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Optimal operation of DG-based micro grid (MG) by considering demand response program (DRP)

Hamed Hosseinnia*, Behrouz Tousi

Faculty of Electric and Computer Engineering, Urmia University, Urmia, Iran

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ABSTRACT

Recently, due to increase of environmental pollution and greenhouse gases, policy makers of electricity industry are forced to consider both of economic and environment performance of renewable energy resources and local dispatchable generators (LDG) in the scheduling problems. This study presents a bi-objective optimization algorithm to optimal scheduling of MG by considering both of operational and environmental costs. The proposed MG includes of combined heat and power (CHP), boiler, heat storage, solar parking lot (SPL), LDG and is considered in grid connected mode. Time of use (TOU) based demand response program (DRP) is employed to modify daily load curve and transfer loads consume from on-peak time to others. To solve such a problem, ε-constraint and fuzzy decision making methods are utilized. The proposed approach is written as mixed-integer linear programming (MILP) being solved by general algebraic modeling system (GAMS). Simulation results verify the efficiency of proposed technique in reducing both of operational and environmental cost under employing DRP up to 2%, 12.45%, respectively.

1. Introduction

Integration different kind of generation units to supply both of thermal and electric energy demands is defined as hub energy system. Combined heat and power (CHP) is used to generate both of thermal and electric energy. Boiler and heat storage (HS) units are used to supply thermal demands. To proper integrating of electrical vehicles (EVs), and utilizing them as a generating units by employing vehicle to grid (V2G) technology, parking lots (PL) are installed in the power system. To minimize destructive emitted gases which are generated by vehicles, fuel cell based electric vehicles (FCEV) which are equipped to hydrogen storage system (HSS) are used in this paper. To improve reliability indices of the MG and enhance efficiency of the proposed eco-emission based problem, MG is connected to a local grid (LG). On the other hand, in this paper solar parking lot (SPL) is used to charge FCEVs. The microgrid operator (MGO) is responsible for managing generation units to supply qualified energy services. Utilizing local diesel generators (LDG) and fossil-based generation units, has made emission problems. The operator of such system, should guide the scheduling decision in reducing of emission problems in beside of operational cost. This is the main motivation of this paper. Similar researches verify efficiency of utilizing ε-constraint and max–min fuzzy decision making methods in formation of Pareto optimal front by solving bi-objective problem and finding and selecting the trade-off among all solutions. Demand response (DR) is described as consumer's interest to shift or reduce their electricity usage from on-peak time to off-peak in response to time-based rates or incentive based programs. Networks reliability has been improved by using DR programs. In this paper, demand response is used to show effect of consumers' participation in load curve modification. Furthermore, DR programs reduce operational cost and value of purchasing electricity from the main grid. Price elasticity of demand is defined as sensitivity of demand quantity with respect to change in price.

Recently, various researches study with different purposes and applications of hub energy systems. Self-adaptive learning with time varying acceleration coefficient-gravitational search algorithm is used to economic dispatch problem of energy hub system [1]. Optimal design of hub energy system to gain maximum profit is investigated in Ref. [2]. In some literatures, utilizing of EVs are investigated for reduction of greenhouse gases emission [3]. Increase penetration of renewable energy resources in the hub energy system can also control environmental issues. In other papers, intelligent parking lot (IPL) have been introduced by utilizing distributed generation units in the parking lots [4]. The authors of Ref. [5] present a probabilistic method that accurately verifies the fulfillment voltage constraints in radial distribution system (RDS) with photovoltaic systems and electric vehicle

* Corresponding author.
E-mail addresses: H.Hoseinnia@urmia.ac.ir (H. Hosseinnia), B.Tousi@urmia.ac.ir (B. Tousi).

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Indices

Indices

f	Index related to linear modeling of minimum on/off time of LDG
i	EV index
j	LDG index
p	Index related to photovoltaic system
t	Sample time index

Parameters

a^j, b^j	Coefficients related to cost of LDG
$DRP^{\max}$	Maximum allowable limitation for participation in DRP
G^t	Hourly irradiation of sunlight
$load_0^t$	Based load with no consideration of TOU
MUT_j	Minimum up time restriction of LDG
MDT_j	Minimum down time restriction of LDG
N_{Ev}	Number of EVs present in IPL
$P_{\min}^{FC}$, $P_{\max}^{FC}$	Minimum/maximum power generation constraints in fuel cell
$P_{\min}^{H2}$, $P_{\max}^{H2}$	Minimum/maximum restriction of pressure available in hydrogen tank
$P_{PV}^{p,t}$	Amount of output power of PV system
$P_{LDG,\max}^{j}$	Maximum power generation restriction of LDG
$P_{LDG,\min}^{j}$	Minimum power generation restriction of LDG
$P_{UG}^{\max}$	Maximum injected power restriction of upstream net
$P_{Ch,\max}^{i}$	Maximum charge restriction of EV
$P_{Dch,\max}^{i}$	Maximum discharge restriction of EV
$\mathfrak{R}$	Value of gas constant
RD^j,RU^j	Ramp up/down of LDG
s^p	Area within which PV is installed
$SOC_{\max}^{i}$	Maximum state of charge (SOC) restriction of EV
$SOC_{\min}^{i}$	Minimum SOC restriction of EV
$SOC_{Arrival}^{i,t}$	Primary SOC of EV at the time arriving at SPL
η^g	Gas efficiency on conversion to power
HV^{gas}	Heating value of natural gas
ρ_{gas}	Price of natural gas
P_{CHP}^{t}	Generated power by CHP
η^{HE}	Efficiency of heat exchanger
HPR	Heat to power ratio of CHP
H_{CHP}^{t}	Value of heat generated by CHP
C_{CHP}^{t}	Operational cost of CHP
C_{SPL}^{t}	Operational cost of solar parking lot
T_a	Temperature of ambient
T_p^i	The time in which EV is present at SPL
T_{H2}	Vessel mean temperature
t_a^i	The time in which EV arrives at SPL
t_d^i	The time in which EV departures from SPL
$\rho_{Ch,Ev}^{i}$	Charging price of EV
$\rho_{Dch,Ev}^{i}$	Discharging price of EV
η_{ch}, η_{dis}	Charge and discharge efficiency values of EV
η^p	PV array efficiency value
ρ_{UG}^{t}	Price of injected power by upstream net
Δt	Sample time for counting number of EVs available in SPL
$\Delta SOC_{\max}^{i}$	Maximum restriction of charge/discharge of EV

Variables

$C_{LDG}^{j,t}$	LDG operating cost
$Dn_{j,f}$	Minimum down time restriction of LDG
DRP^t	Shifted load in TOU
$load^t$	Energy demand under DRP
$M^{i,t}$	Binary variable for attendance of EV in SPL
$N_{H2,t}^{FC}$	Hydrogen consumption by fuel cell
P_{UG}^{t}	Injected power by upstream net
$P_{Ch,Ev}^{i,t}$	EV charging power
$P_{Dch,Ev}^{i,t}$	EV discharging power
$P_{LDG}^{j,t}$	LDG scheduled power
$SOC^{i,t}$	SOC of EV
$SC_{LDG}^{j,t}$	Startup cost of LDG
$SOC_{Departure}^{i,t}$	SOC of EV at the time of departing from IPL
$\mathrm{Up}_{j,f}$	Minimum up time restriction of LDG
$U^{j,t}$	Binary variable for ON/OFF states of LDG
$\delta^{ch\arg e}$	Binary variable for charging state of EV
$\delta^{disch\arg e}$	Binary variable for discharging state of EV
$\Delta SOC^{i,t}$	Change of energy in EV's SOC within two continuous hours

charging loads. To this aim, the proposed probabilistic method involves the calculation of input variable cumulants, the linearization of load-flow equation, and the application of the cumulant method and the Cornish- Fisher expansion. Ref. [6] investigates general analytical technique (GAT) to evaluate the combined impact for an extended time frame. Results verify effectively assessing of the GAT to fulfillment of technical requirements for weekly RDS operating variables as specified in regulations. Furthermore, the computational cost of the GAT is lower than that associated with Monte Carlo simulation, which is used to confirm the GAT accuracy. As a technology that has come a long way in recent years, electric vehicle has turned to be used for environmental objectives in power systems [7,8] used DR concept in micro-CHP in order to reduce variable cost for households. In all of the papers objective function is expressed as an optimization problem. In order to solve these kind of issues, meta heuristic algorithms such as Particle swarm optimization (PSO), Genetic algorithm (GA) or optimization software such as GAMS was used. Likewise, renewable generation system can be also exploited to handle greenhouse gases issues of power systems. Ref. [9] used imperial competition algorithm (ICA) to solve optimal operation of DG under load uncertainties. This paper focused on probabilistic analyses of optimal power dispatch with considering economic aspects of MG. Neyestan et al. [10] used stochastic programming in order to study the operational impact of high wind penetration in Ireland. Tamalouzt et al. [11]. In [13] total cost and emission of the MG is formulated as a multi-objective optimization problem. Authors used from lexicographic optimization and hybrid augmented weighted method and epsilon-constraint method for obtaining the optimal solution of the problem. In Ref. [14], daily operating cost of the MG is modeled as stochastic programming for taking into account the uncertainty of the real-time market price. In Ref. [15], optimal siting and sizing of MG with considering reliability constraints are investigated in the planning horizon. Authors utilized improved adaptive genetic algorithm to solve optimization algorithm. In Ref. [16], accuracy of uncertainties prediction in MG scheduling problem by employing two-point estimate method is investigated. To solve optimization problem phase angle-based particle swarm optimization (PSO) algorithm is utilized. Energy management of microgrid under optimum charge and discharge rates of EV has been investigated in Ref. [17].

As reviewed the literature on optimal scheduling of MG, the optimum scheduling of economic and emission cost of MG in DG-based MG with both kind of thermal and power-based generators has not been addressed in recent studies. This paper proposed a model to optimum eco-emission operation of DG-based MG through a bi-objective optimization model under TOU-based DRP.

In the proposed paper, optimum eco-emission operation MG has been investigated through a bi-objective optimization model under employing TOU-based DRP. The novelties of this paper are expressed as follows:

- Presenting bi-objective model for optimal eco-emission performance of MG including thermal and electrical energy.
- Considering thermal and electrical storage system in to enhance efficiency of operational problem.
- Optimal scheduling of HSS in fuel cell based EVS (FCEVs).
- Utilizing ε-constraint technique to convert bi-objective function to a single objective function and obtain Pareto optimal front solutions.
- Utilizing max–min fuzzy satisfying method to select a trade-off among solutions.

Section 2 presents the mathematical formulation of the proposed approach and problem solution techniques. In Section 3, simulation studies are thoroughly explored. Concluding remarks are reflected in Section 4.

2. Problem formulation

In this paper scheduling problem is introduced as a simultaneous operational and environmental performance optimization problem of the proposed MG under employing TOU-based DRP. As mentioned in the previous, the proposed MG includes, CHP, boiler, heat storage and LDG. To find the optimal commitment of MG components, the main goal of the proposed energy management system (EMS) is compromising both of economic and emission costs. The MGO management strategy in the proposed model is illustrated in the Fig. 1.

2.1. Objective function

Operational cost of MG is equal to start up and operating cost of LDG, as well as power provision from main grid, cost of CHP, PV and PL as follows:

$$OC = \sum_{t=1}^{24}\left(\sum_{j=1}^{G}(C_{LDG}^{j,t} + SC_{LDG}^{j,t}) + P_{LG}^{t} \times \rho_{LG}^{t} + \sum_{i=1}^{n} C_{CHP}^{i,t} + C_{SPL}^{t}\right)$$

$$C_{SPL}^{t} = (-P_{ch,EV}^{l,t} \times \rho_{ch,EV}^{t} + P_{disch,EV}^{l,t} \times \rho_{disch,EV}^{t}) + \sum_{y=1}^{d} P_{PV}^{y,t} \times \rho^{t}$$

$$C^{CHP} = \left(P_{CHP}^{t} \times \frac{\rho^{gas}}{HV_{gas} \times \eta^{g}}\right) \tag{1}$$

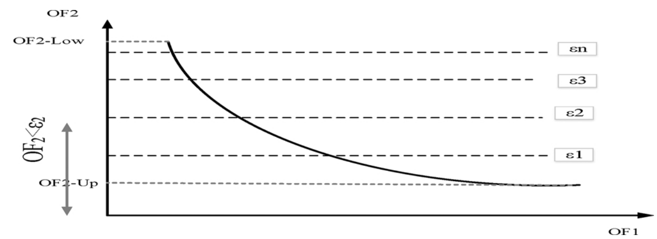

Fig. 2. Pareto optimal front theory.

The emission-based cost of the paper includes the emission due to injected power by local grid and generation of LDG, CHP, boiler and heat storage as follows:

$$EC = \sum_{t=1}^{24}\left(\sum_{j=1}^{G}(C_{LDG}^{j,t}) \times \mathrm{D}_{LDG} + (P_{LG}^{t} \times \mathrm{D}_{LG}) + (\sum_{i=1}^{n}(C_{CHP}^{i,t}) \times D_{CHP}^{i,t}) + \sum_{k=1}^{l}(C_{Boiler}^{k,t} \times D_{Boiler}^{k,t}) + C_{HS}^{t} \times D_{HS}\right) \tag{2}$$

2.2. The proposed two stage solution technique for solving the eco-emission scheduling problem

The proposed solution method includes two stages. In the first stage by utilizing ε-constraint technique and create a single objective optimization problem and set the other one as the constraint for the main objective, the solutions which form the Pareto optimal front are obtained. In the second stage max–min fuzzy decision making algorithm is employed to select the trade-off among obtained Pareto solutions. Both of stages are modeled as follows (Fig. 2).

2.2.1. Stage I (finding the Pareto optimal front)

In multi-objective problems, Pareto optimal front is used to simultaneous optimization of all objective functions. ε-constraint method is one of efficient techniques to obtain Pareto solutions. In this technique, by considering on objective as a main objective function and setting others as a constraints of main objective function, the Pareto front solutions can be obtained [18]. As mentioned, bi-objective function includes emission and operational cost is presented in this paper. Modeling of this bi-objective function as a single-objective function by utilizing ε-constraints technique is written as follows:

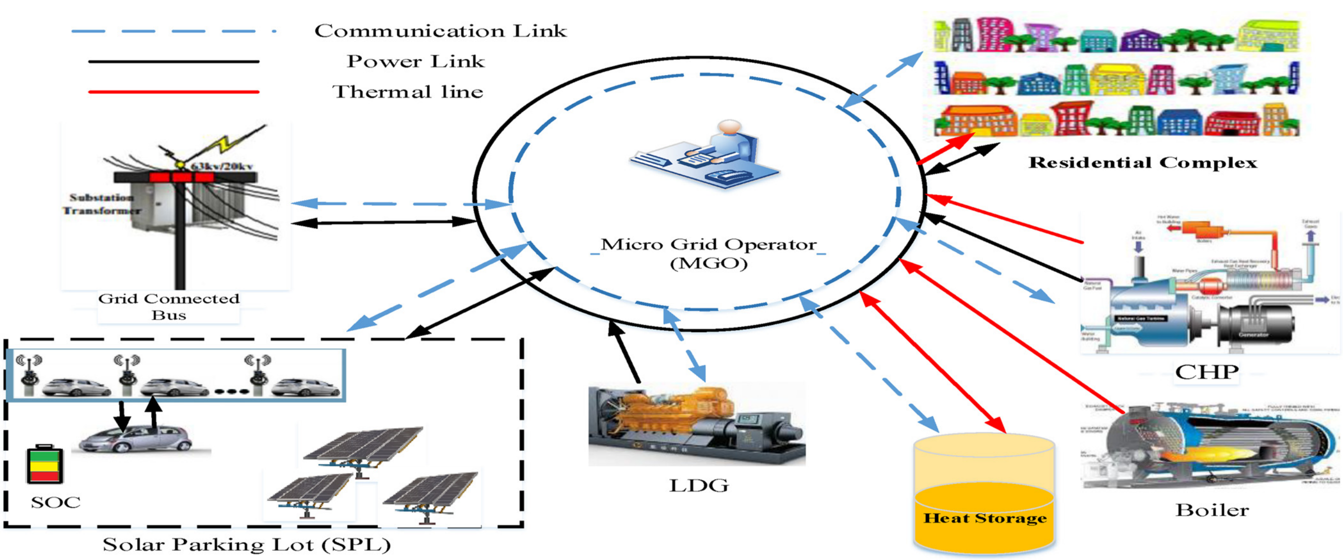

Fig. 1. The proposed MG.

$$OF = min(Cost^{op})$$
$$s.t$$
$$\begin{cases} Em \le \varepsilon \\ all\ equal\ and\ inequal\ constraints \end{cases} \tag{3}$$

2.2.2. Stage II (selecting 'the best' solution)

What is important, is that what is optimal for one objective may not be optimal for another. To make a trade off among all solutions max–min fuzzy method are described in the following steps [19]:

Step 1. Define a membership function $\mu^{f_k(X_n)}$ for each of Pareto solutions (X_n) as follows:

$$\mu^{f_k(X_n)} = \begin{cases} 0 & f_k(X_n) > f_k^{\max} \\ \frac{f_k^{\min} - f_k(X_n)}{f_k^{\min} - f_k^{\max}} & f_k^{\min} < f_k(X_n) < f_k^{\max} \\ 1 & f_k(X) < f_k^{\min} \end{cases} \tag{4}$$

Step 2. Maximize the minimum satisfaction among all objectives as follows:

$$\max_{N=1}^{N_p}(\min_{k=1}^{N_o}(\mu^{f_k(X_n)})) \tag{5}$$

Fig. 3 shows a graph to express Eq. (5).

2.3. Model of all generation units' electrical power

Generation power of units are expressed in this section.

2.3.1. Model of LDG

LDG used in this paper is presented through Eqs. (6)–(15) [20,21]. Operational and start-up cost of LDG has been presented through (6) and (7).

$$C_{LDG}^{j,t} = a^j \times U^{j,t} + b^j \times P_{LDG}^{j,t} \tag{6}$$

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

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

Eqs. (8)–(10) presents ramp-up and down of LDG. Eqs. (11)–(13) presents limitation related to minimum-up/down time of LDG. Furthermore, linearized form of minimum up/down of LDG are expressed through (14) and (15).

$$P_{LDG}^{j,t} \le P_{LDG,\max}^{j} \times U^{j,t} \tag{8}$$

$$P_{LDG}^{j,t} \ge P_{LDG,\min}^{j} \times U^{j,t} \tag{9}$$

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

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

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

$$U^{j,t-1} - U^{j,t} \le 1 - U^{j,t+Dn_{j,f}} \tag{13}$$

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

$$Dn_{j,f} = \begin{cases} ff \le MDT_j \\ 0f > MDT_j \end{cases} \tag{15}$$

2.3.2. Generation of solar parking lot is presented as follows

The total output power of SPL includes generation power of PV and PL input/output power which is described as follows:

$$P_{SPL}^t = P_{PV}^t + P_{ch\arg e-EV}^t - P_{Disch-EV}^t \tag{16}$$

Each terms can be defined as follows.

Output power of solar cells are calculated as follows [22]:

$$P_{PV}^t = \eta^{PV} \times S \times G^t \times (T_a - T_t) \tag{17}$$

Input/output power of parking lot is described as follows:

All constraints related to SPL are, charging and discharging power of EVs, available SOC of EVs, SOC of EVS at different time (vehicle

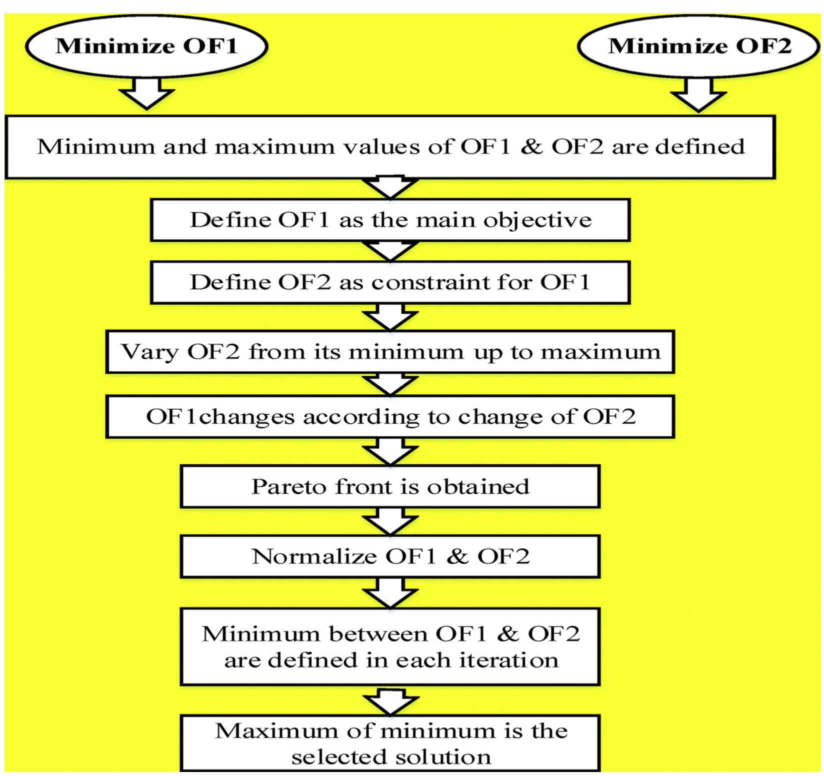

Fig. 3. Flowchart to describe Eq. (5).

Table 1
EVs input parameters.

α	T_P^i	$P_{Ch,\max}^i$	$P_{Dch,\max}^i$	$SOC_{\max}^i$	$SOC_{\min}^i$	$\Delta SOC_{\max}^i$	η_{G2V}	η_{V2G}	$N_{\max}$
0.2	2–8	5–10	5–10	10–20	0	5–10	0.9	0.8	10

Table 2
LDGs parameters.

Source	Type	a $	b $/KW	$P^{\min}$ KW	$P^{\max}$ KW	MUT h	MDT h	t_{on}/t_{off} h	UDC $	RU	RD
1	MT	0.028	0.056	150	700	2	2	3	0.1	350	350
2	MT	0.026	0.052	120	500	2	2	−4	0.04	200	200

Table 3
PV and CHP parameters.

PV parameters			CHP, boiler and HS parameters		
Parameter	Value	Unit	Parameter	Value	Unit
η	15.7	%	η^{HE}	95	%
S	1200	m^2	γ	90	%
T_a	25	°C	η^{Boiler}	80	%

arrives/departure at/from SPL) and binary variables to separate simultaneous charge and discharge process. All of mentioned constraints are formulated through.

$$
\begin{aligned}
&P_{Charge-EV}^t \le \delta^{charge} \times P_{Charge,\max}^i \\
&P_{Disch-EV}^t \le \delta^{Disch} \times P_{Disch,\max}^i \\
&\delta^{Charge} + \delta^{Disch} \le 1
\end{aligned} \tag{18}
$$

$$
\begin{aligned}
&SOC^{i,t} = SOC^{i.t-1} + P_{charge-EV}^{i,t} \times \eta_{G2V} - \frac{P_{Disch-EV}^{i,t}}{\eta_{V2G}} \\
&s.t \\
&SOC_{\min}^i \le SOC^{i,t} \le SOC_{\max}^i
\end{aligned} \tag{19}
$$

$$SOC^{i,t} \ge SOC_{Arrival}^{i,t} \tag{20}$$

$$SOC_{departure}^{i,t} \ge SOC_{\max}^i \tag{21}$$

$$-\Delta SOC_{\max}^i \le SOC^{i,t} - SOC^{i,(t-1)} \le \Delta SOC_{\max}^i \tag{22}$$

2.3.3. Model of CHP

Prime mover of the CHP should not operate below a minimum load (in the case of parallel engines, the minimum value is approximated as 30% of the rated power):

$$
\begin{cases} P_t^{CHP} \ge 0.3 \times Size^{CHP} \\ otherwise 0 \end{cases} \tag{23}
$$

2.3.4. Power balance equation

The constraints related to the electric power balance are expressed as follows:

$$
\begin{aligned}
&\sum P_{CHP-i}^t + \sum P_{PV-j}^t + \sum P_{LDG}^t + \sum P_{Disch-EV}^t + P_{LG-buy}^t \\
&= \sum P_{Ch\,arg\,e-EV}^t + P_{LG-sell}^t + Load^t
\end{aligned} \tag{24}
$$

$$
\begin{aligned}
&P_{LG-buy}^t \le \delta^{LG-buy} \times P^{Grid-buy} \\
&P_{LG-sell}^t \le \delta^{LG-sell} \times P^{Grid-sell} \\
&\delta^{LG-buy} + \delta^{LG-sell} \le
\end{aligned} \tag{25}
$$

2.3.5. Model of thermal generation units

the amount of heat in the heat storage tank has a same value in the beginning of an hour and the previous hour. Eq. (26) formulated the amount of stored heat in the storage tank by considering thermal losses [23].

$$H_{t+1}^{HS} = \eta^{HS} \times H_t^{HS} + H_t^{HS-Out} + H_t^{HS-in} \tag{26}$$

HS other operational constraints are expressed as follows:

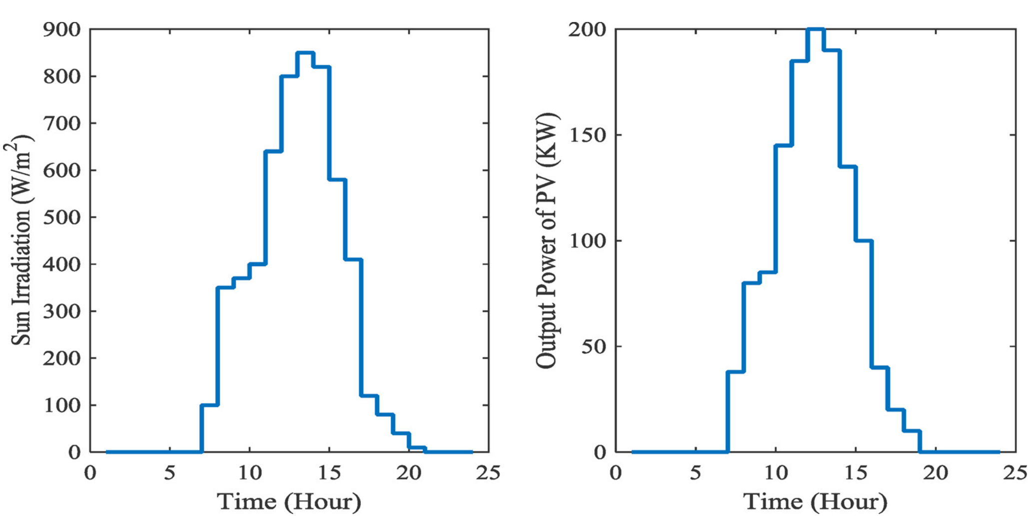

Fig. 4. Forecasted sun irradiation and output power of PV.

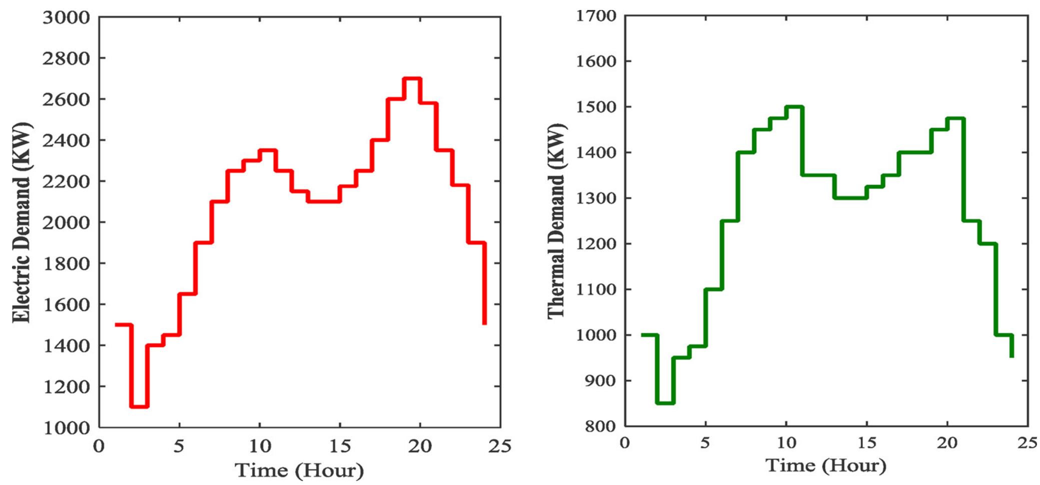

Fig. 5. Base electric and thermal demand in a day.

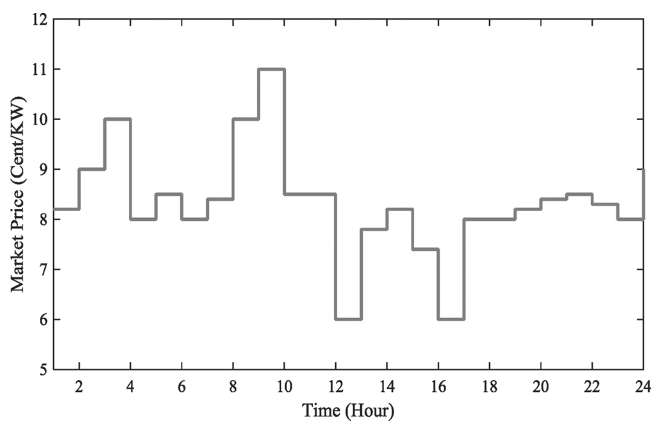

Fig. 6. Forecasted market price.

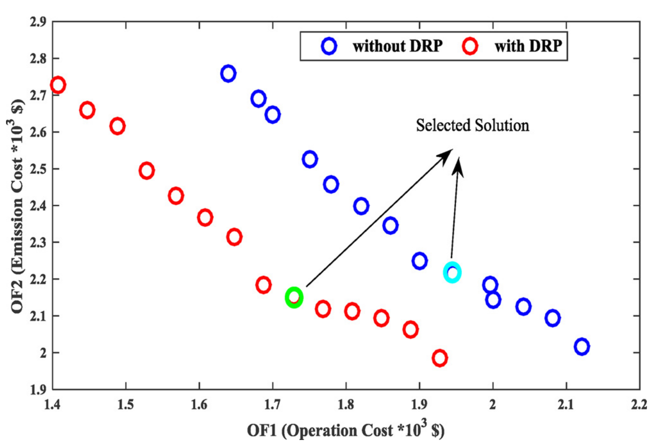

Fig. 7. Obtained Pareto optimal front.

$$H_t^{HS} \leq Size^{HS}$$
$$H_t^{HS-in} \leq \delta_t^{HS-in} \times \overline{H^{HS-in}}$$
$$H_t^{HS-Out} \leq \delta_t^{HS-Out} \times \overline{H^{HS-in}}$$
$$\delta_t^{HS-in} + \delta_t^{HS-Out} \leq 1 \tag{27}$$

The relation between fuel consumption of boiler and amount of heat production is expressed as follows:

$$H_t^{Boiler} = \eta^{Boiler} \times f_t^{Boiler} \times HV$$
$$s.t$$
$$H_t^{Boiler} \leq Size^{Boiler} \tag{28}$$

The heat generated by CHP is calculated as follows:

$$H^{CHP-i} = \eta^{HE} \times HPR \times P_t^{CHP-i}$$
$$s.t.$$
$$P_t^{CHP-i} \leq P^{CHP-i} \tag{29}$$

2.3.6. Heat balance equation

The heat balance condition is defined as follows:

$$\gamma\left(\sum H_{CHP}^t + \sum H_{Boiler}^t + H_{HS-Out}^t - H_{HS-in}^t\right) = H_{Load}^t + H_{Waste}^t \tag{30}$$

The best advantage of CHP units is the utilization of wasted heat exhausted from the prime mover [24].

2.4. Demand response program modeling

To enhance economic performance of MG, consumers shift their energy demands from on-peak time to others. According to basic rule of DR programs, sum of transferred demand within a full period of operating time should be zero.

TOU-based DRP is modeled as equations through (31)–(35) [25].

$$P_t^D = P_t^0 + DRP_t \tag{31}$$

$$P_t^D - P_t^{DR} = DRP_t \times P_t^D \tag{32}$$

$$DRP_t \leq DRP^{\max} \times P_t^0 \tag{33}$$

$$DRP_t \geq -DRP^{\max} \times P_t^0 \tag{34}$$

$$\sum_{t=1}^{T} DRP_t = 0 \tag{35}$$

3. Numerical results

The proposed methodology is applied to large residential complex with 1000 units. The electric and total heat demands are collected on an hourly basis. Eco-emission optimization problem of MG under TOU based DRP has been simulated within introduced algorithms [26,27].

Table 4
Obtained solutions with and without employing DRP.

Without DR program					With DR program				
Solutions	Cost in 10^3 $		Satisfaction		Solutions	Cost in 10^3 $		Satisfaction	
n	Cost	Emission	$\mu^{OF1(X_n)}$	$\mu^{OF2(X_n)}$	n	Cost	Emission	$\mu^{OF1(X_n)}$	$\mu^{OF2(X_n)}$
1	2.015	2.121	1	0	1	1.984	1.948	1	0
2	2.094	2.095	0.89	0.04	2	2.024	1.915	0.94	0.05
3	2.148	2.001	0.82	0.24	3	2.098	1.886	0.83	0.11
4	2.197	1.989	0.75	0.26	4	2.127	1.862	0.79	0.14
5	2.218	1.972	0.72	0.28	5	2.195	1.827	0.71	0.22
6	2.278	1.957	0.68	0.32	6	2.208	1.794	0.68	0.27
7	2.326	1.927	0.58	0.38	7	2.295	1.765	0.56	0.33
8	2.385	1.908	0.50	0.42	8	2.324	1.724	0.51	0.41
9	**2.396**	**1.894**	**0.48**	**0.44**	**9**	**2.348**	**1.658**	**0.49**	**0.46**
10	2.426	1.872	0.44	0.48	10	2.405	1.629	0.41	0.57
11	2.494	1.806	0.39	0.63	11	2.478	1.547	0.32	0.74
12	2.542	1.784	0.28	0.67	12	2.522	1.509	0.27	0.79
13	2.678	1.712	0.05	0.81	13	2.612	1.467	0.14	0.88
14	2.759	1.628	0	1	14	2.724	1.401	0	1

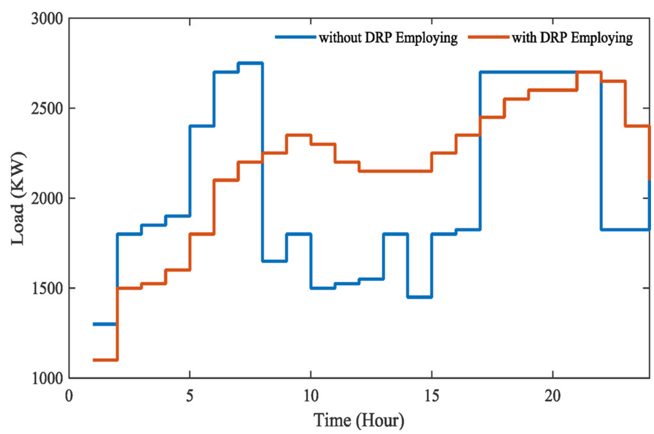

Fig. 8. Daily electric load curve with and without TOU.

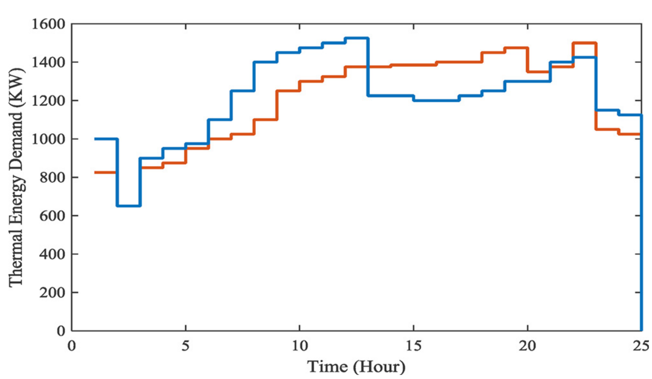

Fig. 9. Daily thermal load with and without TOU.

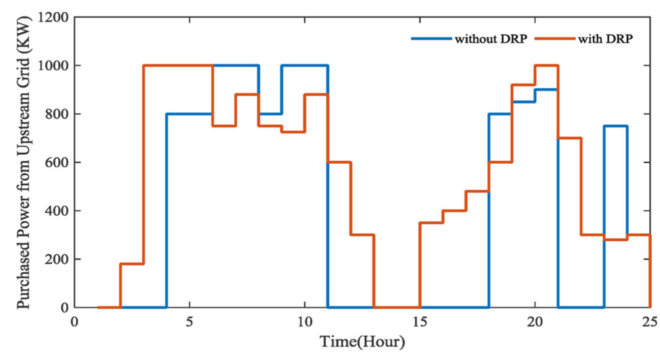

Fig. 10. Purchased power from upstream grid.

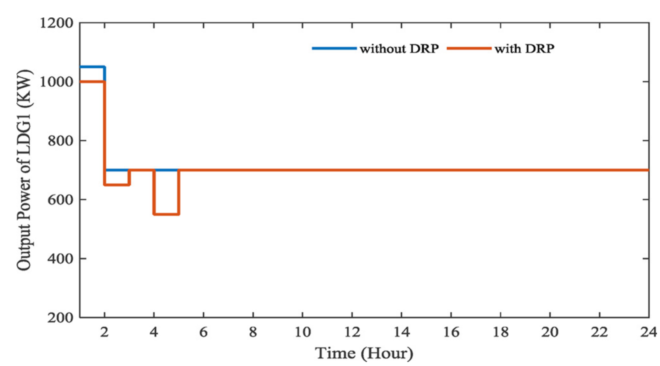

Fig. 11. Output power of LDG1.

3.1. Input data

Technical simulation info and data related to CHP, LDG, boiler and HS are given in Tables 1 and 2. It should be noted that maximum exchanged power between local grid and MG is 1000 KW. The maximum allowable amount of load to be shifted has been assumed to be 20%. Moreover, emission densities of provided power by LDG, CHP, boiler, HS and local grid are 0.32, 0.36, 0.38, 0.31 and 0.58 Kg/KWh, respectively. Parameters of PV and CHP are given in Table 3. Fig. 4 shows forecasted value of sun irradiation and output power of PV in a day. Fig. 5 shows daily-based thermal and electrical energy demand. Fig. 6 shows the predicted value of market price in a day time. Simulation is tackled based on CPLEX solver of general algebraic modeling system (GAMS) [28,29].

3.2. Results

Efficiency of the proposed framework is examined by devising two different scenarios, with and without employing DRP. Fig. 7 shows Pareto solutions which is obtained by solving bi-objective optimization problem subject to all equal and unequal constraints using ε-constraint algorithm [25].

The obtained results of both scenarios are tabulated in Table 4. According to the obtained results, it is clear that both economic and environmental performance of MG have been enhanced under TOU of DRP. In detail under no employing of TOU, operation cost as well as

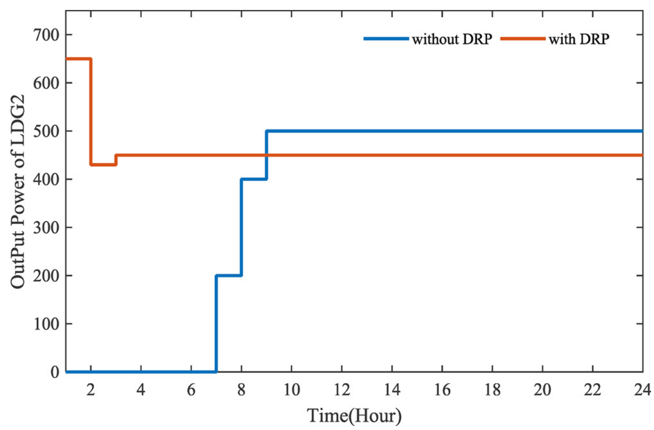

Fig. 12. Output power of LDG2.

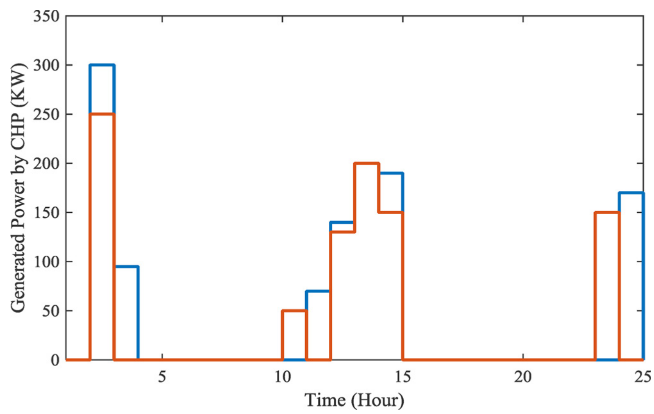

Fig. 13. Output power of CHP unit.

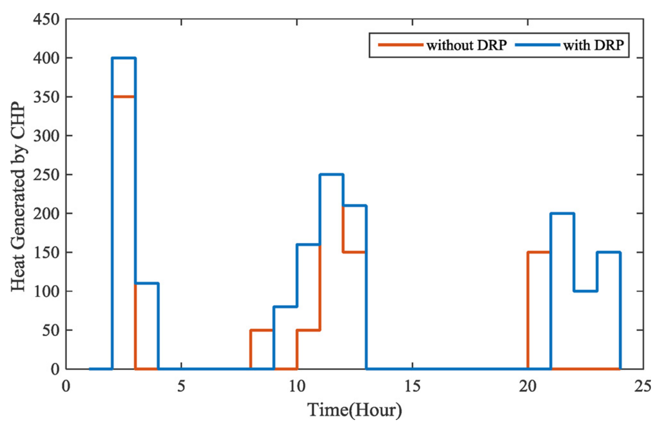

Fig. 14. Heat generation of CHP Unit.

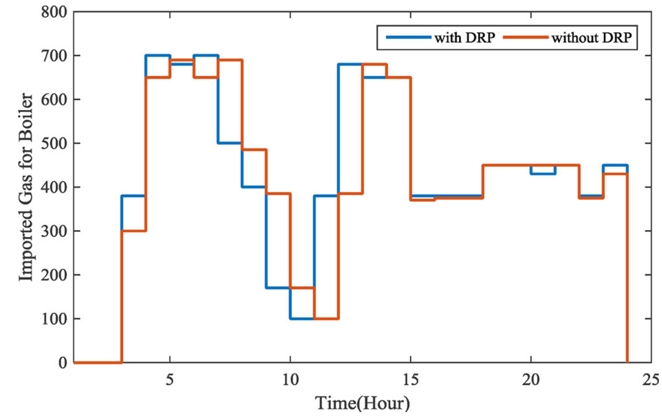

Fig. 15. Imported gas for boiler.

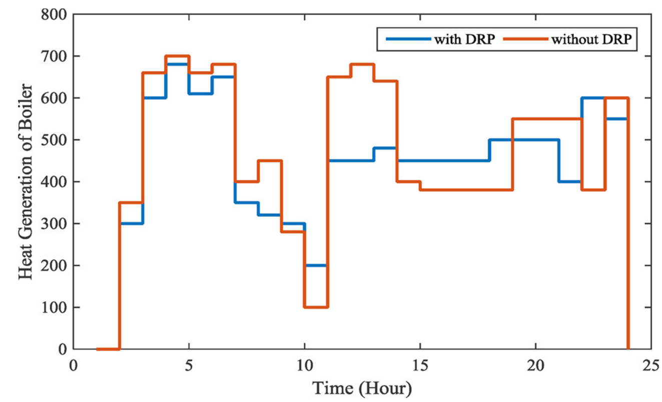

Fig. 16. Heat generation of boiler.

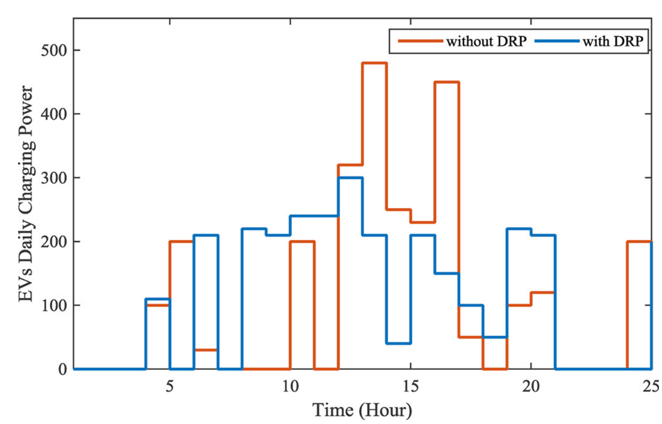

Fig. 17. EVs daily charging power.

emission of studied model are 2396 and 1894, respectively. On the other hand, by successful implementation of TOU, mentioned values are reduced to be 2396$ and 1658$ respectively. Simple comparison between two scenarios, shows that due to the positive impacts of TOU of DRP, total operation cost as well as generated emission have been reduced up to 2% and 12.45%, respectively.

Some other figures representing effects of TOU are presented in the following:

Impacts of DRP on daily load curve modification is captured in Figs. 8 and 9.

According to the figure, it is clear that the load profile under implementation of TOU-DRP is more flatten than scenario without employing DRP.

Injected power by local grid, in both scenarios has been depicted in figure. As it can be seen from Fig. 10, the amount of purchased energy from local grid, enhanced in the off-peak time under TOU and this has provided environmental and economic results for MG.

Generated electric energy by each generation units, are illustrated in Figs. 11–18. As it can be seen from figures, environmental and economic operation of MG will be enhanced by increasing LDG unit's generation in off-peak period. Figs. 11 and 12 show power generated by LDG units. Figs. 13 and 14 show the electric and heat energy which are generated by CHP unit in two case, with and without employing TOU-based DRP. The required amount of gas to CHP is shown in Fig. 13.

Figs. 15 and 16 show the amount of imported gas to the boiler and amount of heat generated by boiler.

Figs. 17 and 18 show charge and discharge of EVs available in the

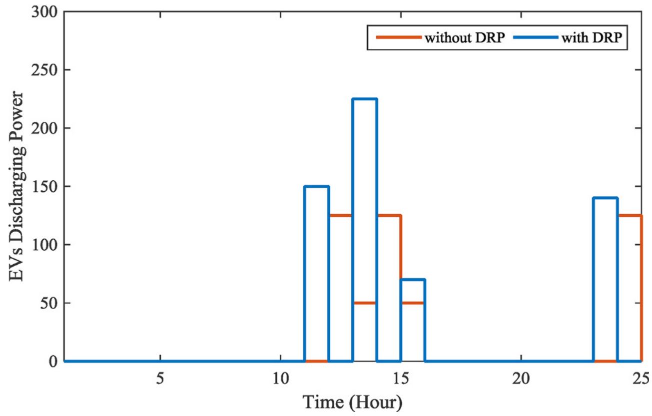

Fig. 18. EVs daily discharge power.

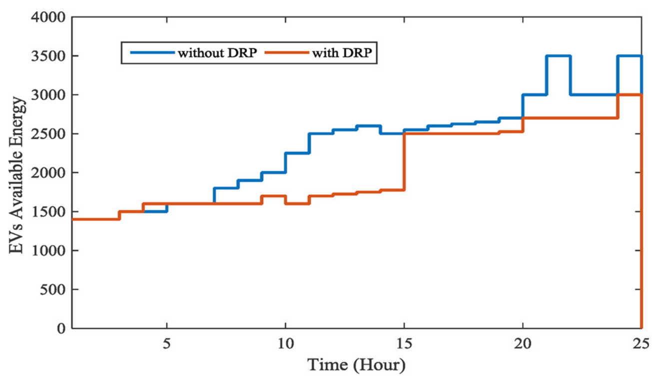

Fig. 19. EVs SOC in a day.

SPL. According to these figures, to help SPL to meet energy demand in the expensive periods, charging process in off-peak periods and discharging process in on-peak periods have been increased.

Available SOC of EVs which is proportional with optimal charge and discharge of EVs is shown in Fig. 19.

4. Conclusion

In this paper eco-emission bi-objective optimization problem has been presented to the proposed DG-based MG. Since the scheduling problem was applied to residential load with both of thermal and electrical demands, the main aim of paper is considered to guide MGO's management approach in satisfying both of economic and environmental issues. To make a flat daily load curve by transferring energy consumption from on-peak time to others, TOU based DRP is employed. To obtain Pareto optimal front solutions and make a trade-off between both of economic and emission solutions, ε-constraint and max–min fuzzy method are used. As it seen from the results, in the case without employing TOU, the value of operation cost as well as emission cost of the MG are obtained equal to 2396$ and 1894$, respectively. In the case with TOU, the obtained results are 2348$ and 1694$, respectively. Doing a simple comparison between the cases with and without employing DRP, the results verify the efficiency of the proposed method by reducing both of operation and emission cost of the MG up to 2% and 12.45%.

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Hamed Hosseinnia receive the BSc and MSc (Honors) degree in electrical engineering from Shahid Madani Azarbayjan-Tabriz and Urmia University, Urmia, Iran, in 2010, 2013, respectively. He received his PhD degree in electrical engineering in the Urmia University, in 2018. His research interests are centered in Smart Grid Technologies, Optimal Operation and planning of active distribution network and renewable energies.

Behrouz Tousi receive the BSc degree from Tabriz University-Tabriz, MSc and PhD from Amirkabir university of technology all on Electric Engineering 1988, 1995 and 2001, respectively. He is currently associated professor in Electric and computer engineering faculty of Urmia university, Urmia, Iran. His research interest is primarily on advanced power system.