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Improvement of regional market management considering reserve, information-gap decision theory, and emergency demand response program

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Abstract. An Regional Market Manager (RMM) is supposed to take into account a variety of items including the participants in the market, technical constraint, price variation/reaction, electricity-price uncertainty, and types of the applied demand response program, to name a few. One of the demand response programs is Emergency Demand Response Program (EDRP) which is employed in this paper. In the present study, the objective function of the RMM is formulated in a market environment in order to determine the optimal demand, incentive, and power purchased with considering some of technical constraints such as incentive limits, demand limits, power purchased, and power balance. Co-evolutionary Improved Teaching Learning-Based Optimization (C-ITLBO) is applied to maximize the RMM's profit. In addition, the demand level in the EDRP is determined based on a logarithmic model that includes Price Elasticity Matrix (PEM). The reserve supplied due to Aggregators (AGGs) is also prioritized using Reserve Margin Factor (RMF). Further, Information-Gap Decision Theory (IGDT) is applied to model uncertainty in the initial electricity price. The above-mentioned items are modeled in a multi-level formulation.

1. Introduction

Load growth in the power system leads to an increase in the electricity price, level of the daily load curve, transmission line loading, and even system instability. In this respect, management or optimization of the energy consumption pattern through Demand Side Management (DSM) gains significance [1]. The DSM, by definition, refers to the activities that reduce or shift electricity consumptions in order to decrease the loading of the distribution system, especially during peak-load hours. One of the most prominent DSM types that has been developed in recent years is Demand Response Program (DRP). In such programs, customer's electricity consumption changes in accordance with the changes in the electricity prices over time or even the monetary incentive payments [2]. A type of DRP is called Emergency Demand Response Program (EDRP) that can be used as a tool for maintaining the confidence ability in the emergency situations when a regional market is facing a shortage of supply resources and, thus, lack of power reserve, which incurs high electricity prices. Peak-load hour is another common

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example of emergency situation. In these situations, the RMM recalls customers or their representatives who are prepared to participate in the EDRP so as to reduce their consumptions [3]. In this study, each representative is considered as an 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 Aggregators (AGGs) who did not answer the phone at the time of calling [4,5].

In recent years, many studies have been conducted on the price and demand determination of the DRPs and EDRP based on definite, random, and uncertainty models among which uncertainty models become more prominent. For example, in [6–12] the price definite models in the DRP was used. More specifically, the EDRP was applied in [6] where a market-based incentive model was proposed to encourage subscribers to reduce their energy consumption. In [7], in order to improve Voltage Stability Margin (VSM), a strategy based on Whale Optimization Algorithm (WOA) was allocated to the EDRP in a range acceptable in the emergencies. In [8], the effects of the EDRP on the reliability improvement of power generating units were investigated. In [9], a hybrid model of Wind Turbine (WT) and DRPs including the EDRP was presented whose objective function was to minimize the operation cost of the RMM. In the presence of wind and gas turbines, a combination of the DRPs including incentive-based programs such as the EDRP [10] was studied. This combination was applied in a random market-clearing framework by the RMM who intended to reduce the pollution as well as the operation costs. In [11], an optimal pricing model for DRP was proposed which was based on the demand-price elasticity. The model was then applied to maximize the profits, reduce the price fluctuations, and improve the system reliability. In [12], a DRP model was developed for the combined programs of the EDRP and TOU based on the concepts of the customers' benefit function and flexible demand elasticity. In order to determine the optimal demand from the viewpoints of "load characteristics" and "economy", Multi-Attribute Decision Making (MADM) was employed as an effective method. In [13–15], the random price and demand models were incorporated in the DRP. In [13], the effect of participation in the EDRP on the performance of a microgrid was investigated in the presence of random models such as the failure of generating units, transmission line outages, and load-forecast error. In [14], a Scenario-Based (SB) stochastic programming framework was used to model the load and wind uncertainty in a problem based on Combined Heat and Power (CHP), WT, and DRP. In addition, Particle Swarm Optimization (PSO) algorithm was employed to achieve the optimal solution. In [15], a model was presented for the optimal control and long-term evaluation of a CHP and Heat Buffer Tank (HBT) in the presence of market price uncertainty. Price uncertainty was modeled using Least-Squares Monte Carlo Regression (LSMCR) random control model. Since the definite methods fail to provide an acceptable and accurate analysis to evaluate the sharp fluctuations of the electricity prices in the market considering the EDRP program [16], Information-Gap Decision Theory (IGDT) uncertainty method was used in the current study. In [17–20] the DRP uncertainty models were employed in a Combined Heat and Power Economic Dispatch (CHPED) problem. To minimize the CHP costs in [17], the DRP price uncertainty was addressed through robust optimization due to the limitations like minimum number of start-ups and shutdowns as well as the ramp rate limits and minimum up/down-time limits of generating units. In [18], to deal with the uncertainties of the wind energy in WT and load demand in DRP, an optimization approach considering unit commitment reliability was proposed based on the RMM with the aim of maximizing the overall social welfare. This issue can be considered as a multi-level programming problem that was formerly employed in the Benders approach to obtain an optimal robust unit commitment schedule. In [19], the IGDT theory was used to analyze the uncertainty of the DRP electricity prices. The optimal bidding strategy for the DRP was presented in order to buy energy from a day-ahead market. In [20], the optimal performance of a microgrid including photovoltaic, fuel cell, and battery in the presence of the DRP was evaluated, taking into account the uncertainty of the electric price to minimize the total cost of the microgrid. The IGDT theory was further employed to model the mentioned uncertainty.

A noticeable criterion, here, is the increase in the power reserve after the EDRP implementation. Obviously, a higher level of participation in the EDRP leads to further reserves of the RMM during emergencies. For this reason, a need is felt to propose an appropriate formulation and encourage more participation in the EDRP since it can boost the economic benefits for the participants as well as the technical benefits for the regional market. An important technical benefit is the reliability improvement resulting from the increased power reserve. Among the literature pieces mentioned above, the power reserve and reliability were studied in [21–24]. Optimum reserve capacity required in the electricity market was studied in [21]. Purchasing spinning reserves and allocating cost with the application of social-welfare analysis were discussed in [22]. In [23], multi-objective stochastic programming was provided for both clearing energy and reserve markets at the same time. In [24], reliability-based unit commitment was solved, and the obtained results were used to clear

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

Ref. No.	DRP	Uncertainty parameters DRP		Uncertainty model	Objective function
		load	**price**		
[6]	IBP	No	No	No	Min cost
[7]	EBDR	No	No	No	Min cost
[8]	IBP	No	No	No	Min cost
[9]	EDRP	No	No	No	Min cost
[10]	EDRP	No	No	No	Min cost & air pollution
[11]	IBP	No	No	No	Non-heuristic
[12]	EDRP & TOU	No	No	No	Non-heuristic
[13]	EDRP	Yes	No	Scenario based stochastic	Min cost & incentive
[14]	IBP	Yes	No	Scenario based stochastic	Maximize Genco & DRP profit
[15]	IBP	Yes	No	LSMCR stochastic	Maximize Genco & DRP profit
[17]	IBP	No	Yes	Robust uncertainty	Min cost, air pollution & DRP
[18]	IBP	No	Yes	Robust uncertainty	Min cost
[19]	IBP	Yes	No	IGDT uncertainty	Clear power market
[20]	IBP	Yes	No	IGDT uncertainty	Min cost
[24]	TBP	Yes	No	IGDT uncertainty	Clear reserve market
Proposed method	**EDRP**	**No**	**Yes**	**IGDT uncertainty**	**Max Profit of the RMM**

Note: EDRP: Emergency Demand Response Program; IBP: Incentive-Based Programs;
TBP: Time-Based Programs; TOU: Time Of Use; Non-heuristic: The optimization algorithm is not used;
IGDT: Information-Gap Decision Theory; RMM: Regional Market Manager; LSMCR: Least Squares Monte Carlo regression;
DRP: Demand Response Program; and Genco: Generation Company.

the reserve market in the presence of the DRP. In addition, the IGDT was applied to include uncertainty of the load demand. Based on the above research and other studies in this field, four main research gaps in the study of DRPs can be as follows:

- In many studies [6–12], it is assumed that the initial electricity demand and price in the model are constant. However, according to [17–20], these parameters are uncertain in DRP;
- Some studies, such as [13–15], used a random model to examine the uncertainty parameter in the proposed problem. However, this model requires a large number of scenarios and sufficient knowledge about Probability Density Function (PDF) to obtain the appropriate answer. Therefore, their approach is complicated, and the solving method will be difficult [16];
- Some studies, such as [13–18], established different frameworks to examine the uncertainty features including fuzzy optimization, scenario-based, and robust optimization. These methods depend on the historical data related to the uncertain variables; in case these data are incorrect or not available, the made decisions are not reliable. However, the most important advantage of the IGDT is that it can be implemented with the least available information about the uncertain parameters. In addition, if the number of scenarios increases in these methods, the computational load of the problem will increase, as well. In addition, the robust optimization is involved with the two-level optimization which is usually difficult to solve; however, a definite framework is considered in the IGDT that can reduce the burden and time of the calculations. In addition, the IGDT technique is also able to investigate extreme uncertainty in the DRP issues.

The proposed model in this paper is developed, considering the reviewed points in Table 1. Although various aspects of the DRPs from the RMM's perspective have been explored in the studies given in Table 1, DRPs' interactions with the RMM have not been modeled in detail yet due to some factors such as reserve settlement and price uncertainty in a day-ahead market, for instance. In this paper, the upstream market is considered price-maker for electrical energy.

During the peak hours, the RMM decides to invoke the EDRP in case of high electricity price and probability of insufficient reliability. It is assumed that customers participate in the EDRP through their agents, i.e., the AGGs. These AGGs communicate with the customers or electricity end-users and inform the RMMs the extent to which they will participate in the

EDRP according to the received incentive amounts. It is assumed that the RMMs seek to maximize their profits by considering these offers, electricity demand, network technical constraints, and energy prices. To model the price uncertainty, the IGDT approach is selected where the RMM decisions to trade energy with the AGGs depend on the level of the RMM price risk. 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 why a logarithmic model was chosen is because the previous studies, i.e., [25], had confirmed the success of this model in providing more conservative responses than values of this model are better than other models. In addition, the Co-evolutionary Improved Teaching Learning-Based Optimization (C-ITLBO) algorithm was used to determine the optimal incentive and demand for the RMM's profit maximization. The problem related to the above points is solved in a 24-hour period.

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

1. Defining a new objective function to calculate the RMM's profit in the presence of the EDRP, incorporating the price uncertainty in a day-ahead market environment;

2. Presenting a new formulation applied by the RMM to prioritize the reservation offered by the AGGs;

3. Proposing a robust strategy obtained from the robustness function of IGDT approach;

4. Developing an opportunistic strategy obtained from the opportunity function of the IGDT approach.

The rest of the study is organized as the following: Section 2 describes the deterministic model of the proposed problem. Section 3 elaborates the proposed algorithm and its implementation in problem solution and describes the IGDT technique to address the uncertainty of the electricity prices in the considered problem. Section 4 presents the simulation results. Finally, Section 4 concludes the study.

2. Original deterministic problem model

In this section, in addition to describing the problem formulation from the RMM point of view, the EDRP model and reserve margin factors are also explained.

2.1. Objective function

In the proposed model, the objective function of an optimization problem is related to determining the purchased demand and received incentives in such a way that the RMM's profit is maximized during the studied periods according to Eq. (1) shown in Box I, where, sentence 1 refers to the revenues received by the RMM including the electricity sales to the AGGs, and sentences 2 and 3 refer to the costs paid by the RMM including the cost incurred by electricity purchase from the upstream market and payment to the AGGs based on the EDRP contract. In the mentioned equation, formulation of the third sentence is in accordance with Ref. [26]. Here, the EDRP contract means paying the RMM to the AGGs to reduce the load during peak hours to implement the EDRP. The relation between the applied factors is assumed to be $\omega_i + \omega_C = 1$, $0 \leq \omega_i \leq 1$, and $0 \leq \omega_C \leq 1$, meaning that the RMM can create a trade-off between ω_i and ω_C.

2.2. Constraints

2.2.1. Incentive limit

The payable incentive for the EDRP is assumed to be in the following range:

$$inc_{\min}(t_i) \leq inc(t_i) \leq inc_{\max}(t_i) \quad \forall t_i \in \varphi_T. \tag{2}$$

This range is applied to the incentive provided by the RMM to the AGGs. The upper and lower limits are considered to be $10 \times \rho_0(t_i)$ and $0.1 \times \rho_0(t_i)$, respectively [4].

2.2.2. Demand limits

According to Eq. (3), the incentive provided by the RMM should not exceed the upper and lower limits of the daily load demand [18]:

$$\min\sum_{k=1}^{n} d^0(k,t_i) \leq d(t_i) \leq \max\sum_{k=1}^{n} d^0(k,t_i) \qquad \forall t_i \in \varphi_T. \tag{3}$$

$$TOF = \text{Max}\left\{ W_i \times \left[\frac{\sum\limits_{t_i \in \varphi_T} \left(\sum_{k=1}^{n} (\rho A(t_i) \times d(k,t_i))\right)}{1}\right] - W_c \times \left[\frac{\sum\limits_{t_i \in \varphi_T} \left(\rho U(t_i) \times P_{grid}(t_i)\right)}{2}\right.\right.$$
$$\left.\left. + \left[\frac{\sum\limits_{t_i \in \varphi_{Peak}} \left(inc(t_i) \times (d^0(k,t_i) - d(k,t_i))\right)}{3}\right]\right]\right\}. \tag{1}$$

Box I

2.2.3. Power purchased

It is assumed that the power purchased by the RMM is in the following range [26]:

$$P_{grid}^{\min} \leq P_{grid}(t_i) \leq P_{grid}^{\max} \quad \forall t_i \in \varphi_T. \tag{4}$$

It should be noted that this limitation represents the exchangeable power between the RMM and upstream grid.

2.2.4. Power balance constraint

The following equation shows the power balance constraint:

$$P_{grid}(t_i) = d(t_i) + P_L(t_i) \quad \forall t_i \in \varphi_T. \tag{5}$$

The mathematical expression of power transmission loss between the power purchased and customers can be obtained based on the following formula [26]:

$$P_L(t_i) = B_0 \times P_{grid}(t_i) \quad \forall t_i \in \varphi_T. \tag{6}$$

2.3. EDRP model

In this study, the optimal incentive rate and optimal demand rate for the EDRP at the peak hours are determined through 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 based on the model mentioned in Eq. (5), considering the incentive rate and participation factors (PF_1, PF_2, etc.) of the AGGs. Since there is a competition among the AGGs to receive the incentive payments, it is assumed that the AGGs are prioritized based on a factor of reserve margin according to their provided reserve. This factor is related to the reserve provided due to participation of the AGGs in the EDRP. Therefore, based on the logarithmic model [26], the EDRP model for AGG_k can be written as:

$$d(k,t_i) = d^0(k,t_i) \times \left\{1 + PF_k \times \sum_{t=1}^{24} E(t_i,t_j) \times \text{Ln}\left(\frac{(\rho(t_j) + inc(t_j))}{\rho_0(t_j)}\right)\right\} \quad \forall t_i \in \varphi_T. \tag{7}$$

2.4. Reserve margin factors

Based on the above-mentioned model, Eqs. (1)–(7) calculate the amount of the provided reserve in a peak-load hour by each of the AGGs participating in the EDRP and announce the obtained number to the RMM. The provided reserve amounts were prioritized in this study based on the reserve margin factors that can be defined as the following:

$$RMF(k,t_i) = \begin{cases} \frac{R(k,t_i) \times RSP(k) \times RV(t_i)}{MAR(t_i)} & \forall t_i \in \varphi_{Peak} \\ 0 & \forall t_i \in \varphi_T - \varphi_{Peak} \end{cases} \tag{8}$$

where:

$$R(k,t_i) = \begin{cases} d^0(k,t_i) - d(k,t_i) & \forall t_i \in \varphi_{Peak} \\ 0 & \forall t_i \in \varphi_T - \varphi_{Peak} \end{cases} \tag{9}$$

$$RSP(k) = \sum_{t=1}^{24} RV(t_i) PR(k,t_i) \; \forall t_i \in \varphi_{Peak} \tag{10}$$

$$RV(t_i) = \begin{cases} RV_{new} = RV_{old} - \left(\frac{d_{old} - d_{new}}{\sum_{k \in PeakLoadHours} d(k,t_i) - d_{avg}^0(t_i)}\right) \\ \qquad \forall t_{(i)} \in \varphi_{Peak} \\ 0 \qquad \forall t_{(i)} \in \varphi_T - \varphi_{Peak} \end{cases} \tag{11}$$

$$MAR(t_i) = \begin{cases} \sum_{k=1}^{n} d^0(k,t_i) - d(t_i) & \forall t_i \in \varphi_{peak} \\ 0 & \forall t_i \in \varphi_T - \varphi_{peak} \end{cases} \tag{12}$$

Therefore, the relations of $RV(t_i)$ and $R(k,t_i)$ are expressed based on Refs. [21] and [24], respectively. According to Eq. (11), the highest demand indicates the highest reserve value, which is equal to 1. Upon decreasing the demands from the highest to the lowest value, the reserve value decreases from one to zero. In case the AGG offers the reserve at hour t_i and this period belongs to the peak hours, $PR(k,t_i)$ is equal to 1; otherwise, it is equal to zero. In this regard, based on Eq. (11), the AGG with a greater RMF is given higher priority for providing the reserve at t_i hour. If $MAR(t_i)$ from Eq. (12) 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 until the MAR is achieved.

3. Proposed method and implementation process

This part includes three subsections: An overview of C-ITLBO in Subsection 3.1; uncertainty analysis based on IGDT in Subsection 3.2, and implementation steps in Subsection 3.3.

3.1. Overview of C-ITLBO

As mentioned earlier, the current study uses the C-ITLBO algorithm in conjunction with Genetic Algorithm (GA) operators, i.e., crossover and mutation. In order not to be trapped in local optima, an improvement phase was added to the Co-evolutionary Teaching Learning-Based Optimization (C-TLBO) to enhance its performance. Here, group means a number of students in a classroom who are trying to learn a lesson together. Then, a specific vector was used to denote each one of the students. The C-ITLBO algorithm is elaborated in the following. During the teacher phase of the algorithm, a student who is more knowledgeable and well informed plays the role of the teacher and tries to increase the classroom knowledge level by teaching other students. In other words, when there is a student who is more qualified than the previous one, the previous one (teacher) is substituted. Eq. (13) expresses the formulation of how a new student or teacher, i.e., S_{new}, is generated from the previous student (S_{old}) [27]:

$$S_{new} = S_{old} + m \times (T - T_F \times \bar{S}_{old}). \tag{13}$$

The relationship for T_F is given as the following:

$$T_F = round[1 + rand(0,1)]. \tag{14}$$

At the student phase of the algorithm, students acquire knowledge based on the quality of the instruction provided by the teacher as well as the status of the students in the classroom. In 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}) than the others, a new student will be generated using Eq. (15) and be substituted with the one with lower quality [27]:

$$S_{new} = S_{worse} + r \times (S_{better} - S_{worse}). \tag{15}$$

There are accordingly six main steps in this algorithm: 1) initialization, 2) competition, 3) teacher phase, 4) student phase, 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. Here, $\mathrm{P_A}$ and $\mathrm{P_B}$ represent these groups. Then, the other three steps (steps 2–4) are repeated and once the termination criterion is met, the algorithm stops. In order to consider the competitiveness, a competition is carried out among the students of both groups, and the student with the highest level of competitiveness in each group is chosen to be the teacher.

Therefore, $\mathrm{T_A}$ is the teacher of the group or class A and $\mathrm{T_B}$ is the teacher of class B. In step 5, followed by applying 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 improve its convergence, the GA operators are applied. The GA operators allow students to compete with each other in acquiring knowledge and becoming a teacher. At the improvement phase (step 6), the students' knowledge level is elevated based on the technique of self-adaptive mutation. Given that students usually move in the direction of the teacher in the C-TLBO, there is a chance that they will be trapped in the local optimum points, which will lead to the reduction of convergence rate. Accordingly, each student moves randomly towards the teacher or the worst student at the improved phase. If this number is less likely to be mutated, the student will perform the mutation; otherwise, he/she will not perform. The mutation can be described as:

$$S_{new} = \begin{cases} S_{old} + \omega(T - S_{old}) & \text{if } \omega > 0 \\ S_{old} + \omega(W - S_{old}) & \text{if } \omega \leq 0 \end{cases} \tag{16}$$

The parameter ω is applied as shown below:

$$\omega = \frac{1}{\sqrt{h}} exp\left[-\left(\frac{1}{2}\right)\left(\frac{\varphi}{h}\right)^2 \cos\left(\omega_d\left(\frac{\varphi}{h}\right)\right)\right], \tag{17}$$

where ω_d is selected as a probability number from 0 to 1. In case ω value is positive, the student moves towards the teacher; otherwise, the student moves to the opposite side. Given that 99% of the total energy of the central frequency of the wavelet is located between $[-2.5,\ 2.5]$, the parameter φ is randomly chosen taking a value between $[-2.5h,\ +2.5h]$. In this equation, h is the dilatation factor, which varies at each iteration, as shown below:

$$h = exp\left[-\ln(\eta) \times (1 - \frac{L}{L_{\max}})^{\sigma} + \ln(\eta)\right]. \tag{18}$$

The upper limit as well as the shape of h are defined by two parameters of η and σ. In this study, the value of η is considered equal to 2, and the value of σ is obtained from the following equation:

$$\sigma = \sigma_{\min} + \left(\frac{\sigma_{\max} - \sigma_{\min}}{2.5}\right), \tag{19}$$

where $\sigma_{\min}$ and $\sigma_{\max}$ are 1 and 3, respectively.

3.2. Uncertainty analysis based on IGDT

The definite model of the considered problem is comprised of Eqs. (1)–(12) through which the objective function is formed to determine the optimal values of the price of and demand for the purchased power in terms of the above constraints. The reserve provided by the AGGs is then prioritized using the RMF. Given that the price is an uncertain parameter, IGDT is used to address this uncertainty. The IGDT uses the opportunity and robustness functions to determine the risk-seeking and risk-averse levels in the considered problem. In other words, followed by determining the value of the objective function of the abovementioned definite model, the minimum and maximum limits of the value that the objective function is allowed to change are determined by the opportunity and robustness functions, respectively [28]. The IGDT consists of three parts namely the system modeling, operating requirements, and uncertainty modeling.

3.2.1. System modeling

The system modeling requires a system of input/output structure. The system model used in this paper is the TOF which is used for evaluating the system response. In other words, the objective function in Eq. (1) represents the system model. In this model, $d(k,t_i)$,$inc(t_i)$, and $P_{grid}(t_i)$ are the decision variables, and $\rho_U(t_i)$ is the uncertainty variable.

3.2.2. Uncertainty modeling

Through the IGDT method, uncertainty can be expressed in different ways [28]. Here, a limited pocket model [29] is used where the value of deviation is proportional to the known value of the uncertainty parameter. Thus, the relation of the uncertainty parameter in the finite packet model at time t_i is expressed in Eq. (20):

$$U(\alpha,\tilde{P}_U(t_i)) = \left\{\bar{P}_U(t) : \frac{|\bar{P}_U(t_i)-\tilde{P}_U(t_i)|}{\tilde{P}_U(t_i)} \leq \alpha\right\}$$

$$\alpha \geq 0. \tag{20}$$

In IGDT, α must be determined such that the value of the objective function will not exceed a certain level compared to the base value.

3.2.3. Operating requirements

In this section, the operating requirements of the studied system are presented in the form of two objective functions. These operating requirements may lead to higher or lower TOF. Operating requirements are evaluated based on the robustness and the opportunity functions and these two functions must be set for the current problem. In addition, for the TOF, these functions are introduced in the followings:

$$\hat{\alpha}(TOF_r) = \underset{\alpha}{\mathrm{Max}}\left\{\alpha : \mathrm{Min}(TOF) \leq TOF_r\right\}, \tag{21}$$

$$\hat{\beta}(TOF_O) = \underset{\alpha}{\mathrm{Min}}\left\{\alpha : \mathrm{Min}(TOF) \leq TOF_O\right\}. \tag{22}$$

Based on the risk-seeking and risk-averse strategies, two different operations of the objective function can be defined in an IGDT model. A risk-averse decision-maker tends to plan to tolerate the adverse deviations of the uncertainty parameter. In the IGDT method, immunity against such adverse deviations is modeled using the robustness function. In this regard, $\hat{\alpha}(TOF_r)$ exhibits resistance to the rise of the electricity prices, hence being more valuable than the desired $\hat{\alpha}(TOF_r)$. It should be noted that the total objective function in this function is more than that in a predefined TOF. Conversely, a risk-seeking decision-maker wants to take advantage of the desired deviations of the uncertainty from the expected value. The information gap method uses the opportunity function to model these potential benefits from the viewpoint of a risk-seeking decision-maker. The maximum value of $\hat{\beta}(TOF_O)$ is 1, which provides the minimum estimate of the total objective function. Therefore, smaller values of $\hat{\beta}(TOF_O)$ are desirable. It should also be noted that the total objective function in this function is less than that in a pre-defined TOF. Moreover, TOF_r is greater than TOF_O in the above equation.

Robustness function

The robustness function can be modeled by considering the risk-averse strategy of the negative aspect of the uncertainty where it is attempted to be immune against the maximum degree of the price fluctuations. The robustness IGDT function can be expressed as follows [30]:

$$\hat{\alpha}(TOF_r) = max\left\{\alpha : \max_{l\in U(\alpha,\tilde{P}_U(t))} TOF \right.$$

$$\left. \leq TOF_r = (1+\mu)TOF_b\right\}. \tag{23}$$

The value of the robustness function is obtained by maximizing α based on the equation given below:

$$\hat{\alpha}(TOF_r) = \max \alpha, \tag{24}$$

subject to:

$$\hat{\alpha}(TOF_r) = \mathrm{Max}[Eq(1)] \leq TOF_r, \tag{25}$$

$$(1-\alpha)\tilde{P}_U(t_i) \leq \bar{P}_U(t_i) \leq (1+\alpha)\tilde{P}_U(t_i), \tag{26}$$

$$\text{Eqs. } (2)-(12). \tag{27}$$

Since the maximum increase in the uncertainty parameters $\bar{P}_U(t_i) = (1+\alpha)\tilde{P}_U(t_i)$ is obtained in the robustness function, the robustness function can be formulated as:

$$\hat{\alpha}(TOF_r) = \max\ \alpha, \tag{28}$$

Subject to:

$$\hat{\alpha}(TOF_r) = \mathrm{Max}[Eq(1)] \leq (1+\mu)TOF_b, \tag{29}$$

$$\bar{P}_U(t_i) = (1+\alpha)\tilde{P}_U(t_i), \tag{30}$$

$$\text{Eqs. } (2)-(12). \tag{31}$$

Opportunity function

Any reduction in uncertainty will be beneficial for the RMM so that the positive effects of uncertainty are modeled using the opportunity function. In addition, the related IGDT opportunity function can be expressed as [30]:

$$\hat{\beta}(TOF_O) = \min\left\{\alpha : \min_{l\in U(\alpha,\tilde{P}_U(t))} TOF \right.$$

$$\left. \leq TOF_O = (1-\gamma)TOF_b\right\}. \tag{32}$$

The opportunity function value can be obtained by minimizing α as shown below:

$$\hat{\beta}(TOF_O) = \min\alpha, \tag{33}$$

Subject to:

$$\hat{\beta}(TOF_O) = \mathrm{Min}[Eq(1)] \leq TOF_O, \tag{34}$$

$$(1-\alpha)\tilde{P}_U(t_i) \leq \bar{P}_U(t_i) \leq (1+\alpha)\tilde{P}_U(t_i), \tag{35}$$

$$\text{Eqs. } (2) - (12). \tag{36}$$

Since the minimum reduction in the uncertain parameters $\bar{P}_U(t_i) = (1-\alpha)\tilde{P}_U(t_i)$ is obtained in the opportunity function, the opportunity function can be formulated as:

$$\hat{\beta}(TOF_O) = \min\ \alpha, \tag{37}$$

Subject to:

$$\hat{\beta}(TOF_O) = \mathrm{Min}[Eq(1)] \leq (1-\gamma)TOF_b, \tag{38}$$

$$\bar{P}_U(t_i) = (1-\alpha)\tilde{P}_U(t_i), \tag{39}$$

$$\text{Eqs. } (2) - (12). \tag{40}$$

3.3. The implementation steps

According to the flowchart shown in Figure 1, the implementation steps of the proposed method are as follows:

Step 1: Enter the initial information, related algorithm, optimization functions and constraints, and required parameters of the formulations for the RMM $t_i = 1$, $\alpha = 0$, $\mu = 0.07$, $\gamma = 0.09$, and so on.

Step 2: If $\alpha = 0$, go to Step 6 and maximize the proposed profit function of the RMM in Eq. (1) according to the constraints in Eqs. (2)–(6), where the RMM's profit is determined without IGDT, TOF_b.

Step 3: If the RMM is looking for a risk-taking or risk-aversion strategy for the uncertainty parameter of the electricity price, the applied IGDT-based robustness and applied IGDT-based opportunity optimizations should be selected, respectively.

Step 4: If the α iteration is not higher than its upper limit, go to Step 5; otherwise, set the best value for the RMM's profit for the robustness optimization and opportunity optimization based on Eqs. (29) and (38), respectively. Then, finish the process.

Step 5: For the robustness optimization, substitute Eq. (30) with $\rho_U(t_i)$ and for the opportunity optimization, replace Eq. (39) with $\rho_U(t_i)$. Then, go to Step 6.

Step 6: If the iteration is not greater than its upper limit, go to step 8; otherwise, report the best values and save the best demand, power purchased, and $inc(t_i)$, the RMM daily objective function.

Step 7: Prioritize the AGGs from the perspective of the power reserve during peak-load hours by Eqs. (8)–(12). Next, $a + 0.05$ returns to Step 3;

Step 8: If t_i is the peak load hours, the inc is determined by $inc = inc_{\min} + (inc_{\max} - inc_{\min}) \times randx([0 \quad 1])$ using Constraint Eq. (2); otherwise, $inc(t_i) = 0$ and go to Step 9.

Step 9: The amount of 24-hour demand for the AGGs in the EDRP program is determined via Eq. (7).

Step 10: The RMM daily objective function is solved based on Eq. (1), considering the constraints given in Eqs. (3)–(6);

Step 11: If the RMM daily objective function is more than its previous value, save the best demand, $inc(t_i)$, reserve prioritization, and RMM daily objective function. Then, consider the next iteration or $It + 1$ and return to Step 6.

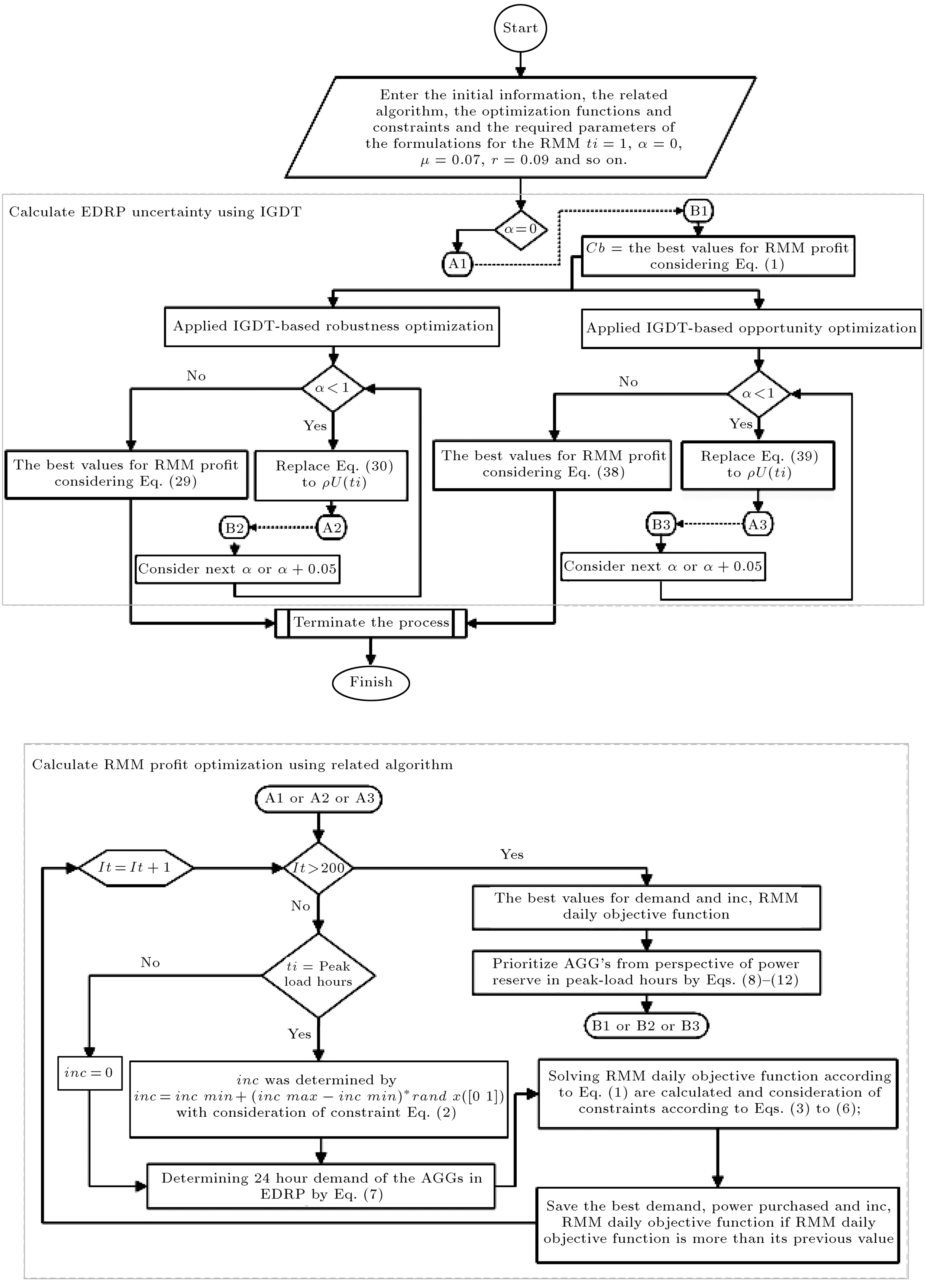
4. Results and Discussion

The effectiveness and feasibility of the proposed method are illustrated in nine different scenarios. The assumptions are listed in Section 4.1, and the results of the proposed method are presented and evaluated in Section 4.2.

4.1. Assumptions

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

- Five AGGs are considered with the initial demands according to Table A.1 in the Appendix and the participation factors $PF_1 = 21\%$, $PF_2 = 23\%$, $PF_3 = 24\%$, $PF_4 = 22\%$, and $PF_5 = 24\%$, respectively.
- Daily load curve in the considered region and parameters of Price Elasticity Matrix (PEM) are depicted in accordance with Figure A.1 and Table A.2 in the Appendix.
- In the load curve, the low-load hours range from 24:00 to 9:00; the middle-load hours from 10:00, 11:00, 17:00 to 19:00 plus 23; and the peak-load hours from 12:00 to 16:00 and from 20:00 to 22:00.
- The initial value of α is 0 and it increases up to $\alpha + 0.05$ at each iteration.
- The prices of electricity sold to the AGGs before and after the implementation of the EDRP for the low-load, middle-load, and peak-load periods are 14, 17, and 20 \$/MWh, respectively. These prices were obtained on conditions that the AGGs would be encouraged to change their consumption patterns only by using incentive payments rather than changing the electricity prices. In other words,



RMM: Regional Market Manager; inc: incentive; AGG's: Aggregators; EDRP: Emergency Demand Response Program; IGDT: Information-Gap Decision Theory

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

Table 2. Studied scenarios.

Scenario	Case study	PEM	Uncertainty model	Sensitivity analysis	Optimization		
					Power transmission loss	EDRP model	Algorithm
S1	First	0	×	×	✓	×	×
S2	Second	E	×	✓	✓	Logarithmic	C-ITLBO
S3	Third	E	×	×	✓	Logarithmic	C-PSO [14]
S4		E	×	×	✓	Logarithmic	C-TLBO [27]
S5		E	×	×	✓	Logarithmic	C-ITLBO
S6	Fourth	E	×	×	×	Logarithmic	C-ITLBO
S7	Fifth	0.5*E	×	×	✓	Logarithmic	C-ITLBO
S8	Sixth	E	IGDT (Robustness)	×	✓	Logarithmic	C-ITLBO
S9		E	IGDT (Opportunity)	×	✓	Logarithmic	C-ITLBO

Note: EDRP: Emergency Demand Response Program; IGDT: Information-Gap Decision Theory;
C-PSO: Co-evolutionary Particle Swarm Optimization; C-TLBO: Co-evolutionary Teaching Learning-Based Optimization;
and C-ITLBO: Co-evolutionary Improved Teaching Learning-Based Optimization

there is no change in the electricity prices before and after the EDRP program.

- Assuming that the percentage of the RMM's share of revenue obtained from purchasing energy from upstream market and selling it to the AGGs is 5%, the market price electricity relation for $\rho_A(t_i)$ can be expressed as $\rho_A(t_i) = 0.95\times\rho_U(t_i)$. This assumption was to motivate the RMM to manage energy in the regional market.
- The simulation time interval is 24 hours.
- For the Co-evolutionary Particle Swarm Optimization (C-PSO), C-TLBO, and C-ITLBO algorithms, the number of iterations is limited to 200; the size of the population is 100; and there are eight scenarios, as shown in Table 2.

4.2. Results of the proposed method

In this section, the results of evaluating the proposed model are investigated with the aim of maximizing the RMM's profit for 24 hours. In order to describe the EDRP in a market area from the RMM's viewpoints, six case studies were conducted according to Table 2. Case 1 is the model proposed according to Scenario S1, which is devoid of the EDRP. Case 2 considers implementation of the sensitivity analysis in the proposed model according to Scenario S2. Case 3 shows the implementation of the proposed model by applying the C-PSO, C-TLBO, and C-ITLBO algorithms in accordance with Scenarios S3 to S5. Implementation of the proposed model without power transmission loss in accordance with Scenario S6 is presented in Case 4. Case 5 presents implementation of the proposed model, where the PEM is halved in accordance with Scenario S7. Case 6 includes price uncertainty in the proposed model by the IGDT model in accordance with Scenarios S8 and S9. Figures 2–7 and Tables 3–6 present the evaluation results of the above-mentioned paragraphs.

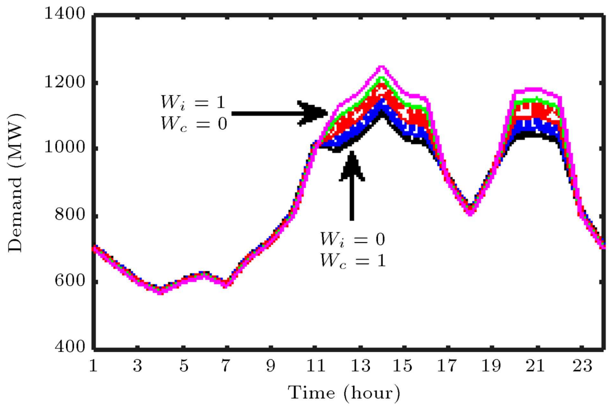


Figure 2. Sensitivity of the daily load curve to the weighting factors.

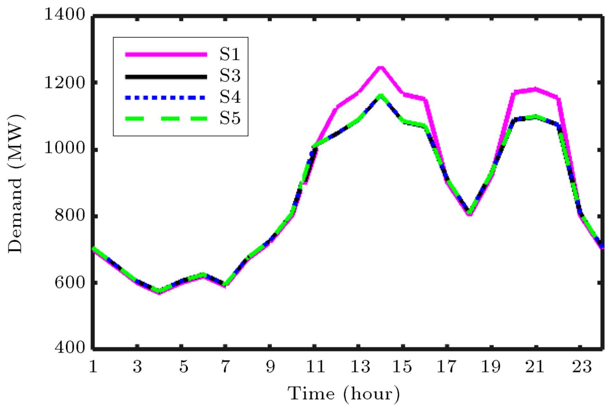


Figure 3. The effect of the EDRP on the daily load curve.

4.2.1. Case study 1: Base case

This case study includes Scenario S1 where the effects of non-implementation of the EDRP in the day-ahead

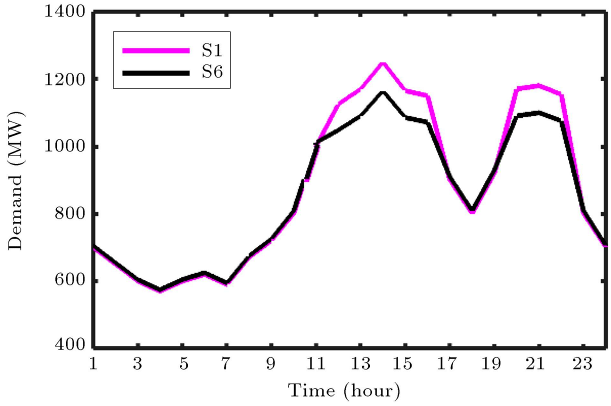


Figure 4. Daily load curve in Case 4.

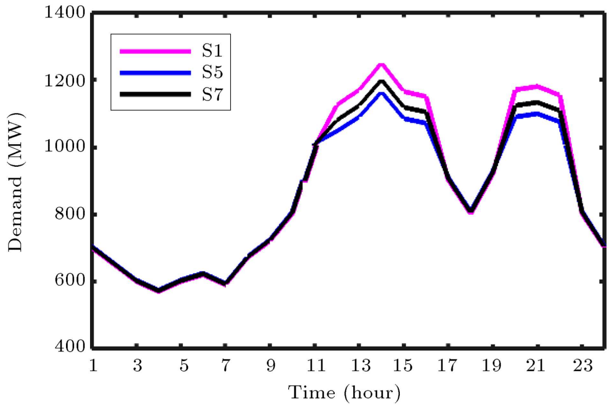


Figure 5. Daily load curve in Case 5.

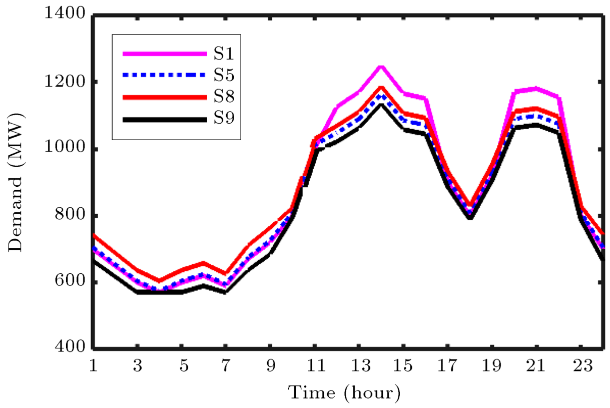


Figure 6. Daily load curve result of Case 6.

market are evaluated. The values of W_i and W_C are equal to 0.6 and 0.4, respectively, and no optimization algorithm is applied in this case study. The reason for choosing the mentioned values for weighting factors is the outcome of the second case study. Scenario S1 indicates the base case in relation with the actual load curve of Figure 2 where the EDRP was not implemented, and there is no incentive for the AGGs. According to Table 6, the lowest amount of the RMM TOF, the lowest incentive rate, and the lowest reserve-used rate among the scenarios can be observed in

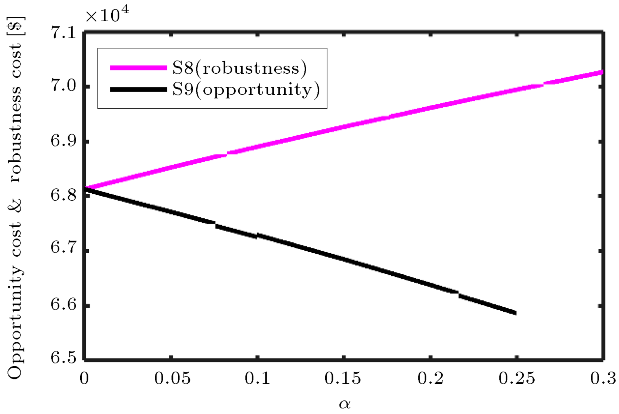


Figure 7. Robust and opportunity functions of the RMM's profit.

Table 3. Evaluation of the sensitivity of the TOF and incentive rate to the weighting factors.

No.	W_i	W_c	TOF	incentive
1	0	1	–367747.20	18.02
2	0.1	0.9	–294403.57	16.15
3	0.2	0.8	–222299.47	15.39
4	0.3	0.7	–150090.73	14.44
5	0.4	0.6	–77925.76	13.49
6	0.5	0.5	–5084.94	11.59
7	0.6	0.4	68124.20	9.17
8	0.7	0.3	141290.11	7.14
9	0.8	0.2	215003.85	4.96
10	0.9	0.1	289065.26	3.15
11	1	0	365900	0

Note: TOF: Total Objective Function

Scenario S1. This shows that for the RMM, EDRP in each scenario favors its non-implementation.

4.2.2. Case study 2: Sensitivity analysis of TOF weighting factors

This case study includes Scenario S2 where the effects of the weighting factors, i.e., W_i and W_C, on the TOF and incentive rate are investigated on the basis of the C-ITLBO algorithm. For this purpose, weight factors are changed according to Table 3, and the TOF and incentive rate sensitivities are calculated. It is observed that upon increasing W_C, the RMM cost functions in the EDRP program become more sensitive than usual. The incentive rate also increases and, consequently, the AGGs are more willing to participate in the EDRP program; however, the RMM's profit decreases. In case the W_i increases, the RMM revenue function shows higher sensitivity and as a result, the RMM's profit increases. In addition, changes in the load demand relative to the weighting factors are plotted in Figure 2.

Table 4. The reserve used by the AGGs in different scenarios during peak hours.

Scenario	AGG1 (MW)	AGG2 (MW)	AGG3 (MW)	AGG4 (MW)	AGG5 (MW)
S1	0	0	0	0	0
S3	128.526	125.778	143.715	123.014	134.788
S4	127.424	124.699	142.482	121.960	133.632
S5	126.318	123.617	141.246	120.901	132.473
S6	125.209	122.532	140.006	119.840	131.309
S7	73.3624	71.7938	82.0320	70.2164	76.9366
S8	92.4160	90.4400	103.337	88.4529	96.9184
S9	169.170	165.553	189.162	161.916	177.412

Note: AGG: Aggregator

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

Scenario	AGG1 ($)	AGG2 ($)	AGG3 ($)	AGG4 ($)	AGG5 ($)
S1	0	0	0	0	0
S3	1179.5	1154.3	1318.9	1128.9	1237
S4	1169.4	1144.4	1307.6	1119.2	1226.3
S5	1159.2	1134.4	1296.2	1109.5	1215.7
S6	1137	1112.6	1271.3	1088.2	1192.3
S7	807.89	790.620	903.36	773.25	847.25
S8	1102.5	1079	1232.8	1055.3	1156.2
S9	1164.4	1139.5	1302	1114.4	1221.1

Note: AGG: Aggregator

Table 6. The rate of Incentive, reserve used and TOF RMM in different scenarios.

Scenari #	Incentive ($/MWh)	Reserve used (MW)	TOF RMM ($)
S1	0	0	65381.93
S3	9.3702	655.8227	67995.40
S4	9.2736	650.1998	68060.96
S5	9.1770	644.5583	68126.22
S6	9.0804	638.8981	75741.95
S7	11.0124	374.3410	69773.73
S8	11.9301	471.5646	70266.63
S9	6.8827	863.2158	65898.31

Note: TOF: Total Objective Function; and RMM: Regional Market Manager

It can be observed that upon increasing W_C, the peak load of the demand curve is reduced. However, increasing W_i results in an increase in the peak load. Based on the results obtained in Figure 2 and Table 3, it can be concluded that the best values for the TOF weighting factors (W_i and W_C) can be considered as 0.6 and 0.4, respectively, in order for the RMM to simultaneously achieve higher profit and lower peak load of the demand curve (with consideration of the constraints of upstream grid and power generation).

4.2.3. Case study 3: Evaluation of different algorithms

This case study includes Scenarios S3-S5 in which the effects of the EDRP on the optimal amount of the incentive rate, power purchased, and demand are investigated, considering the technical constraints in the day-ahead market. The values of W_i and W_C are equal to 0.6 and 0.4, respectively, and the value of the PEM is E. This case study also employs C-PSO, C-TLBO, and C-ITLBO algorithms. It should be noted that the reason for choosing these values for weighting factors is the outcome of the second case study. In this case study, the assumed lowest reserve and incentive payments to the AGGs correspond to Scenario S5 (using the C-ITLBO algorithm) in accordance with the amounts, as shown in Tables 4 and 5. According to Table 6, most of the TOF RMMs, the lowest incentive rate and the lowest reserve are obtained in Scenario S5 which are 68126.22 \$, 9.177 \$/MWh, and 644.55 MW, respectively. Moreover, as shown in Figure 3, the reduction of the peak demand in Scenarios S3 to S5 is approximately equal. Considering the results of Figure 3 and Tables 4–6, in this case study, it can be concluded that the C-ITLBO algorithm is more accurate than the C-PSO and C-TLBO algorithms.

4.2.4. Case study 4: Ignoring the line losses

This case study includes Scenario S6, in which the effects of the EDRP on the optimal incentive rate, power purchased, and demand are investigated by considering technical constraints except the transmission line losses in the day-ahead market. W_i and the W_C are equal to 0.6 and 0.4, respectively, the value of the PEM is E, and C-ITLBO algorithm is applied in this case study. The reason for choosing the C-ITLBO algorithm is that it has been found to be more accurate than the C-PSO and C-TLBO algorithms in the third case study. Compared to Scenario S5, in this scenario, the reserve used and the incentive payments to the AGGs decreased in accordance with the amounts shown in Tables 4 and 5. Table 6 shows the increase of the TOF RMM, the reduction of the incentive rate, as well as the reduction of the reserve rate in Scenario S6, which are 75741.95 \$, 9.0804 \$/MWh, and 638.8981 MW, respectively. Also, Figure 4 shows the reduction of the peak-load curve peak due to the EDRP execution while ignoring the transmission line losses. If line losses are not ignored, the RMM will not need to purchase more power to compensate for the losses. In this situation, the upstream network has a greater backup capacity and the RMM incentive to run the EDRP program is attenuated; as a result, the RMM receives more profit by ignoring line losses.

4.2.5. Case study 5: Variation in price elasticity matrix

This case study includes Scenario S7, in which the effects of the EDRP on the optimal incentive rate, power purchased, and demand are investigated while considering all technical constraints in the day-ahead market. W_i and W_C are equal to 0.6 and 0.4, respectively, the value of the PEM is changed as $0.5\times E$, and C-ITLBO algorithm is applied. Compared to Scenario S5, in Scenario S7, the reserve used and the incentive payments to the AGGs are reduced according to the amounts shown in Tables 4 and 5. Table 6 shows that by increasing TOF of the RMM, the incentive rate increases and the reserve used rate decreases, as obtained in Scenario S7. In this regard, the related values are 69773.73 \$, 11.0124 \$/MWh, and 374.34 MW, respectively. Also, Figure 5 shows the peak-load curve compared to Scenario S5 when the PEM is halved. Considering Figure 5 and Tables 4–6, it can be concluded that if the RMM prefers lower participation of the AGGs in the EDRP, the PEM should be decreased. When the PEM is halved, the AGGs' participation in the EDRP program is reduced compared to that in Scenario S5. In other words, as PEM decreases, the sensitivity of the loads of the AGGs to the incentives in the EDRP program decreases, as well. As a result, the RMM should increase the incentive rate to consider this higher sensitivity. However, in general and according to Tables 4 to 6, despite the increase of the incentive rate, the tendency of the AGGs to participate in the EDRP program is reduced compared to Scenario S5, resulting in fewer incentives for the AGGs.

4.2.6. Case study 6: Evaluating the effects of the IGDT in the considered issue

This case study includes Scenarios S8 and S9, in which the effects the uncertainties (electricity price) in case of using the IGDT in the EDRP program on the optimal incentive rate, power purchased, and demand are investigated while considering technical constraints in the day-ahead market. W_i and the W_C are equal to 0.6 and 0.4, respectively, the value of the PEM is E, and C-ITLBO algorithm is applied in this case study. The risk-averse strategy is used for determining the maximum resistance against the rising of the electricity price by TOF_r, that is, the worst situation of the uncertainty parameter (electricity price) for the maximum profit that the RMM can obtain for finding the optimal incentive rate, power purchased, and demand, as shown in Figure 6. In this figure, the consumer demand is plotted for the optimal $a = 0.3$. Compared to Scenarios S3 and S5, this figure shows that when the primary price of electricity increases and yet, the price remains the same after EDRP, the load demand over peak hours increases and the load curve tends not to be smoother. Moreover, the reserve used and the incentive payments to the AGGs will decrease in accordance with the amounts shown in Tables 4 and 5. According to Table 6, by increasing the TOF of the RMM, the incentive rate increases, but the reserve-used rate decreases, which are 70266.63 \$, 11.9301 \$/MWh, and 471.5646 MW, respectively, as obtained in Scenario S8. The risk-aversion strategy is used for determining the minimum resistance against the lowering of the electricity price by the TOF_O, which translates into the best situation of the uncertainty parameter (electricity price) for the minimum profit that the RMM can obtain for finding the optimal incentive rate, the power purchased, and demand, as shown in Figure 6. In this figure, the consumer demand is plotted for the optimal $a = 0.25$. As shown in this figure, when the primary price of electricity decreases but the price remains the same after EDRP compared to Scenario S5, the load demand over peak hours decreases and the load curve tends to be smoother compared to Scenario S3. Moreover, the reserve used and incentive payments to the AGGs will increase according to the amounts shown in Tables 4 and 5. According to Table 6, by decreasing TOF of the RMM, the incentive rate decreases as well but the reserve-used rate increases, which are 65898.31 \$, 6.8827 \$/MWh, and 863.2158 MW, respectively, as obtained in Scenario S8. Figure 7 shows the ratio of the alpha to the TOF_r. As indicated, by choosing a higher power price than the one in Scenario S3 (neutral power price), the RMM leads to greater TOF_r. If the RMM chooses a higher primary price, a better decision will be made. Furthermore, Figure 7 indicates the ratio of alpha to the TOF_O. According to Figure 7, when the RMM reduces the TOF_O by choosing a lower primary price than Scenario S3 (neutral power price), the RMM's profit is reduced in order to have a more risk-seeking strategy. Therefore, examining price uncertainty in the considered problem creates awareness for the RMM of the limitations of the optimal load changes in exchange for the price changes. This is an acceptable basis for the RMM in purchasing the electricity from the upstream market. In contrast, ignoring the price uncertainty during peak hours makes the RMM vulnerable to the price changes and as a result, the AGGs will have lower participation in the EDRP. In general, it can be concluded that these items can greatly improve the economic benefits, prevent possible outages during peak hours, and finally lead to safe operation of the system.

5. Conclusion

In this article, the RMM-related formulations were presented in a market environment to determine the optimal demand, incentive, and power purchased by taking into consideration some technical constraints such as incentive limits, demand limits, power purchased, and power balance. In addition, the reserve provided by the AGGs was prioritized based on the reserve-margin factors. Due to the uncertainty of the electricity price, an uncertainty model (IGDT) was presented for the considered problem. The positive aspect of uncertainty was represented by the IGDT opportunity function, while its negative aspect was presented by the IGDT robustness function. Using various strategies, the RMM attempted to limit the price uncertainty. For example, by considering the risk-aversion strategy, the AGGs were more inclined to reduce the load during the peak hours and the load curve tended to be smoother. Furthermore, by considering the risk-seeking strategy, the AGGs were less inclined to reduce the load during the peak hours. The inclusion of the price uncertainty in the EDRP program can help RMMs prevent the risks of the load changes, thus greatly affecting the economic benefits and safe operation of the system. In addition, the sensitivity analysis of the effects of weighting factors namely TOF, the PEM changes, effects of line losses, and different algorithms was conducted and investigated. These studies can be useful for the RMM to improve the load curve and prevent unrealistic decisions and financial losses. As for future research, it is possible to extend the proposed formulations by adding more items to the mentioned constraints and objective functions, improving the reserve consideration procedure, applying some newer meta-heuristic algorithms, and investigating the possibility of the RMM interaction with the whole-sale electricity market.

Nomenclature

Sets and Indices

t_i, t_j, k	Indices of time, time and the AGGs
$\varphi_T, \varphi_{peak}$	Sets of time, peak load time

Constants

$P_{grid}^{\min}, P_{grid}^{\max}$	Minimum and maximum value of power purchased from the upstream grid (MW)
$\rho^0(t_i), \rho(t_i)$	Electricity price before and after implementation of the EDRP at time t_i (\$/Mwh)
$\rho^0(t_i), \rho(t_j)$	Electricity price before and after implementation of the EDRP at time t_j (\$/Mwh)
PF_k	Contribution ratio of the AGG no. k
$E(t_i, t_j)$	Price elasticity matrix at time t_i and t_j
$inc_{\min} inc_{\min}$	Minimum and maximum value of incentive given to the AGGs by the RMM (\$/Mwh)
$d^0(k, t_i)$	Energy consumption before implementing the EDRP for the AGG no. k at time t_i (MWh)

Variables

$RMF(k, t_j)$	Reserve-margin factors for the AGG no. k at time t_i
$R(k, t_j)$	Reserve provided by the AGG no. k at time t_i (MWh)
$RV(t_i)$	Reserve value for each of the AGGs which could provide reserve at time t_i
$PR(k, t_j)$	Reserve offers by the AGG no. k at time t_i

$MAR(t_i)$	Maximum achievable reserve for the RMM at time t_i
$RSP(k)$	Reserve service period of the AGG no. k
$inc(t_i)$	Incentive rate from market to the AGG at time t_i (\$/MWh)
$inc(t_j)$	Incentive rate from market to the AGG at time t_j (\$/MWh)
ω_C	Weighting factor for the RMM costs in the objective function
$\tilde{P}_U(t_i)$	Forecasted uncertainty variable at time t_i
TOF_b	Minimum expected TOF of the RMM
TOF_r	Critical TOF for robustness function
TOF_O	Critical TOF for opportunity function
ω_i	Weighting factor for the RMM income in the objective function
$d(k,t_i)$	Energy consumption after implementing the EDRP for the AGG no. k at time t_i (MWh)
μ	Percentage increase in TOF for the RMM
γ	Percentage decrease in TOF for the RMM
$d(t_i)$	Energy consumption after implementing the EDRP at time t_i (MWh)
$P_L(t_i)$	Power transmission loss at time t_i (MWh)
$P_{grid}(t_i)$	Power purchased from the main grid at time t_i (MWh)
T	Teacher (the best student among other students)
P_n	Initial population (initial students group)
M	Randomly selected real number in the range of 0 to 1
$\bar{S}_{old}$	Average value for all students before being taught
S_{old}	Teacher's knowledge
S_{new}	A new member or student created to replace the low-quality member.
T_F	Teaching coefficient
H	Dilatation factor
ω_d	Central frequency of the wavelet
L	Current
$L_{\max}$	Total iterations
W	The worst student
ω	Probability of mutation to each student
α	Uncertainty radius
$\tilde{P}_U(t_i)$	Actual uncertainty variable at time t_i

Function

TOF	Total objective function of the RMM (\$)
$\hat{\alpha}(TOF_r)$	Robustness function
$\hat{\beta}(TOF_O)$	Opportunity function

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Appendix

In Table A.1, five AGGs considered with the initial demands and in Figure A.1 and Table A.2 daily load curve and parameters of PEM are depicted.

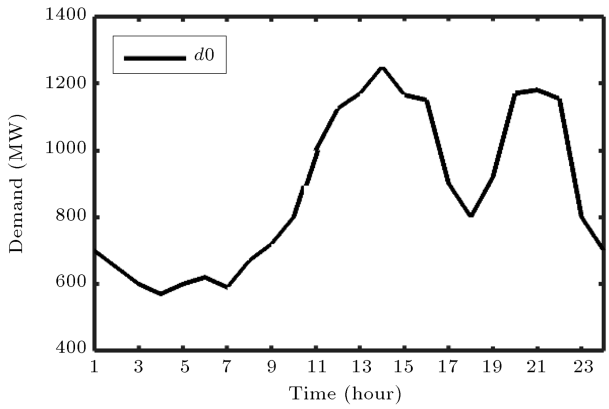

Figure A.1. The considered daily load curve [25].

Table A.1. Initial demand of the AGGs.

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Demand of AGG1 (MWh)	163	136	100	100	110	116	115	133	140	156	193	216
Demand of AGG2 (MWh)	130	125	130	110	130	130	110	130	165	176	210	230
Demand of AGG3 (MWh)	147	139	125	125	125	142	150174	217	244			
Demand of AGG4 (MWh)	125	130	127	119	125	125	122	130	125	137	180	210
Demand of AGG5 (MWh)	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**
Demand of AGG1 (MWh)	233	275	216	256	200	166	226	274	275	246	161	123
Demand of AGG2 (MWh)	245	220	210	230	220	200	240	210	220	214	160	150
Demand of AGG3 (MWh)	242	250	254	264	240	214	240	230	260	204	184	160
Demand of AGG4 (MWh)	224	260	245	197	125	112	108	215	210	258	150	140
Demand of AGG5 (MWh)	226	245	240	203	115	108	106	241	215	232	145	127

AGG: Aggregator

Table A.2. The considered self and cross elasticity in different time periods.

Time period	**Low load**	**Middle load**	**Peak load**	
12–16 and 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

Biography

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