for third parties for facilitating the transactions. Indeed, Blockchain is mainly a decentralized archive, which comprises blocks of data that have time flags, and any modifications in the data are dispersed and confirmed by peers in the communication network via a scheduled agreement procedure. The business deal is then documented inside a block and devoted to a present continuum of blocks [33]. Data documented in blocks (business deal data) relies on the blockchain category. For example, blocks of electrical energy trading comprise data of the electrical energy measured by smart meters, transfer time, and IDs of sellers and buyers. Recently, some researchers have been studied about the block chain-based electrical energy trading. Ref. [34] presents an agreement settlement based on a blockchain system such that it can offer a safe plan for electricity prosumers in a DN. In the same way, Ref. [35] proposes an association blockchain technology to conduct a P2P energy trading system that does not need a third party. Ref. [36] proposes a model to assess the outcome of blockchain P2P trades on the DN and consequently, permit electrical energy transactions without violation of DN constraints. Ref. [37] develops blockchain-based authenticating mechanisms to distinguish interfering efforts on smart meters. Ref. [38], develops a data accumulation plan via groups comprised by small blockchain to guard users' personal information in intelligent DNs.

As regards EVs P2P electrical energy trading, Ref. [39] develops a system based on blockchain-based P2P electrical energy transactions to counterpart charging/ discharging EVs. Ref. [40] presents an optimization model for electricity trading among EVs by a consortium blockchain model. The optimization goal is to optimize the revenue of sellers and buyers by matching bids of the vendors and purchasers through an iterative procedure inspected by legal local aggregators. Ref. [41] presents a blockchain-based P2P energy transaction framework that takes into account EVs as prosumers. The blockchain-based charging piles maintenance system proposed by [42] can provide an end-to-end transparent and high-reliability management mode for multi-agents including the charging pile, power distribution station, maintenance, calibration, and supervision institutions. Ref. [43] proposes a P2P private charging pile sharing system supported by blockchain technology. In this proposed system, the charging records of EV users could be packaged and uploaded into the blockchain, which is immutable and tamper-resistant. Ref. [44] proposes a blockchain-based V2V electricity trading strategy. Firstly, it establishes the cost model and revenue model of EVs, and put forward the EVs' coalition joining strategy and matching mechanism. Then, the consortium blockchain technology is used to build the V2V trading platform.

The abovementioned research on the scheduling of the EV charging and P2P energy trading do not consider user's input into the charging scheduling mechanism. However, it can be noted that users have numerous interactions of their preferences, and consequently, they need various choices to satisfy their likings. The input of EV users is taken into account for EV parked charging stations in some literature [45, 46]. For example, Ref. [45] proposes a pricing mechanism based on the online menu for EV charging stations. The users are offered numerous contracts with various levels of electrical energy and charging hours at various prices. Ref. [46] presents a similar plan but with considering the life span of the battery. However, only Ref. [47] considers the input of EV users into the charging mechanisms that aid each EV user control the optimal charging/ discharging plan for their EVs. Moreover, Ref. [47] does not consider the stochastic behaviors in charger plug-in status, trips, and external signal profiles (P2P and ancillary) together with electricity prices for the day ahead.

1.3. Contributions and organization

As such, this paper considers the users' input to schedule the charging process. The inputs taken into account in this paper are used for providing user control over P2P transactions and ancillary services contribution in addition to battery SOC management and trips regulation. This paper similar to [47] does not consider using smart contracts to afford a dispersed mechanism for leading the energy transaction procedures among EV users. Unlike [47], this paper considers the stochastic behavior of external signal profiles (P2P and ancillary) together with electricity prices as well as charger plug-in status, and trips for the day ahead. Regarding the intrinsic difference between actual data and predicted data and also the inaccessibility to PDF of uncertain parameters, this paper models the stochastic parameters by an RA-IGDT method. Moreover, to enhance the flexibility of DN operation, ToU is considered as a DRP.

Finally, the main contributions of the current paper are as follows:

- Formulating a new model for smart charging/discharging,
- Considering P2P electrical energy trading and provision of ancillary services,
- Integrating user preferences into the charging scheduling process,
- Modelling the stochastic behavior of SOC, trips, and other external signals, and
- Considering DRP as ToU in order to enhance the flexibility of operation.

In this paper, the problem formulation is general; however, the following assumptions are considered within simulations and numerical studies:

- Contribution to the ancillary service market is optional for EV users and they do not have to contribute to this market,
- The EV users have stochastic behavior; therefore, the charging scheduling strategy is adaptive to numerous circumstances, which users determine by adjusting risk level and consequently, controlling robustness parameters of the IGDT.

The rest of the paper organization is as follows: Specification of the proposed model is expressed in Section 2 with special attention to the preference of EV users. Section 3 describes mathematical formulation. The robust optimization method as a tool for modelling uncertainty is stated in Section 4. The application of the solution algorithm to the proposed model is stated in Section 5. Simulation results are presented and discussed in Section 6, and finally, the paper's conclusion is expressed in Section 7.

2. Specification of Proposed Model

Similar to [47], the real world data is gathered from EV owners in Tehran city, Iran to evaluate the prominence of including the preferences of EV users in the charging scheduling strategy. Although there is not any plug-in EV in Tehran, a survey was conducted among 500 gasoline car owners in Tehran. When filling out the questionnaire, they were told to assume they owned an EV. The outcomes are compiled and shown by Fig. 1. It is seen in Fig. 1(a), 93% of respondents are not joined in G2V or V2G EV charging plans. As mentioned in [47], considering EV users input in charging scheduling strategy can boost more contribution to these schemes. Moreover, contribution in these charging strategies limits the flexibility of EV users. This is because EVs have a moving nature and these schemes can restrict EV users. Therefore, contribution to ancillary service trading is optional for EV users.

Fig. 1(b) illustrates that 72% of EV users tend to perform two or fewer trips per day; however, 16% EV of users carry out less than six trips, and only 12% surpass six trips per day. This result specifies that EV users may carry out some of these trips as optional and they can control their trips to improve their operational revenue. The proposed model considers a choice to optimally regulate a trip by considering the kind of trip. In this way, the paper considers three kinds of the trip including Level 1, Level 2, and Level 3 similar to [47]. Level 1 is related to critical trips, which EV users must take within a day, such as regulated trips for traveling to work or medical schedules. Level 2 and level 3 specify non-vital trips that an EV user can change its time or reschedule. The paper assumes that Level 2 trips have higher importance than Level 3. For example, Level 2 trips are shopping or banking, while Level 3 trips have lower priority i.e. leisure actions [47]. Results of the survey in Fig. 1(c) show that 80% of EV users tend to charge their batteries during off-peak hours, while only 20% of them want to charge within peak hours. These results depict that by a selection of a suitable policy, EVs can be encouraged for contributing to V2G and G2V programs. Regarding Fig. 1(d), it is seen that the majority of EV users have access to plug-in connections and they have the readiness to participate in P2P energy market. In addition, Fig. 1(e) shows that EV users are not interested in multiple long trips within the month and they have the willingness to participate in the P2P energy trading. Furthermore, Fig. 1(f) displays that 80% of EV users want to be charged in their hometown that it can help them to participate in the P2P energy market in local DNs wherein they are disclosed. Moreover, Fig. 1(g) and 1(h) exemplify that the majority of EV users tend to drive a typical of 45 km per day although an EV can almost afford an average of 400 km with one completed round of charging. Consequently, the majority of EV batteries are not entirely discharged and it is seen that there is a higher trend to keep reserve [40]. Finally, Fig. 1(h) shows the prominence of energy management for EVs with considering the preferences of users.

3. Mathematical Formulation

3.1. Model of Optimal Scheduling

The proposed smart charging model which considers user preferences to optimally manage EV charging/discharging is illustrated in Fig. 2. It is seen that set points of charging/discharging of EVs are determined by an optimal scheduling algorithm. This algorithm is fed by numerous inputs including (1) specifications of EV, including physical limitations of charging station and capacity of EV's battery; (2) ToU electricity prices; (3) amount of reserve provision for participating in ancillary service trading and P2P energy market; and (4) EV user input comprising estimated position of EV during scheduling time together with the scheduling risk profile. Optimization results are updated by executing the proposed algorithm at each time slot, which is one hour within a day. Therefore, the proposed model can deal with the stochastic behavior of electrical demands which vary at every time slot. The proposed algorithm produces profiles of charging scheduling for time-ahead, sent to the EV user by an interactive GUI. EV users can adjust certain inputs via interaction with the application such that they minimize/maximize the revenue/operational cost of EV. Indeed, EV users via GUI can evaluate the total driving energy cost as well as battery SOC during the operation time horizon. Next, the user can adjust his/her trips and choose if to contribute to various charging/discharging actions pertaining to the ancillary services market and P2P trading. Afterward, the EV user regulates his/her inputs by the GUI and the proposed application will apply these changes considering the input data and finally, a new operation profile is produced. The proposed profile of charging will be sent to the network for coordination with other users of EVs if the user of EV agrees with the changes.

The objective function together with the constraints are formulated as follows:

3.2. Objective Function

The goal of the suggested objective function is to maximize the revenue and/or minimize the operation cost for EV users as follows:

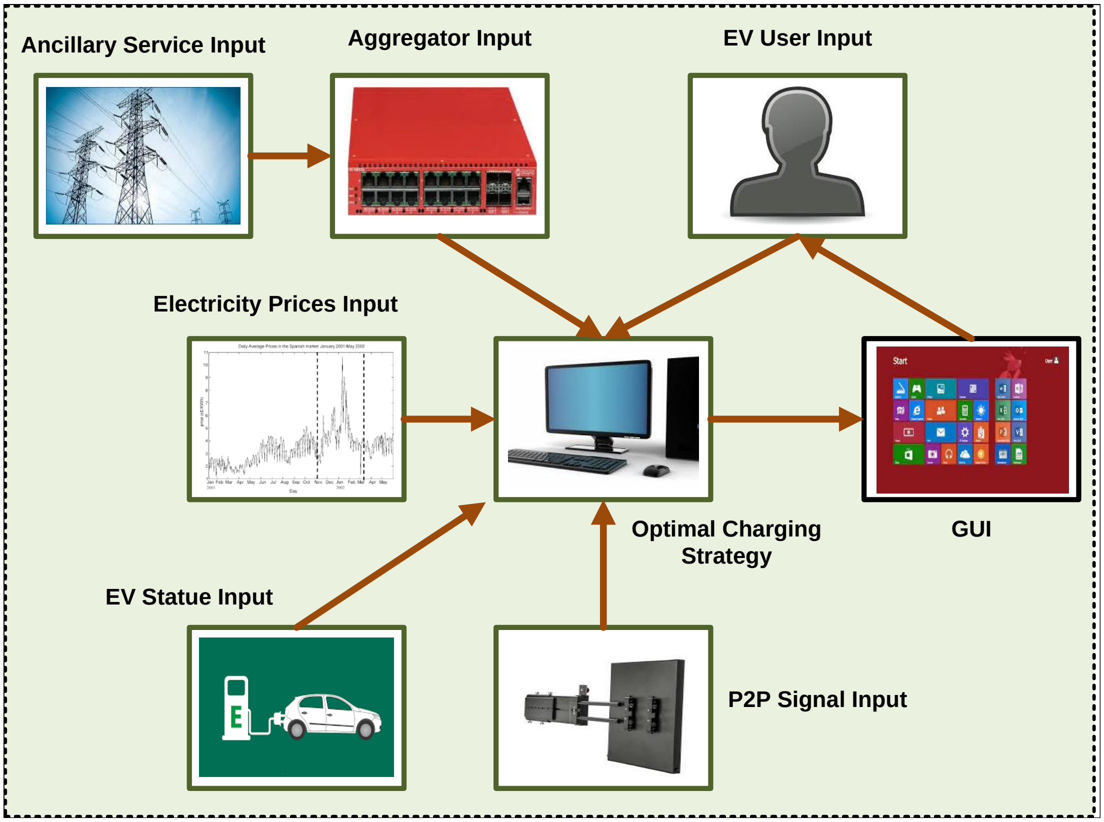


Fig. 2. Proposed charging scheduling

$$\begin{aligned}\mathrm{Max}\{\text{ Revenue }\} = \mathrm{Max}\Bigg\{\sum_{t\in T}\Big[& P^{anci}(t)\times C^{anci}(t)+P^{P2P,\text{ dis}}(t)\times C^{P2P}(t)-P^{\text{Grid}}(t)\times C^{ToU}(t)-P^{P2P,ch}(t)\times C^{P2P}(t)\\ &-\left[P^{anci}(t)+P^{P2P,dis}(t)\right]\times C^{Bat,dis}(t)-\left[P^{Grid}(t)+P^{P2P,ch}(t)\right]\times C^{Bat,ch}(t)\\ &-\mu^{anci}(t)\times\left[P^{anci,\dot{S}}(t)+P^{anci,\ddot{S}}(t)\right]\Big]-\mu^{P2P,ch}(t)\times P^{P2P,ch,s}(t)-\mu^{P2P,\text{ dis}}(t)\times P^{P2P,dis,s}(t)\\ &-\mu^{\text{sto}}(t)\times \text{SOC}^{\text{sto,s}}(t)-\mu^{\text{dod}}(t)\times\text{SOC}^{\text{dod,s}}(t)-\mu^{NCT}(t)\times D^{lev2,s}(t)-\mu^{opt}(t)\times P^{\text{lev 3},s}(t)\Bigg\}\end{aligned} \tag{1}$$

3.3. Constraints

The constraints considered for the untaken optimization problem are outlined as follows:

- **Constraints of the EV driving**

The electrical energy consumed within deriving an EV can be formulated as follows [29]:

$$E^{dri}(t)=(1-ST(t))\times d(t)\times R^{con}(t) \qquad \forall t\in T \tag{2a}$$

$$d(t)=(d^{Level1}(t)\cup d^{Level2}_{Sch}(t)\cup d^{Level3}_{Sch}(t)) \qquad \forall t\in T \tag{2b}$$

Constraint (2a) expresses that the consumption of energy in EVs happens when the EV has no connection with DN. Moreover, (2b) shows total distance derived by EVs in three kinds of trips. It can be noted that three kinds of trips cannot happen simultaneously. Furthermore, trips of the Level 1 is considered as critical ones and consequently, the proposed algorithm does not control them while trips of Level 2 and 3 are taken into account as non-critical and low importance ones as follows [47]:

$$d^{lev2}_{Sch}(t)=D^{lev2}(t)-D^{lev2,S}(t)\times D^{lev2}(t)\,; \quad \forall t\in T \tag{2c}$$

$$d^{lev3}_{Sch}(t)=D^{lev3}(t)-D^{lev3,S}(t)\times D^{lev3}(t)\,; \quad \forall t\in T \tag{2d}$$

It can be noted that binary slack variables $D^{lev2,S}(t)$ and $D^{lev3,S}(t)$ affect tuning of trips in (2c) and (2d).

- **Constraints of charging/discharging EVs**

The charging and discharging of EVs are limited by the following constraints [47]:

$$ST(t)\times P^{min}_{ch}\le P^{ch}(t)\le ST(t)\times P^{max}_{ch}; \quad \forall t\in T \tag{3a}$$

$$ST(t)\times P^{min}_{dis}\le P^{dis}(t)\le ST(t)\times P^{max}_{dis}; \quad \forall t\in T \tag{3b}$$

$$P^{ch}(t)=(P^{Grid}(t)\cup P^{P2P,ch}(t)); \quad \forall P^{dis}(t)=0\ \cap\forall t\in T \tag{3c}$$

$$P^{dis}(t)=(P^{anci}(t)\cup P^{P2P,dis}(t)); \quad \forall P^{ch}(t)=0\ \cap\forall t\in T \tag{3d}$$

Constraints (3a) and (3b) state the limitation of the charging converter when it is connected to DN.

- **Constraints of EV batteries**

The EV batteries are faced with the following physical and operational limitations [47]:

$$\begin{aligned} SOC(t) =& SOC(t-1) + \Big[ST(t) \times P^{P2P,ch}(t) - ST(t) \\ & \times P^{P2P,dis}(t) + ST(t) \times P^{anci}(t) + ST(t) \\ & \times P^{Grid}(t) - (1 - ST(t)) \times d(t) \times R^{con}(t) \\ & - X^{diss} \times SOC(t)\Big] \times \Delta t; \quad \forall t \in T \end{aligned} \tag{4a}$$

$$SOC_{user}^{min} \le SOC(t) \le SOC_z^{max}; \quad \forall t \in T \tag{4b}$$

Constraint (4a) states the stored energy at hour t considering dissipation of the battery of EV and (4b) represents upper and lower bounds of SOC of EV batteries. The upper limit SOC_z^{max} in (4b) is formulated by (4c), which indicates the battery degrading during its lifetime. Degradation is written as follows [48]:

$$SOC_z^{max} = SOC^{\ max} - \sum_{z=0}^{LF} (\omega \times \varepsilon + \theta(z)) \tag{4c}$$

The lower limit of SOC which is SOC_{user}^{min} can be formulated as follows [47]:

$$\begin{aligned} SOC_{user}^{min}(t) =& SOC^{\ min} + SOC^{dod}(t) + SOC^{sto}(t) \\ & - SOC^{sto,S}(t) - SOC^{dod,S}(t); \quad \forall t \in T \end{aligned} \tag{4d}$$

$$0 \le SOC^{sto,S}(t) \le SOC^{sto}(t); \quad \forall t \in T \tag{4e}$$

$$0 \le SOC^{dod,S}(t) \le SOC^{dod}(t); \quad \forall t \in T \tag{4f}$$

It can be noted that $SOC_{user}^{min}(t)$ be subject to on the physical lower bound of the battery as well as reserve and depth of discharge SOC levels prioritized by EV users. In addition, slack variables $SOC^{dod,S}(t)$ and $SOC^{sto,S}(t)$help the algorithm to converge.

- **Constraints of ancillary services**

EV users can contribute to the electricity market as the provider of the ancillary services based on the following limitations [47]:

$$P^{anci}(t) = ST(t) \times S^{anci}(t) - P^{anci,\dot{S}}(t) - P^{anci,\ddot{S}}(t); \ \forall t \in T \tag{5a}$$

$$0 \le P^{anci,\dot{S}}(t) \le S^{anci}(t); \ \forall t \in T \tag{5b}$$

$$0 \le P^{anci,\ddot{S}}(t) \le S^{anci}(t); \quad \forall t \in T \tag{5c}$$

It is can be said that $S^{anci}(t)$ can be either positive or negative signals. Similar to (4), slack variables guarantee the convergence of the algorithm.

- **Constraints of P2P**

P2P proposals obtained by the EV user are adjusted by the succeeding constraints [48]:

$$P^{P2P,ch}(t) - P^{P2P,dis}(t) = \begin{bmatrix} ST(t) \times P^{P2P}(t) \\ -P^{P2P,ch,S}(t) \\ +P^{P2P,dis,S}(t) \end{bmatrix}; \quad \forall t \in T \tag{6a}$$

$$0 \le P^{P2P,ch,S}(t) \le P^{P2P}(t); \quad \forall t \in T \tag{6b}$$

$$0 \le P^{P2P,dis,S}(t) \le P^{P2P}(t); \quad \forall t \in T \tag{6c}$$

Where $P^{P2P}(t)$ represents the amount of exchanged energy among the EV users and other peers.

3.4. Indices of Ancillary Services and P2P Contribution

The following indices enumerate the involvement of users of EV in ancillary services and P2P trading [47]:

$$ASCI = \left\{ 1 - \frac{\sum_{t \in T} (P^{anci,\dot{S}}(t) + P^{anci,\ddot{S}}(t))}{\sum_{t \in T} S^{anci}(t)} \right\}; \ \forall t \in T \tag{7a}$$

$$P2PTI = \left\{ 1 - \frac{\sum_{t \in T} (P^{P2P,ch,S}(t) + P^{P2P,dis,S}(t))}{\sum_{t \in T} P^{P2P}(t)} \right\} \ \forall t \in T \tag{7b}$$

4. Robust Optimization Approach

Uncertainties can be modeled by numerous methods such as possibilistic optimization, probabilistic optimization, stochastic programming, interval optimization, and robust optimization [49] among which, the robust optimization approach is very attractive for researchers and planers due to its powerfully manage risk, having high robustness, and low computational burden [49]. Despite other uncertainties modeling approaches, this approach does not need PDF or membership functions of the uncertain inputs [40]. The following equations express a typical MILP optimization model as [50]:

$$Min \sum_{n \in N} d(n) \times x(n) \tag{8}$$

Subject to

$$\sum_{n \in N} e(m,n) \times x(n) \le f(m); \quad \forall m \in M \tag{9a}$$

$$lx(n) \le x(n) \le ux(n); \quad \forall n \in N \tag{9b}$$

$$\begin{aligned} & x(n) \in Z; \ \forall n = 1, \ 2, \ \ldots, \ k \\ & and \ \ x(n) \in R; \ \forall n = k+1, k+2, \ldots \end{aligned} \tag{9c}$$

In this approach, the input uncertainties are modeled by limited intervals, which are determined concerning sets of uncertainties. Consequently, $d(n)$ and $e(m,n)$ as the uncertain elements are expressed as follows:

$$(n) = \left[\bar{d}(n) - \hat{d}(n), \ \bar{d}(n) + \hat{d}(n)\right] \forall n \in N \tag{10a}$$

$$\begin{aligned} e(m,n) =& [\bar{e}(m,n) - \hat{e}(m,n), \\ & \bar{e}(m,n) + \hat{e}(m,n)] \, \forall n \in N, \forall m \in M \end{aligned} \tag{10b}$$

The proposed RMILP problem is formulated by introducing an integer parameter $\beta(m)$ which controls the conservation level and belongs to the interval $[0, |J(m)|]$. Certainly, $J(m)$ is the set of uncertain elements of not only the objective function ($m = 0$) i.e. $J(0) = \{n \,|d(n) > 0\}$, but also the constraint m i.e. $J(m) = \{n \,|e(m,n) > 0\}$ [51]. Regarding the fact that all of the uncertain elements cannot simultaneously vary from the nominal values, this paper assumes that up to $\beta(m)$ of these elements have a variation between boundaries defined by (10a) and (10b), while the variation of one of them is limited by the following truncated intervals [51]:

$$\begin{aligned} dt(0) =& \Big[\overline{dt}(0) - (\beta(0) - \beta(0)) \times \widehat{dt}(0), \\ & \overline{dt}(0) + (\beta(0) - \beta(0)) \times \widehat{dt}(0)\Big]; \\ & \forall dt(0) \in J(0), m = 0 \end{aligned} \tag{11a}$$

$$et\,(m,n) = \left[\overline{et}\,(m,n) - (\beta\,(m) - \beta\,(m)) \times \widehat{et}\,(m,n)\,, \right. \\ \left. \overline{et}\,(m,n) + (\beta\,(m) - \beta\,(m)) \times \widehat{et}\,(m,n)\right]; \\ \forall et\,(m,n) \in J(m), \forall m \in M \tag{11b}$$

It can be noted that $\beta(m)$ is a real value. For example, if $\beta(m)$ is equal to 2.5, it expresses uncertain elements of two constraints can vary within the full range of defined limitations, while uncertain elements of one of the constraints have a variation within half range.
The RMILP model of the proposed MILP formulated as (1) is given as (12) [50]:

$$Min \sum_{n\in N} \overline{d}(n) \times x(n) + max_{\{\Psi(0)\cup\{\Theta(0)\}|\Psi(0)\subseteq J(0),\ \Psi(0)=\Upsilon(0),\Theta(0)\in J(0)/\Psi(0)\}} \left\{ \sum_{n\in\Psi(0)} \hat{d}(n) \times |x(n)| + \right. \\ \left. (\Upsilon\,(0) - \Upsilon\,(0)) \times \widehat{dt}(0) \times |xt\,(0)| \right\} \tag{12}$$

Subjected to:

$$\sum_{n\in N} \overline{e}\,(m,n) \times x(n) + max_{\{\Psi(m)\cup\{\Theta(m)\}|\Psi(m)\subseteq J(m),\ \Psi(m)=\Upsilon(m),\Theta(m)\in J(m)/\Psi(m)\}} \left\{ \sum_{n\in\Psi(0)} \hat{e}(m,n) \times |x(n)| + \right. \\ \left. (\Upsilon\,(0) - \Upsilon\,(0)) \times \widehat{et}\,(m,n) \times |xt\,(m)| \right\} \leq f(m); \quad forall m \in M \tag{13}$$

as well as (9b) and (9c). The robust problem defined by (12)–(4) and (9b)–(9c) is a nonlinear problem, which is linearized by duality theory [50], and consequently, the resulted RMILP is written as [50]:

$$Min \sum_{n\in N} \overline{d}(n) \times x(n) + z(0) \times \beta\,(0) + \sum_{n\in J(0)} p(0,n) \tag{14}$$

Subjected to:

$$\sum_{n\in N} \overline{e}\,(m,n) \times x(n) + z(m) \times \beta\,(m) \\ + \sum_{n\in J(m)} p(m,n) \leq\ f(m);\ \forall m \in M \tag{15a}$$

$$z\,(0) + p(0,n) \geq \hat{d}(n) \times \theta(n) \forall n \in J(0) \tag{15b}$$

$$z\,(m) + p(m,n) \geq \hat{e}(m,n) \times \theta(n) \forall n \in J\,(m)\,,\ \forall m \in M \tag{15c}$$

$$-\,\theta(n) \leq x(n) \leq \theta(n) \forall n \in N \tag{15d}$$

$$lx(n) \leq x(n) \leq ux(n) \forall n \in N \tag{15e}$$

$$p\,(m,n) \geq 0, \forall n \in J\,(m)\,,\ \forall m \in M \tag{15f}$$

$$\theta(n) \geq 0 \forall n \in N \tag{15g}$$

$$z(m) \geq 0 \forall m \in M \tag{15h}$$

$$x\,(n) \in Z;\ \forall n = 1,\ 2,\ \ldots,\ k \\ and \\ x\,(n) \in R;\ \forall n = k+1, k+2, \ldots \tag{15i}$$

Regarding the proposed RMILP formulated by (14)–(15), the deterministic formulation expressed by (1)–(6) is reformulated.

5. The Application of Presented Algorithm on Model

5.1. EV Scheduling Model

The EV user inputs are incorporated by the proposed algorithm, which tends to maximize revenue and/or minimize the cost of EV action by contributing to the ancillary service market of DN, involvement in P2P electrical energy trading, and utilization of the electricity prices arbitrage. Thereby, the charging scheduling strategy is implemented by considering the benefit of the EV owners. Although the charging scheduling contributes to the ancillary services market of DN, the aim of the proposed model is not to minimize the operational cost of DN. Various profiles of EV users and how they can vary the charging arrangement model, are shown in Fig 3. Different user profiles can be obtained by varying the risk level adjusted by robust optimization.

By selecting a robustness parameter in the algorithm by the GUI, the user of EV can vary the amount of the penalty factor for the slack variables, which are linked to several functionalities as illustrated in Fig. 3. Slack variables are fictitious values selected by the solver of the optimization problem. The solver selects these variables such that it can maximize the revenue of EV users as well as fulfill the requirement of the EV user together with making soft limitations to guarantee the optimization algorithm converges in cases which deviance from the hard limitations is desired. Thus, the parameters of the charging scheduling strategy and the scheduling outcomes are adjusted regarding the selection of EV users. The more risk level rises by the optimizer, the more values of penalty factor on the slack variables of P2P and ancillary service markets will increase. This is because the algorithm tends to force more contributions in these trades. However, the values of penalty factor on slack variables of the battery SOC and trips regulation decrease due to presenting more elasticity to the algorithm in a way that it adjusts set points of charging strategy to maximize the revenue of EV owners. When the slack variable is equal to zero, stiff constraints will be used and consequently, outcomes are not influenced by the slack variable and vice versa.

5.2. Two-Level Mechanism of Smart Contract

The proposed smart contract has two levels as shown in Fig. 4.

The first level comprises executing units of smart contracts. This unit deals with some codes that implement the logic of contracts. The inputs of executing unit are the request of the transaction as well as IDs of smart contracts together with the

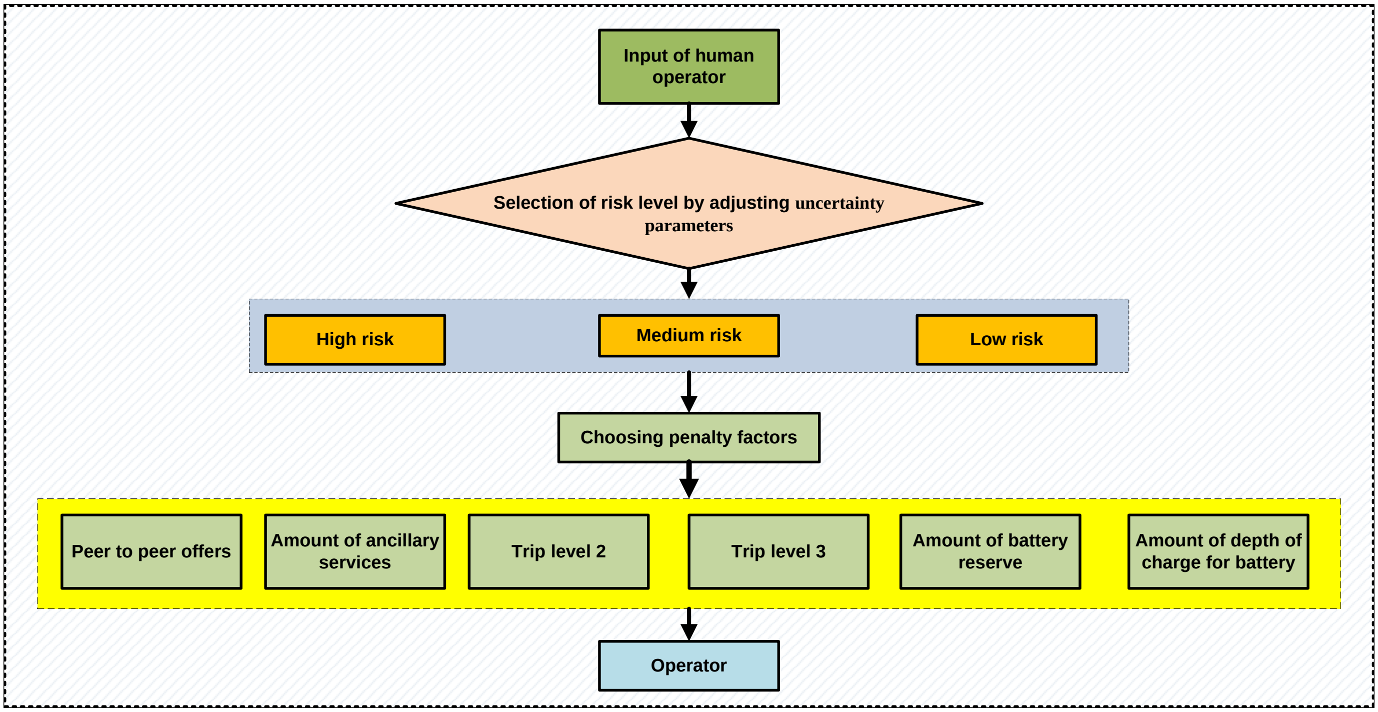


Fig. 3. Flowchart for proposed charging scheduling

credential of users and the current state of the distributed ledger. The executing unit gets the above-mentioned inputs and then, it immediately scans the verification of the credential of users as well as the ID of smart contracts regarding their contents and time stamp. The executing unit accepts the transaction if all of these conditions are yielded; otherwise, the smart contract is entirely rejected. Finally, an approval by the parties of the transaction is sent to the distributed ledger as a new state.

Regarding Fig. 4, the second level executes the smart contract for P2P energy trading of EVs. To begin, the time ahead P2P energy bids existing on the distributed ledger is analyzed by contract. In the second place, the feasibility of the bids is checked by an application linked to the cloud, which communicates data with the upstream grid. The mentioned application evaluates the feasibility of bids in terms of the planned time of energy trading and EV locations. It is clear that bids that are feasible for the peer are considered. Next, the bid with the highest income for EV users is selected by contract. Then, scheduling outcomes are graphically presented to the EV until they can involve their opinion in the scheduling and modify results if there are any unexpected situations. Regarding Fig. 5, an agreement with peers is established by the contract about the confirmation of trading energy by EV users. If an agreement is not obtained, the peer bids are refused and the scheduling procedure is again started with other bids. However, when an agreement is attained, the reserve costs of the contract are paid from the e-wallets of both peers, and therefore, the electrical energy exchange is started. It can be noted that while the energy is exchanged, a nonstop tampering check is performed for the smart meters of both peers. This checking avoids trading parties from fabricating actual energy data given or gotten by the communication network. If tampering is distinguished, the scheduling process is ended, and automatically a penalty is forced on the criminal party. Moreover, if a party is voluntarily disconnected before reaching the amount of the approved electrical energy transfer, a penalty is charged. In addition, the authorized nodes calculate, verify, and validate payments/penalties in all cases after the process is completed. Finally, the expense and discharge of payments from e-wallets in the approved cryptocurrency are given out to the parties based on the final result.

Table 1. The characteristics of EV model

Parameter	Value	Parameter	Value
P_{ch}^{min} (kW)	0	$SOC^{\ max}$(kWh)	75
P_{ch}^{max} (kW)	11.5	R^{con}(kWh/km)	22
P_{dis}^{min}(kW)	0	$SOC^{sto}(\%)$	10
P_{dis}^{max}(kW)	11.5	$SOC^{dod}(\%)$	10

6. Simulation Results

6.1. The Under-Study System

The proposed model is tested by Tesla Model S AWD-P75D, which is a prevalent EV model accessible in the EV market [47]. The specification of this EV model is given in Table 1. Furthermore, this work considers the ToU prices of the electric power distribution company of Tehran, Iran. These prices are presented in Table 2. P2P and ancillary service prices are given in Table 2. It can be noted that prices pertaining to P2P and ancillary service have been set at the midpoint between ToU amounts such that the EV user can sell electrical power at prices higher than those of the distribution company as well as purchase at prices lower than those offered by the distribution company.

It can be noted that the P2P and ancillary service prices are adjusted at mid-point amid dissimilar ToU amounts that an EV user is considering to sell electrical energy at prices upper than utility prices and purchase energy at prices lesser than utility prices. Nevertheless, the algorithm is generically considered in a way that diverse prices and conditions are employed to make the most revenue and/or decrease costs for users of EVs. The presented case study is concentrated on employing operating reserve providing to the distribution network as an ancillary service. Operational reserve services are applied through unpredicted or eventuality circumstances when services of the regulation are not sufficient to retain the equilibrium between the demand and generation [53].

The result pointed in Fig. 1 makes a basement to yield the trip profile of a representative user of EV in this section. Fig. 1 shows 1 to 6 trips per weekdays; therefore, 4 trips are selected for simulation of this section. During a weekday, each EV user prefers an average traveling distance near 50 km, which is selected as the total distance of the needed trips in the simulation results. It

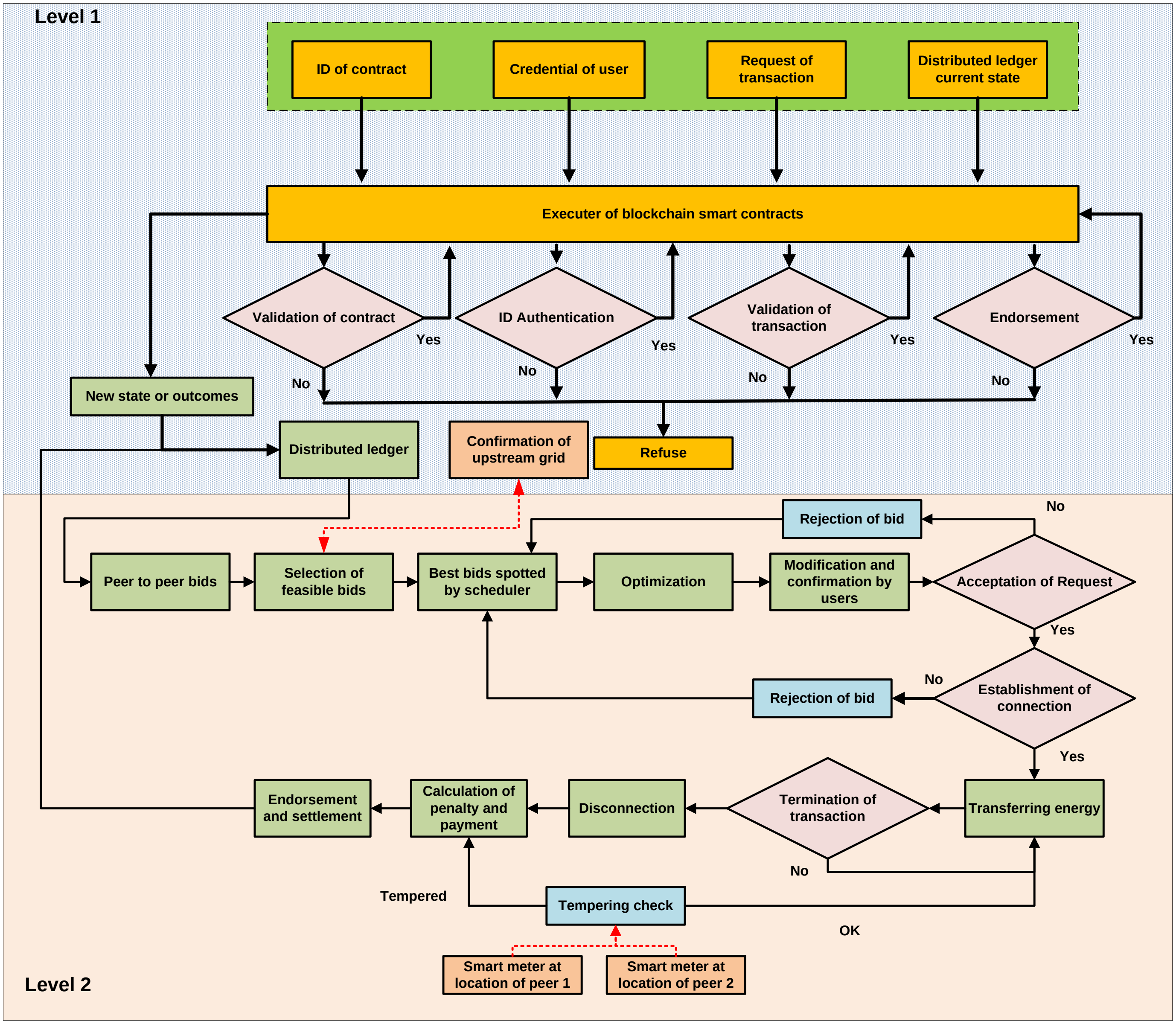


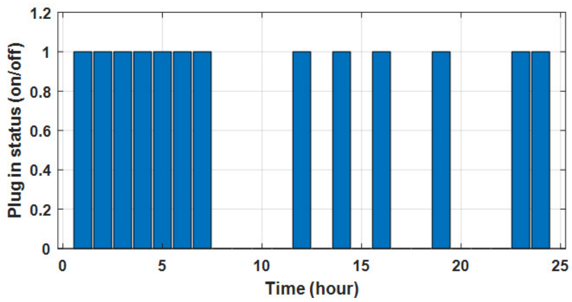
Fig. 4. Flowchart for proposed smart contract mechanism

Table 2. The TOU, P2P, and ancillary service prices

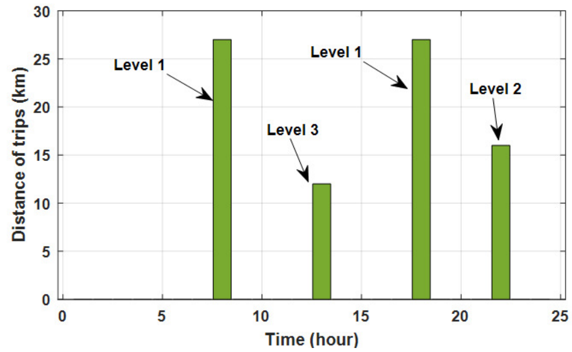
Price (cent/kWh)	Off-peak	Mid-peak	On-peak	Mid-peak
Time	7 p.m-7 a.m	7 a.m-11 a.m.	11 p.m-5 p.m.	5 p.m-7 p.m.
TOU	6.5	9.4	13.2	9.4
P2P	6.5	7.95	11.3	7.95
Ancillary service	13.2	13.2	13.2	13.2

Table 3. Amounts of penalty factors for different EV user profiles

Penalty factors	Low-risk profile $0 \leq \alpha \leq 0.33$	Moderate-risk profile $0.34 \leq \alpha \leq 0.66$	High-risk profile $0.67 \leq \alpha \leq 1$
$\mu^{anci}(t)$	$10^{-6} - 1$	$1 - 10$	$10 - 100$
$\mu^{P2P,ch}(t)$	$10^{-6} - 1$	$1 - 10$	$10 - 100$
$\mu^{P2P,dis}(t)$	$10^{-6} - 1$	$1 - 10$	$10 - 100$
$\mu^{sto}(t)$	> 100	$10^{-6} - 1$	$10^{-6} - 1$
$\mu^{dod}(t)$	> 100	$10 - 100$	$10^{-6} - 1$
$\mu^{NCT}(t)$	> 100	> 100	$10^{-6} - 1$
$\mu^{EST}(t)$	> 100	$10 - 100$	$10^{-6} - 1$



(a)



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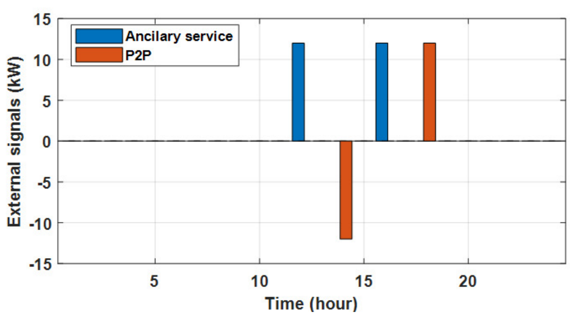


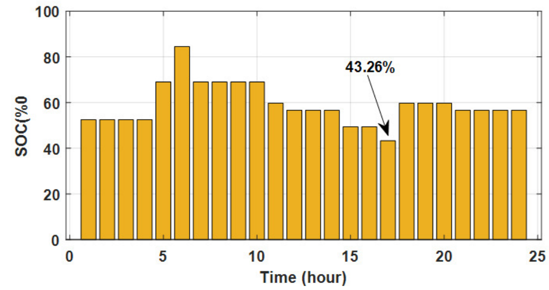
(c)

Fig. 5. (a) Status of EV battery, (b) Distances of the user trip, (c) External signals prepared by the algorithm

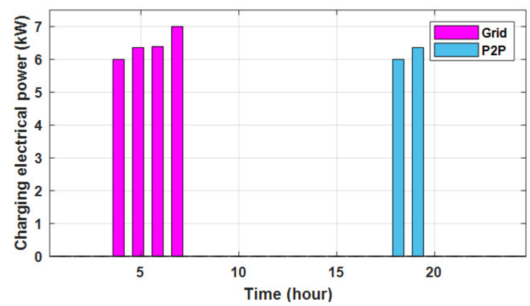
is assumed that the time of the day when charging usually occurs is utilized to make a profile for the plug-in status of the charger. Moreover, it is presumed that EVs have a two-directional charger permitting them to be charged or discharged whenever they want.

The expected plug-in status of the charger, type of trips, and profiles of the external signal for a typical day are shown in Fig. 5. For simulation of the model, it is presumed that user's locations are scrutinized and matched with the maps of online data to make the predictable charger plug-in status profile and predictable duration and distance of the trip as displayed in Fig. 5(a) and 5(b), respectively. It can be noted that the trip duration is taken into account as one hour. The model also presumes to attain the importance of these locations for the EV user to categorize the trips into Level 1, Level 2, or Level 3. After making the EV charger plug-in status, the model evaluates the requests of time-ahead ancillary service and transaction offers of P2P in a way that they meet the predictable connected status during the scheduling time; the resulted information is then used to make signals of the ancillary and P2P in Fig. 5(c).

In this case, the expectation is to be obtainable several P2P offers during the same hour; however, the proposed model selects the optimal ones. The proposed algorithm is implemented for day-ahead and it considers three driving profiles explained in the previous section and uses the input data presented in Fig. 5.



(a)



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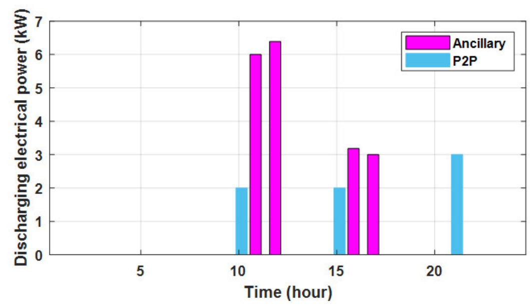
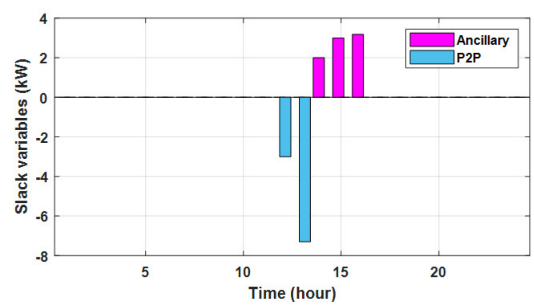
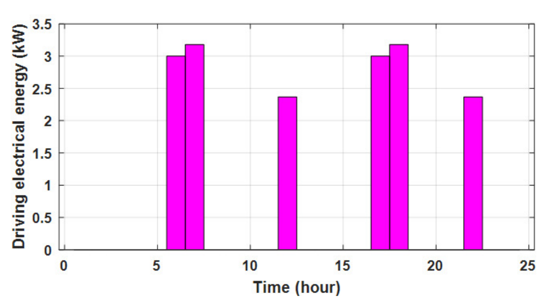


(c)



(d)



(e)

Fig. 6. EV scheduling (set points) for low-risk profile

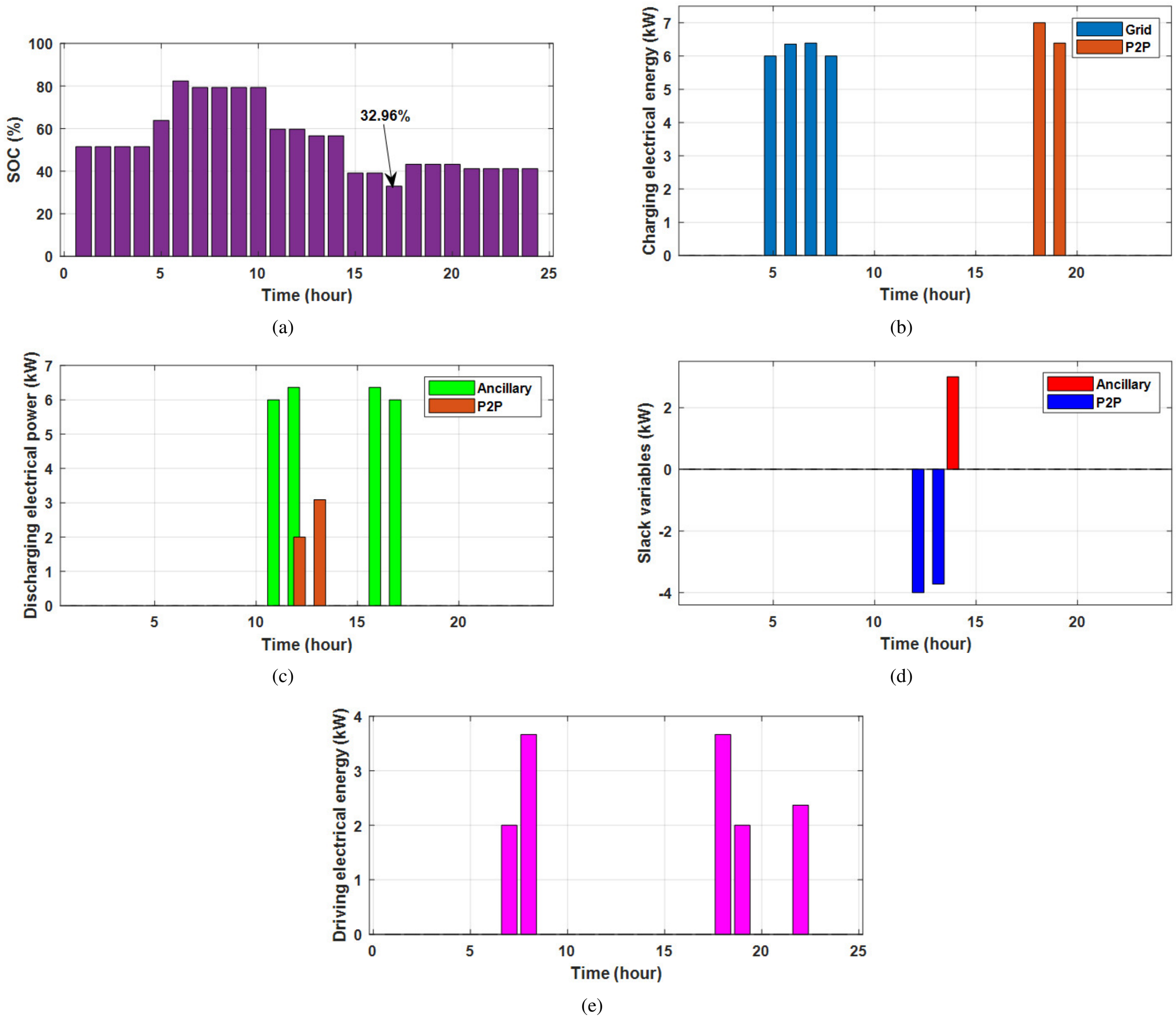


Fig. 7. EV scheduling (set points) for moderate-risk profile

This simulation takes into account one hour as the smallest scheduling time for each decision variable. It also sets the initial SOC equal to 50%. By increasing the percentage of uncertainty in optimization that is α, the penalty factors pertaining to P2P charging/discharging and ancillary service are amplified while the penalty factors for other variables are reduced. The penalty factors assigned to decision variables in the proposed problem are determined in a trial-and-error way and they are expressed in Table 3.

6.2. The Numerical Results

Fig. 6, 7, and 8 display the scheduling results (set points) for three preferences of EV users including low-risk (low uncertainty radius), moderate-risk (moderate uncertainty radius), and high-risk (high uncertainty radius), respectively.

The simulation results in Fig. 6 show that SOC is not below 43.26% in the low-risk profile due to managing battery depth of discharge and reserve levels via the high penalty factors that control their slack variables. However, the algorithm more relaxes the slack variable related to the battery reserve under a moderate-risk profile such that the SOC drops to 32.96 % in Fig. 7. It can be noted that the penalty factors pertaining to SOC act the under a high-risk profile in a way that the SOC reaches 22.66 % without affecting serious degradation to the battery lifecycle. Fig. 6 displays the charging/discharging process under low-risk profile. It is worthwhile to note that participation in P2P dealings and participation in ancillary services are performed in a low manner such that half of the external requests are repealed in the algorithm by the slack variables as depicted in Fig. 6, Figs. 7 and 8 represent the charging/discharging processes under moderate and high-risk profiles, respectively. Regarding Figs. 7 and 8, contribution in the ancillary service market reaches its supreme value in moderate and high-risk profiles even though contribution in P2P deals for high-risk profile is more than that in moderate ones. Therefore, the set points related to high-risk profile have the maximum participation in external energy exchange. Figs. 6, 7, and 8 show the electrical energy of driving in three different profiles. It can be noted that regarding high penalty amounts assigned to the slack variable of trip Levels 2 and 3 in the low-risk profile, all kinds of trips illustrated in Fig. 5 are scheduled to contribute without any modification, as exemplified in Fig. 7. On the contrary, Fig. 8 depicts the setting of trips Level 2 and Level 3 related to the high-risk profile. It shows the aggressive behavior of the proposed

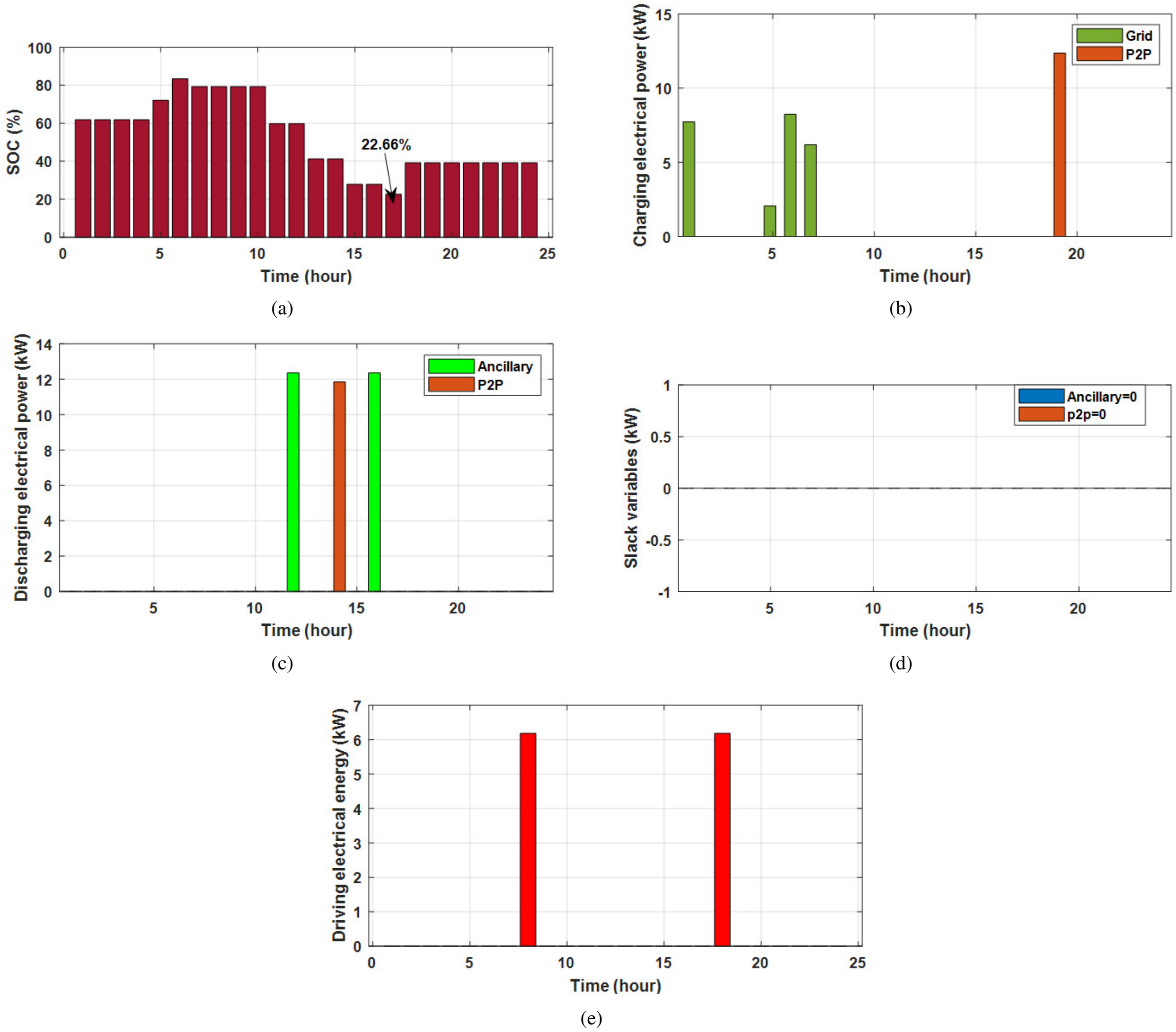


Fig. 8. EV scheduling (set points) for high-risk profile

algorithm to raise revenue. Moreover, the extra accessible electrical energy is obviously used to reply to the external electrical energy requests as illustrated in Fig8.

6.3. ASCI and P2PI

Regarding the data derived by Fig. 1 about driving profile, the proposed algorithm is re-executed for one year. Fig. 9 shows the values of ASCI and P2PI for each uncertainty radius. It can be noted that increasing the risk level in the profiles leads to increasing the values of indices. Given that the radius uncertainties equal to 0.2, 0.5, and 0.8 are considered as reprehensive of conservative, moderate, and high-risk driving profiles, respectively, Fig. 9 shows that ASCI rises to 68.32%, 78.45%, and 90.23% for low, moderate, and high-risk profiles, respectively. Moreover, P2PI increases to 26.45%, 70.65%, and 91.67% for low, moderate, and high-risk profiles, respectively. Table 4 represents the yearly cost and income together with the savings for various operating modes. Indeed, the savings show the cost reductions obtained by the EV user via applying the proposed algorithm.

This paper considers five operating modes: Unoptimized charging is a mode in which the EV user charges EV as needed without considering optimization in a deterministic way. Optimized charging only is a mode in which the EV is charged during

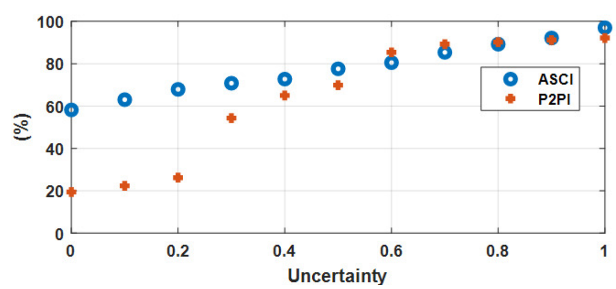


Fig. 9. ASCI and P2PI for different profiles

low electricity price hours without contributing to any external dealings in a deterministic way. The other modes are the same as the profiles defined in the preceding sections. The result reported in Table 4 shows that the yearly cost of electrical charging is decreased by $178 in the second mode. In addition, a rise in electrical charging costs corresponds to a contribution in external dealings in the last three modes. Nevertheless, this rise in cost is somewhat compensated in the low risk and moderate risk profiles with growth in incomes that bring about savings of $452 and 521 for low-risk and the moderate-risk profiles, respectively. Moreover, the EV users earn a minor annual profit of $79 and a great saving

Table 4. Yearly cost/income for different operation modes

Operation mode	Cost ($)	Revenue ($)	Saving ($)
Charging without optimization (deterministic)	546	0	0
Charging with optimization (deterministic)	368	0	183
Low-risk profile	725	645	452
Moderate-risk profile	835	781	521
High-risk profile	784	863	583

Table 5. Yearly cost/income for different operation modes under light trip

Operating mode	Cost ($)	Revenue ($)	Saving ($)
Charging without optimization (deterministic)	314	0	0
Charging with optimization (deterministic)	153	0	145
Low-risk profile	613	724	401
Moderate-risk profile	706	816	413
High-risk profile	713	852	425

Table 6. Yearly cost/income for different operation modes under heavy trip

Operating mode	Cost ($)	Revenue ($)	Saving ($)
Charging without optimization (deterministic)	625	0	0
Charging with optimization (deterministic)	407	0	223
Low-risk profile	774	523	397
Moderate-risk profile	861	746	504
High-risk profile	872	834	576

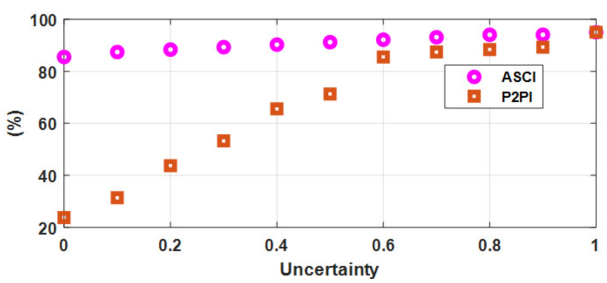


Fig. 10. ASCI and P2PI for different profiles for light driving schedules

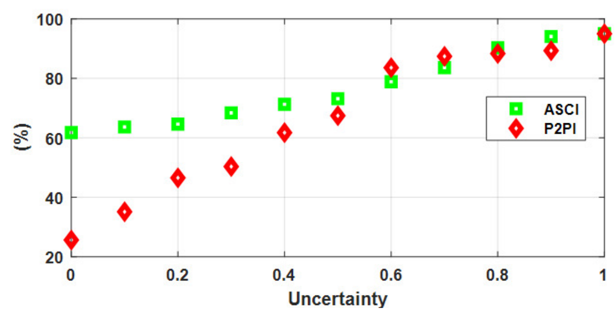


Fig. 11. ASCI and P2PI for different profiles for heavy driving schedules

of $583 for the high-risk profile.

For better evaluation of the proposed algorithm, firstly, two extreme cases including light and heavy driving schedules are implemented for a period of one year. Then, the simulation results are compared with results pertaining to the normal driving profile as illustrated in Fig. 5. The EV user performs two trips and more than five trips per weekday for light and heavy driving schedules, respectively. Figs. 10 and 11 exemplify the amounts of ASCI and P2PI for the light and heavy trips, respectively. Fig. 10 demonstrates that if the EV users prefer a light driving schedule per weekday, they could have more contribution to the ancillary services market and P2P transactions. On the other hand, it is observed in Fig. 11 that the contribution in external dealings is somewhat reduced and corresponds to a smaller amount of battery energy accessible to peers and the grid. For instance, amounts of ASCI and P2PI are reduced by 6.3% for the low-risk profile compared to those achieved under the average driving profile displayed in Fig. 9.

The amounts of the annual cost and revenue together with savings for various operating modes for light and heavy driving schedules are listed in Tables 5 and 6, respectively. Table 3 specifies that the EV user by selecting a light trip schedule could produce revenue under any profile that permits contribution in external dealings. Whereas, by selecting a heavy trip schedule, EV users could decrease the cost of charging without optimization by an extreme of 92.14% via the high-risk profile without producing any revenue.

7. Conclusions

Paper aims to present the role of EV users' preferences including low, moderate, and high-risk profiles in the scheduling process. The above-mentioned risks are modeled by a robust optimization method. The paper shows that by selecting different profiles by the EV user, they contribute differently in cooperative services to the grid. To conclude, this paper suggests a bidirectional electrical charging approach based on blockchain mechanism for involvement in the P2P energy market and ancillary services provided to the grid. The EV user incorporates into the scheduling model via optimization variables and soft constraints and also regulates set points of the scheduling model to be adaptive model in numerous conditions. The proposed algorithm uses the optimization slack variables to manage battery SOC and electrical energy allocation for several services. The numerical results are based on real-world data gathered from car users in Tehran City. Simulation results demonstrate the effectiveness and feasibility of the proposed model. It also reveals how the integration of EV user preferences into the scheduling procedure can improve the income produced.

The main achievements of this work are as follows:

- On a normal trip, the yearly cost of optimal electrical charging is reduced by 32.6% compared to non-optimal ones. In addition, low-risk, moderate-risk, and high-risk profiles increase yearly cost by 97.01%, 126.92%, and 113.04% in comparison to deterministic ones, respectively.

- On a light trip, the annual cost of optimal electrical charging is decreased by 51.2% compared to non-optimal ones. Besides, low-risk, moderate-risk, and high-risk profiles rise yearly cost by 95.2%, 124.8%, and 127.07% in comparison to deterministic ones, respectively.
- On a heavy trip, the yearly cost of optimal electrical charging is lessened by 34.8% compared to non-optimal ones. Also, low-risk, moderate-risk, and high-risk profiles rise yearly cost by 23.8%, 37.7%, and 39.5% in comparison to deterministic ones, respectively.

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