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Multi-Stage Incentive-Based Demand Response Using a Novel Stackelberg–Particle Swarm Optimization

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Abstract: Demand response programs can effectively handle the smart grid's increasing energy demand and power imbalances. In this regard, price-based DR (PBDR) and incentive-based DR (IBDR) are two broad categories of demand response in which incentives for consumers are provided in IBDR to reduce their demand. This work aims to implement the IBDR strategy from the perspective of the service provider and consumers. The relationship between the different entities concerned is modelled. The incentives offered by the service provider (SP) to its consumers and the consumers' reduced demand are optimized using Stackelberg–particle swarm optimization (SPSO) as a bi-level problem. Furthermore, the system with a grid operator, the industrial consumers of the grid operator, the service provider and its consumers are analyzed from the service provider's viewpoint as a tri-level problem. The benefits offered by the service provider to its customers, the incentives provided by the grid operator to its industrial customers, the reduction of customer demand, and the average cost procured by the grid operator are optimized using SPSO and compared with the Stackelberg-distributed algorithm. The problem was analyzed for an hour and 24 h in the MATLAB environment. Besides this, sensitivity analysis and payment analysis were carried out in order to delve into the impact of the demand response program concerning the change in customer parameters.

Keywords: demand response; energy; smart-grid; grid operator; industrial customer; Stackelberg–particle swarm optimization

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Citation: Dayalan, S.; Gul, S.S.; Rathinam, R.; Fernandez Savari, G.; Aleem, S.H.E.A.; Mohamed, M.A.; Ali, Z.M. Multi-Stage Incentive-Based Demand Response Using a Novel Stackelberg–Particle Swarm Optimization. *Sustainability* **2022**, *14*, 10985. https://doi.org/10.3390/su141710985

Academic Editor: Alberto-Jesus Perea-Moreno

Received: 3 August 2022
Accepted: 29 August 2022
Published: 2 September 2022

1. Introduction

A smart grid (SG) epitomizes an unprecedented chance to motivate the energy sector into a new age of dependability, availability, and efficacy, contributing to future economic and environmental conditions. As per the strength, weakness, opportunities, and threat analysis report, the increasing per capita electricity consumption could be controlled by implementing the demand response programs (DRPs) that form a focal point of SG [1]. The evolution of the renewable energy systems, in addition to the altered consumption pattern of the consumers, aids in the effective implementation of DRPs. With the evolution of multi-energy systems (MES), demand response (DR) programming has been broadened into integrated DR [2]. DR is a sub-classification of a broader concept called demand side management, which is further classified into price-based DR (PBDR) and incentive-based DR (IBDR). PBDR relies on pricing in different ways, such as real-time and day-ahead pricing, etc. IBDR programs are based on contracts involving various market entities such as the grid operator (GO), retailers, and customers, etc. An IBDR scheme that provides coupon incentives to the customers was designed by several researchers [3,4]. It benefits both the customers and the load-serving entities (LSE). In [5,6], a novel IBDR scheme has been framed considering the various market operators that benefit the customers and the utilities. The SG technology advancement has made DR program implementation easier. The communication infrastructure of the SG technology has made it possible to implement DR programs for all kinds of customers. The modeling of the IBDR program for the residential customers, including the loads of the customer to reduce the power consumption, are carried out in the intelligent environment, thereby reducing the customer bill. The IBDR models for handling DR problems, with optimization techniques such as the Stackelberg game, GAMS, CPLEX, and others, are used in SG to obtain a better result of demand reduction and cost minimization [7–10]. In recent years, game-theory-based algorithms have been implemented to solve the IBDR strategy bidding model from the SP and GO ends [11–13]. IBDR problems with pricing schemes such as day-ahead pricing and intra-day renewable energy sources for procuring electricity at a minimal cost from the market were proposed in [14,15]. A multi-stage algorithm involving uncertain renewable sources, for serving the loads, considering entities such as GO and SP, was proposed in [16–19]. An integrated IBDR model considering the uncertainties coupled with the renewable sources [20,21] was proposed to improve the profit obtained by the customer [22]. An experimental setup based on flexible incentive-based DR to reduce critical demand and maximize consumer profits was proposed by Luo Zhe [23]. The IBDR was programmed using data mining for a virtual power plant. The authors in [24] proposed the IBDR problem for the Danish low-voltage (LV) grid with battery storage devices. Deepan et al. [25] proposed a novel self-reporting baseline estimation and outperformed the method for solving the IBDR program involving aggregators and consumers. The optimization techniques for effectively handling more variables maximization and minimization problems along with parameter selection and tuning are dealt with in [26–29].

Table 1 summarizes the highlights of the surveyed literature based on the objective of the DR problem, the entities considered, adapted pricing schemes, and optimization technology. The effect of inclusion and the interaction of the three market entities together has not been analyzed, although many algorithms were developed to solve IBDR. The influence of the customer parameters on the IBDR programs has also not been adequately shown. Furthermore, the literature has not concentrated on the IBDR work on 24-h timing, including all of the entities.

Table 1. Highlights of the literature survey.

Reference	Entities/Participants	Pricing Schemes	Objective	Methodology and Simulation Tools
[3]	LSE and retail customers	Flat rate pricing	Optimizing social welfare	CPLEX
[4]	Service provider and customer	A day ahead of electricity pricing	Optimal incentives for SPs	Stackelberg game theory-GAMS tool
[6]	Utility and customers	Spot pricing	Maximizing benefits of retailers	MATLAB Yalmip toolbox
[7]	Grid operator, multi-service provider and customer	Incentive based pricing	Resource utilization in minimizing cost and maximizing profit of operators	Stackelberg game approach
[12]	Service provider and end-user	Real-time pricing	Peak demand and electricity bill reduction	MATLAB toolbox for optimization
[16]	Retailer and end-user	A day ahead of electricity pricing	Minimizing peak demand and finding hourly financial incentives for customers	NSGA II
[19]	LSE and ISO	Real-time market	LSE net revenue maximization	CPLEX

Accordingly, the proposed work compares the changes involved in the inclusion of various entities in the IBDR program using a novel SPSO algorithm. The IBDR problem designed concerning Case 1 (SP-customers) and Case 2 (GO-SP-industrial consumers (IC) customers) was optimized using SPSO algorithms, and was compared with the Stackelberg distributed algorithm for an hour and an entire day. A sensitivity analysis was also adapted by altering the customer parameters, namely the discomfort factor, the customer attitude to demand reduction, and the magnitude of demand change required to review the impact of IBDR. Furthermore, payment analysis was made to focus on the benefits obtained by the entities by varying the customer parameters.

The content of this paper is organized as follows: Section 2 elaborates on the problem formulation of IBDR and Case 1. Section 3 focuses on the problem formulation of Case 2 of the IBDR problem, followed by a briefing on the optimization technique adapted to solve the IBDR problem in Section 4. Section 5 discusses the results obtained for the two different cases. Finally, Section 6 presents the conclusions.

2. Problem Formulation of IBDR with One SP and Two Customers: Case 1

This section modelled and formulated an IBDR problem including GO, SP, IC and customers to maximize or minimize the utility function depending on the entities considered and the demand reduction.

An SP sells electricity to its retail customers and procures their capacity through demand reduction. The SP can even sell the procured capacity and gain profit. The SP provides incentives to those customers who agrees to reduce their demand when they are told to do so by the SP. In this work, a system with one SP and two consumers is considered, and the interaction between them is modelled using Stackelberg's game theory.

a. Customer model

Let N be the total number of customers. Here, N is taken to be 2. Every customer i, when provided with incentives from the SP, tries to increase their demand reduction to gain more incentives. Here, time t ranges from 1 to T, where T is taken as 24. The customer will aim to maximize the utility function by using their demand reduction, and the above can be framed as follows [4]:

$$\max_{D_i} U_i = \sum_{t=1}^{T} D_{i,t} \times \pi_t - \mu_i \times \sum_{t=1}^{T} \varphi_{i,t}(D_{i,t}) \tag{1}$$

which is subjected to

$$0 \le D_{i,t} \le D_{i,t}^{tar} - D_{i,t}^{min}, \ \ \forall\, i \in N, \forall\, t \in T \tag{2}$$

Equation (1) represents the customer utility function, which has to be maximized using demand reduction as the variable. The constraint given by Equation (2) restricts the demand reduction from going beyond $D_{i,t}^{tar} - D_{i,t}^{min}$, which represents the available quantity of demand reduction. The first term of Equation (1) means the income gained by the customer by reducing the demand $D_{i,t}$ for the incentive π_t. The second term represents the discomfort of the customer. The weight factor μ_i decides the level of discomfort each customer can accept. The small value of μ_i represents less importance given to discomfort. The dissatisfaction cost ($\varphi_{i,t}$) represents the customer's discomfort involved in demand reduction. The dissatisfaction cost is modelled as follows:

$$\varphi_{i,t}(D_{i,t}) = \frac{\theta_i}{2}\left(D_{(i,t)}^2 + \lambda_i \times D_{i,t}\right)\theta_i > 0,\ \lambda_i > 0 \tag{3}$$

θ_i and λ_i are parameters set based on the customer's attitude towards demand reduction.

b. Service provider model

The SP gains profit by selling the capacity procured from the customers, and can profit by procuring the capacity (i.e., the demand reduction) at a minimal incentive. Thus, the SP aims to minimize the utility function using the incentive offered as the variable. This can be modeled as follows [4]:

$$\min_{\pi} U_{SP} = \sum_{t=1}^{T}\sum_{i=1}^{N} D_{i,t} \times \pi_t - \sum_{t=1}^{T}\sum_{i=1}^{N} D_{i,t} \times P_t \tag{4}$$

which is subjected to

$$\pi_t^{min} \leq \pi_t \leq \pi_t^{max}, \quad \forall\, t \in T \tag{5}$$

$$\sum_{i=1}^{N} D_{i,t} \geq D_t^{req}, \ \forall\, t \in T \tag{6}$$

The first term of Equation (4) represents the incentive payments given by the SP to the consumers according to their demand reductions, and the second term represents the amount gained by the SP in selling the procured capacity to the market.

c. Stackelberg game formulation and analysis

The interaction between the SP and the customers is framed as a Stackelberg game. Here, the SP acts as a leader and sets incentives for its customers; thus, a one-leader N-follower Stackelberg game is framed (here, one leader and two followers). The SP act provides incentives as a motivation for the customers to reduce their demand. The optimization equations are solved using PSO. The SP model is solved to obtain the optimal incentive set by the SP to its customers, and this is utilized in solving the customer model, thereby obtaining the corresponding optimal demand reduction; this iteration process tries to reach the global condition. The customer and SP models are reformulated using the Stackelberg theory. If the incentive value set by the leader (SP) is identified, then the customer's optimal demand reduction can be obtained.

d. Optimal solution for customers

By solving the first-order derivative of the Equation (1), concerning $D_{i,t}$, the optimal value of the demand reduction can be obtained as:

$$D_{i,t} = \frac{\pi_t - \mu_i \times \lambda_i}{\mu_i \times \theta_i} \tag{7}$$

The value of the second-order derivative of Equation (1) for $D_{i,t}$ gives $-\mu_i\theta_i < 0$. This equation is always negative; as such, the customer utility function is strictly concave for the feasible values of $D_{i,t}$. The optimal value of π_t obtained from the SP is substituted in Equation (7) to obtain the optimal demand reduction.

e. Optimal solution for the service provider

Equation (7) is substituted in Equation (4), and the SP utility function becomes

$$\min_{\pi} U_{SP} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\frac{\pi_t - \mu_i \times \lambda_i}{\mu_i \times \theta_i}\right) \times \pi_t - \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\frac{\pi_t - \mu_i \times \lambda_i}{\mu_i \times \theta_i}\right) \times P_t \tag{8}$$

which is subjected to

$$\pi_t^{min} \leq \pi_t \leq \pi_t^{max}, \quad \forall\, t \in T \tag{9}$$

The constraints can be modified by arranging equation (7) as

$$\pi_t = D_{i,t}(\mu_i \times \theta_i) + \mu_i \times \lambda_i \tag{10}$$

Constraints (5) and (6) can be modified using the above-obtained equations. Thus, the value of π_t^{min} and π_t^{max}, in (9), can be replaced by Equations (11) and (12).

$$\pi_t^{max} = min\left(\pi_t^{max}, min\left\{\left(\left(D_{i,t}^{tar} - D_{i,t}^{min}\right) \times \mu_i * \theta_i + \mu_i \times \lambda_i\right) \forall\, i \in N\right\}\right) \tag{11}$$

$$\pi_t^{min} = max\left(\pi_t^{min}, max\{\mu_i \times \lambda_i, \forall\, i \in N\},\ \frac{D_t^{req} + \sum_{i=1}^{N} \frac{\lambda_i}{\theta_i}}{\sum_{i=1}^{N} \frac{1}{\theta_i}}\right) \tag{12}$$

The optimization equation in (8) is solved using PSO, and the optimal incentive is obtained.

3. Problem Formulation of IBDR with GO, ICs, SPs and Consumers: Case 2

The role of the GO in IBDR is re-studied in this section. Here, IBDR is implemented in a system consisting of GO, ICs, and SPs under the GO, and the customers under each SP. The GO sets the incentive for the ICs and the SPs. The GO procures the capacities from its SPs and ICs to meet the demand deficit. The SPs set the incentive for the customers under them. The SPs procure the capacity from the customers regarding demand reduction and sell it to the GO. The GO meets the required demand deficit of the day either through the generators or by procuring the capacity from the SPs and ICs (i.e., through their demand reductions), and the GO aims to reduce the cost of procuring these capacities. Figure 1 depicts the role of each domain in the smart grid. The mathematical models of the entities are framed and solved using the Stackelberg game theory, where the outcome of the leader is first obtained (i.e., the incentive of GO), and then this outcome is utilized to solve the model of the IC and the customers of the SP for demand reduction.

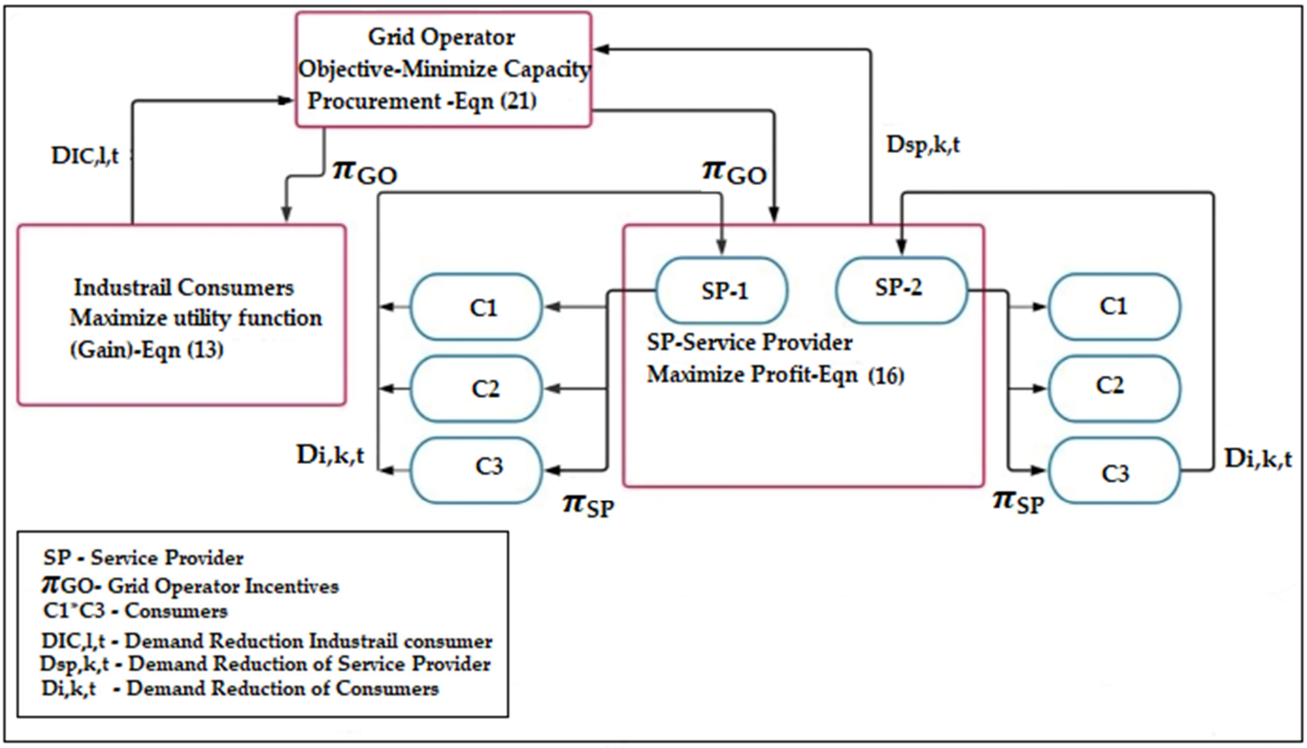

Figure 1. Hierarchy of entities in a smart grid.

a. Industrial consumer model

The IC aims to maximize its utility function, thereby maximizing the gain obtained as an incentive from the GO. The IC's utility function involves the gain obtained by the energy consumed and the incentive profit obtained from the GO for demand reduction. Let L be the total number of ICs. For each IC_l, where $l \in L$, the utility function is given by [15].

$$\max_{D_{IC,l}} U_{IC,l} = \sum_{t=1}^{T} \Psi_l\left(D_{l,t}^{ava} - D_{IC,l,t}\right) + D_{IC,l,t} \times \pi_{GOIC,t} \tag{13}$$

which is subjected to

$$0 \le D_{IC,l,t} \le D_{l,t}^{ava} \tag{14}$$

The constraint in (14) restricts the value of the demand reduction within the range of the available amount of demand reduction, and Ψ_l is the term used to describe the ICs' profit; it is calculated by the following formula:

$$\Psi_l = \begin{cases} \omega_l \times \left(D_l^{ava} - D_{IC,l}\right) - \frac{\sigma_l}{2} \times \left(D_l^{ava} - D_{IC,l}\right)^2 & if\ 0 \le \left(D_l^{ava} - D_{IC,l}\right) \le \frac{\omega_l}{\sigma_l} \\ \frac{\omega_l{}^2}{2\sigma_l} & if\ \left(D_l^{ava} - D_{IC,l}\right) \ge \frac{\omega_l}{\sigma_l} \end{cases} \tag{15}$$

σ_l and ω_l denote the rate and magnitude of the profit change of the IC when the power consumption of the IC is varied. As σ_l increases, the IC gains more by selling its resource to the GO.

b. Service provider model

The SP procures capacity from its customers by giving incentives to them, and it sells the procured capacity to the GO at the incentive rate the GO gives. As such, the utility function of the SP involves these terms. The SP aims to maximize its profit obtained by trading with the GO and its customers. Here, if the SP model is compared with Case 1, the second term of the equation is modified into Equation (16). In Case 1, the second term describes the capacity sold by the SP to the market at the electricity pricing, whereas in (16), it describes the capacity sold by SP to the GO at the incentive rate given by GO. Let K be the total number of SPs, and for each SP, the utility function can be written as follows [15]:

$$\max_{\pi_{SP,k}\ D_{SP,k}} U_{SP,k} = \sum_{t=1}^{T} D_{SP,k,t} \times \pi_{GOSP,t} - D_{SP,k,t} \times \pi_{SP,k,t} \tag{16}$$

which is subjected to

$$D_{SP,k,t} = \sum_{i \in N_k} D_{i,k,t} \tag{17}$$

The customer receives incentives from SP in return for their demand reduction. The utility function of the customers will also involve the dissatisfaction cost. While comparing Equation (18) with Case 1 customer model, it could be seen that the number of SPs considered in Case 2 is more than that in Case 1, and the incentives the SPs give to their customers differ. As such, the customers belonging to different SPs receive different incentives. The utility function of the customers is written as follows [4,7]:

$$\max_{D_{i,k}} U_{i,k,t} = \sum_{t=1}^{T} D_{i,k,t} \times \pi_{SP,k,t} - \mu_{i,k,t} \times \varphi_{i,k,t} \tag{18}$$

which is subjected to

$$0 \le D_{i,k,t} \le D_{i,k,t}^{ava} \tag{19}$$

The dissatisfaction cost function $\varphi_{i,k,t}$ is a function of $D_{i,k}$, and the level of discomfort that a customer might experience due to the reduction of demand is modeled by $\varphi_{i,k}$.

$$\varphi_{i,k} = \frac{\theta_{i,k}}{2}\left(D_{(i,k)}^2 + \lambda_{i,k} \times D_{i,k}\right), \theta_{i,k} > 0,\ \ \lambda_{i,k} > 0 \tag{20}$$

Here, $\theta_{i,k}$ and $\lambda_{i,k}$ are the parameters set based on the customer's attitude towards demand reduction. By increasing the value of $\theta_{i,k}$, the customer is more reluctant towards the demand reduction.

c. Grid operator model

The GO tries to minimize the cost of capacity procurement. Let the expected demand deficit be taken as D^{req}. The GO compensates for the demand deficit by acquiring capacities from SP and IC. The utility function of the GO can be framed as follows [15]:

$$min\ C_{GO} = \sum_{t=1}^{T} C_{gen}(G) + \pi_{GOIC,t} \times \sum_{i \in L} D_{IC,l,t} + \pi_{GOSP,t} \times \sum_{i \in L} D_{SP,k,t} \tag{21}$$

which is subjected to

$$\pi_{GO,t}^{min} \leq \pi_{GOSP,t} \leq \pi_{GOIC,t} \leq \pi_{GO}^{max} \tag{22}$$

$$G = D^{req} - \sum_{i \in L} D_{IC,l} - \sum_{i \in L} D_{SP,k} \tag{23}$$

The value of the cost of generating the required quantity G is calculated as follows:

$$C_{gen}(G) = a\left(G^2\right) + b(G) + c \tag{24}$$

In Equation (21), the first term represents the cost required for generation, and the second and the third terms represent the cost of procuring the capacities from the IC and SP.

d. Stackelberg game formulation and analysis

The interaction between the various entities involved in IBDR is modelled using Stackelberg's game theory. Including GO and IC in the problem makes it a leader–multi-follower game, increasing the complexity compared to Case 1. The GO model is solved, and the optimal incentive set by the GO for IC and SP is found, and then those optimal incentive values are utilized for the calculation of the optimal demand reductions. The GO fixes the incentives for the IC and SP using the following equations:

$$\pi_{GOSP} = \pi_{GO} \tag{25}$$

$$\pi_{GOIC} = \rho \times \pi_{GO},\ \ 0 \leq \rho \leq 1 \tag{26}$$

e. Optimal solution for the industrial consumer

Using the first-order derivative of the utility function in (13) with respect to $D_{IC,l}$ when equated to zero, we can obtain the equation for $D_{IC,l}$, as follows:

$$D_{IC,l} = D_l^{ava} - \frac{\omega_l}{\sigma_l} + \frac{\rho \times \pi_{GO}}{\sigma_l} \tag{27}$$

The total demand reduction of all of the ICs could be summed as

$$\sum_{i \in L} D_{IC,l} = \sum_{l \in L} D_l^{ava} - \frac{\omega_l}{\sigma_l} + \sum_{l \in L} \frac{\rho \times \pi_{GO}}{\sigma_l} \tag{28}$$

For convenience, the constant terms in the equation are taken as follows:

$$\eta = \sum_{l \in L} D_l^{ava} - \frac{\omega_l}{\sigma_l}, \gamma = \sum_{l \in L} \frac{1}{\sigma_l} > 0 \tag{29}$$

For Equation (29), when it is substituted into (28), we obtain

$$\sum_{i \in L} D_{IC,l} = \eta + \gamma \times \rho \times \pi_{GO} \tag{30}$$

The constraint in (14) can be regulated to make the IC contribute the minimum load by replacing the zero to D^{min}.

$$D^{min} = max\left(0, min\left(D_l^{ava} - \frac{\omega_l}{\sigma_l}\right)\right) \tag{31}$$

The optimal demand reduction of IC can be found by substituting the optimal GO incentive using (30).

f. Optimal solution for the service provider and its customers

The optimal demand reduction of the SP can be calculated as follows:

$$D_{SP,k} = \frac{1}{2}\pi_{GO} \times \sum\nolimits_{i \in N_k} \frac{1}{\mu_{i,k} \times \theta_{i,k}} - \frac{1}{2}\sum\nolimits_{i \in N_k} \frac{\lambda_{i,k}}{\theta_{i,k}} \tag{32}$$

The total demand reduction of all SPs could be found as follows:

$$\sum_{k \in K} D_{SP,k} = \frac{1}{2}\pi_{GO} \times \sum_{k \in K}\sum_{i \in N_k} \frac{1}{\mu_{i,k} \times \theta_{i,k}} - \frac{1}{2}\sum_{k \in K}\sum_{i \in N_k} \frac{\lambda_{i,k}}{\theta_{i,k}} \tag{33}$$

For convenience, the constant terms in the equation are taken as follows:

$$\alpha = \sum\nolimits_{k \in K}\sum\nolimits_{i \in N_k} \frac{1}{\mu_{i,k} \times \theta_{i,k}} > 0, \beta = \sum\nolimits_{k \in K}\sum\nolimits_{i \in N_k} \frac{\lambda_{i,k}}{\theta_{i,k}} > 0 \tag{34}$$

For Equation (34), when substituted in (33), we obtain

$$\sum_{k \in K} D_{SP,k} = \frac{\alpha}{2}(\pi_{GO}) - \frac{\beta}{2} \tag{35}$$

In order to solve the customer equation, the second derivative of Equation (18) with reference to $D_{i,k}$ is taken and equated to zero. The demand reduction of each customer under each SP can be found as follows:

$$D_{i,k} = \frac{\pi_{SP,k} - \mu_{i,k} \times \lambda_{i,k}}{\mu_{i,k} \times \theta_{i,k}} \tag{36}$$

g. Optimal solution for the grid operator

The cost function of the GO in (21) can be rewritten by substituting (24) and (23) into it, as follows:

$$\begin{aligned} min\ C_{GO} = a\left(\left(D^{req} - \sum_{i \in L} D_{IC,l} - \sum_{i \in L} D_{SP,k}\right)^2\right) + b\left(D^{req} - \sum_{i \in L} D_{IC,l} - \sum_{i \in L} D_{SP,k}\right) + \\ c + \pi_{GOIC} \times \sum_{i \in L} D_{IC,l} + \pi_{GOSP} \times \sum_{i \in L} D_{SP,k} \end{aligned} \tag{37}$$

By substituting (29) and (34) into (37) and equating the first derivative of the obtained equation to zero, we can realize the optimal incentive of the GO.

$$\pi_{GO}^* = \frac{2a\ (D^{req} + 0.5\beta - \eta) \times (0.5\alpha + \gamma\rho) + b(0.5\alpha + \gamma\rho) + 0.5\beta - \rho\eta}{2a(0.5\alpha + \gamma\rho)^2 + \alpha + 2\gamma\rho^2} \tag{38}$$

The obtained optimal incentive value of the GO is utilized to obtain the optimal demand reduction of ICs and SPs.

h. Stackelberg distributed algorithm

The parameters of the IC and SP customers must be disclosed to the GO, which is difficult in practice. As such, the distributed algorithm is used [15]. Here, the incentive of the GO is used as the variable, and SP and IC demand reductions are found.

The initial value of the GO incentive π^{*}_{GO} is initialized to π^{min}_{GO}. A value of ρ is chosen, and the value of $\pi_{GOIC}\ and\ \pi_{GOSP}$ are calculated. Then, the initial values of $D^{*}_{IC,l}$ and $D^{*}_{SP,k}$ are calculated using Equations (27) and (32), respectively.

The initial value of the procurement cost of the GO is calculated as

$$C^{*}_{GO} = \left(a\big(D^{req} - \sum_{i \in L} D_{IC,l} + \sum_{i \in L} D_{SP,k}\big)^2 \quad + b\left(D^{req} - \sum_{i \in L} D_{IC,l} + \sum_{i \in L} D_{SP,k}\right) + c \right) \\ + \pi_{GOIC} \times \sum_{i \in L} D_{IC,l} + \pi_{GOSP} \times \sum_{i \in L} D_{SP,k} \tag{39}$$

These initial values are then used to calculate the optimal value of C_{GO} with π_{GO} as the variable which is updated for every iteration, as shown below:

Step 1: for the iteration m = m + 1;
Step 2: update the value of π^{m}_{GO} using

$$\pi^{m+1}_{GO} = \pi^{m}_{GO} + \Delta\pi_{GO} \tag{40}$$

where

$$\Delta\pi_{GO} = \delta\left(e^{\omega\left|C^{m}_{GO} - C^{m-1}_{GO}\right|} - 1\right) \tag{41}$$

Step 3: the value of $D^{m+1}_{IC,l}$ and $D^{m+1}_{SP,k}$ are updated from Equations (27) and (32), respectively, and the π^{m+1}_{GO} value;
Step 4: with the values found in step 3, the value of C^{m+1}_{GO} is calculated as follows:

$$\begin{aligned} C^{m+1}_{GO} = \quad & \Big(a\big(D^{req} - \sum_{i \in L} D^{m+1}_{IC,l} + \sum_{i \in L} D^{m+1}_{SP,k}\Big)^2 \\ & + b\left(D^{req} - \sum_{i \in L} D^{m+1}_{IC,l} + \sum_{i \in L} D^{m+1}_{SP,k}\right) + c\Big) \\ & + \pi_{GOIC} \times \sum_{i \in L} D^{m+1}_{IC,l} + \pi_{GOSP} \times \sum_{i \in L} D^{m+1}_{SP,k} \end{aligned} \tag{42}$$

Step 5: f $C^{m+1}_{GO} \leq C^{*}_{GO}$ and $\pi^{m+1}_{GO} \leq \pi^{*}_{GO}$, then update the values of GO as $\pi^{*}_{GO} = \pi^{m+1}_{GO}$ and $C^{*}_{GO} = C^{m+1}_{GO}$;
Step 6: end if;
Step 7: end for;
Step 8: these steps are repeated until the condition shown in (43)

$$\left|C^{m+1}_{GO} - C^{m}_{GO}\right| \leq \varepsilon \tag{43}$$

Step 9: the equilibrium is reached when the value of C_{GO} does not decrease further.

4. Optimization Technique

Optimization techniques are utilized to find the best results from the set of feasible solutions. In this work, the interaction between the market entities is modelled using Stackelberg game theory, and the minimization and maximization equations of the entities are solved using PSO [30]. In the IBDR problem considered, there is a need for a repeated iteration with either maximization or minimization equations for the leader (GO) and the followers (IC, SP and customers) with two to three variables. As the Stackelberg game theory-based IBDR problem considered for optimization is a complicated iterative problem, the inertia-based PSO is considered for optimization in order to reduce its complexity.

In Case 1, the maximization equation of the customer is solved by setting the demand reduction as a variable, and the minimization equation of the SP is solved by setting the incentive as a variable. In Case 2, the industrial customer's maximization equations are solved using the demand reduction as the variable; the SP is maximized by compromising the GO and customer by varying the demand reduction from customers and the incentives.

Furthermore, the GO tries to minimize the cost of capacity procurement with the demand reduction obtained from IC and SP by varying the incentives.

The PSO procedure to solve the formulated Stackelberg-based problem for all of the entities is given below:

Step 1: initialize a set of particles in the search space;
Step 2: each particle will have a position and velocity. Initially, we generate the positions randomly based on the minimum and maximum limits of the variables shown in Table 2;
Step 3: for each particle, evaluate the incentives and utility function (objective) as per Equations (13), (16), (18) and (21), and in the entities, each particle will have a position and velocity;
Step 4: store the local and global best values (*pbest* and *gbest*);
Step 5: if the utility function for the new particle changes, based on maximization or minimization of the problem, update the *pbest* and *gbest* values;
Step 6: update the inertia weight factor by using $w = w \times wdamp$;
Step 7: update the position and velocity of the particle. The velocity update is given in (44);

$$Velocity = w \times velocity + C_1 \times \text{rand}() \times Pbest + C_2 \times \text{rand}() \times gbest \tag{44}$$

Step 8: velocity clamping is performed to maintain the velocity of the particle within the limit;
Step 9: check the termination condition; if satisfied, stop; else, go to Step 3.

Table 2. Variables and their bounds for Case 2's optimization.

Entities	Variables	Lower and Upper Bounds	Number of Variables
Grid operator	Incentive (π_{igo})	(3, 10)	1
Industrial consumer	Demand reduction of IC_1 (D_{IC1})	(0, 45.4)	3
	Demand reduction of IC_2 (D_{IC2})	(0, 36.2)	
	Demand reduction of IC_3 (D_{IC3})	(0, 56.5)	
Service provider	Incentive of SP_1 (π_{SP1})	(3, 10)	2
	Incentive of SP_2 (π_{SP2})	(3, 10)	
Consumer	Demand reduction of customer 1 ($D_{k,1,t}$)	(0, 11.35)	3
	Demand reduction of customer 2 ($D_{k,2,t}$)	(0, 16.55)	
	Demand reduction of customer 3 ($D_{k,3,t}$)	(0, 12.77)	

The optimization is carried out by considering the maximum iteration count as 1000, the number of particles as 100, and the acceleration coefficients C_1 and C_2 as 1.5 and 2. In this work, the inertia weight is dynamic, with a weight-damping ratio of 0.99.

5. Results and Discussions

The IBDR problem for Cases 1 and 2 is analyzed and optimized with the load data and the customer parameters considered.

a. Results of Case 1 with one SP and two customers

In this case, one SP and two customers are considered. The minimum and target demands of customers 1 and 2 for each hour are illustrated in Figures 2 and 3. The customer-related parameters (μ_i,θ_i,λ_i) for the two customers are shown in Table 3.

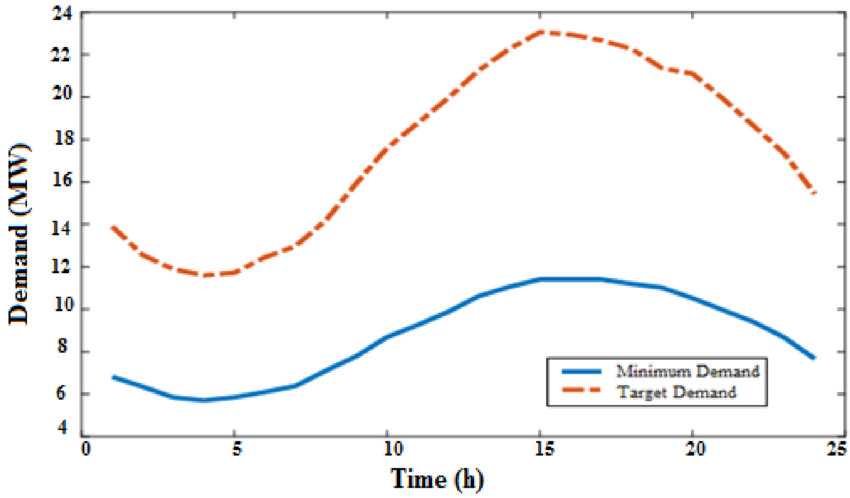

Figure 2. Minimum and target demands of customer 1.

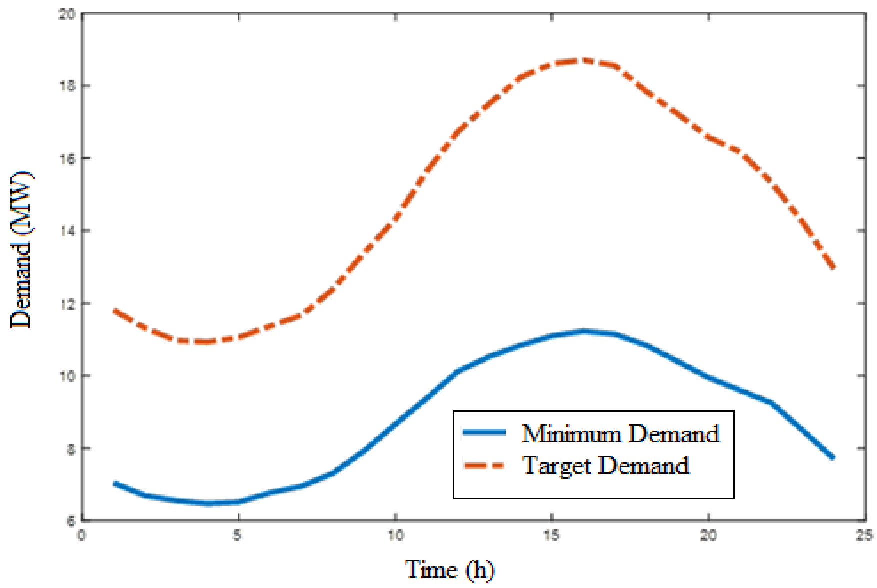

Figure 3. Minimum and target demands of customer 2.

Table 3. Parameters of Case 1, for customers 1 and 2.

Parameters	Customer 1	Customer 2
μ	(0.8, 1)	(0.8, 1)
θ	3.0	4.5
λ	10.0	10.0

The hourly electricity market pricing required for the calculation of the SP's utility function is represented in Figure 4.

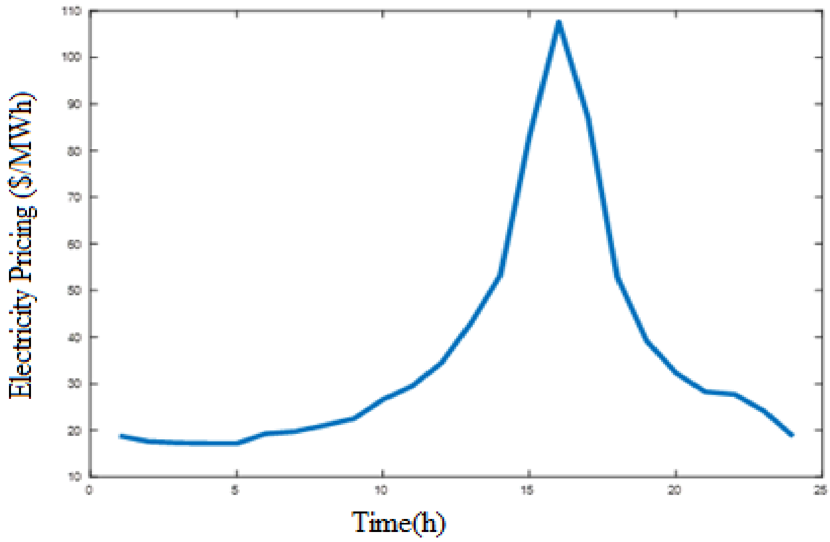

Figure 4. Hourly electricity pricing.

The value of D_t^{req}, i.e., the required demand reduction of the SP and the available demand reduction, are given in Figure 5.

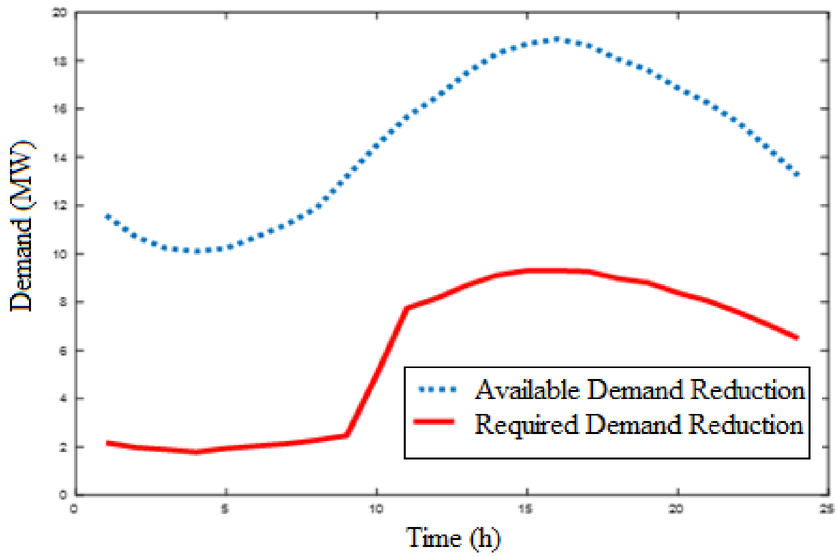

Figure 5. Available and required demand reduction of Case 1.

The optimal incentive of the SP is obtained using PSO for two different values of μ, namely 0.8 and 1, for both customers. The optimal SP incentive and the optimal mean demand reductions of customers 1 and 2 are taken and plotted. The obtained optimal solutions for the corresponding incentives are given in Figures 6 and 7. In order to ensure that the Stackelberg game is implemented correctly, Case 1 is tested with an existing system [4], and the results are obtained. The comparisons of the results for μ = 1.0 and 0.8 are listed in Tables 4 and 5.

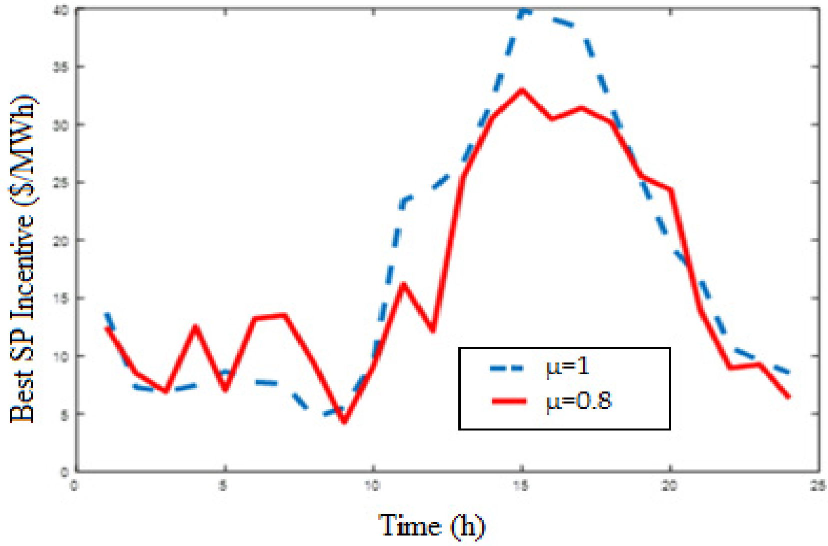

Figure 6. Optimal SP incentive for $\mu_1 = \mu_2 = 0.8$ and $\mu_1 = \mu_2 = 1.0$.

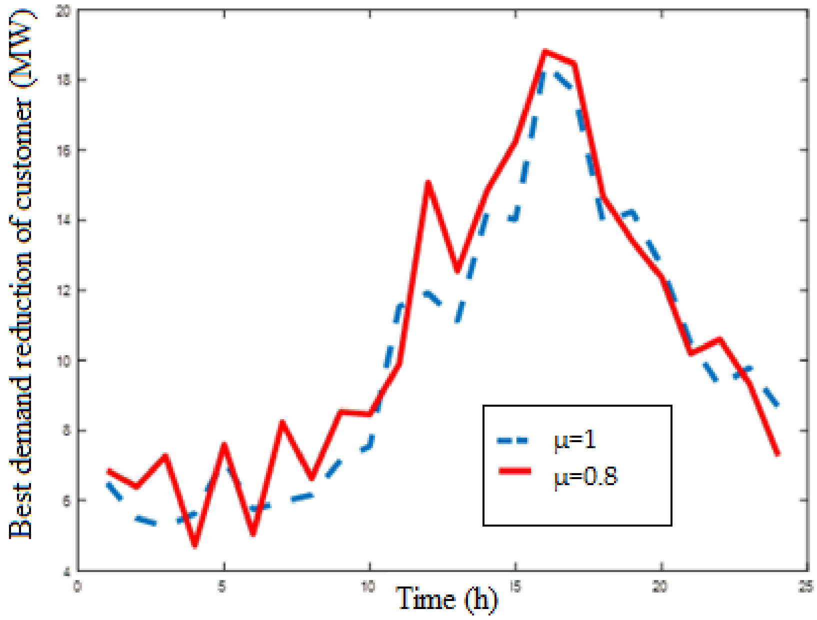

Figure 7. Optimal mean demand reduction for $\mu_1 = \mu_2 = 0.8$ and $\mu_1 = \mu_2 = 1.0$.

Table 4. Comparison with the existing system for μ = 1.0.

Incentive by SP ($)		Demand Reduction (MW)		Incentive by SP ($)		Demand Reduction (MW)	
For one hour (16th hour)				For 24 h			
Stackelberg [4]	SPSO	Stackelberg [4]	SPSO	Stackelberg [4]	SPSO	Stackelberg [4]	SPSO
38	39	18.2	18.3	486.8	425.2	195.4	240.59

Table 5. Comparison with the existing system for μ = 0.8.

Incentive by SP ($)		Demand Reduction (MW)		Incentive by SP ($)		Demand Reduction (MW)	
For one hour (16th hour)				For 24 h			
Stackelberg [4]	SPSO	Stackelberg [4]	SPSO	Stackelberg [4]	SPSO	Stackelberg [4]	SPSO
32	32	18.5	19	439	394.8	230.02	253.44

The tables show that the results obtained are better than the existing system results when optimization is performed using SPSO to solve the IBDR program.

The value of the weight factor represents the importance given by the customer to the discomfort involved in reducing the demand. A small value of μ_i represents less importance given to discomfort. This can be seen in Figure 7. The demand reduction curve for μ = 0.8 is high compared to that for μ = 1.0, which shows that the customers with a smaller μ value impose less weightage on the dissatisfaction cost, i.e., they can afford to have more demand reduction, without giving too much consideration to the discomfort caused. However, the customers with a higher μ value impose more weightage on dissatisfaction, such that they reduce their demand less compared to those with lower values of μ.

b. Sensitivity analysis for Case 1

Here, two conditions for which the value of μ is different for both customers are considered. At first, the values of $\mu_1 = 0.8$ and $\mu_2 = 1.0$ were taken. It could be inferred from the output graphs in Figures 8 and 9 that for the same optimal incentive curve obtained by the SP, the customer with a μ = 0.8 value shows more interest in demand reduction than the customer with μ = 1.0. This also happens when the condition is vice-versa; i.e., when $\mu_1 = 1.0$ and $\mu_2 = 0.8$, the demand reduction is more for customer 2, as depicted in Figures 10 and 11.

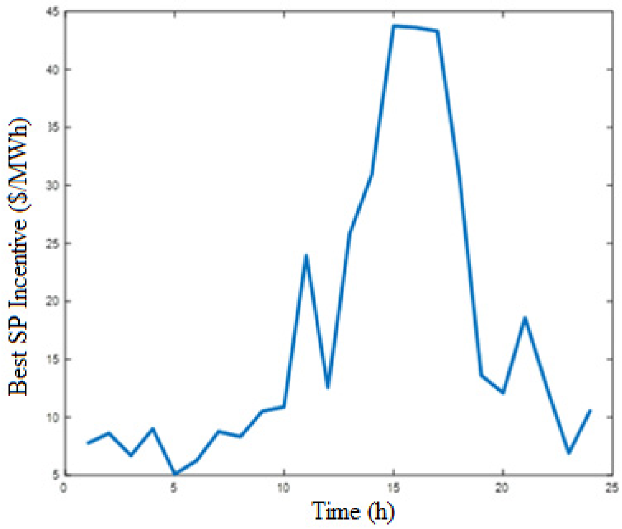

Figure 8. Optimal SP incentive for $\mu_1 = 0.8$ and $\mu_2 = 1.0$.

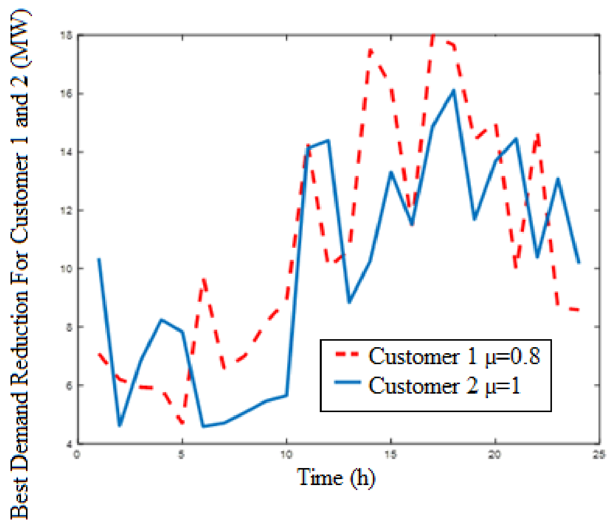

Figure 9. Optimal demand reduction for $\mu_1 = 0.8$ and $\mu_2 = 1.0$.

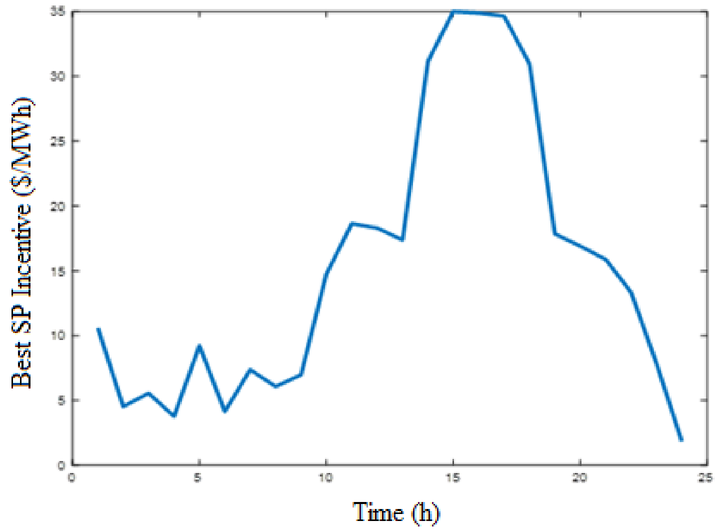

Figure 10. Optimal SP incentive for $\mu_1 = 1.0$ and $\mu_2 = 0.8$.

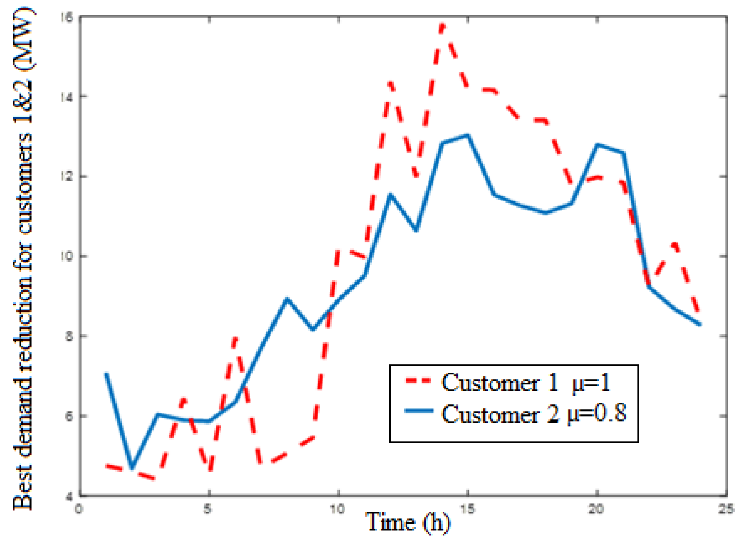

Figure 11. Optimal demand reduction for $\mu_1 = 1.0$ and $\mu_2 = 0.8$.

c. Case 2 with GO, ICS and SPS optimized using Stackelberg-distributed and SPSO algorithms

This case considers GO, IC, SP and its customers. The number of ICs is three and the number of SPs is two, with each SP being connected to three customers. The generator coefficients used are a = 0.2, b = 0, c = 0, and the value of ρ is chosen as 0.6. The value of δ is taken as 2.5, ϖ is taken as 0.13, ε is taken as 10^{-4}, and μ is taken as 1. Initially, the results are tested for SPSO and the Stackelberg-distributed algorithm for an hour using the test data and parameters specified in Tables 6 and 7.

Table 6. Test data used in Case 2 for the ICs [15].

ICs	**IC$_1$**	**IC$_2$**	**IC$_3$**
Load (kW)	45.4	36.2	56.5
σ	0.1	0.12	0.13
ω	8	8	8

Table 7. Test data used in Case 2 for the SPs.

SPs		SP_1			SP_2	
End Users	**User 1**	**User 2**	**User 3**	**User 1**	**User 2**	**User 3**
Load (kW)	11.4	7.5	14.4	5.5	13.7	9.2
θ	3.0	4.5	5.0	4.0	5.5	6.0
λ	2.0	2.0	2.0	3.0	3.0	3.0
μ	1.0	1.0	1.0	1.0	1.0	1.0

Figures 12 and 13 depict the optimal incentive and total cost of GO executed using the Stackelberg PSO. The results show that the SPSO can obtain the optimal converged output obtained by the Stackelberg distributed algorithm [31]. As per [15], the optimal GO incentive should be 7.27 cents/kWh, and that obtained by the distributed algorithm was 7.3, whereas with SPSO, the obtained global optimal solution was exactly 7.273 cents/kWh, as shown in Figure 12. From the results, it can be observed that the optimal incentive for the GO is 7.27 cents/kWh [4]. With the distributed algorithm, the result obtained was 7.29, with an error percentage of 0.275 [15], whereas with SPSO, the result was 7.273, with an error percentage of 0.041.

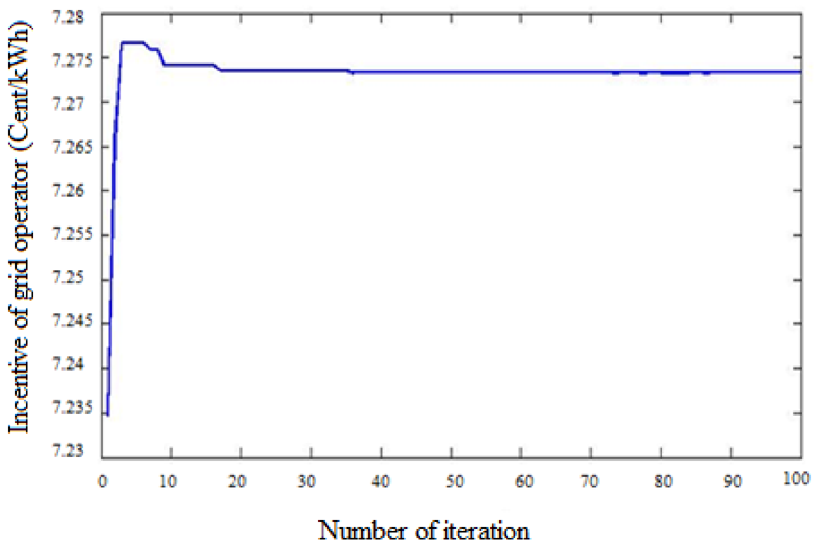

Figure 12. Optimal PSO- GO incentive for one hour.

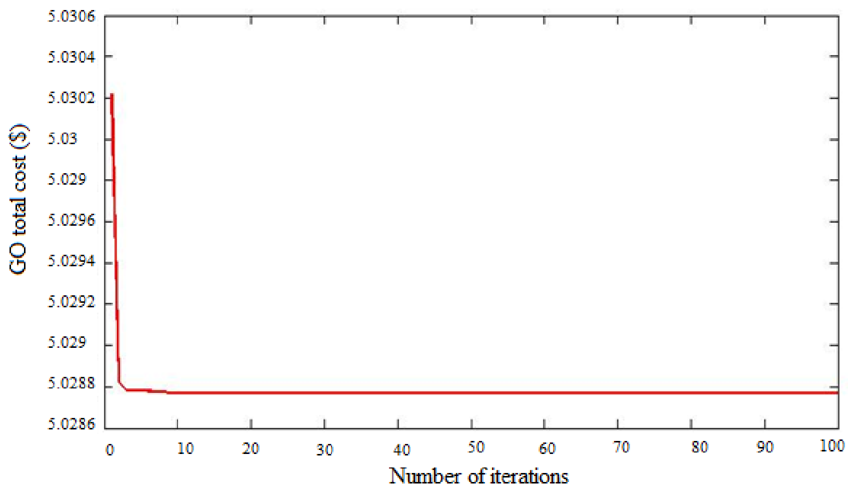

Figure 13. Optimal PSO-total cost of the GO for one hour.

Furthermore, the optimal incentive of the *SPs* obtained is shown in Figure 14, and the demand reduction of the three customers under SP_1 and SP_2 is given in Figures 15 and 16, respectively. The comparison of the obtained optimal incentive for GO, IC, SP, and the total cost of GO with SPSO and the distributed algorithm are tabulated in Table 8. Compared with the Stackelberg distributed algorithm, the SPSO can reach the exact optimal solution. Similarly, Case 2 with GO, IC, SP and its customers is considered for 24 h, and optimization is carried out using both Stackelberg-distributed and SPSO algorithms. Figures 17–19 illustrate the evaluated load data for Case 2 for 24 h of the ICs and the customers under SP_1 and SP_2.

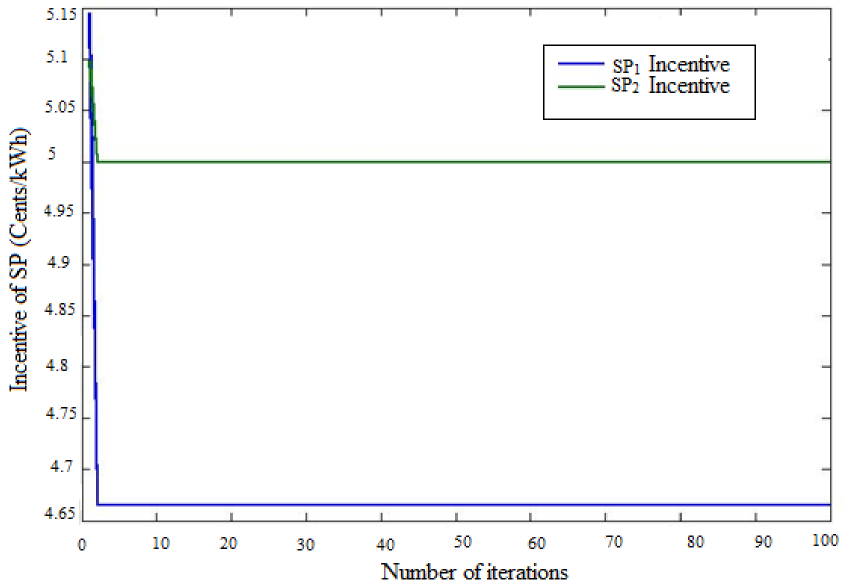

Figure 14. Optimal PSO-SP incentive for one hour.

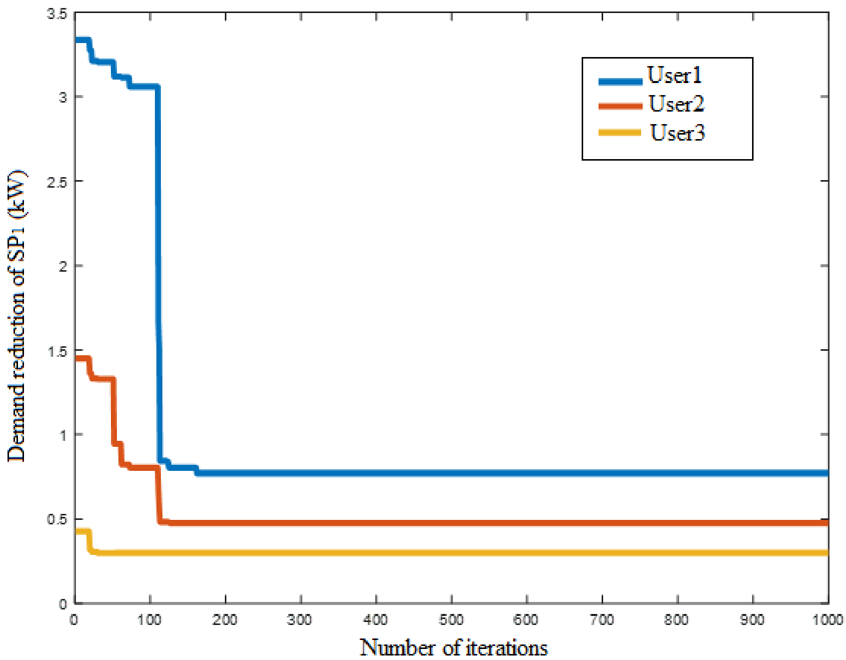

Figure 15. Optimal demand reduction of the three customers of SP_1 for one hour.

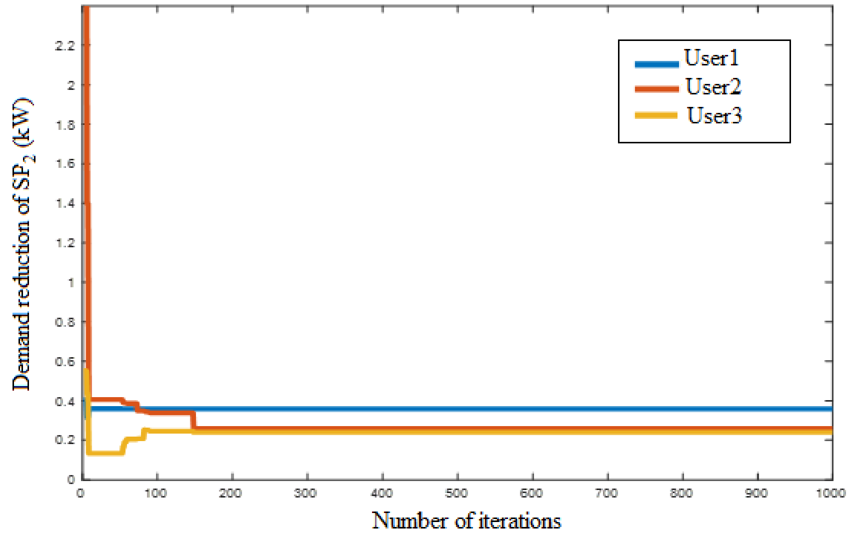

Figure 16. Optimal demand reduction of the three customers of SP_2 for one hour.

Table 8. Result comparison of Case 2's Stackelberg-PSO and distributed algorithm.

Parameters	Stackelberg			
	PSO Algorithm		Distributed Algorithm	
Grid operator incentive (cents/kWh)	7.273		7.290	
Total cost ($)	5.028		5.060	
IC Incentive (cents/kWh)	4.363		4.38	
SP incentive to users (cents/kWh)	SP_1 4.665	SP_2 5.0	SP_1 4.7	SP_2 5.1

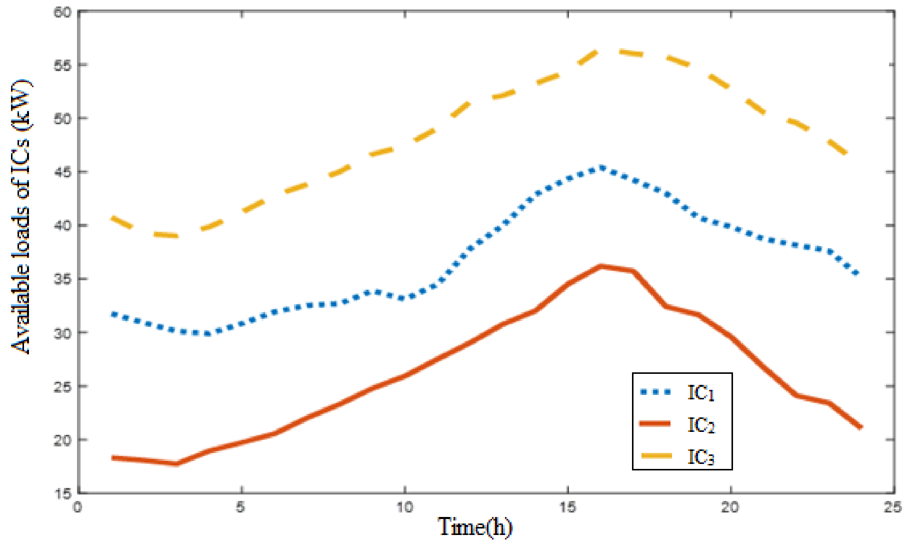

Figure 17. Available load data of the ICs.

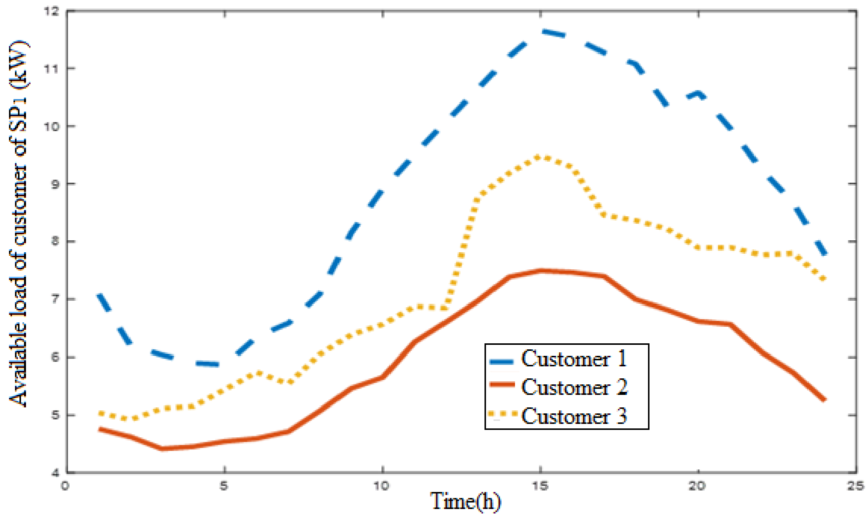

Figure 18. Available load data of the customers belonging to SP_1.

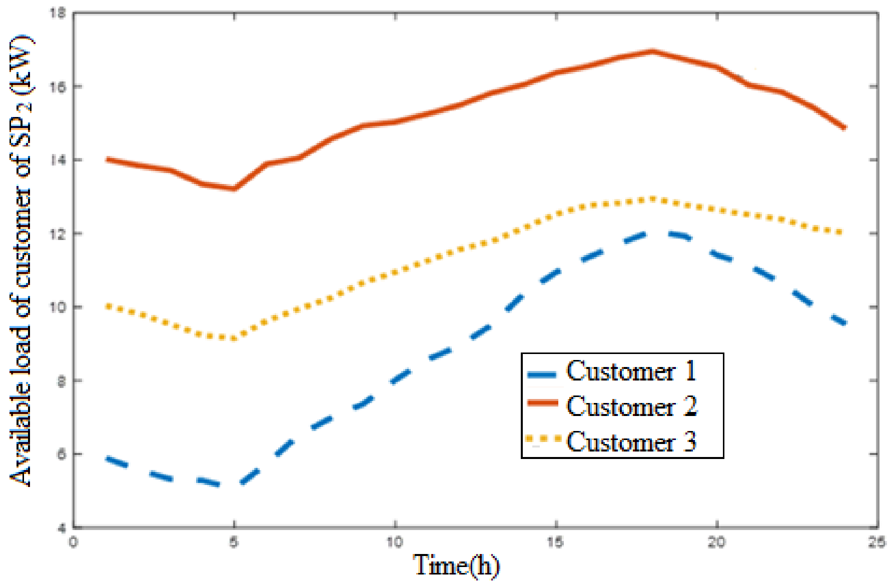

Figure 19. Available load data of the customers belonging to SP_2.

The customer and IC parameters are the same as those in Tables 6 and 7. The load data was taken for the entire day. These parameters remain the same throughout the day. The value of ρ is taken as 0.6. The required demand reduction optimized for the whole day is obtained, as illustrated in Figure 20. This demand reduction was used in the modeling of GO required for the calculation of the quantity of power generated [32].

The optimal incentive of GO is found using the Stackelberg equation which was derived, and the optimized incentives are utilized in the evaluation of the total cost. The total cost is further minimized using SPSO. The optimized incentive and the total cost incurred by the GO in procuring the capacities are depicted in Figure 21. The entire study is conducted for a day; therefore, the incentives and demand reductions vary daily.

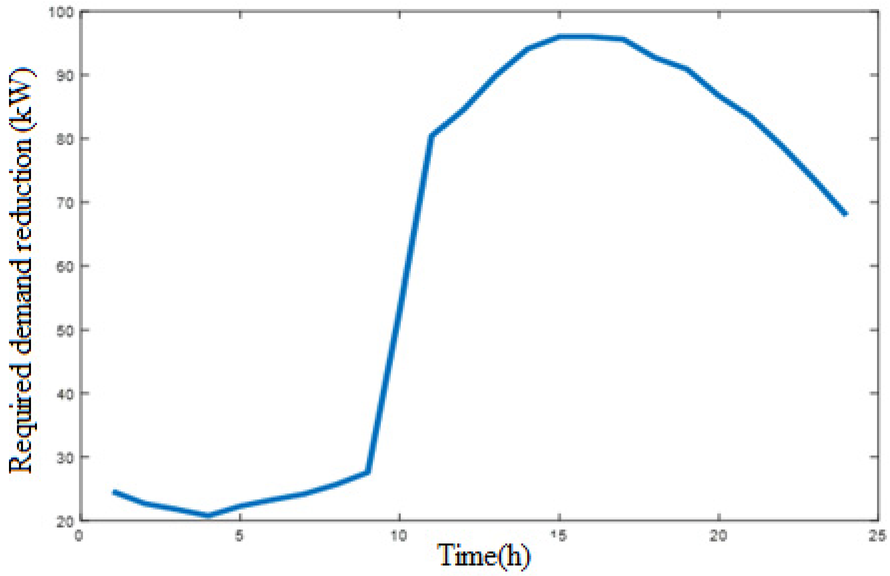

Figure 20. Required demand reduction in Case 2.

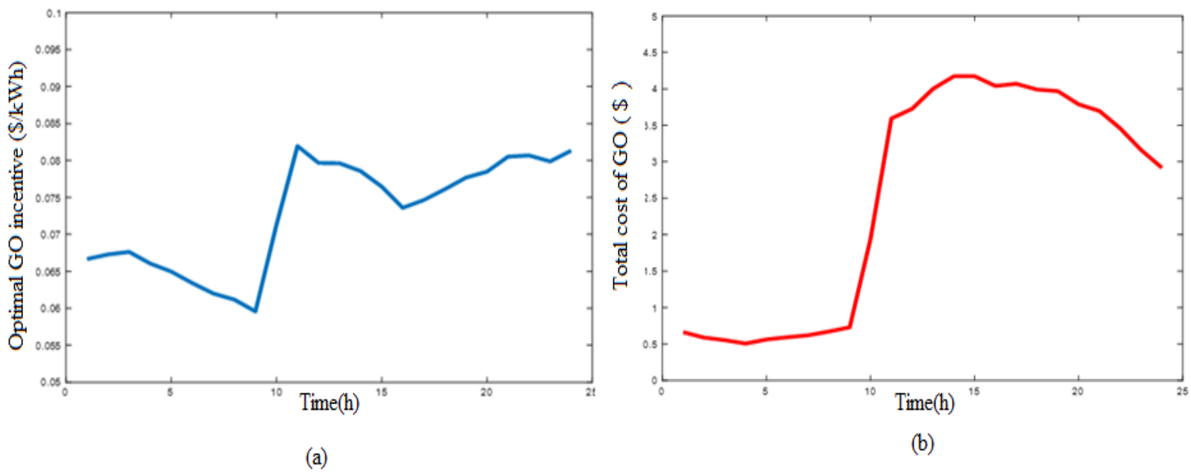

Figure 21. Results obtained: (**a**) the optimal GO incentive, and (**b**) the total cost of the GO.

The demand reductions of each ICs in response to the optimal GO incentive are optimized using PSO, and the results are given in Figure 22a. The customers with a larger value of σ are the ones contributing to more load reduction. It could be observed that customer 3, with a higher σ value, contributes to a greater demand reduction. The optimized GO incentives are utilized, and the incentives for SP_1 and SP_2 are found. The optimized values of the incentives of the SPs are given in Figure 22b. It is seen that SP_2 has a higher incentive compared to SP_1. The corresponding demand reduction of each customer under SP_1 and SP_2 is depicted in Figure 22c,d. These figures show that the demand reduction of customer 1 is high compared to customers 2 and 3.

The effect of various parameters on the results is studied using sensitivity analysis. Before starting with the altering of the parameters, from the results obtained from Case 2, it could be inferred that the demand reduction of customer 1 of SP_1 is higher compared to that of customer 1 of SP_2, which is visible in Figure 22c,d. This result could be attributed to the fact of the θ value. The increase in the θ value means that the customer's interest in demand reduction is low. From the input data of Tables 6 and 7, it is visible that customer 1 of SP_1 has a lower θ value (i.e., 3.0) compared to customer 1 of SP_2 (i.e., 4.0); therefore, the demand reduction is high for customer 1 of SP1. Furthermore, from Figure 22a, it can be said that the ICs with a larger value of σ will reduce more load. It could be seen that customer 3, with a higher σ value, contributes to a greater demand reduction. μ for the SP customers and ω for the ICs are changed to investigate the changes caused by the parameters, and one hour's (hour 16) output was observed and analyzed. Tables 9 and 10 present the input data of the performed analysis. The required demand deficit of the hour considered is 96 kW.

Table 9. Load data of the IC for the hour considered for the sensitivity analysis in Case 2.

ICs	IC_1	IC_2	IC_3
Available load (kW)	45.4	36.2	56.5

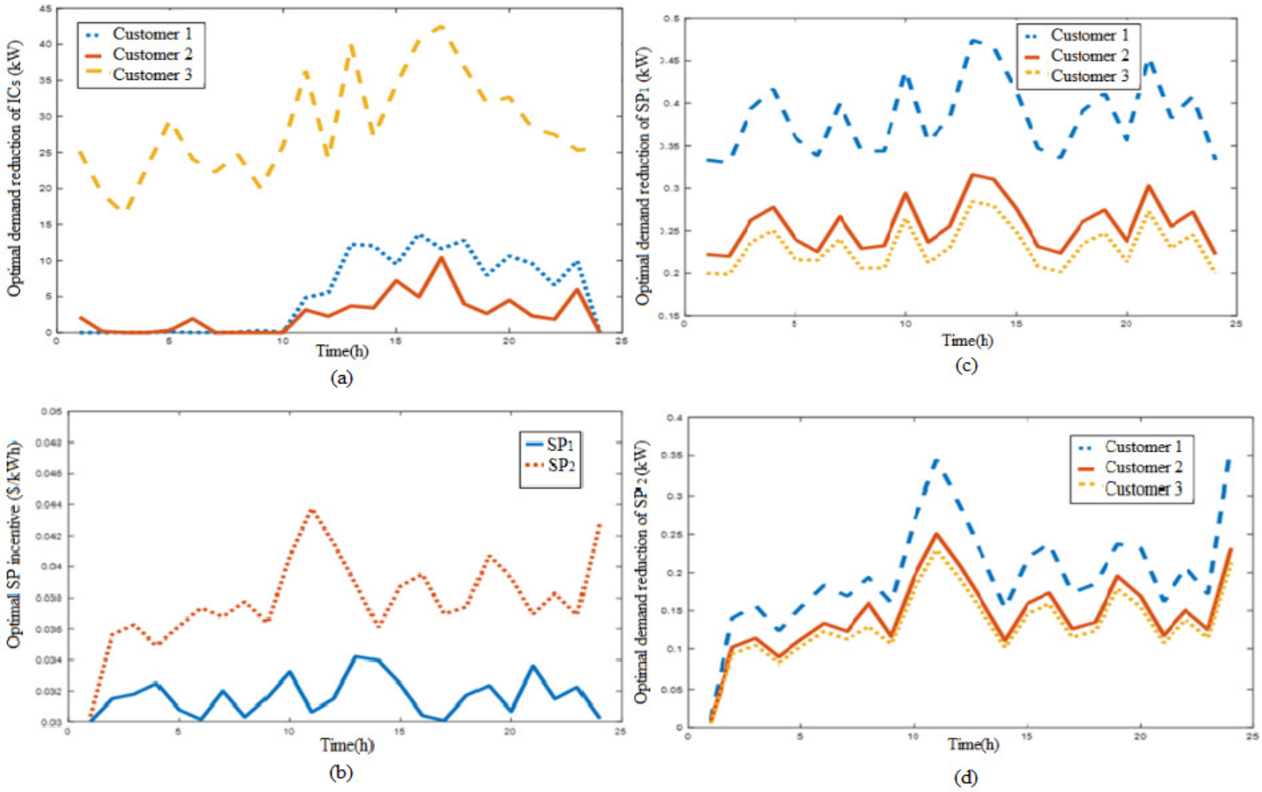

Figure 22. Optimization results: (**a**) the optimal demand reduction of the three ICs, (**b**) the optimal SP incentive, (**c**) the optimal demand reduction of the three customers of SP_1, and (**d**) the optimal demand reduction of the three customers of SP_2.

Table 10. Load data of SP for the hour considered for the sensitivity analysis in Case 2.

SPs		SP_1			SP_2	
Users	User 1	User 2	User 3	User 1	User 2	User 3
Load (kW)	11.54	7.47	9.29	11.35	16.55	12.77

The values of ω of the ICs considered are 8 and 5 for the three ICs. The values of μ for the SP customers considered are 1 and 0.8. These changes in the outputs are also shown in Tables 11 and 12 for IC and SP, respectively. The demand reduction of IC, the total cost of GO, and the incentive of GO are reduced when the value of ω is diminished.

Table 11. Optimized output with changes in the ω value.

Parameters		ω=8			ω=5	
Incentive of GO (cents/kWh)		7.3593			3.3383	
Total cost of GO ($)		4.0397			2.0634	
IC demand reduction (kW)	13.6714	4.9452	40.5349	8.2034	6.3111	34.7609

Table 12. Optimized output for changes in the μ value.

Parameters		μ=1.0			μ=0.8	
Incentive of GO (cents/kWh)		7.3593			9.9254	
Total cost of GO ($)		4.0397			5.2703	
SP incentive (cents/kWh)	3.0415		3.9544	3.1819		3.8468
Demand reduction of SP_1 customers (kW)	0.18	0.12	0.11	0.52	0.35	0.31
Demand reduction of SP_2 customers (kW)	0.11	0.08	0.07	0.42	0.31	0.28

The demand reduction of SP, and the total cost and the incentive of GO increase when the value of μ is reduced. The customer output of both of the SPs shows that as the value of μ is small, the customer shows more interest in demand reduction, and when observed closely, it is noted that the θ value also affects the demand reduction.

As θ increases, the value of the demand reduction decreases, which highlights that the customers show less interest in demand reduction as the value of θ increases.

A payment analysis is used to evaluate the benefits gained by each entity, and the results are tabulated. In Case 1, the demand reductions obtained by this approach for the entire day are much higher—the SP gains by selling these demand reductions at market prices. The incentive payment to be given to the customer is calculated. The incentive given by the SP to its customers is 5263 dollars for $\mu = 1.0$. If the IBDR implementation was not performed, the SP must purchase the required demand reduction at the market price as tabulated in Table 13.

Table 13. Payment analysis in Case 1.

Entity Considered	**Incentive Benefits ($)**
Incentives given by SP to customers in dollars	5263
SP purchasing D_t^{req} at market price (with no IBDR) in dollars	6357.7

The gain obtained by SP_1 and SP_2 can be found in Table 14 as USD 126.77 cents. The total cost incurred by the GO from Figure 22 is USD 60.1813, which is USD 6018.13 cents; lesser than the cost obtained using generators to serve the entire demand. Therefore, all of the entities involved in the IBDR program is benefited.

Table 14. Payment analysis in Case 2.

Entity Considered	**Incentive Benefits (Cents)**
Incentives obtained by IC from GO (cents)	3900
Total incentives obtained by SP1 and SP2 from GO (cents)	237.4676
Total incentives given by SP1 and SP2 to its customers (cents)	110.69

6. Conclusions

A novel IBDR is implemented considering the viewpoint of the SP and the GO. It could be said that the introduction of the GO into the system brings many changes in how incentives are provided, and in the demand reductions being evaluated. The interactions between the various entities are modeled using the Stackelberg game, and the contradicting parameters are brought to equilibrium. In order to solve the optimization problems, PSO is used, which provides the best-optimized results. The interaction between the SP and its two customers is a one-leader, two-follower game, but due to the presence of multiple entities with the introduction of GO, the game becomes a little complex as a one-leader multi-follower game. For the first IBDR case implemented (considering only the SP and its two customers), the incentive of the SP and the corresponding demand reductions of its customers were optimized. For the second case, with the involvement of the GO, the IC, and the SP, the incentives of the GO, the total cost of the GO, the corresponding demand reduction of the ICs under GO, the incentives set by the SP to its customers, and the demand reductions of the customers under SP were optimized. A sensitivity analysis was conducted to study the influence of varying customer parameters on the proposed IBDR program. The results proved that various changes in the outcomes are obtained due to the effect of the customer parameters, and a change made to a parameter of one entity affects the results of other entities. In the first case, the discomfort weight factor and the customer's attitude towards demand reduction are modified, and the outputs are monitored. In the second case, the discomfort weight factor and the customer's attitude towards the demand reduction of the SP and the IC parameters are varied, and the results are evaluated. The results show that the IBDR proves itself as a valuable tool to help the SP and GO procure resource capacities, thereby enabling them to solve the demand deficit issue. This work can be extended in the future by increasing the number of customers, SPs and ICs, and by considering the effect of integrating renewable energy sources on the results.

Author Contributions: Conceptualization: S.D.; methodology: S.D. and R.R.; software, S.D.; validation: R.R., S.D., S.H.E.A.A. and G.F.S.; visualization, M.A.M. and Z.M.A.; investigation: R.R., S.D., S.H.E.A.A., G.F.S., M.A.M. and Z.M.A.; data curation: S.D., S.S.G. and R.R., writing—original draft preparation, R.R. and S.D.; writing—review and editing, R.R., S.D., S.H.E.A.A., G.F.S., M.A.M. and Z.M.A.; supervision, S.D. and S.H.E.A.A.; project administration, S.D. and S.H.E.A.A.; funding acquisition, Z.M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Glossary

DR	Demand response
IBDR	Incentive-based demand response
PBDR	Price-based demand response
SPSO	Stackelberg–particle swarm optimization
LSE	Load serving entities
SG	Smart grid
MES	Multi-energy systems
GO	Grid operator
SP	Service provider
IC	Industrial customer
PSO	Particle swarm optimization
Sets, parameters and variables	
i	Customer
t	Time
π_t	Hourly incentives
μ_i	Weight factor
$D_{i,t}$	Demand reduction
$\varphi_{i,t}(D_{i,t})$	Dissatisfaction cost

$D_{i,k,t}^{min}$	Minimum demand
$D_{i,k,t}^{tar}$	Target demand
D_{t}^{req}	Required demand
P_t	Electricity pricing
π_t^{min}, π_t^{max}	Minimum and maximum incentive
π_{GOIC}	Incentive for the IC
$D_{l,t}^{ava}$	Available load for the IC
$D_{IC,l,t}$	Demand reduction of the IC
Ψ_l	Profit for the IC
$D_l^{ava} - D_{IC,l}$	Energy consumed by the the IC
$U_{IC,l}$	Utility function of the IC
σ_l, ω_l	Rate and magnitude of profit of the IC
K	Number of service providers
N_k	Total number of customers under the kth SP
$D_{SP,k,t}$	Demand reduction of all customers belonging to the kth SP
N_k	Number of customers under the kth SP
$\pi_{SP,k,t}$	Incentive offered by the kth SP
$\pi_{GOSP,t}$	Incentive offered by the GO to the SP
G	Quantity of power being generated
$C_{gen}(G)$	Cost of generating power
a, b, c	Coefficients of generation
π_{GO}	Incentive of the GO
π_{GOSP}	Incentive set by GO for the SP
π_{GOIC}	Incentive set by GO for the IC
$\pi_{GO}^{max}, \pi_{GO}^{min}$	Maximum and minimum incentive of the GO

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