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Improvement of Regional-Market Management Considering Reserve and Emergency Demand Response Program

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Abstract

The emergency demand response program (EDRP) is a type of program that can be utilized as a tool for controlling the price of electricity when there is a lack of reliability in the distribution system. In this study, a formulation is proposed for determining the optimum amount of demands in the EDRP according to the viewpoints of the regional market manager (RMM) aimed at reducing the EDRP costs and smoothening the load curve based on the logarithmic model and the matrix of demand elasticity. The probability that the aggregators should present their available reserves to the RMM in response to the received incentives has also been included in the proposed formulations. The market manager then prioritizes the available reserves using the reserve-margin factor (RMF). Three algorithms including co-evolutionary particle swarm optimization (C-PSO), co-evolutionary teaching learning-based optimization (C-TLBO) and co-evolutionary improved teaching learning-based optimization (C-ITLBO) are used for reducing the EDRP costs. The results show that the proposed formulations are effective in improving the economic performance of the regional market and the load curve. Furthermore, the results indicate the superiority of the C-ITLBO algorithm in terms of the total cost, incentive rate and peak shaving in comparison with C-PSO and C-TLBO algorithms.

Keywords: Emergency demand response program, Electricity market, logarithmic model, Reserve margin factor, Co-evolutionary improved teaching learning-based optimization.

1. INTRODUCTION

For many years, electricity customers have been involved in controlling and managing their energy consumption due to some technical and economic benefits. For this purpose, the concept of demand-side

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management (DSM) was introduced. The DSM, by definition, refers to the activities that reduce or shift electricity consumption in order to decrease the loading of the distribution system, especially during peak-load hours. One of the most prominent DSM types in recent years is demand response (DR) programs. In these programs, customer electricity consumption changes in response to the changes in the electricity prices over time or in response to the monetary incentive payments. DR programs are used for reducing consumption when the cost of electricity is high or when the reliability of the distribution system decreases to insufficient levels [1].

One type of DR is called the EDRP that can be used as a tool for maintaining the confidence ability in emergencies when a regional market is facing a shortage of supply resources and hence a lack of power reserve which resulting in high electricity prices. The peak-load hour is another common example of emergency situation. In these situations, the manager of the regional market recalls customers or their representatives who are prepared to participate in the EDRP to reduce their consumption. In this study, each representative is considered as an aggregator (AGG). In exchange for reducing their consumptions, the participants in the EDRP receive funds as incentives from the RMM. Participation in the EDRP is optional and the RMM does not consider penalties for the customers or their the AGGs who did not answer the phone at the time of calling [2-4].

Various activities have been mentioned in the literature relating to the application of the DR and the EDRP in power systems. For example, the EDRP was applied in [5], in which a market-based incentive model has been proposed to encourage subscribers to reduce energy consumption. In [6], in order to improve the voltage stability margin (VSM), a whale optimization algorithm-based (WOA) strategy was stated for the EDRP in a range acceptable in emergencies. In [7], the effects of the EDRP on improving the reliability of power generating units were investigated. In [8], the effects of DR programs on power system reliability in a restructured environment were evaluated. In [9], an optimal nonlinear model for the pricing of a DR program in a smart grid was presented and solved using the particle swarm optimization (PSO) algorithm. Here, DR pricing means the electricity price schedule that caused peak-load time shift and hence improved the distribution system performance [9]. In [10], an optimal pricing model for DR was proposed which was based on the demand-price elasticity. The model is applied to maximize the profits, reduce the price fluctuations and improve the system reliability.

Most of the articles about DR paid attention to the improvement of DR model, selection of DR program, reduction of DR-program cost and pricing electricity from the perspective of the RMM. However, few articles focused on such items as providing a new method for optimizing the incentives of the EDRP in peak hours as well as the prioritization of the power reserve of the AGGs from the perspective of the RMM. These items are of great importance in this study. As one of the studies that have dealt with incentives, we can refer to [11]. In that study, a two-level optimization is proposed by the independent system operator for determining the optimal schedule of production units in which the upper-level attempts to solve the problems regarding the minimization of fuel consumption cost, air pollution and payable incentives, whereas the lower level minimizes the wind power output strength. In this regard, the upper-level problem is solved by the dominated sorting approach and the lower-level problem is solved by using linear programming. It should also be noted that the responsibilities of the RMM are different from those of the power-system operator. The RMM is mainly involved in the implementation of the DR programs and cash flows. These activities can be considered as assisting tools for the system operator for maintaining the network reliability.

References 12 to 20 can be considered as further examples in this regard. In [12], a dynamic economic model of DR is used based upon the concept of the flexible elasticity of demand and the customer benefit function. Moreover, from the viewpoints of the RMM, the main objective is to prioritize the multipurpose DRP utilizing Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the entropy methods. In [13], linear and nonlinear models were presented for the pricing of electricity. In [14] the demand-price elasticity that is a criterion for assessing demand variations with respect to price variations was presented. Moreover, the demand elasticity of a commodity to its price and the demand stretchiness of a commodity to the price of its substitutable commodity werealso mentioned in [14]. In [15], based on the findings presented in [13] and [14], a linear model was proposed for DR to time-variable tariffs. Similar considerations were reported in [16, 17 and 18] in the forms of linear and nonlinear modeling of DR programs. In [19], the DB and the EDRP were implemented using ISO during time intervals when electricity prices were high. It can be said that high electricity prices are motives for the implementation of these programs in order to reduce electric consumption and price. During high price intervals in the method presented in [19], the ISO determined some supply curves proposed by the participants who took part in the DB and the EDRP as well as the demand curve based on the initial power demand and power producers’ offers, respectively. The intersection of these curves gives the quantity of power demand and its price for the next time interval. In the current study, the energy demand and electricity price have not been optimally determined. In [20], the price-based nonlinear models were presented considering their price elasticity. Different mathematical models were extracted for time-of-use (TOU) programs, and then they were investigated from different viewpoints in order to find out their performance. In [21], a DR model was developed for the combined programs of the EDRP and TOU based on the concepts of the customers' benefit function and the flexible demand elasticity. Furthermore, for determining the optimal demand from the viewpoints of “load characteristics” and “economy”, Multi Attribute Decision Making (MADM) was employed as an effective method.

Logarithmic models were applied in the previous studies for modeling incentive-based DR programs. Another noticeable point is the increase of power reserve after the implementation of the EDRP. Obviously, the greater level of participation in the EDRP leads to further reserves of the RMM during emergencies. Therefore, proposing an appropriate formulation for encouraging more participation in the EDRP is very useful, as it can enhance economic benefits for the participants as well as the technical benefits for the regional market.

An important technical benefit is the improvement of reliability due to the increased power reserve. Among pieces of literature mentioned above, the power reserve and reliability were studied in [22-24]. The optimum reserve capacity required in the electricity market was studied in [22]. Purchasing spinning reserves and allocating cost with the application of social-welfare analysis were discussed in [23]. In [24], multi-objective stochastic programming was provided for simultaneous clearing energy and the reserve markets. Furthermore, the review of the related research showed that PSO algorithm indicated a satisfactory performance in optimizing DR pricing problem [9 and 25]. This algorithm performs based on the particles search (such as a group of birds) to achieve optimal responses (e.g., their food). Another algorithm that is useful to be noted here is teaching learning-based optimization (TLBO), which is used for solving power system problems [26]. Finally, Table 1 summarizes the above reviewed pieces of literature about DR and the electricity market.

Table 1. ***Summary of the literature review about DR and electricity market.***

Ref. No.	**DR program**	**Objective function**	**Reward of the IBDR**	**Prioritize customer power reserve**
[5]	IDRP	Min cost	No	Without prioritizing reserve
[6]	EBDR	Min cost	Fixed	Without prioritizing reserve
[7]	IBDR	Min cost	No	Without prioritizing reserve
[8]	IBDR	Min cost	Fixed	Without prioritizing reserve
[11]	EDRP	Min cost, air pollution & incentive	Variable	Without prioritizing reserve
[15]	TOU & Real time Pricing	Non-Heuristic	No	Without prioritizing reserve
[16]	IBDR	Non-Heuristic	Fixed	Without prioritizing reserve
[17]	TOU	Non-Heuristic	No	Without prioritizing reserve
[18]	EDRP & TOU	Non-Heuristic	Fixed	Without prioritizing reserve
[20]	TOU	Min cost	No	Without prioritizing reserve
[21]	EDRP & TOU	Min cost	Fixed	Without prioritizing reserve
Current Paper	**EDRP**	**Min cost & load curve smoothening**	**Variable**	With prioritizing reserve

* IBDR: Incentive-based demand response *Non-Heuristic: The optimization algorithm is not used

As discussed, the demand curve of the daily market is determined by the power consumption pattern at the initial price of the market. In peak hours, the RMM decides to invoke the EDRP when electricity price and the chance of insufficient reliability are high. For this purpose, in order to reduce power consumption during peak hours, the RMM should provide the responsive loads with incentives that are significantly higher than the electricity prices. Formulations are proposed for determining optimum incentive amounts, which are paid by the RMM to the participants in the EDRP based on the logarithmic model and the elasticity matrix. The optimization algorithm calculates these amounts by taking into consideration the EDRP objective function and DR factor in peak hours as well as the constraints for the maximum incentive rate and demand value. It is assumed that customers participate in the EDRP through their agents, which are the AGGs. These the AGGs communicate with the customers or the electricity end-users and they declare to the RMM the extent they will participate in the EDRP according to the received incentive amounts.

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The main contributions of the current study can be summarized in the following way:

1) Defining a new objecting function for calculating the RMM’s profit in the presence of the EDRP in a day-ahead market environment

2) Presentation of a new formulation applied by the RMM to prioritize the reservation offered by the AGGs.

3) A more realistic definition of the EDRP program, the EDRP is assumed to be implemented in accordance with the NYISO market structure.

In the current study, the AGGs indicate the degree of their participation in the EDRP based on the logarithmic model as well as the participation factors. The reason for choosing a logarithmic model is that the previous studies, i.e., [27] showed that this model provided more conservative responses than values that were in the middle of the values of other models. In this study, a C-ITLBO was used for determining the optimum amount of incentives aimed at the EDRP cost reduction. In the proposed algorithm, the genetic algorithm operators including crossover and mutation as well as an improvement phase were added to the conventional C-TLBO for enhancing its performance in order to reach the global optimal value and not being caught in the optimal local value. Then, in order to increase the provided reserve by the AGGs because of their participation in the EDRP, the RMM took into consideration the concept of the margin reserve. To evaluate the effect of applying the proposed formulas on the system load curve, the peak-to-valley ratio and peak compensation ratio were used. In this study, Ref. [19] is applied as a benchmark for making a comparison with the obtained results. The related problem to the above points is solved for a 24-hour period. Determining the optimal incentive amounts for the EDRP program and evaluating the reserve provided by the AGGs can be considered as two contributions of this paper.

The rest of the study is organized as the following: Section 2 describes the deterministic model of the proposed problem, and in section 3, the proposed algorithm and its implementation in the problem solution are presented. Simulation results are presented in section 4 and the conclusion is presented in section 5, respectively.

2. ORIGINAL DETERMINISTIC PROBLEM MODEL

The deterministic model of the RMM based on the EDRP and taking the reserve into consideration is presented in this section. The objective function of this model includes cost of the EDRP implementation (related to the incentive payments) during the peak hours and the load curve smoothening (related to shape of the system load curve), and the problem constraints are incentive limits, demand limits, the EDRP model and reserve-margin factors.

A. Objective Function

In the proposed model, the objective function minimizes the costs of the EDRP and the load curve smoothening, where its equation is considered to be as the following:

$$\begin{aligned} TOF = {} & \omega_{EDRP} \times \sum_{t_i \in \{PeakLoadHours\}} \left(inc(t_i) \times \sum_{k=1}^{n} \left(d^0(k,t_i) - d(t_i) \right) \right) \\ & + \omega_{LF} \times \left(\rho^0(t_i) \left(\max\left(\sum_{t_i \in \{1,2,..,24\}} d(t_i) \right) - \min\left(\sum_{t_i \in \{1,2,..,24\}} d(t_i) \right) \right) \right) \end{aligned} \tag{1}$$

where:

$$inc(t_i) = \begin{cases} \rho_0(t_i) \times \exp\left(d(t_i) - \sum_{k=1}^{n} d^0(k,t_i) \Big/ PF \times E(t_i,t_i) \times \sum_{k=1}^{n} d^0(k,t_i) \right) - \rho(t_i) \\ \qquad \forall t_i \in \text{Peak Load Hours, Logarithmic model} \\ 0 \qquad \forall t_i \in \text{Off Peak Load Hours, Logarithmic model} \end{cases} \tag{2}$$

In Equation (1), the first part is the incentive payment to the AGGs in the EDRP by the RMM in order to reduce the load curve peak [28-30]. The second part is the cost of the load curve smoothening. One of the criteria for measuring the curve smoothening by the RMM is calculating the difference between the maximum and minimum load characteristics of the AGGs. In the first part, $inc(t_i)$ is determined using Equation (2) for the logarithmic model. ω_{EDRP} and ω_{LF} are the weight factor in the first and the second part of the objective function, respectively.

The relation between these factors is assumed to be as ω_{EDRP} + ω_{LF} = 1 meaning that the RMM should trade-off between ω_{EDRP} and ω_{LF}. If reducing the cost of the EDRP is more important than increasing the DRF, the inequality of $\omega_{EDRP} > \omega_{LF}$ is taken into consideration by the RMM. In the reverse situation, the inequality would be as $\omega_{EDRP} < \omega_{LF}$. In case of the same priority for both of the EDRP cost and DRF, the equality of $\omega_C = \omega_{LF} = 0.5$ is taken into consideration by the RMM where k is the index of the AGG, $inc(t_i)$ is the index of time, $inc(t_i)$ is the peak hour rate per \$ / MWh, $d^0(k,t_i)$ and $d(t_i)$ are the demand for the AGGs before and after the implementation of the EDRP program at t_i hour per MWh, respectively. Moreover, $\rho_0(t_i)$ and $\rho(t_i)$ are the electricity price before and after the implementation of the EDRP program at t_i hour per \$ / MWh, PF is the contribution ratio of the AGGs and E_{t_i,t_i} is the elasticity price at t_i hour.

In the current study, it is assumed that an RMM intends to pay incentives during the peak-load hours to the AGGs who are willing to participate in the EDRP. Receiving the incentives, an AGG could encourage its customers to reduce their electricity consumption. The peak hours are the periods that the distribution system is encountered with a lack of reservation or a sharp increase in the price of electricity. The main issue here is determining $inc(t_i)$ and d (t_i). If $inc(t_i)$ is selected inappropriately, it may impose additional costs on the regional market, and if d (t_i) is selected inappropriately, there will be a probability of an increased load in the other hours. Equation (2) shows the incentive rate at the peak times using a logarithmic model, where $inc(t_i)$ is dependent on d (t_i) variable.

Here, the electricity price is assumed to be the same value before and after the EDRP implementation for the first iteration of the solution process. The reason is that the electricity price is not known after the implementation of the EDRP in the first iteration. In addition to this assumption, no penalty is considered in the EDRP, and there are also no incentive payments during the off-peak hours.

B. Constraints

The constraints mentioned in this section are applicable to all of the logarithmic models described in the next sections.

A) Incentive limit: The Payable incentive for the EDRP is assumed to be in the following range:

$$inc_{\min}(t_i) \le inc(t_i) \le inc_{\max}(t_i) \qquad \forall t_i \in 1,...,24 \tag{3}$$

This range is applied to the incentive provided by the RMM to the AGGs. The upper and lower limits are considered as $10 \times \rho_0(t_i)$ and $1 \times \rho_0(t_i)$, respectively [4].
B) Demand limits: The incentive provided by the RMM should be in a way that it does not exceed the upper and lower limits of the daily load demand according to the Equation (4):

$$\min \sum_{k=1}^{n} d^0(k,t_i) \le d(t_i) \le \max \sum_{k=1}^{n} d^0(k,t_i) \quad \forall t_i \in 1,..,24 \tag{4}$$

C) EDRP model: In this study, the optimal incentive rate and the optimal demand rate for the EDRP at the peak times are determined by using the logarithmic model and the RMM announces this incentive rate to the AGGs. Then, the AGGs declare the level of their participation in the EDRP to the RMM, which is declared by the use of the model mentioned in Equation (5) based on the incentive rate and the participation factors (PF_1, PF_2 etc.) of the AGGs. Since there is competition among the AGGs to receive the incentive payments, it is assumed that the AGGs are prioritized according to their provided reserve, which is performed by using a factor of reserve margin. This factor is related to the reserve provided due to participation of the AGGs in the EDRP. Therefore, based on the logarithmic model [29,31], the EDRP model for AGG_k is written as the following:

$$d(k,t_i) = (1+PF_k) \times d^0(k,t_i) \times \left\{ \sum_{t_j=1}^{24} E(t_i,t_j) \times Ln\left(\frac{\left(\rho(t_j) + inc(t_j)\right)}{\rho_0(t_j)} \right) \right\} \tag{5}$$

D) *Reserve margin factors:* Applying the above-mentioned model, Equations (1)-(5), the amount of the provided reserve in a peak-load hour by each of the AGGs that participates in the EDRP can be calculated and announced to the RMM. The provided reserve amounts are prioritized in this study using reserve-margin factors defined as the following:

$$RMF(k,t_i) = \begin{cases} \dfrac{R(k,t_i) \times RSP(k) \times RV(t_i)}{MAR(t_i)} & \forall t_i \in PeakLoadHours \\ 0 & \forall t_i \in OffPeakLoadHours \end{cases} \tag{6}$$

where:

$$R(k,t_i) = \begin{cases} d^0(k,t_i) - d(k,t_i) & \forall t_i \in PeakLoadHours \\ 0 & \forall t_i \in OffPeakLoadHours \end{cases} \tag{7}$$

$$RSP(k)=\sum_{t=1}^{24} RV(t_i)PR(k,t_i) \qquad \forall t_i \in PeakLoadHours \tag{8}$$

$$RV(t_i)=\begin{cases} \left. RV_{new}=RV_{old}-\left(\dfrac{d_{old}-d_{new}}{\sum\limits_{k\in PeakLoadHours} d(k,t_i)-d_{avg}^{0}(t_i)}\right)\right\} & \forall t_i \in PeakLoadHours \\ 0 & \forall t_i \in OffPeakLoadHours \end{cases} \tag{9}$$

$$MAR(t_i)=\begin{cases} \sum\limits_{k=1}^{n} d^{0}(k,t_i)-d(t_i) & \forall t_i \in PeakLoadHours \\ 0 & \forall t_i \in OffPeakLoadHours \end{cases} \tag{10}$$

In Equation (6), $RMF(k,t_i)$ which is the value of the reserve-margin factors by AGG_k in t_i hour is determined, and $R(k,t_i)$ which is the reserve provided by AGG_k in t_i hour per MWh is calculated using Equation (7) and based on $d(k,t_i)$ demand by AGG_k in t_i hour. Moreover, Equation (8) indicates $RSP(k)$ which is the reserve service period of AGG_k after the EDRP implementation and Equation (9) expresses $RV(t_i)$ which is the reserve value for each of the AGGs which could provide reserve in t_i hour. Therefore, the relations of $RV(t_i)$ and $R(k,t_i)$ are expressed based on references [21] and [24], respectively. According to this equation, the highest demand indicates the highest reserve value, which is equal to 1. By reducing demand from the highest to the lowest amount, the reserve value decreases from one to zero. Furthermore, the extent of the provided reserve by AGG_k in t_i hour is calculated using $PR(k,t_i)$. If this the AGG offers the reserve in t_i hour and this period belongs to the peak hours, $PR(k,t_i)$ will be equal to 1, otherwise it will be equal to zero. In this regard, $MAR(t_i)$ which is the maximum achievable reserve for the RMM in t_i hour is determined using Equation (10).

It is noted that based on Equation (9), an AGG with a greater *RMF* is given higher priority for providing the reserve in t_i hour. If *MAR* from Equation (10) is greater than the reserve capability of the considered AGG, another AGG with the next priority will be called for the reserve provision. This procedure continues in the same way till the *MAR* is achieved.

3. PROPOSED METHOD AND IMPLEMENTATION PROCESS

3.1. Overview of C-ITLBO

In this study, the C-ITLBO algorithm is used together with the GA operators, i.e. crossover and mutation. Furthermore, for enhancing the performance of C-ITLBO algorithm, an improvement phase is added to it in order to not be trapped in the local optimums. The C-ITLBO algorithm can be explained as the following; Teacher T is in fact the best student among students, P_n other students each shown by S_{old} during the teaching processes. In this process, the teacher's knowledge S_{old} is used to generate a new member or student for the group, S_{new} represents a new student Group The number of students in a class who are trying to learn a lesson P_n Individuals who organize the initial population, so-called student group, where a specific vector is used to indicate each one of the students.

Teacher Stage: A student who has more or better information is considered as the teacher and attempts to increase the level of students' knowledge in the classroom by teaching other students. In other words, when a student with higher quality than the previous one is generated, it substitutes the previous one or even the teacher. Equation 14 expresses the formulation of how a new student or teacher, S_{new} is generated from the previous student (S_{old}) [26].

$$S_{new} = S_{old} + r \times \left(T - T_F \times \bar{S}_{old} \right) \tag{11}$$

where, r is a randomly selected real number in the range of zero and one, T_F indicated the teaching coefficient and $\bar{S}_{old}$ shows the average value calculated for the whole of the students before being taught. The relationship for T_F is given as the following:

$$T_F = round[1 + rand\,(0,1)] \tag{12}$$

Students Stage: Students are taught based on the quality of the instruction provided by the teacher as well as the status of students present in the knowledge classroom. In the other words, when two random and distinct students interact with each other, i.e. one with higher quality (S_{better}) and another with lower quality (S_{worse}), a new student will be generated using equation (13) substituting the lower one [26].

$$S_{new} = S_{worse} + r \times \left(S_{better} - S_{worse} \right) \tag{13}$$

There are accordingly 6 main steps in this algorithm, namely 1) initialization, 2) competition, 3) teacher, 4) student, 5) GA operator's application and 6) improvement phase. In the first step (initialization), two groups of students with equal size of P_n are generated and assessed. P_A and P_B are used for representing these groups. After that, the other three steps (steps 2-4) are repeated and once the termination criterion is met the algorithm stops. To find competitiveness, a competition is carried out among the students of both groups and in each group, the student with maximum competitiveness is chosen to be a teacher.

Hence, T_A is the teacher of group or class A and T_B is the teacher of class B. In step 5, byapplying the crossover and mutation operators of the GA, a new population of students is generated. In order to prevent the algorithm from being trapped in a local optimum and also to improve the convergence of the algorithm, the GA operators are applied.

In other words, GA operators lead the students to cooperate with each other during the knowledge acquiring, and sometimes the students compete with each other for selecting the teacher.

In the improvement phase (step 6), based on the technique of self-adaptive mutation, the level of students' knowledge increased. Considering that in the C-TLBO students usually move in the direction of the teacher, there is a chance that they will be trapped in local optimum points and hence the convergence rate is decreased. Accordingly, in the improved phase, each student moves randomly towards a teacher or the worst student. The parameter ω called the probability of mutation is attributed to each student. Then, a probability number from 0 to 1 is selected. If this number is less likely to be mutated, the student will perform the mutation and otherwise it does not perform. The mutation is described as the following:

$$S_{new} = \begin{cases} S_{old} + \omega(T - S_{old}) & if\ \omega > 0 \\ S_{old} + \omega(W - S_{old}) & if\ \omega \le 0 \end{cases} \quad (14)$$

where T is Teacher (best student) and W is the worst student. The parameter ω is applied as the following:

$$\omega = \frac{1}{\sqrt{h}} \exp\left[-(\frac{1}{2})(\frac{\varphi}{h})^2 \cos(\omega_c(\frac{\varphi}{h})) \right] \quad (15)$$

where, ω_C is the central frequency of the wavelet. If ω is positive, the student moves towards the teacher and if it is negative, the student moves towards the opposite side. Taken into consideration that 99% of the total energy of the central frequency of the wavelet is located between [-2.5, 2.5], the parameter φ is chosen randomly with a value between [-2.5h, + 2.5h]. In this equation, h is the dilatation factor, which is varied in each iteration as the following:

$$h = \exp\left[-\ln(\eta) \times (1 - {L}/{L_{\max}})^{\sigma} + \ln(\eta) \right] \quad (16)$$

where, L and $L_{\max}$ are the current iteration and total iterations, respectively. The upper bound and the shape of h are defined by two parameters of η and σ. In this study, the value of η is considered as 2 and the value of σ is obtained from the following equation:

$$\sigma = \sigma_{\min} + (\frac{\sigma_{\max} - \sigma_{\min}}{k_{\max}})k \quad (17)$$

where, σ_{min} and σ_{max} are 1 and 3, respectively.

3.2. C-ITLBO Implementation

Evaluation steps of the proposed formulations correspond to the flowchart shown in Fig. 1 and are as the following:

Step 1: Enter the initial information, the related algorithm, the optimization functions and constraints and the required parameters of the formulations for the RMM;

Step 2: If the t_i hour is not greater than 24, go to the third step, otherwise display the outputs and terminate the process;

Step 3: If the t_i hour belongs to the peak hours, go to the step 4, otherwise consider next hour or $t_i + 1$ and return to the step 2;

Step 4: Assume for the first iteration that $\rho(t_i) - \rho_0(t_i) = 0$;

Step 5: Determine the electricity price after the EDRP, optimal incentive in t_i for the RMM according to equations (1)-(2);

Step 6: If the constraints equations (3,4) are satisfied, go to the next step, otherwise return to the step 5;

Step 7: Select the best $d(t_i)$, $inc(t_i)$ and $\rho(t_i)$ after the EDRP from the perspective of the RMM;

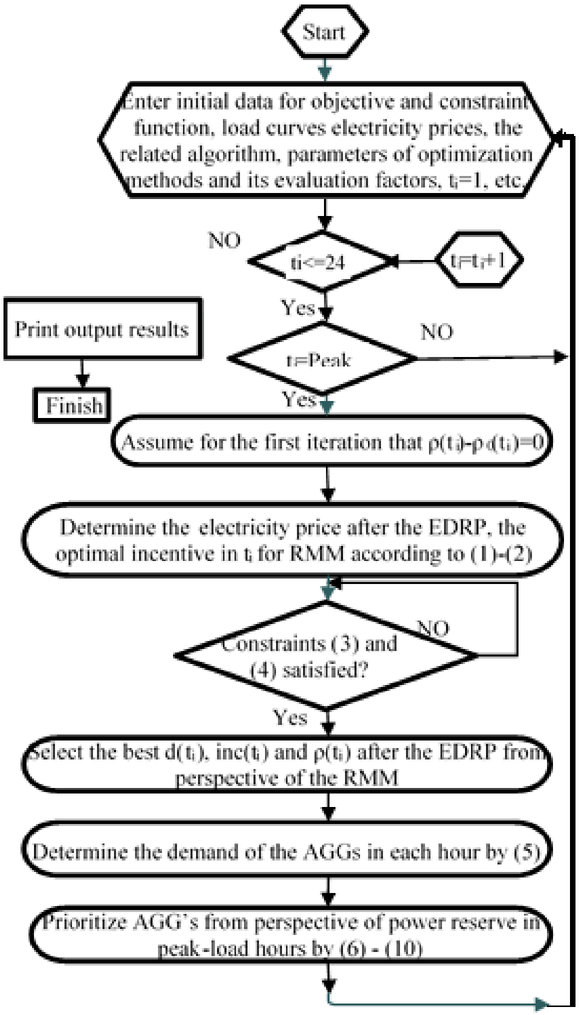

Fig. 1. The flowchart of the evaluation process of the proposed formulations.

Step 8: Determine the demand of the AGGs in each hour by Equation (5);

Step 9: Prioritize the AGG from the perspective of the power reserve in the peak-load hours by Equations (6)-(10);

Step 10: Determine the load-curve smoothening factors according to Equation (15) to Equation (16);

4. RESULTS AND DISCUSSION

The effectiveness and feasibility of the proposed method are illustrated in the form of eight different research scenarios. The assumptions are presented in Section 4.1 and the results of the proposed method are presented and evaluated in Section 4.2, respectively.

4.1. Assumptions

The proposed formulations are evaluated in this section with the following assumptions:

- Five the AGGs are considered with the initial demands according to Table 2 and the participation factors of $PF_1 = 21\%$, $PF_2 = 23\%$, $PF_3 = 24\%$, $PF_4 = 22\%$, and $PF_5 = 24\%$, respectively.

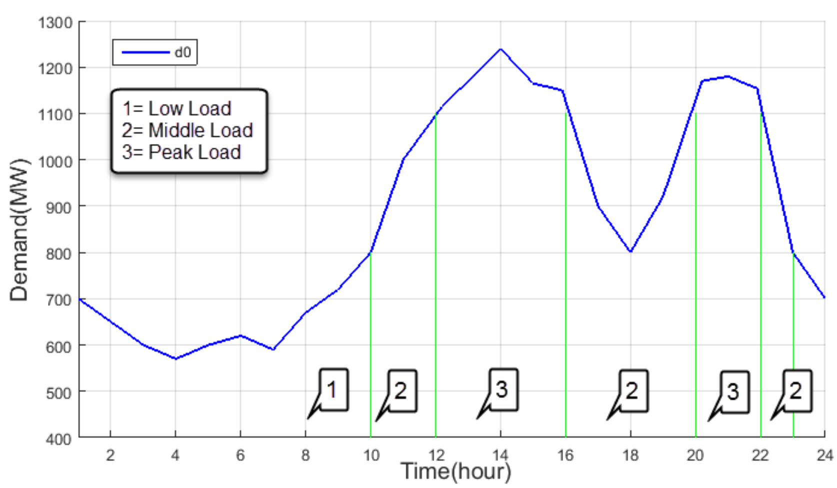

Fig. 2. The considered daily load curve [25].

Table 2. ***Initial demand of the AGGs.***

Hour	1	2	3	4	5	6	7	8	9	10	11	12
(MWh) Demand of AGG1	163	136	100	100	110	116	115	133	140	156	193	216
(MWh) Demand of AGG2	130	125	130	110	130	130	110	130	165	176	210	230
(MWh) Demand of AGG3	147	139	125	125	125	124	129	142	150	174	217	244
(MWh) Demand of AGG4	125	130	127	119	125	125	122	130	125	137	180	210
(MWh) Demand of AGG5	135	120	118	116	110	125	114	135	140	157	200	225
Hour	13	14	15	16	17	18	19	20	21	22	23	24
(MWh) Demand of AGG1	233	275	216	256	200	166	226	274	275	246	161	123
(MWh) Demand of AGG2	245	220	210	230	220	200	240	210	220	214	160	150
(MWh) Demand of AGG3	242	250	254	264	240	214	240	230	260	204	184	160
(MWh) Demand of AGG4	224	260	245	197	125	112	108	215	210	258	150	140
(MWh) Demand of AGG5	226	245	240	203	115	108	106	241	215	232	145	127

- Daily load curve in the considered region and parameters of the elasticity matrix are in accordance with Fig. 2 and Table 3.
- In the load curve, the low-load hours are from 24:00 to 9:00, the middle-load hours are 10:00, 11:00, 17:00 to 19:00 plus 23 and the peak-load hours are from 12:00 to 16:00 and from 20:00 to 22:00.
- Prices of electricity in terms of $/MWh are 13, 17 and 20 in low-, middle- and peak-load hours, respectively.
- The simulation time interval is 24 hours.
- For the C-PSO, C-TLBO and C-ITLBO algorithms, the number of iterations is limited to 200, the size of the population is 100, and also 14 scenarios, as mentioned in Table 4, are considered.

4.2. Results of the Proposed Method

The results of the proposed formulations are presented in two parts. It should be noted that this evaluation is from the viewpoints of the RMM. In the first part, the amount of the optimum incentives was obtained based on the logarithmic model of the EDRP and two cases with different values of elasticity matrix by the use of C-PSO, C-TLBO and C-ITLBO algorithms. These incentives are paid by the RMM to the AGGs participating in the EDRP. In the second part, the amount of the reserve, provided by the AGGs, was determined using the logarithmic model of their demand as well as the participation factors. Then, the priority was given to the reserve of the AGGs in the peak-load hours based on the reserve-margin factors. The evaluation results of the above-mentioned paragraphs are presented in Figs. 3 to 5 and Tables 5 to 8.

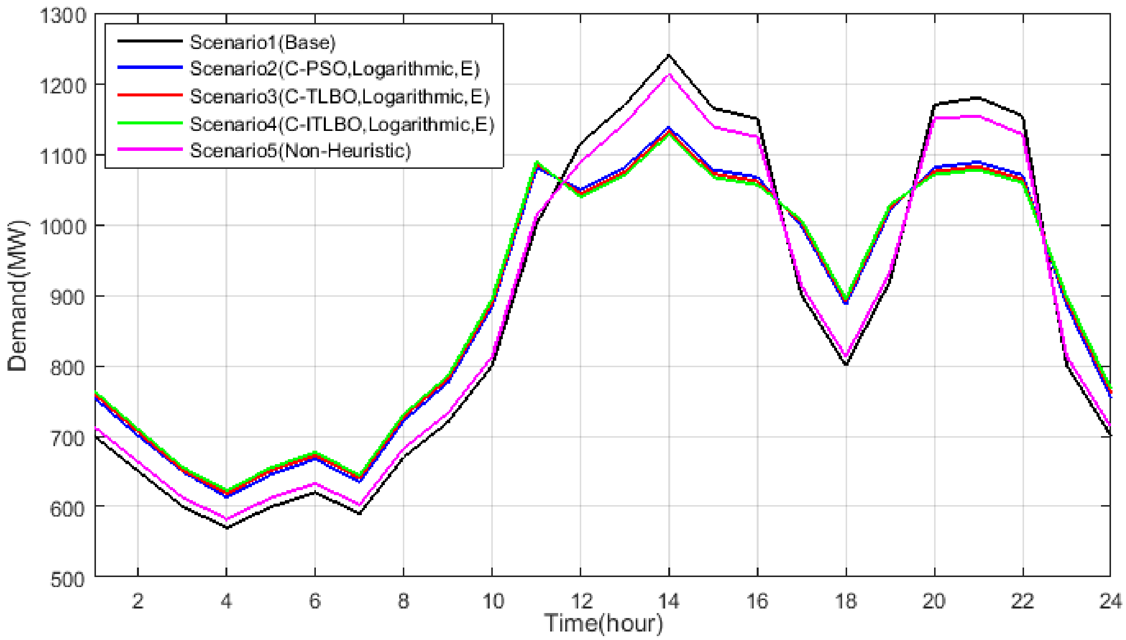

Fig. 3. The effect of EDRP on the daily load curve taking the elasticity matrix case1 into consideration.

Table 3. ***The considered self and cross elasticity in different time periods.***

Time Period	Low Load	Middle Load	Peak Load	
12-16 & 20-22	0.024	0.032	-0.2	Peak Load
10-11, 17-19 & 23	0.02	-0.2	0.032	Middle Load
24-9	-0.2	0.02	0.024	Low Load

Table 4. ***The studied scenarios.***

Scenario	Elasticity matrix	Algorithm	EDRP model
1	Base Case		
2	E	C-PSO	Logarithmic
3	E	C-TLBO	Logarithmic
4	E	C-ITLBO	Logarithmic
5	Non-Heuristic [18]		Logarithmic
6	2×E	C-PSO	Logarithmic
7	2× E	C-TLBO	Logarithmic
8	2×E	C-ITLBO	Logarithmic

Table 5. ***Incentive payments to the AGGs in different scenarios.***

Scenario #	Incentive received ($)				
	AGG1	AGG2	AGG3	AGG4	AGG5
1	0	0	0	0	0
2	3360.2	3038.7	8965.8	8043.4	3138.7
3	3337.8	3023.3	8955.5	8034.5	3123.3
4	3315.4	3007.8	8945.1	8025.7	3107.8
5	926.8	470.8	1021.6	535.6	532.7
6	4470	3369	9476	9373	3379
7	4460	3329	9465	9358	3349
8	4450	3289	9454	9343	3319

Table 6. ***The total cost, reserve used and reserve backup in different scenarios.***

Scenario #	Reserve backup during peak hours (MW)	Reserve used during peak hours (MW)	Total Cost RMM ($)
1	0	0	396947.29
2	2342.5	815.2	392176.31
3	2380.4	816.5	391651.85
4	2418.4	817.7	391281.73
5	495.4658	181	396527.38
6	2591.6	857.8	392144.90
7	2636.3	859	391673.54
8	2681.1	860.3	391202.17

According to Table 4, the elasticity matrix consists of two cases of E and 2×E, which here they are named elasticity matrix case1 and case2, respectively.

In terms of the amounts of the incentive payment at peak hours by the RMM, Table 5 comparing elasticity matrix Case 2 with the elasticity matrix Case 1, shows that by increasing the elasticity matrix, the total incentive which should be afforded by the RMM increased as well, the highest and lowest payments are in the Scenarios 6 and 1, respectively.

In Table 6, the highest cost reduction is observed in Scenario 8, C-ITLBO whereas the lowest cost reduction is associated with

Scenario 1. Moreover, in this table, the highest reserve backup is in Scenario 8 while the lowest reserve backup is in Scenario 1. This result proves the superiority of the proposed algorithm in comparison with C-PSO and C-TLBO algorithms.

By using different algorithms, the total costs of the RMM considering the elasticity matrix case1 and case2 are illustrated in Fig. 3-4. The results showed that the total cost of the RMM was lower in elasticity matrix case2 than the state of elasticity matrix case1.

Furthermore, these figures indicate a better performance of C-ITLBO algorithm in total cost reduction in comparison with C-PSO and C-TLBO algorithms.

Table 7. ***The reserve proposed by the AGGs in different scenarios during peak hours.***

Scenario #	Reserve proposed by (MW)				
	AGG1	AGG2	AGG3	AGG4	AGG5
1	0	0	0	0	0
2	625.33	592.26	695.84	605.61	638.63
3	633.10	599.61	704.49	613.12	646.55
4	640.86	606.96	713.13	620.64	654.48
5	116.89	91.02	121.39	135.10	212.03
6	683.11	646.97	760.12	661.55	697.62
7	692.21	655.60	770.26	670.37	706.92
8	701.32	664.23	780.40	679.20	716.23

Table 8. ***The rate of incentives during peak-load hours in different scenarios.***

Hour / Scenario	Rate of incentive ($/MWh)							
	12	13	14	15	16	20	21	22
1	0	0	0	0	0	0	0	0
2	31.8974	37.6765	46.1028	36.8805	34.0380	37.6765	38.5282	35.4474
3	31.4634	37.2289	45.6283	36.1801	33.5444	37.2289	38.0693	34.7705
4	31.0294	36.7814	45.1538	35.4797	33.0509	36.7814	37.6104	34.0936
5	18	20	19	19	18	19	18	18
6	35.6699	41.1998	50.6386	40.5891	38.7495	41.1998	42.4164	39.2409
7	35.1702	41.0606	50.2411	39.9657	38.1732	41.0606	41.7452	38.6522
8	34.6704	40.9213	49.8436	39.3423	37.5969	40.9213	41.0740	38.0634

According to Table 7, from the perspective of joint consideration of the EDRP and power reserve, it was observed that Scenario 8 (C-ITLBO) was in a better situation whereas Scenario 1 showed the worst situation.

After the EDRP implementation, total demand in the peak hours decreased in all scenarios. Demand reduction in the peak hours, in turn, can increase the power reserve in these hours. The reason is that some of the power that has been previously consumed can be saved and then devoted to the reserve. It was also observed that determining the optimal incentives was useful in reducing the overall cost of the RMM due to the optimality of the related payments.

The rate of considering the incentive elasticity matrix using different algorithms is shown in Table 8. According to Table 8, Scenario 1 indicated a lower rate of incentive and the elasticity matrix case 2 showed more incentive rate in comparison with the state of the elasticity matrix case1. Furthermore, the results show the superiority of C-ITLBO in the lower rate of an incentive than the C-PSO and C-TLBO algorithms.

Peak compensation using C-ITLBO algorithms is shown in Fig. 5 taking the elasticity matrix case 1 and case 2 into consideration. According to Fig. 5, the peak shaving (%) indicated more value considering elasticity matrix case 2 than elasticity matrix case1.

It can be noted that among the scenarios that used the logarithmic model, Scenarios 8 for C-ITLBO indicated the best results while Scenarios 2 showed the worst results. The studied scenarios indicated that determining the optimum incentives along with taking power reserve in the peak hours into consideration not only reduced the RMM cost but also improved the load curve. After evaluating such scenarios using the proposed formulations, it can be concluded that the RMM can make a more realistic decision for

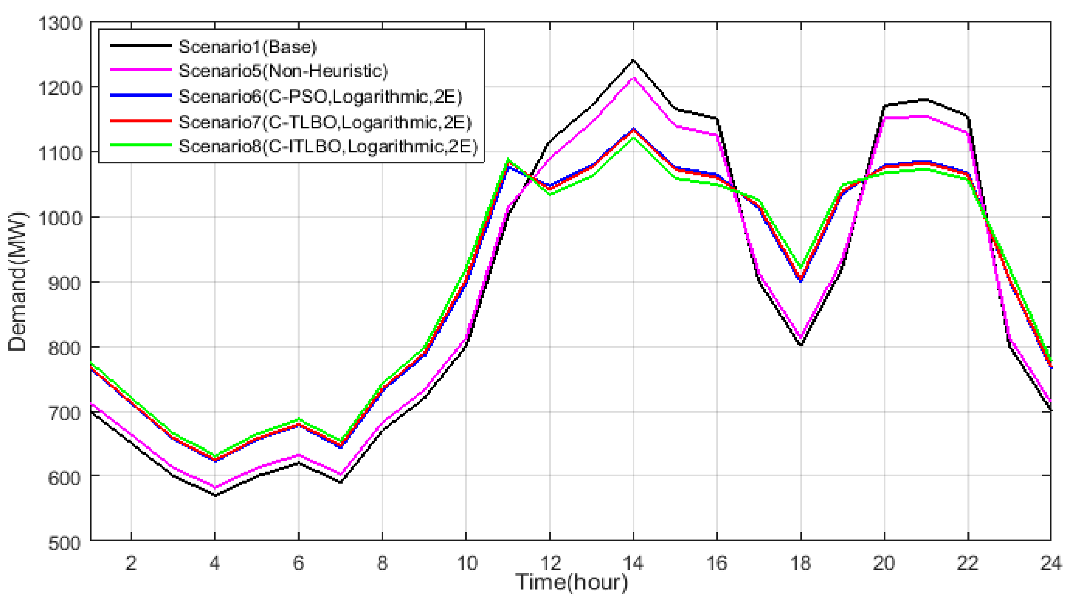

Fig. 4. The effect of EDRP on the daily load curve calculated considering the elasticity matrix case2.

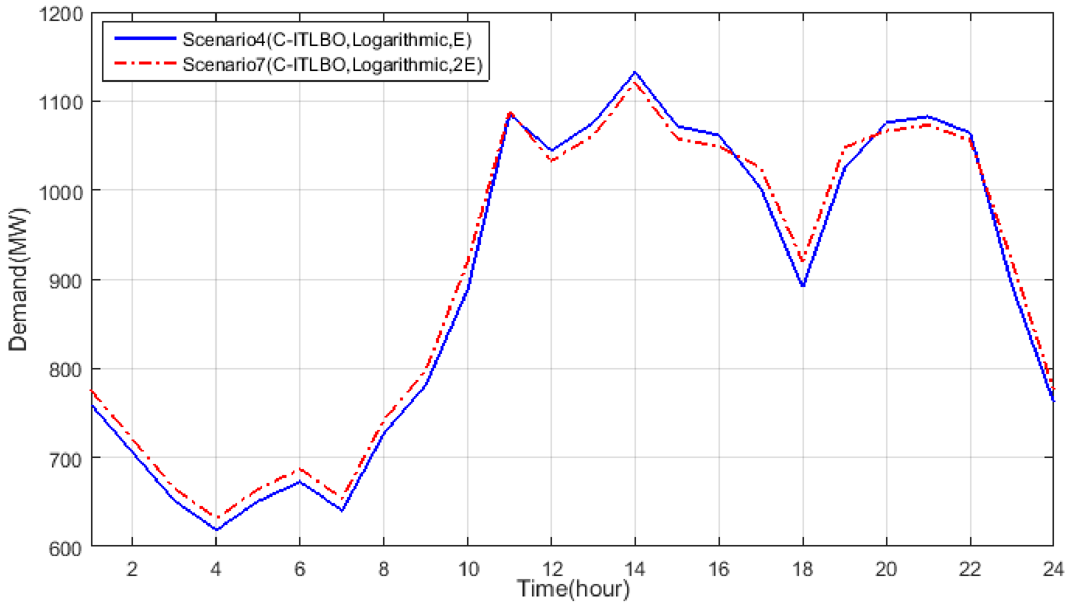

Fig. 5. The effect of EDRP on the daily load curve calculated by the C-ITLBO taking the elasticity matrix case1 and case2 into consideration.

the implementation of the EDRP. The effects of the EDRP on the daily load curve were calculated using C-PSO, C-TLBO and C-ITLBO algorithms taking the elasticity matrix case1 and case 2 into consideration, as illustrated in Figs. 3 and 4.

Scenario 1 indicated the base case regarding the actual load curve of Fig. 2, in which there was no the EDRP implementation and no incentive for the AGGs. In Scenario 2, it is assumed that the elasticity matrix is E and the model used is a logarithmic one. As observed in Fig. 3, the results of this scenario for C-PSO showed that the peak of the load curve decreased from 1240 MW to 1132.1, which is equivalent to about 8.70% reduction. In spite of paying incentive to the AGGs for their participation in the EDRP, Scenario 2 indicated a lower total cost compared to the base case. The same is true for C-TLBO and C-ITLBO as well (Fig. 3). This is mainly due to the reduction of the electricity price after the implementation of Scenario 2. Moreover, this scenario modified the load curve by making it flatter. This modification caused the commitment to be weaker in generating more units during the peak hours.

In addition, compared to Scenario 1, more power reserve was provided for the RMM and hence the distribution network indicated a higher level of reliability. In Scenario 3 for C-TLBO, the logarithmic load model was applied which led to about 8.80% peak-load reduction, i.e. from 1240 MW to 1130.8 MW, as illustrated in Fig. 3. Scenario 3 indicated a lower total cost, lower incentive payments, a flattened load curve and more power reserve compared to Scenario 2. As shown in Fig. 3, the logarithmic model was applied in Scenario 4 for C-ITLBO, which brought about 9.67% peak-load reductions from 1240 MW to 1120.1 MW. This reduction was more than the corresponding amounts in the previous scenarios. Comparison with the previous scenarios can also be considered for some other quantities including the total cost, the incentive payments, the flatness of the load curve and the provided power reserve.

The results of Fig. 3 and also the results in the above tables showed that the RMM was seeking for more peak-load reduction and higher power-reserve supply. In this regard, for more reduction in the total cost, Scenario 8 showed preferable outcomes in terms of load curve flatness and power-reserve. Fig. 3 and also the results in the above-mentioned tables show that the C-ITLBO algorithm also improved the load curve characteristic and the power reserve supply, which are comparable with the C-PSO and C-TLBO algorithms outcomes. By comparing Scenarios 1-8, it can be concluded that C-ITLBO algorithm was more precise than the other algorithm.

The effects of EDRP on the daily load curve were calculated using the C-PSO, C-TLBO and C-ITLBO algorithms taking the elasticity matrix case 2 into consideration, as presented in Fig 4. Doubling the matrix increases peak-load reductions in the mentioned scenarios. For instance, as shown in Fig. 4, the peak-load is lower in scenario 8. Moreover, the elasticity matrix case2 resulted in more demand reaction in the EDRP from the AGGs. Therefore, these scenarios indicated more peak-load reduction, more modification in the load curve and reserve provision. As indicated in the tables of numerical results, C-ITLBO algorithm can provide more precise results compared to the C-PSO and C-TLBO algorithms.

The effects of EDRP on the daily load curve were calculated using C-ITLBO taking the elasticity matrix case 1 and case 2 into consideration, as presented in Fig. 5. As shown in Fig. 5, the elasticity matrix case 2, the load peak is lower than that of the elasticity matrix case 1.

5. CONCLUSIONS

The current study presented some formulations based on a logarithmic model for the EDRP by considering the reserve. Determining the optimum incentives to be paid to the AGGs during peak-load hours, the formulations were applied in an optimization problem from the perspective of the RMM using C-ITLBO, C-TLBO and C-PSO algorithms. Knowing the incentives of the EDRP during the peak-load hours, the AGGs declared their extent of participation to the RMM using the logarithmic model and the participation factors. The participation determines the power reserve provided by the AGGs. The AGGs were then prioritized by the reserve-margin factors.

The optimization problem regarding the proposed formulations was solved using C-ITLBO, C-TLBO and C-PSO algorithms with elasticity matrix case1 and case2 from the perspective of the RMM and for different scenarios in a 24-hour time interval. The results presented the amounts of the RMM cost, the optimum incentives payable to the AGGs, power saving due to the EDRP implementation through considering the reserve in the peak-load hours and the load-curve characteristics.

In general, the results showed a better performance of C-ITLBO algorithm in total cost reduction, a lower rate of incentive and a lower peak compensation in comparison with C-PSO and C-TLBO algorithms. Furthermore, it was observed that the scenario 8 for C-ITLBO showed the best results while the results of scenario 2 for C-PSO indicated the worst results. It was also found that the joint consideration of the EDRP along with the power reserve brought about benefits in the form of cost reduction and load-curve improvement. As for future research, it is possible to extend the proposed formulations by adding more items in the mentioned constraints and objective functions, improve the reserve consideration procedure, apply some newer meta-heuristic algorithms and investigate the possibility of the RMM interaction with the whole-sale electricity market.

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