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ORIGINAL RESEARCH PAPER

Optimal Planning of Intelligent Parking IoT Using Interval Particle Swarm Optimization Algorithm in the Presence of Fuel cell and Electrolyzer as Hydrogen Storage System

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ABSTRACT

Recently, the application of the intelligent parking lot (IPL) in the power market has been exponentially increasing to decrease the greenhouse gasses, the pollution, and to decrease the deviation cost of the energy production based on electric vehicles (EV). IPLs uses charge and discharge features of EVs to exchange the energy in the upstream grid. This paper study on a new interval-analysis based optimal solution of an IPL by considering the interval uncertainties for the price of upstream gird value.

The method based on using an interval-based particle swarm optimization algorithm to optimize an interval objective function with lower and upper limitations with a single-valued output. Simulation results of the presented procedure are compared with a deterministic mixed-integer linear programming to show its superiority. The results show that deviation cost has been decreased up to 10.74% while average cost has been raised into 5.17% which demonstrates the methods high performance in decreasing the average cost of IPL and the reliability of the intelligent parking lot in the presence of uncertainties derived from the upstream grid.

Keywords: *Intelligent parking lot; demand response program; hydrogen storage system; fuel cell; interval analysis; particle swarm optimization*

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1. INTRODUCTION

The environmental issues, resource depletion, and energy dependence have led to the theory of major changes in the overall structure of the transportation system and suggest the replacement of electric vehicles (EVs). Meanwhile, the concept of vehicle-to-grid (V2G) technology has favored electric cars, enabling the ability to exchange electricity with the grid in a new definition. Because of their energy storage capability, V2Gs will be a viable alternative to the supply of thermal and renewable power plants, while the charging and discharging schedules of individual V2Gs are largely uncertain. This undermines their positive impact on the grid; however, in some cases, the one-way relationship of vehicle technology with the network is more favorable to the consumer. The V2G presence model, in addition to preventing overloading the network, makes it possible for the charging station to make effective decisions; however, how the V2G's battery status is affected at different times of the day is important given the probabilistic model at source. V2Gs increase profits in the market but lead to market saturation. On the one hand, according to the source [1], connecting a sufficient number of V2Gs provides the implementation of consumer management programs, but the motivation for automobiles needs to be provided. One of the features of V2G is the contribution to smoothing the load curve of the

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grid [2], although it is more expensive than fossil power plants; therefore, it is economically necessary to provide the power required at peak hours by manufacturers at lower investment costs. On the other hand, charging and discharging V2G and their distance traveled are random, so consideration of the issue of uncertainty will be necessary [3]. Rezaee et al. [4] proposed a new fashion instead of V2G technology. The configuration was called vehicle to park (V2P) and parking to vehicle (P2V) connections.

Malaysia [5] et al. analyzed an overview of designing an intelligent parking system. The difference of their mechanism with other existing systems is that they used a vehicle to parking (V2P) system to make the system more independent of the human-based on cloud computing.

Zhang et al.[6] analyzed the electric vehicles parking-lots by considering a charging scenario at near commercial places that need to extended parking time. The optimal charging strategy was achieved based on a two-stage dynamic programming framework. The results showed that using the presented strategy can principally reduce energy costs.

Jannati et al. [7] studied on designing an optimal efficiency of the electric vehicles parking lot by considering the environmental effects. The method was a bi-objective optimization strategy for PV-based intelligent electric vehicles parking lot. The fuzzy decision-making and the weighted sum algorithms have been employed as tools for system solving [8-10]. The final results declared that using the presented technique reduced the operation cost and the total emission of the parking lot up to 4.3% and 2.7%, respectively.

Rahmani et al. [11] studied the parking lot issues in the energy market modeling. The parking lot was supplied by the renewable energy source with the capability to have bilateral energy transactions with the energy market using the V2G and G2V services. The problem was designed as a mixed-integer linear programming problem. Final simulations declared that the level of PEV penetration, the type of PEV, and the social class of drivers have significant impact on the system performance.

Şengör et al. [12] analyzed the energy management of EV parking IoTs by considering uncertainties. The paper presented an optimal strategy for energy management of EV parking lots based on peak load reduction and Demand Response (DR) programs. The purpose of the study was to maximize the load factor of an EV parking lot in the presence of uncertain behavior of EVs.

Jannati et al. [13] presented multi-objective scheduling for intelligent parking lot of EVs by considering the hydrogen storage system. In that paper, the authors proposed a bi-objective optimization model to reach an environmental and economic performance for the intelligent parking lot (IPL). Fuzzy decision making and ε-constraint procedures were utilized for solving the problem. Simulation results showed that the operation cost and the total emission of the IPL were decreased up to 1.8% and 4%, respectively which showed a satisfying value for both environmental and economic objectives.

Zhang et al. [14] proposed an optimized method to solve the group parking assignment problem to decrease the traveling costs, time consumption, and traffic pressure. The problem was solved based on an adaptive ant colony optimization algorithm. The final results declared that the proposed algorithm gave better results in terms of efficiency and efficacy.

2. SYSTEM MODELING

In this study, a model of non-renewable energy sources as Local dispatchable generators (LDG) such as micro-turbines, local load and Hydrogen storage system (HSS) as well as demand response program as virtual generation units along with different renewable energy sources such as photovoltaic and wind turbine system and has been considered. The upstream grid is also connected to the proposed model to exchange of the power by considering their demands in necessary times. Fig. (1) shows the configuration of the presented IPL model.

It is observed from Fig. (1) that IPL acts as a load and/or energy resource during the charging and discharging of the electric vehicles (EVs), respectively. When IPL charges the EV, it collects the important data of EV like the initial State-of-Charge (SOC) of EV, expected SOC of EV when leaving the IPL, charge and discharge power limitations, and elapsed time of battery life [15]. The received data is then sent to the IPL operator for making satisfied scheduling based on DRP and HSS to decrease the cost of IPL operation. The model includes a central controller as the interface between upstream grid and IPL which has the responsibility to optimize the performance of IPL. In the following, the topology of this model has been explained.

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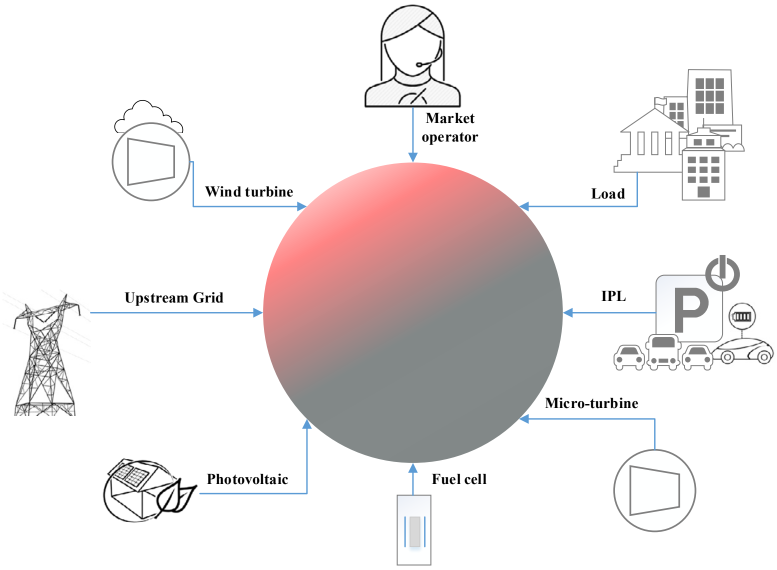

Fig. 1. The configuration of the presented IPL model

The cost of daily operation for IPL contains the cost of purchasing power from the upstream grid, the cost of operational LDG and the revenue/ cost of charge/discharge for EV available in the IPL. To achieve an optimal configuration for IPL, the determined values should be minimized by the following equation [15]:

$$Fitness = \sum_{t=1}^{T} \left[\begin{array}{c} P_{UG}^{t} \times \pi_{UG}^{t} + \sum_{i=1}^{N} \left(\begin{array}{c} P_{Dch,EV}^{i,t} \times \pi_{Dch,EV}^{i} \\ -P_{ch,EV}^{i,t} \times \pi_{ch,EV}^{i} \end{array} \right) \\ + \sum_{j=1}^{G} \left(C_{LDG}^{j,t} + SC_{LDG}^{j,t} \right) \end{array} \right] \quad (1)$$

where, P_{UG}^{t} describes the power purchased from the upstream net, π_{UG}^{t}, $\pi_{ch,EV}^{i}$, $\pi_{Dch,EV}^{i}$ describes the price of upstream net, the charge price for EV in the IPL, and the discharge price of the EV in the IPL, respectively, $P_{ch,EV}^{i,t}$, $P_{Dch,EV}^{i,t}$ represent Electric vehicle charging power and Electric vehicle discharging power, and $C_{LDG}^{j,t}$, $SC_{LDG}^{j,t}$ are local dispatchable generator operating costs and Startup costs of local dispatchable generator, respectively.

2.1. The model of renewable generation units

The output model of the system in the photovoltaic unit and the ambient temperature is given in the following equation.

$$P_{PV}^{p,t} = s^{p} \times \eta^{p} \times \left(1 - 0.005 \times \left(T_a - 25\right)\right) \times G^{t} \quad (2)$$

where, $P_{PV}^{p,t}$ describes the output power of the PV system, s^{p} is the area assumed for PV installation, $ç^{p}$ represents the performance of the PV array, T_a is the ambient temperature around the PV system, and G^{t} describes the irradiation of the sunlight.

The relation for power generation based on a wind turbine is as follows:

$$P_{W}^{k,t} = \begin{cases} 0 & V^{t} < V_{c}^{k} \; or V^{t} \geq V_{F}^{k} \\ \dfrac{V^{t} - V_{c}^{k}}{V_{R}^{k} - V_{c}^{k}} \times P_{R}^{k} \; V_{c}^{k} & \leq V^{t} < V_{R}^{k} \\ P_{R}^{k} & V_{R}^{k} \leq V^{t} < V_{F}^{k} \end{cases} \quad (3)$$

where, $P_{W}^{k,t}$ and P_{R}^{k} are the output power and the rated power of the wind turbine, V^{t} describes the wind speed that is forecasted, and V_{F}^{k}, V_{c}^{k} and V_{R}^{k} are the cut-out, cut-in, and rated speeds, respectively.

2.2. The constraint model for grid

The constraint of the taken (injected) power from (to) IPL by the grid is considered as follows.

$$\left| P_{UG}^{t} \right| \leq P_{UG}^{Max} \quad (4)$$

where, P_{UG}^{Max} represents the maximum power exchange value between the IPL and the upstream net.

2.3. The model of Non-renewable energy sources

The start-up and the operation costs for the local dispatchable generators like micro-turbines given below:

$$C_{LDG}^{j,t} = a^{j} \times U^{j,t} + b^{j} \times U^{j,t} \tag{5}$$

$$SC_{LDG}^{j,t} \geq \left(U^{j,t} - U^{j,t-1}\right) \times UDC^{j} \tag{6}$$

$$SC_{LDG}^{j,t} \geq 0 \tag{7}$$

where, $C_{LDG}^{j,t}$ describes the operating cost of the local dispatchable generator, $U^{j,t}$, a^{j}, and b^{j} represent a two-state switch, and generation cost modeling factors for the local dispatchable generator.

The minimum and the maximum generation constraints for the local dispatchable generators are given in Eq. (8) and Eq. (9), respectively.

$$P_{LDG}^{j,t} \geq U^{j,t} \times P_{LDG,min}^{j} \tag{8}$$

$$P_{LDG}^{j,t} \leq U^{j,t} \times P_{LDG,max}^{j} \tag{9}$$

where, $P_{LDG}^{j,t}$ describes the scheduling power of the local dispatchable generator, and $P_{LDG,\,min}^{j}$ and $P_{LDG,\,max}^{j}$ are the minimum and the maximum constraints for the produced electricity by a local dispatchable generator, respectively.

The formulations for the ramp down and ramp-up of the local dispatchable generators limitations are given in Eq. (10) and Eq. (11), respectively.

$$P_{LDG}^{j,t-1} - P_{LDG}^{j,t} \leq RD^{j} \times U^{j,t-1} \tag{10}$$

$$P_{LDG}^{j,t} - P_{LDG}^{j,t-1} \leq RU^{j} \times U^{j,t} \tag{11}$$

where, RD^{j} and RU^{j} describe the local dispatchable ramp down and ramp-up rate.

The maximum down and up the value of time limitations for the local dispatchable generators have been given in Eq. (12) and (13), respectively.

$$U^{j,t-1} - U^{j,t} \leq 1 - U^{j,t+Dn_{j,f}} \tag{12}$$

$$U^{j,t} - U^{j,t-1} \leq U^{j,t+Up_{j,f}} \tag{13}$$

where,

$$Dn_{j,f} = \begin{cases} f & f \leq \\ 0 & f > MDT_{j} \end{cases} \tag{14}$$

$$Up_{j,f} = \begin{cases} f & f \leq MUT_{j} \\ 0 & f > MUT_{j} \end{cases} \tag{15}$$

where, MDT_{j} and MUT_{j} are the minimum down and up times of the local dispatchable generator.

2.4. The model of constraints for IPL

The IPL attempts for power exchanging with the upstream grid can be properly modeled by considering the power of charge and discharge of the available EVs. These constraints are formulated below:

$$P_{Ch,Ev}^{i,t} \leq W_{Ch}^{i,t} \times P_{Ch,max}^{i} \times M^{i,t} \tag{16}$$

$$P_{Dch,Ev}^{i,t} \leq W_{Dch}^{i,t} \times P_{Dch,max}^{i} \times M^{i,t} \tag{17}$$

where, $M^{i,t}$ represents the two-state parameter for the EV parking in the IPL , $P_{Ch,Ev}^{i,t}$ and $P_{Dch,Ev}^{i,t}$ describe electric vehicle charging and discharging power, and $W_{Ch}^{i,t}$ and $W_{Dch}^{i,t}$ describe two-state values that determine the charging and discharging states of the EV in IPL which can be restricted through the following equation:

$$W_{Ch}^{i,t} + W_{Dch}^{i,t} \leq M^{i,t} \tag{18}$$

And the switching process between these two states is formulated as follows:

$$\sum_{t=t_a^i}^{t_d^i} W_{Ch}^{i,t} + W_{Dch}^{i,t} \leq N_{\max} \tag{19}$$

where, N_{max} describes the switching constraints between charging and discharging states.

And the constraints for the State-of-charge (SOC) of EV available in IPL is achieved as follows:

$$SOC^{i,t} = SOC^{i,t-1} + P_{Ch,Ev}^{i,t} \times \eta_{G2V} - \frac{P_{Dch,Ev}^{i,t}}{\eta_{G2V}} \tag{20}$$

where, $SOC^{i,t}$ describes the SOC condition of an electric vehicle, η_{G2V} and η_{V2G} are the efficiency of the G2V and V2G.

The SOC constraint of the EV when it enters to the IPL is as follows:

$$SOC^{i,t} \geq SOC_{Arrival}^{i,t} \tag{21}$$

And the SOC vehicle during that vehicle try to leave IPL is as follows:

$$SOC_{Departure}^{i,t} \geq SOC_{Max}^{i} \tag{22}$$

And finally, the maximum rates for charge and discharge of EV are as follows:

$$-\ddot{A}SOC^{i}_{Max} \leq SOC^{i}_{Max} - SOC^{i,t-1} \leq \ddot{A}SOC^{i}_{Max} \quad (23)$$

where, $\ddot{A}SOC^{i}_{Max}$ represents the maximum charge or discharge limitation of EV, and $SOC^{i,t}_{Arrival}$ and $SOC^{i,t}_{Departure}$ are primary SOC of EV during the vehicle entering/departures at/from IPL.

2.5. The Model of the hydrogen storage system

The following subsection contains the technical constraints of the *hydrogen storage system* (HSS). The HSS contains three principal parts including fuel cell, tank, and electrolyser. In off-peak intervals, the electrolyzer forms hydrogen molar with the help of electricity due to the fewer cost of electricity price in that time period. The formulation between generated hydrogen molar and consumed electricity is given below:

$$N^{EL}_{H_2,t} = \frac{P^{EL}_{t} \times \eta^{EL}}{LHV_{H_2}} \quad (24)$$

where, P^{EL}_{t} describes the power consumption of electrolyzer, $ç^{EL}$ represents the efficiencies of electrolyser, and LHV_{H_2} is the lower heating value of hydrogen.

The maximum and the minimum constraints for the consumed power by the electrolyzer are achieved as follows:

$$P^{EL}_{t} \leq U^{EL}_{t} \times P^{EL}_{max} \quad (25)$$

$$P^{EL}_{t} \geq U^{EL}_{t} \times P^{EL}_{min} \quad (26)$$

where, P^{EL}_{max} and P^{EL}_{min} represent the maximum and minimum limit of the consumed power in electrolyser, respectively.

Then, the maximum produced of hydrogen molar based on electrolyzer has been described as follows:

$$N^{EL}_{H_2,t} \leq U^{EL}_{t} \times N^{EL}_{H_2,max} \quad (27)$$

where, $N^{EL}_{H_2,t}$ describes the hydrogen molar generation by the electrolyzer unit.

The produced hydrogen molar has been stored in specific tanks and the minimum and the maximum initial pressure constraints have been determined to be the following limitations.

$$P^{H_2}_{t} \geq P^{H_2}_{min} \quad (28)$$

$$P^{H_2}_{t} \leq P^{H_2}_{max} \quad (29)$$

$$P^{H_2}_{t0} = P^{H_2}_{initial} \quad (30)$$

where, $P^{H_2}_{t}$ describes the available pressure within pressure tank, $P^{H_2}_{t0}$ and $P^{H_2}_{initial}$ describe the primary pressure of the hydrogen tank at the start time, and $P^{H_2}_{min}$ and $P^{H_2}_{max}$ represent the available minimum and maximum limitations, respectively.

$$N^{FC}_{H_2,t} \leq U^{FC}_{t} \times N^{FC}_{H_2,max} \quad (31)$$

$$P^{FC}_{t} \geq U^{FC}_{t} \times P^{FC}_{min} \quad (32)$$

$$P^{FC}_{t} \leq U^{FC}_{t} \times P^{FC}_{max} \quad (33)$$

where, $N^{FC}_{H_2,t}$ is hydrogen molar consumption by fuel cell production system, $N^{EL}_{H_2,t}$ describes the hydrogen molar generation by fuel cell unit, P^{FC}_{min} and P^{FC}_{max} represent the minimum and maximum limitation of the fuel cell, respectively.

At last, the equation for declaring the relation between the consumed hydrogen molar and the generated electricity is achieved as follows:

$$N^{FC}_{H_2,t} = \frac{P^{FC}_{t}}{\eta^{FC} \times LHV_{H_2}} \quad (34)$$

where, P^{FC}_{t} describes the power consumption of fuel cell, and η^{EL} represents the efficiencies of the fuel cell,

The dynamic model for the pressure of HSS as follows:

$$P^{H_2}_{t} = P^{H_2}_{t-1} + \mathbb{R} \times \frac{T_{H_2}}{V_{H_2}} \times \left(N^{EL}_{H_2,t} - N^{FC}_{H_2,t}\right) \quad (35)$$

where, $\mathbb{R}$ is the constant of gas, T_{H_2} describes the temperature of the vessel mean, and V_{H_2} represents the tank volume.

And the constraint of HSS in the charge and the discharge states is as follows:

$$U^{EL}_{t} + U^{FC}_{t} \leq 1 \quad (36)$$

where, U^{EL}_{t} and U^{FC}_{t} describe the two-state variables which determine the on-off states of the fuel cell and the electrolyzer.

2.6. The model of demand response

This study assumed that load is considered as a part of the demand response program (DRP) to decrease the payments and consequently reducing the collected operating cost of IPL. The DRP is applied to improve the capability of the loads to achieve economic productivity by transition of the demand from peak times to the off-peak times with this assumption that the value of the shifted demand has been limited in a determined interval. The constraints of the demand response are as follows:

$$Load^{t} = Load_{0}^{t} + DRP^{t} \tag{37}$$

$$DRP^{t} \leq +DRP^{max} \times Load_{0}^{t} \tag{38}$$

$$\mathrm{DRP}^{t} \geq -\mathrm{DRP}^{max} \times \mathrm{Load}_{0}^{t} \tag{39}$$

$$\sum_{t=1}^{T} \mathrm{DRP}^{t} = 0 \tag{40}$$

where, Load^{t} is the new energy demand under DRP implementation DRP^{max} describes the maximum limitation of DRP, and DRP^{t} represents the possible increased/decreased load in DRP.

2.7. The total model of power balance constraint

In the following, the relation of the power balance by considering the generated power and the consumed power in the IPL is mathematically determined:

$$\mathrm{P}_{UG}^{t} + \mathrm{P}_{t}^{FC} + \sum_{k=1}^{K} \begin{matrix} \mathrm{P}_{W}^{k,t} + \sum_{p=1}^{P} \mathrm{P}_{LDG}^{p,t} \\ + \sum_{j=1}^{G} \mathrm{P}_{LDG}^{j,t} \sum_{i=1}^{N} \mathrm{P}_{Dch,EV}^{i,t} \end{matrix}$$

$$= \mathrm{Load}^{t} + \mathrm{P}_{t}^{EL} + \sum_{i=1}^{N} \mathrm{P}_{Ch,EV}^{i,t} \tag{41}$$

As can be observed, the right side of the equation provides a new load with considering the DRP instead of baseload.

3. METHODOLOGY

In this section, the analyzed cost function is studied by considering the impacts of DRP and HSS. The main objective of this study is to minimize the operating cost of IPL by considering the economic and technical constraints. This objective can be modeled as an optimization problem. A practical optimization problem includes equal and/or unequal constraints. The standard optimization algorithms don't consider the uncertainties of the algorithm [16-19]. One method to consider the uncertainties in the optimization is to use the interval optimization algorithm.

Based on the interval procedure, all the uncertain parameters in a system can be placed in a limitation with lower and upper bounds [20]. This modeling turns all the constraints and consequently the objective function into the interval with lower and upper bounds. For instance for interval values $[\underline{u}, \overline{u}]$ where $\underline{u}$ and $\overline{u}$ are the lower and the upper value of the interval variable, the interval objective function can be considered as follows:

$$\underline{f}(X) = \min_{\sigma \in u} f(X) \tag{42}$$

$$\underline{f}(X) = \max_{\sigma \in u} f(X) \tag{43}$$

where, σ describes the uncertain parameter.

In this paper, an interval PSO algorithm has been used for optimization.

4. INTERVAL PARTICLE SWARM OPTIMIZATION ALGORITHM

In recent years, the application of metaheuristic algorithms in solving the optimization problems, especially NP-hard problems has been increased [21-24]. This large family of problems has many interesting characteristics that have led to many approximate methods to solve each of them over time [25, 26]. The traditional meta-heuristics have the ability to solve the determined optimization problems [27-32]. Recently there are also some different meta-heuristics for solving problems with uncertainties. This study uses an interval-based particle swarm optimization algorithm due to the presence of interval uncertainty in the proposed system. However interval-based particle swarm optimization has been used in some studies [33, 34], most of them solve the problems based on decision maker's point of view that gives interval solutions.

The objective of this study is to use an interval-based PSO algorithm with a single-value solution. Based on [10, 35-38], the conventional PSO algorithm generates a vector of random particles in the search space and these particles are then moved to find the best solution. But in the present work, the distribution of the particles has been performed in vast solution space. Here, interval value has been used to determine a particle. Fig. (2) shows the diagram flowchart of the proposed interval PSO algorithm.

where, rangeCoefficient determines a compact parameter to compress the interval to prevent the interval solution expanding.

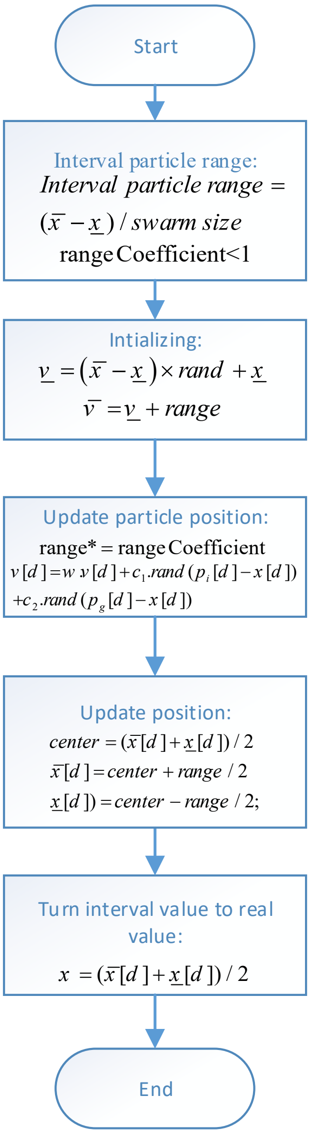

Fig. 2. The flowchart diagram of interval PSO algorithm

5. SIMULATION RESULTS

The required data of local dispatchable generators including microturbine has been taken from [39] and the required data to model the PV system, electric vehicles characteristics, wind speed, and wind turbine, generated power through PV system, hydrogen storage system, demand and sunlight irradiation profiles have been taken from [39]. The simulation has been performed by the Matlab R2017b platform on a laptop with configuration Intel (i) Core ™ i7-4720HQ CPU@2.6 GHz laptop with 16 GB installed memory.

Fig. (3) shows the maximum, the expected and the minimum values for the market price [39]. The capacity interval for EVs is assumed [9 kWh, 19 kWh] with 230 capacity number and capacity interval for SOC is assumed [0.1-0.8]. The charging and the discharging prices of i^{th} EV in the IPL have been modeled by random values in the interval [0.1, 0.25] and [0.20, 0.35], respectively. The maximum value for power exchanged between IPL and the grid is assumed 1100 kWh.

5.1. The simulation results based on deterministic simulations

By considering the cost (Fitness) function in Eq. (1), subject to the described constraints from Eq. (2) to Eq. (41), and solving it with mixed-integer linear programming as deterministic methodology, the following results have been achieved for average and deviation of the IPL in with and without DRP (Table 1).

From Table 1, it can be observed that DRP decreases the operation cost of IPL from $1960.31to $1902.17 that is a 2.96% reduction. Indeed, the total purchased power reduction from the grid makes IPL operate LDG to supply demand for daily operation cost reduction of IPL.

5.2. The simulation results based on Interval simulations

By applying the proposed interval PSO algorithm to the interval-based cost function based on Eq. (42) and Eq. (43) subject to the previous constraints, the Pareto front of the optimal operation of IPL in the presence of uncertainties is achieved and shown in Fig. (4).

As can be observed from Fig. (4), the average cost of IPL by not considering the DRP is obtained $2015 while the deviation cost of IPL in this condition is $498. In the following, exploiting the demand response program, makes average cost of $2006 for IPL while deviation cost is $450. By comparing the proposed method by the deterministic approach [39], the deviation cost has been decreased up to 10.74% while average cost has been raised into 5.17%. This shows that the presence of the DRP based on the presented interval method not also have positive efficiency on the system, but also decreases the average cost of IPL and increases the reliability of the IPL in the presence of uncertainties derived from the upstream grid. In the following, some more results have been illustrated to determine the effect of the proposed methods. Fig. (5) and Fig. (6) show the energy demand with and without DRP in

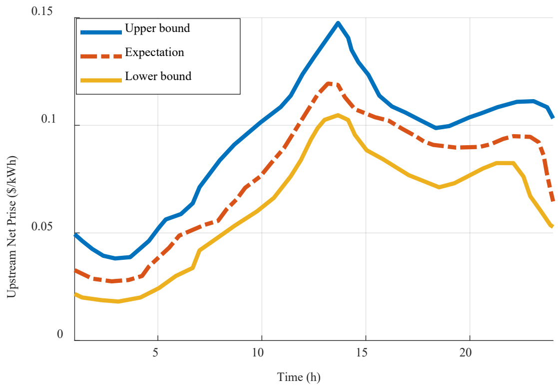

Fig. 3. the maximum, the expected and the minimum values for the market price

Table 1. The results of deterministic simulations

Parameter	Unit	With DRP	Without DRP
IPL charge cost	$	973.34	950.84
IPL discharge cost	$	325.19	342.38
Daily operation cost	$	1912.43	1960.63
Startup cost of LDG	$	53.46	19.98
Operation cost of LDG	$	1792.28	1618.12
Cost of upstream net	$	915.47	695.11
Deviation cost	$	504.17	549.52
Average cost	$	1902.17	1960.31
Total cost reduction	%	3.16	0.00

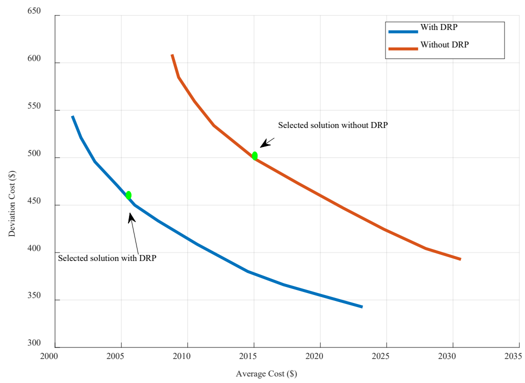

Fig. 4. The Pareto front of the optimal operation for IPL in the presence of uncertainties

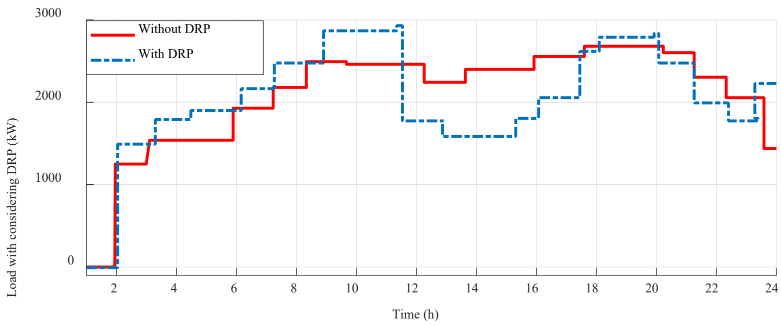

Fig. 5. The energy demand with and without DRP based on the deterministic method

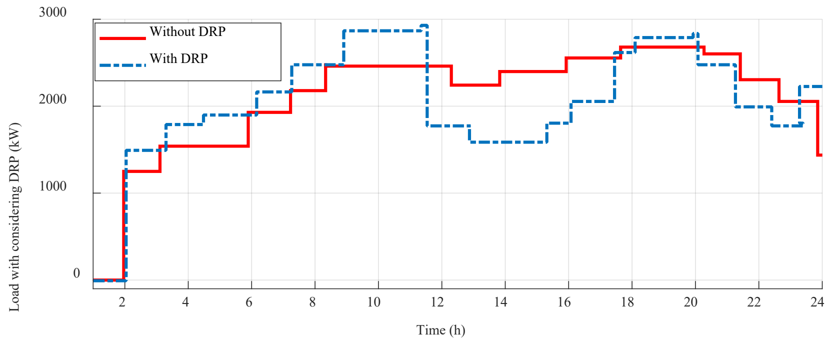

Fig. 6. The energy demand with and without DRP based on Interval PSO algorithm

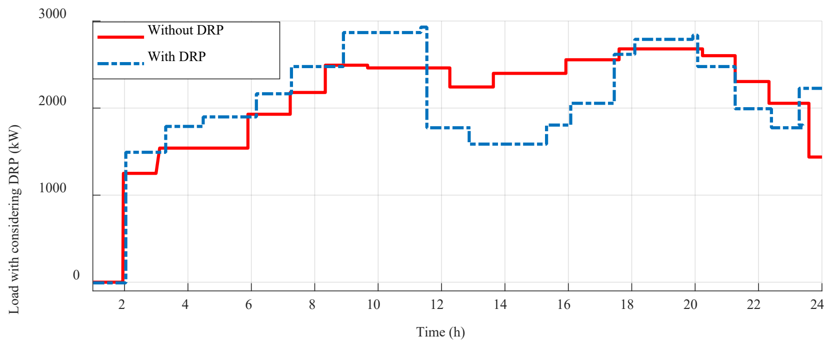

Fig. 7. The profile of the power generation with and without DRP by the deterministic method

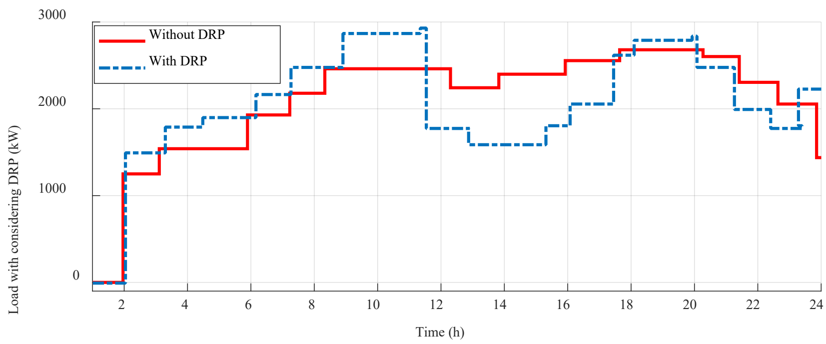

Fig. 8. The profile of the power generation with and without DRP based on interval PSO algorithm

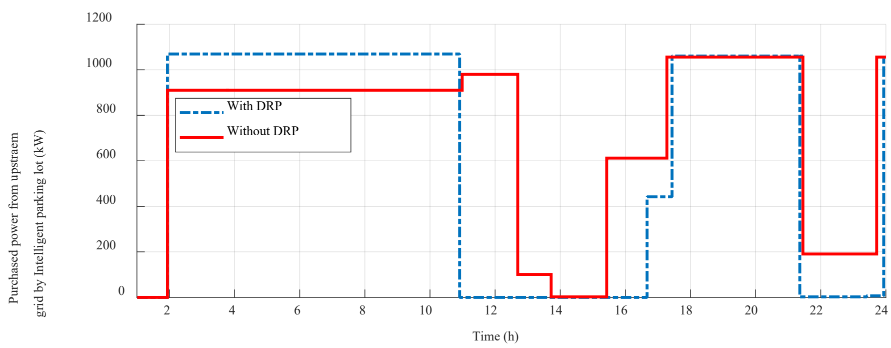

Fig. 9. The profile of the purchasing power from the upstream grid by lot with and without DRP by deterministic method

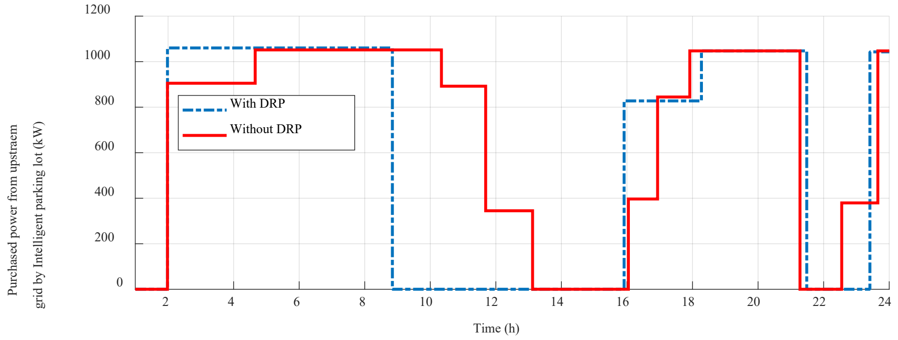

Fig. 10. The profile of purchasing power from the upstream grid by lot with and without DRP based on interval PSO based methods

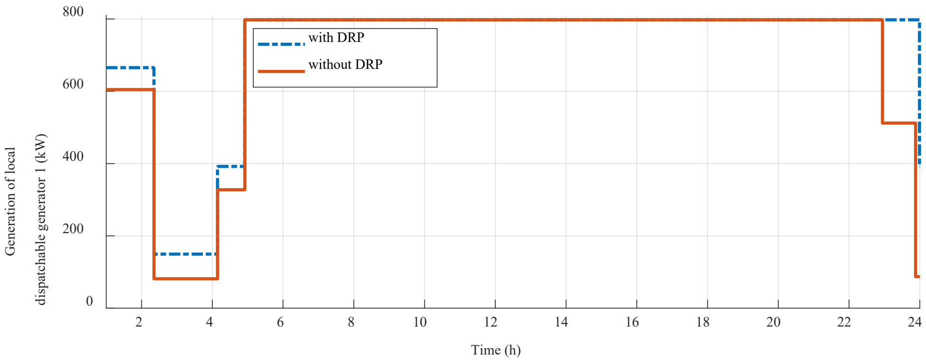

Fig. 11. The profile of power generation of LDG1 with and without DRP by the deterministic method

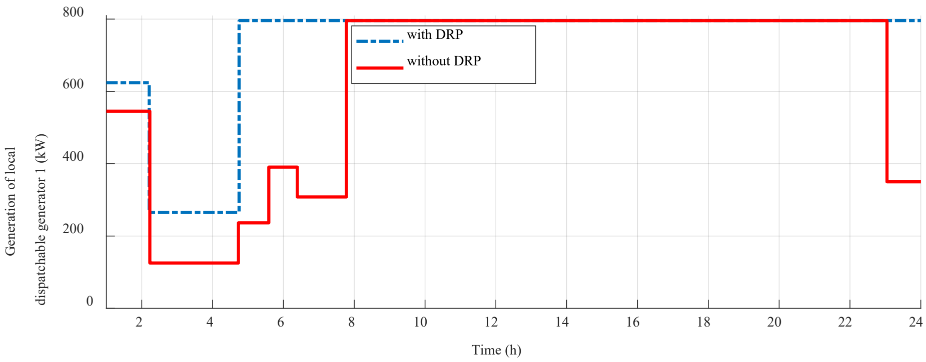

Fig. 12. The profile of power generation of LDG1 with and without DRP based on interval PSO algorithm

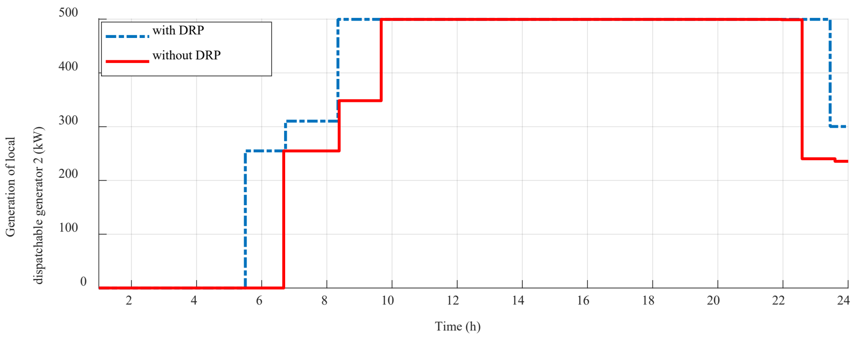

Fig. 13. The profile of power generation of LDG2 with and without DRP by the deterministic method

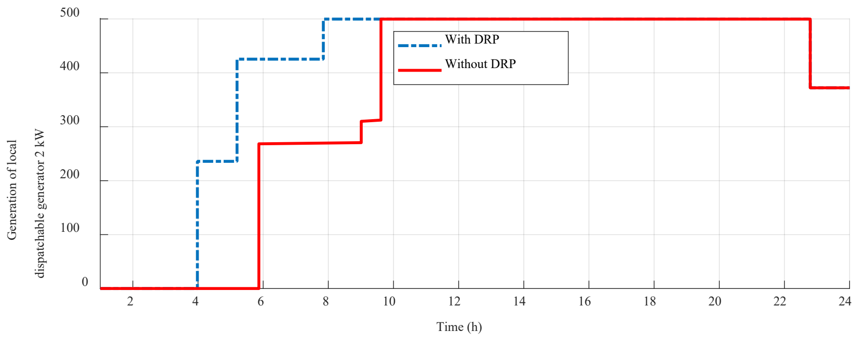

Fig. 14. The profile of power generation of LDG2 with and without DRP based on interval PSO algorithm

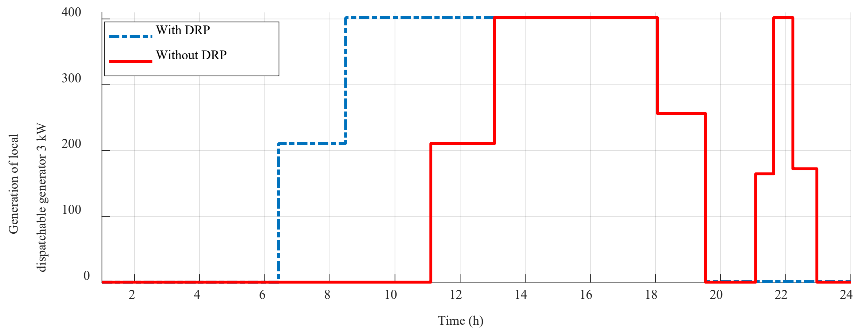

Fig. 15. The profile of power generation of LDG3 with and without DRP by the deterministic method

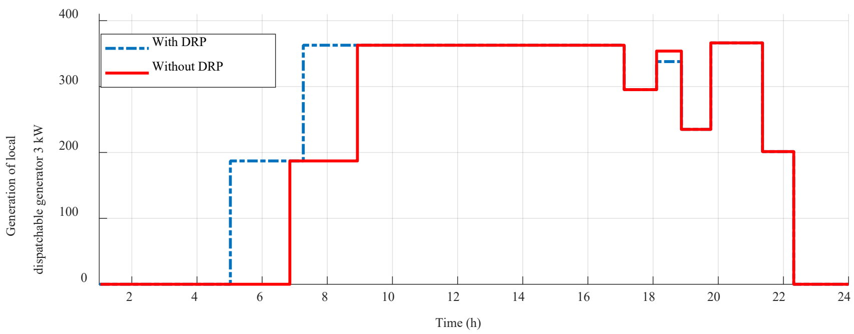

Fig. 16. The profile of power generation of LDG3 with and without DRP based on interval PSO algorithm

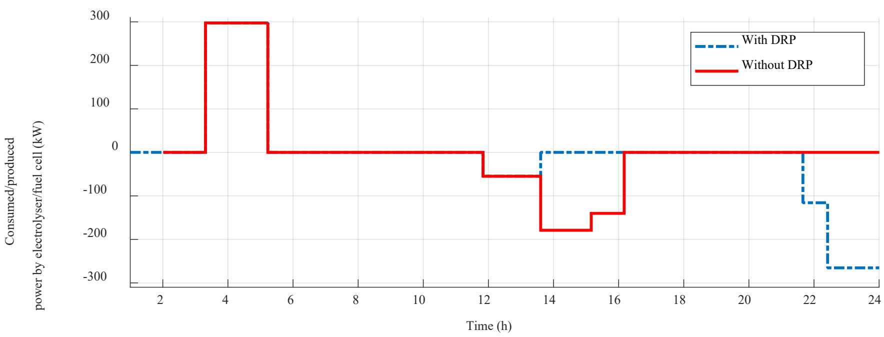

Fig. 17. The Charge/discharge profile of the hydrogen storage system with and without DRP by the deterministic method

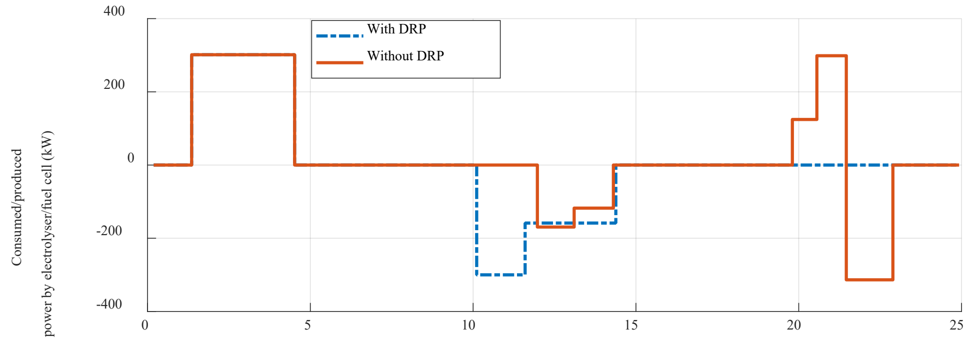

Fig. 18. The Charge/discharge profile of hydrogen storage system with and without DRP based on interval PSO algorithm

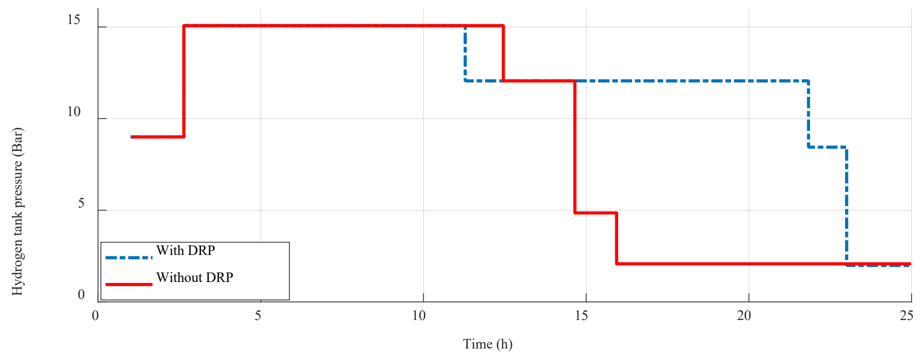

Fig. 19. The profile of available tank pressure of hydrogen storage system with and without DRP based on interval PSO algorithm

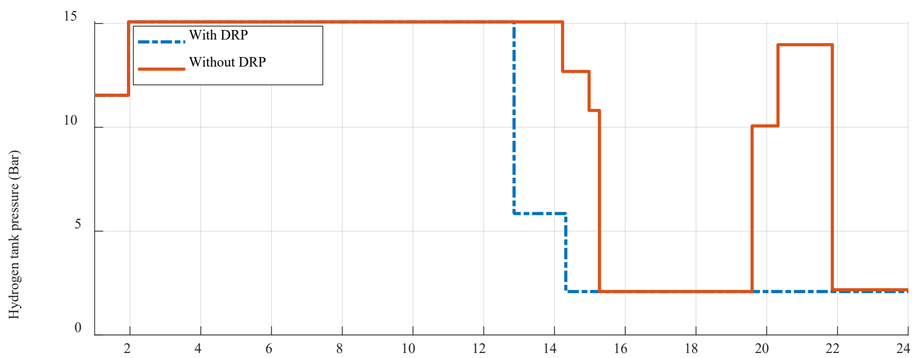

Fig. 20. The profile of available tank pressure of hydrogen storage system with and without DRP based on interval PSO algorithm

both deterministic [39] and interval PSO based methods, respectively.

As can be seen, according to the positive effect of the DRP, generally the position of the load is changed from peak times into off-peak times which make its curve so flattened. This case can consequently decrease the daily cost of operation in IPL. Due to the considering the peak period in the price profile, the demand response program assumes the fact to transfer the load from peak period to the other times which makes most of the power to be purchased from the grid in off-peak periods that consequently decreases the cost of daily operation for IPL.

Fig. (7) and Fig. (8) shows the profile of the power procurement with and without DRP in both deterministic [39] and interval PSO based methods, respectively.

Since upstream grid sharing for providing power demand is reduced in peak time periods, the local dispatchable generators sharing for providing the power demand in the determined periods has been enhanced. Fig. (9) and Fig. (10) show the purchasing power from the upstream grid by lot with and without DRP in both deterministic [39] and interval PSO based methods, respectively.

Fig (11)-Fig. (16) show the profile of power generation for three local dispatchable generators.

By performing the optimal operation of intelligent parking lot and production units under DRP in deterministic and the proposed interval PSO algorithm, optimal charge/discharge processes for the hydrogen storage system through fuel cell and the electrolyzer unit has been achieved. Fig. (17) and Fig. (18) show this process.

Finally, Fig. (19) shows the available pressure of the hydrogen storage system that depends on the rates of charge/discharge in the HSS system.

6. CONCLUSION

Today, due to the development of distributed generation sources in the distribution network, the use of electric cars has reduced pollution, greenhouse gas emissions and the use of fossil fuel sources. The deployment of scattered production and parking of electric cars with no technical planning will cause some economic problems for the parking investor and some technical problems for the distribution network operator. This paper studied on optimal operation of intelligent parking lot in the presence of upstream grid price uncertainties under demand response program. Since the uncertainties of the system were considered interval, an interval optimization algorithm, called interval PSO algorithm were used for optimal solving the system in the presence of interval uncertainties. The results were compared with the deterministic linear programming which showed that the deviation cost was decreased up to 10.74% while average cost was raised into 5.17% which declared the positive efficiency on the system in decreasing the average cost of IPL and increasing the reliability of the intelligent parking lot in the presence of uncertainties derived from the upstream grid.

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