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A Comprehensive Analysis of Demand Response Pricing Strategies in a Smart Grid Environment Using Particle Swarm Optimization and the Strawberry Optimization Algorithm

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Abstract: In the modern world, the systems getting smarter leads to a rapid increase in the usage of electricity, thereby increasing the load on the grids. The utilities are forced to meet the demand and are under stress during the peak hours due to the shortfall in power generation. The abovesaid deficit signifies the explicit need for a strategy that reduces the peak demand by rescheduling the load pattern, as well as reduces the stress on grids. Demand-side management (DSM) uses several algorithms for proper reallocation of loads, collectively known as demand response (DR). DR strategies effectively culminate in monetary benefits for customers and the utilities using dynamic pricing (DP) and incentive-based procedures. This study attempts to analyze the DP schemes of DR such as time-of-use (TOU) and real-time pricing (RTP) for different load scenarios in a smart grid (SG). Centralized and distributed algorithms are used to analyze the price-based DR problem using RTP. A techno-economic analysis was performed by using particle swarm optimization (PSO) and the strawberry (SBY) optimization algorithms used in handling the DP strategies with 109, 1992, and 7807 controllable industrial, commercial, and residential loads. A better optimization algorithm to go along with the pricing scheme to reduce the peak-to-average ratio (PAR) was identified. The results demonstrate that centralized RTP using the SBY optimization algorithm helped to achieve 14.80%, 21.7%, and 21.84% in cost reduction and outperformed the PSO.

Keywords: smart grid; demand-side management; dynamic pricing; time of use; real-time pricing; strawberry algorithm; particle swarm optimization; peak-to-average ratio

1. Introduction

The energy sector has been subjected to an increase in energy demand over several years. In addition, ample storage of electricity is not possible, as the current technology is incapable of storing a vast amount of energy [1]. As the generation capacity is a function of demand, the total generation capacity is considered to depend on the energy demand. According to a survey conducted in the United States on electricity consumption, home appliances consume 42% of the energy, but these domestic loads fluctuate during the day [2]. This fluctuation leads to a large difference between the peak and the average power consumption and a higher cost of energy consumption for consumers. It necessitates the setup of a considerable number of power-generating plants to meet the increase in fluctuating peak demand, which adds to the cost of the system [3]. Such a setup is not possible in developing countries due to scarce financial resources. This brings in the ideology of DSM-embraced smart grids (SGs) to meet the peak loads without increasing power generation. Even though it is a relatively recent concept, SGs are rapidly becoming a reality worldwide [4], as shown in Figure 1. SGs calculate, automate, and communicate the various parts and operations of the grid and coordinate the functioning and maintenance thereof [5]. Generally, SGs are known for their customer-friendliness and are adapted for acquiring better efficiency when compared with the conventional power system. Smart pricing is a fundamental aspect of SGs, which is used in conjunction with demand-side management (DSM), influenced by incentive strategies, real-time penalties, etc. [6,7].

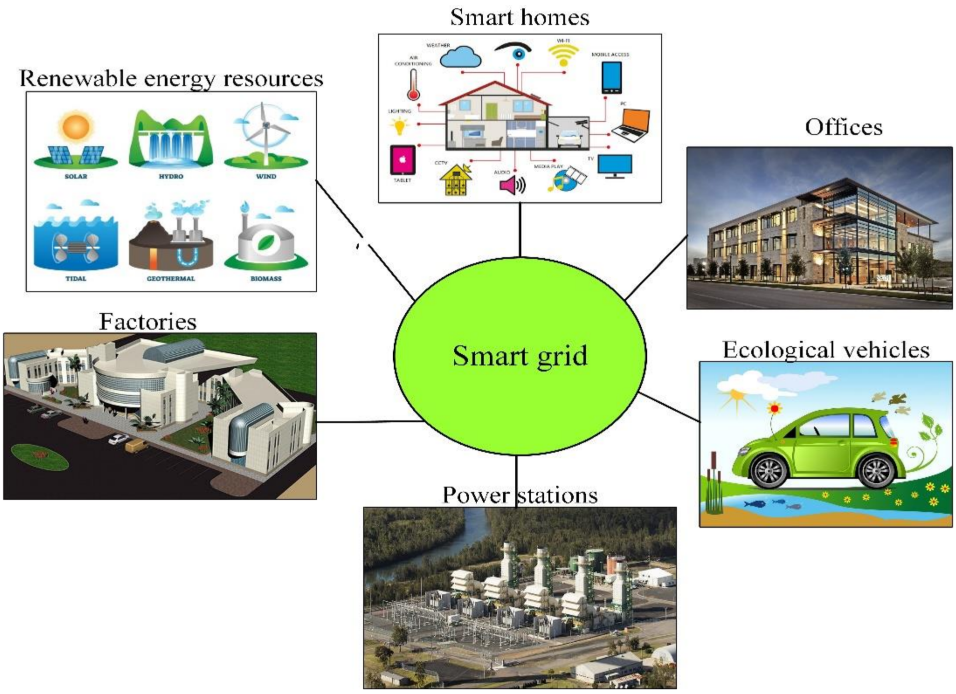

Figure 1. Smart grid representation.

Demand response (DR) is defined as a change in electricity consumption to standard consumption patterns [8]. The load curve reshaping is a cornerstone of DSM and SG [9]. It involves algorithms and programs intending to change the consumption pattern of electrical energy by consumers [10]. This is achieved by altering the amount of power needed for a particular hour, which is achieved by modifying the load profile of the distribution system [11]. The main objective of the DR is to decrease the peak of the load curve without increasing the amount of generated power [12]. Peak reduction can be implemented by shifting the controllable loads from the peak period to the off-peak hours, remodeling the load curve, and possibly decreasing the overall pricing. This is known as the price-based demand response (PBDR) program [13]. In addition, establishing a sustainable network model aids in reducing carbon emissions. An effective method of DSM involves disconnecting loads from high-priced times, which proves to be beneficial for both the utilities and the customer. From the customer's end, disconnection of electricity utilization during the peak hours and connection during the off-peak hours is advantageous. Thus, a consumer can reduce the electricity expenses by a considerable margin due to load shifting [14]. From the utilities' point of view, load shifting can protect the grid systems from the likelihood of outages, elevate the power generators' utilization, and enhance the grid's reliability [15]. Peak shaving, valley filling, etc. are the other types of DSM techniques that work by decreasing the peak demand and improving the grid's secured operation [16].

Bidirectional communication and power flow are the crucial features of SGs enabling the DP schemes for the customers. Compared to flat-rate pricing, dynamic pricing (DP) rates reflect the demand and supply interrelation more precisely. The most fundamental type of the PBDR program is established on the time of use (TOU). The TOU has three components to it, namely the peak, shoulder-rate, and off-peak hours [17]. Other pricing schemes include day-ahead pricing (DAP), critical peak pricing (CPP), extreme-day pricing (EDP), and real-time pricing (RTP), where RTP is evinced to be the most efficient method in the SG market [18]. Recent technological developments have given rise to smart appliances like wireless communication devices, which are built-in electrical appliances to gather RTP data from the Internet or smart meters. These appliances have the potential to time their working based on RTP [19]. In every method, the electricity price is presumed to be known or at least it is assumed to be predictable. The DR strategies are classified based on the motivation with which they are offered, according to the decision variables considered and the controlling mechanism adopted [20].

Further, the motivation-based DR is broadly classified as DP and incentive-based pricing. Various research works are put forward using DP methodologies. Logenthiran et al. [21] proposed the TOU algorithm to perform load shifting for a benchmark microgrid (MG) system with three different users. Park et al. [22] proposed a heuristic optimization technique (HOT) for solving the multiuser DR problem based on RTP and progressive-based pricing by sorting, scheduling residential appliances, and reducing customer discomfort. The nonconvex optimization problem considered was reformulated to obtain the optimal solution using a linear programming optimization technique. Yang et al. [23] proposed a conventional game theory algorithm to implement an RTP strategy in a residential area to reduce the cost involved in electricity pricing. That approach elucidates the methodology for conserving energy and tackling the problem of energy conservation using smart sockets. Sharma and Saxena [24] proposed whale optimization to reduce the cost and peak demand using the RTP method. The results obtained for demand-side management (DSM) techniques produced considerable savings while lowering the peak load demand of the smart grid. Taherian et al. [25] proposed dynamic load scheduling using the priority of loads in a residential SG environment with the utilization of the TOU algorithm to reduce the peak of the load curve, thereby reducing the cost. Niharika and Mukherjee [26] proposed DSM implementation using the DAP market for scheduling loads on an hourly basis to obtain the minimum operating cost of the system. That approach utilized symbiotic search optimization based on the cohabitation of organisms for optimization of the peak load for residential, commercial, and industrial customers using the TOU pricing strategy. Alwan et al. [27] proposed a decentralized algorithm to perform optimal load scheduling for residential and commercial facilities with local renewable generation. The cost minimization problem was subjected to operating constraints such as the maximum demand limit, penalty cost limit, etc. Arun and Selvan [28] proposed a DSM strategy by shedding the loads and minimizing the cost of electric power consumption along with the penalty cost over 24 h. Rocha et al. [29] performed block rate and RTP-based scheduling of loads for different types of consumers based on their priority level. Gellings [30] proposed a DR strategy to minimize electricity consumption costs and reduce the peak demand in a UK-based system. In addition, optimization of power consumption patterns using various procedures such as load shifting, valley filling, etc. was discussed. Abushnaf and Rassau [31] proposed a multivariable genetic algorithm-based cost minimization technique for scheduling residential loads integrating DR strategies and sustainable energy sources (SES). Sisodiya et al. [32] proposed particle swarm optimization (PSO)-based optimal load rescheduling using the RTP algorithm for reducing the cost of energy consumed and the cost of generation with SES considered in the system. Subrata Saha et al. [33] proposed a modified flower pollination algorithm to obtain an optimal pricing scheme in order to maximize the retailer's profit by employing promotional pricing and a trapezoidal rate for the demand. Table 1 depicts the comparative analysis of the references based on the objective, techniques, and contribution.

Table 1. Comparison of the references based on their objective and techniques.

References	Objective	Technique/Model	Contribution
[14]	To assess the technical and economic impact of DR for systems with renewable energy sources (RES)	Integrated co-optimization planning method	An optimization model for long-term decision-making modeled with the impact of short-term variability of demand and RES
[16]	To minimize the electricity purchase cost	Binary integer programming	Scheduling of different domestic appliances with response to the real-time pricing signal is solved
[17]	To maximize the supplier's profit	Bilinear bilevel mixed-integer	The insights of the user demand flexibility, capacity profile, and price structure are provided
[19]	Social welfare maximization	Smoothing Newton algorithm	The developed utility function is more beneficial than the quadratic and logarithmic utility functions in reducing the user demand
[20]	Analysis of scheduling of appliances at the user's side	Deep learning modeling	DR modeling for domestic customers conducted with a learning model designed with the strategy stated by users
[22]	To obtain approximated optimal solutions in a progressive policy	Heuristic evolutionary algorithms	Problem models designed to meet DR management for different electricity bill policies
[23]	To optimize TOU pricing strategies	Game theory model	An optimal game theory TOU electricity pricing strategy designed for utility companies and users using the Nash equilibrium to provide optimal prices
[25]	To support a retail electric provider (REP) to make the best day-ahead dynamic pricing decisions	Adaptive neuro-fuzzy inference system	A profit maximization algorithm developed to obtain optimal costs under appropriate market constraints
[26]	Modeling of DSM using a day-ahead load shifting approach as a minimization problem	Symbiotic organisms search algorithm	A comparison of outcomes achieved using different algorithms with the recommended algorithm carried out based on peak load reduction, reducing a utility bill
[29]	To reach a compromise between energy cost and the user comfort	Artificial intelligence techniques	Numerical simulations with actual data obtained from a smart home, the *k*-means clustering technique determined the user comfort levels
[31]	To minimize the overall daily cost of electricity consumed by household appliances	Genetic algorithm	The power limit violation level decreases near the original settings compared with the use of EV batteries for energy storage
[32]	To minimize the operational cost of energy with consumer comfort preferences	Particle swarm optimization	Scheduling for building EMS optimized in the RTP scheme
[33]	Optimal pricing scheme and replenishment schedule	Modified flower pollination algorithm	Proposes a dynamic rate based on various types of pricing (dynamic and trapezoidal) based on demand
Proposed method	A techno-economic analysis to minimize the cost of power consumption and the PAR using dynamic pricing strategies of TOU and RTP (distributed and centralized algorithms)	Particle swarm and the strawberry algorithm	Load scheduling performed for industrial, commercial, and residential loads with 109, 1992, and 7807 controllable loads using the TOU, distributed RTP, and centralized RTP. Furthermore, the PAR reduction along with a techno-economic analysis for PSO and the SBY optimization algorithm based on the implemented DP strategies.

The literature concludes with the following research gap:

- The pricing adopted based on the RTP location is less fair than the purchase history pricing;
- The impact towards the increase in controllable devices, selection of the DP methodology and optimization techniques is not contributed;

- Techno-economic analysis considering different load scenarios and different DP strategies is not focused. Comparative analysis of the PAR based on DP and optimization is not projected.

Thus, this study emphasizes implementation of various DR strategies that can benefit the utilities and different types of users, such as residential, commercial, and industrial customers with both controllable and uncontrollable loads. The highlights of this study are as follows:

- Analysis of the DP schemes of DR such as TOU and RTP for industrial, commercial, and residential load scenarios is formulated.
- A techno-economic comparative analysis of PSO and the strawberry (SBY) optimization algorithm for solving the DP strategies with 109, 1992, and 7807 controllable industrial, commercial, and residential loads is performed.
- An RTP algorithm is considered using both distributed and centralized algorithms.
- A comparative analysis of the peak-to-average ratio (PAR) calculated for all load conditions with both PSO and the SBY optimization algorithm using the TOU and RTP strategies is performed.

The rest of the article is organized as follows: Section 2 elaborates on the dynamic pricing strategies. Section 3 illustrates the optimization algorithms chosen for solving the dynamic pricing problem followed by the techno-economic analysis of DP strategies in Section 4. Finally, the results obtained are discussed in Section 5.

2. Pricing Algorithms

The DP schemes taken into consideration were the TOU pricing and the RTP. The pricing schemes were used in a combination of optimization algorithms that are addressed in detail in Section 3.

2.1. Time-of-Use Pricing

The TOU technique is similar to the pricing based on block rates considered for a particular time of day and week when the customers consume electricity. The TOU rates are the fixed electricity prices charged to both residential and small-scale industries. The price of electricity may vary over the day and is updated daily. Besides, the consumers are allowed to schedule their usage according to their preferences. The proposed scheme has three TOU periods: off-peak, mid-peak, and on-peak periods.

Off-peak is when the energy demand is low, whereas mid-peak occurs when the energy requirement is moderate. In addition, on-peak occurs when there is the maximum energy demand. Consequently, it requires more expensive forms of electricity to be used. In this way, it ensures that the amount paid by the consumers is economically reasonable [21]. The purpose of DR is to schedule the connection time of each shiftable device so that the forecasted load for every user is shifted so that it is as close to the assumed objective consumption curve as possible. The objective function of DR using the TOU is given in Equation (1):

$$\sum_{t=1}^{24} \min(Pload(t) - objective(t))^2 \tag{1}$$

where $objective\ (t)$ represents the power value of the objective curve at time t. The objective load curve is chosen in such a way that it is inversely proportional to the electricity market prices.

$$objective(t) = \frac{P_{avg}}{P_{max}} \times \frac{1}{P(t)} \sum_{t=1}^{24} forecast(t) \tag{2}$$

where P_{avg} denotes the average price during period t, P_{max} represents the maximum price throughout the day, $P(t)$ denotes the maximum price at time t, T represents the total number of hours in the day, $forecast(t)$ is the forecasted consumption at t, and $P_{load}(t)$ represents the power consumed at time t after shifting the load and is described in Equation (3):

$$Pload(t) = forecast(t) + connect(t) - disconnect(t) \quad (3)$$

where $connect(t)$ and $disconnect(t)$ represent the devices that are connected and disconnected at a particular time t, respectively; $connect(t)$ is divided into two terms: the first term includes the increase in the load due to the connection of the devices that were to be connected at time t; the second term includes the increase in the load due to the connection of the devices scheduled for the preceding time t [21].

$$connect(t) = \sum_{i=1}^{t-1}\sum_{k=1}^{D} Y_{ki(t)} \times P_{1k} + \sum_{l=1}^{j-1}\sum_{i=1}^{t-1}\sum_{k=1}^{D} Y_{ki(t-1)} \times P_{(1+l)k} \quad (4)$$

Parameter $disconnect(t)$ is also divided into two terms: the first term is to decrease power consumption by means of delay in the connection of the devices that were to be connected at time t; the second term includes the decrease in the demand owing to the delay in the connection of the devices that were expected at the preceding time t [21].

$$disconnect(t) = \sum_{q=t+1}^{t+m}\sum_{k=1}^{D} Y_{k(t)q} \times P_{1k} + \sum_{l=1}^{j-1}\sum_{q=t+1}^{t+m}\sum_{k=1}^{D} Y_{k(t-1)q} \times P_{(1+l)k} \quad (5)$$

where $Y_{ki(t)}$ denotes the number of appliances of type k which are rescheduled for operation from time i to t, D denotes the number of equipment types, P_{1k} and $P_{(1+1)k}$ are the power consumption at time steps '1' and '1 + l', respectively, for device type k, and j is the total time required for the consumption of device type k. The implementation steps of the TOU are depicted in Figure 2.

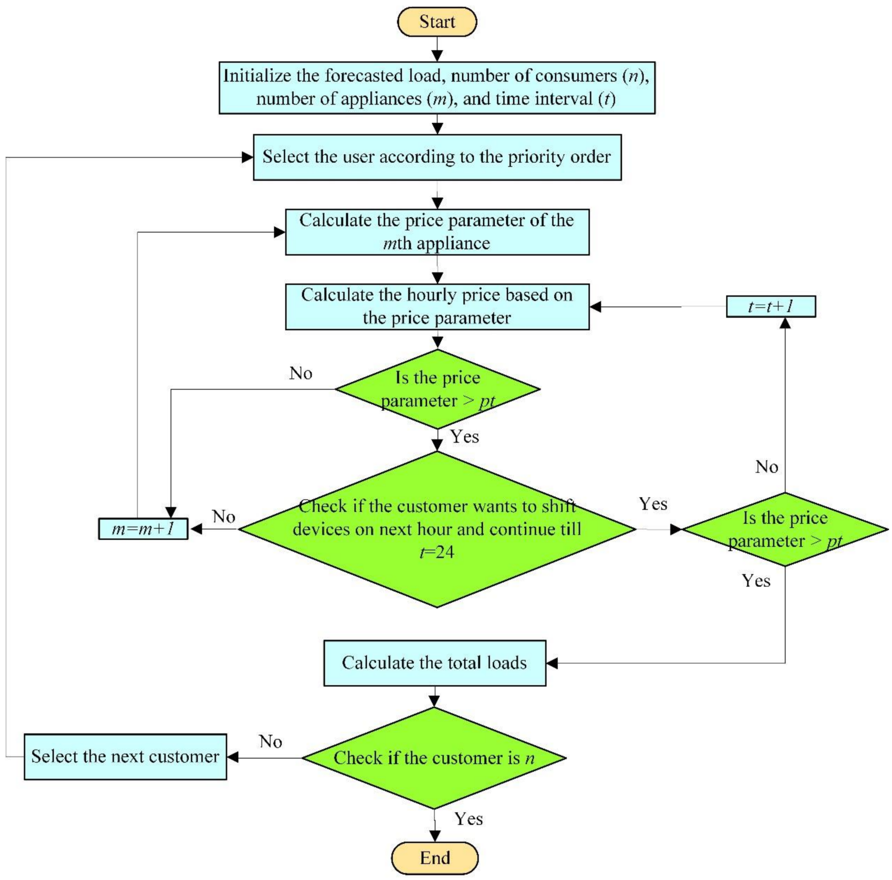

Figure 2. TOU flowchart.

2.2. Real-Time Pricing

This section focuses on the load scheduling problem, which is framed as an optimal stopping problem. RTP is chosen as the arbitrary variable, and the home appliance's starting operation is the action. The purpose is to select the most optimal time to start the action to decrease the cost or increase the profit. The RTP is updated periodically, mostly every 30 min. Each period of one hour in a day is considered as one timeslot. The electricity consumption rate is presumed to be fixed for each timeslot, but it can change across different timeslots, and hence it can be classified as a discrete-time model. Let us assume T to be the duration of the total timeslot in a day, which is typically fixed as one hour. Additional assumptions would be that the devices' operation can only commence at the start of a timeslot. Furthermore, we assume that the duty cycles are less than T. Thus, when a device starts its operation, during the duty cycle, the price remains fixed. Furthermore, if the timeslot of operation of the device exceeds one hour, the task is broken down into multiple subtasks by the process of task decomposition [34].

3. Formulation of the RTP Load Scheduling Problem

The concept of an optimal stopping rule and its application have been framed as an optimal stopping problem. The optimal stopping rule (OSR) depends on whether to maximize the reward or minimize the compensation. In this regard, it is required to select an optimal stopping time t to decrease the generally expected returns.

The RTP signals constantly vary in nature, e.g., for every hour of a day. The load scheduling problem using RTP [34] is framed in this work by presuming the RTP signal to be an arbitrary variable. This study aimed to reduce the cost of power consumption by considering the timeslot for a day as a variable. Furthermore, electrical devices are segregated into three segments based on their power consumption, i.e., base, regular, and burst load. The loads that possess low energy consumption and have long duty cycles fall under the category of base loads. These loads encompass lightning, networking devices, and computers. Regular loads include devices where the power consumption of the particular load is higher than that of base loads. However, their duty cycle is for an extended period as well. For instance, refrigerators, HVAC, and water heaters are included. The devices whose operation time is constant but add to the peak load form the burst load [35]. For instance, washing machines, dishwashers, and clothes dryers are included. Generally, the peak power period is considered for scheduling; thereby, the scope of this article was also extended to the complete time of device operation. The objective was to reduce the cost of power consumed by the device and the waiting time. The waiting time was modeled as the cost to achieve it. Thus, the objective function can be estimated using the following formula:

$$\min_{N \in C} \lim_{M \to \infty} \frac{1}{M} \sum_{t=0}^{M} \left(\sum_{i \in S_t} \left[C_i^P + C_i^W \right] \right) \quad (6)$$

where the cost of electricity can be described as follows:

$$C_i^P = g_i \times P(N(i)) \quad (7)$$

The cost due to the waiting time can be described as follows:

$$C_i^W = \mu_i \times \tau \times N(i) \quad (8)$$

M is the total number of timeslots, St is the set of appliances arriving at timeslot t, τ denotes the length of one timeslot (i.e., one hour), N is the scheduled operation timeslot of the device, C is the class of optimal stopping rules which satisfies $C = \{N: N \geq 0, E[T] < \infty]$, T is the total time spent running each appliance including the waiting time, g_i is the power consumption of appliance i, $P(N(i))$ is the RTP signal for the timeslot, and μ_i is the time factor/priority of appliance i.

For practical reasons, the formula considered is simplified as Equation (9). Reduction of the operating costs for a single appliance reduces the overall cost, so the cost formula can be simplified as in [36]:

$$\min_{N \in C} \left[C^P + C^W \right] \tag{9}$$

The optimal stopping rule helps in solving the mathematical condition above. There are two constraints considered in RTP:

3.1. Tentative Scheduling

At this stage, the threshold for each device can be described by the following equation:

$$Z_i = \sqrt{\frac{2(P_p - P_0)\mu\tau}{g}} + P_0 \tag{10}$$

where real-time pricing is assumed to be distributed uniformly over the interval $(P_p - P_0)$. The device will operate in the timeslot only if the threshold of the device in consideration is lower than the real-time pricing of that hour, i.e., $Z_i < P(t)$.

3.2. Power Allocation

For each timeslot, it was made sure that enough power was available to operate the device under consideration. This inequality condition can be formulated as follows:

$$\sum_{i=1}^{t} \sum_{i \in S_l} g_i \times \delta(N(i), t \leq Q) \tag{11}$$

where S_l is the set of devices waiting to run at timeslot l, $\delta(N(i), t \leq Q)$ is a binary variable indicating the operation status of appliance i. If $N(i) =$ t, $\delta(N(i), t \leq Q) = 1$, otherwise $\delta(N(i), t \leq Q) = 0$, and Q is the maximum power allowed in each timeslot t. The constraint can be further reduced to the following equation, where L_t is the list of devices waiting to run at the t^{th} timeslot:

$$\sum_{i \in L_t} g_i \leq Q \tag{12}$$

Two methods of implementing RTP were taken into consideration, the distributed scheduling algorithm (DSA) and the centralized scheduling algorithm (CSA). For any appliance, two types of costs were calculated: the cost due to the waiting time and the cost of electricity consumption. This helps in minimizing the mean cost for all the appliances in the long run [36]. The DSA works on the first-come, first-served basis. Here, each device is made to operate autonomously. The controllable load and the price of electricity at a particular time of operation are the data required for the DSA algorithm. If the timeslot for operating the device is unsatisfactory, the same process must be repeated in the next immediate timeslot until no more devices are scheduled [37]. It can be summarized as follows [38]:

3.3. Distributed Scheduling Algorithm

→ Begin;
→ Set the value of $t = 0$;
→ At time t the device $i \in S_t$ prepares to enter the operating mode;
→ For each device i calculate the pricing threshold value (Z_i);
→ Check if Z_i is lower than the RTP at t;
→ Check the power constraint;
→ If the available power is greater than the power consumed by the device (g_i), run the device in that hour t, otherwise proceed to step 5;
→ Increment t and go to step 2. Perform until $t = 24$.

In the CSA, the calculation of the cost equation consists of two segments: the cost of electricity and the postponement cost for each device. Due to the devices getting postponed, additional costs are included as the waiting cost. The cost involved in the delay of each appliance is required for the total time to minimize the total cost. The cost involved in postponing a device is given as follows [39]:

$$C_i^a = g\left(\frac{Z + P_0}{2} - P(t)\right) + \mu \frac{P_P - P_0}{Z - P_0} \tag{13}$$

3.4. Centralized Scheduling Algorithm

The CSA algorithm is as follows:

- Initialize the timeslot $t = 0$;
- At any time t, the appliance $i \in S_t$ is made to run;
- For each appliance i in a smart home, the threshold Z_i is calculated, and a signal is sent to the home energy controller (HEC);
- Check for the current electricity price (t) set by the HEC. Then, select the delayed appliances whose Z_i is lower than $P(t)$ and list them in queue L_t;
- Solve the load-shifting problem to select the devices which can get connected and list them in queue O_t; the leftover appliances in L_t should wait for the next available timeslot;
- Run all the appliances waiting in the O_t queue;
- Increment $t = t + 1$ and go to step 2; continue till $t = 24$.

According to the above algorithm, there is a requirement for the central scheduler to allocate the devices concerning the threshold power setting. Before the central scheduler settles on a choice, all the devices must forward their price limit and power utilization.

3.5. Peak-to-Average Ratio (PAR)

The ultimate objective of DR is to shift the peak load demand to the non-peak hours and thereby reduce the cost of power consumption without shedding the load. Thus, the main focus of DR is to reduce the PAR of the given demand curve. The equation for PAR calculations can be given as follows:

$$Average\ power\ (L_{avg}) = \frac{1}{T}\sum_{t\in T} L_t \tag{14}$$

where T is the total timeslot (24 h) and L_t is the total power consumed by users from $t = 1$ to T hours.

$$Peak\ power\ (L_{max}) = \max_{t\in T} L_t \tag{15}$$

where L_{max} is the peak power of the load curve.

$$PAR = \frac{L_{max}}{L_{avg}} \tag{16}$$

4. Optimization Algorithms

Optimization algorithms are used in combination with pricing algorithms to obtain cost minimization. PSO and the SBY optimization algorithm were considered based on their effective operation towards getting the global best solution in fewer iterations and ease of handling more controllable loads. The complexity of optimization increases as the controllable loads are increased. Moreover, PSO is employed for ease of implementation, adaptability of control parameters, and as it is widely used for the search for the global best value. SBY was selected as it has some features of the genetic and the PSO algorithms. The optimization algorithms implemented in this study were PSO and the SBY optimization algorithm.

4.1. Particle Swarm Optimization (PSO)

PSO is a metaheuristic optimization algorithm that is used to solve a wide range of problems [39–42] with ease of implementation and adaptability of control parameters. It is widely employed in the search for the global best value. To locate the optimal solution of an objective function, PSO generates randomly distributed particles. These particles travel randomly and reach a convergence point. The inputs given to the optimization problem are swarm size, the total number of iterations, weights, positions, and learning variables. It associates velocity to each particle as follows [39]:

$$V(t+1) = W \times V(t) + C_1 \times rand[.] \times (global_{best} - curr_{best}) + C_2 \times rand[.] \times (loc_{best} - curr_{best}) \tag{17}$$

where W is the inertia weight that lies between 0 and 1, C_1 and C_2 are random numbers such that $C_1 + C_2 \leq 4$, rand[.] denotes the random variable that lies between 0 and 1. The position of the particle and the inertia weight is updated as follows:

$$X(t+1) = X(t) + V(t+1) \tag{18}$$

$$W = W \times W_{damp} \tag{19}$$

where $x(t)$ is the position update for the particle at time t, $V(t+1)$ is the updated velocity value for time $t+1$, W_{damp} is the weight damping ratio.

4.2. Strawberry Optimization Algorithm (SBY)

The SBY optimization algorithm is inspired by the strawberry plant with some of the features of the genetic and the PSO algorithms [43,44]. The strawberry plant uses both runners and roots for propagation, search for water resources and minerals. This propagation ideology is used to solve complicated engineering problems. The algorithm has three differences compared to PSO, namely duplication and elimination of agents at every iteration, all the agents are subjected to both small and large movements from the beginning to the end, and lack of information exchange between agents. The algorithm can very effectively solve even a complicated optimization problem [45]. The SBY optimization algorithm is as follows:

1. Select the number of mother plants (e.g., N), the number of roots (N_{root}), and the number of runners (N_{runner}) so that $N_{runner} >> N_{root}$. Set a group for the number of devices. The combination of devices is considered as a variable. Consider the best pattern after running the permutation for the set of devices in the group; for the best pattern of devices, run the strawberry optimization algorithm. The grouping of controllable devices is considered as the mother plant in this DR problem.
2. Set the number of mother plants in the search space, as well as the iteration count.
3. Randomly generate two points, the roots and the runners for every mother plant ($2N$ points). The possible allocation of the devices in the group will be obtained as $2N$ vectors.
4. Evaluate fitness (function to be optimized, e.g., fitness ($x(i)$)) for every mother plant.
5. Using the roulette wheel, the best $N/2$ fitness out of the $2N$ vectors is selected, as well as the elite selection selects the best $N/2$ fitness. The total of N best solutions from the obtained $2N$ fitness value is selected. The left-out N values are eliminated. The best N value takes part in the next iteration.
6. Repeat steps 3–5 until the termination condition is satisfied.

4.3. System Input Data

A sample system with residential, commercial, and industrial loads was considered for the implementation of DR strategies. The chosen input data were simulated for the different pricing schemes using SBY and PSO. The devices considered in the system are categorized into controllable and uncontrollable devices. The list of controllable devices is tabulated in Tables 2–5. The forecasted load areas are shown in Figure 3. For the industrial load, the total number of shiftable devices considered was 109 (listed under six different types of equipment). Similarly, the total number of devices in the commercial area was 1992, with eight different types of devices. Furthermore, the total number of devices listed in the residential area was 7807, with 14 types of devices. The TOU and RTP pricing in $/kWh is depicted in Figure 4.

Table 2. Controllable loads present for the industrial area.

Type of Devices	First-Hour Load (kWh)	Second-Hour Load (kWh)	Third-Hour Load (kWh)	Fourth-Hour Load (kWh)	Fifth-Hour Load (kWh)	Sixth-Hour Load (kWh)	Number of Devices
Water heater	12.5	12.5	12.5	12.5	-	-	39
Welding machine	25.0	25.0	25.0	25.0	25.0	-	35
Fan	30.0	30.0	30.0	30.0	30.0	-	16
Arc furnace	50.0	50.0	50.0	50.0	50.0	50.0	8
Induction motor	100.0	100.0	100.0	100.0	100.0	100.0	5
DC motor	150.0	150.0	150.0	-	-	-	6
			Total devices				109

Table 3. Hourly pricing and hourly load forecast.

Time (h)	TOU Pricing ($/kWh)	RTP Pricing ($/kWh)	Forecasted Load in the Residential Area (kWh)	Forecasted Load in the Industrial Area (kWh)
24–1	0.0865	0.100	475.7	974.0
1–2	0.0811	0.100	412.3	876.6
2–3	0.0825	0.080	364.7	827.9
3–4	0.0810	0.085	348.8	730.5
4–5	0.0814	0.125	269.6	730.5
5–6	0.0813	0.090	269.6	779.2
6–7	0.0834	0.130	412.3	1120.1
7–8	0.0935	0.205	539.1	1509.7
8–9	0.1200	0.275	729.4	2045.5
9–10	0.0919	0.280	713.5	2435.1
10–11	0.1227	0.175	713.5	2629.9
11–12	0.2069	0.170	808.7	2727.3
12–13	0.2682	0.170	824.5	2435.1
13–14	0.2735	0.165	761.1	2678.6
14–15	0.1381	0.140	745.2	2678.6
15–16	0.1731	0.080	681.8	2629.9
16–17	0.1642	0.075	666.0	2532.5
17–18	0.0983	0.078	951.4	2094.2
18–19	0.0863	0.085	1220.9	1704.5
19–20	0.0887	0.060	1331.9	1509.7
20–21	0.0835	0.065	1363.6	1363.6
21–22	0.1644	0.060	1252.6	1314.9
22–23	0.1619	0.060	1046.5	1120.1
23–24	0.0887	0.060	761.1	1022.7

Table 4. Controllable loads present in the commercial area.

Type of Devices	First-Hour Load (kWh)	Second-Hour Load (kWh)	Third-Hour Load (kWh)	Number of Devices
Water dispenser	2.50	-	-	349
Dryer	3.50	-	-	168
Electric kettle	3.0	2.50	-	192
Microwave oven	5.0	-	-	255
Coffee maker	2.0	2.0	-	343
Fan	3.50	3.0	-	284
AC	4.0	3.5	3.0	245
Lights	2.0	1.75	1.50	156
		Total		1992

Table 5. Controllable loads present in the residential area.

Type of Devices	Hourly Consumption of a Device			Number of Devices
	First-Hour Demand (kWh)	Second-Hour Demand (kWh)	Third-Hour Demand (kWh)	
Dryer	1.20	-	-	308
Dishwasher	0.70	-	-	430
Washing machine	0.50	0.5	-	967
Microwave oven	1.30	-	-	375
Iron box	1.00	-	-	830
Vacuum cleaner	0.40	-	-	970
Fan	0.20	0.2	0.2	734
Electric kettle	2.00	-	-	752
Toaster	0.90	-	-	198
Rice cooker	0.850	-	-	277
Hairdryer	1.50	-	-	230
Blender	0.30	-	-	933
Frying pan	1.10	-	-	582
Coffee maker	0.80	-	-	221
Total devices				7807

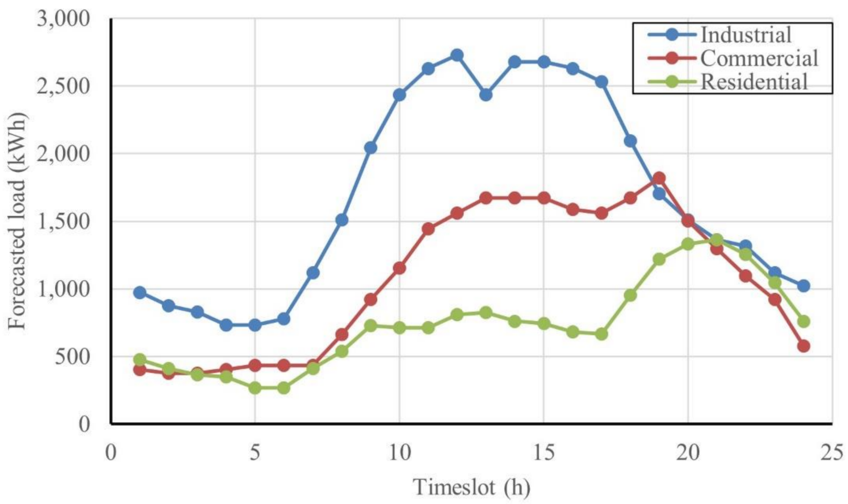

Figure 3. Forecasted industrial, commercial, and residential loads.

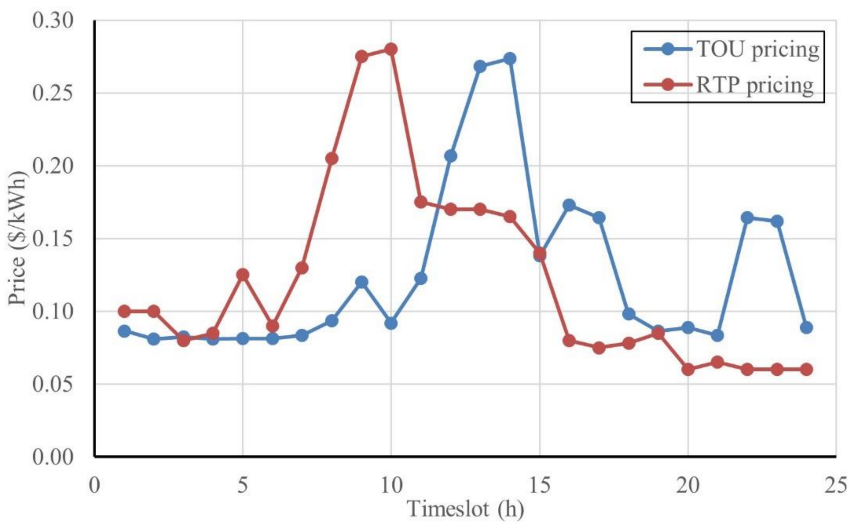

Figure 4. Pricing for each hour for RTP and TOU.

5. Techno-Economic Analysis

The realization of DR with TOU and RTP pricing strategies was performed using the SBY optimization algorithm and PSO to get the best optimal solution. The optimization problem was executed for 24 h of load data. The combination of devices was considered as the variable for this cost minimization problem. The SBY and PSO-based cost minimization problem was executed with the number of mother plants and the swarm size of 12 for TOU and 10 for RTP. The variable considered for both PSO and the SBY optimization algorithm is the number of devices. Thereby, the complexity of this DR problem becomes tangled as the number of variables increases.

The optimization results of DR implementation in a sample test system with the residential, commercial, and industrial demand using PSO and SBY with TOU pricing were obtained. The hourly costs for the three loads before and after the DR implementation are displayed in Figures 5–10. According to the cost optimization results for the residential area before and after DSM with TOU-PSO, the cost reduced when the load decreased at the peak periods and was postponed to the off-peak periods. Before DSM, the total cost was \$2302.879, which is \$134.81 more than the cost obtained by implementing the DR strategy. Similarly, for the commercial load, a cost reduction of \$182.76 was obtained with TOU-PSO. Likewise, the cost minimization for the industrial load demand with TOU-PSO was obtained at \$546.855.

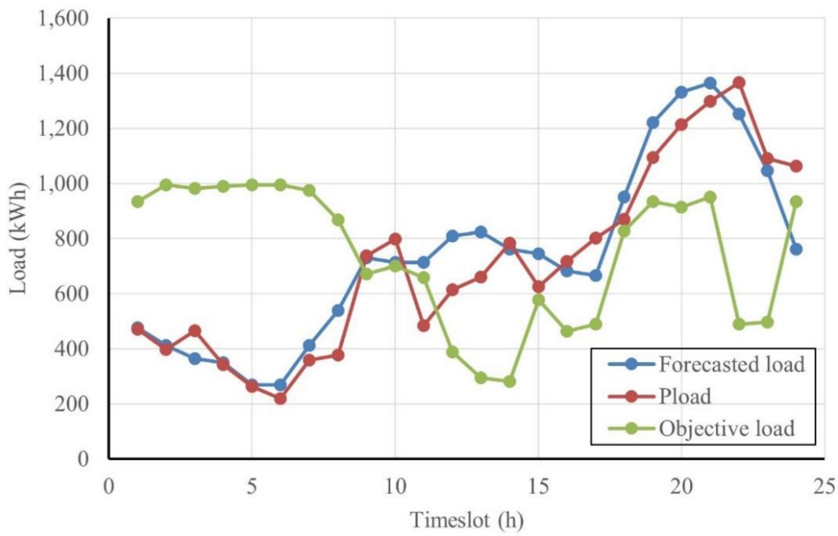

Figure 5. Hourly residential load before and after shifting using TOU-PSO.

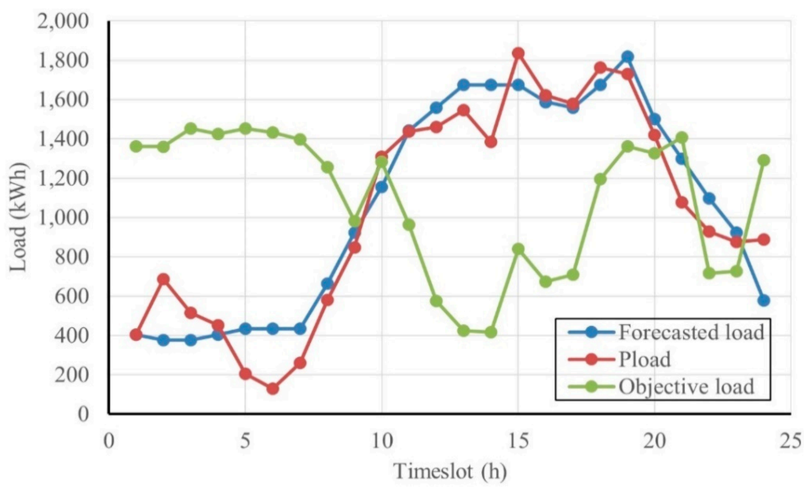

Figure 6. Hourly commercial load before and after shifting using TOU-PSO.

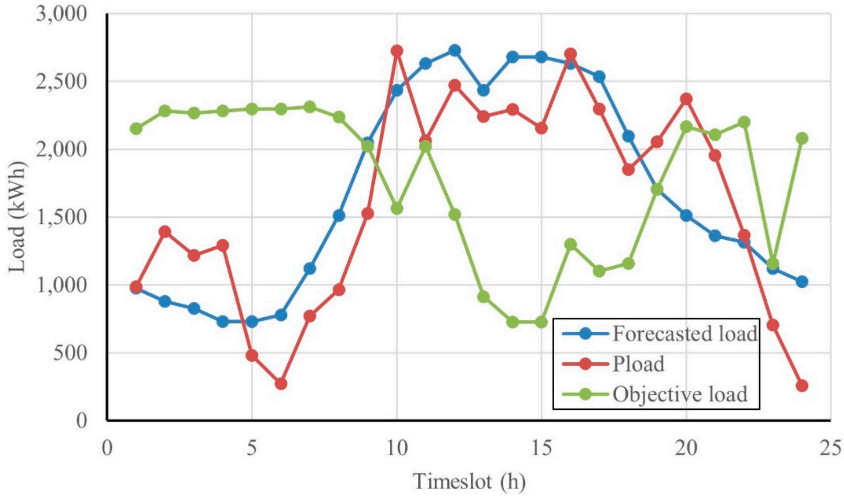

Figure 7. Hourly industrial load before and after shifting using TOU-PSO.

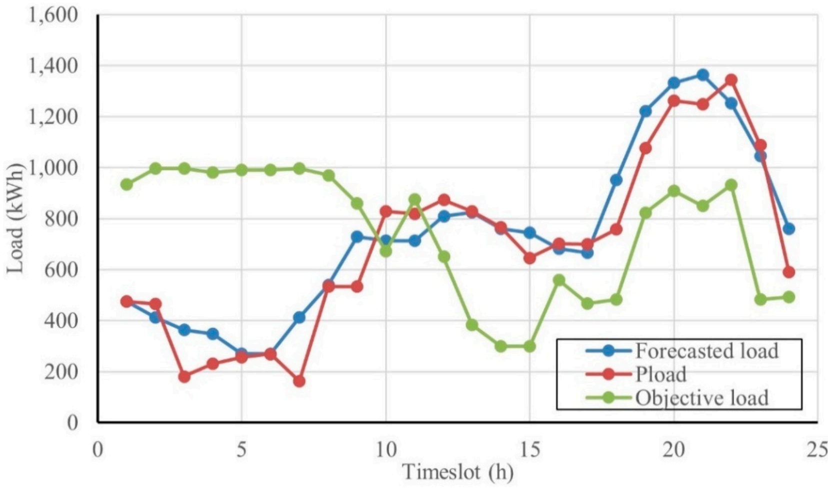

Figure 8. Hourly residential load before and after shifting using TOU-SBY.

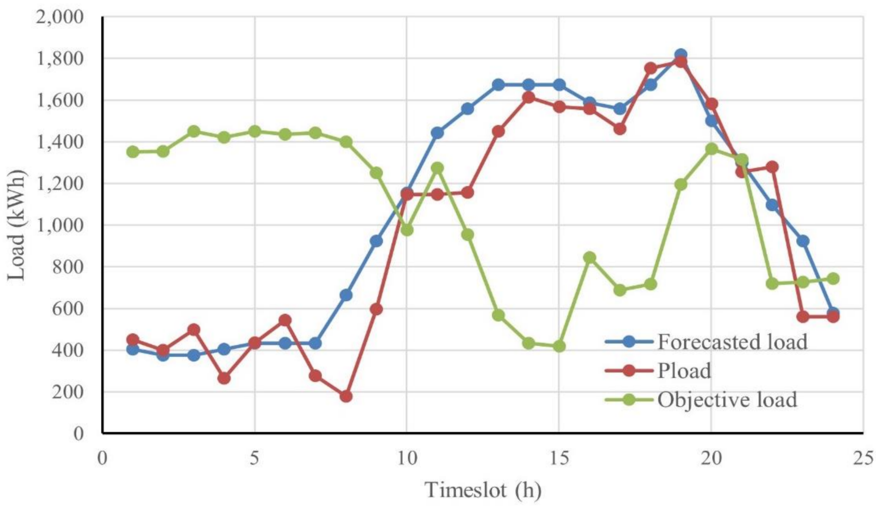

Figure 9. Hourly commercial load before and after shifting using TOU-SBY.

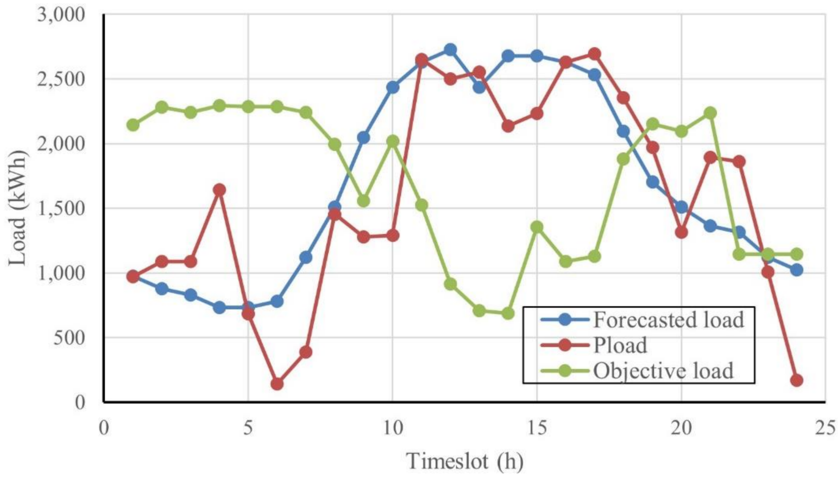

Figure 10. Hourly industrial load before and after shifting using TOU-SBY.

Further, the analysis was continued with SBY-based TOU to yield a better optimal solution. The cost results for the residential, commercial, and industrial loads were obtained. The SBY-based TOU provided a cost reduction of $174.17, $188.74, and $286.18 in the residential, commercial, and industrial areas, respectively. It was also observed that, when compared with PSO-TOU, the SBY-based TOU provided an additional cost reduction of $39.36 (residential), $5.78 (commercial), and $28.11 (industrial) for 24 h.

Similarly, the RTP-based strategy using the distributed and the centralized algorithms was executed using PSO and SBY. RTP-DP algorithms proceeded with tentative and power allocation scheduling. Figures 11–16 display the optimal load curve after the distributed RTP algorithm implementation using PSO and the strawberry optimization technique for the residential, commercial, and industrial areas.

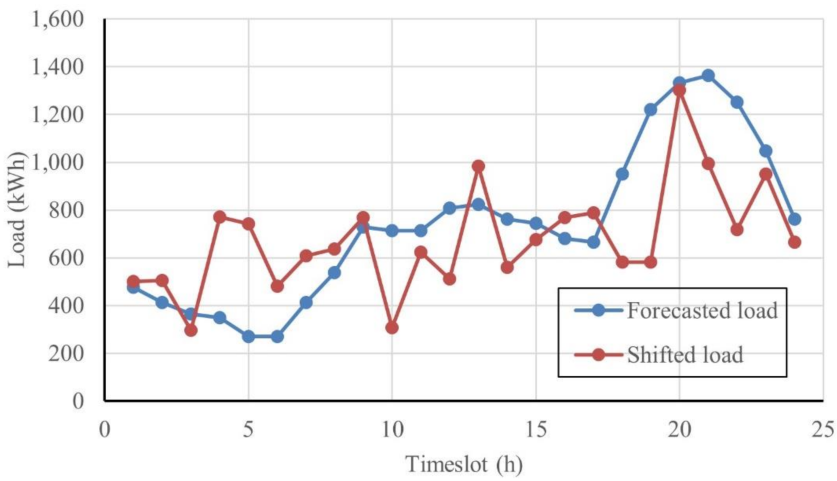

Figure 11. Hourly residential load before and after DSM using the distributed algorithm (RTP-PSO).

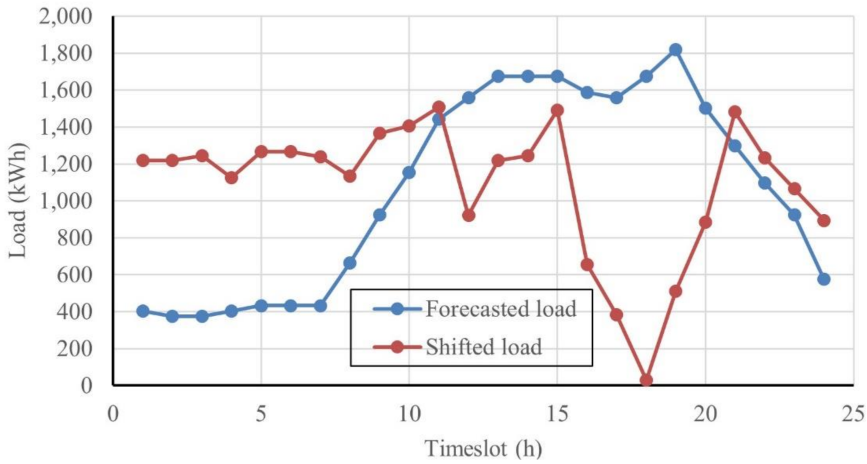

Figure 12. Hourly commercial load before and after DSM using the distributed algorithm RTP-PSO.

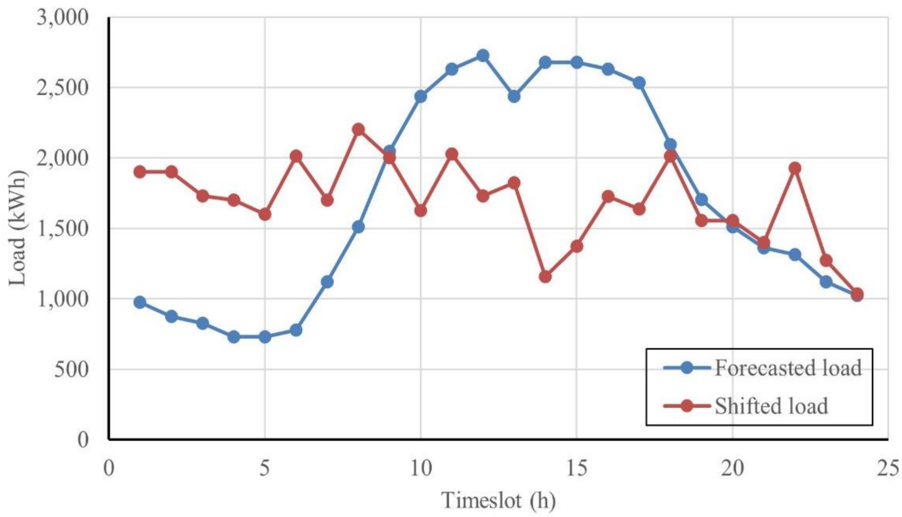

Figure 13. Hourly industrial load before and after DSM using the distributed algorithm RTP-PSO.

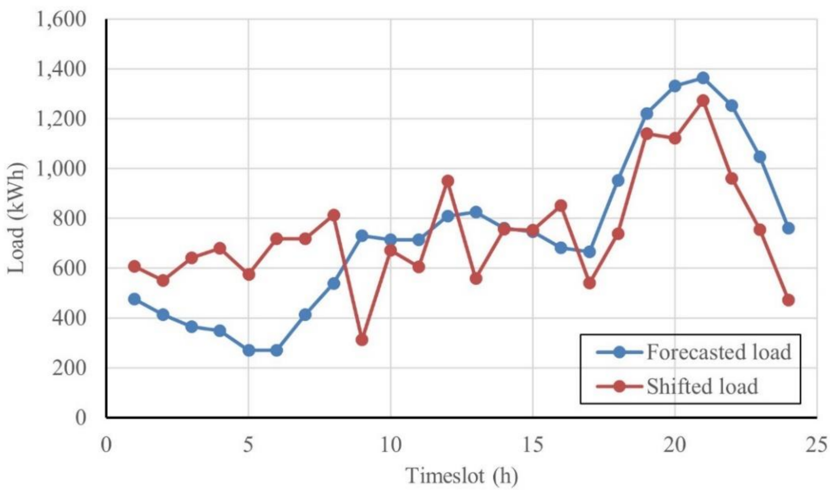

Figure 14. Hourly residential load before and after DSM using the distributed algorithm RTP-SBY.

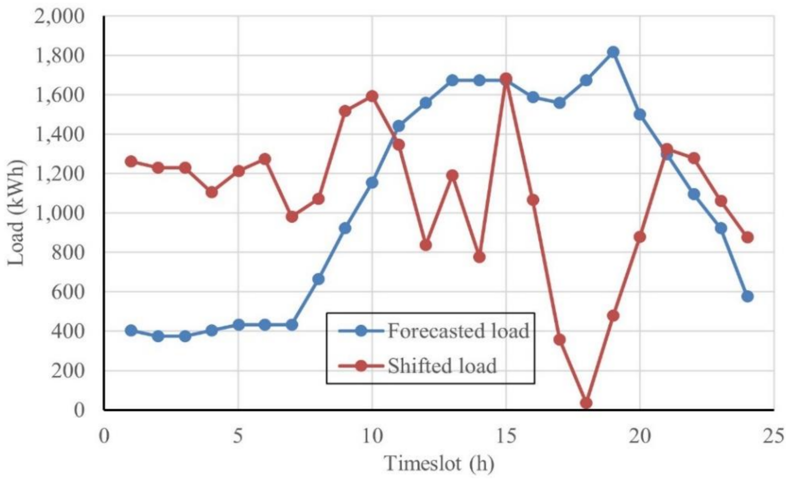

Figure 15. Hourly commercial load before and after DSM using the distributed algorithm RTP-SBY.

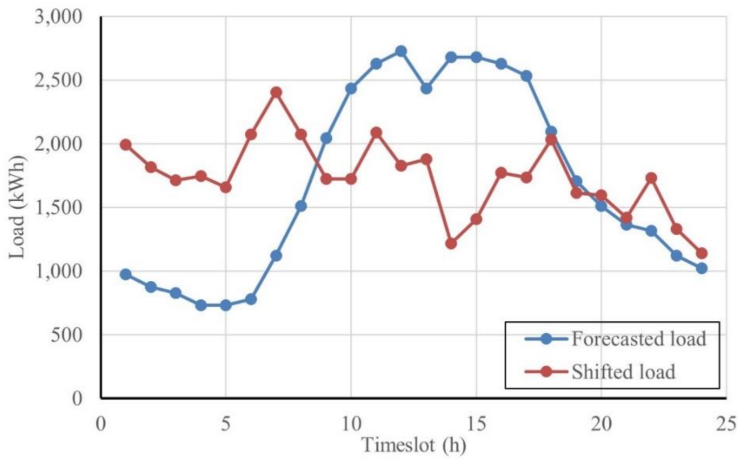

Figure 16. Hourly industrial load before and after DSM using the distributed algorithm RTP-SBY.

The optimal load scheduling results for 24 h after implementing the centralized RTP algorithm in the residential, commercial, and industrial areas for the test system deploying PSO optimization are shown in Figures 16–19. The results indicate that the cost reduction using the centralized RTP algorithm for the residential, commercial, and industrial loads was 2.45, 3.63, and 1.85% higher than with the distributed algorithm.

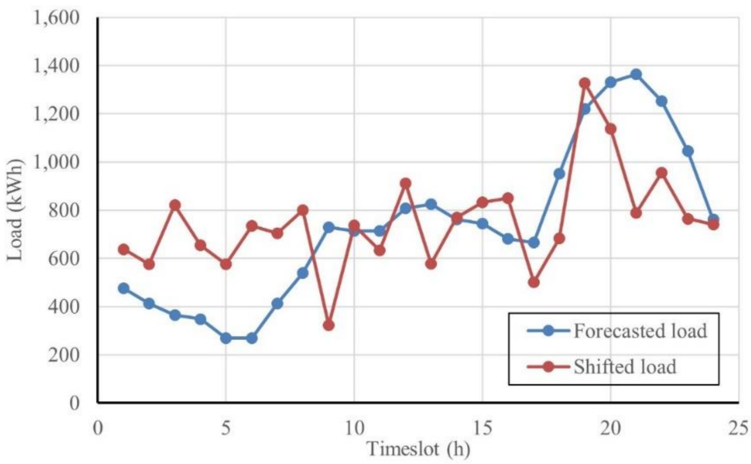

Figure 17. Hourly residential load before and after DSM using the centralized algorithm RTP-PSO.

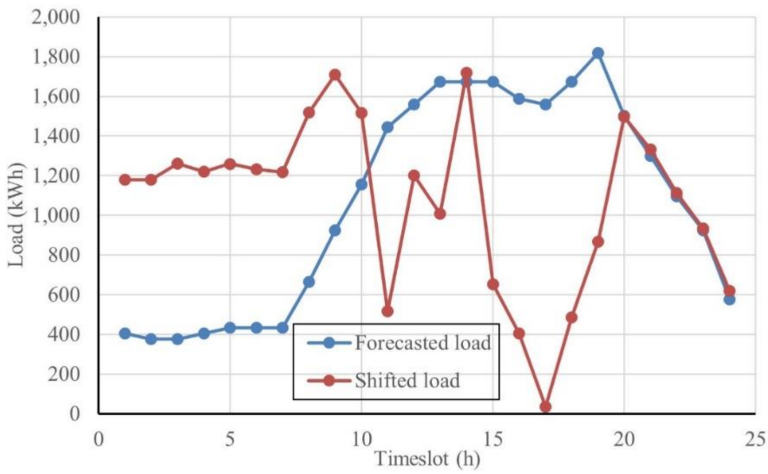

Figure 18. Hourly commercial load before and after DSM using the centralized algorithm RTP-PSO.

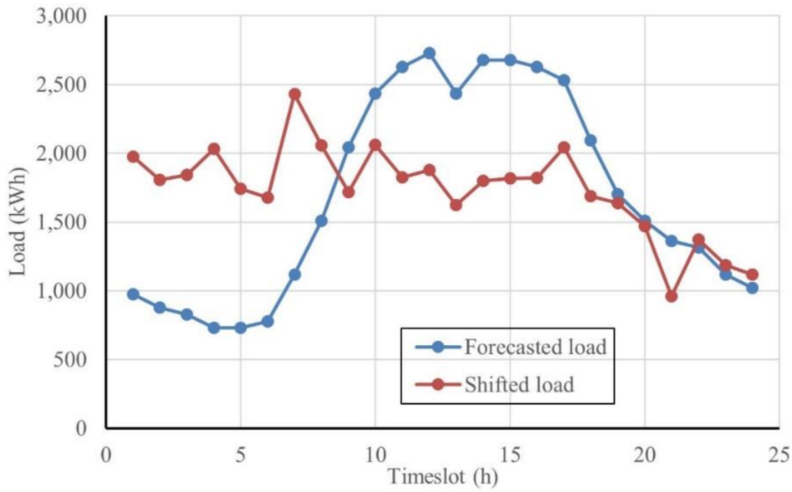

Figure 19. Hourly industrial load before and after DSM using the centralized algorithm RTP-PSO.

The results of the DSM implemented in the residential, commercial, and industrial areas for the sample system with the SBY optimization algorithm adopting centralized RTP are shown in Figures 20–22. The results perceived that the cost reduction obtained for the centralized RTP algorithm was 4.1% (residential), 4.21% (commercial), and 3.81% (industrial) more than for the distributed algorithm. The centralized scheduling algorithm is based on both costs of electricity and postponement costs. Since the cost involved for the delay of each appliance is considered, it minimizes the total cost of energy consumption for a day and gives a better result compared to the distributed algorithm. Thus, the centralized RTP algorithm provides better cost reduction. The comparison between the centralized and distributed algorithm results is provided in the last section.

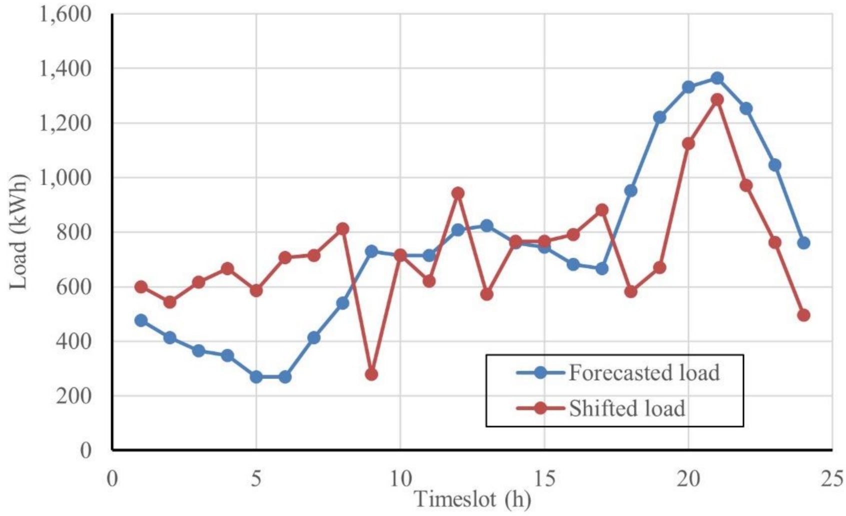

Figure 20. Hourly residential load before and after DSM using the centralized algorithm RTP-SBY.

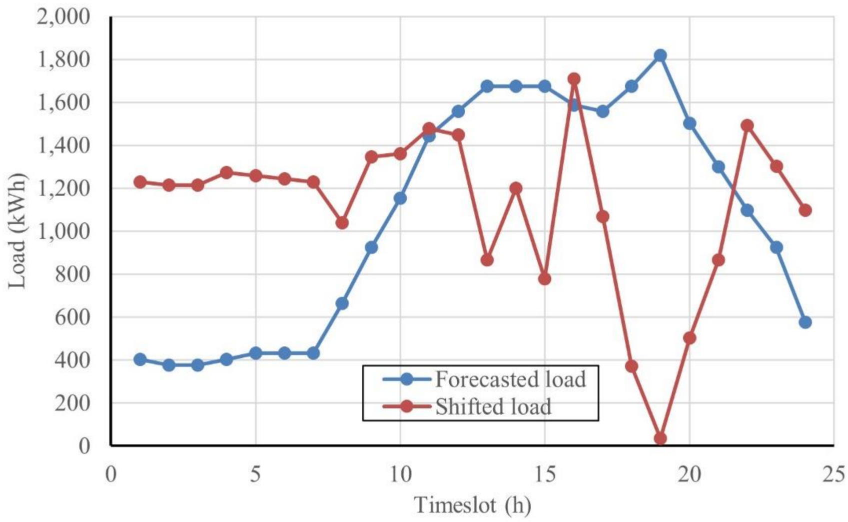

Figure 21. Hourly commercial load before and after DSM using the centralized algorithm RTP-SBY.

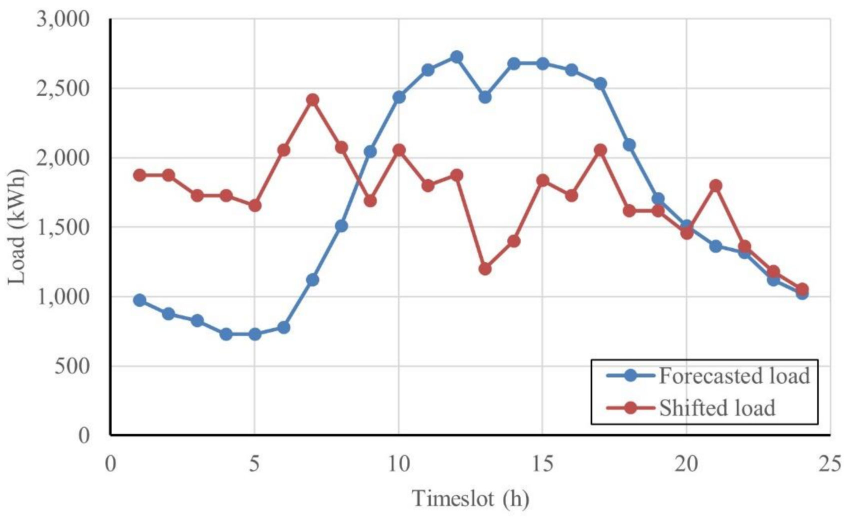

Figure 22. Hourly industrial load before and after DSM using the centralized algorithm RTP-SBY.

6. Results and Discussion

The comparison of the DSM results with the TOU and RTP pricing (using both the centralized and the distributed algorithms) for the residential, commercial, and industrial areas are provided in Tables 6–8. The results illustrate that the DR implementation provided a cost reduction of up to 14.8–21.84% depending on the demand and the DP strategy. It was observed that the RTP is more economical than TOU for the system considered. Furthermore, centralized-RTP fared better than distributed-RTP in scheduling the load economically. This holds for both systems considered.

Table 6. Comparison of DSM with the TOU and RTP pricing for the industrial area.

Pricing and Optimization	Cost before DSM ($)	Cost after DSM ($)	Cost Reduction (%)
TOU-PSO	5423.271	5165.19	4.750
TOU-SBY		5137.09	5.280
Distributed RTP-PSO		4855.70	10.50
Distributed RTP-SBY		4827.20	10.99
Centralized RTP-PSO		4632.36	14.60
Centralized RTP-SBY		4621.00	14.80

Table 7. Comparison of DSM with the TOU and RTP pricing for the commercial area.

Pricing and Optimization	Cost before DSM ($)	Cost after DSM ($)	Cost Reduction (%)
TOU-PSO	3636.60	3443.88	5.30
TOU-SBY		3437.90	5.46
Distributed RTP-PSO		2994.00	17.70
Distributed RTP-SBY		2973.00	18.20
Centralized RTP-PSO		2885.26	20.70
Centralized RTP-SBY		2847.70	21.70

Table 8. Comparison of DSM with the TOU and RTP pricing for the residential area.

Pricing and Optimization	Cost before DSM ($)	Cost after DSM ($)	Cost Reduction (%)
TOU-PSO	2302.879	2168.06	5.85
TOU-SBY		2128.71	7.56
Distributed RTP-PSO		1871.30	18.74
Distributed RTP-SBY		1842.50	19.99
Centralized RTP-PSO		1814.80	21.19
Centralized RTP-SBY		1799.90	21.84

Further, when the DSM results were compared on the optimization basis (PSO and SBY), the SBY optimization algorithm offered a better cost reduction as shown in Figure 23. Tables 9–11 provide the detailed analysis of the PAR calculation for the residential, commercial, and industrial demand. The PARs of the forecasted residential, commercial, and industrial loads were 1.8527, 1.701, and 1.6173, respectively.

Table 9. PAR calculation for the residential load.

Pricing and Optimization	PAR
TOU-PSO	1.852
TOU-SBY	1.825
Distributed RTP-PSO	1.770
Distributed RTP-SBY	1.729
Centralized RTP-PSO	1.760
Centralized RTP-SBY	1.712

Table 10. PAR calculation for the commercial load.

Pricing and Optimization	PAR
TOU-PSO	1.684
TOU-SBY	1.646
Distributed RTP-PSO	1.543
Distributed RTP-SBY	1.525
Centralized RTP-PSO	1.477
Centralized RTP-SBY	1.422

Table 11. PAR calculation for the industrial load.

Pricing and Optimization	PAR
TOU-PSO	1.607
TOU-SBY	1.589
Distributed RTP-PSO	1.421
Distributed RTP-SBY	1.415
Centralized RTP-PSO	1.426
Centralized RTP-SBY	1.409

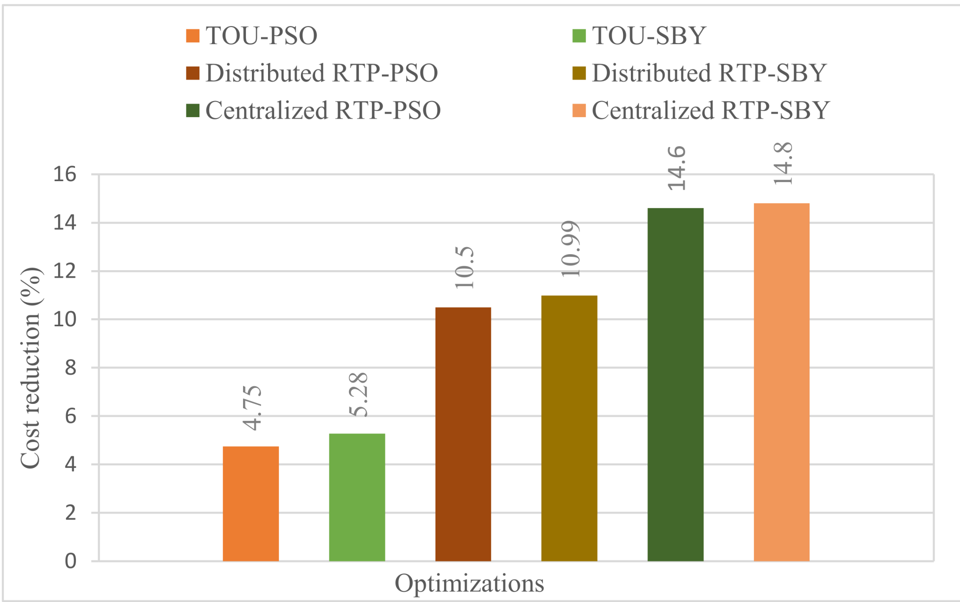

Figure 23. Cost reduction with the implementation of the demand response strategy.

The results obtained show that the PAR of the demand curve reduced with the DP implementation. Moreover, the PAR obtained using SBY-based RTP was much better compared to the PSO-based RTP algorithm. Thereby, the reduction of the peak load stress is higher using the centralized RTP-SBY optimization algorithm.

7. Conclusions

This work focused on implementing DR strategies that are implemented using two different optimization techniques for the industrial, commercial, and residential loads. The DR program was performed using the TOU and RTP algorithms with PSO and the SBY optimization technique on a test system with the residential, commercial, and industrial loads. The RTP pricing algorithm was performed using both the distributed and the centralized methodology. Despite complexity of the periodically varying pricing strategy, the results obtained after shifting the load prove that DSM implementation is economical. It reduces the peak load stress on the utilities and is highly beneficial for the customer in terms of electricity consumption cost reduction. When the techno-economic analysis was performed to solve the DR problem, the SBY optimization algorithm worked better for all the load scenarios considered.

Further, the comparative analysis performed for DP strategies showed that centralized RTP using SBY provided a better solution than centralized RTP using PSO. Moreover, it was found that the SBY optimization technique provided a lower PAR ratio for all the three types of load considered. Thus, it can be concluded by the user that DSM with RTP provides more significant benefits. When the distributed and the centralized RTP algorithms were compared, the centralized algorithm offered better results for the test system. The analysis would motivate the usage of DR in a smart grid environment since these DR algorithms reduce the cost involved in power consumption.

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

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

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