INTERNATIONAL JOURNAL OF HYDROGEN ENERGY 44 (2019) 24997–25009

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Optimal scheduling of intelligent parking lot using interval optimization method in the presence of the electrolyser and fuel cell as hydrogen storage system

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HIGHLIGHTS

- Optimal energy management of IPL including non-renewable and renewable generation units.
- Implementing interval optimization method for uncertainty modeling of upstream net price.
- Transforming uncertainty based problem into a deterministic multi-objective model with deviation and average costs.
- Employing DRP for reduction of deviation and average costs of IPL.

ARTICLE INFO

Article history:
Received 8 May 2019
Received in revised form
24 June 2019
Accepted 29 July 2019
Available online 23 August 2019

Keywords:
Energy management
Intelligent parking lot
Uncertainty
Interval optimization approach
ε-constraint technique
Fuzzy approach

ABSTRACT

These days, a new concept called intelligent parking lot (IPL) has been extensively paid consideration to be used in power system industry. Using charge/discharge of electric vehicles (EV), IPLs attempt to exchange power with the upstream grid. In addition to IPL, studied model involves non-renewable and renewable units such as wind turbine, photovoltaic (PV) system, local dispatchable generator (LDG) like micro-turbine and hydrogen storage system (HSS) which are used all together to satisfy energy demand. In this work, optimal scheduling of an IPL has been studied under time-of-use (TOU) rate of demand response program (DRP) in which price of upstream gird is set to be uncertain which uncertainty is modeled via interval optimization technique. This technique transforms uncertainty based model into a deterministic multi-objective model with deviation and average costs as the inconsistency objective functions. Then, applying ε-constraint technique and fuzzy approach, mentioned multi-objective problem is solved. Obtained Pareto results as well as selected trade-off results in various case studies have been compared to prove efficiency of employed techniques. Obtained results revealed that due to positive influence of DRP, increase of average cost of IPL has been reduced up to 2.46% while deviation cost of IPL has been decreased up to 12.49%.

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https://doi.org/10.1016/j.ijhydene.2019.07.226

Nomenclature

Acronyms

TOU	Time-of-use
DRP	Demand response program
IPL	Intelligent parking lot
EV	Electric vehicles
PV	Photovoltaic
LDG	Local dispatchable generator
HSS	Hydrogen storage system
MUT	Minimum up time
MDT	Minimum down time
SOC	State-of-charge
G2V	Gird to vehicle
V2G	Vehicle to grid
GAMS	General algebraic modeling system

Indices

f	Auxiliary index for linear modeling of minimum up/down times of local dispatchable generator starting from 1 up to {MUTj, MDTj}
i	Electric vehicle index
j	Local dispatchable generator index
k	Wind turbine index
p	Index of photovoltaic unit
t	Hour index

Parameters

a^j, b^j	Generation cost modeling factors of local dispatchable generator
DRP^{max}	Maximum limitation of DRP
G^t	Sunlight irradiation
$load_0^t$	Base energy demand
LHV_{H2}	Lower heating value of hydrogen
$M^{i,t}$	Binary parameter for parking of electric vehicle in the IPL
MUT_j, MDT_j	Minimum up and down times of local dispatchable generator
N_{Ev}	Number of electric vehicles present in the IPL
$N_{H2,max}^{EL}$	Maximum limitation of generated hydrogen molar in electrolyser
$N_{H2,max}^{FC}$	Maximum limitation of used hydrogen molar by fuel cell
N_{max}	Switching limitation between charging and discharging states
$P_{max}^{EL}, P_{min}^{EL}$	Maximum/minimum limitation of consumed power in electrolyser
$P_{max}^{FC}, P_{min}^{FC}$	Maximum/minimum limitation of generated power by fuel cell
$P_{initial}^{H2}, P_{t0}^{H2}$	Hydrogen tank primary pressure in the start time
$P_{max}^{H2}, P_{min}^{H2}$	Maximum/minimum limitation of available pressure in the hydrogen tank
P_R^k	Wind turbine rated power
$P_W^{k,t}$	Wind turbine output power
$P_{PV}^{p,t}$	PV system output power
$P_{LDG,max}^j$	Maximum limitation of generated power by local dispatchable generator
$P_{LDG,min}^j$	Minimum limitation of generated power by local dispatchable generator
P_{UG}^{max}	Maximum limitation of power exchange between upstream net and IPL
$P_{Ch,max}^i, P_{Dch,max}^i$	Maximum charge and discharge limitations of electric vehicle
$\Re$	Constant of gas
RD^j, RU^j	Ramp down/up rate of local dispatchable generator
s^p	Area assumed for PV installation
SOC_{max}^i, SOC_{min}^i	Maximum and minimum state-of-charge (SOC) limitations of electric vehicle
$SOC_{Arrival}^{i,t}$	Primary SOC of electric vehicle at the time vehicle arrives at IPL
T_a	Temperature of ambient around PV system
T_p^i	The time electric vehicle is assumed to be park at IPL
T_{H2}	Vessel mean temperature
t_a^i	The time electric vehicle is assumed to be arrived at IPL
t_d^i	The time electric vehicle is assumed to be departure from IPL
V_c^k, V_R^k, V_F^k	Wind turbine cut-in, rated, and cut-out speeds
V^t	Forecasted wind speed
V_{H2}	Tank volume
η^{EL}, η^{FC}	Efficiencies of electrolyser and fuel cell units
$\pi_{Ch,Ev}^i$	Price of charge of electric vehicle in the IPL
$\pi_{Dch,Ev}^i$	Price of discharge of electric vehicle in the IPL
η_{ch}, η_{dis}	Charge/discharge efficiency of electric vehicle
η^p	PV array efficiency
π_{UG}^t	Price of upstream net
Δt	Sampling time to count number of electric vehicle in the IPL
ΔSOC_{max}^i	Maximum charge/discharge limitation of electric vehicle

Variables

$C_{LDG}^{j,t}$	local dispatchable generator operating cost
$Dn_{j,f}$	Variable modeling minimum down time limitation of LDG
DRP^t	Possible increased/decreased load in DRP
$load^t$	New energy demand under DRP implementation
$N_{H2,t}^{FC}$	hydrogen molar consumption by fuel cell generation system
$N_{H2,t}^{EL}$	hydrogen molar generation by electrolyser unit
P_{UG}^t	Power purchased from upstream net
$P_{Ch,Ev}^{i,t}$	Electric vehicle charging power
$P_{Dch,Ev}^{i,t}$	Electric vehicle discharging power
$P_{LDG}^{j,t}$	local dispatchable generator scheduling power
P_t^{H2}	Available pressure within pressure tank
P_t^{EL}	power consumption of electrolyser
P_t^{FC}	power generation of fuel cell
$SOC^{i,t}$	SOC condition of electric vehicle
$SC_{LDG}^{j,t}$	Startup cost of local dispatchable generator
$SOC_{Departure}^{i,t}$	SOC condition of electric vehicle at the time vehicle departures from IPL

$Up_{j,f}$	Variable modeling minimum up time limitation of LDG	$W_{ch}^{i,t}, W_{Dch}^{i,t}$	Binary variables representing charging and discharging state of electric vehicle in IPL
U_t^{EL}, U_t^{FC}	Binary variables representing off/on state of electrolyser and fuel cell	$\Delta SOC^{i,t}$	Change of energy in electric vehicle's SOC in two continual hour
$U^{j,t}$	Binary variable representing on/off state of local dispatchable generator		

Introduction

Nowadays, industry of electric vehicle (EV) [1] has been under real development to be employed for emission reduction policies [2,3]. Furthermore, renewable based energy resources have been extended to be used for environmental objectives like reducing greenhouse gases emission [4,5]. Also, smart based microgrids have been appeared recently within which local generation units are available to satisfy electrical energy demand [6]. These microgrids benefit from non-renewable and renewable energy units like wind turbine [7], PV system [8,9], micro-turbines [10,11] and fuel cell [12,13] for satisfaction of load. Implementation of DRP [14,15] and electric vehicle intelligent parking lot [16,17] can provide mentioned microgrids higher efficiencies and economic results.

Instead of old-fashioned gird to vehicle (G2V) or vehicle to grid (V2G) technologies, new concepts like parking to vehicle and vehicle to parking connections have been studied in Ref. [18]. Optimal charge management process of EV has been obtained through Game theory in Ref. [19]. Parking lot services for residential and commercial places have been studied using dynamic programming in Ref. [20]. Optimal discharge of electric vehicles in private parking lots has been studied with taking vehicle parking pattern and real movement into account in Ref. [21]. The way electric vehicles behave in joint reserve and energy market has been studied in Ref. [22]. Uncertainty based optimal allocation of electric vehicle parking lot in distribution system with taking uncertainty of electrical vehicle driving pattern into account has been discussed in Ref. [23]. Using fuzzy system, online intelligent load has been coordinated between distributed system and electric vehicle under optimal allocation of electric vehicle in Ref. [24]. In order to predict intelligent parking lot capacity limitation involving PV based roof, a new mathematical model has been presented in Ref. [25]. With aim of participating in reserve market, battery of electric vehicle has been modeled as energy storage system in Ref. [26]. In order to minimize power losses and satisfy reliability indices, optimal allocation of IPL has been done in Ref. [27]. In order to enhance discharge and charge process of EV, a traditional parking lot has been changed to IPL in Ref. [28]. With the aim of enhancing capacity of electric vehicle battery, some additional actions and projects have been investigated in Ref. [29]. Effect of optimal charging and discharging process on the microgrid energy management has been studied in Ref. [30]. Large numbers of EVs in an urban IPL have been optimally scheduled in Ref. [31]. Charging and discharging processes of intelligent parking lot involving local generators and PV system have been scheduled using the stochastic programming in Ref. [32]. Furthermore, with the aim of finding optimal size and place for installation of intelligent parking lot, multi-objective optimization framework has been presented in Refs. [33–35] in which energy consumption and reliability of system have been tried to be improved. Finally, integrations of renewable energy sources, storage units, and demand response programs with parking lot are studied in Refs. [36–38]. The comparison of literature review from different perspectives is presented in Table 1.

This paper is followed by worthy references [36–38] which is clearly compared in Table 1 from different perspectives. It should be noted that the deterministic-based operation cost as first objective function is studied in Ref. [36]. Also, emission function as second objective function as well as the deterministic-based operation cost as first objective function is proposed as multi-objective model in the references [37,38], which the weighted sum approach and epsilon constraint method are used to solve the presented multi-objective model, respectively. But, in this work, uncertainty-based operation cost of an intelligent parking lot is studied within uncertainty of upstream grid price which this uncertainty is modeled via interval optimization technique. This technique transforms uncertainty-based operation cost as a single-objective model into a deterministic multi-objective model with deviation and average costs as the inconsistency objective functions. Finally, to solve such multi-objective problem, ε-constraint technique and max-min fuzzy approach are employed.

Therefore, the novelty of this work can be briefly expressed as below.

- Optimal energy management of IPL in the presence of upstream net price uncertainty.
- Implementing interval optimization method for uncertainty modeling of upstream net price.
- Transforming uncertainty based problem into a deterministic multi-objective model with deviation and average costs.
- Using ε-constraint method for solving multi-objective problem of interval method.
- Utilizing max-min fuzzy approach for selecting trade-off result of interval based multi-objective problem.

Remained parts of proposed work are categorized as: Mathematical modeling of optimal operation of IPL within upstream met price uncertainty under DRP is provided in Section Formulation. Uncertainty modeling technique, interval optimization approach is briefly presented in Section Uncertainty modeling technique. Section Numerical

Table 1 – The comparison of literature review from different perspectives.

Ref.	Objective	Power market	Renewable energy	Storage unit	Demand response	Uncertainty modeling
[18]	Min Cost	Yes	No	No	No	Stochastic
[19]	Min Charge power	Yes	No	No	No	No
[20]	Min Cost	Yes	No	No	No	Stochastic
[21]	Min Revenue	Yes	No	No	No	Stochastic
[22]	Min Cost	Yes	No	No	Yes	Stochastic
[23]	Min Cost	Yes	No	No	No	Stochastic
[24]	Max Energy delivered	Yes	No	No	No	No
[25]	Min Cost	Yes	No	No	No	No
[26]	Max Profit	Yes	No	No	No	Stochastic
[27]	Min Cost	Yes	No	No	No	Stochastic
[28]	Min Cost	Yes	Yes	Yes	No	No
[29]	Max Profit	Yes	No	No	No	No
[30]	Min Cost	Yes	Yes	Yes	No	Stochastic
[31]	Min Cost	Yes	Yes	Yes	No	Stochastic
[32]	Min Cost	Yes	Yes	Yes	No	Stochastic
[33]	Min Cost	Yes	Yes	Yes	No	Stochastic
[34]	Min Cost	Yes	No	No	No	No
[35]	Min Cost	Yes	No	No	No	No
[36]	Min Cost	Yes	Yes	Yes	Yes	No
[37]	Min Cost	Yes	Yes	Yes	Yes	No
[38]	Min Cost	Yes	Yes	Yes	Yes	No
This work	Min average Cost Min deviation Cost	Yes	Yes	Yes	Yes	Interval optimization technique

simulation presents the simulations and corresponding results. Finally, conclusion is reported in Section Conclusion.

Formulation

A model has been used for IPL within which non-renewable and renewable generation units as well as EV have been used to support IPL to supply demand in addition to the purchased power from upstream grid. Schematic diagram of studied model is taken from Ref. [36] which is composed of micro-turbine, fuel cell, PV system, wind turbine and intelligent parking lot containing electric vehicles.

The problem formulation of IPL model is presented in below.

Objective function

Daily operation cost of IPL involving purchased power cost from the upstream grid, operational cost of LDG as well as cost/revenue of discharge/charge of EV available in the IPL should be minimized Eq. (1) [36].

$$OBJ = \sum_{t=1}^{T}\left[\left(P_{UG}^{t} \times \pi_{UG}^{t} + \sum_{j=1}^{G}\left(C_{LDG}^{j,t} + SC_{LDG}^{j,t}\right) + \sum_{i=1}^{N}\left(P_{Dch,EV}^{i,t} \times \pi_{Dch,EV}^{i} - P_{Ch,EV}^{i,t} \times \pi_{Ch,EV}^{i}\right)\right) \times \Delta t\right] \tag{1}$$

Upstream grid constraint

The injected/taken power to/from IPL by the upstream grid is constrained through Eq. (2) [30].

$$\left|P_{UG}^{t}\right| \le P_{UG}^{max} \tag{2}$$

Model of renewable generation units

The relationship between ambient temperature and PV unit output is expressed through Eq. (3) [36]. Also, the pattern that wind turbine unit uses for power generation is expressed through Eq. (4).

$$P_{PV}^{p,t} = \eta^{p} \times s^{p} \times G^{t} \times (1 - 0.005 \times (T_a - 25)) \tag{3}$$

$$P_{W}^{k,t} = \begin{cases} 0 & V^{t} < V_{c}^{k} \text{ or } V^{t} \ge V_{F}^{k} \\ \dfrac{V^{t} - V_{c}^{k}}{V_{R}^{k} - V_{c}^{k}} \times P_{R}^{k} & V_{c}^{k} \le V^{t} < V_{R}^{k} \\ P_{R}^{k} & V_{R}^{k} \le V^{t} < V_{F}^{k} \end{cases} \tag{4}$$

Model of non-renewable generation units

Operating cost as well as start-up cost of local dispatchable generators like micro-turbines is presented through Eqs. (4)–(6) [32].

$$C_{LDG}^{j,t} = a^{j} \times U^{j,t} + b^{j} \times P_{LDG}^{j,t} \tag{4a}$$

$$SC_{LDG}^{j,t} \ge \left(U^{j,t} - U^{j,t-1}\right) \times UDC^{j} \tag{5}$$

$$SC_{LDG}^{j,t} \ge 0 \tag{6}$$

Technical limitations of local dispatchable generators are presented through Eqs. (7)-(14). Maximum and minimum generation limitations of local dispatchable generators are presented in Eqs. (7) and (8), respectively. Ramp up and down limitations of local dispatchable generators are expressed through Eqs. (9) and (10), respectively. Maximum up and down time limitations of local dispatchable generators are presented in Eqs. (11) and (12), respectively. Finally, linear model of minimum down and up time limitations are expressed in Eqs. (13) and (14), respectively [32].

$$P^{j,t}_{LDG} \le P^{j}_{LDG,max} \times U^{j,t} \tag{7}$$

$$P^{j,t}_{LDG} \ge P^{j}_{LDG,min} \times U^{j,t} \tag{8}$$

$$P^{j,t}_{LDG} - P^{j,t-1}_{LDG} \le RU^{j} \times U^{j,t} \tag{9}$$

$$P^{j,t-1}_{LDG} - P^{j,t}_{LDG} \le RD^{j} \times U^{j,t-1} \tag{10}$$

$$U^{j,t} - U^{j,t-1} \le U^{j,t+Up_{j,f}} \tag{11}$$

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

$$Dn_{j,f} = \begin{Bmatrix} f & f \le MDT_j \\ 0 & f > MDT_j \end{Bmatrix} \tag{13}$$

$$Up_{j,f} = \begin{Bmatrix} f & f \le MUT_j \\ 0 & f > MUT_j \end{Bmatrix} \tag{14}$$

Constraints of IPL

Using charge/discharge power of available electric vehicles in the IPL, IPL attempts to exchange power with upstream grid. Limitations of charge/discharge power of electric vehicles available in the IPL are presented through constraints (15)–(16), respectively. Simultaneous charge/discharge process is restricted through Eq. (17). Switching process between charging and discharging states is limited through Eq. (18). Finally, SOC of EV available in IPL is declared and limited via Eqs. (19) and (20), respectively [37].

$$P^{i,t}_{Ch,EV} \le P^{i}_{Ch,max} \times W^{i,t}_{ch} \times M^{i,t} \tag{15}$$

$$P^{i,t}_{Dch,EV} \le P^{i}_{Dch,max} \times W^{i,t}_{Dch} \times M^{i,t} \tag{16}$$

$$W^{i,t}_{ch} + W^{i,t}_{Dch} \le M^{i,t} \tag{17}$$

$$\sum_{t=t^i_a}^{t^i_d} W^{i,t}_{ch} + W^{i,t}_{Dch} \le N_{max} \tag{18}$$

$$SOC^{i,t} = SOC^{i,t-1} + P^{i,t}_{Ch,EV} \times \eta_{G2V} - P^{i,t}_{Dch,EV} \Big/ \eta_{V2G} \tag{19}$$

$$SOC^{i}_{min} \le SOC^{i,t} \le SOC^{i}_{max} \tag{20}$$

State-of-charge of electric vehicle at the time that electric vehicle enters to the IPL is limited through Eq. (21) [37]. State-of-charge of electric vehicle at the time that vehicle attempts to leave IPL is limited through Eq. (22). Maximum rates for discharge and charge of EV are expressed through Eq. (23).

$$SOC^{i,t} \ge SOC^{i,t}_{Arrival} \tag{21}$$

$$SOC^{i,t}_{Departure} \ge SOC^{i}_{max} \tag{22}$$

$$-\Delta SOC^{i}_{max} \le SOC^{i,t} - SOC^{i,t-1} \le \Delta SOC^{i}_{max} \tag{23}$$

Model of hydrogen storage system

In this section, technical constraints and limitations, which are designed according to HSS, are presented [38]. HSS is in fact composed of three parts: tank, electrolyser, and fuel cell. In off-peak intervals, since electricity price is low, electrolyser generates hydrogen molar using electricity in these periods. The relationship between consumed electricity and produced hydrogen molar is expressed through Eq. (24) [38].

$$N^{EL}_{H2,t} = \frac{\eta^{EL} P^{EL}_{t}}{LHV_{H2}} \tag{24}$$

Maximum and minimum limitation of consumed power by electrolyser is expressed through Eqs. (25) and (26), respectively.

$$P^{EL}_{t} \le P^{EL}_{max} \times U^{EL}_{t} \tag{25}$$

$$P^{EL}_{t} \ge P^{EL}_{min} \times U^{EL}_{t} \tag{26}$$

Finally, maximum generation of hydrogen molar by electrolyser is expressed in Eq. (27).

$$N^{EL}_{H2,t} \le N^{EL}_{H2,max} \times U^{EL}_{t} \tag{27}$$

Generated hydrogen molar is stored in special tanks which maximum/minimum as well as initial pressure limitations are expressed through Eqs. (28)–(30), respectively [38].

$$P^{H2}_{t} \ge P^{H2}_{min} \tag{28}$$

$$P^{H2}_{t} \le P^{H2}_{max} \tag{29}$$

$$P^{H2}_{t0} = P^{H2}_{initial} \tag{30}$$

Stored hydrogen molar is later consumed in peak periods by fuel cell to generate electric power to be used for supplying energy demand. Maximum hydrogen molar consumption limitation in fuel cell is presented through Eq. (31). Maximum and minimum power generation constraints of fuel cell are presented through Eqs. (32) and (33), respectively.

$$N^{FC}_{H2,t} \le N^{FC}_{H2,max} \times U^{FC}_{t} \tag{31}$$

$$P^{FC}_{t} \ge P^{FC}_{min} \times U^{FC}_{t} \tag{32}$$

$$P^{FC}_{t} \le P^{FC}_{max} \times U^{FC}_{t} \tag{33}$$

Finally, the relationship between produced electricity and consumed hydrogen molar is expressed through Eq. (34) [38]. Dynamic model for pressure of HSS is presented through Eq.

(35). A simultaneous charge/discharge process of HSS is restricted through Eq. (36).

$$N^{FC}_{H2,t}=\frac{P^{FC}_t}{\eta^{FC}LHV_{H2}} \tag{34}$$

$$P^{H2}_t=P^{H2}_{t-1}+\frac{\Re T_{H2}}{V_{H2}}\left(N^{EL}_{H2,t}-N^{FC}_{H2,t}\right) \tag{35}$$

$$U^{EL}_t+U^{FC}_t\le 1 \tag{36}$$

Demand response program modeling

In this paper, it has been assumed that load can participate in DRP to reduce its payments and this leads to reduction of total operating cost of IPL. Demand response program has been implemented to make loads capable of gaining economic benefits through shifting their demand from peak times to off-peak times. Shifted demand cannot exceed a predefined limitation. It should be noted that sum of increased and decreased loads within a day should be zero. Mathematical form of TOU of DRP is presented in (37)–(40) [39,40].

$$load^t=load^t_0+DRP^t \tag{37}$$

$$DRP^t\le +DRP^{max}\times load^t_0 \tag{38}$$

$$DRP^t\ge -DRP^{max}\times load^t_0 \tag{39}$$

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

Constraint of power balance

Demand after applying DRP, charged power of EV, and consumed power by electrolyser in the studied model are served through power procurements from upstream grid, wind turbine, PV system, micro-turbines, discharged power of EV and generated power by fuel cell.

$$P^t_{UG}+\sum_{k=1}^{K}P^{k,t}_{W}+\sum_{p=1}^{P}P^{p,t}_{PV}+\sum_{j=1}^{G}P^{j,t}_{LDG}+\sum_{i=1}^{N}P^{i,t}_{Dch,EV}+P^{FC}_t = load^t+\sum_{i=1}^{N}P^{i,t}_{Ch,EV}+P^{EL}_t \tag{41}$$

Uncertainty modeling technique

Employed technique for uncertainty modeling of upstream grid price is explained within this section [41,42].

Interval optimization technique

Each optimization problem can be transformed into a standard optimization problem. An optimization problem subject to unequal and equal constraints and ρ as uncertainty parameter is expressed in standard form as follows:

$$Min\,f(X,U,\rho) \quad \text{s.t.} \tag{42}$$

$$h(X,U,\rho)\le 0 \tag{43}$$

$$g(X,U,\rho)=0 \tag{44}$$

According to the interval approach, uncertain parameter is represented as an interval variable including a lower and an upper values, $[U^{Min},\ U^{Max}]$. Therefore, all limitations and consequently the objective function will involve a lower and an upper bounds, $[f^-(X),f^+(X)]$. These values are calculated based on (45) and (46), respectively.

$$f^-(X)=\min_{\rho\in U}f(X) \tag{46}$$

$$f^+(X)=\max_{\rho\in U}f(X) \tag{45}$$

Since fluctuation of the uncertain parameter affects the objective function, these changes are expressed as an interval. So, instead of an interval-based objective function to be minimized, a bi-objective model involving deviation cost and average cost is created that is expressed through Eqs. (47)-(49):

$$Min\,f(X)=Min\left(f^M(X),f^W(X)\right) \tag{47}$$

where,

$$f^M(X)=\frac{f^+(X)+f^-(X)}{2} \tag{48}$$

$$f^W(X)=\frac{f^+(X)-f^-(X)}{2} \tag{49}$$

It should be noted that $f^M(X)$ and $f^W(X)$ are average and deviation costs of IPL, respectively.

Multi-objective problem

An ε-constraint technique and fuzzy approach are applied to solve bi-objective model [43]. At first, maximum/minimum rate of each objective function is calculated. Then, one of the objectives including higher importance is set as the main objective function and the other objective with less importance is set as a constraint for the main problem [43].

$$OF=\min\left(f^M(X)\right)\quad \text{s.t.}\ \begin{cases}\text{All equal \& inequal constraints}\\ f^W(X)\le\varepsilon\end{cases} \tag{50}$$

Afterward, second objective function is changed within its maximum and minimum values $(f^W_{min}(X),f^W_{max}(X))$ which consequently changes main objective function accordingly and as a result of that, Pareto curve is generated.

After that the Pareto front is obtained, per unit amounts of each objective function in all iterations are computed and then minimum amount between calculated values in each iteration is selected. Maximum selected value among chosen minimums is set to be trade-off result of bi-objective model.

This part is done by fuzzy decision making approach which steps are expressed using Eqs. (51)–(54) [43]:

$$f^M(X)_{pu} = \frac{f^M(X) - f^M_{max}(X)}{f^M_{min}(X) - f^M_{max}(X)} \quad (51)$$

$$f^W(X)_{pu} = \frac{f^W(X) - f^W_{max}(X)}{f^W_{min}(X) - f^W_{max}(X)} \quad (52)$$

$$f^n = \min\left(f^n_1, \ldots, f^n_N\right); \forall\ n\ = 1, \ldots, N_P \quad (53)$$

$$f^{max} = \max\left(f^1, \ldots, f^{N_P}\right) \quad (54)$$

Numerical simulation

In order to carry out simulations related to uncertainty based optimal scheduling of IPL within uncertainty of upstream grid price under DRP, following input data have been utilized. It is noteworthy that the mentioned simulations are implemented under CPLEX solver of GAMS [44].

Input data

Input data of local dispatchable generators containing micro-turbine is taken from Ref. [36]. The data used for modeling wind turbine and PV system, wind speed, demand and sunlight irradiation profiles, generated power through PV system, and wind turbine are taken from Ref. [36]. The minimum, expected and maximum amounts of market price has been shown in Fig. 1 which the expected amount is taken from Ref. [36].

The parameters of hydrogen storage system and electric vehicles characteristics are taken from Ref. [36]. Each electric vehicle has a capacity of 10–20 kWh with capacity number 230 and SOC of 0.1–0.7. A random number between 0.15 and 0.3 is considered for charging price of ith-EV in the IPL. Likewise, a random number between 0.25 and 0.4 is considered for discharging price of ith-EV in the IPL. Maximum limitation of exchanged power between upstream grid and IPL is 1000 kWh.

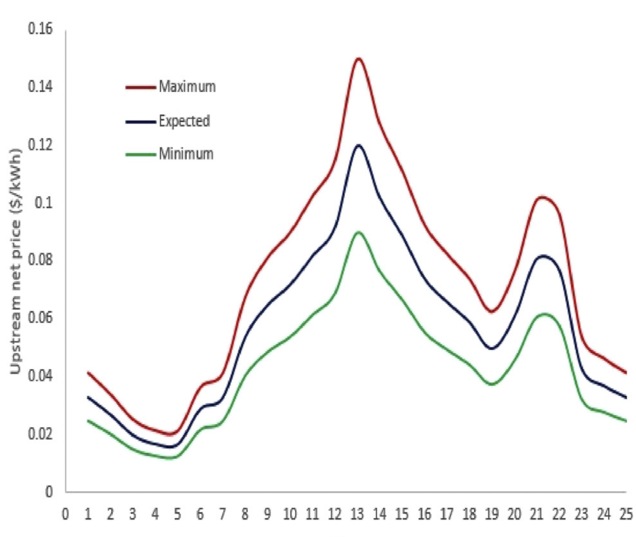

Fig. 1 – Market price.

Deterministic based results of simulations

Solving the objective (1) subject to limitation (2)–(41) in deterministic case, the results for average and deviation ýcosts of IPL in with and without DRP are presented in Table 2.

It can be understood from Table 2 that by exploiting DRP, daily operation cost of IPL has been decreased from $1957.425 to $1907.336 which is reduced about 2.55%. In fact, by reducing total purchased power from the upstream grid, IPL has operated LDG to supply demand and this has led to reduction of daily operation cost of IPL.

Interval based results of simulations

Solving the interval based objective function (47) with respect to all unequal and equal constraints, Pareto optimal front for the uncertainty based optimal operation of IPL is obtained and illustrated in Fig. 2.

According to the obtained results shown in Fig. 2, average cost of IPL without considering DRP is equal to $1980.722 while deviation cost of IPL in this condition is $414.054. In versus the deterministic condition, average cost of IPL is raised 1.19%

Table 2 – Obtained results of deterministic case.

Parameters	Deterministic case	
	Without DRP	With DRP
Daily operation cost ($)	1957.425	1907.336
Cost of upstream net ($)	914.209	693.432
Operation cost of LDG ($)	1617.676	1790.437
Startup cost of LDG ($)	50.080	52.020
IPL charge cost ($)	−951.331	−971.833
IPL discharge cost ($)	326.791	343.280
Average cost ($)	1957.426	1907.336
Deviation cost ($)	548.083	502.137
Total cost reduction (%)	0	2.55

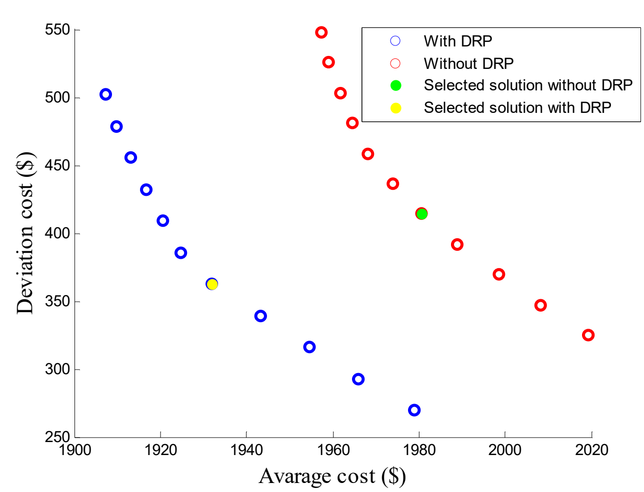

Fig. 2 – Pareto front of IPL.

Table 3 – Pareto solutions.

With DRP						Without DRP					
#	Average cost ($)	Deviation cost ($)	Φ_1(p.u.)	Φ_2(p.u.)	min (Φ_1, Φ_2)	#	Average cost ($)	Deviation Cost ($)	Φ_1(p.u.)	Φ_2(p.u.)	min (Φ_1, Φ_2)
1	1907.336	502.137	1	0	0	1	1957.425	548.083	1	0	0
2	1909.937	478.866	0.964	0.100	0.100	2	1958.997	525.745	0.975	0.100	0.100
3	1913.170	455.595	0.918	0.200	0.200	3	1961.667	503.407	0.932	0.200	0.200
4	1916.618	432.324	0.870	0.300	0.300	4	1964.701	481.069	0.883	0.300	0.300
5	1920.467	409.053	0.816	0.400	0.400	5	1968.162	458.731	0.827	0.400	0.400
6	1924.720	385.783	0.757	0.500	0.500	6	1974.014	436.393	0.732	0.500	0.500
7	**1932.060**	**362.512**	**0.654**	**0.600**	**0.600**	7	**1980.722**	**414.054**	**0.624**	**0.600**	**0.600**
8	1943.349	339.241	0.496	0.700	0.496	8	1988.994	391.716	0.491	0.700	0.491
9	1954.562	315.970	0.339	0.800	0.339	9	1998.530	369.378	0.337	0.800	0.337
10	1965.973	292.699	0.180	0.900	0.180	10	2008.253	347.040	0.180	0.900	0.180
11	1978.826	269.428	0	1	0	11	2019.430	324.702	0	1	0

The bold solution shows the trade-off solution based on max-min fuzzy approch.

while deviation cost is decreased up to 24.45%. By exploiting DRP, average cost of IPL is $1932.060 while deviation cost is $362.512. Comparing to the deterministic approach, average cost is raised 1.30% while deviation cost is decreased up to 27.81%. It is concluded that the positive effects of DRP employment, in versus the deterministic case, not only average cost of IPL has been reduced but also robustness of IPL toward uncertainty of upstream grid price has been strengthened. Also by comparing the trade-off results obtained in with and without DRP, it is shown that by using DRP average cost of IPL has been reduced up to 2.46% while deviation cost of IPL has been decreased 12.49% compared to the without DRP case. This means that by using DRP not only average cost will be reduced but also robustness of IPL against the uncertainty of upstream grid price is strengthened. For more clarification, obtained Pareto set is numerically presented in Table 3.

Some other illustrative figures have been presented in the following to show influence of employed techniques. Energy demand without and with DRP in both deterministic and interval approaches has been captured through Fig. 3. According to this Fig, due to positive influence of DRP, load has been mostly moved from peak times to other times and this has made load curve more flattened and leads to reduction of daily operation cost of IPL.

According to the peak period defined in price profile, by using DRP since load is transferred from peak times to off-peak times, most of the power is purchased from upstream grid in off-peak periods and this has reduced daily operation cost of IPL. Power procurement profile is captured through Fig. 4.

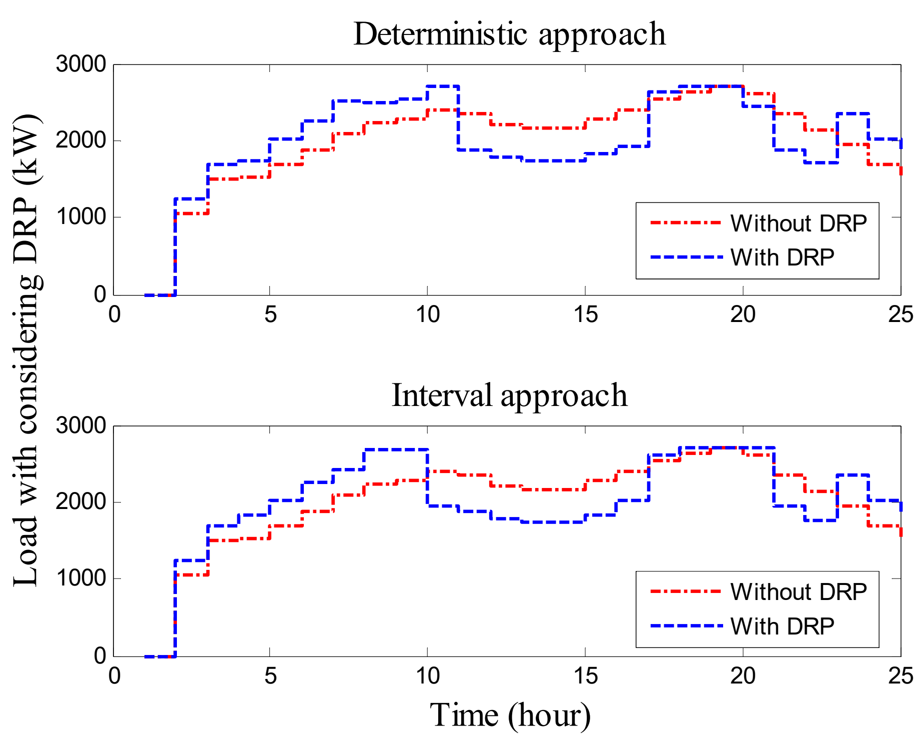

Fig. 3 – Load with and without DRP.

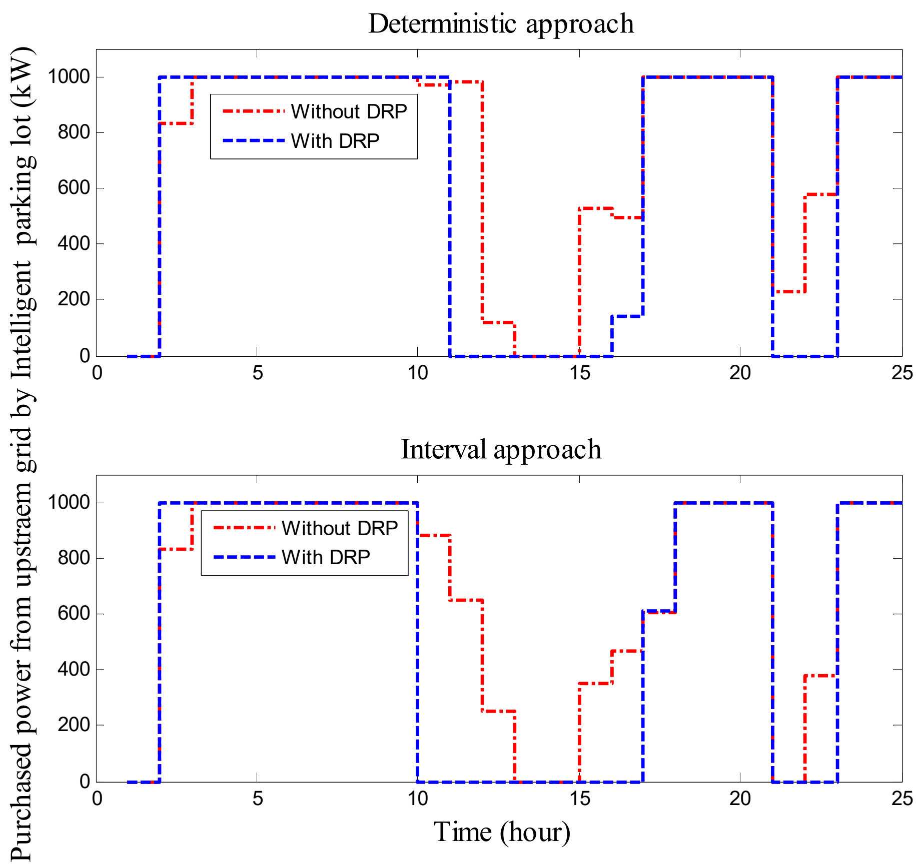

Fig. 4 – Power procurement with and without DRP.

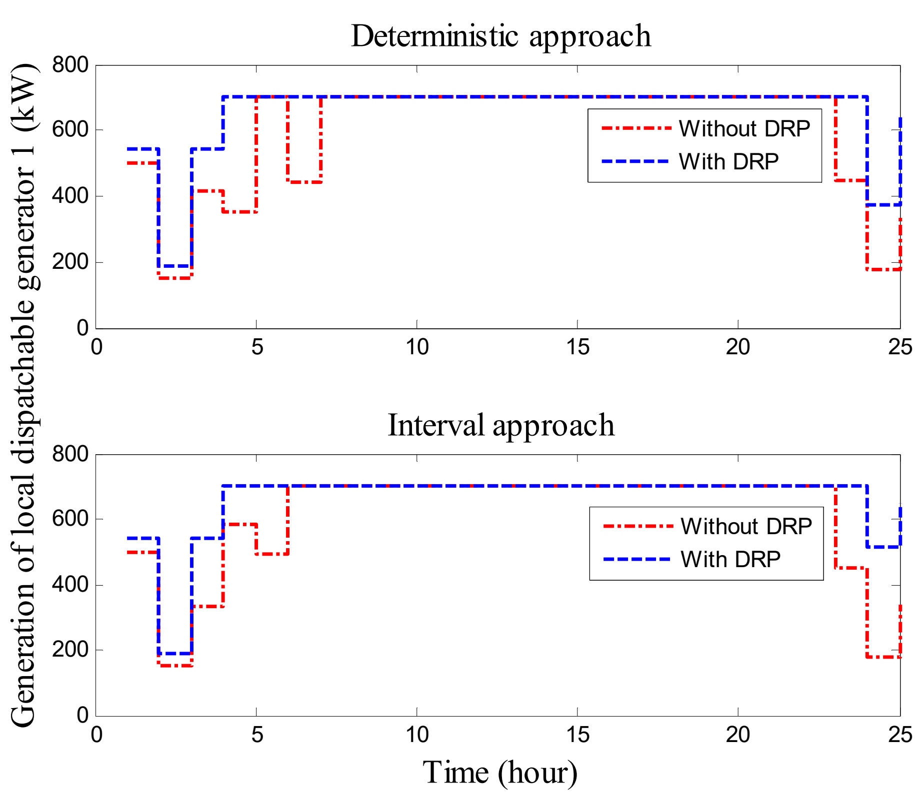

Fig. 5 – Power generation of LDG1.

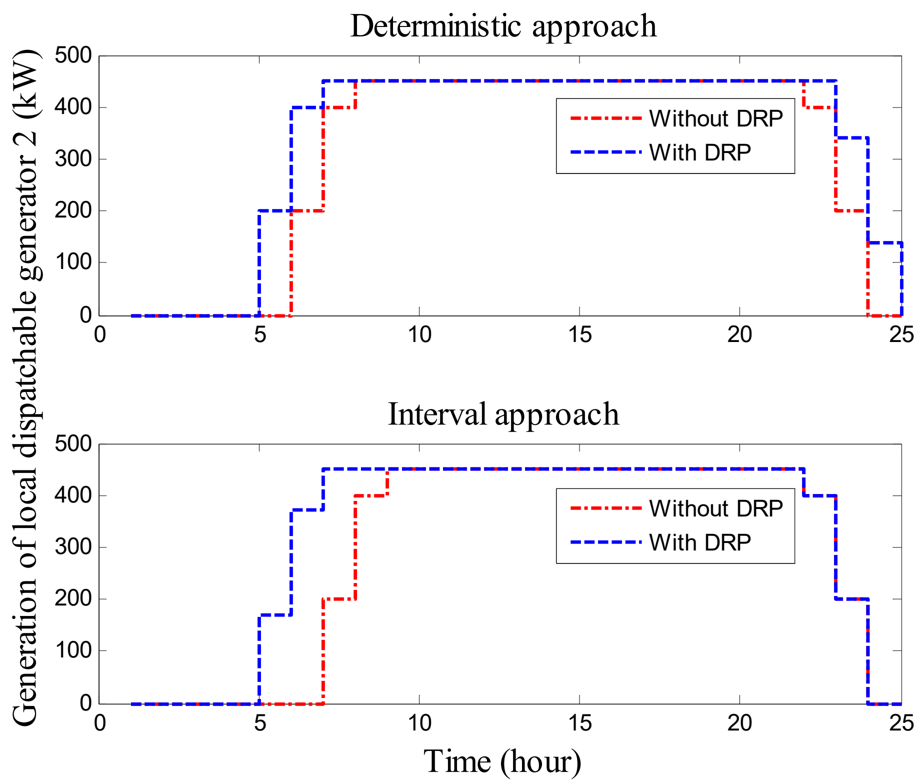

Fig. 6 — Power generation of LDG2.

Since share of upstream grid in supplying energy demand is decreased in peak time intervals, share of local dispatchable generators in supplying energy demand in the mentioned intervals is increased. Generation profiles of local dispatchable generators are captured through Figs. 5–7.

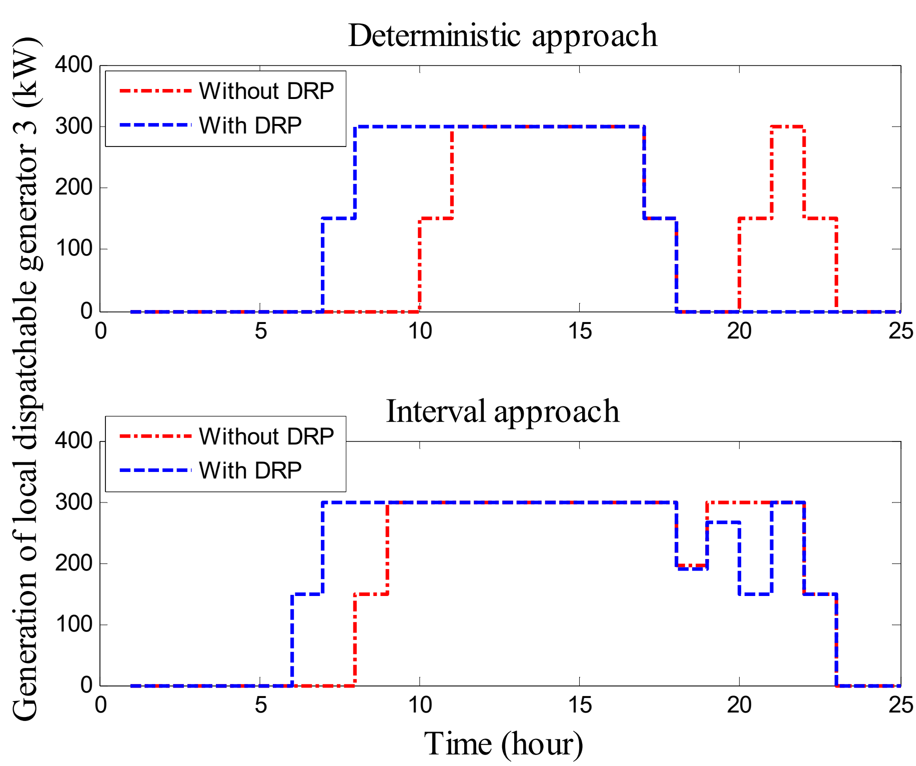

Fig. 7 — Power generation of LDG3.

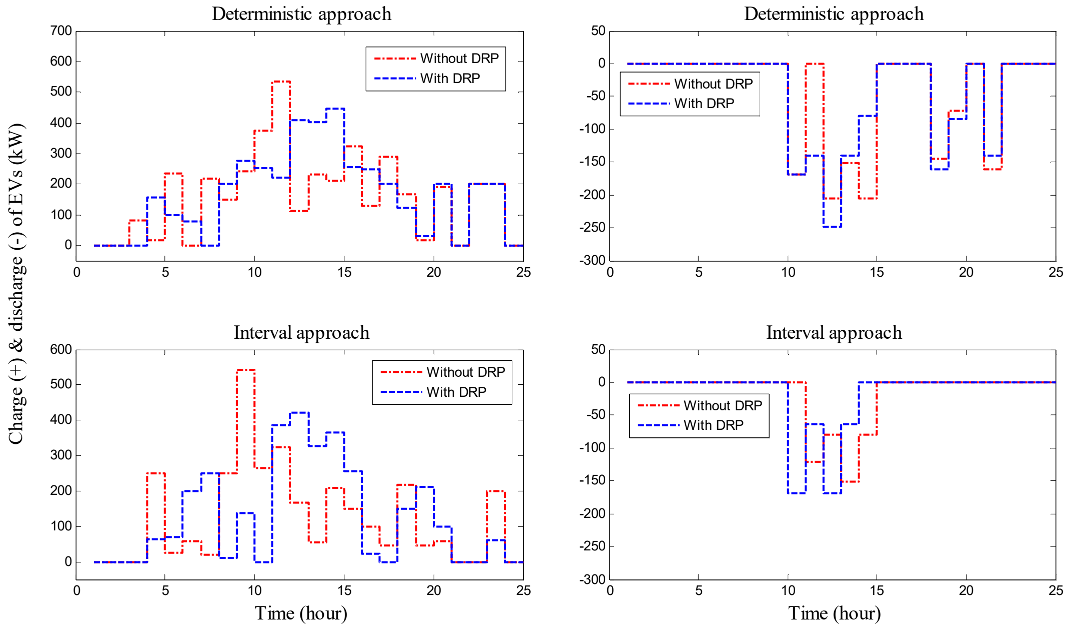

Fig. 8 – Discharge and charge of EV.

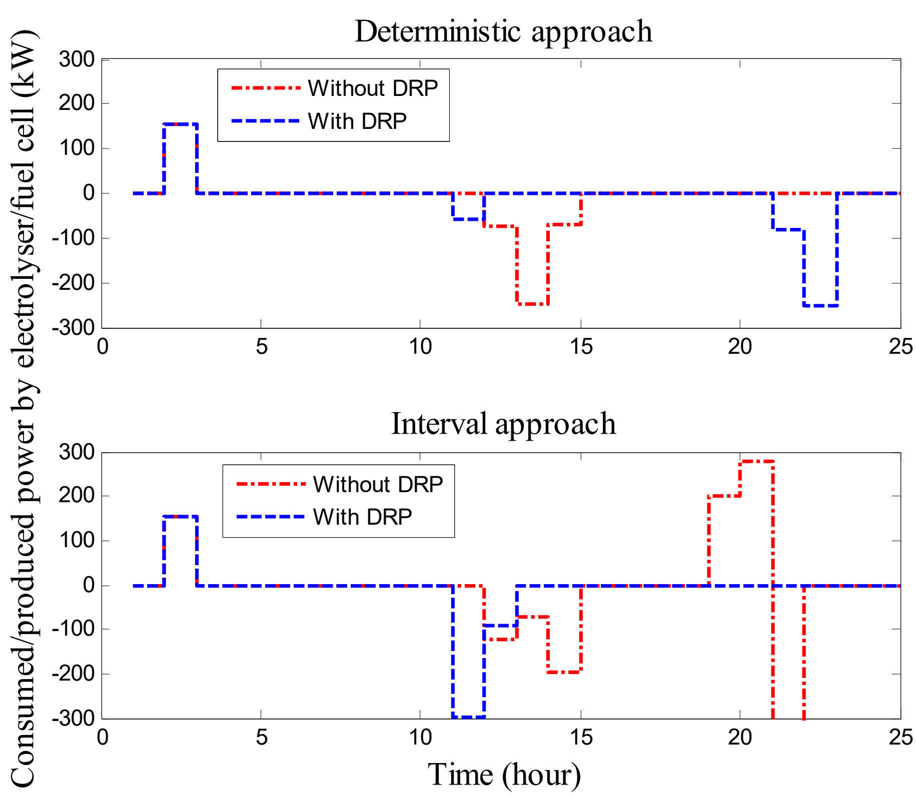

Fig. 9 – Charge/discharge of HSS.

Discharge and charge processes of EV in with and without DRP under deterministic and interval approaches are shown in Fig. 8. According to this Fig, charging rates of EV in off-peak intervals has been increased while discharge rates of EV in peak intervals has been raised to help IPL to satisfy demand. According to the optimal operation of IPL and generation units under DRP in deterministic and interval approaches, optimal charge/discharge processes of HSS through electrolyser and

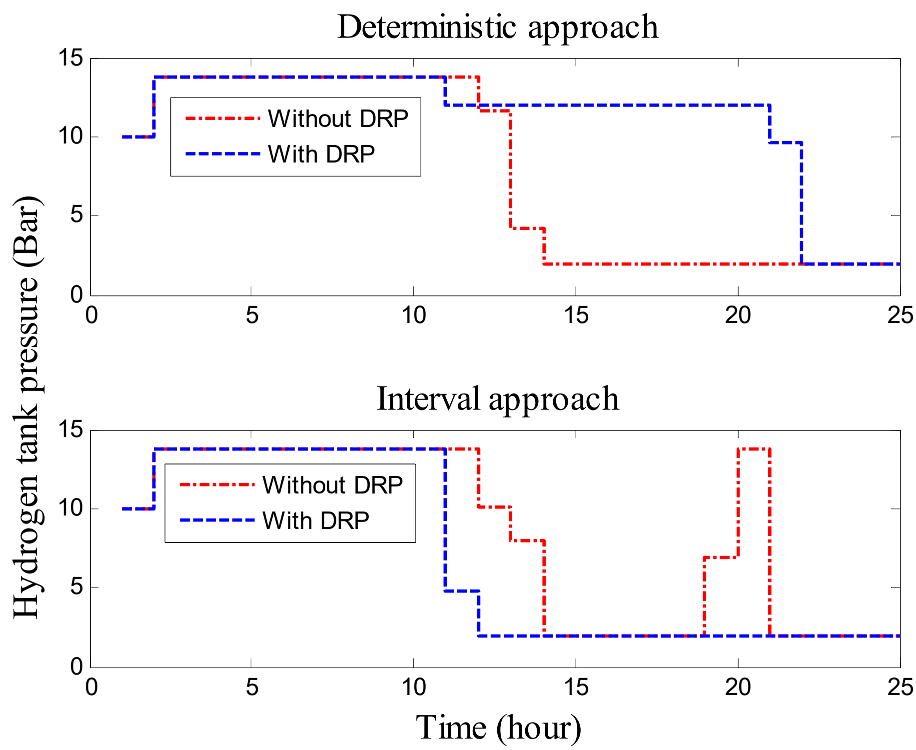

Fig. 10 – Available tank pressure of HSS.

fuel cell unit is obtained which is captured in Fig. 9. Also, available pressure of HSS, which is based on charge/discharge rates of HSS, is shown in Fig. 10.

Conclusion

Optimal operation of intelligent parking lot within sever uncertainty of upstream grid price under DRP is analyzed in this paper. Using interval based optimization technique, single objective uncertainty based optimization problem is transformed into a bi-objective deterministic model with average and deviation costs which is later solved using the ε-constraint technique and fuzzy approach. Obtained results revealed that due to positive influence of DRP, operation cost of IPL in deterministic approach is decreased up to 2.55%. Also, interval based trade of results expressed that due to positive impact that DRP has provided, raise of average cost of IPL has been decreased up to 2.46% while deviation cost of IPL has been decreased up to 12.49%. This means by less increase of average cost in the presence of DRP, robustness of IPL toward uncertainty of upstream grid price has been strengthened. The proposed interval optimization approach is applicable for uncertainty modeling for any integrated energy systems and emission reduction which can be studied in the future works.

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