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.

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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
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 cost 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
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

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

| Ref. No. | DRP         | Uncertainty parameters DRP | Uncertainty model          | Objective function          |
|----------|-------------|----------------------------|---------------------------|-----------------------------|
| [6]      | IBP         | No                         | No                        | Min cost                    |
| [7]      | EBDR        | No                         | No                        | Min cost                    |
| [8]      | IBP         | No                         | No                        | Min cost                    |
| [9]      | EDRP        | No                         | No                        | Min cost                    |
| [10]     | EDRP        | No                         | No                        | Min cost & air pollution    |
| [11]     | IBP         | No                         | Non-heuristic             |                             |
| [12]     | EDRP & TOU | No                         | Non-heuristic             |                             |
| [13]     | EDRP        | Yes                        | Scenario based stochastic | Min cost & incentive        |
| [14]     | IBP         | Yes                        | Scenario based stochastic | Maximize Genco & DRP profit|
| [15]     | IBP         | Yes                        | LSMCR stochastic          | Maximize Genco & DRP profit|
| [17]     | IBP         | No                         | Robust uncertainty        | Min cost, air pollution & DRP|
| [18]     | IBP         | Yes                        | Robust uncertainty        | Min cost                    |
| [19]     | IBP         | Yes                        | IGDT uncertainty          | Clear power market          |
| [20]     | IBP         | Yes                        | IGDT uncertainty          | Min cost                    |
| [21]     | TBP         | Yes                        | IGDT uncertainty          | Clear reserve market        |

Proposed method | EDRP | No | 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.
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 $\omega_i$ and $\omega_C$.

2.2. Constraints

2.2.1. Incentive limit

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

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

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]:

$$\min \sum_{k=1}^{n} d^s(k, t_i) \leq d(t_i) \leq \max \sum_{k=1}^{n} d^l(k, t_i) \forall t_i \in \varphi_T. \quad (3)$$
2.2.3. Power purchased
It is assumed that the power purchased by the RMM is in the following range [26]:
\[
P_{\text{grid}}^{\text{min}} \leq P_{\text{grid}}(t_i) \leq P_{\text{grid}}^{\text{max}} \quad \forall t_i \in \varphi_T.
\] (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:
\[
P_{\text{grid}}(t_i) = d(t_i) + P_L(t_i) \quad \forall t_i \in \varphi_T.
\] (5)

The mathematical expression of power transmission loss between the power purchased and customers can be obtained based on the following formula [26]:
\[
P_L(t_i) = B_0 \times P_{\text{grid}}(t_i) \quad \forall t_i \in \varphi_T.
\] (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:
\[
d(k, t_i) = d^0(k, t_i) \times \left\{1 + PF_k \times \sum_{t=1}^{24} E(t_i, t_j) \right. \\
\times \ln \left( \frac{\rho(t_j) + inc(t_j))}{\rho_0(t_j)} \right) \left. \right\} \quad \forall t_i \in \varphi_T.
\] (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:
\[
R(k, t_i) = \begin{cases} 
R(k, t_i) \times RSP(k) \times RV(t_i) \times MAR(t_i) 
\text{if } R(k, t_i) > 0 \\
0 
\text{if } R(k, t_i) < 0 
\end{cases}
\] (8)

where:
\[
RV(t_i) = \begin{cases} 
RV_{\text{new}} = RV_{\text{old}} - \frac{\sum_{t=1}^{24} d(t_i) - d^0(t_i) - d^0(t_j)}{d^0(t_j) - d^0(t_i)} 
\text{if } t_i \in \varphi_T \text{ and } t_j \in \varphi_T \\
0 
\text{if } t_i \in \varphi_T - \varphi_{\text{peak}} 
\end{cases}
\] (11)

\[
MAR(t_i) = \begin{cases} 
\sum_{t=1}^{24} d^0(k, t_i) - d(t_i) 
\text{if } t_i \in \varphi_{\text{peak}} \\
0 
\text{if } t_i \in \varphi_T - \varphi_{\text{peak}} 
\end{cases}
\] (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 IGDIT 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]:

$$S_{new} = S_{old} + m \times (T - T_F \times S_{old}).$$  \hspace{1cm} (13)

The relationship for $T_F$ is given as the following:

$$T_F = \text{round}(1 + \text{rand}(0,1)).$$  \hspace{1cm} (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]:

$$S_{new} = S_{worse} + r \times (S_{better} - S_{worse}).$$  \hspace{1cm} (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, $P_A$ and $P_B$ 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, $T_A$ is the teacher of the group or class A and $T_B$ 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:

$$S_{new} = \begin{cases} S_{old} + \omega(T - S_{old}) & \text{if } \omega > 0 \\ S_{old} + \omega(W - S_{old}) & \text{if } \omega \leq 0 \end{cases}$$  \hspace{1cm} (16)

The parameter $\omega$ is applied as shown below:

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

where $\omega_d$ is selected as a probability number from 0 to 1. In case $\omega$ 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 $\varphi$ 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:

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

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

$$\sigma = \sigma_{\text{min}} + \left( \frac{\sigma_{\text{max}} - \sigma_{\text{min}}}{2.5} \right),$$  \hspace{1cm} (19)

where $\sigma_{\text{min}}$ and $\sigma_{\text{max}}$ 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, \( d(t_i) \text{inc}(t_i) \) and \( P_{\text{req}}(t_i) \) 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 packet 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):

\[
U(\alpha, \hat{P}_V(t_i)) = \left\{ \hat{P}_V(t) : \left| \frac{\hat{P}_V(t_i) - \hat{P}_V(t_i)}{\hat{P}_V(t_i)} \right| \leq \alpha \right\}
\]

\[
\alpha \geq 0.
\] (20)

In IGDT, \( \alpha \) 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:

\[
\hat{\alpha}(TOF_r) = \max_{\alpha} \left\{ \alpha : \min(\text{TOF}) \leq TOF_r \right\},
\] (21)

\[
\hat{\beta}(TOF_O) = \min_{\alpha} \left\{ \alpha : \min(\text{TOF}) \leq TOF_O \right\}.
\] (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 \( \hat{\beta}(TOF_r) \). It should be noted that the total objective function in this function is more than that in a pre-defined \( TOF \). 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]:

\[
\hat{\alpha}(TOF_r) = \max_{\alpha} \left\{ \alpha : \max_{l \in U(\alpha, \hat{P}_V(t_i))} \text{TOF} \leq TOF_r = (1 + \mu)^{\text{TOF}_B} \right\}.
\] (23)

The value of the robustness function is obtained by maximizing \( \alpha \) based on the equation given below:

\[
\hat{\alpha}(TOF_r) = \max_{\alpha} \alpha,
\] (24)

subject to:

\[
\hat{\alpha}(TOF_r) = \max[Eq(1)] \leq \text{TOF}_r,
\] (25)

\[
(1 - \alpha)\hat{P}_V(t_i) \leq \hat{P}_V(t_i) \leq (1 + \alpha)\hat{P}_V(t_i).
\] (26)

Eqs. (2) – (12).

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]:

\[
\hat{\beta}(TOF_O) = \min_{\alpha} \left\{ \alpha : \min_{l \in U(\alpha, \hat{P}_V(t_i))} \text{TOF} \leq TOF_O = (1 - \gamma)^{\text{TOF}_B} \right\}.
\] (32)

The opportunity function value can be obtained by minimizing \( \alpha \) as shown below:
\[ \hat{\beta}(TOF_{O}) = \min \alpha, \]  
(33)

Subject to:

\[ \hat{\beta}(TOF_{O}) = \operatorname{Min}[Eq(1)] \leq TOF_{O}, \]  
(34)

\[ (1 - \alpha)\hat{P}_{V}(t) \leq \hat{P}_{V}(t) \leq (1 + \alpha)\hat{P}_{V}(t), \]  
(35)

Eqs. (2) - (12).  
(36)

Since the minimum reduction in the uncertain parameters \( \hat{P}_{V}(t) \) and \( (1 - \alpha)\hat{P}_{V}(t) \) is obtained in the opportunity function, the opportunity function can be formulated as:

\[ \hat{\beta}(TOF_{O}) = \min \alpha, \]  
(37)

Subject to:

\[ \hat{\beta}(TOF_{O}) = \operatorname{Min}[Eq(1)] \leq (1 - \gamma)TOF_{b}, \]  
(38)

\[ \hat{P}_{V}(t) = (1 - \alpha)\hat{P}_{V}(t), \]  
(39)

Eqs. (2) - (12).  
(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

**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 IGD, \( TOF_{b} \).

**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 IGD-based robustness and applied IGD-based opportunity optimizations should be selected, respectively.

**Step 4:** If the \( \alpha \) 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 (30), respectively. Then, finish the process.

**Step 5:** For the robustness optimization, substitute Eq. (30) with \( \rho_{V}(t) \) and for the opportunity optimization, replace Eq. (39) with \( \rho_{V}(t) \). 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 \( \text{inc}(t_{i}) \), 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 \( \text{inc} \) is determined by \( \text{inc} = \text{inc}_{\text{min}} + (\text{inc}_{\text{max}} - \text{inc}_{\text{min}}) \times \text{randc}[0, 1] \) using Constraint Eq. (2); otherwise, \( \text{inc}(t_{i}) = 0 \) 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, \( \text{inc}(t_{i}) \), reserve prioritization, and RMM daily objective function. Then, consider the next iteration or \( n + 1 \) 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 \( \alpha \) 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,
Enter the initial information, the related algorithm, the optimization functions and constraints and the required parameters of the formulations for the RMM ti = 1, α = 0, μ = 0.07, r = 0.09 and so on.

Calculate EDRP uncertainty using IGDT

A1

Cb = the best values for RMM profit considering Eq. (1)

B1

No

α < 1

Yes

Applied IGDT-based robustness optimization

The best values for RMM profit considering Eq. (29)

Replace Eq. (30) to μ/(tt)

B2

Consider next α or α + 0.05

A2

B3

Applied IGDT-based opportunity optimization

No

The best values for RMM profit considering Eq. (38)

Replace Eq. (39) to μ/(tt)

Yes

α < 1

A3

Consider next α or α + 0.05

Terminate the process

Finish

Calculate RMM profit optimization using related algorithm

A1 or A2 or A3

Yes

T = T + 1

T ≥ 200

No

Ti = Peak load hours

No

inc = 0

inc was determined by

inc = inc min + (inc max – inc min) rand x([0, 1])

with consideration of constraint Eq. (2)

Determining 24 hour demand of the AGGs in EDRP by Eq. (7)

B1 or B2 or B3

No

The best values for demand and inc, RMM daily objective function

Prioritize AGG’s from perspective of power reserve in peak-load hours by Eqs. (8)-(12)

Solving RMM daily objective function according to Eq. (1) are calculated and consideration of constraints according to Eqs. (3) to (6):

Save the best demand, power purchased and inc, RMM daily objective function if RMM daily objective function is more than its previous value

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.
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 \( p(t_i) \) can be expressed as \( p(t_i) = 0.95 \times pc(t_i) \). 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 IGDGT model in accordance with Scenarios S8 and S9. Figures 2–7 and Tables 3–6 present the evaluation results of the above-mentioned paragraphs.

#### 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
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 reserved rate among the scenarios can be observed in 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.

| Scenario | Incentive Reserve used | TOF RMM # |
|----------|------------------------|-----------|
|          | ($/MWh)                | (MW)      |
| S1       | 0                      | 65381.93  |
| S3       | 9.8702                 | 655.8227  |
| S4       | 9.3973                 | 650.1998  |
| S5       | 9.1770                 | 644.5583  |
| S9       | 6.8827                 | 863.2158  |

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-TTLBO 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-TTLBO algorithm) in accordance with the
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 $W_C$ 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 $68126.22$ $\$/MWh, and $644.55$ $\$/MWh, 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 $69773.73$ $\$/MWh, and $374.04$ $\$/MWh, 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 of the uncertainty (electricity price) in the IGDT program on the optimal incentive rate, power purchased, and demand are investigated while considering 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 $E$, 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 $TOF$, 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 $\alpha = 0.3$. 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 $70266.63$ $\$/MWh, and $471.5646$ $\$/MWh, 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 $TOF$, 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 $\alpha = 0.25$. 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 65808.31 $, 6.8827 $/MWh, and 863.2158 MW, respectively, as obtained in Scenario S8. Figure 7 shows the ratio of the alpha to the TOF. As indicated, by choosing a higher power price than the one in Scenario S3 (neutral power price), the RMM leads to greater TOF. 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. According to Figure 7, when the RMM reduces the TOF 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
\( \varphi_T, \varphi_{\text{peak}} \) Sets of time, peak load time

Constants

\( p_{\text{grid}}^{\min}, p_{\text{grid}}^{\max} \) Minimum and maximum value of power purchased from the upstream grid (MW)
\( \rho^j(t_i), \rho(t_i) \) Electricity price before and after implementation of the EDRP at time \( t_i \) ($/MWh)
\( \rho^j(t_i), \rho(t_j) \) 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 \( t_j \)
\( inc_{\min}^{\text{max}},inc_{\min} \) Minimum and maximum value of incentive given to the AGGs by the RMM ($/MWh)
\( d^j(k, t_i) \) 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 \( t_i \)
\(M\ AR(t_i)\): 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 \(t_i\) ($/\text{MWh})

\(inc(t_j)\): Incentive rate from market to the AGG at time \(t_j\) ($/\text{MWh})

\(\omega_C\): Weighting factor for the RMM costs in the objective function

\(\hat{P}_U(t_i)\): Forecasted uncertainty variable at time \(t_i\)

\(\hat{P}_E(t_i)\): Actual uncertainty variable at time \(t_i\)

\(TOF_b\): Minimum expected \(TOF\) of the RMM

\(TOF_{-}\): Critical \(TOF\) for robustness function

\(TOF_O\): Critical \(TOF\) for opportunity function

\(\omega_i\): 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)

\(\mu\): Percentage increase in \(TOF\) for the RMM

\(\gamma\): 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

\(\bar{s}_\text{old}\): Average value for all students before being taught

\(s_{_\text{old}}\): Teacher’s knowledge

\(s_{_\text{new}}\): A new member or student created to replace the low-quality member.

\(T_F\): Teaching coefficient

\(H\): Dilatation factor

\(\omega_d\): Central frequency of the wavelet

\(L\): Current

\(L_{\text{max}}\): Total iterations

\(W\): The worst student

\(\omega\): Probability of mutation to each student

\(\epsilon\): Uncertainty radius

**Function**

\(TOF\): Total objective function of the RMM ($)

\(\hat{\delta}(TOF_r)\): Robustness function

\(\hat{\beta}(TOF_O)\): Opportunity function

**References**

1. Bazydo, G., and Wermuth, S. “Demand side management through home area network systems”, *International Journal of Electrical Power & Energy Systems*, 97, pp. 174–185 (2018).

2. Akbari-Dibavari, A., Farahmand-Zahed, A., and Mohammad-Ivatloo, B. “Concept and glossary of demand response programs”, *Demand Response Application in Smart Grids*, pp. 1–20, Springer (2020).

3. FERC, Staff Report. “Assessment of Demand Response and Advanced Metering”, [Online] Available: http://www.ferc.gov (2008).

4. Orans, R. “Phase I results: incentives and rate design for energy efficiency and demand response”, *LBL-60133*, Energy and Environmental Economics Inc, Carson City, NV, USA (2006).

5. NYISO Auxiliary Market Operations “Demand response manual New York independent system operator”, [Online] Available: http://www.nyiso.com (May, 2019).

6. Wang, Y., Zhang, F., Chi, C., et al. “A market-oriented incentive mechanism for emergency demand response in colocation data centers”, *Sustainable Computing: Informatics and Systems*, 22, pp. 15–25 (2019).

7. Annoum, M., Bouktir, T., and Musirin, I. “Power system voltage instability risk mitigation via emergency demand response-based whale optimization algorithm”, *Protection and Control of Modern Power Systems*, 4(1), pp. 1–14 (2019).

8. Aghaei, J., Alizadeh, M.-I., Siano, P., et al. “Contribution of emergency demand response programs in power system reliability”, *Energy*, 103, pp. 688–696 (2016).

9. Hajibandel, N., Shafiee-Khalil, M., Osório, G.J., et al. “A heuristic multi-objective multi-criteria demand response planning in a system with high penetration of wind power generators”, *Applied Energy*, 212, pp. 721–732 (2018).

10. Hajibandel, N., Ehsan, M., Soleymani, S., et al. “Prioritizing the effectiveness of a comprehensive set of demand response programs on wind power integration”, *International Journal of Electrical Power & Energy Systems*, 107, pp. 149–158 (2019).
11. Asadinejad, A., and Tomovic, K. “Optimal use of incentive and price based demand response to reduce costs and price volatility”, Electric Power Systems Research, 144, pp. 215-223 (2017).

12. Yu, D., Xu, X., Dong, M., et al. “Modeling and prioritizing dynamic demand response programs in the electricity markets”, Sustainable Cities and Society, 53, pp. 109-121 (2020).

13. Pourghasem, P., Sohrabi, F., Jabari, F., et al. “Combined heat and power stochastic dynamic economic dispatch using particle swarm optimization considering load and wind power uncertainties”, In Optimization of Power System Problems, pp. 143-169, Springer (2020).

14. Imani, M.H., Nilnejad, P., and Barzegaran, M. “The impact of customers’ participation level and various incentive values on implementing emergency demand response program in microgrid operation”, International Journal of Electrical Power & Energy Systems, 96, pp. 114-125 (2018).

15. Kitaplayev, Y., Moriarty, J., and Mancarella, P. “Stochastic control and real options valuation of thermal storage-enabled demand response from flexible district energy systems”, Applied Energy, 137, pp. 823-831 (2015).

16. Soroudi, A. and Ammoe, T. “Decision making under uncertainty in energy systems: State of the art”, Renewable and Sustainable Energy Reviews, 28, pp. 376-384 (2013).

17. Alipour, M., Zare, K., Seyedi, H., et al. “Real-time price-based demand response model for combined heat and power systems”, Energy, 168, pp. 1119-1127 (2019).

18. Nourozhi, R., Nojavan, S., and Zare, K. “Risk-based purchasing energy for electricity consumers by retailer using information gap decision theory considering demand response exchange”, Electricity Markets, pp. 135-168, Springer (2020).

19. Nojavan, S., Majidi, M., and Zare, K. “Risk-based optimal performance of a PV/fuel cell/battery/grid hybrid energy system using information gap decision theory in the presence of demand response program”, International Journal of Hydrogen Energy, 42(16), pp. 11857-11867 (2017).

20. Zhao, C., Wang, J., Watson, J.-P., et al. “Multi-stage robust unit commitment considering wind and demand response uncertainties”, IEEE Transactions on Power Systems, 28(3), pp. 2708-2717 (2013).

21. Najafi, M., Eshet, M., Fotuhi-Firuzabad, M., et al. “Optimal reserve capacity allocation with consideration of customer reliability requirements”, Energy, 35(9), pp. 3883-3890 (2010).

22. Ahmadi-Khatir, A., Fotuhi-Firuzabad, M., and Goel, L. “Customer choice of reliability in spinning reserve procurement and cost allocation using well-being analysis”, Electric Power Systems Research, 79(10), pp. 1431-1440 (2009).

23. Amirahmadi, M. and Foroud, A.A. “Stochastic multi-objective programming for simultaneous clearing of energy and spinning reserve markets considering reliability preferences of customers”, International Journal of Electrical Power & Energy Systems, 53, pp. 691-703 (2013).

24. Ghalary, K., Abbodlali, A., Rashidinejad, M., et al. “Optimal reserve market clearing considering uncertain demand response using information gap decision theory”, International Journal of Electrical Power & Energy Systems, 101, pp. 213-222 (2018).

25. Aalami, H., Moghaddam, M.P., and Yousefi, G. “Modeling and prioritizing demand response programs in power markets”, Electric Power Systems Research, 80(1), pp. 426-435 (2010).

26. Abdi, H., Delnabi, E., and Mohammadi, F. “Dynamic economic dispatch problem integrated with demand response (DEEDR) considering non-linear responsive load models”, IEEE Transactions on Smart Grid, 7(6), pp. 2586-2595 (2015).

27. Nia, M., Golestaneh, F., and Sadeghi, M.S. “Multi-objective teaching-learning-based algorithm for dynamic economic emission dispatch”, IEEE Systems Journal, 6(2), pp. 318-327 (2012).

28. Ben-Haim, Y., Info-Gap Decision Theory Decisions Under Severe Uncertainty, Elsevier (2006).

29. Mohammad-Ivatloo, B., Zareipour, H., Aminyadi, N., et al. “Application of information-gap decision theory to risk-constrained self-scheduling of GenCos”, IEEE Transactions on Power Systems, 28(2), pp. 1093-1102 (2012).

30. Liu, W., Huang, Y., Li, Z., et al. “Optimal allocation for coupling device in an integrated energy system considering complex uncertainties of demand response”, Energy, pp. 172-179 (2020).

Appendix

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

![Figure A.1. The considered daily load curve [25].](image-url)
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     | 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     | 236     | 274     | 275     | 246     | 161     | 123     |
| Demand of AGG2 (MWh) | 245     | 230     | 210     | 230     | 220     | 200     | 240     | 210     | 230     | 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 19-22 | 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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