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Optimal pricing in time of use demand response by integrating with dynamic economic dispatch problem

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A R T I C L E I N F O

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A B S T R A C T

DED (Dynamic economic dispatch) problem schedules generation units during the whole dispatch period in order to minimize the fuel costs. On the other hand DRPs (Demand Response Programs) focus on increasing customers' benefit and improving network reliability. If these two problems are optimally integrated considering their interactions at each side, they will be implemented more effectively. One of the main concerns in the TOU (Time of Use) DRP is the optimal pricing during different periods. In this paper, TOU which focuses on the demand side has been intelligently integrated with the DED problem which focuses on the supply side. In the combined problem namely DEDTOU, a new procedure for the optimal pricing will be presented so that the fuel costs in the DED problem are minimized and the optimal prices during different periods i.e. valley, off-peak, and peak periods in TOU are determined simultaneously. By the way, not only the network reliability and customers' benefit are increased but also fuel costs are decreased and generation units are optimally scheduled. Actually, DEDTOU is a win-win game both for the demand and supply sides. DEDTOU is applied on a ten units test system and results indicate the effectiveness of the proposed model.

1. Introduction

SG (Smart Grid) is a kind of grid in which the electrical energy is able to be transmitted in a controlled and smart way from the supply side to the demand side. In SG, there is a two-sided communication between the supply and demand sides. Customers play an important role in SG, so that with modifying their consumption patterns due to the information, incentives, and some limitations, cause the cost reduction and reliability improvement. Nowadays, with development of SGs, a tendency for implementing the DSM (Demand Side Management) is growing more than ever [1]. The concept of DSM includes all the activities which aim at modifying the consumption load curve. The complete integration of DSM requires communication systems and sensors such as the smart metering and AMIs (Advanced Metering Infrastructures). System stability and the share of renewable energy can be enhanced through using DSM [2]. Generally, DSM activities are divided into two main categories as follows [1].

- EE (Energy Efficiency): including the activities in order to decrease the required energy to provide services or productions.
- DR (Demand Response): including the activities at the demand side in order to modify the customers' consumption patterns by changing electricity prices during different periods, paying incentives or even imposing penalties when the costs of electricity generation, transmission, or distribution are high or when the network reliability is jeopardized.

AMI can be counted as a start point for the implementation of DRPs (Demand Response Programs). In fact, AMI is the connector of the utility and customers which includes smart meters, communication modules, LAN (Local Area Network), data collectors, WAN (Wide Area Network)), NMS (Network Management System), MDM (Meter Data Management), and DMS (Data Management System) [3].

DRPs are divided into the incentive based and price based programs. This paper mainly focuses on the TOU (Time of Use) which is a common price based DRP in which by changing the electricity prices during different periods; the customers are motivated to modify their consumption's patterns. In TOU, the electricity price during the peak period is high and it is low during the valley period. This pricing pattern motivates customers to cut and reduce their

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consumption during the peak period or shift it to the valley or off-peak periods [4,5].

In Refs. [6], an optimal load management strategy has been proposed for the residential customers. The communication infrastructures are used in their proposed strategy and the electricity price and demand are forecasted. They investigated an optimal connection between the electricity prices and the residential devices and electrical vehicles. This model allows customers to control their daily loads and electricity prices and consequently minimizes their electricity bills.

Ref. [7] investigates the methods of better implementation of TOU. In their proposed model, the real time pricing method has been used for the multi-periods loads. They also simulated the effects of their proposed model on the load curve and power market balance. Finally, they chose the Iran's network daily load curve for investigation the effects of real time pricing in TOU. Also, they showed that optimal implementation of TOU can effectively increase the customers' benefits and improve the network reliability.

A pricing algorithm has been proposed in Ref. [8] which automatically schedules the energy storage devices in such a way that they store electrical energy when the electricity price is low and put it available when the electricity price is high. Their simulation results showed that their proposed algorithm can decrease or even omit the peak period that consequently reduce the total electricity price up to 39%.

Effects of DRPs cooperated with AMIs on the electricity price swing and also the reliability improvement have been investigated in Ref. [9]. In Refs. [9], the effects of DRPs and smart metering infrastructures such as AMIs on the system reliability and price fluctuation have been investigated. Actually, the optimal incorporation of DRPs and smart metering has been investigated. Also, the concept of strategic interaction between generation units and DRPs enabled with the smart metering has been modeled too. In their model, customers can also sell electricity to the grid. They showed that whatever the price of electricity bought from customers was high the network reliability would be more improved. They took into account different amounts of the smart meters installation. They also showed that a more reliable and competitive long term electricity market is achieved by applying more DR resources.

In Refs. [10], the mathematical modeling of DRPs was presented. They applied their model on the peak load curve of the Iranian power grid on 28/08/2007. They compared different DRPs in the cost reduction and reliability improvement and finally they prioritized different DRPs based on the SSIs (Strategy Success Indexes).

All the above mentioned works focuses on increasing the customers benefit at the demand side neglecting the cost of implementing DRPs at the supply side and consequently they do not determine the optimal prices or incentives in DRPs. Actually, if DRPs are implemented intelligently, they make profits both for the demand and supply sides and not just for the customers at the demand side.

One of the main ISO's (Independent System Operator's) goals in the electrical power system is the increase of reliability with smoothing the load curve which can be achieved by the peak shaving and valley filling. On the other hand determining the optimal prices during different periods (valley, off-peak, and peak) in the price based DRPs and also incentive in the incentive based DRPs is one of the ISO's challenges and it should be appointed based on a feasible and economical approach. Otherwise, high additional costs (the cost of implementing DRPs) may be imposed at the supply side or new peaks may be created when DRP ends [11], and the network reliability may be decreased [12] (a large number of customers begin consuming power when the time of DRP ends) which is not based on ISO's point of view. Therefore, the electricity prices during different periods in the price based DRPs and also the incentive in the peak hours in the incentive based DRPs should be appointed optimally. If they are determined according to the supply side, so that the cost of DRPs' implementation (the reduced income of the generation companies due to changing electricity prices in the price based DRPs or total incentives paid to the customers in the incentive based DRPs), are taken into account in the total objective function, the optimal prices and incentives would be determined optimally and this procedure prevents high additional cost or new peaks.

One of the important problems in the power system operation is the ED (Economic Dispatch) problem which focuses on the supply side. In this problem, the main goal is the optimal scheduling of generation units in order to minimize the fuel costs subject to some constraints [13]. The DED (Dynamic economic dispatch) problem schedules generation units during the whole dispatch periods in order to minimize the fuel costs subject to some quality and inequality constraints [14]. With increasing the size of power systems, the DED problem becomes complicated. Consequently, as there are a lot of local optimal solutions, finding the optimal solution will be more difficult. Population based meta-heuristics algorithms can usually solve non-convex and non-smooth optimization problems successfully.

In this paper, by integrating TOU with DED, the supply side is connected to the demand side. In other words, in the combined problem i.e. DEDTOU the generation units are optimally scheduled, so that the fuel costs are minimized. Also, the optimal prices during different periods i.e. peak, off-peak, and valley periods in TOU are determined concurrently.

DEDTOU including some linear and non-linear practical constraints such as the valve point loading effect, Ramp Rate limits, and SRRs (Spinning Reserve Requirements) is a complicated optimization problem with non-smooth, non-convex objective function which has been solved be a population based meta-heuristic optimization algorithm namely ICA (Imperialist Competitive Algorithm). Also, to show the correctness of the proposed method and the strength of the ICA versus other techniques, the total cost has been obtained by different optimization algorithms namely PSO (Particle Swarm Optimization) [15], GA (Genetic algorithm) [16], ABC (Artificial Bee Colony) algorithm [17], and BCO (Bee Colony Optimization) [18]. Furthermore, the proposed model has been applied on three types of customers with different values of PEMs (Price Elasticity Matrixes) i.e. one, half, and two times of PEM. Moreover, the effects of intelligent implementation of TOU on improving SRRs have been investigated too.

Ref. [19] presents the solution method of DED by ICA without integration to any DR programs. It should be noted that when DED is optimally integrated with DR, the new optimization problem i.e. DEDDR is completely different from simple DED with different objective function and constraints which has a completely different solution method and handling constraints which is necessary to be developed.

There are a few works related to the ED problem integrating with the DRPs. References [20–23] have integrated the incentive based DRPs with the ED problem. A. Ashfaq et al. presented a combined model of ED integrating with the incentive based DR [20]. In their model, incentives are paid to the customers to reduce their demand during peak hours. However, just peak hours have been taken into account and it has not been applied to the whole day. Also, they have neglected some practical constraints such as the valve point loading effect, Ramp Rate limits, and SRRs. N.I. Nwulu and X. Xia investigated the incentive based DR integrating with the economic and environmental dispatch [21]. In their model, at the all periods (even at valley period) incentives are paid to the customers to reduce their consumption. This is not a reasonable and realistic procedure; also this may not be based on the ISO's point of view. Moreover, the valve-point loading effect, and SRRs have not been considered in their model. In the above mentioned works, the incentive based DRPs have been taken into account. In both of them, the generation units are optimally scheduled and the optimal incentive is determined concurrently.

Ref. [22] is actually an extension of [21]. Ref. [21] was under a regulated environment. In Refs. [22], an integrated model of DEED (dynamic economic emission dispatch) and incentive based DR has been presented which is under a deregulated environment. Actually the authors have presented a new solution method for solving their proposed model namely the closed-loop strategy. This strategy is able to give feedback and update inaccurate solutions. The proposed solution yields better results such as the lower cost, emission, and losses. Actually [22], focuses on presenting a new solution method for the proposed combined problem.

In our previous work i.e. Ref. [23], an integrated model of DED and EDRP (Emergency Demand Response Program)/DLC (Direct Load Control) has been presented considering non-linear responsive load models. In the combined problem namely DEDDR the fuel costs are minimized and the optimal incentives in EDRP/DLC are determined simultaneously. Also, a new scheme for appointing the most reliable load model (linear, potential, exponential, and logarithmic) has been presented too. Beside a complete work in Refs. [23], this model is just for the incentive based DRPs and cannot be applied to the price based DRPs.

Ref. [24] integrates TOU and DEED (dynamic economic emission dispatch) problem. The authors have presented a combined model of TOU and ED which is not so easy to be implemented on practical systems. In other words, a practical and clear procedure for determining the optimal prices in TOU has not been presented which is the main goal of intelligent integration of TOU and ED problem. Also, some practical constraints such as the SRRs and valve point loading effect and also investigating the effects of DR on the load curve characteristics have been neglected in their work. Moreover, the solution method and handling constraints have not been presented in Ref. [24]. Furthermore, the AIMMS (Advanced Interactive Multidimensional Modelling System) software has been used to solve the combined optimization problem. Generally, applying a flexible framework and the solution method in order to handling various practical constraints related to different complicated, nonlinear, non-smooth, and non-convex optimization problems, is necessary. Because some softwares may not be able to solve such problems successfully. On the other hand in Refs. [24], there is no comparison with the other solution methods to validate results while this task has been carried out well in the presented paper. Furthermore, the DR participation percent has been neglected which is taken into account in many certified papers [4,10,23,29–32].

The main contributions of this paper are organized as following. (i) Intelligently integration of a common price based DRP namely TOU with the DED problem. (ii) Presenting a new and clear optimal pricing in TOU by optimal integration of DED and TOU. (iii) Considering some practical constraints such as the valve point loading effect, SRRs, Ramp Rate limits etc. in the DEDTOU. (iv) Investigation the effects of DEDTOU on improving the load curve characteristics, SRRs, and cost reduction. (v) Presenting the solution method and handling constraints of DEDTOU by meta-heuristics algorithms with a focus on ICA. (vi) Showing the correctness, effectiveness, and applicability of DEDTOU by considering different PEM values and optimization algorithms.

The rest of this paper is organized as following. In Section 2 the problem formulation of the proposed model i.e. DEDTOU is presented. The solution method of DEDTOU is given in Section 3. Numerical simulation and results are presented in Section 4. Finally in Section 5 the conclusion is drawn.

2. Problem formulation

DED is one of the important optimization problems used in power systems operation to obtain the optimal scheduling of the generation units over the entire dispatch period. The cost function of the DED problem considering value-point loading effects is as Eq. (1) [25,26].

$$F_i(P_{i,t}) = a_i + b_iP_{i,t} + c_iP_{i,t}^2 + \left|d_i sin\left(e_i\left(P_i^{\min} - P_{i,t}\right)\right)\right| \quad (1)$$

where $P_{i,t}$ is the power output of the ith unit at the tth interval, a_i, b_i, c_i are the fuel cost coefficients of the ith unit, and d_i, e_i indicate the valve point loading effect.

The cost of implementing TOU is as Eq. (2).

$$C_{TOU}(t) = \rho_0(t)\cdot d_0(t) - \rho(t)\cdot d(t) \quad (2)$$

This cost is actually the reduced income of generation companies due to implementation of TOU which should be taken in the account in the final objective function (see Eq. (3)). Finally, the objective function of DEDTOU is minimization of Eq. (3).

$$TOF(P_{i,t}) = \sum_{t=1}^{T}\left\{\left[\sum_{i=1}^{N_g}\left\{a_i + b_iP_{i,t} + c_i(P_{i,t})^2 + \left|d_i \sin\left(e_i\left(P_i^{min} - P_{i,t}\right)\right)\right|\right\}\right] + C_{TOU}(t)\right\} \quad (3)$$

where Ng is the number of the generating units and P_i^{min} is the minimum power generation. To calculate the optimal prices during different periods, the parameter σ is applied to change the prices during different periods as Eq. (4). In other words one of the main goals of DEDTOU is optimally determination of this parameter.

$$\rho = \begin{bmatrix} \rho_{Peak} \\ \rho_{Off-Peak} \\ \rho_{Valley} \end{bmatrix} = \begin{bmatrix} \rho_{ave} + \sigma \\ \rho_{ave} \\ \rho_{Vave} - \sigma \end{bmatrix} \quad (4)$$

where ρ is the price matrix during whole dispatch interval (in this paper T = 24 h), ρ_{ave} is the initial average electricity price and ρ_{Peak}, $\rho_{Off-Peak}$, and ρ_{Valley} are the new modified electricity prices during peak, off-peak, and valley periods, respectively. Actually with increasing σ, the peak electricity price (ρ_{Peak}) is increased too while the valley electricity price (ρ_{Valley}) is decreased. This procedure will be continuing until the optimal amount of σ (when the objective function in DEDTOU i.e. Eq. (3) has the least possible amount) and consequently the optimal electricity price matrix i.e. ρ in TOU (See Eq. (4)) are determined. In fact, this procedure motivates customers to modify their consumption patterns so that they reduce their consumption in the peak period or shift it to the valley or off-peak periods.

2.1. Constraints

The proposed model i.e. DEDTOU should meet the following equality and inequality constraints.

Power balance constraint:

$$\sum_{i=1}^{N_g} P_i(t) = d(t) + P_L(t)\ t = 1, \ldots, T \quad (5)$$

where $d(t)$ and $P_{L,t}$ are the load demand and the power loss of transmission line at the tth time interval. $d(t)$ is calculated by Eq. (23) which is obtained due to Eqs. (13)–(22) and $P_L(t)$ is calculated by Kron's loss formula which can be given as (6).

$$P_L(t) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_{i,t} B_l(i,j) P_{j,t} \tag{6}$$

where $B_l(i,j)$ is the power loss coefficient of the transmission network.

Limits of the parameter σ:

$$\sigma(t)^{min} \le \sigma(t) \le \sigma(t)^{max} \tag{7}$$

In this paper $\sigma(t)^{min}$ and $\sigma(t)^{max}$ are considered to be 0.25 and 25 $ per MWh, respectively.

Power generation limits

$$P_i^{min} \le P_{i,t} \le P_i^{max} i = 1, 2 \ldots N_g \tag{8}$$

where P_i^{min} and P_i^{max} are the lower and upper generation limits for the ith unit.

Generator ramp rate limits

The increase and decrease rates of the generators' power output are usually called the RU (Ramp Up) () and RD (Ramp Down), respectively. So, the operating ranges of the ith unit are as Eq. (9).

$$\begin{cases} P_{i,t} - P_{i,t-1} \le RU_i \\ P_{i,t-1} - P_{i,t} \le RD_I \end{cases} \tag{9}$$

where RU_i and RD_I are the Ramp Up and Ramp Down limits of the ith unit, respectively and are usually expressed in MW/h.

SRRs (Spinning reserve requirements)

SRRs for the DED problem are expressed by Eqs. (10)–(12) [27,28].

$$D1_t = \sum_{i=1}^{Ng} P_i^{max} - (d(t) + P_{L,t} + SRR_t) \ge 0, \quad t = 1, \ldots, T \tag{10}$$

$$D2_t = \sum_{i=1}^{Ng} (min(P_i^{max} - P_{i,t}, RU_i)) - SRR_t \ge 0, \quad t = 1, \ldots, T \tag{11}$$

$$D3_t = \sum_{i=1}^{Ng} \left(min\left(P_i^{max} - P_{i,t}, \frac{RU_i}{6} \right) \right) - SRR_t^{'} \ge 0, \quad t = 1, \ldots, T \tag{12}$$

where SRR_t and $SRR_t^{'}$ are the SRRs for the 60 and 10 min compensation time in the tth hour and are expressed in MW.

2.2. Economic model of the responsive load

To obtain the optimal consumption at the demand side, the elasticity is defined as the sensitivity of the demand respect to the price as Eq. (13) [29–32].

$$E\left(t, t^{'}\right) = \frac{\rho_0(t^{'})}{d_0(t)} \frac{\partial d(t)}{\partial \rho(t^{'})} \begin{cases} E(t, t^{'}) \le 0 & if t = t^{'} \\ E(t, t^{'}) \ge 0 & if t \ne t^{'} \end{cases} \tag{13}$$

where E is the elasticity, $d(t)$ and $d_0(t)$ are the customer's demands after implementing TOU and before it during the period t, $\rho(t^{'})$ and $\rho_0(t^{'})$ are the elasticity price and the initial electricity price during the period $t^{'}$, respectively.

For 24 h in a day, the self and cross elasticity values can be given as a 24 × 24 matrix as Eq. (14).

$$\begin{bmatrix} \frac{\Delta d(1)}{d_0(1)} \\ \frac{\Delta d(2)}{d_0(2)} \\ \frac{\Delta d(3)}{d_0(3)} \\ \cdots \\ \frac{\Delta d(24)}{d_0(24)} \end{bmatrix} = \begin{bmatrix} E(1,1) & \cdots & E(1,24) \\ \vdots & \ddots & \vdots \\ E(24,1) & \cdots & E(24,24) \end{bmatrix} \times \begin{bmatrix} \frac{\Delta \rho(1)}{\rho_0(1)} \\ \frac{\Delta \rho(2)}{\rho_0(2)} \\ \frac{\Delta \rho(3)}{\rho_0(3)} \\ \cdots \\ \frac{\Delta \rho(24)}{\rho_0(24)} \end{bmatrix} \tag{14}$$

The net-profit of the customer is as Eq. (15) which is related to the customer's income because of the electricity consumption and producing their commodities.

$$NP(t) = B(d(t)) - d(t)\rho(t) \tag{15}$$

where B is the profit which customers obtain by consuming power.

To maximize the customer benefit, the derivative of Eq. (15) should be zero.

$$\frac{\partial NP(t)}{\partial d(t)} = \frac{\partial B(d(t))}{\partial d(t)} - \rho(t) = 0 \tag{16}$$

$$\frac{\partial B(d(t))}{\partial d(t)} = \rho(t) \tag{17}$$

Taylor series of B is as Eq. (18).

$$\begin{aligned} \mathrm{B(d(t))} &= B(d_0(t)) + \frac{\partial B(d_0(t))}{\partial d(t)}[d(t) - d_0(t)] \\ &+ \frac{1}{2}\frac{\partial^2 B(d_0(t))}{\partial d^2(t)}[d(t) - d_0(t)]^2 \end{aligned} \tag{18}$$

To get the optimal consumption by which the customers obtain the maximum profit, from Eq. (18):

$$\begin{aligned} \mathrm{B(d(t))} &= B(d_0(t)) + \rho_0(t)[d(t) - d_0(t)] \\ &+ \frac{1}{2}\frac{\rho_0(t)}{E(t,t)d_0(t)}[d(t) - d_0(t)]^2 \end{aligned} \tag{19}$$

Differentiating:

$$\frac{\partial B(d(t))}{\partial d(t)} = \rho_0(t)\left(1 + \frac{d(t) - d_0(t)}{E(t,t)d_0(t)}\right) \tag{20}$$

By combining Eqs. (20) and (17), for the single-period model of the responsive load:

$$d(t) = d_0(t) \times \left(1 + \frac{\rho(t) - \rho_0(t)}{\rho_0(t)} E(t,t)\right) \tag{21}$$

The multi period model is as Eq. (22):

$$d(t) = d_0(t) \times \left\{ 1 + \sum_{\substack{t^{'}=1 \\ t^{'} \ne t}}^{24} E\left(t, t^{'}\right) \times \frac{\rho(t^{'}) - \rho_0(t^{'})}{\rho_0(t^{'})} \right\} \tag{22}$$

Finally, the complete and combined model including the single and multi-period models of the responsive load is as Eq. (23).

$$d(t) = d_0(t) \times \left\{ 1 + \sum_{t'=1}^{24} E\left(t, t'\right) \times \frac{\rho(t') - \rho_0(t')}{\rho_0(t')} \right\} \tag{23}$$

3. Solution method of the DEDTOU problem

In this part a procedure for solving the DEDTOU problem by ICA has been presented. However, the presented solution method can be extended for the other population based meta-heuristic algorithms. The possible solutions in ICA [19,33] are called countries, in PSO [15] particles, in GA [16] chromosomes, in ABC algorithm [17] food sources, in BCO [18] bees etc.

In DEDTOU, the population's parameters are the same power outputs of generation units which should be determined in a way that minimize the objective function in Eq. (3).

In fact, in DEDTOU every scheduled generating units output at each hour comprises a candidate. The kth candidate (PG_k) at each hour is defined as Eq. (24).

$$PG_k = \left[P_{k,1}, P_{k,2}, ..., P_{k,j}, ..., P_{k,N_g}\right], \quad k = 1, 2...PS \tag{24}$$

where PG_k is the current position of the kth vector, N_g is the number of generation units, PS is the population size, j is the generator number, and $P_{k,j}$ is the power output of the jth generation unit.

The power balance constraint (see Eq. (5)) can be met by adding a penalty factor to Eq. (3). By the way the evaluation function of DEDTOU is minimization of Eq. (25).

$$EF(P_{i,t}) = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_g} TOF(P_{i,t}) + K_n \cdot abs\left(\sum_{i=1}^{N_g} P_{i,t} - d(t) - P_{L,t} \right) \right\} \tag{25}$$

where K_n is the penalty factor which can be written as Eq. (26) [34].

$$K_n = 500 \times \sqrt{n} \quad n = 1, 2...N_{iter} \tag{26}$$

where n and N_{iter} are the number of iteration and the maximum number of iterations at each hour. Due to Eq. (26), K_n increases with the number of algorithm's iteration.

As mentioned before to meet the power balance constraint (Eq. (5)), a penalty factor (Kn) has been added to the objective function (Eq. (3)) which forms the Evaluation Function (Eq. (25)). Kn is a positive real number that has been added to omit insufficient candidates in ICA, so that if a candidate violates the power balance constraint (Eq. (5)), due to the amount of violation, it gets a related Evaluation Function. By the way, the candidates which have better situation in meeting the power balance constraint will have a smaller Evaluation Function and insufficient candidates have a larger Evaluation Function. Therefore, candidates which have small objective function and penalty term will be selected as the optimal answer. With performing the process during different iterations of the program, a candidate which simultaneously has the least objective function and penalty term (least Evaluation Function) will be selected as the optimal answer. Therefore, the above mentioned process will guarantee that when the iterations end, the final answer meets the power balance constraint [23,35,36].

The flowchart of the solution method and handling constraints of DEDTOU by ICA is given in Fig. 1.

It should be noted that the main difference between the evolutionary algorithms is the way of population's convergence to the optimal solution. In this paper, ICA has been used in which every population member (candidate) is a country. Initial population members are divided into some imperialists and colonies. Then, colonies by assimilation policy are divided between imperialists. In each imperialist, colonies in direction of improving their indexes (optimizing the objective function) move toward their imperialists. If the situation of a colony in an imperialist gets better, the colony replaces the imperialist. In other words, a Revolution happens. Then, the imperialist competition begins between imperialist, so that the weakest colony is separated from the weakest imperialist and is divided between the other imperialists and the imperialist that loses all its countries will fall.

After this procedure, one iteration of the ICA algorithm finishes. This procedure continues until the number of iterations finishes and then the best imperialist (with the minimum evaluation function) will be selected as the solution of problem. For more information about these processes refer to [19,33,37].

4. Numerical simulation and results

To show the correctness and effectiveness of the proposed model (DEDTOU), it is applied on the ten units test system. The ten units test system's characteristics and transmission line coefficients are taken from Refs. [38] and [39], respectively. Moreover, to consider the SRRs, the SRRs for the 60 and 10 min compensation time (SRR_t and SRR'_t) have been set to 10% and $\left(\frac{10}{60}\right) \times 10\%$ of the load demand as shown in Eqs. (10)–(12). Also, PEM is given as Table 1 [29–32].

Daily load curve is divided into the peak period (11 a.m.–16 p.m. & 20 p.m.–24 p.m.), the off-peak period (8 a.m.–10 a.m. & 17 p.m.–19 p.m.), and the valley period (1 a.m.–7 a.m.). Participation percentage of TOU is considered to be 20%. It means that 20% of the total load participates in the TOU. The initial average electricity price (ρ_{ave}) is considered to be 25 $/MWh. Three different groups with different values of PEM (different consumption patterns) have been taken into account. Scenario one is the base case without implementing TOU; scenarios two, three, and four are after implementing TOU with the PEMs equal to 1, 0.5, and 2 times of Table 1, respectively.

To evaluate the performance of TOU in improving the load curve characteristics, some factors i.e. the load factor, peak to valley, and peak compensate are defined as Eqs. (27)–(29), respectively.

$$LF\% = 100 \times \left(\frac{\sum_{t=1}^{T} d(t)}{T \times d^{max}(t)} \right) \tag{27}$$

$$PV\% = 100 \times \left(\frac{d^{max}(t) - d^{min}(t)}{d^{max}(t)} \right) \tag{28}$$

$$PC\% = 100 \times \left(\frac{d_0^{max}(t) - d^{max}(t)}{d_0^{max}(t)} \right) \tag{29}$$

In all scenarios after implementing TOU, the total cost reduces in comparison with the base case. Implanting TOU imposes an additional cost (C_{TOU}) which is the reduced income of generation companies due to implementing TOU. But, the total cost which is sum of the cost of generating units and the total incentive, reduces. It is because of the fact that customers who participate in the TOU reduce their consumption during the peak hours or shift it to the valley or off-peak periods.

As expected, by increasing elasticity, C_{TOU} is increased and vice versa. Scenario three has the most cost reduction by 8697.6526 $ (1009268.1377–1000570.4851) and scenario four has the least one by 4976.8155 $ (1009268.1377–1004291.3222). Also, in all

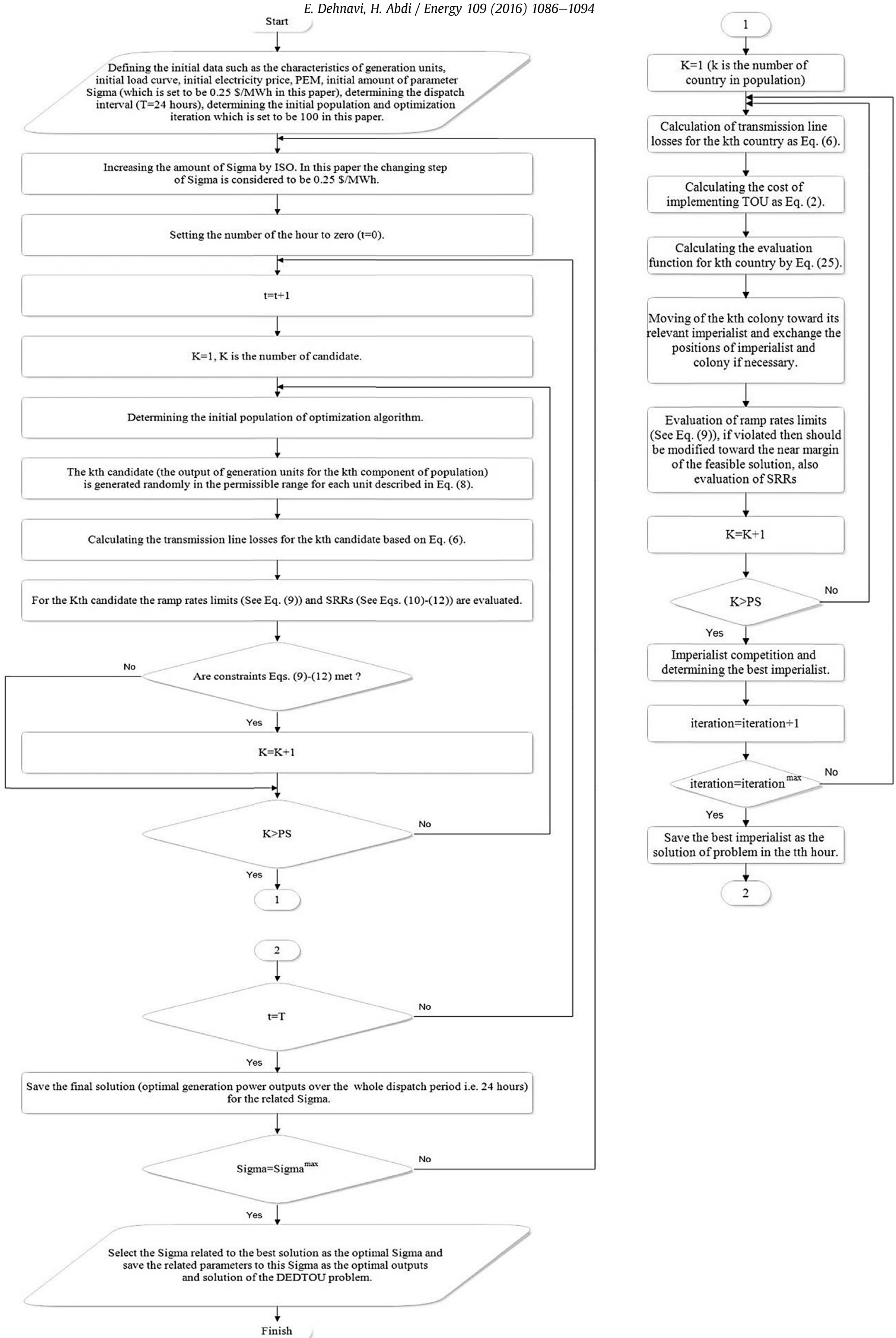

Fig. 1. The solution method of DEDTOU by ICA.

Table 1
Self and cross elasticity values.

	Peak	Off-peak	Valley
Peak	−0.10	0.016	0.012
Off-peak	0.016	−0.10	0.01
Valley	0.012	0.01	−0.10

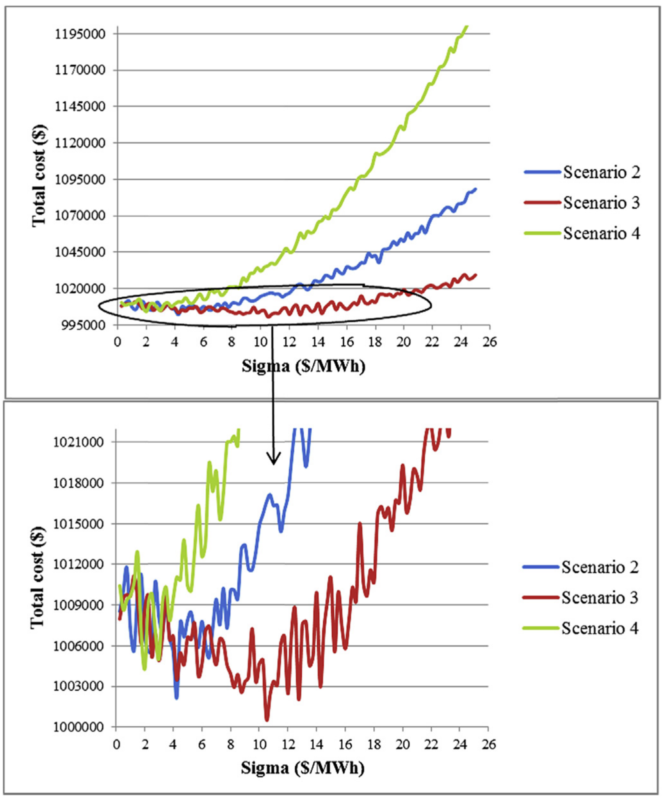

Fig. 2. Cost variation v.s. σ for three different groups.

scenarios after implementing TOU total losses decrease too. On the other hand the amount of parameter σ decreases with the amount of PEM as expected. For example, customers with biggest PEM (two times of Table 1, scenario four) have the least amount of σ (2.00 $/MWh) as expected and with a same argument, customers with smallest PEM (half times of Table 1, scenario three) have the biggest amount of σ (10.50 $/MWh) as expected too. It is because of the fact that, for customers with largest PEM, if σ has a big value, it will impose a high additional cost i.e. C_{TOU} in the objective function and consequently will increase the total cost. Total cost variation against σ for three different groups have been illustrated in Fig. 2.

From Fig. 2, the non-linear nature of DEDTOU is clear and the optimal amounts of σ by which the least amount of total cost (See Eq. (3)) is obtained, are 4.25, 10.50, and 2.00 $/MWh for scenarios 2–4, respectively (Also, as shown in Table 2).

All characteristics of the load curve i.e. load factor, peak to valley, and peak compensate are improved for all scenarios as given in Table 2. The load curves before and after implementing TOU in the all groups are illustrated in Fig. 3. As is clear from Fig. 3, the demands at the peak hours decrease and shift to the valley periods. Also, the optimal generators' power output after implementing TOU (scenario 2) and its equality error (to show the accuracy of DEDTOU in meeting the power balance constraint in Eq. (5)) are given in Table 3.

To compare the performances of DED and DEDTOU in meeting three *SRRs* constraints described in Eqs. (10)–(12), the amounts of $D1_t$, $D2_t$, and $D3_t$ for the scenarios one and two are given in Fig. 4. As is clear from Fig. 4, $D1_t$, $D2_t$, and $D3_t$ are positive in all hours. Also, these amounts get bigger values in the peak hours for the scenario two. In other words, after implementing TOU the *SRRs* improve and consequently the network reliability is less jeopardized at the peak hours.

In order to validate results and as there is not a similar work for comparing results, the total cost has been obtained by different optimization algorithms [15–18]. From Table 4, the obtained results are validated and also it is shown that the used algorithm i.e. ICA has better results than the other ones. Moreover, Refs. [21–24] showed that optimal integration of DRPs can decrease the customers and generation costs which validates results too.

5. Conclusion

Cost reduction and reliability improvement are two important effects of DRPs implementation. If DRPs are implemented intelligently, not only the customers' benefit and network reliability are increased but also the generation costs are decreased. This is only possible by choosing the optimal prices during different periods. In this paper a new and comprehensive procedure for the optimal pricing in TOU was presented. It was shown that intelligent implementation of TOU can decrease both the generation and consumption costs as well as improving the network reliability. The solution method and handling constraints of the proposed model i.e. DEDTOU by ICA was presented via some descriptions and the flowchart. To show the correctness and effectiveness of DEDTOU, the total cost was obtained by four meta-heuristic optimization algorithms namely PSO, GA, ABC, and BCO. Comparing with the other methods, it was shown that ICA has better results. Furthermore, the results were obtained and compared for three type of customers with different consumption patterns (with different PEM values) and results showed that customers with biggest PEM value have the least amount of σ as expected and with a same argument, customers with smallest PEM value have the biggest

Table 2
Effects of implementing DEDTOU in different scenarios.

	Scenario one	Scenario two	Scenario three	Scenario four
Optimal σ ($/MWh)	–	4.25	10.50	2.00
Total generation cost ($)	1009268.1377	998465.4514	997924.9702	999462.7126
C_{TOU} ($)	–	3682.9973	2645.5149	4828.6096
Total cost ($)	1009268.1377	1002148.4487	1000570.4851	1004291.3222
Total power saved (MWh)	–	270.8457	334.5741	254.9136
Total power losses (MW)	1168.5154	1158.6736	1150.7145	1164.2994
Load factor%	81.41	83.62	84.16	83.48
Peak to valley%	42.11	38.46	37.56	38.68
Peak compensate%	–	3.35	4.13	3.15

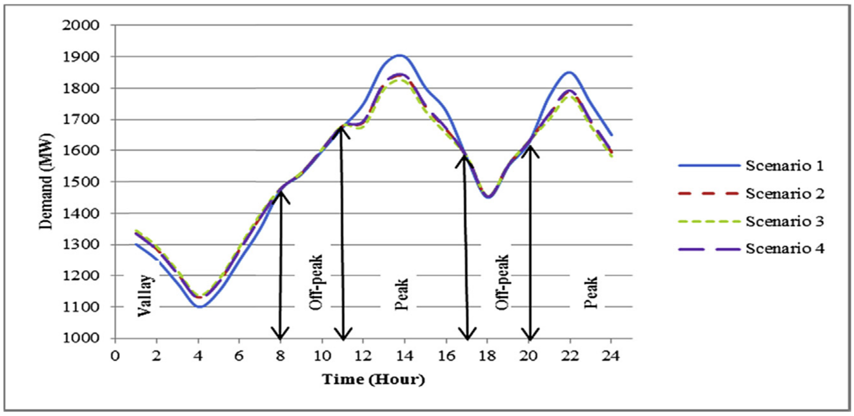

Fig. 3. Load curve before and after implementing TOU.

Table 3
Best dispatch found by DEDTOU for scenario 2.

Hour	*Load*	P_1(MW)	P_2(MW)	P_3(MW)	P_4(MW)	P_5(MW)	P_6(MW)	P_7(MW)	P_8(MW)	P_9(MW)	P_{10}(MW)	Violation of the equality constraint $\sum_{i=1}^{Ng}(P_i) - d - P_L = 0$
1	1300	442.8523	219.0288	73.0000	300.0000	123.3443	147.3512	129.9946	47.0000	47.4874	27.7800	0.0000
2	1250	362.8523	184.6778	137.9834	295.9415	170.8484	102.3862	130.0000	77.0000	20.0450	12.2844	0.0000
3	1175	291.9060	135.0000	217.9834	245.9415	120.8484	130.2495	100.0000	85.4335	30.8440	42.2844	0.0000
4	1100	227.4273	215.0000	137.9834	195.9415	153.0874	138.3567	91.4326	115.4335	21.6374	12.2844	0.0000
5	1150	307.4273	135.0000	217.9834	150.0951	122.6938	160.0000	121.4326	93.8544	51.6374	10.0000	0.0000
6	1250	227.4273	214.1012	297.9834	199.7909	172.6938	160.0000	91.4326	82.8065	23.3388	22.0813	0.0000
7	1350	307.4273	294.1012	340.0000	149.7909	179.5668	124.4405	121.1380	68.4792	20.0000	11.9409	0.0000
8	1475	227.4273	307.0464	267.2895	199.7909	129.5668	128.9955	130.0000	58.3241	49.7729	41.9409	−0.0003
9	1525	307.4273	308.6799	192.8411	205.7710	179.5668	115.6714	130.0000	88.3241	36.0654	30.3263	0.0000
10	1600	379.2825	296.1500	176.2476	183.1380	227.8387	121.4795	130.0000	114.7580	37.5623	10.0000	0.0004
11	1675	459.2825	221.9094	256.2476	177.8148	243.0000	143.7502	101.8524	91.6140	53.0217	10.0131	−0.0002
12	1750	380.0134	141.9094	245.5578	127.8148	193.0000	107.3142	95.5955	91.0632	23.0217	40.0131	0.0000
13	1875	381.0359	221.9094	181.4116	86.1469	243.0000	155.1889	125.5955	71.8440	44.1866	41.3179	0.0000
14	1900	301.0359	301.9094	261.4116	136.1469	216.0002	122.4425	95.5955	94.9397	31.2469	11.3179	0.0000
15	1800	301.9469	221.9094	294.4987	139.7764	180.5088	133.3175	99.8251	84.7086	20.0000	10.0000	0.0000
16	1725	233.0923	222.6186	214.4987	168.9966	230.5088	115.5134	93.6005	83.0536	50.0000	10.0000	0.0001
17	1575	313.0923	302.6186	294.4987	172.1877	210.6932	138.1374	63.6005	86.4223	38.0145	29.5013	0.0000
18	1450	393.0923	222.6186	214.4987	199.0124	160.6932	116.6121	93.2340	85.3926	20.0000	10.0000	0.0000
19	1550	426.4722	302.6186	294.4987	149.0124	110.6932	106.6996	119.0173	55.3925	20.2892	40.0000	0.0001
20	1625	346.4722	382.6186	317.4220	133.5041	160.6932	123.8654	89.0173	85.3925	22.9397	42.9210	0.0000
21	1775	266.4722	302.6186	285.2628	182.6512	138.7096	109.7385	59.0173	55.3925	52.8133	13.3589	−0.0067
22	1850	307.0898	222.6186	205.2628	232.6512	172.0551	120.3078	89.0173	85.3925	55.7464	38.5444	0.0003
23	1750	227.0898	302.6186	180.8315	182.6512	179.3884	160.0000	59.0173	89.9402	52.2188	10.0000	0.0000
24	1650	304.7972	222.6186	137.4699	184.1222	129.3884	119.3636	89.0173	82.6220	50.4167	40.0000	0.0000

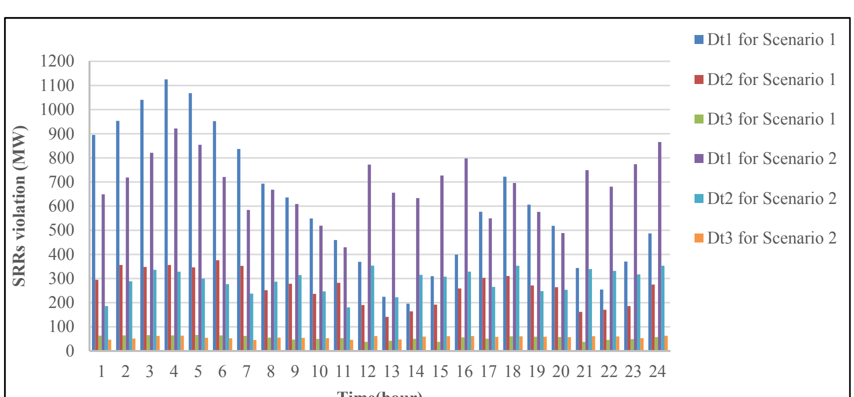

Fig. 4. SRRs violation (MW).

Table 4
Total cost obtained by different algorithms.

Scenario	PSO [15]	GA [16]	ABC [17]	BCO [18]
1	1009985.7942	1010687.4931	1010183.9766	1010355.2419
2	1002856.6711	1003029.4127	1002734.1976	1002681.4973
3	1001459.8419	1001549.2219	1001377.4679	1001179.2974
4	1005127.4415	1006637.3417	1005736.3455	1004988.7491

amount of σ as expected too. In the proposed model, the fuel costs are minimized and the optimal prices during different periods are determined simultaneously. Improving SRRs is another important benefit of DRPs which was investigated in this paper too. In the future work the effects of DRPs on the voltage improvement and frequency control will be investigated.

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