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*Original Article*

# The Impact of Nature-Inspired Optimization Techniques on Peak and Electricity Cost in Distribution Systems

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***Abstract*** - *In recent years, smart household appliances have led to an increase in residential electricity usage. Peak loads are created by these appliances in residential distribution systems. At peak times, residential distribution power consumption exceeds grid power. The imbalance in power demand results in low voltage in the distribution system, affecting household appliances. Increasing or decreasing grid power demand is necessary to protect these household appliances. The authors implemented renewable energy sources to address this issue, increasing grid power and demand-side management techniques to reduce energy consumption. Despite various research on optimal peak and cost reduction, a lack of different nature-inspired optimization techniques has been evident. The present paper proposes a demand-side load-shifting algorithm for peak load control in a residential building. This multi-objective load-shifting algorithm employs nature-inspired optimization techniques, including MBO, CSO, and AFSO, to reduce the utility's peak load and the consumer's electricity cost simultaneously. A comparison is made between the above-mentioned nature-inspired optimization approaches in this paper. Finally, the MBO's results are superior to other nature-inspired optimization methods.*

***Keywords*** - *Peak Load Management (PLM), Demand Side Management (DSM), Load Shifting Algorithm (LSA), Monarch Butterfly Optimization (MBO), Crow Search Optimization (CSO), Artificial Fish Swarm Optimization (AFSO).*

## 1. Introduction

The reliance on electricity in modern society is widespread, as it is used for all activities. The invention of electricity has made life easier for people today because they can use it for various daily tasks, including lighting, heating, cooling, and using various electrical appliances. Throughout history, people have consumed increasing amounts of energy as technology advances. Initially, the average daily consumption was about 3 kWh per person. US and German citizens' daily electricity consumption 2020 was about 202 and 110 kWh, respectively. But, the daily energy consumption of an Indian is just 18 kWh in 2020 [1].

The demand for energy met by India also stands at a record high of 4,700 million units. There were 21 million units of electricity shortfall, with a peak deficit of 578 MW. During peak hours, energy management needs to be focused on reducing this deficit. As part of energy management, energy production and consumption units are planned and operated, and energy distribution and storage systems are set up for continuous and smooth operation. Consumers use energy for various activities at home, including watching television, washing clothes, heating, bathing, and using computers. Globally, residential energy use accounts for approximately forty percent of total energy use. Therefore, it is necessary to emphasize energy management in dwellings. Peak load management is lowering the demand for electricity at peak times, which can save a lot of money. If numerous buildings used all of their powered gadgets simultaneously, but there was insufficient electricity in the grid to match this demand, the power from the grid may be overdrawn, resulting in disastrous brownouts, blackouts, and other unexpected outages. PLM and Demand Response (DR) are concerned with reducing energy demand at a specific time. DR is a programme that requires participants to respond to utility requests when demand is excessive, and insufficient energy satisfies the grid's peak.

S. Yilmaz et al. [2] evaluated the effects of energy efficiency policies and measures, such as minimum energy performance criteria, on peak load using time-use data. After modelling fourteen different types of appliances and replacing them with the most energy-efficient labels, the study found that the highest potential for reducing evening peak demand was achieved by changing light bulbs to LED. This change resulted in a 38% reduction in peak electricity consumption during the evening and a 21% reduction during noon. The results indicate a significant decrease in electricity demand across various domains. There was an 18.8% decrease in appliance electricity demand, a 14.2% decrease in overall residential electricity demand, and a 5.0% decrease in national electricity demand. Olawale Popoola et al. [3] proposed a peak load control technique that utilized an event detection algorithm to control the User's Preferred Appliance (UPA) and found that it resulted in a peak demand reduction of 3% to 20% and an overall energy savings of at least 14.5%. In addition to being completely optional, PLM significantly impacts the Sustainable Development Goals (SDGs), particularly SDG-07, which targets 7.3 to double energy efficiency by 2030.

The UN adopted the Sustainable Development Goals (SDGs), also called the Global Goals 2015. By 2030, these goals aim to solve many global concerns, including eliminating poverty, creating a sustainable environment, and promoting prosperity and peace. The SDGs recognize the interconnectivity of various issues and emphasize the need for a balanced approach considering social, economic, and environmental sustainability. Countries have pledged to prioritize progress for those nations that are lagging in achieving these goals. The Sustainable Development Goals (SDGs) aim to tackle various global challenges, including poverty, hunger, AIDS, and gender inequality. Achieving these goals requires a collaborative effort, with society utilizing its collective creativity, knowledge, technology, and financial resources. Nihit Goyal et al. [4] performed bibliometric and computational text analyses on over 2,700 articles related to India's energy policy research to identify primary themes, geographical locations, and policy features.

Evaluating the effects of demand-side management on technology, well-being, behaviour, and sustainability is critical for effective policy implementation and fostering long-term growth. The HEM problem was modelled with mixed integer linear and nonlinear programming, and various case studies and scenarios were considered. The case studies were separated into three categories: without renewables and battery, with renewables and without battery, and with renewables and battery. The scenarios were divided into three categories for single houses and multi-household buildings: minimizing only the consumer's power costs, minimizing only the system's peak demand, and minimizing both the consumer's electricity and the system's peak demand. These scenarios were implemented separately for single houses and multiple houses. This author did not use a meta-heuristic optimization approach to solve their HEM problem.

This paper uses various meta-heuristic optimization techniques to implement the proposed load model. Bruno Canizes et al. [5] proposed a genetic algorithm-based load-shifting model in a 236-bus residential distribution network to maintain the voltage limit. Also, due to this voltage profile implementation, consumers' energy consumption costs are reduced considerably. The proposed model was implemented in 20 loads with a time interval of 15 minutes, which is 96 periods/day. As a result, system reliability and service quality were improved, network stress was reduced, and component life was extended. Alwyn Mathew et al. [6] proposed a deep reinforcement learning model for demand response on five residential consumers to reduce the consumer's electricity bill and the grid's peak load. The proposed model was implemented using a mixed integer linear programming method, and the results were compared both before and after DSM implementation.

In the future, the article will be extended to include selecting the preferred time for each appliance and identifying devices with power ratings as low as 0.1 kW. Milad Afzalan et al. [7] investigated a data-driven approach for applying load-shifting algorithms in deferrable loads like EVs, dryers, washing machines, dishwashers, and AC. This investigation was conducted with scenarios like the maximum potential of load shifting/shedding and user compliance modelling in Austin, TX, households. The electricity consumption in that household area was observed to be reduced to 160MWh, which is only 20% of household participation. Swati Sharda et al. [8] explored the practical challenges of implementing DSM for IoT-enabled HEMS due to its stochastic nature. They emphasised employing various optimisation strategies to address the multi-objective energy management problem. The different optimization strategies were thoroughly compared to various DSM techniques and load models, with only a few nature-inspired algorithms explored in the context of HEMS.

As a result, this article implements the three nature-inspired algorithms in HEMS. Subhasis Panda et al. [9] conducted a detailed review of Residential Demand-Side Management (RDSM) models, analysing different optimization techniques such as classical optimization, uncertainty-based optimization, evolutionary or meta-heuristic optimization, game theory, and soft-computing-based optimization. As a result, nature-inspired optimization techniques were seldom utilized in RDSM models, and the combination of load shifting and Time of Use (TOU) techniques was rarely explored. Further, none of the reviewed articles selected the objective function of simultaneously minimizing consumer electricity costs and utility peak loads. This article introduces three different optimization techniques applied to residential demand-side management.

These techniques aim to minimize consumer electricity costs and peak loads for utilities. The combined DSM techniques of load-shifting and time-of-use tariff are utilized to achieve these goals. The nature-inspired optimization approach, MBO, CSO, and AFSO, are implemented as a multi-objective problem. Finally, the results are compared, and the MBO optimization method showed the best among the other optimization techniques. This author reviewed peak energy management in various fields, including techniques, applications, and ancillary services. The author also discussed peak load reduction in low-voltage Microgrid systems to manage the voltage of the distribution system. This paper is divided into the following sections. Section 2 discusses the residential peak load management architecture and mathematical modelling. Section 3 describes the different nature-inspired optimization techniques like MBO, CSO and AFSO. The results and discussions are discussed with graphs in Section 4. Finally, Section 5 concludes the residential peak load management with future extensions.

## 2. Residential Peak Load Management Architecture and Modelling

The domestic distribution transformers become overloaded during peak hours due to the daily rise in the demand for electricity in residential homes. For this reason, peak load management is mandatory for all residential houses. The RPLM architecture and its mathematical modelling are described in detail in this section.

### *2.1. RPLM Architecture*

The proposed Residential Peak Load Management architecture is shown in Figure 1. The article divides residential loads into three categories based on their characteristics. These are Essential Running Appliances (ERAs), Time-Adjustable Appliances (TAAs) and Rechargeable Appliances (RCAs). ERAs are categorized as uncontrollable appliances in residential households, such as fans, lights, televisions, refrigerators and air conditioners. TAAs are controllable but uninterruptible appliances such as washing machines, dishwashers, water heaters, mixer grinders, electric kettles, iron boxes, vacuum cleaners, water pumps, water purifiers, and microwave ovens.

RCAs such as laptops, mobile phones, and battery banks have a maximum and minimum power limit. Consumers decide their daily energy requirements and preferred periods. Through power lines and communication media, Wi-Fi-enabled smart meters connect the utility grid to residential consumers. The centralized DSM controller sends instructions to the Wi-Fi smart meter about when and which to connect various household appliances.

The electric grid provides the hourly cost data to this DSM controller, which also receives information from residential customers about different home appliances and preferred times. Using various nature-inspired scheduling strategies, other home appliances are efficiently planned based on the data gathered. This optimal scheduling information is sent to the Wi-Fi-enabled smart meter to control multiple household appliances. The residential consumer's preferred load data is listed in Table 1.

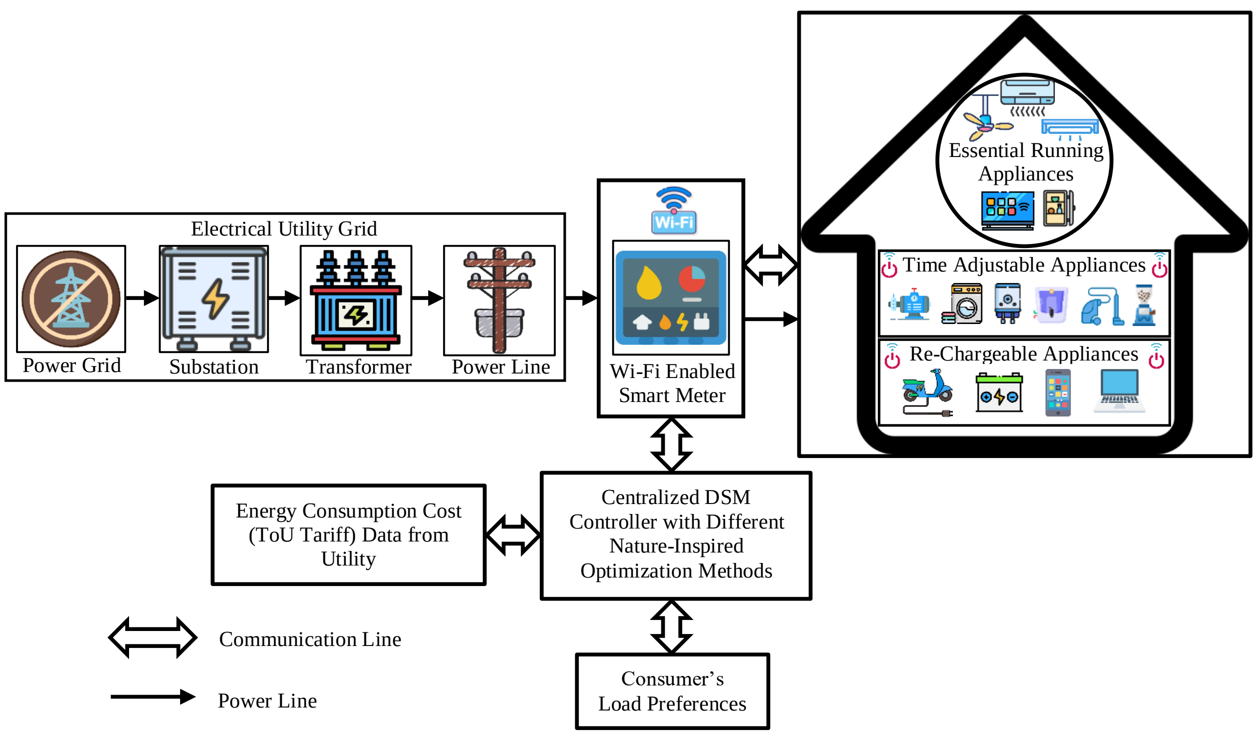


**Fig. 1 Architecture of residential peak load management**

**Table 1. Residential house load data**

| ERAS | Suggested Time Period | Running Time (hr) | Power Rating (kW) |
|---|---|---|---|
| Fan-1 | 5 pm to 10 pm | 6 | 0.072 |
| Fan-2 | 6 am to 8 am | 3 | 0.072 |
| Light-1 | 6 pm to 10 pm | 5 | 0.022 |
| Light-2 | 6 am to 7 am | 2 | 0.022 |
| Television (TV) | 8 pm to 10 pm | 3 | 0.135 |
| Refrigerator (RF) | 12 am to 12 pm | 24 | 0.107 |
| Air Conditioner (AC) | 10 pm to 6 am | 9 | 1.8 |
| **TAAs** | **Suggested Time Period** | **Running Time (hr)** | **Power Rating (kW)** |
| Heater | 11 am to 2 pm | 0.25 | 3 |
| Washing Machine (WM) | 10 am to 2 pm | 1 | 0.5 |
| Water Pump (WP) | 10 am to 4 pm | 2 | 0.75 |
| RO Water Purifier | 11 am to 3 pm | 0.5 | 0.04 |
| Vacuum Cleaner (VC) | 10 am to 4 pm | 1 | 1.4 |
| Grinding Machine (GM) - Mixer | 10 am to 4 pm | 0.1 | 0.75 |
| **RCAs** | **Suggested Time Period** | **Everyday Energy Requirement** | **Power Limit (kW)** |
| Computing Devices (CD) - Laptop | 6 pm to 10 pm | 1.0 kWhr | 0.1 – 0.3 |
| Renewable Battery Bank (RBB) | 12 am to 5 am | 1.8 kWhr | 0.2 – 0.4 |
| Electric Bike (EV) - Hero Nyx E5 | 8 pm to 6 am | 1.344 kWhr | 0.1 – 0.35 |

### *2.2. Mathematical Modelling of RPLM*

This paper develops a multi-objective RPLM problem with nature-inspired optimization to minimize utility peak load and customer electricity cost. The following are the objective functions and constraints [10].

#### *2.2.1. Objective Function*

The objective function Equation (1) describes the minimization of utility peak demand, and Equation (2) indicates the minimization of consumers' electricity bills. These two objective functions are combined through a weighted sum approach in the Equation (15).

- Minimization of utility peak load demand

$$Min\, F_1 = Max(L^1, L^2, \ldots, L^t, \ldots L^T);\ \forall\ t \in T \quad (1)$$

- Minimization of consumers' electricity bill

$$Min\, F_2 = \sum_{t=1}^{T} C(t) \quad (2)$$

$$C(t) = \tau . L^t . \rho(t) \quad (3)$$

$$L^t = L_D^t \quad \forall\ t \in T \quad (4)$$

$$L_D^t = \sum_{a=1}^{N} \left[L_{era,a}^t + L_{taa,a}^t + L_{rca,a}^t\right];\ \forall\ t \in T \quad (5)$$

$$L_D = [L^1, L^2, \ldots, L^T]; \quad (6)$$

#### *2.2.2. Constraints*

The scheduling of the total load demand constraint is indicated in Equation (7), and Equation (8) explains the equality constraint of the total energy required per day of each appliance. Equations (9) and (10) give the power demand of essential running and time-adjustable appliances at each time period, respectively. The power limit of rechargeable appliances is illustrated in Equation (13), and Equation (14) represents the minimum load demand inequality constraint at each time period.

- Total load demand at time t,

$$L_D^t = \sum_{a=1}^{N} \left[L_{era,a}^t + L_{taa,a}^t + L_{rca,a}^t\right];\ \forall\ t \in T \quad (7)$$

- Total energy required per day of appliance a,

$$\sum_{t=1}^{T} L_a^t = DR_a;\ \forall\ a \in N \quad (8)$$

- Power demand of essential running appliances at time t,

$$L_a^t = P_{rat,a};\ \forall\ a \in ERAs,\ \ \forall\ t \in [t_a^s, \ldots, t_a^e] \quad (9)$$

- Power demand of time adjustable appliances at time t,

$$L_a^t = U_{a,taa} * P_{rat,a};\ \forall\ a \in TAAs \quad (10)$$

Where,

Status of time adjustable appliance a,

$$U_{a,taa} = [u_a^1, u_a^2, \ldots, u_a^T]; \tag{11}$$

Constraint for status of appliance a at time t,

$$u_a^t \in \{0,1\}; \forall\, t \in T \tag{12}$$

- Power limit constraint for rechargeable appliance a,

$$P_{a,t}^{min} \leq L_a^t \leq P_{a,t}^{max}; \forall\, t \in [t_a^s, \ldots, t_a^e]; \forall\, a \in RCAs \tag{13}$$

- Hourly power demand constraint,

$$L_D^t \geq 0 \tag{14}$$

- The multi-objective function is finally combined using the weighted sum method, which is given below,

$$\text{Min } F = w_1 \times F_1 + w_2 \times F_2 \tag{15}$$

Where,

$w_1$ and $w_2$ are the weighting factors of the utility's peak demand and consumer's electricity cost, here, $w_1$ and $w_2$ are chosen as 0.6 and 0.4, respectively.

## 3. Optimization Methodologies

The following section discusses some of the nature-inspired optimization methodologies used in this article. The nature-inspired optimization techniques are classified into Ant Colony Optimization (ACO), Simulated Annealing (SA), Differential Evolution (DE), Particle Swarm Optimization (PSO), Biogeography-Based Optimization, Cultural Algorithms etc. Three different nature-inspired optimization techniques are described, which are not implemented in RPLM problems such as MBO, CSO, and AFSO.

### *3.1. Monarch Butterfly Optimization*

The MBO algorithm's technique is based on the behavior of Monarch butterflies. The approach is built to be straightforward, obtaining butterfly position updates through migration and adjustment operators rather than more complicated computations and operators. As a result, the reactions will be noticeably quicker.

The total number of monarch butterflies is considered as a population (NP) where these populations are divided into two subpopulations (Land-1(NP1=p*NP) and Land-2(NP2=NP-NP1)) based on migration period. Migration and butterfly adjusting operators are used to update the revised positions of subpopulations in Land-1 and Land-2. The movement of individual i in subpopulation1 (Land-1) on the kth dimension can be expressed mathematically as follows [11]:

$$x_{i,k}^{t+1} = \begin{cases} x_{r1,k}^t, & if\ r \leq p \\ x_{r2,k}^t, & else \end{cases} \tag{16}$$

Where,

$x_{i,k}^{t+1}$ – kth dimension of $x_i$ at generation t+1
r1, r2 – Integer index randomly selected in subpopulation-1 and 2
p – Adjusting ratio
r – rand * peri

Where,

rand – [0, 1] – Random number between 0 & 1
peri – Migration period

In subpopulation 2, the new individual is generated as follows:

$$x_{i,k}^{t+1} = \begin{cases} x_{best,k}^t & if\ rand \leq p \\ x_{r3,k}^t & if\ rand > p\ \&\ rand \leq BAR \\ x_{i,k}^{t+1} + \alpha * (dx_k - 0.5) & if\ rand > p\ \&\ rand > BAR \end{cases} \tag{17}$$

Where,

$x_{best,k}^t$ – kth component of generation 't's current global optimum
r3 – Randomly generated integer from subpopulation -2
BAR – Butterfly Adjusting Rate
α & dx – Weighting factor
Smax – Max walk a step
dx = Levy ($x_j^k$)
$\alpha = S_{max} / t^2$

In the Monarch Butterfly Optimization (MBO) algorithm, the best fitness value for the monarch population is updated by comparing the parent's previous fitness value with the child's new fitness value. If the child's fitness value improves, it replaces the last best fitness value. This essential step ensures the algorithm maintains the most effective solutions discovered during optimization. Furthermore, MBO utilizes a method to consolidate the best fitness values from different subpopulations within the algorithm. These values are recombined to create an integrated and refined fitness measure, offering a comprehensive understanding of the fitness landscape.

This strategy enhances the algorithm's ability to converge toward optimal solutions by leveraging the collective knowledge of various subpopulations. Sukhwinder Singh Dhillon et al. [12] applied Monarch Butterfly Optimization to address frequency deviations in a three-area power system with mixed-generation sources, yielding positive outcomes. Pushpendra Singh et al. [13] utilized Monarch Butterfly Optimization to optimize the integration of distributed energy resources, resulting in significant performance enhancements. Vivek Yadav et al. [14] harnessed the Monarch Butterfly Optimization algorithm to enhance the optimal power flow in IEEE standard test power systems, surpassing other methods regarding fuel expenses, voltage deviation, and power loss. Given the remarkable performance of the Monarch Butterfly Optimization algorithm in diverse power system applications, it was chosen for implementation in residential peak load management, marking a novel and promising approach that has not been previously applied to this crucial challenge.

### *3.2. Crow Search Optimization*

The swarm intelligence system was developed and used on Crow Search Optimisation (CSO) based on crow food-hiding behaviour. The population's fitness is assessed and stored, and the crow's position is updated if the awareness probability exceeds the random value; otherwise, it moves to a random position. The step-by-step process of the crow search optimization algorithm is described below [15]:

**Step 1:** Initialize the Problem and Parameters: Set up the optimization problem and initialize critical parameters such as flight length, flock size, awareness probability, and maximum number of iterations.

**Step 2:** Initialize the Crow Positions and Memory: Start by creating a population of N crows and place them randomly in a d-dimensional space, representing their positions with an N x d matrix. Simultaneously, initialize the memory of each crow, which includes essential information about the environment and past experiences to aid in decision-making during optimization.

**Step 3:** Fitness Evaluation: For each crow's existing position, determine the fitness value by assessing the objective function. This fitness value quantifies the solution's quality based on the problem's defined criteria.

**Step 4:** Follow and Discover: Each crow selects another crow randomly from the flock and follows it to explore new positions by learning from its discoveries. All crows in the population repeat this pattern, searching for better positions within the search space collectively.

**Step 5:** Examine Feasibility: Verify the feasibility of each crow's newly generated position. The crow adjusts its existing position if it decides that the new position is feasible. If the new position is impossible, the crow retains its current location and refrains from moving to the generated place.

**Step 6:** Compute New Fitness: Determine the fitness value for each newly created crow position.

**Step 7:** Memory Updating: Compare the fitness value of the new position for each crow with the value previously stored in memory. If the new situation improves, update the memory; otherwise, retain the same position.

**Step 8:** Termination Criterion: Repeat Steps 4–7 until the maximum iteration is reached. When the termination criterion is met, report the best position stored in memory, corresponding to the optimisation problem's solution based on the objective function value.

Oscar Danilo Montoya et al. [16] effectively estimated photovoltaic module parameters using the Crow Search Algorithm (CSA) with manufacturer data, demonstrating efficient and robust results. Surender Reddy Salkuti [17] proposed the CSA to optimize reactive power dispatch, improving power losses and voltage stability.

Teena Johnson et al. [18] compared CSA to traditional methods like Binary Integer Linear Programming (BILP) and Particle Swarm Optimization (PSO) for PMU placement, with CSA providing multiple optimal solutions. Murilo E. C. Bento et al. [19] introduced a CSA-based approach for calculating load margins considering small-signal and voltage stability. Notably, CSA has been successfully applied in various applications, but it is being implemented for the first time in Residential Peak Load Management Problems in this article.

### *3.3. Artificial Fish Swarm Optimization*

The AFSO algorithm, a very effective optimization tool in swarm intelligence, was inspired by fish movement and social behaviours. The benefits of this method included faster convergence, fault tolerance, high accuracy, and flexibility. The flowchart of the AFSO algorithm is shown in Figure 2. Surender Reddy Salkuti [20] utilized the global search capabilities of the Artificial Fish Swarm Optimization Algorithm (AFSOA) to tackle the power system state estimation problem.

The algorithm's performance was demonstrated on a six-bus test system, showcasing its effectiveness compared to existing approaches. CH. Hariprasad et al. [21] introduced the application of the Ant Colony Optimization Technique (ACOT) and Artificial Fish Swarm Optimization Technique (AFSOT) for optimizing the allocation of Distributed Generation (DG) sources in IEEE 14 and 33 bus distribution systems.

Additionally, K. Prakash Kumar et al. [22] proposed day-ahead generating unit scheduling, jointly considering battery and renewable energy sources within a microgrid system using Artificial Fish Swarm intelligence techniques. Notably, the Artificial Fish Swarm Algorithm is not typically employed in residential peak load management problems, but the author introduces this algorithm's application in this article.

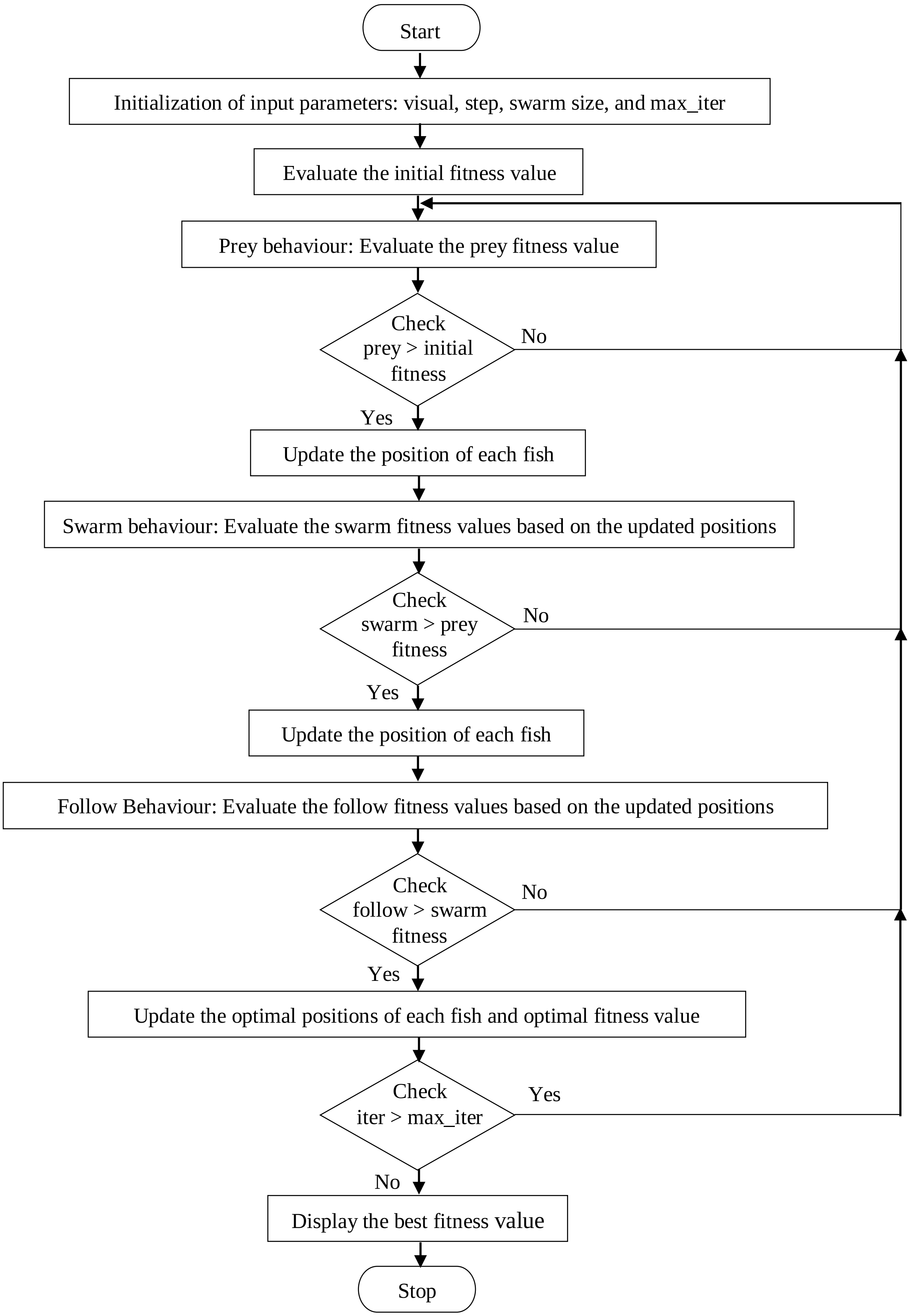


**Fig. 2 Flow chart of artificial fish swarm optimization algorithm**

## 4. Results and Discussion

This session explores the validation of the proposed RPLM model using single and multi-objective functions. The objective functions are minimizing the consumer's electricity cost and the utility's peak load. There are three cases in this RPLM model that evaluate single objective functions individually.

### *4.1. Single-Objective Approach*

Minimizing costs and peak demand separately. In this case, the single objective function is considered as a minimization of the consumer's electricity cost in the RPLM model. Figure 3 shows the consumer's electricity cost and the maximum peak demand consumption for a residential house. In that graph, the consumer's electricity consumption cost in the MBO method is around $ 8.285, lower than other nature-inspired optimization techniques.

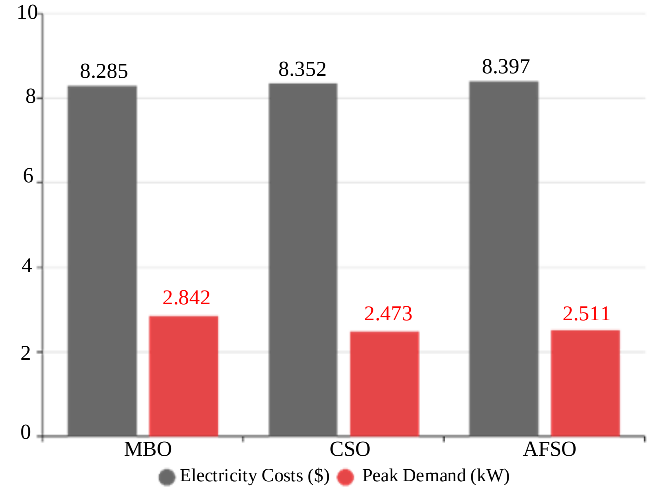


**Fig. 3 Electricity Cost and Maximum Peak Demand for Cost Minimization**

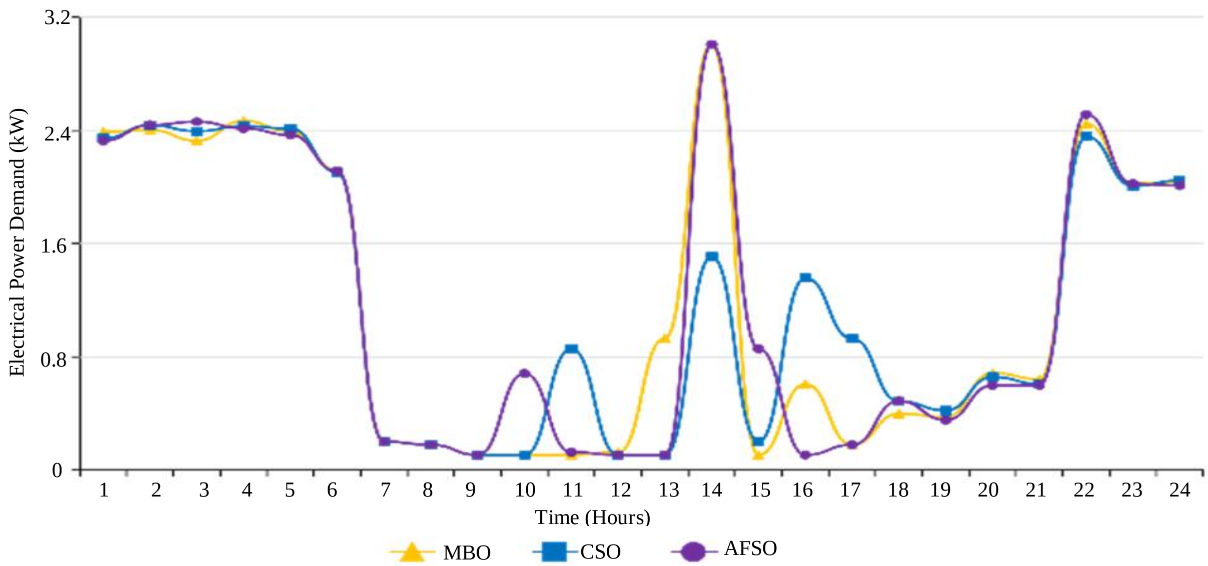


**Fig. 4 Daily load curve for cost minimization**

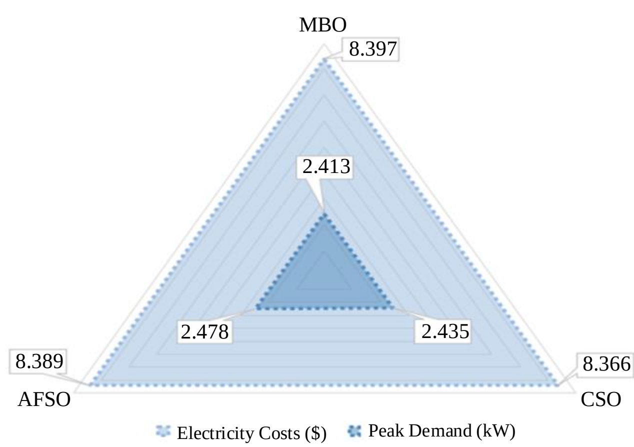


**Fig. 5 Electricity cost and maximum peak demand for load minimization**

In this case, the maximum peak demand for residential houses increases when the MBO method is used. This is because the maximum load is occupied during low electricity cost periods. The average of the fifty best results is calculated by repeating this nature-inspired optimization technique many times. Based on these average values, a graph comparing electricity costs and peak demand between nature-inspired optimization techniques is drawn. Figure 4 shows a typical daily load curve based on different nature-inspired optimization techniques for residential buildings. Furthermore, maximum peak demand minimization is considered a single objective function. A radar chart is shown in Figure 5 to show the electricity cost and maximum power demand values for the various nature-inspired optimization techniques. The daily maximum peak demand of the MBO method is 2.413 kW. It is less than other traditional nature-inspired optimization methods. The daily load curve for minimizing maximum power demand is shown in Figure 6.

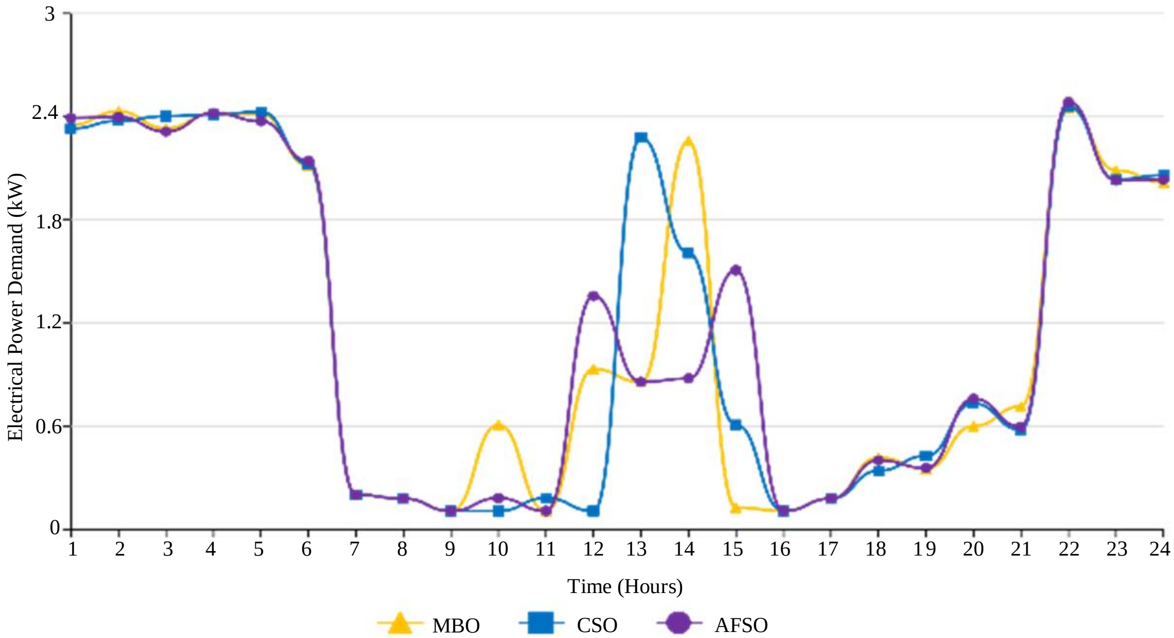


**Fig. 6 Daily load curve for load minimization**

### *4.2. Multi-Objective Approach*

Minimizing costs and peak demand together. This session considers the minimization of consumer's electricity cost and minimization of maximum power demand as multi-objective functions. Figure 7 shows the bubble charts of fitness values obtained from the best ten iterations using various nature-inspired optimization techniques. A comparison of the MBO results with other nature-inspired optimization methods shows that MBO results are less in both maximum peak demand and consumer electricity costs. In the bubble charts populated by the Pareto front, most of the fitness values are MBO values. In the peak period, the MBO method reduces peak load by at least 4.5%. Figure 8 illustrates a sample daily load curve for a multi-objective function where the AFSO algorithm achieves maximum peak loads.

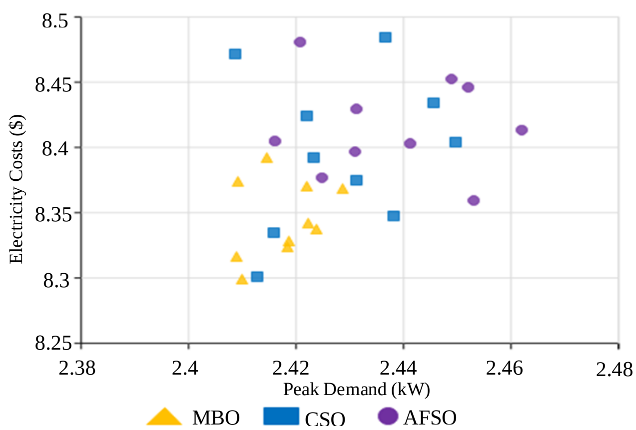


**Fig. 7 Comparison of electricity cost and maximum peak demand in multi-objective optimization**

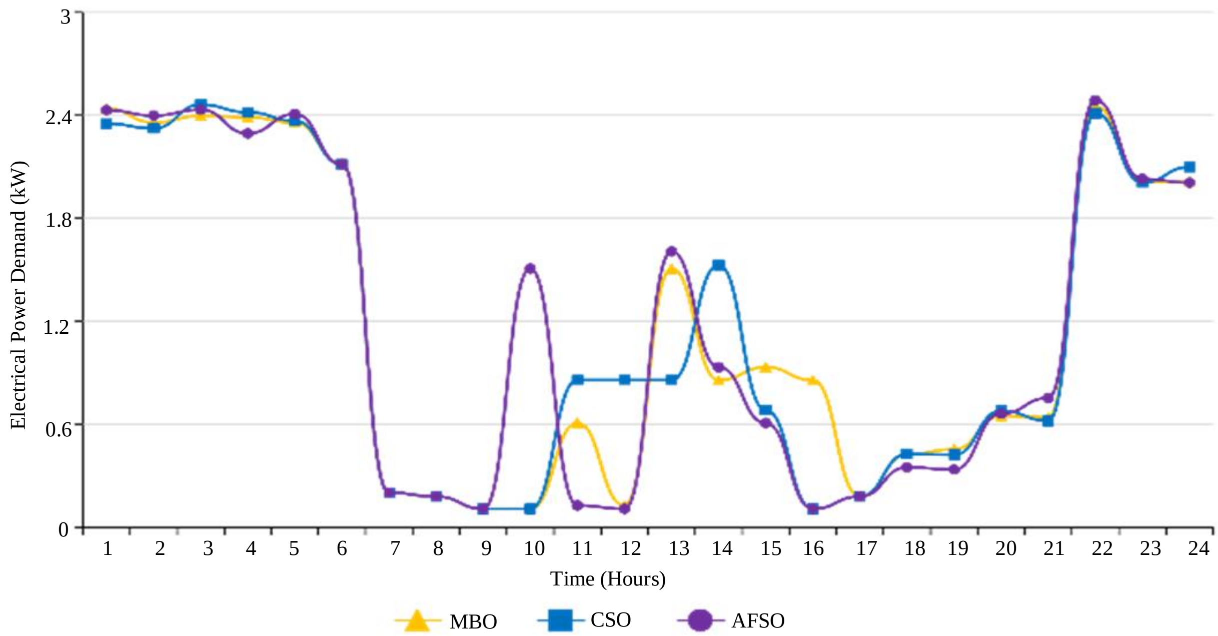


**Fig. 8 Daily load curve for multi-objective optimization**

## 5. Conclusion

The results of this study indicate that the Monarch Butterfly Optimization (MBO) method is highly effective in implementing Residential Peak Load Management (RPLM) in residential households. The MBO method reduces consumer electricity costs, and utility peak demand more efficiently than other nature-inspired optimization techniques such as CSO and AFSO. According to this study, the MBO method and demand-side management strategies such as load shifting and time-of-use pricing effectively reduce electricity costs and peak electricity consumption in residential households.

The MBO nature-inspired optimization technique effectively reduces peak loads by 4.5% during peak times while considering multiple objectives. The MBO method will be integrated with the CSO method to create a hybrid nature-inspired optimization technique for implementing RPLM solutions. Because the MBO and CSO methods consistently provide the best results compared to the AFSO method.

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