The CVaR-based risk assessment of the electric vehicle's intelligent parking lots with energy storage devices including equalizers and fuel cell

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The close attention to the utilization of electric vehicles (EVs) causes the penetration of intelligent parking lots (IPL) to increase. Also, vehicle-to-grid (V2G) strategy next to the grid-to-vehicle (G2V) strategy improves the profitability of the IPLs. In addition to vehicle charge and discharge management, the IPLs can gain more profit by installing and accessing loads and resources. In this paper, the IPLs next to the hydrogen storage system (HSS) containing electrolysis, hydrogen, and fuel cell storage reservoirs are considered to serve the loads in the upstream grid that is modeled through a scenario approach based on stochastic optimization. The uncertainties in the electrical load, market price, the arrival and departure time of vehicle, primary state-of-charge (SOC), and desired car with appropriate SOC are modeled in the proposed method. According to the uncertainty of the proposed hydrogen storage-based intelligent parking lot values, the financial risks are investigated by the conditional value-at-risk (CVaR) method to get the risk-neutral and risk-averse methods during the system function. The obtained results demonstrate that the uncertain parameters significantly impact smart parking operators' profitability, so considering uncertainty is a critical issue for parking lots. Risk results also represent that the variation of financial risk in the higher deviation of uncertain parameters is more than risk variation in lower deviations.

keywords: *Stochastic optimization, conditional value-at-risk, scenario, vehicle to grid, grid to vehicle, hydrogen tank*

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NOMENCLATURE

EV Electrical vehicles
G2V Grid to vehicle
V2G Vehicle to grid
PV Photovoltaics
PHEV Plug-in hybrid electrical vehicles
Sp Stochastic programming
WT Wind turbines
A Initial investment cost
SOC State-of-charge
n Lifetime
MT Microturbine
RES Renewable-energy-resources
HSS Hydrogen stored system
IPL Intelligent parking lots
t Index of of time
v Index of vehicle type
ω Index for scenarios
C_V Battery Capacity
C^{FC} Exploitation expense of the fuel cell
C^{EL} Exploitation expense of the electrolyzer
$H_t^{TANK-FC}$ Rate of hyrogen dicharged from the tank to fuel cell
$P_t^{TANK-FC}$ Hourly tank power
E_{H_2} Hydrogen energy
$H_t^{EL-TANK}$ Compressed hydrogen in tank
$P_t^{EL-TANK}$ Electrolyzer power outcome in t
M_t^{TANK} Hydrogen storagein the tank in t
$M_{t-\Delta t}^{TANK}$ Hydrogen storagein the tank in $t-\Delta t$
η^{TANK}, η^{FC} Tank and FC efficiencies

Δt The time period
P_t^{IPL-EL} Power delivered of IPL-to- electrolyzer
η_V^D Discharging efficiency of EV battery
η_V^C Charging of EV battery efficiency
$P_t^{V,C}$ charged power of the battery in EV
$P_t^{V,D}$ Discharged power of the battery in EV
t_V^a Approximate arrival time of vehicle
t_V^d Approximate departure time of vehicle
m_{G2V} Set-up To test electric V-to-G
λ_C^t Charging rate of the EV in t
U_t^V A binary variable in t
$SOC_{t_V^d}$, $SOC_{t_V^a}$ The primary and Final state of charging of EV
$\lambda_t^{c,V2G}$,$\lambda_t^{sell-load}$ Charging rate of the V2G EV in t
$\lambda_t^{d,V2G}$ Discharging rate of the V2G EV in t
SOC_V^{max} Maximum SOC of vehicle
SOC_V^{min} Minimum SOC of vehicle
$P_t^{sell-grid}$ The rate of energy sold which by IPL
C^ω Expense of scenario ω
η^ω Auxiliary variable
$\lambda_t^{sell-load}$ Price of sold power to load
$SOC_{desired}^V$ Desired SOC of vehicles
ζ Value of risk
β Coefficient to achieve suitable swap between cost and calculated conditional value at risk.

1. INTRODUCTION

A. *motivation*

The wide range of electric vehicles (EVs) in the power network are considerable electric loads that may lead to a challenge in the system operator. Increasing the electric vehicle penetration forces the electrical grid operators to equip themselves to encounter this new challenge. A large penetration of the EVs has turned them as active players in the power network system that potentially affects the operation of the optimum system due to their unreliable behavior. Proper integration and management of IPLs and storage systems are efficient and reliable solutions for reducing the negative effects of uncertain parameters [1, 2]. As well as, the plug-in electric vehicle (PEV) charger is committed as a quick charger. In addition, smart electricity networks can provide various auxiliary services to the grid for allowing bidirectional energy transfer [3, 4]. The utilization of IPLs can contribute to the vehicle-to-grid (V2G) technology. All-electric vehicles for supply to power their electric motors are equipped with batteries. In charging mode, PEVs can receive energy and in discharging mode, can deliver energy to the grid. The connection of PEVs in IPLs is in the form of bidirectional flow. Indisputably, PEVs can be used as a burden and power source unit from a smart grid vision [5–7]. By planning the battery charging strategy simultaneously, can investigate the revenue and profit of the smart grid. Further, this mode of PEVs causes receiving income to PEV's owners when their cars are parked [8].
Perhaps, by considering the type of energy conversion, the electricity storage systems could be categorized into four sections, including battery, compressed air, electrical and mechanical systems [9]. Hydrogen storage is a type of chemical energy storage in which the conversion of electricity into hydrogen, the state of discharge, and the conversion of hydrogen into electricity is the state of charge. Electrolysis is a procedure in which chemical changes occur to break down water molecules into oxygen and hydrogen as electricity passes through the article. During this process, the first oxygen and hydrogen are obtained by electrolysis of water, and then by the fuel cell's conversion stage continues. All this reaction occurs in the electrolytic cell [10, 11]. A major advantage of the hydrogen system is hydrogen storage in the hours that electricity consumption and tariffs are less and its conversion into electricity through the fuel cell at peak times and rising electricity prices. Hydrogen can be stored in various ways, the most important of which is compression, which can be stored as pressurized gas [12].
Currently, the number of electric vehicles is increasing, and IPLs are considered a charging place, so there is a pressing need to study. Several samples of the study of connecting IPLs to the upstream network and charging / discharging of vehicles are presented [13]. The authors have evaluated the coordination of the distribution networks and IPLs to reduce the cost of demand for electric vehicles in the parking lot [14]. In [15, 16] an approach is proposed for controlling and saving electricity consumption through optimization of vehicle charge and discharge is presented. The effects of IPL on the security constrainted unit commitment problem is investigated in [17]. Considering the swapping station of electrical vehicles, the optimal scheduling of a smart mocrogid is investigated in [18]. In [19], electric vehicle parameters such as the amount of energy consumed at the time of entry and exit being modeled using a non-parametric distribution for intelligent parking. In [20], increasing the revenue and profitability of parking owners offers a solution taking into account the restriction of electric vehicle drivers, especially the final SOC of vehicle, when leaving the parking lot. In terms of uncertainty modeling methods in similar systems, in [21], IPL with PV generation uncertainty is offered for random charging and discharging in PEVs. Here, to solve PV uncertainty, energy management in smart parking is investigated. Optimization of IPLs management by considering to price changes in electricity markets in [22] is presented wherein the parameter is modeled non-linear, using Info-gap decision theory (IGDT). In [23], the IGDT-based method is used to model the risk of uncertain parameters in a renewable microgrid. The robust optimization is another well-known approach in risk-assessment that in [24] is used to model the uncertainties of hybrid energy system considering the power-to-gas technologies. By the combination of the stochastic optimization and robust optimization approach, in [25] a hybrid robust/stochastic is proposed to risk modeling of the multi-energy retailers in several energy markets. Also, in [26] the hybrid robust/stochastic is used to model electricity market clearing e in rail transportation system. In [27], optimization of IPLs considering the indeterminacy upstream grid cost based demand response program modeling is analyzed. This approach has increased the strength of IPL toward the inconstancy of generating station cost. Furthermore, in [28], the CVaR risk assessment approach is used to model the financial risk asocieted to hydrogen storage-based multi-carrier energy systems in the risk-constrained stochastic scheduling considering power, gas, and heating network constraints. Moreover, the risk assesement of the power-to-hydroge technology has been investigated in [29]. The CVaR-based framework is proposed in [30] to

investigate the risk-based operation of the renewable-based microgrid. Also, the chnance constrainted method is proposed in [31] for risk investigation of the renewable-based microgrid.

B. *novelty and contributions*

The IPL's operators are searching for an effective way to deal with the uncertainties due to their function's significant effects. Therefore an appropriate uncertainty dialing approach would be welcomed by the IPL operators to utilize in its optimal operations. Based on the reviewed papers, various methods are proposed to model IPL's operation problems' uncertainty. A significant lack of researchers in the uncertainty modeling approaches is a comprehensive approach to model the hole uncertainties. In other words, most of the techniques are modeled the financial risk of limited and special uncertain parameters. Thus, this paper is tried to model all significant uncertainties, simultaneously, that IPL operator is faced in its operation. The uncertain parameters are the arriving and leaving times of the EVs, SOC in the arrival time, desired SOC, electrical demand, and market price. Furthermore, to model financial risks of the uncertain parameters, the well-known and influential CVaR method is required to model the financial risks of the uncertain parameters appropriately that is not used previously in the related research. Therefore, considering all mentioned uncertainties, the model's financial risks are investigated by the CVaR method, which is the most popular and robust approach in linear programming problems. the novelty of this paper can be summarized as below:

• Considering the V2G and G2V vehicles and the uncertainties related to their stochastic behavior and effects on the IPL operation, Simultaneously.

• A comprehensive risk analysis of the most uncertain parameters of the IPL, including the arrival and departure times, load and market price uncertainties on its operation, and proposing the risk-based operation strategy in the uncertain environment.

• Modeling the financial risks by considering the uncertain parameters in the IPL by using the CVAR method.

2. METHODOLOGY OF THE INTELLIGENT PARKING LOT PROCEDURE

In this paper, the integration of the IPL and hydrogen storage is considered to supply the internal loads and power exchange with the grid to obtain profit. Actually, IPL's meanwhile providing the charging of electric vehicles (internal loads), with accepting the participates in the pool market, transmits the electrical energy to the distribution grids.

A. Hydrogen energy storage

In the electrolysis model, hydrogen is considered then stored in high-pressure in composite tanks or bottles. The costs of the discharged hydrogen from the reservoir into the fuel cell and the cost of its storage are presented in Eq. (1) and Eq. (2), respectively.

$$H_t^{TANK-FC} = \frac{P_t^{TANK-FC}}{E_{H_2}} \tag{1}$$

$$H_t^{EL-TANK} = \frac{P_t^{EL-TANK}}{E_{H_2}} \tag{2}$$

Here, E_{H_2} indicates the value of hydrogen energy in each kg. The amount of stored energy in the storage tank obtained from Eq. (3).

$$M_t^{TANK} = M_{t-\Delta t}^{TANK} + (H_t^{EL-TANK} - H_t^{TANK-FC} \times \eta_{TANK}) \times \Delta t H_t^{EL-TANK} = \frac{P_t^{EL-TANK}}{E_{H_2}} \tag{3}$$

Where, $M_{t-\Delta t}^{TANK}$ and M_t^{TANK} are the mass of hydrogen that stored in per unit t and $t-\Delta t$, respectively, Δt shows each period's term and is equal to one hour and η_{TANK} is the tank's efficiency [32].

B. Electrolyzer

Hydrogen is an available element with the advantages of availability, flexibility, and high purity for its widespread applications. Using electrolyzed water to produce hydrogen needs an improvement in energy efficiency, safety, operability, durability, portability, and reduction in installation and operation costs. Actually, by water electrolysis, the element hydrogen and oxygen is produced and used for fuel cells [33].
The power output of the electrolyzer system in per unit t can $P_t^{EL-TANK}$ be calculated using Eq. (4) [34]:

$$P_t^{EL-TANK} = P_t^{IPL-EL} \times \eta_{EL} \tag{4}$$

Where, P_t^{IPL-EL} this power is the electrical energy delivered by the IPL to the electrolyzer, which is the electrolyzer's efficiency.

C. Fuel cell

Common environmental effects and high conversion efficiency are fuel cells' specifications in converting chemical energy into electrical energy [35]. The power input of fuel cells can be obtained of Eq. (5).

$$P_t^{TANK-FC} = \frac{P_t^{FC-IPL}}{\eta_{FC}} \tag{5}$$

The term P_t^{FC-IPL} is the power that the IPL receives from the Fuel Cell, η_{FC} which is the fuel cell's efficiency.

D. V2G mode of EVs

EVs have different capabilities, the main feature of which is the discharge mode (V2G). In this article, the IPL management strategy offers discounts and motivates owners of an EV to take part in the V2G program. [36–38].
The SOC in each PEVs (SOC_V^t) in IPL connected mode, depends on the SOC of a battery in a former time ($SOC_V^{t-\Delta t}$), current of EVs' battery charging and discharging mood obtained in Eq. (6) [39, 40].

$$SOC_V^t = SOC_V^{init} + \left(\frac{\eta_v^c P_t^{V,C}}{C_V} - \frac{P_t^{V,d}}{\eta_v^d C_V}\right) \times \Delta t \quad ; t_V^a < t \leq t_V^d \tag{6}$$

$$-P_{MAX}^{EL} \leq P_t^H \leq P_{MAX}^{FC} \tag{7}$$

Here, η_v^c and η_v^d are battery efficiencies, respectively. $P_t^{V,C}$ and $P_t^{V,d}$ are charged and discharge powers, respectively. While C_V is the rate of battery capacity, t_V^d and t_V^a are the departure and arrival times, respectively. The IPL in communication with electric vehicles has the following income and expenses :

• The payment of sell G2V
• The payment of sell V2G
• The payment of buying V2G
• The payment of using the former charge of the batteries for the grid
• The cost of failures to provisions of EVs charging penalty factor

Income from selling electricity to EVs is presented in Eq. (8) [27]:

$$R_t^{PHEV-m_{G2V}} = \sum_{V=1}^{m_{G2V}} (P_t^{V,C} \times \lambda_C^t) \times U_t^V \times \Delta t \tag{8}$$

In the bellow constraint (8), the $P_t^{V,C}$ indicates the energy that flows into the battery. The term λ_C^t is payment for charging of EVs, and U_t^V is a binary parameter that indicates the connectivity state of the PEVs. Battery SOC at EVs departing times $SOC_{t_v^d}$ suggests that the EV as a seller or as a buyer of energy, in V2G mode. The vehicle is the seller if the battery final SOC is lower than the battery initial SOC, but the buyer is considered more than the initial SOC.

We can calculate the income through sell energy of vehicles to grid, in Eq. (9).

$$R_t^{PHEV-m^{V2G}} = \sum_{V=1}^{m^{V2G}} (SOC_{t_v^d} - SOC_{t_v^a}) \times C_V \times \lambda_t^{c,V2G} \times \zeta_V^d \tag{9}$$

Here, $SOC_{t_v^a}$ and $SOC_{t_v^d}$ show the initial charging and average SOC after charging, respectively. $\lambda_t^{c,V2G}$ represents the V2 G's charging price per unit t, ζ_V^d is the departing figures time of the EV.

The expense of buying power of V2G computed by using Eq. (10):

If $SOC_{t_v^d} < SOC_{t_v^a}$

$$C_t^{PHEV-m_{V2G}} = \sum_{V=1}^{m_{V2G}} (SOC_{t_v^d} - SOC_{t_v^a}) \times C_V \times \lambda_t^{d,V2G} \times \zeta_V^d \tag{10}$$

Here, $\lambda_t^{d,V2G}$ is the V2G discharging cost per unit t. Also, the IPL management inflicts certain expense constraints for using EVs' usable capacity every hour. This cost is obtained using Eq. (11) [41]:

$$C_t^{cap-V2G} = \sum_{V=1}^{m_{V2G}} (SOC_v^{max} - SOC_v^{min}) \times C_V \times \lambda_t^{cap,V2G} \times U_t^V \tag{11}$$

Here, SOC_v^{min} and SOC_v^{max} shows the minimum and maximum SOC in battery electric vehicles, respectively, also $\lambda_t^{cap,V2G}$ is the rate of the available capacity in per unit t.

The expense of failures to EVs charging (penalty factor) pays with the manager when SOC is not desirable SOC and its cost is indicated by Eq. (12).

$$C_t^{penalty} = \sum_{V=1}^{m_{V2G}} (SOC_{desired}^V - SOC_V^{td}) \times C_V \times \lambda_t^{penalty} \times \zeta_V^d \tag{12}$$

Here, $\lambda_t^{penalty}$ shows the tariff rate of the penalties.

3. DETERMINISTIC FORMULATION

In this paper a IPL is incorporated with hydrogen-based system constructure from the Electrolyzer, fuel-cell and tanke to supply the internal loads with the help of the upstream grid. The overview of the proposed IPL system is illustrated in Fig. 1.

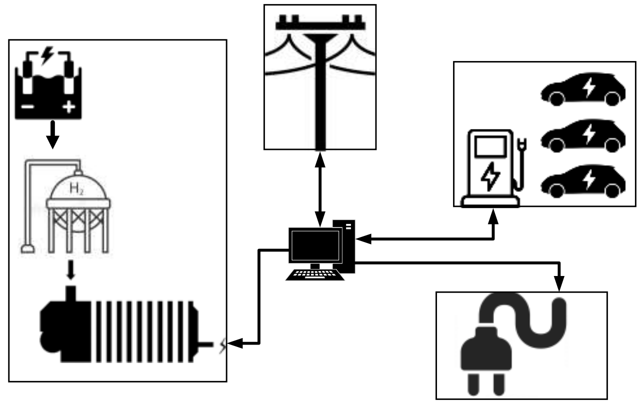

Fig. 1. The overview of the proposed IPL.

A. the objective of the optimization

The economic benefits of the IPL is calculated considering the distinction between expense and income, through Eq. (13). In this equation, the terms $p_t^{buy-grid}$ and $p_t^{sell-grid}$ represent the received and delivered power in the upstream grid. Besides, P_t^L indicates the electrical load in period t , $\lambda_t^{sell-load}$ is the price of electricity sales by IPLs for load. C_t^{FC} is operating and maintenance costs for fuel cell. C_t^{TANK} is the operation and maintenance cost of the hydrogen tank. C_t^{EL} is the operation and maintenance cost of the electrolyzer.

When the power is heading to the upstream grid, $p_t^{sell-grid}$ is equal to power interchanged with the upstream electricity grid p_t^{grid} and $p_t^{buy-grid}$ equal to zero. The power that flowed out of the upstream electricity grid to the IPL ($p_t^{buy-grid}$) is equivalent to power interchanged with the upstream electricity grid p_t^{grid}, $p_t^{sell-grid}$ is similar to zero [41].

Finally, to get the maximum profit of IPL, equation Eq. (14) can be considered in the proposed model.

$$OF = MAX(Profit) \tag{14}$$

B. limitations for IPL

Actually, to increase secure implementation of the intelligent parking and the objective functions optimize, restrictions (15–21) have been imposed [42–44].

$$SOC_V^{min} \leq SOC_t^V \leq SOC_V^{max} \tag{15}$$

$$-P_{max}^{V,D} \leq P_t^V \leq P_{max}^{V,C} \tag{16}$$

$$-P_{max}^{EL} \leq P_t^H \leq P_{max}^{FC} \tag{17}$$

$$M_t^{TANK} \leq M^{max} \tag{18}$$

$$M_0^{TANK} = M_{24}^{TANK} \tag{19}$$

$$P_t^{IPL-EL} + P_t^L + P_t^C + P_t^{sell-grid} = P_t^{FC-IPL} + P_t^{buy-grid} + P_t^d \tag{20}$$

$$P_t^{grid}; |P_t^{grid}| \leq P^{grid-max} \tag{21}$$

The constraint Eq. (15) shows maximum and minimum SOC for each EV. It also guarantees that the battery's charge and discharge energy are less than the space inside the battery's capacity. The amount of energy in batteries and the battery

$$profit = \sum_{T=24}^{t=1} \left(\begin{array}{l} ((P_t^{sell-grid} \times \lambda_t^{grid}) - (P_t^{buy-grid} \times \lambda_t^{grid})) \times \Delta t + (\lambda_t^{sell-load} \times P_t^L) \times \Delta t \\ (R_t^{PHEV-m_{G2V}} + R_t^{PHEV-m_{V2G}}) - (C_t^{cap-V2G} + C_t^{PHEV-m_{V2G}} + C_t^{penalty}) \\ -(C_t^{FC} + C_t^{EL} + C_t^{TANK}) \end{array} \right) \quad (13)$$

charger's maximum capacity is indicated by Eq. (16). The electrolyzer/fuel cell's full power is described in Eq. (17), maximum capacity in the hydrogen storage tank is expressed by Eq. (18). Constraint (19) presents the mass of H2 into the beginning of the tank and the final utilization that must be the same to meet the need for hydrogen the next day. Constraint (20), provides the power balance of IPL, P_t^C is the sum of charging and discharging the energy of PEVs. In Eq. (21), the maximum capacity of transmission-lines that is connected to the grid is presented.

4. CVAR METHODOLOGY

Recent progress on the uncertainty based optimization problems is considered a risk management method to measure the imposed financial risks. In the optimization problem to avoid undesirable conditions for manufacture and make the right decisions in the face of adverse circumstances in the objective function, uncertainty is considered [31]. This paper models the uncertainties by assuming the worst-case scenario with a CVaR method, which is one of the risk control procedures in stochastic programming. According to the uncertain parameters, the CVaR model is used for managing the risk in a stochastic environment [45]. Among other risk measures, stochastic programming (SP) for uncertainties with scenarios CVaR method is chosen as a risk measure because it is strong and benefits such as stability of calculations and numeric efficiency. CVaR can be formulated through Eq. (22)-Eq. (24) [46]:

$$Max\zeta - \frac{1}{1+\alpha} \sum^{\omega \in N_W} \lambda^{\omega} \times \eta_{\omega} \quad (22)$$

Subject to:

$$Profit^{\omega} + \zeta \leq \eta^{\omega} \quad (23)$$

$$\eta^{\omega} \geq 0 \quad (24)$$

Where $Profit^{\omega}$ is the profit of scenario ω and value at risk ζ . If ζ is lower than $Profit^{\omega}$, η^{ω} equal is 0. η^{ω} is auxiliary variable that allocated for discrepancy relevant to the expense and value at risk. Based on the formulation as mentioned above, the final problem formulation of the model can be modeled as below:

$$\eta^{\omega} \geq 0 \quad (27)$$

Subject to:
Constraints (1)-(12) and (15)-(21)

5. CASE STUDY

This paper, models optimal scheduling of EV parking lots by mixed-integer programming that CPLEX solves in the general algebraic modeling system (GAMS) optimization tool. In the proximity of hydrogen storage and load and smart grid, IPL seeks to maximize its profit. At last, IPL in electric vehicles is equipped with G2V and V2G.
The results of this paper are represented for two case studies as below:
Case 1: Without considering the risk imposed from the uncertain parameters as risk-neutral strategy.
Case 2: Considering the financial risk og the uncertain parameters as risk-averse startegy.

A. Input data

In this paper, the relevant uncertainties to the electrical load, network power, the arriving and leaving times, primary SOC, and desired terminal SOC of the vehicles are modeled via stochastic programming and the CVaR strategy, which is used to determine the possible risk. The simulation is carried out according to the following data: input data of market and demand price that is illustrated in Fig. 2. The expected values are provided to generate dependent scenarios for vehicles arriving and leaving time, the primary and desired SOC in Table 1. Deterministic-based input data for IPL, HSS, PHEVs, and predicted PHEVs' data is achieved from the reference [47].

Table 1. Information of stochastic parameters to scenario generation

Stochastic parameter	Mean	Standard deviation
t^a	8	3
t^d	17	3
SOC^{init}	30%	10%
$SOC^{desired}$	85%	10%

B. Results

Fig. 3 displays the expected profit based on cost versus (β). When the Beta increases from 0 to 0.3, the amount of profit comes down from \$ 62.7 to \$ 44 (\$18.7 profit reduction), while from 0.4 to 1 the profit is reduced by about \$10. It is observed that the slope of profit in this amount of Beta is considerably decreased. As can be seen, the profit sensitivity is much higher in lower betas. Beta's increase means that the conditions of uncertainty worsen, and the closer the Beta to 1, the profit is minimized. In other words, according to Fig. 3 it can be shown that for β from 0 to 0.3 that refers to the near to risk-neutral strategy, the profit is reduced with a high slope while the slope of profit reduction is slightly reduced for β amounts near to risk-averse strategy.
In this paper, due to the uncertainties of existing parameters, investigating the risk management level with the CVaR index is introduced in two different risk management strategies: risk-averse and risk-neutral. The risk-averse approach is the best possible condition scenario, such as network price, network demand, and vehicle conditions in the parking lot, which reduces the risk and increases job security. But in risk-neutral, getting the maximum benefit with the highest risk is considered.
The risk-averse and risk-neutral functions for acquiring power from the market are indicated in Fig. 4. According to Fig. 4, the purchased IPL electricity from the grid is performed almost every hour, but selling power to the grid is carried out during a short period. The purchased energy from the market at

$$
\begin{aligned}
&Max: \\
&\sum_{\Omega}^{\omega\in N\omega} \pi^{\omega} \sum_{T=24}^{t=1} \left(\begin{array}{l} ((P_{t,\omega}^{sell-grid} \times \lambda_{t,\omega}^{grid}) - (P_{t,\omega}^{buy-grid} \times \lambda_{t,\omega}^{grid})) \times \Delta t + (\lambda_{t,\omega}^{sell-load} \times P_{t,\omega}^{L}) \times \Delta t + \\ (R_{t,\omega}^{PHEV-m_{G2V}} + R_{t,\omega}^{PHEV-m_{V2G}}) - (C_{t,\omega}^{cap-V2G} + C_{t,\omega}^{PHEV-m_{V2G}} + C_{t,\omega}^{penalty}) - \\ (C_{t,\omega}^{FC} + C_{t,\omega}^{EL} + C_{t,\omega}^{TANK}) \end{array} \right) \times (1-\beta) + \\
&\beta \times \left[\varsigma - \frac{1}{1+\alpha} \sum_{\Omega}^{\omega\in NW} \pi^{\omega} \times \eta_{\omega} \right]
\end{aligned} \tag{25}
$$

$$
\sum_{T=24}^{t=1} \left(\begin{array}{l} ((P_{t,\omega}^{sell-grid} \times \lambda_{t,\omega}^{grid}) - (P_{t,\omega}^{buy-grid} \times \lambda_{t,\omega}^{grid})) \times \Delta t + (\lambda_{t,\omega}^{sell-load} \times P_{t,\omega}^{L}) \times \Delta t \\ (R_{t,\omega}^{PHEV-m_{G2V}} + R_{t,\omega}^{PHEV-m_{V2G}}) - (C_{t,\omega}^{cap-V2G} + C_{t,\omega}^{PHEV-m_{V2G}} + C_{t,\omega}^{penalty}) \\ -(C_{t,\omega}^{FC} + C_{t,\omega}^{EL} + C_{t,\omega}^{TANK}) \end{array} \right) + \varsigma \le \eta^{\omega}, \forall \omega \tag{26}
$$

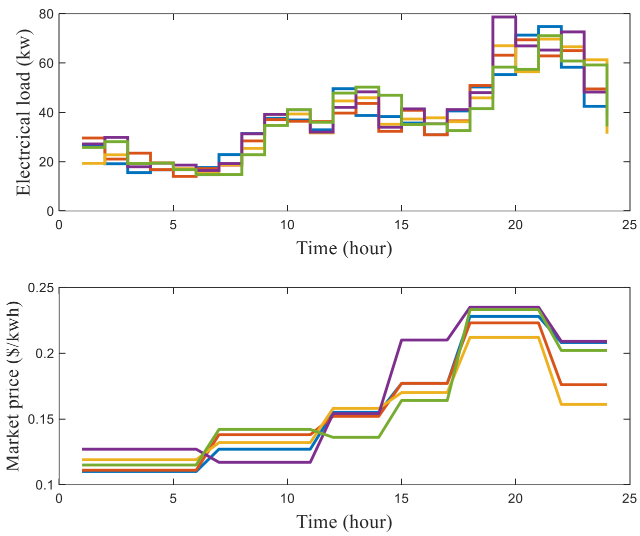

Fig. 2. Electrical load and Market price.

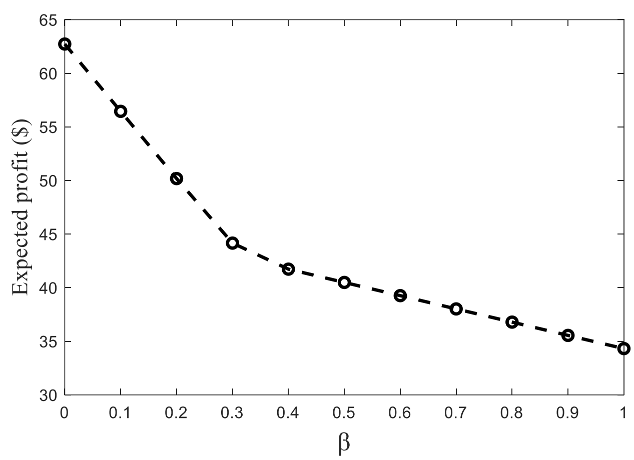

Fig. 3. Cost versus β of expected profit.

peak hours, such as 10 and 22, has the highest amount. In the risk-averse scenario, which is considered the worst scenario, the purchasing power is notable during off-peak hours when the price is in the lowest amount. While, in risk-natural, the pur-

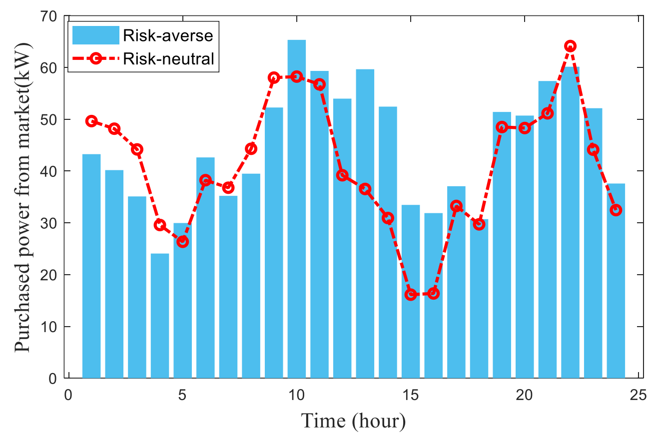

Fig. 4. Bought power of market.

chasing of power in off-peak hours is less than risk-averse.
Fig. 5 shows charged power of grid-to-vehicle. The amount of energy the cars are received in the risk-averse and risk-neutral strategies is zero, and it is indicated during 1 to 4 hours when the vehicles were out of the parking lot. The figure shows that the amounts of charged power of G2V in the risk-neutral are higher than the risk-averse. Because in this case, the vehicles are in the parking place for a long time, so in risk-neutral, vehicles' charged power in the early hours of 10-15 is higher. Furthermore, by comparison of the Figs. 4 and 5 it can be concluded that in the risk-averse strategy at the high price hours, the purchasing power from the grid is reduced, and the IPL operator relies more on the internal resources etc. vehicles and storages.
Fig. 6 is picturing the level of stored hydrogen in the tank. The hydrogen tank is charged for peak hours and discharged from 15 to 24. As shown in Fig. 6, in the risk-neutral to attainment more profit, the amount of stored hydrogen in the reservoir at the same hours is excellent, compared to risk-averse. Besides, in the risk-neutral, the amount of stored energy in the system is increased.
Fig. 7 shows the risk-neutral performance and charge and discharge power of EVs in the IPL in risk-averse. Due to the absence of vehicles from the parking lot in the first hours, the amount of energy is zero. The cars are also charged from 5 to 1 because of less price. In addition, The price of the scenarios at 11.am is increased. The vehicles are discharged, and the IPL performance is considered as a seller to network. Finally, in the risk-averse,

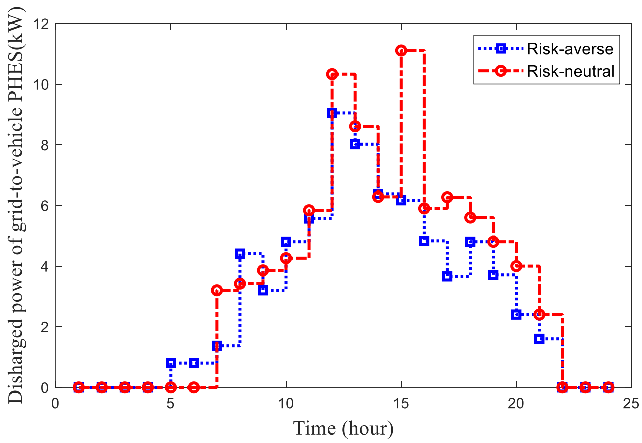

Fig. 5. Charged power of grid-to-vehicle.

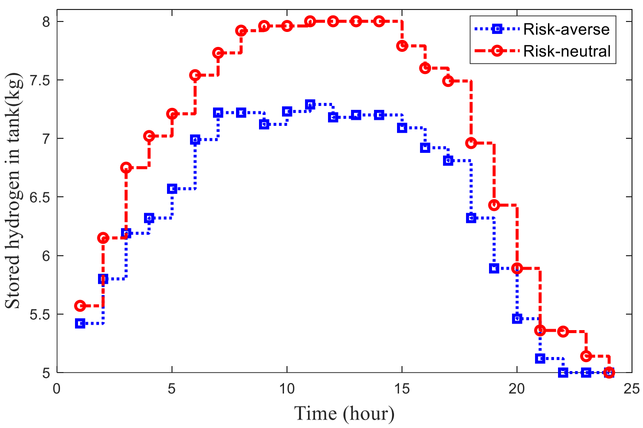

Fig. 6. The level of stored hydrogen in the tank.

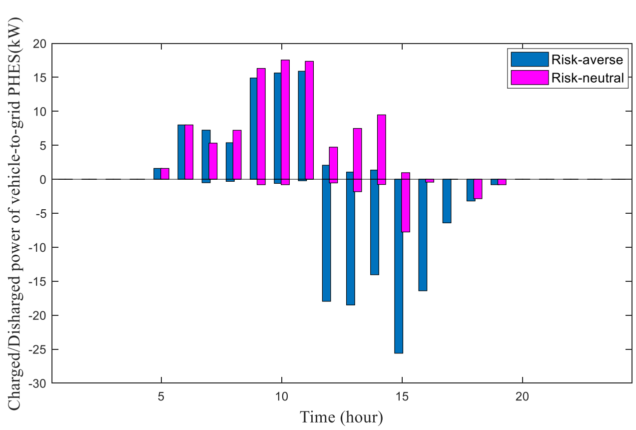

Fig. 7. Charged and discharged power of V2G.

the vehicle's discharge is higher than the risk-neutral because of the risk-averse strategy.

6. CONCLUSION

This work considers PHEVs with the G2V and V2G system and the CVaR stochastic optimization of IPL and discussed the uncertainties. Also, a hydrogen system is used as a storage unit available for the IPL. This work aims to show the impact of risk and uncertain parameters on the IPL. PHEVs with a G2V and V2G system are considered in this work, and stochastic optimization for the IPL operation. Thus the uncertain parameters such as electrical loads, network power, arriving and leaving time, primary SOC, and desired terminal SOC of theV2G and G2V vehicles are analyzed in various scenarios. The benefit of IPL and the risk related to this scenario are investigated using the CVaR methodology. The IPL is examined by considering the unexpected scenarios in both risk-averse and risk-neutral methods. According to results, the profit is significantly raised in risk-neutral, while the uncertainties and risks are in their maximum level. In comparison with risk-neutral, the amount of profit is considerably reduced in risk-averse. Furthermore, based on the obtained results, the profit reduction versus β from 0 to 0.3 is \$18.7, while for the highest beta amounts (from 0.4 to 1) the profit is reduced by \$10. Thus, it can be concluded that the risk reduction slope will be reduced by closing to the worsk realization of uncertainparameters.

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