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Optimizing the Performance of Commercial Demand Response Aggregator Using the Risk-Averse Function of Information-Gap Decision Theory

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Abstract: Power systems face challenges with regard to handling the high penetration of renewable energies, including energy intermittency and fluctuations, which are not present in conventional electricity systems. Various flexibility models have been developed to address these fluctuations, including demand-side flexibility, which offers a practical solution with which to overcome these challenges in all demand sectors, including the commercial sector. This paper proposes a new structure for the participation of the commercial sector in the electricity market to integrate and coordinate the consumption of the commercial sector. Unlike previous studies that had commercial consumers participate in the electricity market individually and sometimes fail to meet the requirements for flexibility programs, this study adopts a commercial aggregator to enhance the responsiveness of commercial systems. The proposed structure includes a mathematical model for commercial systems, e.g., shopping centers, with responsive ventilation systems to achieve demand flexibility. The study also uses the information-gap decision theory to address time-based commercial demand response planning from 24 h ahead to near real time. Moreover, a multi-layered structure is proposed to integrate the flexibility of shopping centers from the demand side to the supply side through a newly invented commercial demand response aggregator. The proposed approach was implemented in the New York electricity market, and the results show that it provides demand flexibility for up to 18% of the nominal level of electricity consumption compared to the traditional system. The paper aims to present a responsive structure for commercial systems, addressing the challenges of integrating renewable energies with the electricity system.

Keywords: renewable energy; demand response; flexibility; demand response aggregator; information-gap decision theory

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1. Introduction

How to safeguard power systems against renewable energy fluctuations and intermittency constitutes the main issue raised by the increased penetration of renewable energies [1]. The development of more adaptable resources to facilitate the integration of renewable energy into power systems is still considered a crucial need, even though recent studies have suggested numerous methods with which to coordinate the operation of renewable resources with battery storage [2] and pumped hydraulic storage [3] systems. Future power systems could be in grave danger if strategic reserves are insufficient. If the potential for demand-side flexibility is sufficiently integrated and coordinated such that all types of residential, commercial, and industrial consumers are included, the supply-side stability of a power system during a renewable electricity shortage can be guaranteed. A demand response aggregator (DRA) efficiently combines the electricity flexibility of commercial and residential consumers into a single power system. Therefore, the main challenge is giving DRAs a workable structure to hedge against the intermittent nature of renewable energy.

Electricity demand has risen globally in developed and developing nations over the last few decades [4]. Remote communities and places without electricity are among the main concerns in some poor developing countries [5]. Uncertainty on the supply side has grown to be one of the major challenges in developed nations with a high penetration rate of renewable energy [6]. Due to the growth of distributed resources based on renewable energy sources, traditional electric power systems are undergoing a transitional period. Power systems have experienced issues due to the recent enormous increase in the number of renewable resources available [7]. On the other hand, consumers' demand profiles for electricity are drastically changing. Additionally, as social welfare rises, the rate of global electricity consumption (kWh per capita) is increasing [8].

Due to the increase in intermittency and fluctuation on the supply side and the rise in electricity consumption on the demand side, new types of flexibility are required to maintain the current power systems. Therefore, the demand side must be flexible to ensure a power system's flexibility [9]. Actors on both the production and consumption sides can exploit power systems as load-responsive applications grow. One of the apparent requirements is reviewing and changing the operation and scheduling models of power systems due to the growing involvement of consumers in exploitation and scheduling [10]. Shopping center buildings are of particular interest to the commercial sector because they have HVAC (heating, ventilation, and air conditioning) systems that are flexible enough to implement the demand response (DR) process [11]. Commercial building HVAC systems operating as DR sources offer several significant benefits. HVAC systems use about 37% of all the electricity used in commercial buildings. This amount met more than 13% of the country's electricity demand in 2017 [12]. Advances in building energy management systems (BEMS) and variable speed drives (VSDs), in particular, have enhanced HVAC systems' control technology [13]. The direct HVAC control approach was used in [13,14]. The direct control method changes the reference power input to keep the indoor temperature within a reasonable range. The reference power input of the VSD is roughly equal to the power input of the HVAC system, which accounts for its quick response time. Additionally, HVAC systems are necessary for commercial buildings and do not require the installation of additional hardware. The DR of HVAC systems has been the subject of some studies. DR studies can be categorized as (1) studies on the control of DR resources as price receivers and (2) studies on optimal pricing for implementing DR. For instance, the cost of electricity was predetermined in [14,15]. The building operator scheduled the HVAC systems' ideal power consumption profiles [15] to reduce the overall cost of operation. Ref. [16] proposed a pricing strategy to help Electric Utility Companies (EUCs) and building operators achieve an optimal DR of price-elastic HVAC systems while considering peak load reduction. Retail prices for distribution network operations were best determined [17] with respect to DR services in HVAC systems. Ref. [18] discussed the optimal operation and scheduling of commercial air-conditioning systems by considering the DR required for maximum benefit. The paper collected the operating data of chiller units used by commercial users, calculated the cooling load of each unit, and derived the relationship between the cooling loads and power consumption of each unit. Ref. [19] proposed a DR framework to plan the daily operation of an air-conditioning system to minimize energy costs and guarantee thermal comfort. The framework included an electrically analogous thermal model and the formulation of an energy optimization problem with thermal and electrical constraints. Ref. [20] presented a complete model of a commercial building HVAC system consisting of a chiller, a water pump, and multiple AHUs (Air Handling Units) and developed a two-level control system to follow five-minute energy market signals and four-second frequency regulation signals. The first-level coarse control system provided commands for both water and air loop variables. The second-level fine control system adjusted the fan commands while maintaining the water loop inputs within the five-minute control period. As a result, the water loop power served as a basis for tracking energy market signals, and the air loop fan control system could be adjusted flexibly for frequency regulation. The authors of [21] focused on aggregating and scheduling multi-chiller HVAC systems in terms of continuous time stochastic unit commitment. The continuous time modeling method was utilized to handle the sub-hourly variability of wind power and the intra-hour flexibility of the HVAC systems. A cooling model was formulated based on a chiller load-sharing strategy and linearization method to describe the electricity consumption characteristics of an HVAC system with multiple chillers. Ref [22] proposed a novel reinforcement learning (RL) architecture for efficiently scheduling and controlling an HVAC system in a commercial building while harnessing its DR potentials.

Some recent studies have discussed the modeling of DR aggregators and their difficulties in electricity markets. The difficulties DR aggregators face in electricity markets were highlighted in some studies [23]. Ref. [24] presented a smart contract based on an optimal proposal strategy for an aggregator that considers customer acceptance. First, it attempted to determine the customer's acceptance of various incentives, where the Home Energy Management System (HEMS) introduced load regulation for electrical appliances. Second, the integrator adopted a rational approach to applying the optimal proposed strategy and program for energy storage systems (ESS) to generate economic benefits. Using stochastic programming and robust optimization, the authors of [25] suggested a new approach for DR aggregators in day-ahead markets. According to the authors of [26], market participants can use demand response exchange markets to negotiate with one another, but balancing markets are not included in the market model under consideration. As established in [27], DR is essentially an optional contract allowing the aggregator to sell their DR on electricity markets while ignoring demand-side uncertainty. The formulation of DR using the coexistence of elastic and inelastic loads was presented [28] as a two-level model. Additionally, numerous studies have accounted for both the supply and demand sides concurrently. For instance, ISO and DR aggregators were implemented in a hierarchical market [29] through household interaction analysis. An ideal strategy was proposed for a sizable consumer who is price-sensitive [30]. The wind power and market price variables were uncertain in this approach.

The authors of [31] suggested an approach based on game theory to obtain the best bidding strategy for DR aggregators in the electricity market. The proposed scheme employed an economically responsive load model for a DR approach based on customer benefit function and price elasticity. The authors of [32] suggested that combining DR and CHP generation is the best approach. The corresponding model employed the IGDT (Information-gap decision theory) technique but only considered the day-ahead market prices as an uncertain parameter and ignored how DR would be implemented on the demand side. Using thermostatically controlled loads, the authors of [33] presented a bottom-up strategy for convincing DR aggregators to participate in reserve markets. Ref. [34] proposed a two-stage structure for trading in the day-ahead and balancing markets, focusing on the DR load incurred by thermal heating. Ref. [35] suggested a game-theory-based bidding strategy. The aggregator aimed to lessen consumer annoyance and load through load-shedding applications. To overcome the risks of various uncertain factors in electricity markets and realize the economic benefits of DR, the authors of [36] proposed a dynamic bidding strategy that allowed demand-side resources to be incorporated in the frequency regulation market via a DRA. Ref. [37] presented a market-based mechanism that allowed DR resources to be integrated in a day-ahead wholesale electricity market. A DR exchange (DRX) market was developed to allow a DRA to trade DR resources with DR providers, wherein the DRA could bid strategically and compete with other participants in the wholesale electricity market. Ref. [9] used a multi-stage model to simulate industrial and residential DRAs while considering the volatility of electricity market prices. The stochastic programming method employed eliminated uncertainty in the proposed model. A DR aggregator model was presented to achieve flexibility in the agricultural sector of the electricity market while accounting for price uncertainty in day-ahead and equilibrium markets [38]. In the commercial sector, various consumers, such as shopping centers equipped with HVAC systems, can enable flexibility in terms of electricity system operation through the use of DR programs. The main feature of demand-side management for the commercial consumer is that if the DR programs are not well coordinated and cannot provide the minimum comfort required, the owners and users of the services of different commercial sectors may become dissatisfied. Implementing DR programs in different parts of a commercial sector may result in user dissatisfaction and financial loss for commercial sector owners. Commercial consumers can individually participate in DR programs to reduce peaks; however, the lack of coordination between commercial consumers when participating in an electricity market is an existing problem. Therefore, it is necessary to present a model for the participation of commercial consumers due to the penetration of intermittent renewable resources in power systems.

To model the aggregator of the commercial sector, we first examine and categorize different types of commercial consumers and evaluate the potential and ability of DR in different sectors. This structure considers the "consumer of the commercial sector" as the most important participant in the DR program. After the consumers of the commercial sector are identified, they are mathematically modeled. In the next step, different commercial consumption sectors are presented as a single aggregator, and the conditions of their presence in implementing the DR plan are checked. In the following step, the capacity provided by the DR aggregator is purchased by the operator and other market participants in accordance with "ancillary services, reservation, or balancing services." Therefore, DRAs provide a capacity for the power system that is absent in the electricity market. A multi-stage electricity market is used to settle the market for commercial DRAs participating in the electricity market. In addition, it is assumed that the power share of the electricity market is small compared to the whole market and that it cannot change the price of electricity. As a result, the electricity market price is determined based on forecasts. This paper presents a multi-stage framework and mathematical modeling concerning the DR of the commercial sector's aggregator, thus strengthening consumers' participation in the electricity market. The suggested model can consider the uncertainties precipitated by electricity market prices. IGDT is used in the scheduling process, which guarantees a predetermined profit by the aggregator and reduces the computational burden caused by employing scenario-based methods such as stochastic scheduling.

In general, the main contributions of this study can be expressed as follows:

(1) This study proposes mathematical models for both commercial demand response aggregators and consumers;
(2) This study aims to integrate commercial demand flexibility into dynamic electricity markets;
(3) An electrical energy storage system is utilized to attain real-time commercial demand response;
(4) This study proposes a multi-layered structure to integrate the flexibility of the commercial sector utilizing a commercial demand response aggregator (CDRA);
(5) The study addresses information-gap decision theory (IGDT) in the scheduling process of the commercial aggregator.

The rest of the paper is organized as follows. Section 2 presents the general framework of the MAS (multi-agent system). The structure of the first layer is explained in Section 3. In addition, the second- and third-layer agents are introduced in Sections 4 and 5, respectively. In Section 6, the operational mechanism of the multilayer structure is presented. The simulation results and discussion are presented in Section 7. Finally, the conclusions of the paper are presented in Section 8.

2. The Multi-Agent Structure of CDRA

The components of the network in this paper consist of several market-based agents, including CDRAs, large/small consumers (such as shopping centers), and electrical energy storage systems. Due to the increase in the size and number of actors in our network, we use a Multi-Agent System (MAS) to categorize and solve large problems more easily. This technique divides large problems into smaller ones, making it much easier to model participants in the market. In the multi-stage structure, new entities are formed by aggregating several previous characters. Additionally, commercial consumers are simulated as aggregators representing a set of commercial subscribers. For this reason, a multi-stage model named the MAS structure is herein proposed to adjust the complexity of the problem and simulate problems with a large number of characters. The remarkable advantage of this structure is its ability to facilitate the modeling of mutual interactions between market-based entities and the classification of different characters into sub-layers. The main components of the MAS structure are market agents and a simulation platform with a graphical user interface. Each level represents some market players, including CDRAs and large or small consumers. Market actors are divided into different factors and are categorized into three layers to simulate the MAS. All characters that have the same behavioral profile are placed in one layer. Figure 1 shows a schematic of the suggested structure. The structure presented in Figure 1 reduces the number of actors and uses aggregators to bridge commercial subscribers and the electricity market based on contracts concluded with subscribers and access to DR plan suppliers.

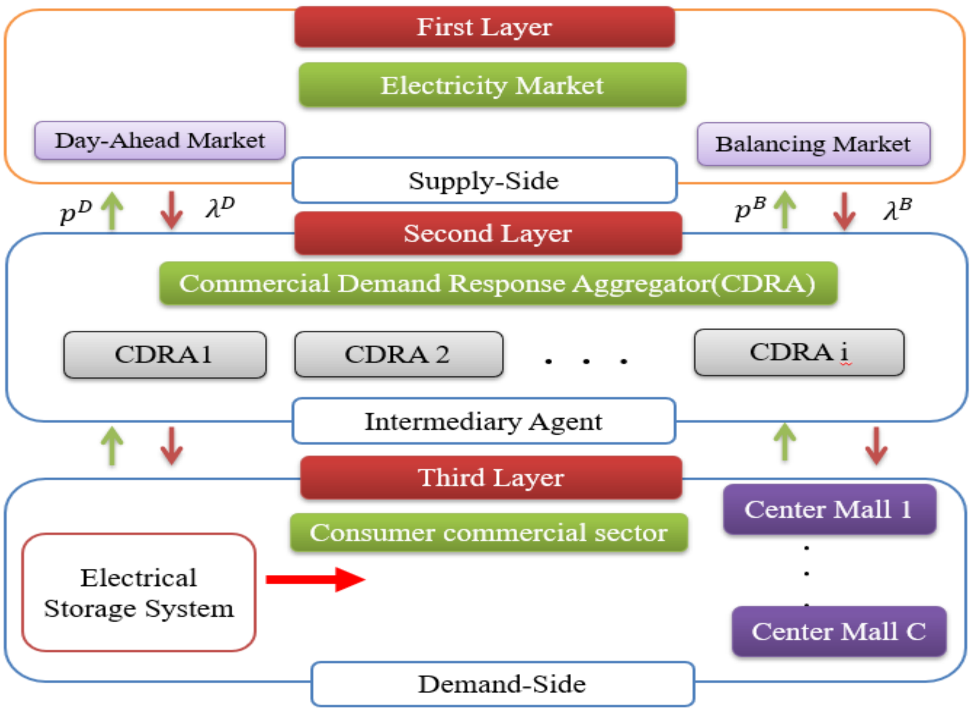

Figure 1. The multi-layered structure of different commercial sectors.

In this section, the factors of each layer are examined separately to attain a better understanding of the main components of the presented model's layers. There is an electricity market structure in the first layer, in which the CDRA participates on behalf of the shopping centers in two consecutive markets, i.e., the balancing market and the day-ahead market, to supply energy to the consumers of the contracting parties. CDRAs act as an intermediary between the electricity market and responsive consumers, collecting the demand proposals of shopping centers and participating in the electricity market on their behalf. Therefore, the CDRAs collect data related to operational restrictions, such as the minimum amount of cooling required, and regulate the demand proposals of contracting parties for energy supply. On the one hand, the DRAs regulate the demand-side offers to send energy to the market; on the other hand, they optimize the performance of consumers based on the concluded contract. Subsequently, different segments of consumers are examined to obtain maximum profits. DRAs are for-profit entities that participate in the DR plan based on their demand proposals. Some percentages of the profit are predetermined as a commission fee for the DRAs. This profit is allocated to them in exchange for implementing the DR plan. The DRAs' revenue is assumed to be equal to a predetermined percentage of the consumers' profit. Therefore, the DRAs and responsive consumers benefit from the DR plans by obtaining maximum profit and minimum cost.

The commercial, responsive consumers embedded in the third layer of the structure are the same shopping centers. Small consumers of power systems cannot participate directly in an electricity market. As a result, a set of consumers exhibiting similar behaviors is connected and assigned to the DRA. Therefore, the DRA directly finalizes a specific contract for energy supply with the commercial consumers and enables flexible operation in the power system. For example, commercial consumers, i.e., shopping centers, consume vast amounts of energy and can participate in this structure. Accordingly, different consumers of these shopping centers are examined to evaluate the DR opportunities compatible with long-, medium-, and short-term plans.

Figure 2 describes the transfer of information from one agent to another to show the interaction between different agents sending data. Based on the figure, the electricity market is located on the supply side, and the responsive consumers, i.e., shopping centers, are situated on the demand side. The DRAs, including CDRAs, are intermediaries between supply and demand. Firstly, on the demand side, the DRAs receive energy consumption data from the contracted consumers. The main duty of the DRAs is to optimize the operation of the consumers to achieve two main aims: (1) provide power flexibility to the power system through DR programs and (2) optimize the energy consumption of the consumers.

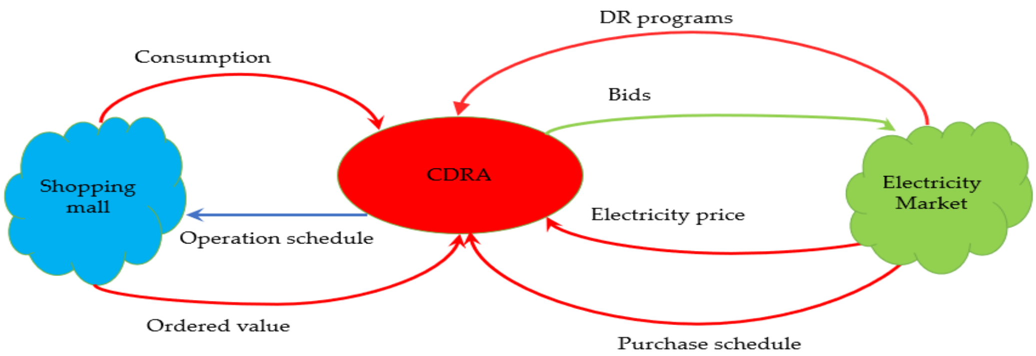

Figure 2. Flow diagram of the interactions between different agents.

Therefore, on the supply side, the DRAs receive electricity prices and DR program data from the electricity market. The DRAs construct demand bids by aggregating the data from the electricity market with the received consumption data from consumers. Therefore, the DRAs participate in the electricity market on behalf of the consumers. After clearing the electricity market, the DRAs determine the final operation schedule for the contracted consumers during the next 24 h. Note that the DRAs are considered to prevent many consumers from participating in the electricity market individually. The DR aggregates the demand bids of the consumers to participate in the electricity market on their behalf.

3. The First Layer: Dynamic Electricity Market

The dynamic electricity market is modeled in the first layer of the newly introduced multilayer structure. This study aims to understand the short-term and 24 h in advance to nearly real-time flexibility of commercial shopping centers in a power system with a high level of renewable energy penetration. An electricity market with multiple classes is considered to safeguard the system from the fluctuation of renewable energy. Two trading classes, day-ahead and balancing markets, are available in the electricity market. CDRAs embedded in the second layer are the first-layer participants. One of the most efficient energy markets, the day-ahead market, settles 24 h before the delivery of electricity. Participants in the market, such as CDRAs, trade in this class of contracts based on the anticipated intermittent capacity of renewable resources for the next 24 h. At this stage, CDRAs expend the majority of their energy on planning. As the moment of the delivery of electricity draws near, uncertainties relating to renewable energies become progressively less significant.

As a result, CDRAs participate in the balancing market to offer ancillary services to the power system to guarantee renewable energy availability in trading strategies. A CDRA can purchase or sell energy in deficit or surplus from or to shopping centers. At this point, it should be clear that the participating shopping centers can switch their electricity on or off and alter its usage. Finally, a CDRA engages in the balancing market to meet the high or low regulations for the electricity system. The balancing market reaches its final settlement a few seconds before the time at which electricity is delivered. In a short time, CDRAs can offer the flexibility of the centers to the power market. Shopping centers reacting to DR signals in seconds can compete in this market.

4. The Second Layer: CDRA

As mentioned earlier, CDRAs are in the second layer. A CDRA is defined as an intermediary entity between the electricity market and the network's commercial consumers that informs the contracting parties about the flexibility of their demand. In addition, integrating flexibility potentials accumulated in the power system facilitates the purchasing and selling of electrical energy in the first layer, i.e., the electricity market. By participating in the electricity market, a CDRA determines trading strategies 24 h in advance while considering the uncertainties associated with electricity prices in two trading classes, including day-ahead and balancing markets. To optimize trading strategies influenced by severe uncertainties, an uncertainty-based scheduling approach is used, which incorporates the IGDT method. This method guarantees the profit predetermined by the aggregator, while also adjusting the calculations produced by scenario-based methods such as stochastic programming. The performance of a CDRA under electricity-market-related price uncertainty will be described in the next sections.

4.1. Information-Gap Decision Theory (IGDT)

To provide a clearer understanding of how IGDT is applied in power system scheduling, this section broadly defines the concept of IGDT. The three main components of IGDT are the system model, the performance requirements, and uncertainty modeling. The system model describes how inputs and outputs are related. The system model can be written as y (q; l) based on IGDT, where q is the decision variable and l is the uncertainty parameter. For instance, the system model for an economic problem, including cost (an objective function) and market price (an uncertainty parameter), can be represented as C (q; l), where C (q; l) is the system model's cost function. Furthermore, q and l denote the market price and the choice variable, respectively. Robustness and opportunity functions are two immunity functions included in information gap decision theory. Since the operator's decisions depend on these functions, these functions are major and significant components of IGDT.

The robustness function (risk-averse) is used to mitigate the drawbacks of uncertainty. α is the parameter that models this function. This function [39] determines the maximum level of uncertainty that the adopted techniques can manage.

$$\overline{\alpha} = \mathrm{Max}_{\alpha}\{\alpha : \text{ greatest total } \cos \text{t is less than a specified limit.}\} \quad (1)$$

Opportunity function (risk-seeker): This risk-averse function models the advantages and positive results that can be achieved through uncertainty. β is the parameter that models this function:

$$\overline{\beta} = \mathrm{Min}_{\beta}\{\beta : \text{ least total cost is less than a specified limit.}\} \quad (2)$$

IGDT uses the uncertainty set to increase the value of objective function versus the uncertainty of the input parameters. The displayed uncertainty model $X\,(\alpha, \widetilde{\chi})$ can be developed using several methods via IGDT. One of the common functions used to present an uncertainty model is the fractional uncertainty model, as shown below:

$$X(\alpha, \widetilde{\chi}) = \{\chi : |\frac{\chi - \widetilde{\chi}}{\widetilde{\chi}}| \leq \alpha\}, \alpha \geq 0 \quad (3)$$

where $X(\alpha, \widetilde{\chi})$ represents the gap between predicted values (χ) and known values ($\widetilde{\chi}$). The horizon of the uncertain parameter is defined by α. For higher α values, the range of possible alterations of the uncertain parameter increases. The gap information uncertainty model has a nested and contractive nature. Its contractive nature means that $X(0, \widetilde{\chi})$ is the unit set $\{\widetilde{\chi}\}$. Its nested nature shows that the relation $X\left(\alpha^1, \widetilde{\chi}\right) \subseteq X\left(\alpha^2, \widetilde{\chi}\right)$ if $\alpha^1 \subseteq \alpha^2$ holds. In addition, due to the nature of the variable α, it should find the lower and upper limits of the uncertainty horizon. This definition of the uncertainty model states that the length of the uncertainty horizon depends on the uncertain parameter values. The multi-level model based on IGDT is formulated as follows [39,40]:

$$\underset{x}{MAX}\, \mathcal{F}^{upper\ level}(\rho, \varsigma^*), \quad (4)$$

s.t

$$h^{upper\ level}(\rho, \varsigma^*) \leq 0 \quad (5)$$

$$\varsigma^* = \arg\left\{\underset{\rho}{Min}\, f^{upper\ level}(\rho, \varsigma^*)\right. \quad (6)$$

s.t

$$z^{l0w\ level}(\rho, \varsigma) \leq 0 \quad (7)$$

$$\mathcal{R}^{l0w\ level}(\rho, \varsigma) = 0 \quad (8)$$

4.2. Commercial Aggregator Modeling

The analysis considers both the day-ahead and balancing (real-time) power markets. It is necessary for all market participants to exchange any energy they generate or require in the power pool. Participants in the market should plan their consumption based on the day's market. If the actor requests a different quantity than scheduled, the difference is determined using the balancing market method. If the market's power exceeds the aggregator's level of power consumption under this process, the surplus power is settled at the cost of a positive imbalance. The excess imbalance price is lower than or equal to the day-ahead settled price in the energy market. If the amount of electricity purchased on the previous day is less than the commercial aggregator's predetermined quantity, the surplus power is resolved at a negative imbalance price. The negative imbalance price is larger than or equal to the day-ahead energy-market-settled price. The negative (positive) imbalance price is equal to the day-ahead settlement market price when the total system's purchased power exceeds (declines) the demand. As a result, the day-ahead settlement price is equal to one of the positive and negative imbalance prices. Figure 3 reflects the suggested diagram for commercial aggregators, including shopping centers. As shown in the figure below, by receiving the demand of commercial consumers, the commercial aggregator provides the conditions for their presence in the electricity market. Subsequently, the commercial aggregator applies the DR process to the consumers. In this model, the electrical storage system plays a balancing role.

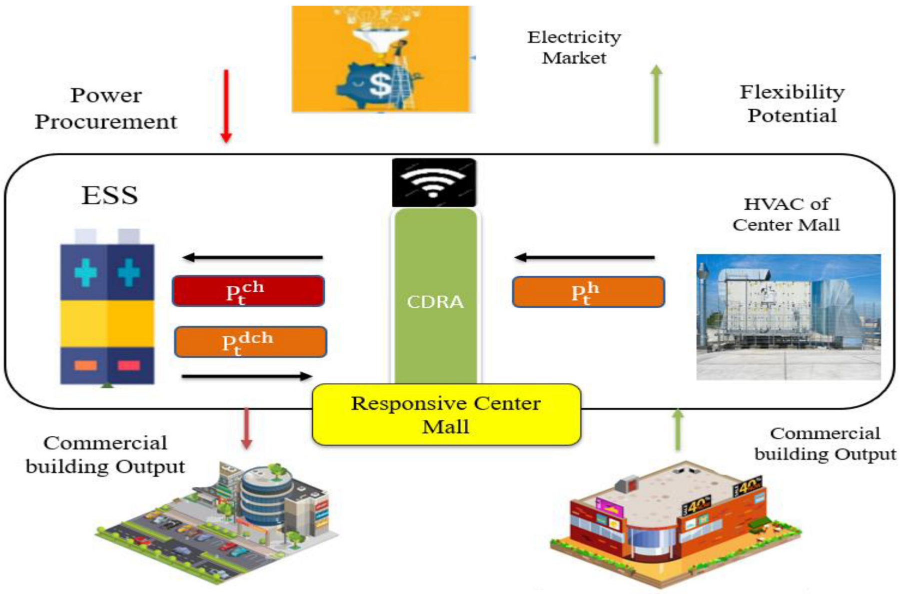

Figure 3. Diagram for commercial aggregator.

4.3. Commercial Aggregator Modeling without Considering Uncertainty

Initially, the IGDT model should be solved with definite data and without considering uncertainty. Then, the outputs of the deterministic problem can be considered as the input of the IGDT model. Predictive values (average values) are used instead of uncertainty values for deterministic modeling. Considering that this study considers day-ahead and balance market prices as uncertainty variables, these variables are considered as the input of the problem based on the predicted values (average values) of the electricity market.

$$F = \underset{\left(P_t^D, P_t^{B+}, P_t^{B-}\right)}{\text{Min}} \cdot \sum_{t=1}^{\tau} \{\bar{\lambda}_t^D P_t^D + \bar{\lambda}_t^{B+} P_t^{B+} - \bar{\lambda}_t^{B-} P_t^{B-}\} \tag{9}$$

$$0 \le P_t^D \le \left(\sum_{i=i}^{N_i} \sum_{c=1}^{N_c} \sum_{h=1}^{N_h} P_{t,h}^{i,c}\right) \tag{10}$$

$$P_t^{B+} \le \left(\sum_{i=i}^{N_i} \sum_{c=1}^{N_c} \sum_{h=1}^{N_h} P_{t,Pc}^{i,c}\right) \tag{11}$$

$$P_t^{B-} \ge -\left(\sum_{i=i}^{N_i} \sum_{c=1}^{N_c} \sum_{h=1}^{N_h} P_{t,pd}^{i,c}\right) \tag{12}$$

$$P_t^D + P_t^{B+} - P_t^{B-} = \sum_{i=1}^{N_i} P_t^i + P_{t,pc}^{i,c} - P_{t,pd}^{i,c} \tag{13}$$

Based on the variables used in the decision-making process for the traded power value of the two electricity markets, Equation (9) represents the objective function used to minimize costs, i.e., for the day-ahead and balancing markets $\left\{P_t^D, P_t^{B+}, P_t^{B-}\right\}$, considering the certainty of the electricity market price, $\left\{\bar{\lambda}_t^D, \bar{\lambda}_t^{B+}, \bar{\lambda}_t^{B-}\right\}$. The minimum and maximum limits of the power acquired in the day-ahead market are specified by Constraint (10). The maximum power purchased in the day-ahead market is limited to the contracting party's total nominal power produced by its shopping centers, $\sum_{i=i}^{N_i} \sum_{c=1}^{N_c} \sum_{h=1}^{N_h} P_{t,h}^{i,c}$. This variable has a minimum value of zero, indicating that the commercial aggregator is not permitted to sell power in the day-ahead market. Constraints (11) and (12) demonstrate that energy storage devices can be integrated in the market for balancing purposes. These storage devices can drastically reduce power consumption in a short amount of time (within a few seconds). It is recommended that HVAC systems are used for electrical energy storage in shopping centers to attain high and low regulation in the balancing market. $P^{i,c}_{t,pc}$ and $P^{i,c}_{t,pd}$ reflect the aggregator's charging and discharging states in phases of excess or deficit power consumption, respectively. The power balance in the electricity market is shown in Constraint (13). In the electrical market, the power acquired must be equivalent to the electricity offered in trading classes plus the electricity utilized by the contracting party's shopping centers.

In this study, three distinct states can occur for the power traded from the electricity market. The balancing electricity market price adheres to the following rules:

Case 1: If the imbalance of the power system is negative (i.e., there is an energy shortage in the electrical market), the balancing price is as follows:

$$P^D_t < \sum_{i=1}^{N_i} P^i_t \tag{14}$$

$$\overline{\lambda}^{B+}_t = \overline{\lambda}^D_t \tag{15}$$

$$\overline{\lambda}^{B-}_t \geq \overline{\lambda}^D_t \tag{16}$$

Case 2: If the power system imbalance is positive (i.e., there is surplus energy in the electrical market), the balancing price is as follows:

$$P^D_t > \sum_{i=1}^{N_i} P^i_t \tag{17}$$

$$\overline{\lambda}^{B-}_t = \overline{\lambda}^D_t \tag{18}$$

$$\overline{\lambda}^{B+}_t \leq \overline{\lambda}^D_t \tag{19}$$

Case 3: If the power system balance is zero, i.e., there is neither an energy surplus nor a deficit in the electrical market, the balancing price is as follows:

$$P^D_t = \sum_{i=1}^{N_i} P^i_t \tag{20}$$

$$\overline{\lambda}^{B-,+}_t = 0 \tag{21}$$

$\sum\limits_{i=1}^{N_i} P^i_t$ represents the total power of the commercial consumer.

4.4. Modeling Using IGDT Considering Uncertainty (Robust Function)

The considered uncertainty parameters include the day-ahead electricity market price (λ^D_t) and balancing market price (λ^{B-}_t and λ^{B+}_t). Therefore, according to the IGDT model, the uncertainty parameters for t time intervals can be represented as $U_t = \left\{\lambda^D_t, \lambda^{B+}_t, \lambda^{B-}_t\right\}$. The decision variable is the amount of power that should be offered to the day-ahead market p^D_t. It is assumed that the predicted values (average values) of the uncertainty parameters are available. The predicted values for the uncertainty parameters are the day-ahead electricity market price $\overline{\lambda}^D_t$, the positive balancing price $\overline{\lambda}^{B+}_t$, and the negative equilibrium price $\overline{\lambda}^{B-}_t$. The set of predicted values of the uncertainty parameters can be shown in the form of the following set: $\overline{U}_t = \left[\overline{\lambda}^D_t, \overline{\lambda}^{B+}_t, \overline{\lambda}^{B-}_t\right]$. The decision variables include day-ahead power, surplus power, and deficit power, which are shown in the following set: $q = \left[P_t^D, P_t^{B+}, P_t^{B-}\right]$. The public form of the robust function in the IGDT-based method is presented in (1). The robust scheduling of the commercial aggregator can be modeled using the following equations.

$$\text{Obj func}: \ \overline{\alpha} = \max\alpha \tag{22}$$

$$\text{s.t}: \Delta\ \Delta\ C_r = (1-\sigma)\times F_b \tag{23}$$

$$0 \ \le\ P_t^D \ \le\ P_t^{D(\max)}\ \forall t \tag{24}$$

$$\Delta = \underset{\left(\lambda_t^D, \lambda_t^{B+}, \lambda_t^{B-}\right)}{\text{Max}} \sum_{t=1}^{\tau}\left\{\lambda_t^D P_t^D + \lambda_t^{B+}P_t^{B+} - \lambda_t^{B-}P_t^{B-}\right\} \tag{25}$$

$$P_t^D + P_t^{B-} + P_{t,pd}^{i,c} = \sum_{i=1}^{N_i} P_t^i + P_t^{B+} + P_{t,pc}^{i,c} \tag{26}$$

$$P_t^D = P_{t,Buy}^D - P_{t,sold}^D \tag{27}$$

$$0 \ \le\ P_t^D \ \le\ \left(\sum_{i=i}^{N_i}\sum_{h=1}^{N_h}\sum_{j=1}^{N_j} P_{t,j}^{i,h}\right) \tag{28}$$

$$\left|P_t^{B+}\right| \ \le\ \left(\sum_{i=i}^{N_i}\sum_{c=1}^{N_c}\sum_{h=1}^{N_h} P_{t,pc}^{i,c}\right) \tag{29}$$

$$\left|P_t^{B-}\right| \ \ge\ -\left(\sum_{i=i}^{N_i}\sum_{c=1}^{N_c}\sum_{h=1}^{N_h} P_{t,pd}^{i,c}\right) \tag{30}$$

$$\lambda_t^{B+} \le\ \lambda_t^D \tag{31}$$

$$\lambda_t^{B-} \ \ge\ \lambda_t^D \tag{32}$$

$$P_t^{B-} \times P_t^{B+} = 0 \tag{33}$$

$$(1-\alpha)\,\overline{\lambda}_t^D \le\ \lambda_t^D \ \le\ (1+\alpha)\overline{\lambda}_t^D \tag{34}$$

$$(1-\alpha)\overline{\lambda}_t^{B+} \le\ \lambda_t^{B+} \le (1+\alpha)\overline{\lambda}_t^{B+} \tag{35}$$

$$(1-\alpha)\overline{\lambda}_t^{B-} \le \lambda_t^{B-} \le\ (1+\alpha)\overline{\lambda}_t^{B-} \tag{36}$$

The robust scheduling function based on IGDT in a two-level problem is given in the above equation. The maximum possible cost (at the low level) depends on the uncertainty interval. This uncertainty interval is solved through the high-level model. Equations (22) to (24) express the high-level formula determining the maximum possible value of the uncertainty horizon (α) such that the cost is less than the critical cost C_r. As shown in (23), C_r represents the critical cost, which is a percentage of the deterministic cost $\mathcal{F}_b$. $\mathcal{F}_b$ is determined by solving the deterministic problem described in the previous section. In addition, the deviation coefficient σ determines the risk aversion of the DR aggregator, which is set by the operator. Equations (25) to (36) express the low-level formulas used to determine the maximum cost in a certain range of uncertainty. The objective function shown is a robust function representing the worst-case scenario. Therefore, Equation (25) provides the maximum commercial aggregator for the supplied power P_t^D and the uncertainty interval (α). The first term of this equation represents the cost of purchasing power in the day-ahead market. The sales revenue or the cost of purchasing surplus and shortage power in the balancing market are shown in the second and third terms, respectively. Equations (26) to (30) were described in the previous section of the deterministic model. The logical limits of the uncertain parameters are expressed in Equations (31) to (32). Equations (34) to (36) show the information gap model for non-deterministic variables and express the upper and lower limits of uncertain parameters according to the uncertainty interval and predicted values of these variables.

4.5. One-Level Equivalent Model of IGDT

The model that was described in the preceding section has two levels. Equations (22) and (25) need to be maximized at the upper and lower levels, respectively. The higher level defines uncertainty. The lower-level model is transformed into a single-level model utilizing conventional techniques such as the Kuhn–Tucker method [41]. Additionally, Constraint (33) renders the issue non-convex. It is illogical to reduce the two-level model to a one-level problem using first-order optimum conditions. Therefore, we employ the approach suggested in [42] as follows. The low-level problem's goal is to ascertain the planned value of P_t^D as well as the values of uncertain parameters such as market prices that generate important costs for particular values of the uncertainty horizon. Consequently, for each hour, the following two conditions are considered:

(a) Surplus conditions Surplus conditions occur when the power supply in the day-ahead market is greater than the power requested by the commercial aggregator in the electricity market. $P_t^D > \sum\limits_{i=1}^{N_i} P_t^i$.

$$\Delta_t^+ = \underset{(\lambda_t^D, \lambda_t^{B+})}{\text{Max}} \quad . \sum_{t=1}^{\tau} \left\{ \lambda_t^D P_t^D + \lambda_t^{B+} [P_t^D - \sum_{i=1}^{N_i} P_t^i] \right\} \tag{37}$$

Equation (37) yields the maximum cost of commercial aggregators in surplus conditions. To achieve the worst possible scenario, i.e., the maximum cost, the day-ahead market price and the imbalance price should be equal to their maximum value. Therefore, the uncertainty parameters in the surplus case are as follows:

$$(1+\alpha)\bar{\lambda}_t^D = \lambda_t^D \tag{38}$$

$$(1+\alpha)\bar{\lambda}_t^{B+} = \lambda_t^{B+} \tag{39}$$

(b) Deficit conditions

This situation occurs when the power supplied in the day-ahead market is less than the power requested by the commercial aggregator in the electricity market. $P_t^D < \sum\limits_{i=1}^{N_i} P_t^i$.

$$\Delta_t^- = \underset{(\lambda_t^D, \lambda_t^{B-})}{\text{Max}} \quad . \sum_{t=1}^{\tau} \left\{ \lambda_t^D P_t^D - \lambda_t^{B-} [\sum_{i=1}^{N_i} P_t^i - (P_t^D)] \right\} \tag{40}$$

Equation (40) yields the greatest profit of the commercial aggregator in deficit conditions. To achieve the worst possible scenario, i.e., the maximum cost, the day-ahead market price and the imbalance price should be equal to their maximum and minimum values, respectively. Therefore, the uncertainty parameters in the deficit case are as follows:

$$(1+\alpha)\bar{\lambda}_t^D = \lambda_t^D \tag{41}$$

$$(1-\alpha)\overline{\lambda}_t^{B-} = \lambda_t^{B-} \tag{42}$$

According to the mentioned conditions, surplus and deficit situations are possible if the amount of power required by the commercial consumer is greater or less than the power supplied in the day-ahead market. To specify the deficit ($\phi_t = 0$) and surplus ($\phi_t = 1$) conditions, a binary variable ϕ_t is used in each period. As a result, the equivalent single-level formula is presented in Equations (43) to (52). In this approach, Equation (25) in the lower level of the two-level model is replaced by two new equations. These two equations reflect surplus and deficit conditions. Thus, this equation (maximum total cost) is replaced by Equations (37) to (39) (maximum cost in surplus conditions) and Equations (40) to (42) (maximum cost in deficit conditions).

$$obj\ func:\ \overline{\alpha} = \max\alpha \tag{43}$$

$$\text{s.t}: \Delta \leq C_r = (1-\sigma)\times F_b \tag{44}$$

$$0 \leq p_t^D \leq p^{max}\forall t \tag{45}$$

$$\Delta^* = \sum_{t=1}^{\tau}\left\{\Delta_t^+ \times \phi_t + \Delta_t^- \times (1-\phi_t)\right\}\forall t \tag{46}$$

$$\Delta_t^+ = \lambda_t^D P_t^D + \lambda_t^{B+}\left[P_t^D - \sum_{i=1}^{N_i} P_t^i\right] \tag{47}$$

$$\Delta_t^- = \lambda_t^D P_t^D - \lambda_t^{B-}\left[\sum_{i=1}^{N_i} P_t^i - (P_t^D)\right] \tag{48}$$

$$P_t^D \leq \sum_{i=1}^{N_i} P_t^i + (1-\phi_t)\times H \tag{49}$$

$$P_t^D \geq \sum_{i=1}^{N_i} (P_t^i - \phi_t)\times H \tag{50}$$

$$(1+\alpha)\overline{\lambda}_t^{D} = \lambda_t^{D} \tag{51}$$

$$(1+\alpha)\overline{\lambda}_t^{B+} = \lambda_t^{B+} \tag{52}$$

$$(1-\alpha)\overline{\lambda}_t^{B-} = \lambda_t^{B-} \tag{53}$$

In the above equations, a large constant coefficient $P_t^D \leq H$ is considered. In addition, the binary coefficient ϕ_t for surplus and deficit is considered equal to 1 and 0, respectively.

5. The Third Layer: Responsive Shopping Centers

The commercial consumer considered in this research is a collection of responsive shopping centers, which are the components of the commercial aggregator. HVAC systems are among the major consumers of electrical energy in the commercial sector, especially in shopping centers. An HVAC system is a simple heating and cooling converter using water or a direct expansion system as a cooling method. HVAC systems' pumps transfer hot or cold water to converters. Then, fans transfer the hot or cool air created in the converters to the desired building. In this section, we examine an HVAC system as a major consumer in a shopping center and model its main components mathematically. An HVAC system consists of three main parts: (1) pumps, (2) a cooling tower, and (3) an electric chiller system.

The attached pumps are of the VFD (Variable Frequency Drive) type in this model. Figure 4 shows an example of an HVAC system.

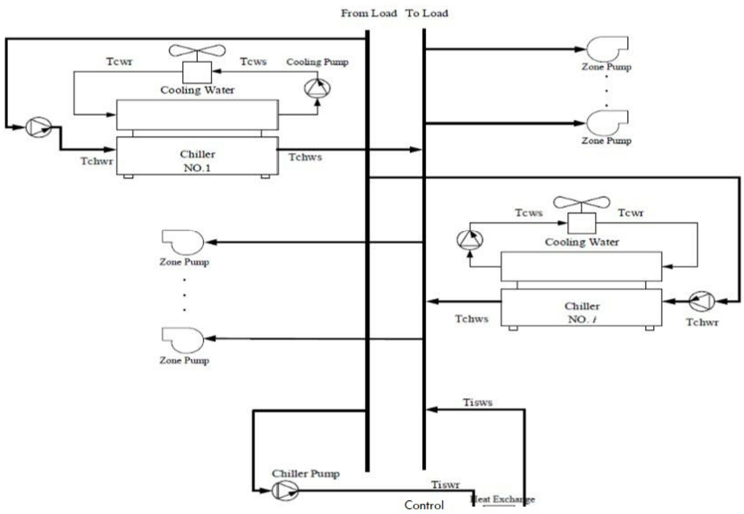

Figure 4. Heating, ventilation, and air-conditioning (HVAC) system.

In this research, the HVAC system of the central building facilitates the flexibility of the power system as follows:

- By using an electric energy storage system;
- By shutting down chiller units to provide minimum cooling.

The mathematical formulation of the HVAC system of the shopping center is defined as follows.

$$P_t^i = \sum_{i=1}^{I} P_t^{i,c} \tag{54}$$

$$P_t^{i,c} = \sum_{c=1}^{C} P_{t,h}^{i,c} \tag{55}$$

$$P_{t,h}^{i,c} = \sum_{e=1}^{E} P_{t,e}^{i,c} + \sum_{p=1}^{P} P_{t,p}^{i,c} + \sum_{ct=1}^{Ct} P_{t,ct}^{i,c} + \sum_{l=1}^{L} P_{t,l}^{i,c} \tag{56}$$

$$P_{t,l}^{i,c} = a_l + b_l \times \Omega_l + c_l \times \Omega^2 + d_l \times {\Omega_l}^3 \tag{57}$$

$$P_{t,ct1}^{i,c} = \overline{P}_{t,ct}^{i,c} \times \Theta_{t,ct}^{i,c} \tag{58}$$

$$P_{t,ct2}^{i,c} = P_{\ t,ct2}^{\ i,c} \times \varpi_{t,ct}^{i,c} \tag{59}$$

$$P_{t,ct}^{i,c} = P_{t,ct2}^{i,c} + P_{t,ct1}^{i,c} \tag{60}$$

$$P_{t,p}^{i,c} = \overline{P}_{t,p}^{h,c}(\upsilon) \times \varpi_{t,p}^{h,c}(\upsilon) \tag{61}$$

The commercial aggregator i includes shopping centers c = {1, 2, 3, . . . , C}. Shopping centers, denoted as C, include a set of HVAC systems H = {1, 2, 3, . . . , H}, and these HVAC systems also consist of a set of chiller sub-systems l = {1, 2, 3, . . . , L}, pumps P = {1, 2, 3, . . . , P}, cooling towers CT = {1, 2, 3, . . . , Ct}, and an electrical energy storage system e = {1,2,3, . . . , E}.

The parameter p_t^i in Equation (54) denotes the total power consumption of shopping center C. In Equation (55), $P_t^{i,c}$ is the total power consumption of shopping center ventilation systems $h = \{1, 2, 3, \ldots, H\}$. In Equation (56), $P^{i,c}_{t,h}$ denotes the total power consumption of the main parts of the ventilation system (chillers, pumps, cooling tower, and electrical energy storage system). In Equation (57), taken from reference [38], $P^{i,c}_{t,l}$ represents the power consumption of the chiller system, which is proportional to the load cooling capacity Q_l. The regression coefficients (a_l, b_l, c_l, d_l) constitute a function of load cooling capacity and chiller consumed power. In Equation (58), $P^{i,c}_{t,ct1}$ is the consumed power of the cooling tower and is a function of the rated power of the cooling tower pump $\overline{P}^{i,c}_{t,ct}$ and the air flow rate $\Theta^{i,c}_{t,ct}$. In Equation (59), $P^{i,c}_{t,ct2}$ represents the consumed power of the cooling tower, which is a function of the rated power of the cooling tower fan $\overline{P}^{i,c}_{t,ct2}$ and the water flow rate $\varpi^{i,c}_{t,ct}$. Equation (60) provides the total power consumption of the cooling tower. In Equation (61), $P^{i,c}_{t,p}$ denotes the pumps' power consumption, which is a function of the pumps' rated power consumption $\overline{P}^{h,c}_{t,p}(f)$ and the water flow rate $\varpi^{h,c}_{t,p}(f)$, which are dependent on the frequency of the motors.

$$\Theta^{i,c}_{t,ctmin} \leq \Theta^{i,c}_{t,ct} \leq \Theta^{i,c}_{t,ctmax} \tag{62}$$

$$\varpi^{i,c}_{t,ctmin} \leq \varpi^{i,c}_{t,ct} \leq \varpi^{i,c}_{t,ctmax} \tag{63}$$

$$\varpi^{h,c}_{t,pmin}(\upsilon) \leq \varpi^{h,c}_{t,p}(\upsilon) \leq \varpi^{h,c}_{t,pmin}(\upsilon) \tag{64}$$

$$\frac{P^{i,c}_{t,p}(\upsilon_2)}{P^{i,c}_{t,p}(\upsilon_1)} = \left(\frac{\upsilon_2}{\upsilon_1}\right)^3 \tag{65}$$

$$\nu^{lo} \leq \nu \leq \nu^{up} \tag{66}$$

$$\sum_{l=1}^{L} Q_l(t) \times U_l(t) \geq CL_t \tag{67}$$

$$\Omega = \frac{(Q_L)}{(Q_{nL})} \tag{68}$$

$$0.3 \leq \Omega_l \leq 1 \tag{69}$$

$$U_l(t) = [0, 1] \tag{70}$$

$$\sum_{l=1}^{L} Q_n(l) \times \delta(t) = CL_t \tag{71}$$

Equation (62) shows the maximum and minimum bounds of the air flow rate from the cooling tower. The maximum and minimum bounds of the water flow rate from the cooling tower are given in Equation (63). Equation (64) states the maximum and minimum bounds of the pumps' water flow rate. Equation (65) describes the adjustable level of power consumption based on the third power of the frequency. In addition, Equation (66) expresses the upper and lower bounds of the set frequency. Finally, the cooling load balance at time t is stated in Equation (67). The total cooling capacity provided by the ventilation systems must be greater than the total cooling load of the system at time t. CL_t is determined according to the ventilation system's temperature and rated capacity. Equation (68) yields the chiller's part load ratio (Ω). According to the manufacturer's recommendation, the lower limit of the chillers in operating mode should not be less than 30% (Equation (69)). Equation (70) shows the chillers' binary coefficient for minimum cooling, representing the on and off states as 1 and 0, respectively. Equation (71) denotes the total cooling load adjusted based on a coefficient of the nominal cooling capacity of the chillers and proportional to the temperature and electricity prices.

- *An Electric Energy Storage System*

$$\mathrm{soc}^{\mathrm{i}}(\mathrm{t}) = \mathrm{soc}^{\mathrm{i}}(\mathrm{t}-1) + \mathrm{p}^{\mathrm{ch}}(\mathrm{t})\xi_{\mathrm{ch}}^{\mathrm{st}} - \frac{\mathrm{p}^{\mathrm{dch}(\mathrm{t})}}{\xi_{\mathrm{dch}}^{\mathrm{st}}} \tag{72}$$

$$\mathrm{soc}^{\mathrm{i}}(\mathrm{t}) = \mathrm{soc}^{\mathrm{i}}(\mathrm{T}) \tag{73}$$

$$\mathrm{soc}^{\mathrm{i,min}}(\mathrm{t}) \leq \mathrm{soc}^{\mathrm{i}}(\mathrm{t}) \leq \mathrm{soc}^{\mathrm{i,max}}(\mathrm{t}) \tag{74}$$

$$0 \leq \mathrm{p}^{\mathrm{ch}}(\mathrm{t}) \leq \vartheta_{\mathrm{ch}} \times \varnothing \times \mathrm{soc}^{\mathrm{i,max}}(\mathrm{t}) \tag{75}$$

$$0 \leq \mathrm{p}^{\mathrm{dch}(\mathrm{t})} \leq \vartheta_{\mathrm{dch}} \times \varnothing \times \mathrm{soc}^{\mathrm{i,max}}(\mathrm{t}) \tag{76}$$

$$\vartheta_{\mathrm{ch}} + \vartheta_{\mathrm{dch}} \leq 1 \tag{77}$$

For each HVAC system, an electric storage system's charging and discharging states are considered to respond during an accident or when the electricity market price increases. $soc(t)$ is the state of charge at time t. In addition, $\xi_{\mathrm{ch}}^{\mathrm{st}}$ and $\xi_{\mathrm{dch}}^{\mathrm{st}}$ represent the charge and discharge efficiency, respectively. $\mathrm{p}^{\mathrm{ch}}(\mathrm{t})$ and $\mathrm{p}^{\mathrm{dch}(\mathrm{t})}$ represent the charge and discharge power, respectively. The parameters $\mathrm{soc}(\mathrm{t})^{\mathrm{max}}$ and $\mathrm{soc}(\mathrm{t})^{\mathrm{min}}$ reflect the minimum and maximum capacity of the ESS. In Equation (72), the parameter $\mathrm{soc}(\mathrm{t})$ is determined every hour by considering the ESS's charging and discharging values. According to Equation (73), the value of $\mathrm{soc}(\mathrm{t})$ must be equivalent at the beginning and end of the process. Value of $\mathrm{soc}(\mathrm{t})$ is bounded under its limit in Equation (74). The amount of charge or discharge is limited to the maximum capacity of the ESS in (75) and (76). According to Equation (77), the discharging and charging of the storage system cannot occur simultaneously.

The flow of information between different participants is depicted in Figure 5. By collecting the abovementioned information, the CDRA determines the optimized operation for the contracted industries during the next 24 h. The coordination mechanism between the CDRA and the commercial agent is described sequentially in Figure 6 to clarify the problem.

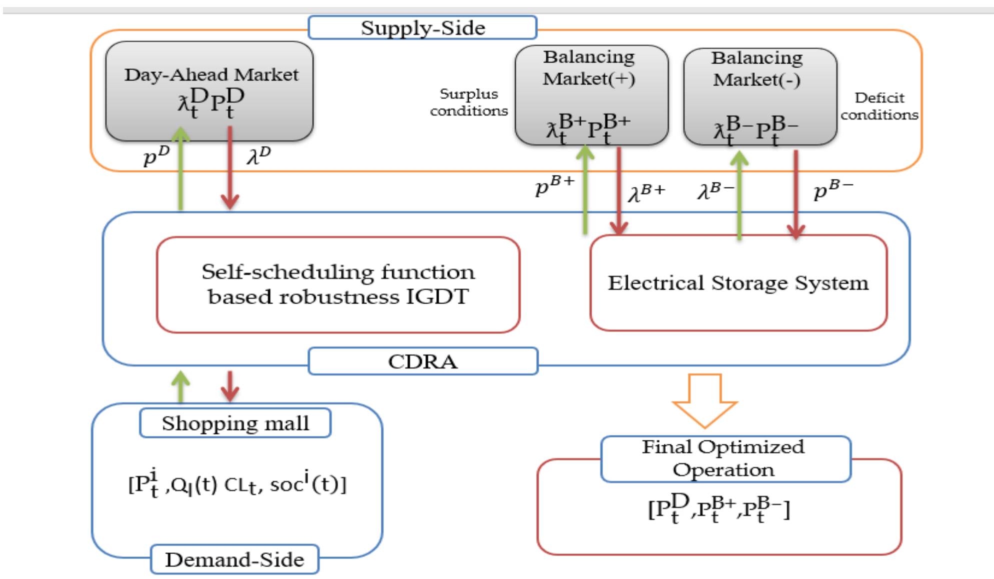

Figure 5. The information flow of the proposed approach.

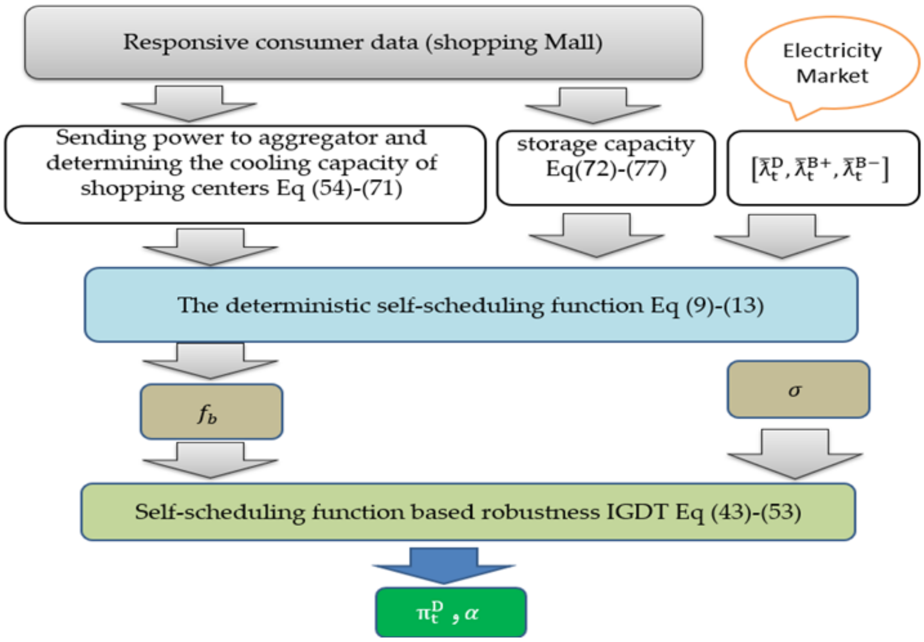

Figure 6. The steps of the operational optimization for IGDT-based commercial DR aggregator.

6. The Operating Mechanism of The Suggested Model for The Commercial Aggregator

The steps of the operational optimization method of the commercial DRA based on the suggested IGDT method are shown in Figure 6. In the first step, the commercial aggregator's power is determined using shopping center data and is proportional to both the cooling capacity (according to Equations (54) to (71)) and the storage power (according to Equations (72) to (77)). In the next step, the final cost f_b of the aggregators is calculated using the predicted inputs $\left[\bar{\lambda}_t^{D}, \bar{\lambda}_t^{B+}, \bar{\lambda}_t^{B-}\right]$ and the values obtained from the previous step. Then, the critical cost of the aggregators Δ is calculated using f_b and σ. As explained earlier, Δ is equivalent to the highest possible cost for the DRA. The output of the prior step is used to implement IGDT-based scheduling in the day-ahead energy market while considering all uncertainties.

7. Simulations and Discussion

This paper's study horizon is a single day (24 h). The suggested approach is implemented during this period to supply the responsive consumers on one side and provide power flexibility to the power system on the other side.

7.1. Case Study and Problem Data

The commercial DR aggregator includes two shopping centers, each with an HVAC system. These HVAC systems are multi-chiller systems and are considered major electricity consumers in these shopping centers. The HVAC systems include six chillers (two sets of chillers with a nominal cooling capacity of RT550 and four sets of chillers with a nominal cooling capacity of RT1000), two primary and secondary pumps with the ability to change their speed, and a cooling tower system. The cooling capacity for each RT is 13,910 KJ/h. The air-conditioning system works in two (ON or OFF) functional modes (depending on whether it is day or night) and has a minimum cooling capacity. Table 1 shows the ON/OFF performance curve coefficients for chillers 1 to 6.

Table 1. Curve coefficients of chillers' performance [43].

Chiller	a	b	c	d
chiller1	1.249×10^{-9}	1.3707×10^{-8}	0.1961	65.7772
chiller2	-2.628×10^{-8}	1.139×10^{-4}	0.0449	128.7969
chiller3	-7.599×10^{-9}	4.13921×10^{-5}	0.1418	68.2033
chiller4	-1.467×10^{-9}	1.87115×10^{-5}	0.1181	107.7250
chiller5	-2.660×10^{-8}	0.000228205	−0.4555	623.2087
chiller6	-1.141×10^{-8}	6.87455×10^{-5}	0.0851	101.5365

Table 2 shows the nominal cooling capacity of chillers 1–6 in the air-conditioning systems of the studied shopping centers. The nominal cooling capacity for chillers 1 and 2 and 1 to 4 are RT550 and RT1000, respectively (according to Tables 2–4).

Table 2. The nominal cooling capacity of chillers.

Chiller Number	Chiller1	Chiller2	Chiller3	Chiller4	Chiller5	Chiller6
nominal cooling capacity (RT)	1000	1000	1000	1000	550	550

Table 3. Specifications of electric storage system.

ESS	$\mathbf{soc(t)^{max}}$	$\mathbf{soc(t)^{min}}$	η_{ch}^{st}	η_{dch}^{st}
value	400	100	0.95	0.9

Table 4. The upper and lower bounds of variables and parameters of the uncertainty model.

Parameter	B_t^{+up}/B_t^{-up}	B_t^{+lo}/B_t^{-lo}	σ
value	50,000	0	0–0.7

The water flow output rate ranges from 50 to 500 cubic meters per hour. As the cooling towers are equipped with air fans, the level of power consumption is proportional to the rate of air input and output, which varies between 60 and 600 cubic meters per hour. The technical specifications of the energy storage systems (ESSs) of the shopping centers are presented in Table 3. The bounds of the charging mode, charging, and discharging rates of the ESSs considered in this research are presented in Table 3.

The maximum and minimum bounds of the variables and parameters of the IGDT uncertainty model are presented in Table 4. In addition, B_t^{+up} and B_t^{+lo} are the maximum and minimum bounds of the aggregator's profit when surplus conditions occur. B_t^{-up} and B_t^{-lo} are the upper and lower bounds of the aggregator's profit, respectively, when deficit conditions occur. The profit deviation coefficient σ indicates the risk aversion level of the aggregator. The higher the value of σ, the more risk-averse the aggregator.

This research considers the market price in the day-ahead electricity and balancing markets as uncertainty variables. The IGDT robust scheduling model considers the average or predicted values of the uncertainty variables. Therefore, as shown in Figure 7, the average day-ahead values were extracted from the New York electricity market [44] for a 24 h period. In this article, the New York electricity market was considered an exemplary electricity market due to the increasing penetration of renewable sources and because of its well-known and comprehensive nature. The surplus and deficit balancing electricity market prices are considered 0.9 and 1.1 of the day-ahead price, respectively. Under the deficit of the network, the balancing market price is higher than the day-ahead market price.

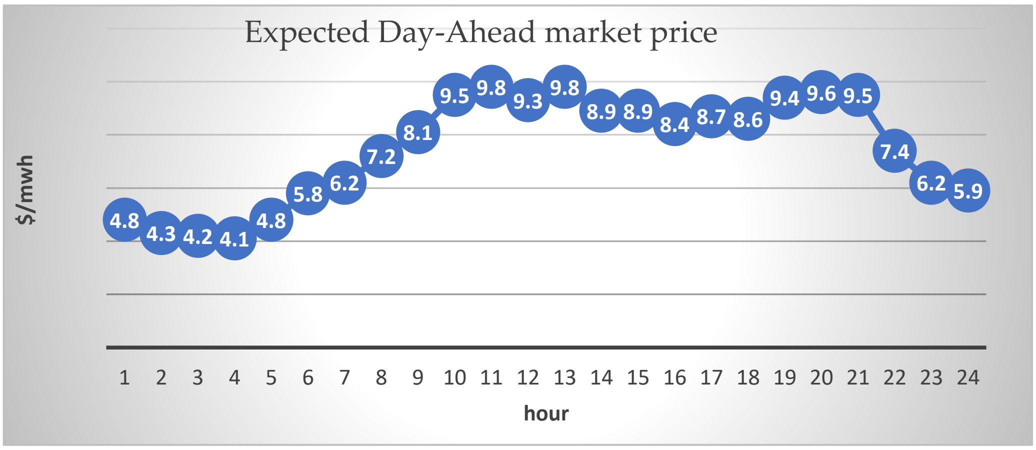

Figure 7. Average day-ahead electricity market price.

The total cooling load required by the shopping centers is adjusted based on the multiple of $\delta(t)$ according to the temperature and electricity price in the suggested model, and the nominal cooling capacity of the chillers is obtained. $\delta(t)$ is a number between zero and one. This parameter is closer to 1 during peak hours when the temperature of the shopping centers is high. The considered values for $\delta(t)$ are shown in Figure 8 for different hours of the day. As shown, the hourly value of this parameter is between zero and one.

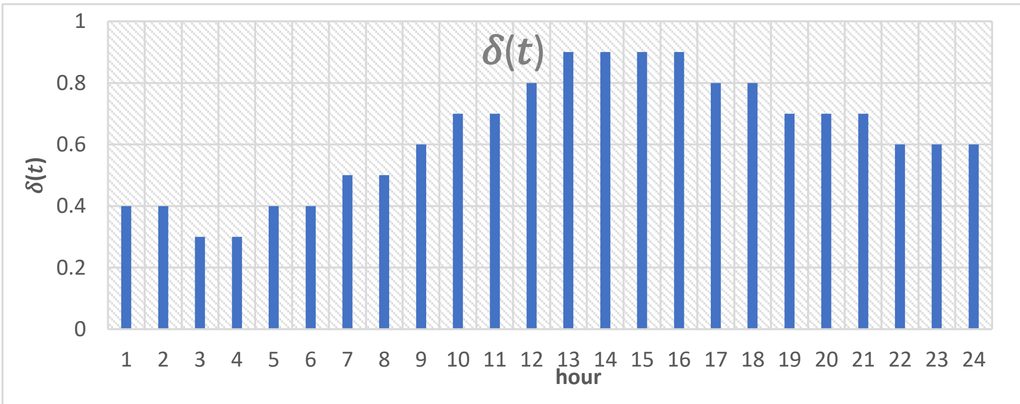

Figure 8. Cooling load capacity coefficient $\delta(t)$.

7.2. Analysis of Simulation Results

In this section, we apply our model, developed in the GAMS 24.1.2 software environment, to a commercial, responsive aggregator to determine its effectiveness and the efficiency of uncertainty modeling based on IGDT. The presented problem is processed using an integer nonlinear programming (MINLP) model implemented using the DICOPT solver for optimization in the GAMS software environment. The simulation process was executed on a PC with 4 GB of RAM and a 2 GHz processor.

In shopping centers, responsive HVAC systems must provide the minimum cooling capacity necessary for the comfort of owners and users. They should also respond to the operational plans applied by the aggregator according to the electricity market price. Accordingly, the minimum cooling load required for the shopping centers is shown in Figure 9. As shown in the figure, the maximum cooling load of the shopping centers occurs between 12–16 h. The HVAC systems of the shopping centers should provide this cooling load such that the DR schedule is realized. Since HVAC systems are considered multi-chiller systems, the chillers of the HVAC system work according to their power consumption in on and off schedules.

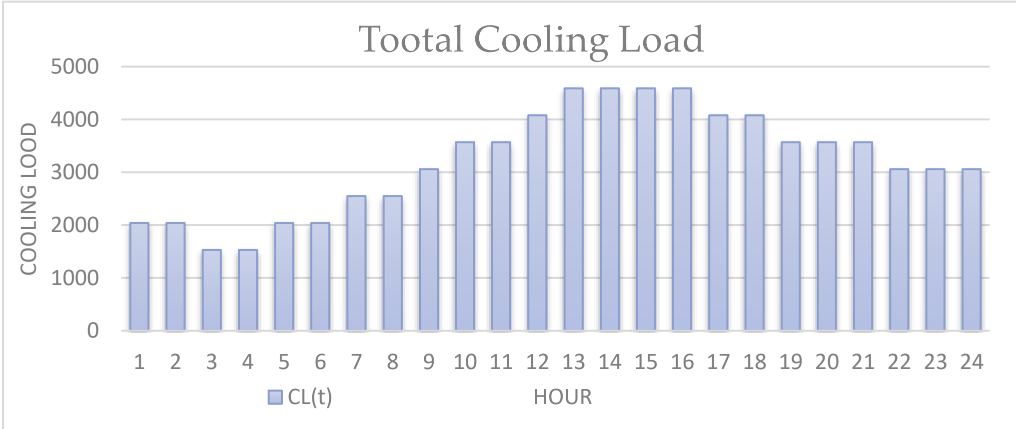

Figure 9. The total cooling capacity of the shopping center.

Figure 10 shows the cooling load ratio of the chillers to the nominal part load ratio (PLR). The figure shows that the PLR coefficient for the working chillers varies between 0.3 and 1.

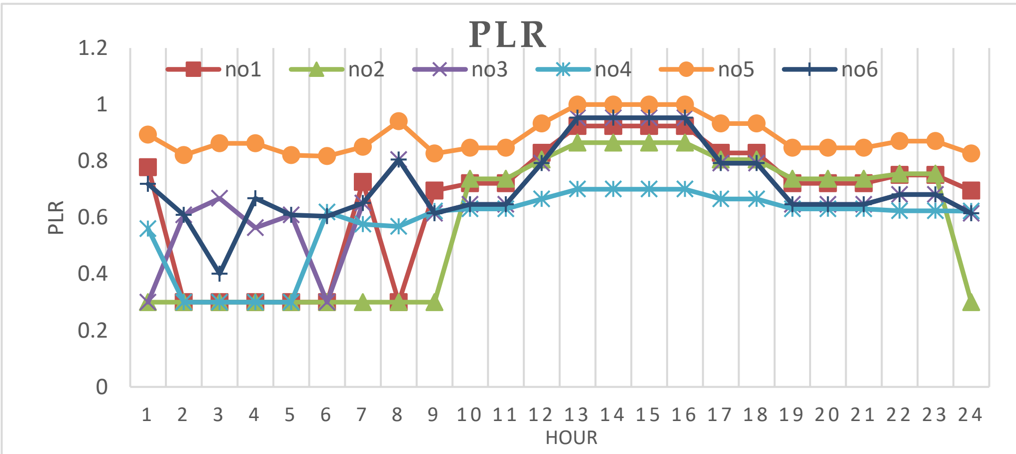

Figure 10. PLR value for working chillers over 24 h.

Table 5 shows the results of the application of the HVAC system schedule over a 24 h period. According to the minimum cooling load of the shopping centers and the price of electricity, the chillers are programmed to provide minimum cooling and implement DR scheduling in the form of on and off modes. In Table 5, the numbers 1 and 0 indicate whether the chillers are on or off, respectively. According to Table 5, at time 1, chillers 4, 1, and 6 are turned off according to their cooling capacity, and chillers 3, 2, and 5 are turned on so that the required cooling capacity is met at time 1, as shown in Figure 10.

Additionally, based on the hourly DR schedule, the most optimal and least expensive chiller is turned on according to its regression coefficients and cooling capacity. The last column shows the power consumption of the HVAC systems' chillers. The maximum power is consumed from 12–16.

According to the data presented in Table 5, the power consumption of the HVAC system over 24 h is shown in Figure 11.

Figure 12 shows the cooling capacity of the chillers. As shown, the brown line represents the minimum cooling load required for shopping centers, which must be provided by the HVAC systems' chillers so that the HVAC system consumes the minimum amount of power.

Table 5. Schedule of turning chillers off and on.

hour	Chiller1	Chiller2	Chiller3	Chiller4	Chiller5	Chiller6	(MWH)
1	0	1	1	0	1	0	1078.696
2	1	1	1	0	1	0	1037.604
3	0	0	1	0	1	0	800.2
4	0	0	0	0	1	1	800.2
5	0	1	0	0	1	1	1078.696
6	0	0	1	0	1	1	1062.392
7	0	1	1	0	1	1	1327.317
8	1	0	1	0	1	1	1322.781
9	1	1	1	0	1	1	1595.656
10	1	1	1	1	1	1	1884.176
11	1	1	1	1	1	1	1884.176
12	1	1	1	1	1	1	2279.53

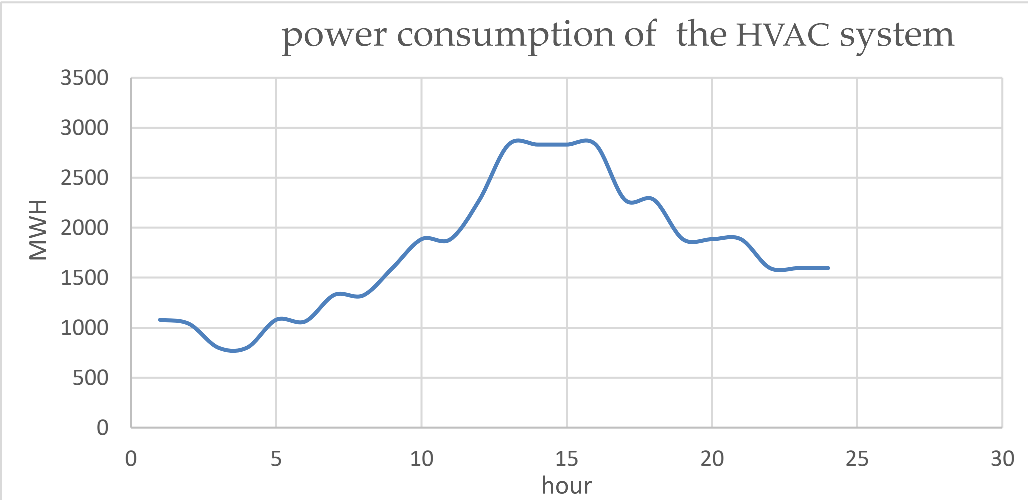

Figure 11. Power consumed by the HVAC system.

Figure 13 shows the price of the day-ahead electricity market and the balancing market, for which the uncertainty in the deviation coefficient of σ = 0.05 is considered. For a given uncertainty horizon, achieving the worst possible scenario, i.e., the maximum cost, is possible only if the day-ahead market price and the imbalance price are equal to their maximum value. As shown in Figure 13, the day-ahead electricity market and balancing market prices are obtained as uncertainty parameters in the worst possible scenario in the IGDT model. This figure shows the process of changing the values of these variables in the direction of robust optimization in the worst scenario. Based on these figures, the market price in the power deficit state has decreased after optimization (a decrease in the radius $(1-\alpha)$), but the price of the day-ahead market and the surplus market has increased (an increase in the radius $(1+\alpha)$).

In the surplus condition of the network, the ESSs of the shopping centers are charged. Subsequently, in deficit conditions, the ESS load is discharged to compensate for the deficit in the network. By participating in the electricity market, the ESSs help balance the energy supply and demand, thus preventing energy shortages. Figure 14 shows the process of charging the electric energy storage device connected to the HVAC systems under surplus conditions of the network. As shown in the figure, the electric energy storage system is charged at hours 24, 19, 18, 16, 12, 4, and 3 when the network is under surplus conditions and the price of electricity is decreased.

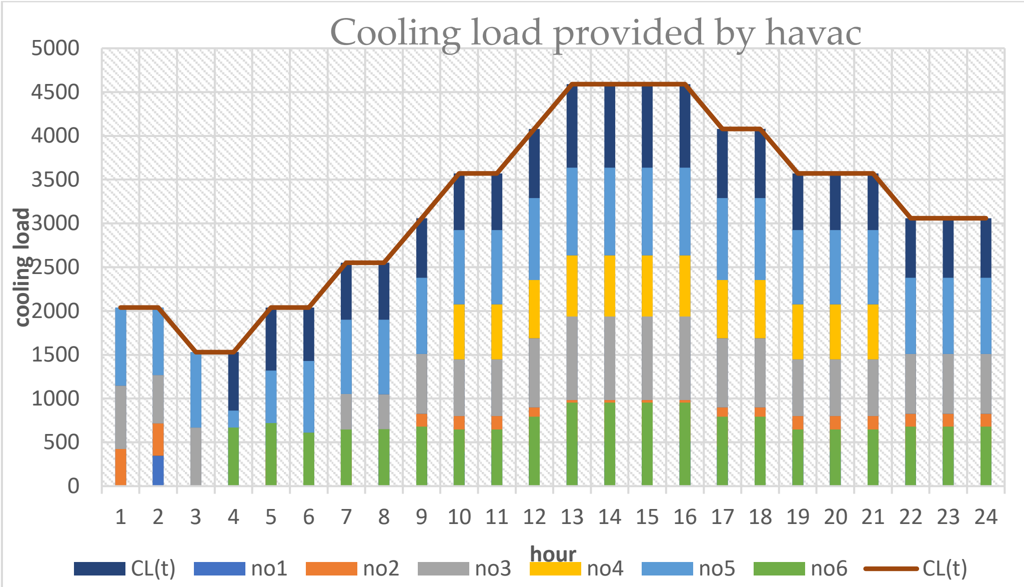

Figure 12. Cooling capacity provided by chillers.

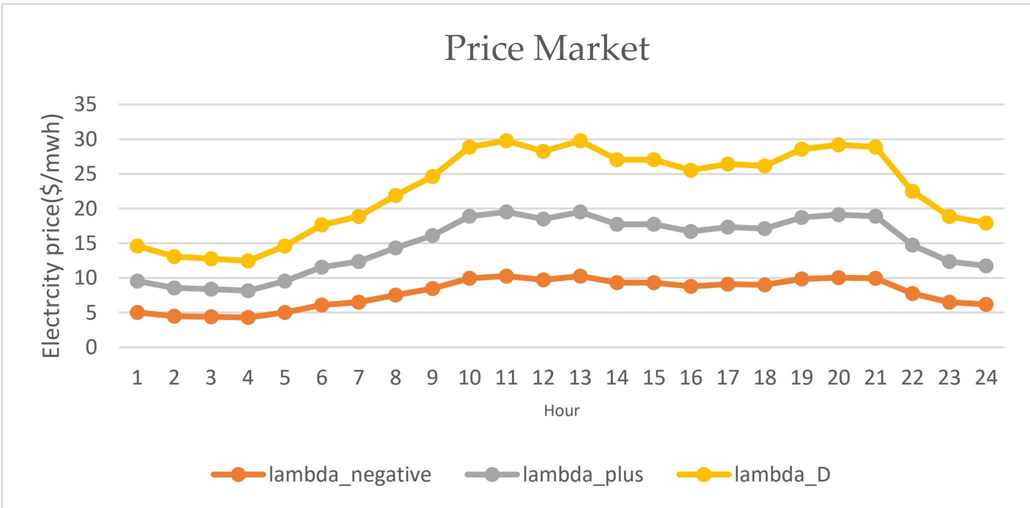

Figure 13. Day-ahead electricity market price and balancing market price while considering the uncertainty in the deviation coefficient σ = 0.05.

Figure 15 shows the optimal performance of the electric energy storage system for participation in the equilibrium market under deficit conditions. According to Figure 15, at hours 21, 20, 13, 11, 10, and 1, the ESS's power is provided to the network when the network is in a deficit state and the price of electricity increases.

The power supplied by the commercial aggregator in the balancing electricity market under surplus and deficit conditions is shown in Figure 16. According to Figure 16, the stored power is sold in the electricity market under deficit conditions. In the case of excess supply, the stored charge is purchased from the electricity market.

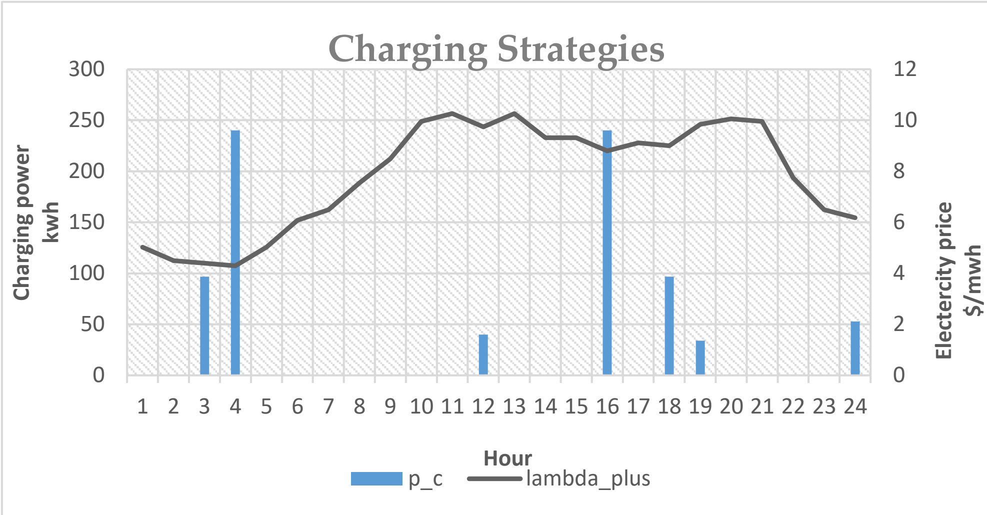

Figure 14. The process of charging the energy storage system in surplus conditions.

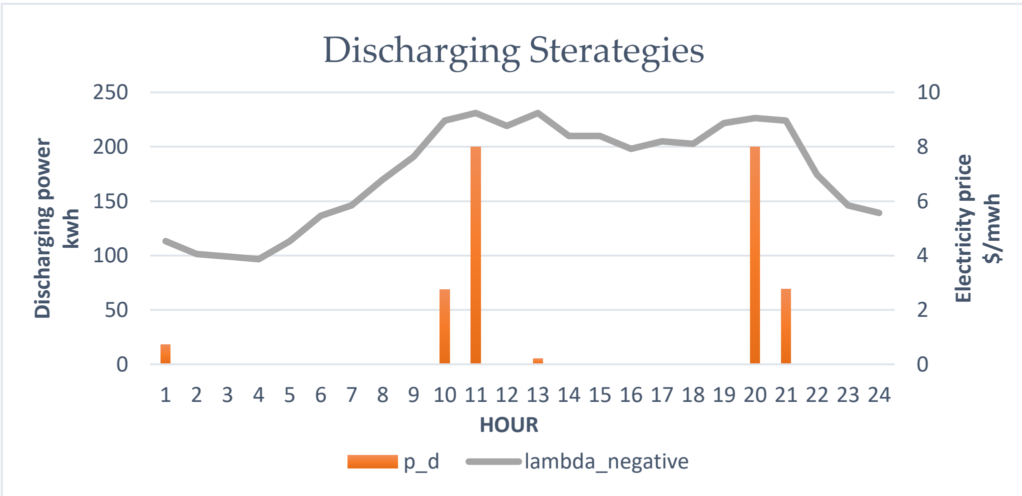

Figure 15. The process of discharging the energy storage system under deficit conditions.

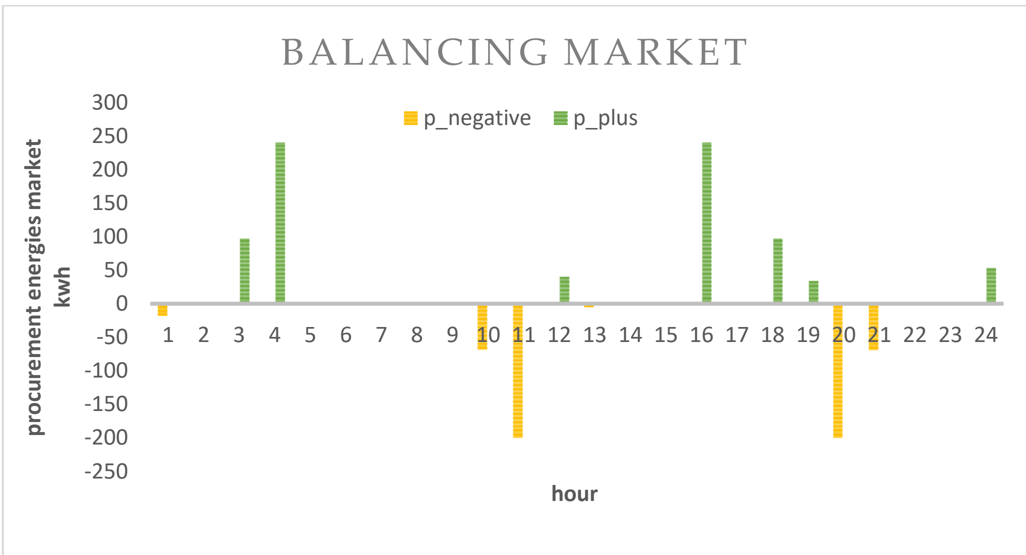

Figure 16. Power supply in the balancing electricity market.

Figure 17 shows the power purchased by the CDRA in the electricity market. The HVAC systems' chillers participate in the DR scheduling of commercial aggregators according to the minimum cooling load they must provide for shopping centers to satisfy the users and owners. Chillers can be turned off or on to respond to the DR schedule. In different situations of deficit or surplus, the ESS balances the network via successive charging and discharging. As shown in the figure, at hours 21, 20, 13, 11, 10, and 1, the deficit has been compensated by the energy storage system. In the same way, at hours 24, 19, 18, 16, 12, 4, and 3, the surplus production has charged the energy storage system.

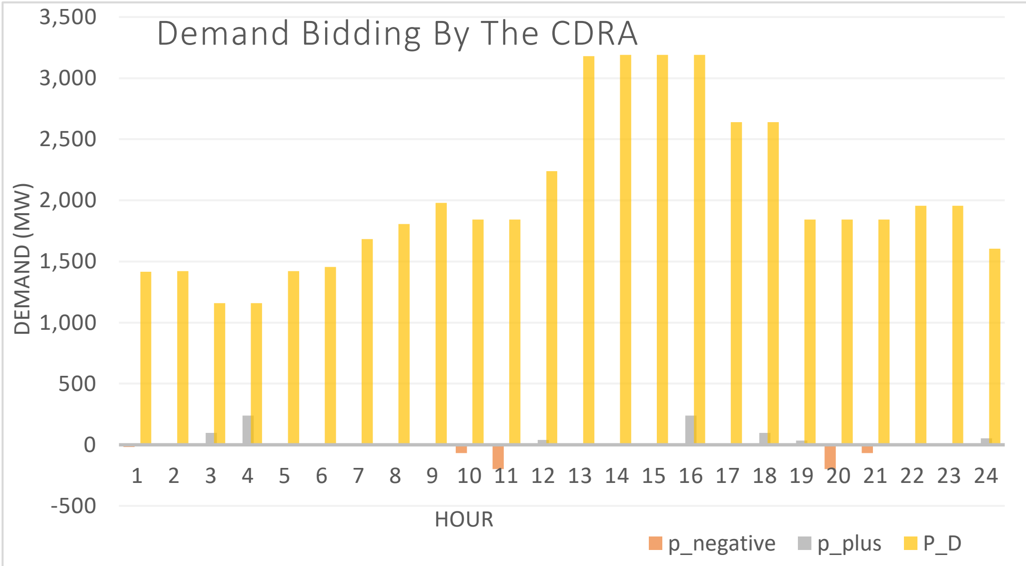

Figure 17. Power provided by CDRA.

Figure 18 compares the CDRA profiles between two modes: (1) a responsive system and (2) a non-responsive system (conventional). A responsive system refers to our suggested approach: the use of an electric storage system and chillers that can be turned on and off. On the other hand, the traditional model contains conventional systems without an electric storage system and chillers that can be turned on and off. As shown in the plot, when the temperature rises, the traditional HVAC system consumes the required electricity regardless of the consumption power of the chillers. Consumption increases again in the midday hours, i.e., at the peak of heat. The demand profile of the prevalent system follows the temperature rise pattern regardless of the electricity price. In such a system, there is no flexibility in terms of demand. Unlike the previous case, the suggested responsive aggregator can match the dynamic electricity market and achieve demand flexibility according to the electricity price. The numerical results show that the commercial aggregator can reduce power consumption by 18% by participating in DR scheduling compared to non-participation.

Table 6 displays the outcomes of the IGDT variables. The deviation coefficient (σ) is defined to model the highest cost of the DRA, as demonstrated in the problem formulation section. Different deviation coefficient (σ) values are displayed in the first column, ranging from 0.00 to 0.09 with 0.01-point increments. Since the cost of executing the suggested approach (the robust cost) is greater than the aggregator's total revenue for values greater than 0.09, the robust ideal value of IGDT is unsatisfactory. The critical cost is equal to USD 441,710 for the deviation coefficient σ = 0.02, and the definite cost determined from the IGDT certain model was determined to be $(1-0.2)\ f_b = USD\ 396,620$. Table 6 shows that a given deviation coefficient's critical cost can only be realized if the participants' errors in the power market are less than 0.081. Additionally, the DRA tends to transform into a risk-free actor when the deviation coefficient is close to zero. For instance, the crucial cost for σ = 0.01 is around USD 400,660, which is quite close to the cost of the risk-free aggregator.

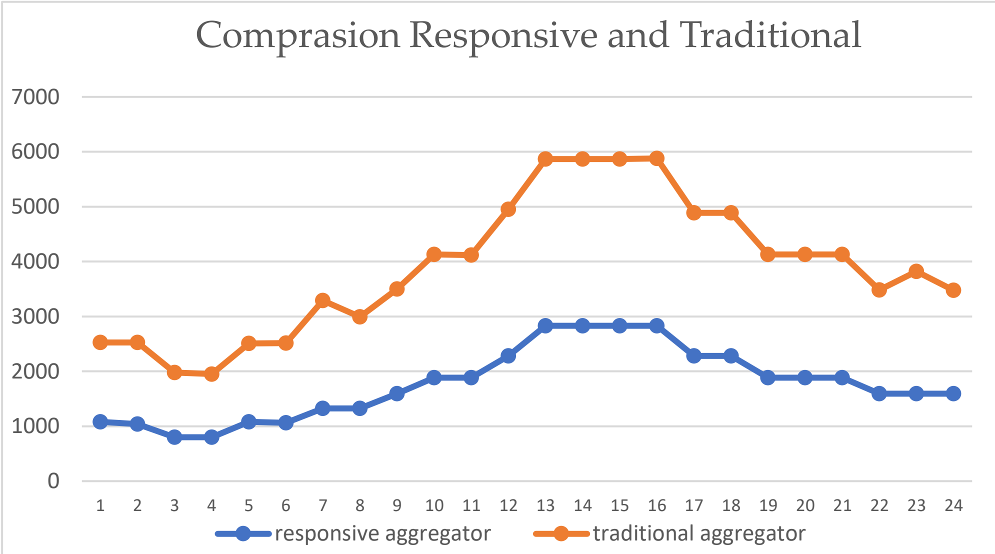

Figure 18. Comparison of power consumption between responsive and non-responsive aggregator modes.

Table 6. Optimal robustness function value and schedule.

(σ)	Critical Cost (USD)	Robust Optimal Value $\overline{(\alpha)}$
0.00	404,710	0.103
0.01	400,660	0.092
0.02	398,640	0.081
0.03	392,570	0.070
0.04	388,520	0.059
0.05	384,470	0.048
0.06	380,430	0.037
0.07	376,380	0.026
0.08	372,330	0.015
0.085	370,310	0.009
0.090	368,290	0.004

Higher values facilitate the creation of a more reliable self-scheduling strategy for the deviation coefficient (σ), and the calculated critical cost applies to a larger range of uncertain variables. In light of the maximum tolerable cost, an aggregator can modify the robustness level of the suggested method. One of the main benefits of the proposed strategy is that it requires less information compared to previous non-deterministic techniques such as stochastic programming, fuzzy optimization, and resilient optimization. Consequently, it is easy to adopt the suggested IGDT-based method. After employing the suggested strategy, σ performs the function of an adjustment operator. Depending on its preferences, the aggregator can be adjusted to obtain the optimal trade-off between the allowable uncertainty range and the crucial cost. The best resilient function ($\overline{\alpha}$) against various important costs is depicted in Figure 19. The value of the ideal robust function ($\overline{\alpha}$) increases linearly as the critical cost increases, as depicted in the image. When the aggregator anticipates a lower cost, the optimal robust function's lower values ($\overline{\alpha}$) are reached. The worst-case scenario is the set of values for the day-ahead market prices, that is, the positive and negative equilibrium prices, which are the highest and lowest, respectively. Aggregator expenses are decreased due to the scheduler implementing the IGDT robust function. It should be noted that there are no errors in the projected uncertain parameters. Therefore, the resulting unknown parameters are close to the anticipated values. In this case, the cost acquired from the risk-free aggregator is higher than that from the risk-averse aggregator if the IGDT robust model is used.

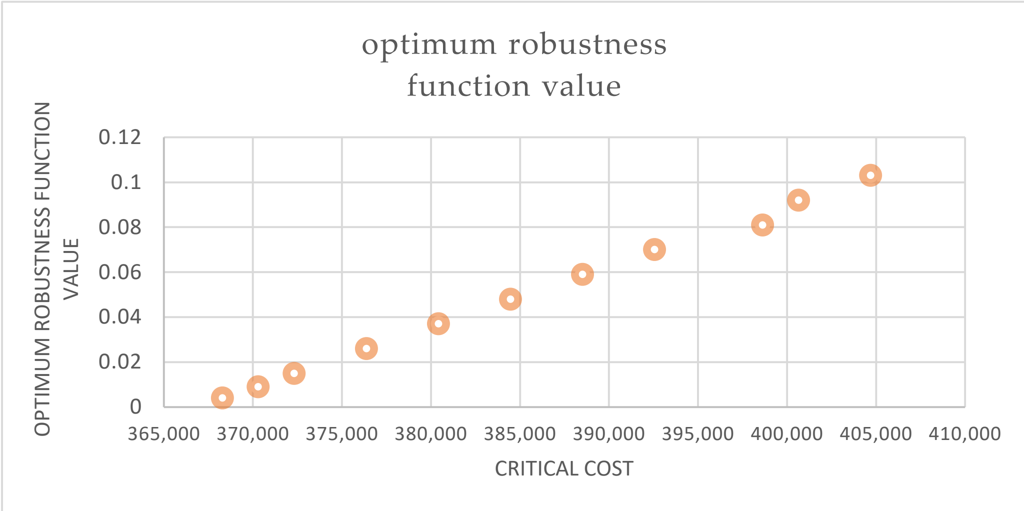

Figure 19. Robust optimal function versus critical cost.

Rugged cost is the distinction between the risk-free aggregator cost and the risk-averse aggregator cost (RC). Figure 20 displays the robust cost for various robust function ($\overline{\alpha}$) values. As shown in the figure, the decrease in $\overline{\alpha}$ leads to an increase in the robust cost. Self-scheduling incurs more expenses and raises the aggregator's cost as they approach the projected levels.

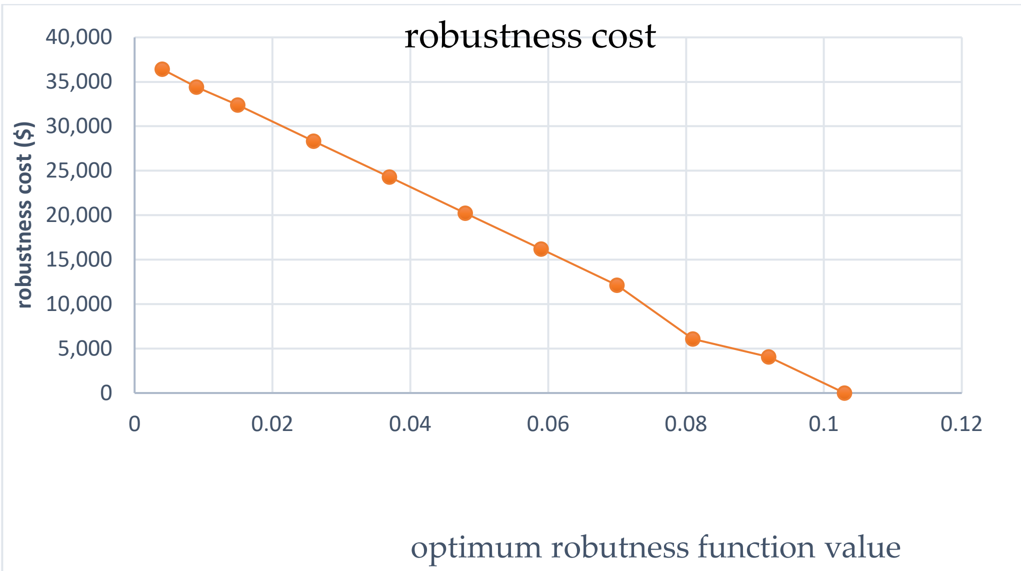

Figure 20. Robust cost versus robust optimal function.

The robust self-scheduling function based on IGDT is a two-level problem because the maximum required cost (at the lower level) depends on the uncertainty interval. The minimum conceivable value for the uncertainty horizon (α) equals 0.004. In addition, the predetermined cost Δ is equal to USD 368,290 dollars. Δ is the critical cost, which is considered a percentage of the fixed cost, i.e., $\mathcal{F}_b$. $\mathcal{F}_b$ is determined based on solving the deterministic problem described in the previous sections, whose solution is USD 404,710.

The objective function shown is robust and represents the worst-case scenario. Figure 21 shows the optimal scheduled day-ahead power for σ = 0.05 and α = 0.048. In this case, the certain and critical costs are equal to USD 404,710 and USD 384,470, respectively.

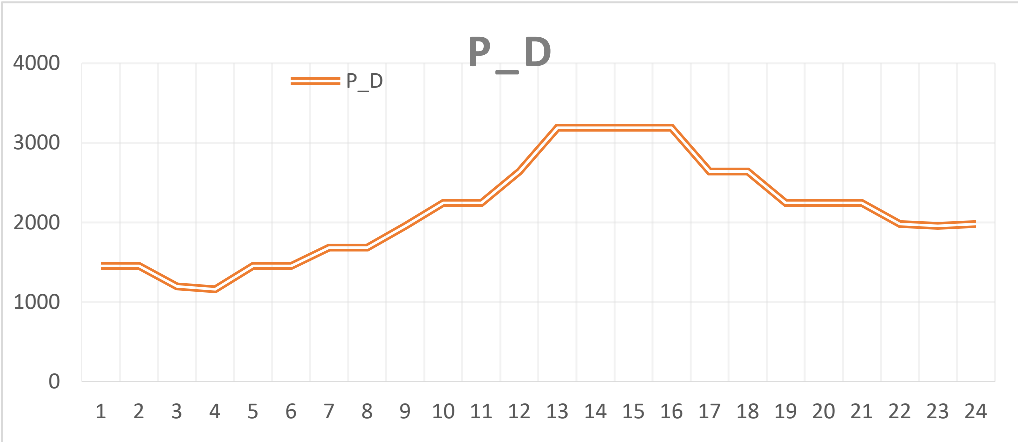

Figure 21. Optimal scheduled power with σ = 0.05.

Table 7 shows the surplus and deficit conditions for σ = 0.05 and α = 0.048. As shown in the table, after implementing the demand response scheduling for the commercial aggregator, for which uncertainty and optimization based on the IGDT model were accounted for, surplus conditions have occurred at hours 21, 20, 19, 11, 10, 4, and 3. In addition, deficit conditions occurred for the remaining hours of the day. It should be noted that β_t is a binary number and indicates surplus and deficit states. This parameter equals 1 and 0 for surplus and deficit conditions, respectively.

Table 7. Surplus and deficit (shortage) conditions for σ = 0.05 and α = 0.048.

hour	βt	Condition
1	0	Shortage
2	0	Shortage
3	1	Surplus
4	1	Surplus
5	0	Shortage
6	0	Shortage
7	0	Shortage
8	0	Shortage
9	0	Shortage
10	1	Surplus
11	1	Surplus
12	0	Shortage
13	0	Shortage
14	0	Shortage
15	0	Shortage
16	0	Shortage
17	0	Shortage
18	0	Shortage
19	1	Surplus
20	1	Surplus
21	1	Surplus
22	0	Shortage
23	0	Shortage
24	0	Shortage

8. Conclusions

This study addressed the flexibility potentials of the commercial demand sector, considering electricity markets with highly penetrable renewable power. A responsive shopping center system was mathematically modeled. In addition, a non-profit organization known as a CDRA was suggested to facilitate the integration of shopping centers' flexibility into the electricity market. A three-layer framework was proposed to incorporate shopping centers' flexibility in a hierarchical DR scheduling program from 24 h ahead until near real-time under severe uncertainty. A short-term self-scheduling model based on IGDT for DR aggregators was developed, which considers market price uncertainty when creating DR schedules. In the self-scheduling approach, the day-ahead and balancing markets, which are the most active, were also adequately considered. The IGDT-based robust function is designed to ensure the highest predetermined critical cost. The simulation results indicate that a significant amount of the required energy is purchased from the day-ahead market during periods with low electricity costs. The balancing market enables the CDRA to incorporate the predictability of renewable electricity generation into its trading strategies.

The CDRA utilizes the electrical storage system to balance a power system when there is excess electricity or a shortfall in the electricity market. Finally, the balancing market offers real-time high or low-regulation supply conditions for the power system. According to a comparison of electricity usage between the traditional and responsive systems, the responsive system can provide demand flexibility to the power system at up to 18% of the nominal electricity consumption level. The integration of commercial flexibility with the electricity system was the main focus of this study, and it has been regarded as a significant challenge for energy policymakers. Further research is needed in this area.

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Nomenclature

A. Index and sets	
t	Index of time t
i	Index of CDRAs
c	Index of the shopping center
h	Index of HVAC system
B. Parameters	
$\overline{\lambda}_t^D$	Expected day-ahead market price (USD/MWh)
$\overline{\lambda}_t^{B-}$ / $\overline{\lambda}_t^{B+}$	Deficit (excess) imbalance prices (USD/MWh)
C_r	Critical cost (USD)
σ	Cost deviation coefficient
Δ	The minimum cost obtained from the deterministic state (USD)
$a_l, b_l, c_l, d_l,$	The regression coefficient of chillers
$P_{t,ct}^{i,c}$	Rated power of the cooling tower pump (MW)
$\Theta_{t,ct}^{i,c}$	Air flow rate of the cooling tower fan
$\varpi_{t,ct}^{i,c}$	Water flow rate of cooling tower pumps
$P_{t,p}^{h,c}(\upsilon)$	Rated power of water circulation pump (MW)

$\varpi_{t,p}^{h,c}(\upsilon)$	Water flow rate of water circulation pumps (m^3/h)
$\Theta_{t,ctmax}^{i,c}$	Maximum air flow rate of the cooling tower fan (m^3/h)
$\Theta_{t,ctmin}^{i,c}$	The minimum air flow rate of the cooling tower fan (m^3/h)
$\varpi_{t,ctmin}^{i,c}$	The minimum water flow rate of cooling tower pumps (m^3/h)
$\varpi_{t,ctmax}^{i,c}$	Maximum water flow rate of cooling tower pumps (m^3/h)
$\varpi_{t,pmin}^{h,c}(\upsilon)$	Maximum water flow rate of water circulation pumps (m^3/h)
$\varpi_{t,pmin}^{h,c}(\upsilon)$	Minimum water flow rate of water circulation pumps (m^3/h)
H	A sufficiently large constant
Δ_t^+/Δ_t^-	The maximum cost of the aggregator under deficit (excess) conditions (USD)
$\xi_{dch}^{st}, \xi_{ch}^{st}$	Charging/discharging efficiency of ESS
$Q_n(l)$	Chiller's nominal cooling capacity (RT)
$\delta(t)$	Total cooling capacity determination factor
C. Variables	
P_t^D	Power trade with day-ahead energy market at time t (MWh).
P_t^{B-}/P_t^{B+}	Power trade in the electricity market with negative (positive) balance (KW)
$P_{t,pd}^{i,c}$	Discharge power of ESS (KW)
$P_{t,pc}^{i,c}$	Charging power of ESS (KW)
$\overline{\alpha}$	The optimal robustness function value
α	The horizon of the uncertain parameter
λ_t^D	Day-ahead market price (USD/MWh)
$\lambda_t^{B-}/\lambda_t^{B+}$	Deficit (Excess) imbalance price (USD/MWh)
ϕ_t	A binary variable that determines imbalance conditions
$P_t^{i,c}$	Power consumption of the shopping center (MW)
$P_{t,h}^{i,c}$	Power consumption of the HVAC system (MW)
$P_{t,p}^{i,c}$	Power consumption of pumps (MW)
$P_{t,ct}^{i,c}$	Power consumption of the cooling tower (MW)
$P_{t,l}^{i,c}$	Chiller power consumption (MW)
Ω	The ratio between the cooling capacity of chiller L to the nominal capacity of chiller L
$\mathbf{U_l(t)}$	A binary variable indicating whether the chiller is on or off
$\mathbf{CL_t}$	The total cooling capacity of the mall (RT)
$\mathbf{Q_l(t)}$	Chiller's cooling capacity (RT)
$\mathbf{soc(t)}$	State of charge (SOC) (kWh)
$\mathbf{p^{ch}(t), p^{dch(t)}}$	Charging/discharging power of the ESS (kW)
$\vartheta_{ch}/\vartheta_{dch}$.	Binary variable indicating the state of charging/discharging
D. Acronyms	
ADRA	Agricultural Demand Response Aggregator
CDRA	mmercial Demand Response Aggregator
IDRA	Industrial Demand Response Aggregator
RDRA	Residential Demand Response Aggregator
DRA	Demand Response Aggregator
ESS	Energy Storage System
MAS	Multi-agent System
DR	Demand Response
HVAC	Heating, Ventilation, and Air Conditioning
IGDT	Information-Gap Decision Theory

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