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RESEARCH ARTICLE

Grey Wolf Optimization Based Demand Side Management in Solar PV Integrated Smart Grid Environment

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ABSTRACT Most of world's electrical energy demand is fulfilled by natural resources (Oil, Coal, Gas, etc.) and there is a huge gap between demand and supply. Therefore, utilities are facing the problem of peak load burden. Broadly speaking, to sustain future electricity demand renewable/alternate sources (solar, wind etc.) of energy must be integrated with smart grid (SG) to cope with energy demand. These sources are freely available, inexhaustible and can be used as an alternate source of energy. For smart utilization of electrical energy, a balance between supply and demand is required at all instants of time. In the SG environment, the most promising solution to reduce the peak load burden on utility is demand side management (DSM) which is possible because of the property of smart grid inertia. DSM permits all types of consumers to alter their energy consumption pattern to reduce the cost of energy and it helps the utility to reduce peak load burden and reshape load profile. In this study, DSM has been formulated as a single objective minimization problem to reduce peak load burden on utility. Although several optimization techniques has been listed in the literature which reduces the peak load and cost of energy, but integration of renewable energy is limited to residential consumers only. In this paper, a robust optimization algorithm inspired by the lifestyle of grey wolves, popularly known as grey wolf optimization (GWO) algorithm is utilized to solve the proposed DSM minimization problem. The DSM minimization problem optimization using GWO is demonstrated on three different cases-residential, commercial, and industrial loads in time of use (TOU) pricing scheme with and without solar PV energy (SPVE). Validation of GWO displays remarkable reductions in peak load on utility and cost of energy of consumers with and without SPVE. Also, GWO optimization results are compared with existing research papers having identical data sets.

INDEX TERMS Demand side management, smart grid, appliance scheduling, grey wolf optimization, solar PV energy, time of use pricing, peak load, cost of energy.

I. INTRODUCTION

In a traditional grid system, energy management is maintained with limited static controls. Now, it has become the need of time for better utilization of renewable energy resources with more reliability along with the reduced cost of energy utilization by moving in a SG environment [1]. Smart grid implementation has become a burning topic for the national energy strategy of a country. The smart grid is featured with modern control technologies and paved the way for smart controls starting from generation centers, distribution stations to load centers. All the stakeholders of SG can actively participate in the primary challenge of maintaining the balance between supply and demand to alleviate the peak load burden on the utility [2]. The worldwide development in all sectors needs a continuous and reliable supply of electricity having less carbon emission and good power quality [3]. The rapid growth in electricity demand with the huge limitations on the installation of new generating plants is opening a new era of DSM to fulfil the energy needs of a country.

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DSM can provide an expedient solution to the difficulty such as limited natural resources producing a major portion of energy, lack of utilization of renewable energy sources, and limited controls on utility and users [4]. The bidirectional information and energy flow between prosumer and utility pronounces the application of DSM in SG [5]. A dynamic programming approach has been used for optimization of dispatch of direct load control (DLC) to maximize the fuel cost saving in Taiwan power system [6]. For the utility profit, a linear programming optimization algorithm is used in DLC scheduling along with two different pricing scheme TOU and flat rate tariff to differentiate cost based and profit based DLC [7]. A linear programming optimization algorithm has been used to schedule the load of residential, commercial, and industrial area at Florida Power and Light company to reduce the system peak load [8].

There are various DSM techniques such as load shifting, peak clipping, valley filling, strategic conservation, and strategic load growth used for the alteration of consumer load, but load shifting is the most extensively used technique in the literature [9]. The DSM techniques encompass cost of energy reduction, alleviating utility peak load burden, and enhancing the utility revenue by incorporating the derived objective function with constraints for various DSM techniques [10]. In all the available DSM techniques load shifting provides a promising solution that incorporates maximum benefits and flexibility to end users and generates good revenue to concern utility [11] The objective of energy cost minimization of the consumer is validated using Binary Particle Swarm Optimization (PSO) with reduced maximum demand on utility. As the alteration of consumer loads takes place to lower electricity tariff hours the maximum demand on utility decreases inherently [12]. In [13] a hybrid GA-PSO algorithm is used to reduce the cost of energy by optimal allocation of generations and loads in a day ahead market. Also, PSO outperforms GA in this study. Optimal scheduling of generations and loads in a microgrid having commercial and industrial loads has been conducted by GA and significant saving in consumers electricity bill is achieved [14]. In [15] deep enforcement learning is utilized to optimize the energy cost and dis-satisfaction of the consumer in a home by formulating the consumer shiftable appliances as a Markov decision process (MDP) problem for cost minimization and thereby demonstrated a remarkable reduction in energy cost and dis-satisfaction level of end users.

A universal load management system with intelligent control for implementation of DSM in a group of consumers from an apartment is considered to minimize only the cost of energy of end users. The Binary PSO and GWO optimization algorithms are used for the alteration of electrical appliances. The result demonstrates the superiority of binary GWO over Binary PSO for residential consumers and a remarkable reduction in energy cost along with minimization of peak to average ratio (PAR) and peak load has been noticed [16]. Utilizing the concept of bidirectional information flow between utility and consumer, an approach of game theory is used to schedule consumer appliances by the consumer itself who are participating in the game. This game theory approach achieves the minimization in PAR and cost of energy of residential load consumers [17]. A GWO approach is used for electrical appliances power scheduling in a smart home to optimize energy cost, PAR, and user satisfaction seven consumption profile with the variable tariff is considered for its validation and finally, a significant reduction is seen in the results [18]. DSM employing day ahead shifting using integer genetic algorithm (GA) is proposed to optimize peak load burden on utility and thereby a reduction in cost of energy has been also achieved in context to Indian utility [19]. In [20] the bacterial foraging optimization (BFO) algorithm is used to solve the load scheduling in a smart grid network comprising of residential, commercial, and industrial loads to minimize the peak load on utility and results achieved a significant reduction in peak load along with saving in energy cost. A day ahead load shifting DSM technique is used for the alteration of non-critical consumer's load and it is mathematically formulated as a peak load minimization problem and an Evolutionary Algorithm (EA) based on heuristics was developed for solving this minimization problem in [21]. The simulation generates peak load reduction with saving in energy cost in the residential, commercial, and industrial areas having a huge number of controllable devices. The DSM has been formulated as a minimization problem using the day ahead load shifting technique for peak load reduction in a residential and commercial area which is optimized using the moth flame optimization (MFO) algorithm and a significant peak load reduction is observed [22]. Although, a significant saving in energy cost is still superior in PSO. In [23] the DSM using GA for peak load optimization in an industrial area is carried out by AC load shifting in a DC microgrid equipped with solar PV installations and battery energy storage system and a remarkable reduction in utility peak load and cost of energy is seen.

The DSM for load shifting has been carried out in three types of residential scenarios traditional homes, smart homes and smart homes installed with renewable solar PV energy using BPSO, GA and Cuckoo search algorithm and a significant reduction in peak load and the cost is observed and cuckoo search algorithm outperforms the other two algorithms [24]. GA based DSM has been implemented for allocation of residential loads to maximize the user satisfaction along with minimization of cost of energy. The cost per unit satisfaction index is derived for the estimation of user satisfaction while shifting the load [25]. DSM has become the need of present as well as future scenarios to alleviate the energy shortage by postponing the installation of new generating stations along with the integration of renewable energy resources. The integration of renewable resources reduces the dependency on fossil fuels in the smart grid thereby decreasing carbon emissions and increasing the diminishing timespan of fossil fuels.

TABLE 1. Nomenclature.

Variable Name	Representation
$O_F(t)$	Objective Function
$F_L(t)$	Forecasted load
$O_L(t)$	Objective Load
CADSM(t)	Cost after DSM
LDBDSM(t)	Load before DSM
LDADSM(t)	Load after DSM
$B_L(t)$	Base Load (Non-shiftable load)
$C_L(t)$	Connected Load
$D_L(t)$	Disconnected Load
$X_P(t)$	Position of Prey
X(t)	Position Vector of Grey wolf
SPVE	Solar PV Energy
A, C	Coefficients of grey wolf
D	Distance vector of grey wolf
Dα	Distance vector of α grey wolf
Dβ	Distance vector of β grey wolf
Dδ	Distance vector of δ grey wolf
Xα	Position of α Grey wolf
Xβ	Position of β Grey wolf
Xδ	Position of δ Grey wolf
X1	Best Position of α Grey wolf
X2	Best Position of β Grey wolf
X3	Best Position of δ Grey wolf

In reviewed papers, some authors have considered the cost minimization objective function, and some have used peak load minimization objective function only and it can be grouped as single objective minimization problems. In a single objective, if cost is optimized then there will be a reduction in peak load also and if peak load is optimized then the cost of energy also reduces. Some authors have considered renewable energy integration with DSM in the home energy management system but in the case of a large area containing a huge number of devices renewable energy is not considered with DSM so far extensively.

In this paper, DSM using the most popular load-shifting technique has been carried out through the GWO algorithm with and without solar PV energy (SPVE) in residential, commercial, and industrial areas having a huge number of shiftable devices. The DSM is formulated as a single objective peak load minimization problem.

The rest of the portion is organized as follows. Section II presents the related work and motivation. Section III describes the problem formulation and required constraints. Section IV explains the proposed GWO algorithm. Section V describes the SG environment for DSM implementation. Section VI illustrates the results and discussion. Section VII concludes the paper with future scopes. All the abbreviations used in this paper has been listed in Table 1.

II. RELATED WORK AND MOTIVATION

Smart grid is a collection of different efficient technologies for smart transmission, distribution, and utilization of electricity with excellent communication infrastructure among all stakeholders. DSM is the most important feature of SG which mange the entire or portion of system load by avoiding the expansion of power generation, replacement of overloaded components in the existing network. DSM basically alters the energy consumption of consumer's non-critical devices to reduce peak load burden on utility and cost of energy of consumer. Various pricing schemes such as TOU, critical peak pricing (CPP), Real time pricing (RTP) etc. are popularly used in DSM implementation. TOU is widely used in the literature and proves to be most economical among all other pricing scheme [26]. In urban area of India, TOU pricing is applicable for large industrial and commercial consumers but in residential area variable pricing schemes are not applicable so far [19]. The residential consumers become isolated form variable pricing scheme because they pay flat rate tariff for the electricity consumption and unable to familiar the saving in cost of energy with this scheme [27]. In this study, residential area has been revealed with TOU pricing to show the potential in cost and peak load reduction in DSM. The traditional linear and dynamic programming algorithm of DSM [6], [7], [8] depicts significant reduction in considered parameters but unable to handle huge number of controllable devices of different types having complex constraints [21]. Some papers has given more importance to consumers energy cost reduction rather than utility in case of home energy management [12], [15], [16], [17], [18], [24], [25]. Many researchers have taken peak load [20], [21], [22], [23] as main objective because literature portrays that utility profit is more essential rather than consumer as utility is the utmost importance for consumer services. The DSM minimization problems has been solved by evolutionary algorithm in the literature [13], [14], [20], [21], [22], [23], [24], [25] and revealed many benefits in DSM scheduling. In general, according to the statistical analysis, swarm-based algorithms are more accurate and robust than evolutionary algorithms. However, evolutionary algorithms are faster than swarm-based in terms of algorithm run time. [28]. In this paper, a robust optimization algorithm inspired by the lifestyle of grey wolves, popularly known as grey wolf optimization (GWO) algorithm is utilized to solve the proposed DSM minimization problem. GWO displays remarkable reductions in peak load on utility and cost of energy of consumers when compared with existing research papers [20], [21], [22] having identical data sets.

The contribution of this works are as follows:

1) The mixed integer non-linear nonconvex DSM problem is solved with GWO algorithm which validates declining peak load on utility along with the reduced cost of energy of consumers.
2) Integration of solar PV Energy (SPVE) in smart grid demonstrate more reduction in the cost of energy after deploying DSM in all the three cases.
3) The results produced by an optimization technique can be validated by the equation of load equalization presented in this research.

III. PROBLEM FORMULATION

The load-shifting single objective strategy of DSM has been proposed here for the optimization of peak load on utility. The load-shifting technique of DSM is used to schedule shiftable loads of residential, commercial, and industrial areas at different hours of the day to bring the final load curve closer to the objective load curve. The objective load curve has different value for each slot with time of use pricing (TOU) which provides maximum benefits to consumers. The load shifting strategy of DSM is mathematically formulated as a single-objective minimization problem as given by (1) and the nature of DSM minimization is nonlinear, mixed integer having non-convex properties.

$$O_F(t) = \left(\sum\nolimits_{t=1}^{t=N} \left(P_L\left(t\right) - O_L\left(t\right)\right)^2\right) \tag{1}$$

where $O_F(t)$ is the value of the objective function for peak load optimization, $P_L(t)$ is the actual load consumption and $O_L(t)$ is the objective Load at any time slot t respectively. N is the number of one hour time slots in a day.

A. ACTUAL LOAD IN DSM WITHOUT SPVE

The actual load consumption in each slot at any time t is given by (2). The value of the actual load is given by different equations in DSM without SPVE and DSM with PV.

$$P_L\left(t\right) = F_L\left(t\right) + C_L\left(t\right) - D_L\left(t\right) \tag{2}$$

Here, $P_L(t)$ and $F_L(t)$ are actual load consumption and forecasted load respectively and $C_L(t)$ and $D_L(t)$ are the numbers of loads connected and disconnected at time slots t respectively in the shifting process of load.

B. ACTUAL LOAD IN DSM WITH SPVE

The actual load is given by (3). For the validation of the GWO algorithm with SPVE, an hourly generated solar energy profile is considered in the simulation. While executing the algorithm firstly it checks for the availability of SPVE. If SPVE available, then iteration moves to the next execution step and generates a random ON/OFF schedule for all the shiftable devices. Thereafter, it calculates the power consumption of shiftable devices and *SPVE* is subtracted from the summation of shiftable devices power and base load before proceeding to minimization of the objective function and executing all the steps to complete the iterations. Finally, a reduction in the cost of energy is surely achieved and increases with higher hourly available *SPVE*. More reduction in peak load occurs when *SPVE* is available in the slot where peak load occurs.

$$P_L\left(t\right) = F_L\left(t\right) + C_L\left(t\right) - D_L\left(t\right) - \mathrm{SPVE}\left(\mathrm{t}\right) \tag{3}$$

The GWO algorithm for DSM developed has capability to handle a huge number of controllable loads of different natures. The designed algorithm will be able to address the complex nature of devices such as different consumption patterns and duration. Also, the model supports a variable delay for different devices.

C. CONNECTED LOAD

The connected load is given by (4)

$$C_L(t) = \sum\nolimits_{i=1}^{i=t-1} \sum\nolimits_{k=1}^{k=n} X_{kit} P_{1k} + \sum\nolimits_{l=1}^{l=j-1} \sum\nolimits_{i=1}^{i=t-1} \sum\nolimits_{k=1}^{k=n} X_{ki(t-1)} P_{(1+l)k} \tag{4}$$

Connected load $C_L(t)$ consist of two terms, the first term is the increase in load at time t due to the placement of devices to this time slot and the second term represents the increment in load at time t due to devices already scheduled for a time that precedes time t. Here X_{kit} is the type k devices number that are replaced from time slot i to t. P_{1k} is the power consumed at time step i for device type k. J is the operation time of type k device and n is the nature of available devices.

D. DISCONNECTED LOAD

The disconnected load is represented by the equation-(5). This equation comprises of two parts: the first part is the reduction in load because of interruption given to the connection time of devices that were planned to consume energy at time step t and the second part is due to the operation time of devices which are operating for more than one hour. The term in this equation has a similar meaning as that of the (4). Here, d is the maximum interruption time in shifting the devices.

$$D_L(t) = \sum\nolimits_{q=t+1}^{q=t+d} \sum\nolimits_{k=1}^{k=n} X_{ktq} P_{1k} + \sum\nolimits_{l=1}^{l=j-1} \sum\nolimits_{q=t+1}^{q=t+d} \sum\nolimits_{k=1}^{k=n} X_{k(t-1)q} P_{(1+l)k} \tag{5}$$

The connection and disconnection of loads are illustrated in Fig. 1 and Fig. 2. In Fig. 1 load A and B are shiftable but in the current situation these creates a burden on utility. This burden is alleviated after the implementation of the DSM program. Fig. 2 depicts the lessening of peak load on utility. The shiftable load A has been shifted from time slots t_1, t_2 to t_4, t_5 and load B from t_6, t_7, t_8 to t_{12}, t_{13}, and t_{14} respectively.

E. OBJECTIVE LOAD

In variable pricing schemes such as TOU pricing, the objective load curve is preferred load curve for the utility. The objective load becomes an ideal load curve for the utility. This ideal load curve offers maximum profit irrespective of any DSM scheduling algorithm. In the TOU pricing scheme, every optimization technique aims to attain the load curve after DSM closer to the objective curve. In actual practice, the load curve after shifting deviates from the objective load curve because off-peak hours slots are not able to adjust shiftable loads entirely. The objective load in a time slot can be computed by the expression given in (6).

$$O_L\left(t\right) = \frac{\left\{\frac{\left(\sum_{t=1}^{24} \mathrm{LDBDSM(t)}\right)}{\left(\sum_{t=1}^{24} \frac{1}{\mathrm{TOU(t)}}\right)}\right\}}{\mathrm{TOU}\left(\mathrm{t}\right)} \tag{6}$$

Here, *LDBDSM(t)* is the load before applying DSM and *TOU(t)* is the TOU pricing at different hours of the day. Since our main consideration in DSM is to reduce the consumer electricity bill to motivate consumers to take part in load shifting. Thus, the objective load is chosen inversely proportional to TOU pricing which corresponds to the maximum possible reduction in the electricity bill of end users.

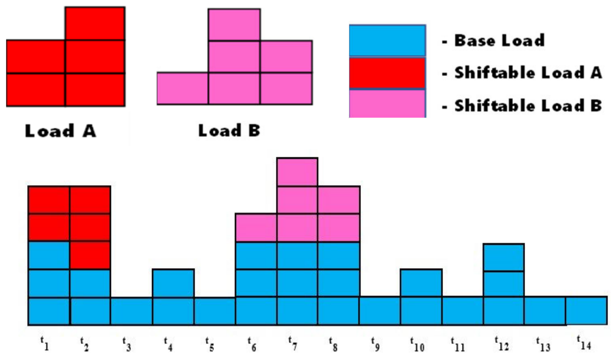

FIGURE 1. Load in different time slots before DSM.

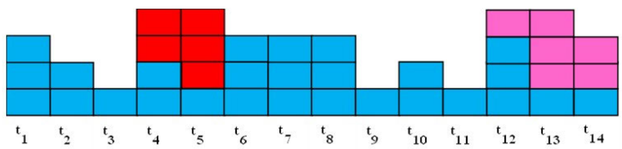

FIGURE 2. Load in different time slots after DSM.

F. CONSTRAINTS

The required inequality constraints are given here by the (6) and (8). Equation (9) is the required equality constraint for the validation of an algorithm in DSM implementation.

G. INEQUALITY CONSTRAINTS

$$X_{kit} > 0, \ for\ every\ i, \quad j\ and\ k \tag{7}$$

That is the shiftable devices number cannot be negative.

Also,

$$\sum\nolimits_{t=1}^{t=N} X_{kit} \leq Controllable\ (i) \tag{8}$$

This constraint validates that number of shiftable devices available in a particular time slot are only eligible for shifting to other time slots. Here Controllable (i) is the number of type k devices of accessible for control at time slot i.

H. EQUATION OF LOAD EQUALIZATION

The load equalization equation is the equality constraints and indicates that the load has been moved only from one-time slot to another time slot in minimization of objective function. The total load before DSM and after DSM remains same and it validates that load shifting has been taken place properly for all shiftable devices. Although it can also be observed from area under load curves of objective load, load before DSM and load after DSM which will be same for all the curves for a particular area. However, equation-(9) proves exact load shifting by calculating load before DSM and after DSM. Here, *LDBDSM(t)* is evaluated from addition of base load with initial schedule kW in each slot and *LDADSM(t)* is taken from algorithm execution.

$$\sum\nolimits_{t=1}^{24} \mathrm{LDBDSM}\ (t) = \sum\nolimits_{t=1}^{24} \mathrm{LDADSM}\ (t) \tag{9}$$

I. COST OF ENERGY

In proposed algorithm peak load minimization has been formulated and load after shifting is compared with objective load to minimize the difference. The objective load corresponds to minimum cost irrespective of any algorithm and after application of DSM cost of energy must be reduced. Here, to calculate the cost reduction (11) is utilized.

$$\begin{aligned} \mathrm{CostReduction} = & \sum\nolimits_{t=1}^{24} \mathrm{LDBDSM(t)} * \mathrm{TOU(t)} \\ & - \sum\nolimits_{t=1}^{24} \mathrm{LDADSM(t)} * \mathrm{TOU(t)} \end{aligned} \tag{10}$$

The first term in this equation represents cost of energy before DSM, which is obtained after multiplication of LDBDSM(t) with TOU(t) in each time slot. Second term represents the cost of energy after DSM and LDADSM(t) is the load in each time slot after execution of algorithm. Finally, cost reduction is obtained from the difference of two terms in (11).

IV. PROPOSED ALGORITHM FOR DSM

The implementation of DSM in the future smart grid has a variety of challenges due to the huge number of devices to be controlled in different areas. The devices of different areas like residential, commercial, and industrial have an array of constraints. Therefore, the algorithm should have excellent intelligence power to tackle all these complexities. Although various appliance scheduling techniques listed in the literature have been implemented for scheduling, these turn out to be insufficient when a huge number of controllable devices are available for scheduling. In the proposed GWO algorithm these difficulties are eliminated due to the inherent capabilities of the proposed algorithm to cope up with the scheduling of many devices having huge constraints. This algorithm provides promising solutions to schedule devices of a smart home to even a huge smart grid dealing with various areas like residential, commercial, and industrial. GWO optimization algorithm is based on the hunting of wolves, and it has been extensively utilized to optimize the various parameters of real-world problems [29]. Grey wolves tend to live in packs and a leader among wolves named alpha, is selected to monitor various activities such as hunting, sleeping, and escorting the packs. Alpha being the leader of the pack is the decision-making body and others in the pack must obey the instruction issued by the alpha. Also, alpha may not be the strongest but maybe having the quality of a manager to manage the activities of a group. The second and third in the social hierarchy are beta and delta wolves and must work like subordinates in an organization in which the alpha is the leader [30]. Group hunting is the most interesting behavior of grey wolves in which the main activities performed are tracking, chasing, and approaching the prey followed by pursuing, encircling, and harassing the prey until it stops moving. The mathematics involved in encircling the prey and hunting is described below.

In mathematical modelling of social behavior, alpha is taken as the fittest solution followed by beta and delta.

(11) and (14) represents the encircling behavior in GWO optimization [31].

$$\mathbf{D} = |\mathbf{C}\mathbf{X}_\mathbf{P}(\mathbf{t}) - \mathbf{X}(\mathbf{t})| \tag{11}$$

$$\mathbf{X}(\mathbf{t}+\mathbf{1}) = \mathbf{X}_\mathbf{P}(\mathbf{t}) - A\mathbf{D} \tag{12}$$

Here for the current iteration t, X_P (t) describes the position of prey while X(t) is the position vector of the grey wolf. The coefficient vectors A and C are evaluated by (13) and (14) respectively.

$$A = 2(a \times r_1) - a \tag{13}$$

$$C = 2 \times r_2 \tag{14}$$

Here r_1 and r_2 are random vectors between 0 and 1 and the component of a is linearly reduced from 2 to 0 in until the convergence of iterations. Grey wolf updates its positions using (11) and (12) in the entire working space available for optimization.

The hunting is driven by the instruction of alpha which is the fittest solution, and the best three solutions alpha, beta and delta are utilized further for evaluating the position of other search agents. The following (15)-(17) evaluate the positions of the remaining agents.

$$\begin{aligned} \boldsymbol{D_\alpha} &= |\boldsymbol{C_1 X_\alpha - X}|, \quad \boldsymbol{D_\beta} = |\boldsymbol{C_2 X_\beta - X}|, \\ \boldsymbol{D_\delta} &= |\boldsymbol{C_3 X_\delta - X}| \end{aligned} \tag{15}$$

$$\begin{aligned} \boldsymbol{X_1} &= (\boldsymbol{X_\alpha - A_1 D_\alpha}), \quad \boldsymbol{X_2} = (\boldsymbol{X_\beta - A_2 D_\beta}), \\ \boldsymbol{X_3} &= (\boldsymbol{X_\delta - A_3 D_\delta}) \end{aligned} \tag{16}$$

$$\boldsymbol{X}(\boldsymbol{t}+\mathbf{1}) = (\boldsymbol{X_1 + X_2 + X_3})/\mathbf{3} \tag{17}$$

GWO allows all other search agents to update their position according to alpha, beta and delta followed by attacking the prey.

$$\text{Fitness Function} = \frac{1}{\left\{1 + \sum_{t=1}^{t=N} (P_L(t) - O_L(t))^2\right\}} \tag{18}$$

The fitness function used in GWO optimization is given by (18). This demand side management algorithm using the grey wolf optimization algorithm (GWO) is developed in MATLAB which uses the load shifting technique to shift the non-critical load in the given area. The algorithm labelled the devices responsible for generating peaks in a time slot and a proper shifting mechanism is used to redeploy the shiftable devices. GWO provides a near-optimal solution to the given problem. DSM is carried out at the start of the day and when the DSM controller receives a request for the appliance scheduling for the next day.

The flowchart for the execution of the GWO algorithm shown in Fig. 3 clearly explains the GWO steps. Algorithm initially generates the random ON/OFF schedule of devices after validating all the constraints. The number of population corresponds to number of ON/OFF schedule for each device and fitness values are evaluated. Now, first best, second best and third best fitness values corresponds to three schedules of devices, identified as $X_\alpha, X_\beta,$ *and* X_δ respectively.

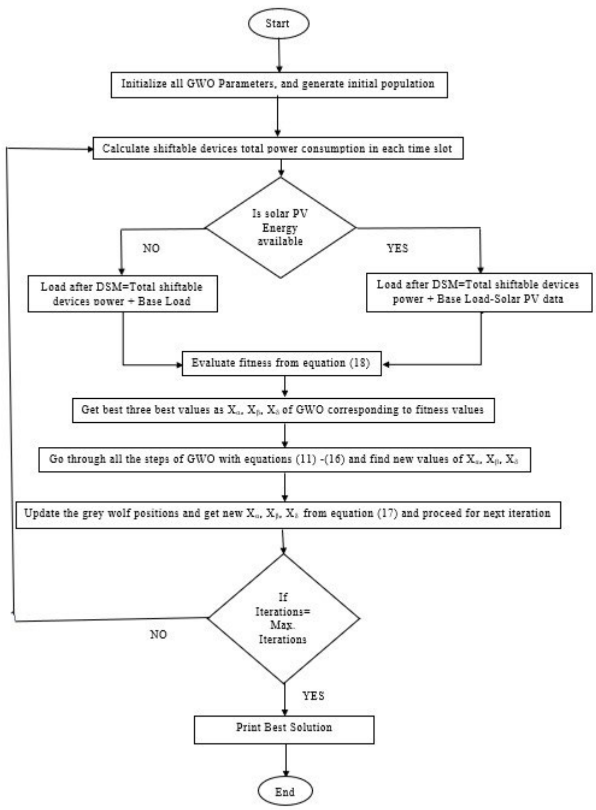

FIGURE 3. Flowchart for execution of GWO optimization algorithm.

Now, first iteration starts and calculate the three different values of A and C as A_1, A_2,A_3 and C_1,C_2, C_3 from (13) and (14) corresponding to first fitness value termed as first wolf. Then Evaluate D_α,D_β,D_δ given by equation (15). Now, values of X_1, X_2,$X_3$are calculated by the expression mentioned in (16). Finally, X(t+1) is calculated by (17) which is assumed to be the new best value. Now, value of fitness function is calculated from this new value and compared with previous value followed by replacement if better fitness value is achieved otherwise retained for the considered solution. Same process is repeated for all the initial generated schedule. After completion of this step first iteration ends and algorithm proceeds for next iteration. After the execution of all the iteration best global schedule of all the concerned devices are displayed. Further, a sensitivity analysis has been carried out in GWO and observed that if population size is increased the better result may be achieved. In case of increased number iterations algorithm takes large run, time and may produce improved results.

V. SMART GRID ENVIORNMENT FOR DSM IMPLEMENTATION

A paradigm shift from the traditional grid to a smart grid occurs through the integration of various advanced technologies such as smart sensors, measurement, and bidirectional flow of information and energy among users and utility

TABLE 2. Load before DSM and objective load of different areas [21].

Time Slot	TOU Pricing (INRs)	Residential		Commercial		Industrial	
		LDBDSM (t) (kW)	$O_L(t)$ (kW)	LDBDSM (t) (kW)	$O_L(t)$ (kW)	LDBDSM (t) (kW)	$O_L(t)$ (kW)
8	12	729.4	660.58	923.5	959.35	2045.5	1513.28
9	9.19	713.5	862.56	1154.4	1252.69	2435.1	1976.00
10	12.27	713.5	646.04	1443	938.24	2629.9	1479.98
11	20.69	808.7	383.13	1558.4	556.41	2727.3	877.69
12	26.82	824.5	295.56	1673.9	429.24	2435.1	677.08
13	27.35	761.1	289.83	1673.9	420.92	2678.6	663.96
14	13.81	745.2	574	1673.9	833.61	2678.6	1314.95
15	17.31	681.8	457.94	1587.3	665.06	2642.4	1049.07
16	16.42	666	482.76	1558.4	701.11	2532.5	1105.93
17	9.83	951.4	806.4	1673.9	1171.13	2094.2	1847.34
18	8.63	1220.9	918.53	1818.2	1333.98	1904.5	2104.22
19	8.87	1331.9	893.68	1500.7	1297.88	1797.2	2047.28
20	8.35	1363.6	949.33	1298.7	1378.71	1363.6	2174.78
21	16.44	1252.6	482.17	1096.7	700.26	964.9	1104.59
22	16.19	1046.5	489.62	923.5	711.07	970.1	1121.64
23	8.87	761.31	893.68	577.2	1297.88	1022.7	2047.28
24	8.65	475.7	916.4	404	1330.89	974	2099.35
1	8.11	414.3	977.42	375.2	1419.51	876.6	2239.14
2	8.25	364.8	960.84	375.2	1395.44	827.9	2201.14
3	8.1	348.8	978.63	404	1421.26	730.5	2241.90
4	8.14	269.6	973.82	432.9	1414.28	730.5	2230.88
5	8.13	269.6	975.02	432.9	1416.02	779.2	2233.65
6	8.34	412.3	950.47	432.9	1380.36	1120.1	2177.39
7	9.35	539.1	847.8	663.8	1231.25	1509.7	1942.18
Total Load		17666.21	17666.21	25665.55	25656.55	40470.7	40470.70

with efficient edge computing control [32]. Dynamic pricing scheme such as time-of-use pricing depicts an important characteristic of a smart grid system

equipped with advanced metering infrastructure and smart meters. With the evolution of the smart grid, the intelligent optimization of electrical assets like the upgradation of bulk area consumers, implementation of new technologies along with the active participation of consumers [33]. The deployment of Advanced Metering Infrastructure (AMI) in the smart grid facilitates energy management in the area connected with the grid. The feature of AMI enables the utility and consumers equipped with smart meters to perform a variety of activities like the bidirectional flow of information, outage reporting, connect or disconnect request execution, reconfiguring after the occurrence of a fault, and billing of the consumers [34]. Also, the AMI allows efficient implementation of challenging new technologies like demand side management. Smart meters installed in the user premises play a vital role while executing DSM activities in the selected area. A smart meter records the consumption of energy in user premises and shares these data with the utility for further processing. Smart meters can remotely schedule the user appliance as per DSM instructions [35].

VI. RESULT AND DISCUSSION

The GWO algorithm has been examined on three different area residential, commercial, and industrial in SG having various types of devices. Simulations has been carried out without SPVE and with SPVE in all the three areas. An objective load curve is evaluated for all the three cases and actual load curve tries to attain values close to objective load data in each time slot. The delay provided to shiftable devices of

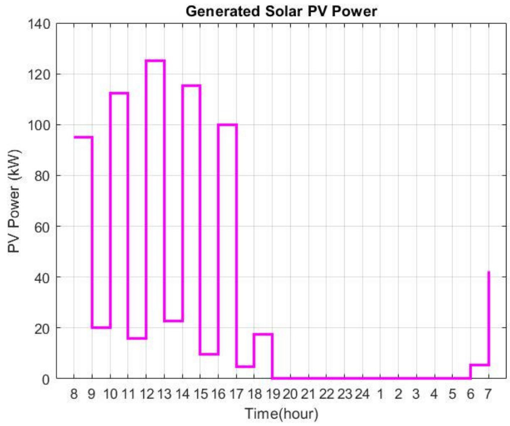

FIGURE 4. Available SPVE hourly output.

TABLE 3. Controllable devices of residential area [21].

Device Name	No of Devices	Power Consumption of Devices (kW)		
		1st Hour	2nd Hour	3rd Hour
Toaster	48	0.9	0	0
Fan	288	0.2	0.2	0.2
Frying Pan	101	1.1	0	0
Iron	340	1	0	0
Blender	66	0.3	0	0
Coffee Maker	56	0.8	0	0
Oven	279	1.3	0	0
Dishwasher	288	0.7	0	0
Vacuum Cleaner	158	0.4	0	0
Dryer	189	1.2	0	0
Hair Dryer	58	1.5	0	0
Kettle	406	2	0	0
Rice Cooker	59	0.85	0	0
washing m/c	268	0.5	0.4	0

is 0 to 12 hours in [20], [21], and [22] and in proposed study of this paper. Table 2 represents the data of load before DSM and objective load of all the cases along with TOU pricing which is same for all the areas. The peak load occurring in residential, commercial, and industrial areas in this study are 1363.6 kW, 1818. kW and 2727.3 kW respectively and total loads are 17666.21 kW, 25656.55 kW and 40470.70 kW. Here one point must be noticed that the peak load and total load are same in [20], [21], and [22]. The load shifting hours are taken from the 8 AM of the current day to the 7 AM of the following day.

A. SOLAR PV DATA SELECTION

The data on solar PV used in projected research has been calculated using solar radiation on the earth's surface by Photovoltaic Geographic Information System (PVGIS). PVGIS has facilitated open access to solar PV data incidents at any

TABLE 4. Cost of energy and peak load of residential area after DSM.

Parameter	[20]	[21]	[22]	Proposed without SPVE	Proposed with SPVE
Peak Load (kW)	1106.3	1114.4	1067.15	1039.3	1031.9
% Peak Load Reduction	18.87	18.3	21.74	23.76	24.30
% Cost of Energy Reduction	7.4	5	5.12	7.52	12.55
Technique Used	BFO	EA	MFO	GWO	

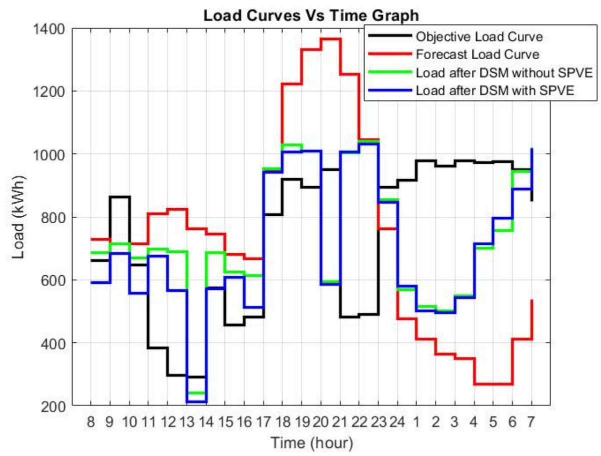

FIGURE 5. DSM results of residential area with and without SPVE.

place on earth [36]. In this article, 500-kW solar PV array data is calculated, and the available power has been utilized in the optimization algorithm. Based on incident solar radiation hourly available PV power is estimated here and given in Fig.4. The same solar PV generated power is used in all the areas to exhibit the benefits of integrating renewable energy in the smart grid DSM environment. The solar profile used in this research has been taken for a cloudy day which proves to be the worst solar profile and thereby improvement in output parameters indicates the efficacy of the proposed algorithm.

B. CASE 1. RESIDENTIAL AREA

In the GWO algorithm, the initial population and maximum of iterations are 40 and 200 respectively. The results are shown in detail after testing the algorithm on the residential data of the smart grid test system. The controllable devices in a residential area are given in Table 3 and a total of 2604 controllable devices of 14 different types having different power consumption are available for control. The forecasted load data is evaluated with the initial slot of controllable devices and a base load of a residential area. GWO optimization

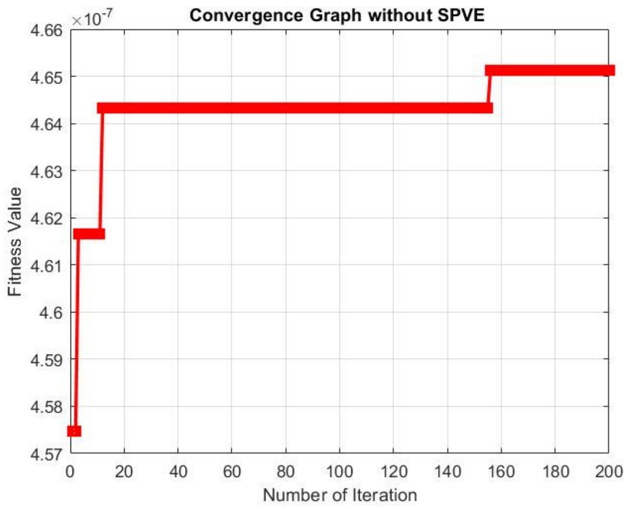

FIGURE 6. Convergence Graph of residential area without SPVE.

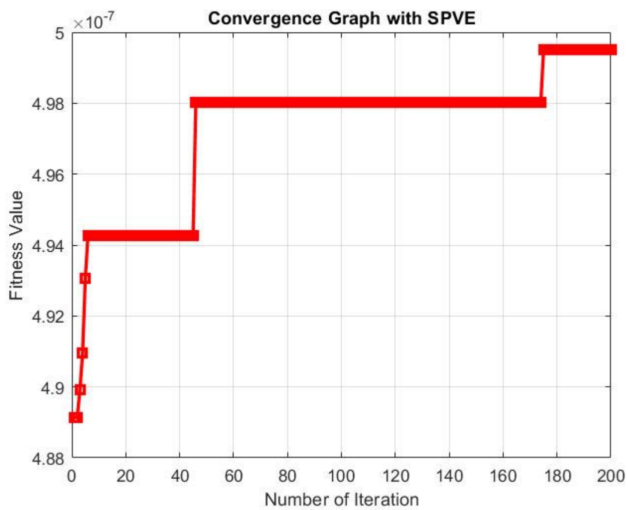

FIGURE 7. Convergence Graph of residential area with SPVE.

algorithm generates random ON and OFF schedules of controllable devices for its shifting to new time slots and calculates the value of loads and cost of energy in each slot for the current iteration. The first three best solutions are considered for the next iteration to get the best result in the optimization of peak load and cost of energy and finally the best scheduling is achieved with significant reduction after the completion of all the iteration.

The DSM results are shown in Fig. 5 and a reduction in peak load without and with SPVE is observed as compared with the forecasted load curve. The peak load before DSM was 1363.6 kW and reduces to 1039.3 kW and 1031.9 kW without and with SPVE respectively. Peak load in [20], [21], and [22] reduces from 1363.3 kW to 1106.3, 1114.4 and 1067.15 kW respectively. The proposed algorithm gives a maximum reduction in peak load in comparison to [20], [21], and [22]. The peak load reduction with SPVE is more than

TABLE 5. Controllable devices of commercial area [21].

Devices	No. of Devices	Power Consumption of Devices (kW)		
		1st Hour	2nd Hour	3rd Hour
Kettle	123	3	2.5	0
Dryer	117	3.5	0	0
Oven	77	5	0	0
Fan	93	3.5	3	0
Coffee Maker	56	0.8	0	0
Air Conditioner	56	4	3.5	3
Lights	87	2	1.75	1.5
Water Dispenser	156	2.5	0	0

TABLE 6. Cost of energy and peak load of commercial area after DSM.

Parameters	[20]	[21]	[22]	Proposed without SPVE	Proposed with SPVE
Peak Load (kW)	1462.5	1485.2	1459.09	1438.7	1442.7
% Peak Load Reduction	19.29	18.3	19.74	20.87	20.65
% Cost of Energy Reduction	5.93	5.8	4.9	9.33	12.42
Technique used	BFO	EA	MFO	GWO	

without SPVE as the worst solar profile is considered here and SPVE is not available in that time slot.

Results of DSM with and without SPVE integration are presented in Table 4. Results depict a remarkable reduction in peak load of 23.76% without SPVE and 24.30 % with SPVE.

Also, the reduction in the cost of energy is 7.52 % without SPVE and 12.55 % with SPVE as shown in Table 5. The cost of energy before DSM was 230290 INRs and reduces to 212950 INRs which is the maximum reduction as compared with [20], [21], and [22].

The convergence graph shown in Fig. 6 and Fig. 7 converges to maximize the fitness value because the fitness function is inversely proportional to the objective function. It means as the fitness function approaches maximum value the objective function minimizes which in turn gives reduced peak load and cost of energy.

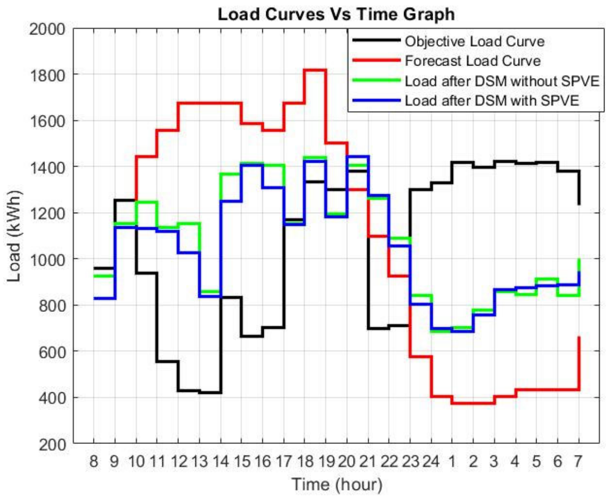

FIGURE 8. DSM results of commercial area with and without SPVE.

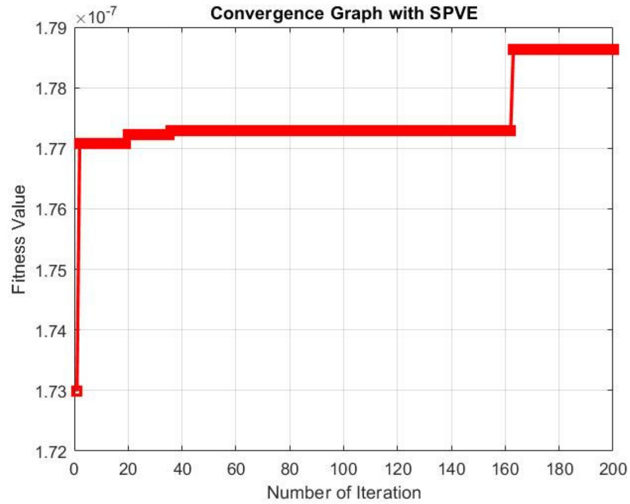

FIGURE 10. Convergence Graph of Commercial area with SPVE.

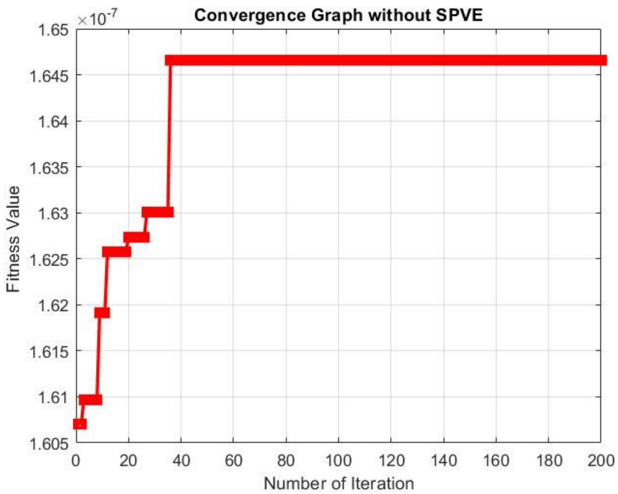

FIGURE 9. Convergence Graph of Commercial area with SPVE.

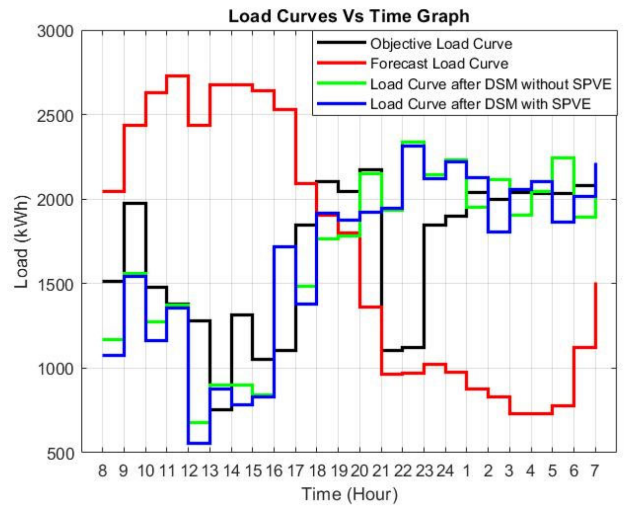

FIGURE 11. DSM results of industrial area with and without SPVE.

The proposed GWO algorithm converges in less than 10 iterations which prove its superiority over other algorithms in the literature and the convergence graph is shown in Fig.6 and Fig. 7.

Also, during peak load on utility high running cost generators are operated to fulfil the demand and thus reduction in peak load reduces the utility operational cost.

C. CASE 2. COMMERCIAL AREA

The controllable devices of commercials having 8 different types of 808 devices with their power consumption are shown in table 5.

The DSM results of the commercial area are shown in Fig. 8 and the reduction in peak load without and with SPVE is reduced as compared with the forecasted load curve. The peak load before DSM was 1818.2 kW and reduces to 1438.7 kW and 1442.7 kW without and with SPVE respectively. The peak load reduction with SPVE is slightly less than without SPVE as the worst solar profile is considered here and SPVE is not available in that time slot.

It has been noticed from table 6 that a significant reduction of 20.87% without SPVE and 20.65% with SPVE

in peak load. Also, a reduction in the cost of energy is 9.33% without SPVE and 12.42% with SPVE is achieved. The cost of energy before DSM was 362660 INRs and reduces to 328820 INRs without SPVE and 317600 INRs with SPVE. The proposed algorithm gives a maximum reduction in peak load and cost as compared with [20], [21], and [22]. The population and number of iterations taken here are 40 and 200 respectively.

The convergence graph shown in Fig. 9 and Fig. 10 converges to maximize the fitness value as the fitness function is reciprocal to the objective function. It implies as the fitness function approaches maximum value the objective function minimizes which in-turning gives reduced peak load and cost

TABLE 7. Controllable devices of industrial area.

Devices	No. of Devices	Power Consumption of Devices(kW)					
		1st Hour	2nd Hour	3rd Hour	4th Hour	5th Hour	6th Hour
Arc Furnace	8	50	50	50	50	50	50
Induction Motor	5	100	100	100	100	100	100
DC Motor	6	150	150	150	0	0	0
Welding Machine	35	25	25	25	25	25	0
Water Heater	39	12.5	12.5	12.5	12.5	0	0
Fan AC	16	30	30	30	30	30	0

TABLE 8. Cost of energy and peak load of industrial area.

Parameters	[20]	[21]	[22]	Proposed without SPVE	Proposed with SPVE
Peak Load (kW)	2338.6	2343.6	2372.75	2335.1	2315.1
% Peak Load Reduction	14.25	14	13	14.38	15.11
% Cost of Energy Reduction	10.09	10	5.2	18.81	20.60
Technique used	BFO	EA	MFO	GWO	

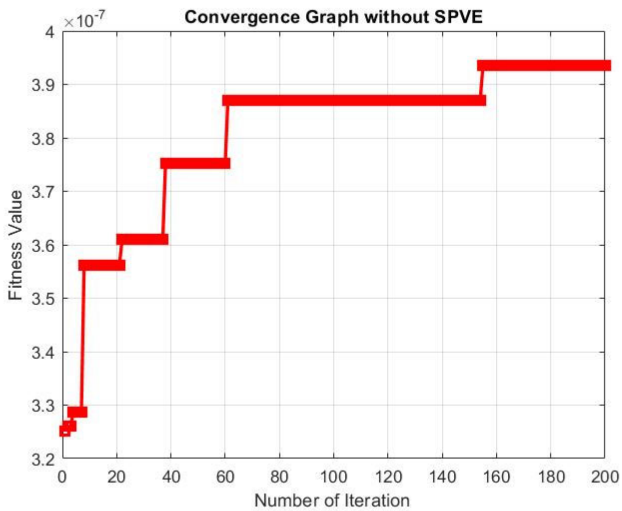

FIGURE 12. Convergence graph of industrial area without SPVE.

of energy. The proposed GWO algorithm converges in less than 40 iterations in commercial area appliance scheduling without and with SPVE.

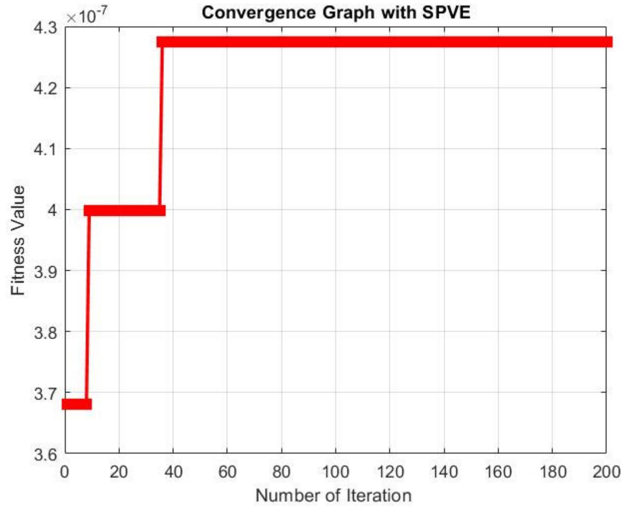

FIGURE 13. Convergence Graph of Industrial area with SPVE.

D. CASE 3. INDUSTRIAL AREA

The controllable devices of industrial area having 6 different types of 109 devices with their power consumption are shown in table 7. The controllable devices are the smallest among all the three cases.

The controllable devices in industrial areas are limited and base load or non-controllable devices are high. Industrial devices are operated continuously for many hours.

The DSM results of the industrial area are shown in Fig. 11 and the reduction in peak load without and with SPVE is reduced as compared with the forecasted load curve. The peak load before DSM was 2727.3 kW and reduces to 2335.1 kW and 2315.1 kW without and with SPVE respectively. The peak load reduction with SPVE is slightly more than without SPVE as the SPVE is available in that time slot.

The optimization results of the industrial area depicts a significant reduction of 14.38% without SPVE and 15.11% with SPVE in peak load as given in table 8. Here reduction in peak load with SPVE as peak load is occurring in 18-19 hours and in this time slot SPVE is available.

Also, a reduction in the cost of energy is 18.81% without SPVE and 20.60% with SPVE is achieved. The cost of energy before DSM was 567510 INRs and reduces to 460760 INRs and 450570 INRs without and with SPVE respectively. It has been noticed here that the maximum reduction in the cost of energy occurs in industrial areas as compared with residential and commercial cases as bulk load consumption occurs in the industrial area.

The proposed GWO algorithm converges in less than 20 iterations as shown in Fig. 12 and Fig. 13 demonstrating its effectiveness in the optimization of real-world problems.

VII. CONCLUSION AND FUTURE SCOPE

The proposed DSM minimization problem has been solved with the application of the GWO algorithm and tested on three different cases residential, commercial, and industrial load. The model was aimed to reduce utility peak load burden and consumer's cost of energy and proves a successful implementation of DSM using the GWO algorithm. The results achieved with the worst solar profile

considered here, depict a significant reduction in cost of energy in all the cases and open prospects for great savings with improved solar generation profiles in future smart grid.

Thus, consumers of each area can be motivated to use more and more renewable energy to reduce the cost of energy and thereby reduced $CO_2$for a sustainable green and pollution-free environment in future energy scenarios. The prosumers with smart control facilities can create a new sustainable electricity cloud for future smart grid.

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