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Demand Side Management In Smart Grid Optimization Using Artificial Fish Swarm Algorithm

[*1]H. Lakshmi, [2]Dr. M. P. Flower Queen
[*1]Research Scholar, Dept of EEE, Noorul Islam Centre for Higher Education
[*1]Corresponding Author Email: hlakshmi2023@gmail.com
[2]Professor, SRM TRP Engineering College, Trichy

Abstract- The demand side management and their response including peak shaving approaches and motivations with shiftable load scheduling strategies advantages are the main focus of this paper. A recent real-time pricing model for regulating energy demand is proposed after a survey of literature-based demand side management techniques. Lack of user's resources needed to change their energy consumption for the system's overall benefit. The recommended strategy involves modern system identification and administration that would enable user side load control. This might assist in balancing the demand and supply sides more effectively while also lowering peak demand and enhancing system efficiency. The AFSA and BFO algorithms are combined in this study to handle the optimization of difficult problems in a range of industries. Although the BFO will be used to exploit the search space and converge to the optimum solution, the AFSA will be used to explore the search space and retain variation. In terms of reduction of peak demand, energy consumption, and user satisfaction, the AFSA-BFO hybrid algorithm outperforms previous techniques in the field of demand side management in a smart grid context, using an AFSA. According to simulation results, the genetic algorithm successfully reduces PAR and power consumption expenses.

Keywords: Demand side management, Smart Grid, AFSA.

I. INTRODUCTION

Demand Side Management (DSM) is a technique used to regulate customer energy demand during peak hours, hence regulating their power use. Because it may lower energy consumption and peak demand, which lowers the overall cost of energy generation, transmission, and distribution, this method is becoming more and more crucial for smart grid optimization. Power systems' efficiency and peak leveling are improved via smart grids [1]. Complex optimization issues can be resolved using the AFSA a metaheuristic optimization tool. It draws inspiration from natural selection and looks for the best answer using strategies including crossover, mutation, and selection creating a way to perform ADSM on homes connected to smart grids to lower customer power costs and help delay the need for system expansion investments if peak charging times coincide with peak electricity rates of the day [2]. Utilizing the Stackelberg game and its established Nash equilibria, fundamental and improved interaction methods between a grid and buildings are devised. The grid optimizes the pricing to increase its net profit and decrease demand fluctuation, while each building optimizes its hourly power usage to lower its electricity cost and the consequences of demand varying from the baseline [3]. Presupposes that each grid user is capable of owning a PV system and a side battery. Solar energy can be captured and used to satisfy the specific energy needs of a customer, stored in the battery for later use, or sold back to the grid during peak use hours to reduce electricity costs and the overall load on the system [4]. Utilizing machine learning (ML) for the grid that is connected to the Internet of Things (IoT). According to priorities, the planes DSM engine is in charge of maintaining energy use that is as efficient as possible. The control of incursions into the smart grid is presented using a unique resilient paradigm. Using the ML classifier, the resilient agent predicts the dishonest entities [5]. suggests a demand side management solution using agent-bases architectures and a small office deployment [6]. In comparison to the usual no-load shift situation, the suggested load shifting algorithm raises the renewable energy portion by 6.34%, decreases operating costs by 6.06%, and enhances the operation of the microgrid by modifying the load pattern [7]. Using the hourly load profile data from the Office of Energy Efficiency & Renewable Energy (EERE) for a business sector, ten daily activity profiles from ten distinct persons were gathered to reflect the community's population [8]. An overall cost decrease of 5.44% was achieved when the scheduling strategy was compared to the current ant colony optimization-based energy management controller. Hence, comparison work

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shows that the suggested work is superior in terms of lowering costs, peak loads, waiting times, and peak-to-average ratio [9]. The research's findings are a useful addition to the resilience-boosting strategies already in place, enabling the utility to make full advantage of the power system already in place and a cutting-edge smart grid operating plan to handle the challenge of natural disasters [10]. Using the multi-objective particle swarm optimization (MOPSO) technique, the modes problem's goals are simultaneously minimized [11]. To ensure the smooth and secure implementation of the suggested scheme, new blockchain technologies are provided, demonstrating how a decentralized demand side management strategy works [12]. The issue can be resolved by the suggested decentralized optimization technique, which first relaxes the restrictions on the appliances before utilizing the gradient descent algorithm to break down and solve the realistic schedules for the devices over the scheduling period [13]. DSM techniques for the SMG's scheduling issue in the presence of wind energy reduce overall operating costs and pollution emissions while raising the CS and WTP indices [14]. Expect a wider range of workable pricing ratios and various off-peak prices. ToU tariff structure is modified depending on the fixed power cost and the system's profile [15].

The aforementioned studies provide an overview of various DSM strategies and their contribution in cost reduction, and the suggested hybrid AFSA and BFO algorithm addresses the optimization of maintenance costs and other SMG objectives. Section 1 provides an introduction, section 2 discusses the review of various literatures, section 3 explains the proposed methodology and in section 4 discusses the results of the proposed strategy along with previous studies, and section 5 concludes the paper.

II. LITERATURE REVIEW

In 2020, Cakmak and Altaş. [16] have presented an innovative appliance leveled billing (apple bill)-based charging strategy for fair and efficient demanded side management. The suggested apple bill concept offers a billing technique that allows) in a home have been billed separately rather than at the same rate as all other power used. Three possible schemes were included in the proposed apple bill idea.

In 2018, Wang *et al.* [17] have proposed a costed function thought up of the billing, generating, and discomfort costed. Also, a distributed energy management system based on game theory was created in DSM without disclosing user privacy and was employed as an internal optimization in our suggested distributed energy storage planning strategy. Created an energy management system based on game theory without compromising user privacy in DSM.

In 2021, Scarabaggio *et al.* [18] have proposed a distributed demand side management (DSM) strategy for smart grids that took wind power forecasting uncertainty into consideration. Both conventional and active consumers were included in the smart grid concept. Prosumers participate in a DSM programme used a rolling-horizon strategy with the goal of lowering their costed in the face of erratic wind energy production. had made the assumption that each user formulates their grid optimization issue as a competitive game.

In 2018, Li *et al.* [19] have suggested optimum DSM model from an intractable mixed-integer nonlinear programming (MINLP) issue into a mixed-integer convex programming (MICP) problem. The numerical analysis demonstrates tight quasi-convex hull relaxation and the computing effectiveness of the resultant MICP issue. demanded response framework taking into account a flexible irrigation system.

In 2020, Babar *et al.* [20] have proposed utilizing machine learned (ML) for the grid that was internet of things (IOT) enabled. The suggested DSM engine was in charge of maintaining priority-based energy used that was as efficient as possible. To prevent intrusions into the smart grid, a special resilient paradigm was suggested. The ML classifier was used by the resilient agent to forecast the dishonest entities.

In 2019, Khan *et al.* [21] have proposed priority-induced DSM technique based on the load shifting method taking into account different appliance energy cycles. To reduce the rebound peaks, the day-ahead load shifted method was mathematically developed and translated to numerous knapsack problems. The suggested autonomous energy management controller incorporates the AFSA, improved differential evolution, and binary particle swarm optimization meta-heuristic optimization approaches.

In 2018, Barth *et al.* [22] have Provided a comprehensive modelling framework that incorporates the bulk of the limitations from many current models to mathematically characterize demanded side flexibility in smart grids. had offer a framework for modelling demanded side flexibility that was universally applicable, and could assess its viability by examining how effectively mixed-integer linear program (MIP) solvers could optimize the resulting models.

In 2018, Bazydło and Wermiński. [23] have suggested technique include the efficient and practical design of the HAN algorithm, the flexible maintenance of HAN systems, and a gained in energy reduction at a relatively low costed. The latter benefit was made feasible by the used of contemporary FPGAS, which permit the HAN controller's dynamic reconfiguration. That means that a user's HAN algorithm may been altered without affecting other residential users' power. A computation of the possible benefits from used the suggested technique were also offered.

In 2019, Sharma and Saxena. [24] have developed mathematically for the minimization issue. For resolving this minimization issue, the whale optimization algorithm (WOA) was created. On a test smart grid with two service zones, one with residential customers and the other with business consumers, simulations were performed. By comparing the outcomes with spider monkey optimization and biogeography-based optimization, WOA demonstrated its effectiveness.

In 2019, Khan. [25] have investigated the potential of this energy-saving behavior as a DSM approach for the least developed economies. According to the research, energy-saving practices might lower energy consumption by a maximum of 21. 9%. Yet, it appeared that Bangladesh's national DSM programme had undervalued this potential DSM scheme. According to the energy efficient and conservation master planned (EECMP) of Bangladesh.

The existing literature comes with cost reduction bill strategies [16,17] and give a novel idea of rolling horizon incorporated wind energy cost reduction [18] and response of the demand side[19] flexibility is analyzed [22] and metaheuristic optimization algorithms[21,23,24] used to reduce cost with IoT [20] integration lowers the energy consumption[25]. Table.1 gives summarized research gaps that have been present in previous literature.

TABLE 1. Research Gaps

Author	Aim/ Process	Research Gaps
Puttamadappa and Parameshachari [1]	To improve a few load demand features	Parametric building energy models are ineffective.
Tang *et al.* [3]	Price-based demand response of smart grids uses interactive demand side management that is based on game theory to respond to dynamic pricing.	• Day-ahead optimization not achieve real-time dynamic pricing and building power
Liu *et al.* [4]	Uncertain Renewable Power Production and Bi-Directional Energy Trading	• Not consider unpredictable energy requirements
Zheng *et al.* [7]	Demand Side Managed Biomass-Integrated Renewable Energy Microgrid under Uncertainty	Environmental implications are not mentioned Not include effect abatement costs
Cheng *et al.* [8]	Demand-side management in residential communities implementing sharing economy with bidirectional PEV	Dynamic pricing models and environments with greater complexity cannot applied
Li *et al.* [10]	To increase the robustness of the bulk power system in hurricanes	Extreme weather conditions may not even consider

The review of the literature demonstrates the direction of current research in the field of smart grid demand side management. At this time, a lot of attention was being paid to develop an ideal load schedule with the use of right optimization methods and algorithms. Demanded side management was used in smart grid optimization to increase energy efficiency, decrease peak energy demand, and eventually lower energy expenditures.

The proposed model needs to meet the solution for the addressed research gaps such that it have to be an effective model[1] having real-time dynamic pricing capability[3,8]for the unpredictable demand [4]during various environmental implications on the grid[7,10] and reduces the waiting time along with decreasing the operational cost.

III. PROPOSED METHODOLOGY

Each sort of load has a unique consumption pattern and operating duration, so the design strategy should be able to account for all of these differences. However, due to their complexity, many recommended strategies in the literature that are frequently used for scheduling, such as linear programming and dynamic programming, are unable to manage such a huge number of appliances. A near-optimal solution to the given problem can potentially be found using an evolutionary algorithm like. Thus, a scheduling method based on AFSA is developed to address the cost optimization problem. The appliances ask the DSM controller for authorization to connect. By resolving the minimization problem, the DSM controller cumulatively handles the appliances in each time slot and provides an entire pattern. When an appliance delivers a request to the DSM controller, the controller acts depending on the findings of the DSM technique that was used.

An electric network with information technology integrated into it is referred to as a "smart grid". This work suggests utilizing AFSA to lower the overall cost of electricity in a smart grid. To meet demand, the system under consideration uses battery banks separate from the grid and renewable energy sources. A widely used technique for global search and optimization, the AFSA is a direct, parallel stochastic method. The three major tenets of natural evolution natural selection, reproduction, and species diversity are used by the group of evolutionary algorithms (EA) of which AFSA is a member.

A. Problem Formulation

The desired load consumption curve is near to being met by the suggested demand side management technique, which plans the connection moments of each shiftable device in the system. Mathematically, the proposed load-shifting approach is presented as follows [24].

Minimize

$$\sum_{m=1}^{n}(A\ Load\ (m) - Objective\ (m))^2 \quad (1)$$

where $ALoad\ (m)$ is the actual consumption at time m, and $Objective\ (m)$ is the value of the objective curve at time m.

The following equation yields the $ALoad\ (m)$:

$$ALoad\ (m) = Consumption\ (m) + Connect\ load\ (m) - Disconnect\ load\ (m) \quad (2)$$

where $Consumption\ (m)$ is the forecasted consumption at time, $Connect\ load\ (m)$ and $Disconnect\ load\ (m)$ is the number of connected and disconnected loads at time (m) during the load shifting, respectively.

$Connect\ load\ (m)$ is divided into two parts: the increase in load at time caused by shifting device connection timings and the increase in load at time caused by connections planned for times before the $Connect\ load\ (m)$. The following equation yields the.

$$Connect\ load\ (m) = \sum_{f=1}^{m-1}\sum_{S=1}^{N} d_{sfm}.W_{1S} + \sum_{L=1}^{r-1}\sum_{f=1}^{m-1}\sum_{S=1}^{N} d_{sf(m-1).W_{(1+L)S}} \quad (3)$$

where d_{sfm} is the quantity of the sort of devices S that are advanced by a time step r to m, d is the number of device types, W_{1S} and 1and (1+L) are the power consumptions at time steps. Therefore, r and represent the overall consumption time for the corresponding device type S . As seen $Connect\ load\ (m)$, $Load\ y$ is shifted from my to $(m-1)$ and $Load\ z$ is shifted from mz to m.

Similarly, $Disconnect\ load\ (m)$ also has two components: the decrease in load caused by a delay in connection times for devices that were initially intended to start using the system at time step, as well as the decrease in load caused by a delay in connection times for devices that were intended to use the system at time steps that precede (m). The $Disconnect\ load\ (m)$ following equation yields the:

$$Disconnect\ load\ (m) = \sum_{e=m+1}^{m+u}\sum_{m=1}^{N} d_{sme}.W_{1S} + \sum_{m=1}^{r-1}\sum_{e=m+1}^{m+u}\sum_{s=1}^{N} d_{s(m-1)e\ .\ W_{(1+L)S}} \quad (4)$$

where d_{sme} is the quantity of type S devices that are delayed from time step m to time step e, The longest delay permitted is u. disconnect t is shown with $Load\ y$ moved from $m-1$ to my and $Load\ z$ transferred from m to mz.

The aforementioned limitations apply to this minimization issue. It is impossible for the number of devices to be negative.

$$d_{sfm} > 0 \quad \forall\, f, r, S. \quad (5)$$

The total number of devices that can be controlled at a time step cannot exceed the total number of devices that have been relocated away from that time step.

$$\sum_{m=1}^{B} d_{sfm} \leq Ctrlable\ (f) \quad (6)$$

where $Ctrlable\ (f)$ represents the quantity of type S devices that are accessible for control at time step f.

Thus, the problem of the delayed waiting time response during load sharing is formulated and the cost of the operation is another objective function needed to consider and it is mathematically expressed as,

$$\text{Min } R_{low} = 2 * R_{medium} - R_{high};\ R_{low} \in N \quad (7)$$

$$R_{low} \geq \left(R_{flat} - Price_{fixed} + Price_{fuel}\right) \times 0.65 \quad (8)$$

Where, R_{flat} is the lowest rate per kWh and R_{medium} is the average demand rate per kWh.

B. Proposed Algorithm

Smart grid's DSM algorithms must be built to handle a high number of controlled devices of various sorts. Additionally, each sort of controlled load may have various heuristics and varied consumption characteristics that vary over a short period of time. As a result, the algorithm used should be capable of handling these difficulties. In this area, both linear and dynamic programming are frequently used. Nevertheless, the methods for linear programming and dynamic programming are both inadequate for handling these complications. In other fields, evolutionary computing techniques have demonstrated a promise for overcoming such challenging issues. In addition to yielding outcomes that are close to optimum, these algorithms have a number of benefits over more conventional mathematical methods including higher cost and waiting time. In order to overcome

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the challenge, a heuristic-based evolutionary method is presents in this work. The suggesting algorithm not only makes it simple to alter the problem's heuristics, but also offers an effective and affordable solution.

The flexibility with which the suggesting algorithm may be built and developed, which cannot be offered by any other traditional techniques, is one of its key benefits. Due to the evolutionary algorithm's flexibility, features that simulate load demand patterns based on consumer lifestyles may be included, minimising the discomfort to the customers. For illustration, take the coffee maker and the washing machine as two controllable loads. They start their consumptions early in the day. Due to the clients' lifestyle, the coffee maker usually runs in the morning. In light of this, the algorithm might try to move the coffee maker as early as feasible in the morning. A later time can be chosen because the washing machine has no such preference.

The algorithm can also take into account the fact that some loads may have a greater priority than others such that, in accordance with their importance, these loads are moved to the proper time stages. These kinds of stresses may be observed in the test scenarios examined in this study, where the controllable devices have properties that allow connection periods to be merely postponed, not advanced. The suggested algorithm's capacity to manage several controlled devices of various sorts is another key benefit.

Just the length of the evolutionary algorithm's chromosomes is impacted by the issue size.

The demand side management issue is characterised by, among other things, connection times of devices that can only be postponed and not brought forward.

$$d_{sfm} = 0 \; \forall f > m. \tag{9}$$

The contract options restrict the amount of time steps that devices may be relocated to and specify the maximum permissible time delay for all devices, which results in

$$d_{sfm} = 0 \; \forall (m - f) > x \tag{10}$$

where x is the maximum permissible delay.

With the foregoing, the following equation may be used to determine the maximum number of time steps B:

$$B = \left((24 - x) \times x + \sum_{b=1}^{x-1} b \right) \tag{11}$$

where b is the variety of device kinds.

1) Artificial fish swarm algorithm

A metaheuristic optimization approach is called the Artificial Fish Swarm Algorithm (AFSA). The method simulates the behaviour of a school of fish, with each fish standing in for a possible answer to the optimization issue. The fish navigate across the search space according to their individual and group behaviour and communicate with one another using a set of predetermined rules.

Each fish's location is updated by the algorithm after each iteration depending on both its own fitness value and the fitness values of nearby fish.

Step.1 AF-prey

If S_a and F_a both express the fitness value and the current a AF state, then the formula (10) is Chosen for status S_U at random from its visual, then use the fitness value function to get the state's fitness value. If $F_U > F_a$, move in that direction and use formula (11) to get S_a to a new and improved condition $S_{a\backslash next}$. Instead, do formula (10), continue to randomly choose a state S_U and then explain whether or not it satisfies the forward criterion. Repeat the operation until the criterion is satisfied or the anticipated maximum number of attempts, try number, has been made, whichever comes first. If the forward requirement still cannot be satisfied after the projected maximum number of AF tries, *try number*, execute the formula (12), and then go on to the next step in visual so that S_a can achieve a new and improved state $S_{a\backslash next}$.

$$S_U = S_a + rand\ (0,1) \times visual \tag{12}$$

$$S_{a\backslash next} = S_a + rand\ (0,1) \times step \times \frac{S_U - S_a}{\|S_U - S_a\|} \tag{13}$$

$$S_{a\backslash next} = S_a + rand\ (0,1) \times step \tag{14}$$

S_a is the current state of the a AF in the formula. $S_{a\backslash next}$ is the a AF's next state, and rand (0,1) is a randomly generated value between 0 and 1. where the distance betweenS_U and S_a is $\|S_U - S_a\|$.

Step.2 Bacterial foraging based updation:

The performance of AFO is improved by incorporating the strategy of BFO. Specifically, chemotaxis strategy is considered into the AFO. Therefore, the AFO's performance is improved and local optima is avoided moreover, the reformulation of the BF based AF-prey's mathematical model is shown below.

$$S_{a\backslash next} = S_a + rand\ (0,1) \times \ step\ z(e) \times \frac{S_{min} - S_a}{\|S_{min} - S_a\|} \times \frac{\triangle\ (e)}{\sqrt{\triangle^t\ (e)\ \triangle\ (e)}} \tag{15}$$

$z(e)$ represents the chemotaxis step length that is (a strategy of BFO algorithm) for the eth fish to move. $\triangle$ is random vector between the range of [-1,1], and $\frac{\triangle(e)}{\sqrt{\triangle^t(e)\triangle(e)}}$ represents the unit vector.

Step.3 AF-Swarm

According to AF-Swarm, each fish makes an effort to go towards the center, where its companion fish are, to avoid being crowded. Let $S_a$represent the current a AF, F_a represent the fitness value, nl the number of its

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companion artificial fish inside its location as the center, and these artificial fish together represent a set T_a. In the event that the set, $T_a \neq \emptyset(\emptyset$ is null set,) In the a AF's image, there are more men. i.e., $nl \geq 1$. According to the following formula, the set's S_{Centre} center location is determined.

$$T_a = \{S_a | \|S_b - S_a\| \leq Visual, b = 1,2, \dots, a+1, \dots n\} \quad (16)$$

$$S_{Center} = \frac{\sum_{b=1}^{nl} S_b}{nl} \quad (17)$$

If S_{Center} fits the condition for the center (16), if the center fellow is not a densely populated area, use formula (17) to advance a step to the center position; otherwise, use the prey behaviour.

$$F_{Centre} < F_a \quad and\; nlF_{centre} < \delta F_a(\delta > 1) \quad (18)$$

$$S_{a\backslash next} = S_a + rand\;(0,1) \times step \times \frac{S_{Center} - S_a}{\|S_{Center} - S_a\|} \quad (19)$$

In the equation $\|S_{Center} - S_a\|$ the distance between S_{Center} and S_a. If the set $T_a = \phi$, then $nl = 0$ indicates that there are no additional teammates visible in the a AF. Behaviour of a prey.

Step.4 AF - Follow

Fish have a tendency to follow the neighboring bodies that are the most active. Let F_a express the fitness value and S_a express the current a AF. According to the current condition, the AF S_a looks for the comrade S_{min} with the lowest fitness value in its field of view. Execute prey behaviour if $F_{min} \geq F_a$; else, the number of AF in seeking and the visual distance centered a S_{min} are nl. If the condition in formula (18) is satisfied, the position state is favorable. if the environment is not too congested, use formula (19) to advance to the minimal fellow S_{min}; otherwise, use prey behaviour.

$$F_{min} < F_a \text{ and } nl\; F_{min} < \delta\; F_a(\;\delta > 1) \quad (20)$$

$$S_{a\backslash next} = S_a + rand\;(0,1) \times step \times \frac{S_{min} - S_a}{\|S_{min} - S_a\|} \quad (21)$$

The distance between S_{min} and S_a is given in the formula as $\|S_{min} - S_a\|$. Execute the prey action if there are no other people visible in the a AF's field of view at time, or if $nl = 0$.

Step.5 Behavior selection

According to the characteristics of the issues that need to be resolved, the current AF environment is assessed. Choose one of the appropriate behaviors from the list above.

Step.6 Set bulletin board

Create a bulletin board in AFSA to list the ideal AF states desired and the corresponding fitness score. Each AF is comparing the fitness value of their current condition following each activity. If the own state and its fitness value are greater to the similar value, they will replace it on the bulletin board, allowing it to record the best status discovered and the state's fitness value. In other words, after the algorithm is finished, the value of the final message board is the system's optimal response.

With the selection of these behavior's, the AFSA creates a sort of extremely effective optimization technique. Eventually, artificial fish tend to congregate around a few local extrema, with more artificial fish congregating around the extrema with higher value. Also, the AFSA implements the design concept from top to bottom and begins with the realization of individual AF behaviour. Individuals' autonomic conduct causes a slow building of population effect, which allows the ultimate outcomes to be seen. The method solely makes use of the target problem's fitness value and has some flexibility in how it searches the space. The effectiveness of optimization is enhanced when numerous artificial fish hunt simultaneously.

This algorithm is capable of coping with the drifting of the extreme point owing to changes in work status or other circumstances. The following figure 1 contain the basic flow of AFSA hybrid with BFO algorithm.

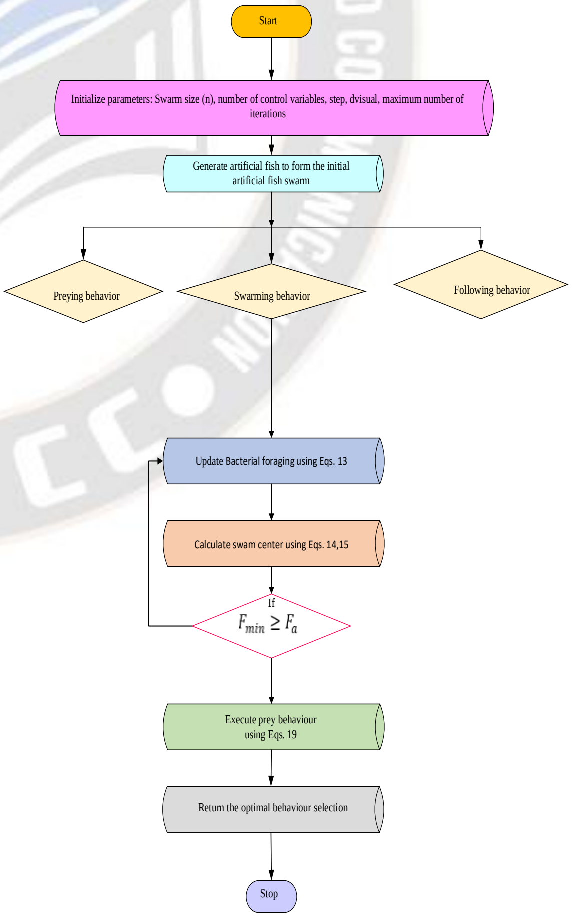

Figure 1. Flow chart of AFSA hybrid with BFO

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TABLE 2. Controllable Devices in The Residential Area

Device	No. of hours for one unit consumption	Power Consumption
Zero watt bulb	66.5	15
CFL bulb	66.5	15
Tube light	25	40
Ceiling fan	16.5	60
Air Conditioner	0.5	1500
Mixie	2	450
Two sets of TV	3.5	270
Water pump	1.3	750
Washing machine	3	325
Iron box	1.3	750
Mobile charger	200	5
computer	6.25	160
refrigerator	10	100
microwave	0.99	1010
Audio system	25	40

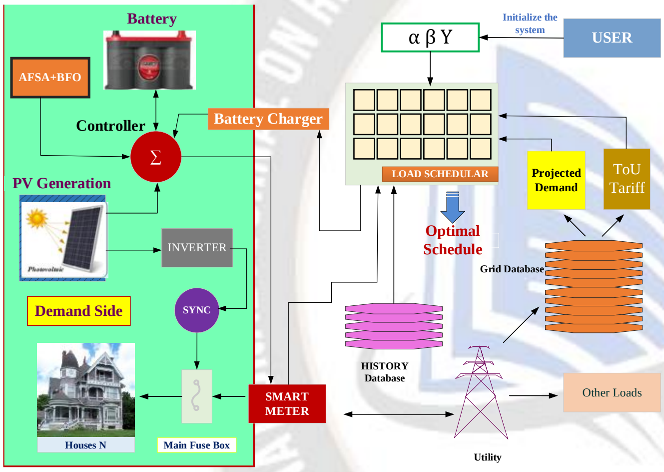

Figure 2: Schematic diagram of the smart grid.

The inelastic load for 24 hours will vary depending on how much energy is used by appliances during each time slot, or t. The majority of the inelastic demand, which is time-specific, is supplied by batteries, which are charged by grid power and renewable energy sources. The hybrid optimization seeks to discharge the battery during periods of high electricity price and charge it during periods of low power price.So that the cost for the energy decreased in resoinse with less delay time. A multi-variable, single-objective genetic algorithm is used to optimise a 24-hour data set of real-time electricity prices, renewable energy production, and total utility inelastic energy demand. The above figure 2 is shows Schematic diagram of the smart grid.

IV. SIMULATION RESULTS

In this part, the outcomes of the suggested modeling technique were analyzed using the MATAB Simulink environment with the objective of operating cost and waiting delay time is minimization. The following assumptions were considered during the modelling of the proposed hybrid AFSA+BFO algorithm.

TABLE 3. The parameters of the AFSA+BFO values used in the modelling

Parameters	Values
Population size	20
n (Swarm size)	10
Iteration count	19
$F_a(fitness\ function\ of\ a)$	0.9
S_a (Current value of fitness initiation of a)	0.1

1) *Cost*

The suggested optimization approach is used to estimate the cost of energy use for a set of electrical appliances that are included in the schedule. The simulation output is shown in Fig. 3.

TABLE 4. Cost of energy use for each month of the year

Month	Energy using (kWh)	Cost (USD)
Jan	1000	100
Feb	800	90
Mar	700	80
Apr	600	70
May	500	60
Jun	400	50
Jul	300	40
Aug	400	50
Sep	500	60
Oct	600	70
Nov	700	80
Dec	900	95

This table 4 shows the energy usage and cost for each month of the year. The energy usage is measured in kilowatt-hours (kWh), while the cost is measured in US dollars (USD). As you can see, the energy usage decreases during the summer months and increases during the winter months. This is typical for areas with cold winters and hot summers, where heating and cooling needs are high. The cost of energy also varies throughout the year, with higher costs in the winter and lower costs in the summer. This is due to the different rates charged by energy providers for peak and off-peak usage. The below figure 3:is shows Energy consumption trends and costs

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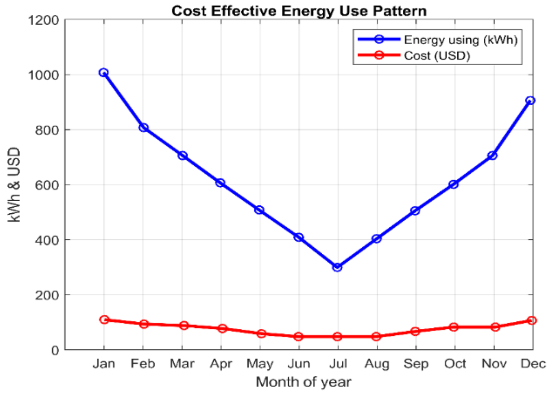

Figure 3: Energy consumption trends and costs

2) *Delay*

The fitness value comparison between the standard execution flow and the suggested waiting time delay optimization is shown in Fig. 4.

TABLE 5. The effect of waiting time on productivity

Waiting Time (min)	Productivity Score
0	100
5	95
10	90
15	85
20	80
25	75
30	70

The table 5 displays how waiting time affects productivity, expressed as a productivity score. While the productivity score is a percentage that reflects the degree of production attained during that period, the waiting time is calculated in minutes. As you can see, the productivity score goes down as the waiting time goes up. The reason for this is that waiting is a sort of downtime that cuts into the amount of time available for useful activity. As a result, while waiting, employees could get disinterested, distracted, or demotivated. This can cause productivity to drop, which would be bad for corporate operations.The below figure 4 is shows Consequences of waiting

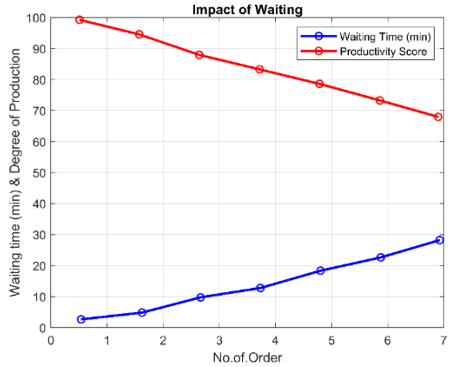

Figure 4: Consequences of waiting

3) *Cost vs. Delay*

The objective function parameters of cost and delay are compared in Fig. 5. There is a clear trade-off between cost and delay, as seen by the values in the graph.

TABLE 6. The cost and delay for a series of orders

Order	Cost	Delay
1	100	0
2	95	1
3	90	2
4	85	3
5	80	4
6	75	5
7	70	6
8	65	7
9	60	8
10	55	9

This table 6 displays the price and turnaround time for a number of order where the cost goes down as the wait gets longer. This shows that the cost savings from delivery delays may outweigh the extra expenses of keeping goods on hand or other associated charges. Similar to the longer wait, a shorter delay could incur more expenditures owing to faster delivery, extra work, or other associated charges. When making decisions regarding inventory management, logistics, and customer service, businesses must carefully weigh the tradeoffs between cost and delay. The most cost-effective solutions may be found in this table, which also helps to visualise the tradeoffs. The below figure 5 is shows Balancing between delay and cost

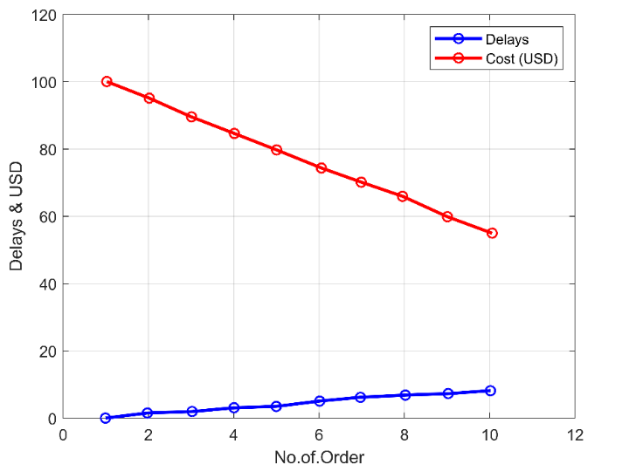

Figure 5: Balancing between delay and cost

4) *Impact of Proposed Algorithm for Deferred State*

The outcomes of the optimization for the postponed delay and the usual delay are shown in Fig. 6.

TABLE 7: Time Delay Comparison

Order	Normal Delay Cost	Deferred Delay Cost
1	100	95
2	95	90
3	90	85
4	85	80
5	80	75
6	75	70
7	70	65
8	65	60
9	60	55
10	55	50

Table 7 contrasts the delayed delay cost with the typical delay cost for a group of orders. Normal delay is the common delivery time delay, whereas postponed delay is a delivery time delay that has been pre-agreed upon. Each order's postponed delay cost is less than its typical delay cost. This is because the postponed delay enables better resource planning and management, which reduces costs. By comparing the costs and advantages of various delay options, businesses may use this chart to determine which option is most cost-effective for their operations. The below Figure 6 is shows Delay time comparison

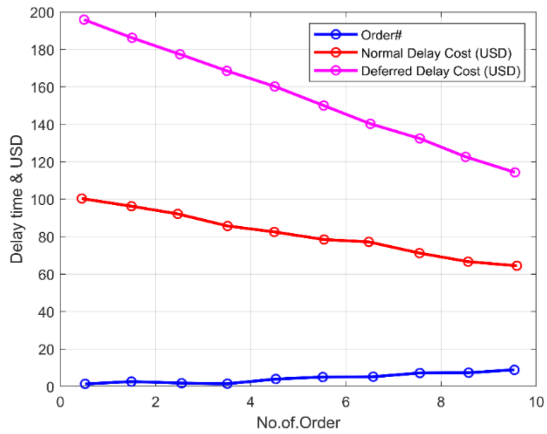

Figure 6: Delay time comparison

5) *Energy Usage Pattern for Day*

Figure 7 displays an average day's worth of energy use. It displays the trend of daily energy consumption bills according to the ToU power pricing model [15].

TABLE 8: Hours of energy use

Time (Hour)	Energy Usage (kWh)
1	0.8
2	0.3
3	0.6
4	0.4
5	0.5
6	0.8
7	1.3
8	1.5
9	1.2
10	1.8

The table 8 shows the hourly energy usage in kilowatt-hours (kWh) for a given day, from hour 1 to hour 10. For example, at hour 1, the energy usage was 0.8 kWh, and at hour 10, it was 1.8 kWh. This table can be used to track and analyze energy usage patterns over time.

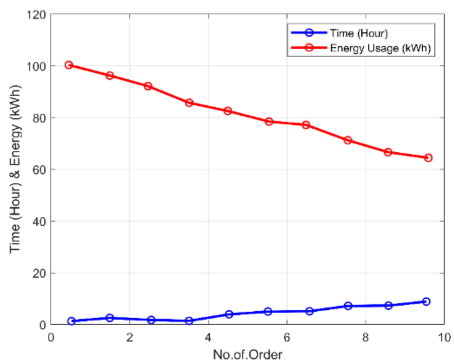

Figure 7: Energy Use hours

6) *Time spent waiting with Admission Control*

TABLE 9: Comparative Analysis of Admission

S.no	No of app	Not deferred	Random	Least	Longest
1	10	78.52	76.94	75.8	76.12
2	11	75.2	72.5	80.4	77.96
3	12	83.9	82.6	96	80.83
4	13	88.6	95.6	91.7	99.5
5	14	102.4	106.8	112.2	115.12

Several forms of admission control mechanism are utilised to maintain the energy use under the threshold value. The results of the admissions control are displayed in Fig. 8. The outcome clearly demonstrates that the delay time without an admission control mechanism is 83.9 seconds, while suggested admission control schemes like random (Random AC), least recently entered (Last entered AC), and longest running time consume 82.6 seconds, 96.00seconds, and 80.83 seconds, respectively (Longest run AC). Table.9 displays the typical delay time in seconds for a variety of appliances on various admission control systems. The admission control system with the longest runtime has the shortest wait time in some circumstances.

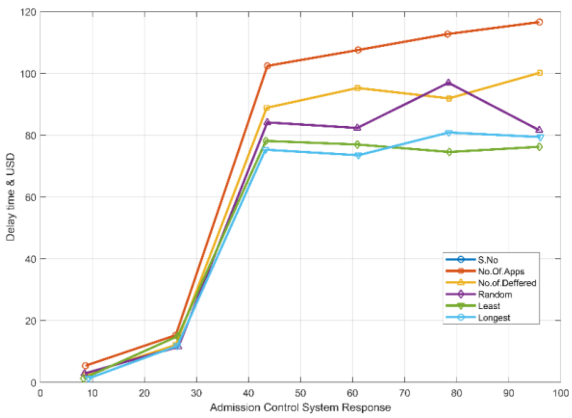

Figure 8: Admission Control Delay

7) *Comparison of Results*

Table.10 contrasts the results of the suggested optimized model with past studies [26]. It was proven that the proposed one significantly cut down the waiting time to 1.26 minutes and overall expense to 190.52-USD.

TABLE.10 Comparison of cost and delay time with existing methods

Optimization Method	Cost (USD)	Delay time(Min)
GA	656.99	2.58
BFOA	556.9	1.35
BPSO	408	2.3
HBFPSO	280.8	2.2
GBPSO	400.54	2.32
AFSA+BFOA (Proposed)	190.52	1.26

V. CONCLUSION

This work investigated the viability of rescheduling the consumer goods under heavy loads and system overloads to met distribution system requirements. It enables the total load curve to converge to the best load factor. In this research, the short-term time averaged electricity cost was minimised in order to optimise the total cost of electricity for consumers with inelastic load in a smart grid.

DSM in smart grids optimized using proposed artificial fish swarm algorithm (AFSA),which is a metaheuristic optimization tool. The performance of AFSA was enhanced even further by combining it with another optimization technique, such as bacteria foraging optimization (BFO). With the use of a different search strategy of BFO, this hybrid approach improved AFSA's search capabilities. DSM in smart grids efficiently optimised by the hybrid AFSA-BFO algorithm, resulting in reduced waiting delay time of 1.26 minutes (48%) while increase the energy efficiency and cost savings to 29% (190.52-USD). To fully explore the possibilities of this hybrid algorithm in many contexts and environments, more study will be necessary.

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