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Multi-Objective Residential Load Scheduling Approach Based Pelican Optimization Algorithm with Multi-Criteria Decision Making

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Abstract

The existing energy grid faces challenges in meeting the escalating energy demands driven by annual population growth and the proliferation of energy-consuming devices in the contemporary era. This research proposes an optimum multi-objective pelican optimization method for smart grid load control. The proposed algorithm effectively explores diverse solutions by minimizing customer energy costs and reducing peak loads for utility companies, identifying a Pareto front that represents optimal trade-offs among the three objectives: energy cost minimization, peak load reduction, and a third objective (user inconvenience). An ELimination ET Choix Traduisant la REalite (ELECTRE) method then rigorously ranks the Pareto-optimal solutions, guiding the selection of the most advantageous alternative that harmonizes the competing objectives. Energy bills are reduced by more than 42.66% using the proposed method. Additionally, the reduction in peak energy consumption by 20.66% has benefited the power suppliers for a sampling time of (30 minutes). When applied (60 minutes) sampling time, energy bills are reduced to 40.74 % and peak load to 30% with acceptable levels of inconvenience. Furthermore, the proposed load management provides 42.66 % and 20.66% cost and peak savings compared to other work in the state of the arts.

Keywords: Demand response; Multi-objectives optimization; Multi-Criteria Decision Making Optimization Algorithm; Smart grid

1. Introduction

The residential sector consumes over 45% of global energy, yet millions of dollars are squandered due to carelessness and ineffective management [1]. The management of energy consumption is a topic that needs significant attention. Considering the increasing number of smart devices made available by a wide range of consumers in the residential and commercial sectors [2]. Most current power grids are outdated and inefficient; therefore, needed to be transformed into smart grids. An electric power grid integrated with a communication network system that operates in both directions is referred to as a smart grid [3],[4]. The smart grid is a concept that aims to improve the efficiency of power use from the point of production to the point of end-user, effectively all generations, and to enable customers to participate in demand-side management programs (DSM) [5]. Smart grid software and hardware allow utilities to rapidly detect and resolve problems between consumers and energy producers that might compromise power supply consistency and quality [6],[7]. Demand response (DR) is an important technology that helps smart grids achieve a balance between supply and demand. Information exchange between electrical grids and power consumers may boost generating facility energy efficiency and lower power usage [8]. DSM is a key smart grid domain. It helps energy suppliers lower demand during peak hours and restructures the load profile, improving smart grid sustainability, energy costs, and carbon emissions [9]. DR programs are classified into two types: price-based and incentive-based. Price-based programs encourage users to adjust their consumption to changing power rates. On the other hand, incentives-based programs seek to decrease customers' energy usage by offering fixed or variable incentives that consider periods of high stress on the power system [10],[11].

Scheduling and controlling household loads have been investigated using various methods within the past ten years. Ge et al. [12] focused on transactive control systems that allow buildings to take part in demand response for electricity. Experimental research on campus buildings found it possible to maintain the highest building energy revenue level while significantly minimizing peak demand. Yousaf et al. [13] have proposed an improved residential electricity load forecasting model using a machine-learning-based feature selection approach and a proposed integration strategy. The proposed model has three main stages: feature selection and a binary genetic algorithm (BGA). A feedforward adaptive-network-based fuzzy inference system (ANFIS) forecasts the residential electricity load. The forecasts from multiple ANFIS models are integrated using a proposed decision integration strategy. The total improvement calculated for ten buildings is 17%. Nazemi et al. [14] have used a nonlinear optimization model to solve load scheduling challenges within a community of smart buildings. The three main objectives are to minimize total energy costs, maximize the benefits given to each customer, and minimize inconvenience. The proposed approach is assessed through two case studies involving a residential and a commercial building community. Results illustrate reduced total energy costs while improving participant satisfaction, and peak demand was reduced by 53%. Veras et al. [15] proposed a multiple-objective nonlinear programming problem to find the most efficient schedule for home appliances within a specific period. It considers limitations and is solved using the Non-Dominated Sorted Genetic Algorithm (NSGA-II). The stated results saved around 8.65% on electricity costs.

Yahia and Pradhan [16] proposed a Mixed Integer Linear Programming (MILP) approach to address a multiple-objective deterministic optimization problem involving several households. The weighted sum and compromise methods helped to achieve a desirable solution. According to the findings, coordinated over-aggregated methods are more successful than aggregated approaches to reducing peak load. Compared to an aggregated method, the coordinated method's simulation findings demonstrated a 10%–30% reduction in peak energy consumption. Ayub et al. [17] have proposed an optimal home appliance scheduling strategy to provide the highest level of satisfaction while minimizing energy costs. The multi-objective grey wolf accretive satisfaction algorithm (MGWASA) generates trade-off solutions for optimal load patterns based on the cost per unit satisfaction index and percentage satisfaction. The TOU price pattern is used during the scheduling period. The appropriate scheduling of home loads resulted in a 44% decrease in annual energy costs. Rahman et al. [18] have presented a demand-side residential load management system that optimizes energy consumption and reduces peak loads in the smart grid. Both deferred and curtailable appliances are thought to be highly responsive to real-time price changes. The results show significantly reduced peak loads and energy costs for customers. Specifically, the system reduced peak loads by 38.80% and minimized total energy costs by 22.55% for customers.

A price-driven DR was proposed by Niu et al. [19] for use in a distributed electrical energy system. Each flexibility measure responds effectively to time-of-use pricing. According to the results, it can decrease between 1.7% and 12.9% of the system's operating costs. Ahmed et al. [20] have utilized two types of optimization methods, namely, particle swarm optimization (PSO) and strawberry optimization algorithm (SBY), to solve the DR problem for different loads (residential, commercial, and industrial). Time-of-use (TOU) and real-time pricing (RTP) can reduce cost and peak load. The results of the distributed RTP algorithm and the centralized RTP algorithm showed that the centralized algorithm provided better cost reduction. The findings of utilizing the SBY optimization algorithm in centralized RTP resulted in cost reductions of 14.80%, 21.7%, and 21.84% for industrial, commercial, and residential, surpassing the performance of the PSO method. The SBY optimization algorithm demonstrated superior cost reduction. Wang et al. [21] have used a better chicken swarm optimization algorithm for the interruptible load scheduling model to lower the system's peak load and operating costs, taking into account the user subsidy rate. Interrupt load scheduling management can meet the load scheduling needs to reduce the peak load on the grid and save costs by 1.74%. Results show that this approach outperforms previous swarm intelligence algorithms for running speed, accuracy, and optimal fitness.

Jasim et al. [22] have used two types of optimization methods, namely, Earth Worm Optimization Algorithm (EWOA) and Virulence Optimization Algorithm (VOA). The system utilizes Renewable electricity Resources (RERs), Renewable Energy Sources (RES), and electricity from the utility grid to power the load appliances. A time-of-use (TOU) dynamic pricing scheme has determined users' power bills. The performance of the selected optimization techniques is compared to well-known meta-heuristics and evolutionary algorithms (genetic algorithm GA, cuckoo search optimization CSO, and binary particle swarm optimization BPSO). The outcomes demonstrate that VOA performs better than the other algorithms without RES and provides a 59% reduction in energy use's peak-to-average ratio (PAR). By including RES, the EWOA and the VOA provide less variance and a lower PAR. VOA saves 76.19% of PAR, whereas EWOA saves 73.8%. Muhsen et al. [23] introduced a novel differential evolution method for multi-objective optimization to provide optimal solutions by reducing a load's cost and peak demand. A multi-criteria decision-making approach was utilized to arrange the optimal solutions in descending order to allow consumers to choose the most suitable time for their schedule. The final results from the proposed approach illustrate cost and energy reductions of approximately 46% and 47%, respectively.

The aforementioned reviews indicate that most research has focused on combining demand-side and supply-side advantages. The main weaknesses of these older approaches' gaps are: First, commercial software was used to solve the majority of multi-objective models. Multiple objectives are often combined into a single objective using an aggregated weighted sum. Finally, multi-criteria decision-making is rarely utilized to sort all alternatives.

Based on the mentioned research gaps for the current works of state of arts for load management for residential customers, the contributions of this paper are as follows:

1. This research delves into the effective management of residential energy consumption within smart grids,

offering substantial advantages for utilities and consumers. The focus on reducing peak loads during high-demand periods not only diminishes the requirement for costly peak-hour generation infrastructure but also decreases consumer electricity expenses. Furthermore, optimized appliance scheduling minimizes inconvenience, creating a mutually beneficial scenario that aligns with the goals of a more sustainable and efficient energy future.

2. The Pelican optimization algorithm (POA) is a novel and interesting method compared to previous algorithms like GA, DE, and PSO. POA is a population-based algorithm that can prevent being caught in local optima. It works well for problems such as financial optimization, scheduling, and engineering design.
3. Dominance Count Method: Incorporating dominance count in this research fosters a more efficient and targeted approach to identifying solutions that effectively balance multi-objective peak load reduction and cost minimization in residential load management.
4. Assigning Weights: CRITIC assigns weights to each objective, reflecting their relative importance in decision-making.
5. MCDM: the compromise alternatives are rated using a multi-criteria decision-making method that integrates both objectives and employs the ELECTRE method to choose the optimal solution considering pre-determined priorities.
6. Time-of-Use (ToU) is a dynamic pricing model that applies varying electricity rates depending on the time of day. This system analyzes and compares the effectiveness of different pricing approaches.

2. Problem formulation

Cost, peak load, and customer inconvenience are the primary objectives of this paper. Every customer uses a variety of appliances connected to the power grid. A smart meter connected to a central utility is installed in every residence. The smart meter sends all relevant data about customer usage to the central scheduler via a Neighborhood Area Network (NAN), operating within a Home Area Network (HAN) framework. Household appliances are connected to smart meters and managed within a home network using Internet of Things (IoT) technology. This paper aims to optimize household appliance scheduling to minimize energy costs for users while simultaneously reducing peak load on the power grid. However, shifting appliance usage to off-peak hours can inconvenience users.

The following subsections utilize objective mathematical formulas to improve the system.

2.1 Energy cost

The utility supplies the price of power (electricity) $\mathrm{Pr}_{\mathrm{ts}}$ for each ts = [1, 2., T], time slot. End-user appliances can have optimal load control by reducing energy bills and using less power at peak hours. The formula below is used to determine energy cost (ENC) [24]:

$$ENC = \sum_{a=1}^{A_a} \sum_{ts=1}^{T} Pr_{ts}\, P_a\, NF^{o}{}_{a,ts} * \Delta t \qquad (1)$$

Whereas $\mathrm{A_a}$ refers to the total count of household appliances (loads), a is the value of each item, and $\mathrm{P_a}$ is the power consumption value in (Kw). $\mathrm{NF^o}_{\mathrm{a,ts}}$ represents the best ON/OFF status for $\mathrm{a^{th}}$ appliance at $\mathrm{ts^{th}}$ (time slot). Δts represents sampling time.

2.2 Peak load

Reducing peak demand saves money for both the utility company and its customers. The peak energy demand has to be:

$$PL = \sum_{a=1}^{A_a} P_a\, NF^{o}{}_{a,ts} \quad ; \forall\, ts \in [1, T] \qquad (2)$$

PL indicates how much electricity is utilized during a specific time.

2.3 Customer's inconvenience

The consumer desires to reduce the cost of their energy bill without changing their preferences. Any deviation from the usual consumption pattern of the consumer will result in inconvenience for the customer. The customer's inconvenience may be expressed as follows:

$$INCON = \sum_{a=1}^{A_a} \sum_{ts=1}^{T} |NF^{o}{}_{a,ts} - NF^{b}{}_{a,ts}| \quad (3)$$

Where $\mathrm{NF^b}_{\mathrm{a,ts}}$ and $\mathrm{NF^o}_{\mathrm{a,ts}}$ are the state of $\mathrm{a^{th}}$ appliance at $\mathrm{ts^{th}}$ time slot for baseline (preferred scheduling from customer) and optimal scheduled, respectively.

3. Theoretical Background

To manage the objective function properly, the optimization method known as POA should be applied. This method allows for the best load scheduling solution while lowering peak load, customer inconvenience, and cost.

3.1 Pelican Optimization Algorithm (POA)

Pelicans often work together as a group, actively participating in cooperative hunting strategies [25]. Based on pelicans' natural behavioral patterns, the POA consists of exploitation and exploration phases to find the most optimal solution. The mathematical model of the Pelican Optimization Algorithm (POA) has two phases: an exploration phase where pelicans move towards prey and an exploitation phase where they skim the water's surface [26].

3.1.1 Initialization

The POA is a population-based method that considers all members of the pelican population as a potential solution. An initial population POP comprised of np solutions is created at the start of the optimization process. The search area of each vector in the set includes DV decision variables that are evenly distributed. The range of possible solutions is defined by its minimum (lower) and maximum (upper) limits, expressed as Xl and Xh. The process begins by generating the initial solution as follows:

$$X^{G}{}_{J,I} = Xl_{J,I} + rand * \left(Xh_{J,I} - Xl_{J,I}\right) \quad (4)$$

Where $rand$ represents a random number between 0 and 1 while G ranging from 1 to Gmax, represents the current generation.

Whereas the index I relates to the solutions I = [1, 2,3, ..….np]. The vector variables are indexed as J = [1, 2, DV].

3.1.2 Advancing towards Food Source (Exploration Phase)

The pelican identifies its target during this stage and swiftly dives to capture it. The random distribution of prey enhances the pelican's search capabilities. Equation (5) models the pelican's position and how it changes with each iteration.

$$X_{J,I}^{P1} = \begin{cases} X_{J,I} + rand \cdot \left(P_J - Ip \cdot X_{R,J}\right) & F_P < F_I \\ X_{J,I} + rand \cdot \left(X_{J,I} - P_J\right) & else \end{cases} \quad (5)$$

Here, $X_{J,I}^{P1}$ Here, IP1 denotes the updated position of the I^{th} pelican in the J^{th} dimension, calculated during the first phase. P_J represents the prey's location in the J^{th} dimension, and F_P is the function's value. The Ip Parameter's value is randomly selected 1 or 2.

In the proposed POA (Pelican Optimization Algorithm), a pelican's new position is accepted only if the objective function's value improves at that location. This type of updating, known as effective updating, keeps the algorithm from moving to less-than-ideal areas.

$$X_I = \begin{cases} X_I^{P1}, & F_I^{P1} < F_I \\ X_I & else \end{cases} \quad (6)$$

Variable X_I^{P1} represents the updated status of the I^{th} pelican, whereas F_I^{P1} denotes the value of the desired function obtained from step one.

3.1.3 Winging on the water surface (exploitation phase)

In the exploitation phase, pelicans glide across the water's surface, utilizing their wings to guide fish toward shallower regions, making them more accessible for catch. Equation (7) is a possible mathematical representation of this behavior:

$$X_{J,I}^{P2} = X_{J,I} + R \cdot \left(1 - \frac{G}{Gmax}\right) \cdot (2 * rand - 1) \cdot X_{J,I} \quad (7)$$

Where $X_{J,I}^{P2}$ represents the updated status of the I^{th} pelican in the J^{th} dimension, considering phase two. Gmax is the maximum number of iterations, while R is a constant with a value of 0.2.

Equation (8) implements an effective update mechanism to determine whether the new pelican position should be accepted or rejected.

$$X_I = \begin{cases} X_I^{P2} & F_I^{P2} < F_I \\ X_I & else \end{cases} \quad (8)$$

In this context, X_I^{P2} represents the pelican's updated position, while F_I^{P2} represents the corresponding objective function value calculated during the second phase.

Algorithm 1: Pseudo-code for the Pelican Optimization Algorithm (POA)

1. Input information related to the optimization problem.
2. Initialize the positions of pelicans and compute the objective function.
3. For each iteration (G) from 1 to $\mathbf{G_{max}}$:
4.
5. Randomly generate the position of the prey.
6. Calculate the new status of the $\mathbf{J^{th}}$ dimension using Equation (5).
7. End the exploration phase.
8. Update the $\mathbf{I^{th}}$ population member using Equation (6).
9. Phase 2: Glide on the water surface (exploitation phase).
10. For each dimension (J) in the solution space**.**
11. Calculate the updated state of the $\mathbf{J^{th}}$ dimension using the specified equation (7).
12. End the exploitation phase.
13. Update the $\mathbf{I^{th}}$ population member by applying Equation (8).
14. End.
15. Update the best candidate solution.
16. End iteration.
17. Provide the optimal solution obtained through POA.

3.2 An Introduction to Dominance-Based Methods

In a multi-objective optimization problem (MOOP), multiple objective functions must be minimized or maximized simultaneously. As in a single-objective optimization problem, all feasible solutions, including all optimum solutions, must meet a set of constraints [27].

The existence of multiple objectives in a problem results in Pareto-optimal solutions, which cannot be definitively ranked as better or worse than one another without further context. To handle this, dominance-based ranking methods—such as dominance rank, dominance depth, and dominance count—are frequently employed. This research uses dominance count to evaluate and compare solutions in each generation by analyzing their dominance relationships. In multi-objective optimization problems (MOOP), dominance count measures the effectiveness of a solution by determining how many alternative solutions are inferior to it across all objectives [28].

For example, as seen in Fig. 1, solution A seems to dominate solution B if it outperforms B in every criterion without being inferior. Numerous alternative solutions in the population are inferior to those with a high dominance count.

3.3 The Criteria importance through inter-criteria method (CRITIC)

This CRITIC method was first introduced by Diakoulaki et al. (1995), as cited by Mohamadghasemi [29]. The decision-making process in this method does not include any weights represented by decision-makers preferences. This method's weight is called the objective weight. It is based on the intensity with which one criterion contrasts with the others and how conflicts between criteria are measured using standard deviation and correlation coefficient, respectively [29].

Let DM= $[Y_{ij}]_{m\,x\,n}$ be the decision matrix that is clear and concise for an MCDM in which there are M various alternatives A_i(i= 1, …, M) in terms of N criteria C_j(j= 1, …, N) and y_{ij} stands for the evaluation scale for alternative i about criterion j. The representation of the DM is as follows:

$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{bmatrix} \tag{9}$$

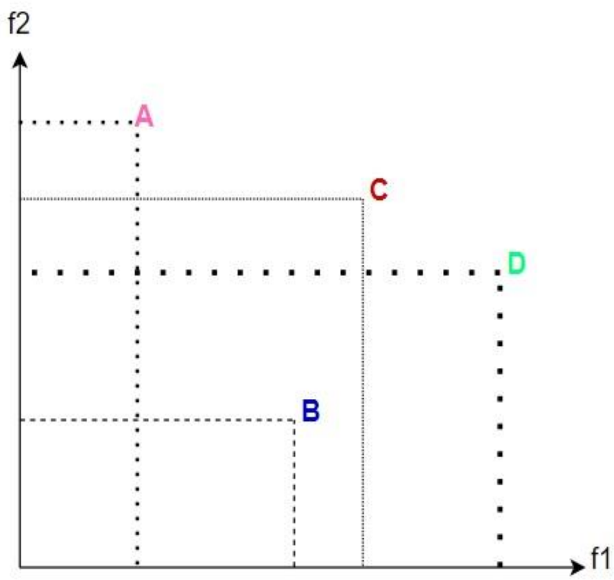

Figure 1. Number of bi-objective space solutions

The objective weights determined by the CRITIC method are shown in the following steps:

1. Normalized a decision matrix $y_{i,j}$ used to evaluate i^{th} alternative in relation to j^{th} criteria using equations (10) and (11).

$$P_{i,j} = \frac{y_{i,j} - y_j^{min}}{y_j^{max} - y_j^{min}} \qquad i = 1,.., m\,;$$

j=1,..,n for benefit criteria (10)

$$P_{i,j} = \frac{y_j^{max} - y_{i,j}}{y_j^{max} - y_j^{min}} \qquad i = 1,..., m\,;$$

j = 1,..., n for cost criteria (11)

2. Calculate the standard deviation σ_j for the j^{th} criterion's vector.

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(P_{i,j} - P_j)^2}{m-1}} \tag{12}$$

$$\text{Where} \quad P_j = \frac{\sum_{i=1}^{m} P_{i,j}}{m} \tag{13}$$

3. Calculate the coefficient of linear correlation ρ_{j_j} between the criteria values in the matrix.
4. Compute the quantity of information by combining the aforementioned two quantities using the subsequent formula for multiplicative aggregation:

$$LCC = \sigma_j \sum_j^n (1 - \rho_{jj}) \tag{14}$$

5. The objective weights are calculated according to the following equation:

$$W_j = \frac{LCC_j}{\sum_{k=1}^{n} LCC_k} \tag{15}$$

3.4 The ELECTRE (ELimination Et Choix Traduisant la REalite) method

The ELECTRE is a method of multi-attribute decision-making (MADM) that does not include compensation and operates based on comparing alternatives while considering individual criteria. In 1966, Ben,ayoun, et al. first proposed the ELECTRE evaluation method. The method works by selecting a desired choice from a set of alternatives that fulfill separate demands [30]. The ELECTRE technique may be explained via the following steps:

1. Normalizing the Decision Matrix DM = $[Y_{ij}]_{m\,x\,n}$ to create the normalized decision matrix (r), by which each member is normalized.

$$r_{ij} = \frac{y_{ij}}{\sum_{u=1}^{m} y_{uj}} \tag{16}$$

2. Construction of the weighted normalized decision matrix to include the impact of weight, which was already determined by the CRITIC method, into the decision matrix:

$$v_{ij} = r_{ij} \times W_j \tag{17}$$

3. Determine the concordance and discordance sets to divide the choice criterion matrix into two independent subsets (C_{Kl} (concordance) and D_{Kl} (discordance):l $\neq K$) for every pair of choices. When two options are considered, they are compared based on the category of criteria (cost or benefit types). Then, the concordance and discordance

sets are determined based on which alternative is better or worse. Consequently, the concordance and discordance sets can be shown as:

$$C_{Kl} = \{j\ ,\ \ v_{Kj} \geq v_{Lj}\} \tag{18}$$

For j = 1, 2,… n

$$D_{Kl} = \{j\ ,\ \ v_{Kj} < v_{Lj}\} \tag{19}$$

for j = 1, 2, … n

4. The construction of the concordance matrix. After identifying concordance and discordance sets, the total of the weights linked to the criteria in the concordance set is the concordance index c_{KL}

$$c_{KL} = \sum_{j\in C_{KL}}^{n} W_j \tag{20}$$

The concordance index estimates the relative significance of alternative A_K compared to alternative A_l. Define the concordance matrix C as follows:

$$C = \begin{bmatrix} 0 & c_{12} & \dots & c_{1m} \\ c_{21} & 0 & \dots & c_{2m} \\ c_{m1} & \cdots & c_{m(m-1)} & \dots \end{bmatrix} \tag{21}$$

5. Constructing a discordance matrix.

Most of the focus in this step is on how much an alternative is even worse than the others. To compute the discordance index, use the following equation:

$$d_{KL} = \frac{\max_{j\in DR_{KL}} |v_{Kj} - v_{Lj}|}{\max_{j\in 1,..n} |v_{Kj} - y_{Lj}|} \tag{22}$$

It is possible to define the discordance matrix as follows:

$$D = \begin{bmatrix} 0 & d_{12} & \dots & d_{1m} \\ d_{21} & 0 & \dots & d_{2m} \\ d_{m1} & \cdots & d_{m(m-1)} & \dots \end{bmatrix} \tag{23}$$

The matrix indicates that greater values of d_{Kl} indicate A_K is less favorable than A_l in terms of the discordance criterion. The range of d_{Kl} values is from 0 to 1.

6. Calculating the dominance matrix for the concordance index. A threshold value is applied to the concordance index to generate the concordance dominance matrix.

An alternate A_K can only dominate alternative A_l if its concordance index c_{Kl} surpasses a threshold value c_{th}.

$$c_{Kl} \geq c_{th} \tag{24}$$

The value of c_{th} may be found using multiple ways. The calculation can be determined using the following equation.

$$c_{th} = \frac{1}{m(m-1)} \sum_{\substack{k=1 \\ k\neq l}}^{m} \sum_{\substack{l=1 \\ l\neq k}}^{m} c_{kl} \tag{25}$$

The concordance dominance matrix (F) members are calculated based on the threshold value.

$$f_{kl} = \begin{cases} 1 & if \quad c_{kl} \geq c_{th} \\ 0 & if \quad c_{kl} < c_{th} \end{cases} \tag{26}$$

Each "one value" assigned to an element in the matrix denotes "the degree of dominance one alternative has over another alternative."

7. Calculating the dominance matrix for the discordance index. In the same way, a threshold valued d_{th} is used to determine the discordance dominance matrix G. Where d_{th} could be defined as follows:

$$d_{th} = \frac{1}{m(m-1)} \sum_{\substack{k=1 \\ k\neq l}}^{m} \sum_{\substack{l=1 \\ l\neq k}}^{m} d_{kl} \tag{27}$$

And

$$d_{kl} = \begin{cases} 1 & if \quad d_{kl} \geq d_{th} \\ 0 & if \quad d_{kl} < d_{th} \end{cases} \tag{28}$$

8. Determine the aggregate dominance matrix. This step aims to merge the matrices f and G and compute the aggregate dominance matrix, which is the product of the F and G matrices. The dominance matrix E is defined below.

$$e_{kl} = f_{kl} \times g_{kl} \tag{29}$$

9. Eliminate the Less Favorable Alternatives. The partial preference ordering of alternatives can be derived from the aggregate dominance matrix. If $e_{kl} = 1$=1, it indicates that alternative A_K is better than alternative A_l based on the concordance and discordance factors.

Fig. 2 shows the proposed POA optimization and hybrid MCDM methods for residential load scheduling.

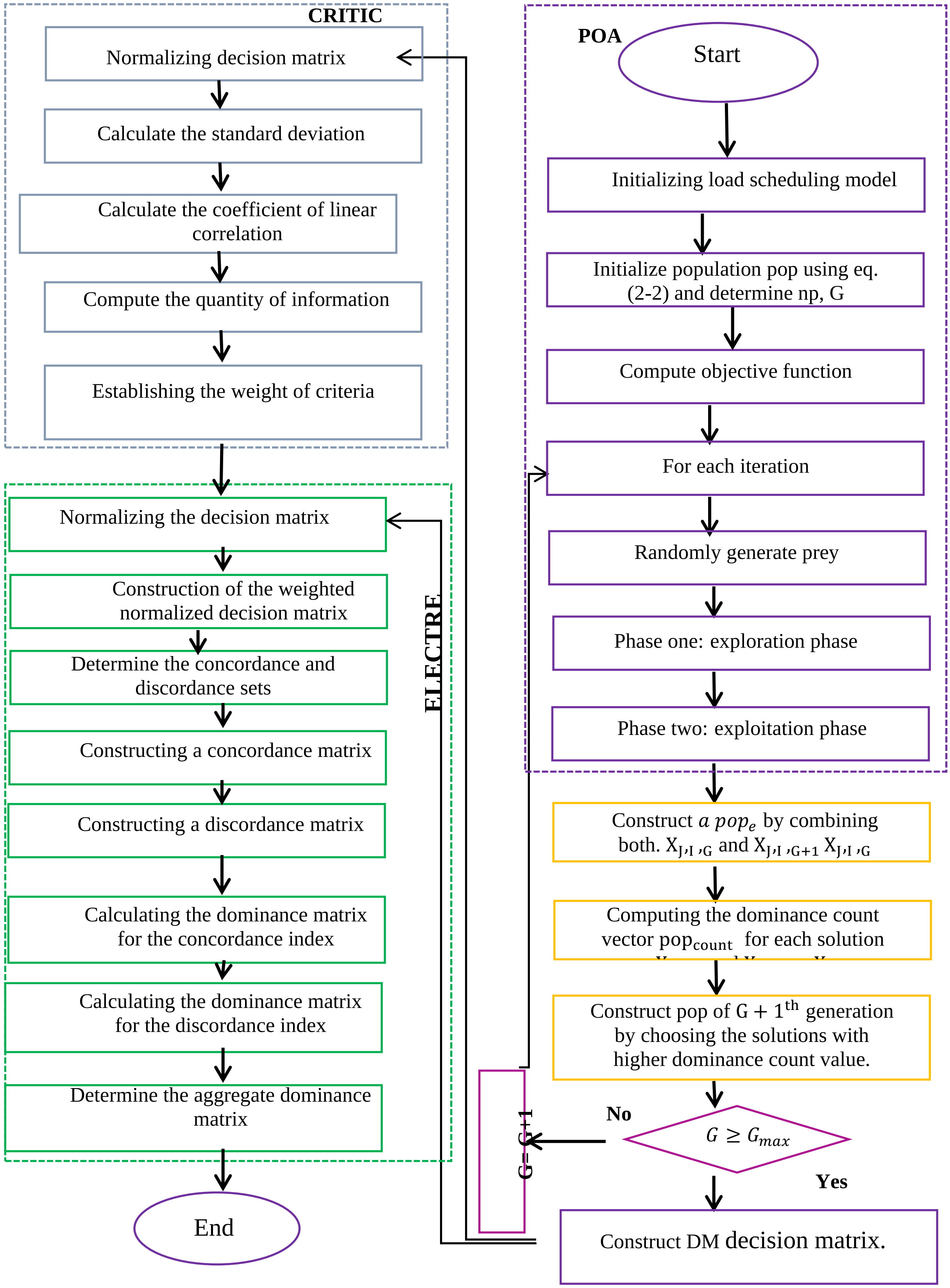

Figure 2. Integrated MOPOA– CRITIC – ELECTRE method for solving residential load scheduling.

4. Case Study

The end-user energy use profile data from [31] is used in this research. The optimum scheduling model for a normal residential home is used to choose the twenty appliances. An electrical provider has established the ToU pricing, as shown in Table 1 [31]. The hours of 11:00 to 14:00 and 18:00 to 23:00 are the highest (peak). Valley timings are from 0:00 to 7:00, and flat periods from 8:00 – 10:00 and 15:00 – 17:00. Table 2 presents the details of home appliances, including each device's power rating, start times (St) and end times (Et), and the duration required for normal operation.

Table 1. The TOU Pricing [31]

Loads	Power price ($/Kwh)	Time ranges
Peak	0.84	11:00 to 14:00 18:00 to 23:00
Valley	0.31	00:00 to 07:00
Flat	0.61	8:00 to 10:00 15:00 to 17:00

5. Results and Discussion

A novel methodology that combines MCDM methodologies with a multi-objective optimization algorithm is proposed to achieve optimal load scheduling for different appliances. The MATLAB software is used to execute the proposed algorithm. As the operating time taken into consideration in this research is one day, the complete day could be divided into 48 slots if a sample period of thirty minutes is used. Twenty decision variables (DV), equal to the total number of household devices, must be optimized using the POA approach in the optimization algorithm. POA was applied to the target functions for 50- and 100 individuals. The algorithm's exploratory capability has increased due to population growth, and more desirable solutions have been found. It tested 50, 100, and 200 iterations of the algorithm and found that increasing iterations beyond 50 did not significantly improve the finding of optimum solutions while reducing both objectives. This suggests that 50 iterations strike a good balance between computational efficiency and achieving optimal solutions. An MOPOA algorithm minimizes cost, peak, and user inconvenience as a third objective to shift load to minimize peak times to provide best sets within a Pareto-front and reduce average energy costs. The Pareto optimal front, comprising 300 values representing different trade-offs between objectives, is illustrated in Fig 3. Minimum cost, peak value, and end-user dissatisfaction are 29.786 $, 4.45 kW, and 42, respectively. Upon completion of the MOPOA algorithm, a set of optimal solutions (Pareto front) is generated.

Consequently, a multi-criteria decision-making method ranks the alternatives from best to worst.

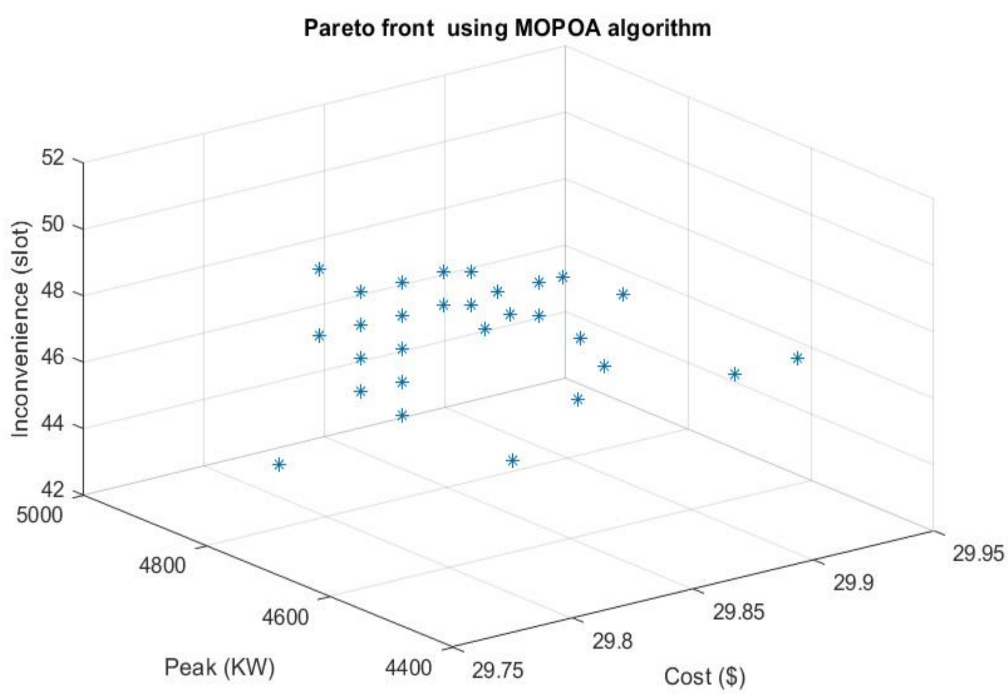

Figure 3. The Pareto optimal front using the MOPOA algorithm. The "*" refers to the solutions in objective space.

Table 2. Deferrable Load Data for Household Appliances [31]

Appliance	power rating(Kw)	Starting time(St)	and	Ending time(Et)	Duration (h)
Dishwasher	0.73	8:00	to	12:00	1
Dishwasher	0.73	20:00	to	23:00	1
Dishwasher	0.73	6:00	to	7:30	1
Rice cooker	0.8	15:00	to	17:00	1
Rice cooker	0.8	6:00	to	9:30	1
Washing machine	0.38	18:00	to	20:30	2
Washing machine	0.38	00:00	to	9:00	2
Humidifier	0.15	14:00	to	20:30	4
Humidifier	0.15	9:00	to	12: 00	4
Laundry drier	1.26	20:00	to	23:00	1.5
Laundry drier	1.26	4:00	to	8:00	1.5
Water heater	1.85	16:00	to	20:00	2
Water heater	1.85	21:00	to	24:00	2
Electric kettle	1.5	6:00	to	7:30	0.5
Electric kettle	1.5	20:00	to	23:30	0.5
Electric kettle	1.5	9:00	to	12:30	0.5
Electric oven	1.3	15:00	to	17:00	1
Electric oven	1.3	19:00	to	22:00	1
Air conditioner	2.2	11:00	to	15:00	4
Air conditioner	2.2	17:00	to	23:00	4

The CRITIC method was utilized to determine the weights for three criteria. The weights of the MCDM problem's criteria are presented in Table 3. The weights indicate the relative importance of one criterion compared to another.

Table 3: Criteria's weight via CRITIC Method

weight (Cost)	weight (Peak)	Weight(INCON)
0.32132	0.30313	0.37555

Following this, the ELECTRE method, renowned for its effectiveness in decision-making processes, was applied to fine-tune the selection of optimal solutions by comparing and ranking alternatives based on multiple criteria, considering objective weights. First, it normalizes the decision matrix to ensure the requirements are comparable. Then, it calculates concordance and discordance indices to assess how well one alternative outperforms another. Based on these measures, it establishes outranking relationships, identifying which alternatives generally "outrank" others. Finally, it creates a final ranking of alternatives.

Fig. 4 illustrates the cost breakdown before implementing our scheduling method, revealing a total cost of $51.95. This analysis underscores the potential for significant savings. Additionally, Fig. 4 emphasizes the peak load before scheduling, exceeding 6 kW. This high peak load strains the grid and can potentially increase energy costs.

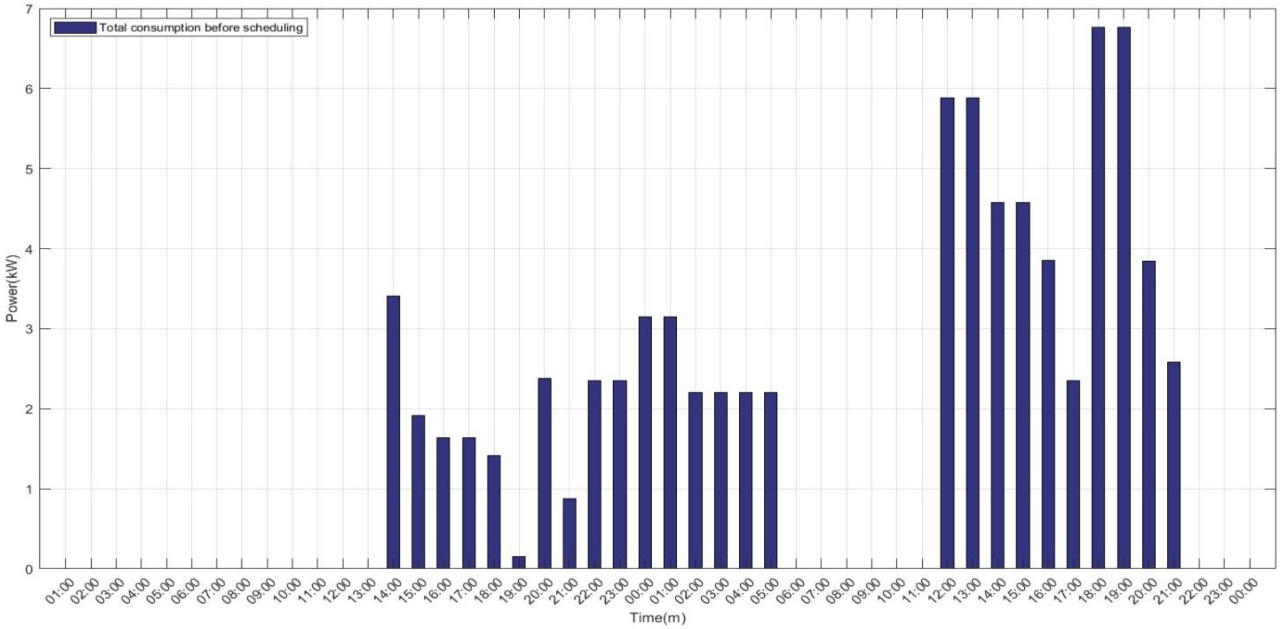

Figure 4. Daily power consumption before scheduling

Implementing our load scheduling approach resulted in substantial enhancements in both cost and peak load, as shown in Fig. 5. This figure demonstrates a reduction in cost to $29.786 and a reduction of 4.760 KW in peak load, indicating improved grid stability and cost savings.

Therefore, the savings increase to 42.66% for costs and around 20.66% for peak load. All these savings are for the first-rank solution. These solutions show the significance of weights. Table 4 shows a summary of Cost and Peak Savings for the five best-ranking solutions obtained using the ELECTRE method.

According to the findings in Table 4, the first-ranking solution emerges as highly promising based on the weight obtained. Therefore, the savings increase to 42.66% for costs and around 20.66% for peak load. All these savings are for the first rank solution. These solutions show the significance of weights. Table 4 shows a summary of Cost and Peak Savings for the five best-ranking solutions obtained using the ELECTRE method. According to the findings in Table 4, the first-ranking solution emerges as highly promising, based on weight obtained through the CRITIC method. This ranking signifies optimal performance in terms of cost reduction (42.66%) and peak load management (20.66%) with user inconvenience 50. All the best-ranked solutions achieved overall cost savings ranging from 42.56-42.66% and peak load reductions of 20.66% due to the scheduling process. While the top solutions achieved significant cost and peak load improvements, they also introduced moderate user inconvenience (INCOV 50 or 49). This suggests a trade-off between energy optimization and user comfort, which warrants careful consideration in implementation. Notably, the total energy consumption remained unchanged before and after scheduling, indicating that the savings were not due to reduced energy usage but rather to more efficient load distribution. This highlights the ability of the scheduling to optimize energy patterns without compromising overall energy needs.

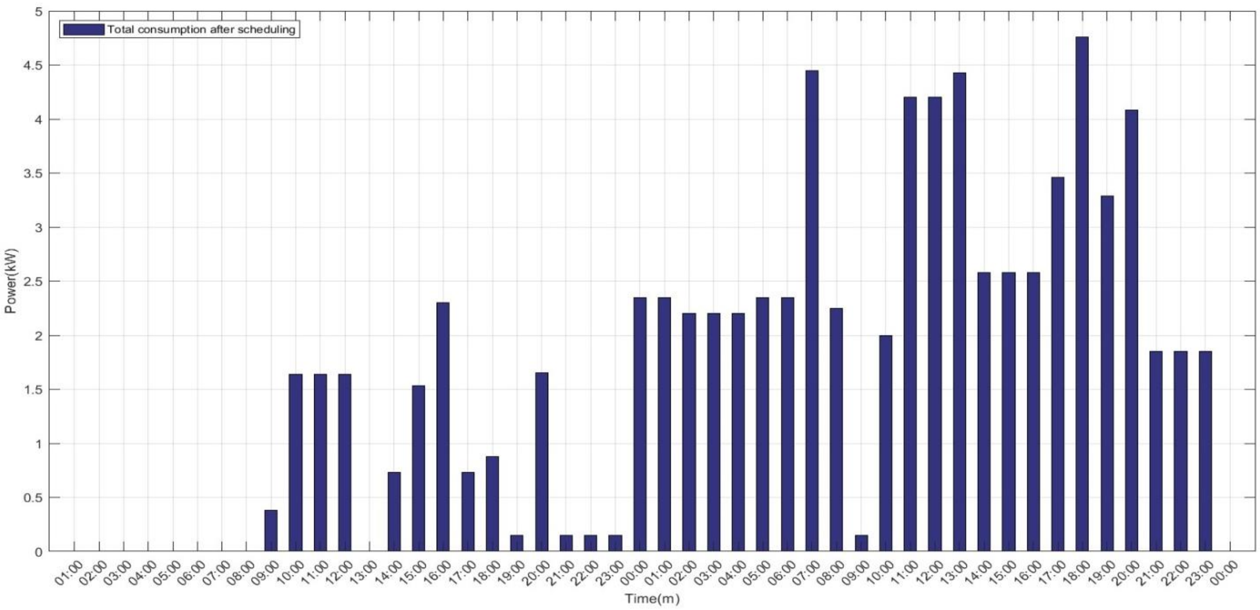

Figure5. Daily power consumption after scheduling

Table 4: Summary of Cost and Peak Savings for Top 5 Ranking Solutions

Before Scheduling				**After Scheduling**					
Rank	**Total energy (kWh)**	**Peak load (kW)**	**Total cost ($)**	**Total energy (kWh)**	**Peak load (kW)**	**Total cost ($)**	**INCON**	**Cost saving %**	**Peak saving %**
1	80.28	6	51.95	80.28	4.760	29.786	50	42.66	20.66
2	80.28	6	51.95	80.28	4.760	29.786	50	42.66	20.66
3	80.28	6	51.95	80.28	4.760	29.838	49	42.56	20.66
4	80.28	6	51.95	80.28	4.760	29.838	49	42.56	20.66
5	80.28	6	51.95	80.28	4.760	29.821	49	42.59	20.66

These MCDM techniques played a pivotal role in enhancing our decision-making process, ensuring a thorough assessment of alternatives, and contributing to the overall success of the study by offering nuanced insights into the trade-offs and benefits associated with each solution.

For evaluating the proposed scheduling of loads algorithm's effectiveness and performance, a comparison is made with [31]. All methods use the same consumer data and pricing system (ToU). A comparison of different methods is shown in Table 5. Before scheduling, Rong et al. [31] indicated a maximum peak load was 6 kW, the total electricity consumption was 80.28 kWh, and the overall cost was $51.95. Without considering inconvenience, the optimized cost and peak load reduction achieved a 25.71% cost reduction and an 8.3% peak load reduction.

The suggested load scheduling algorithm was implemented using sample times of 60 and 30 minutes to reduce peak demand and increase cost savings. The 30-minute sampling interval results in a significant cost reduction of 42.66% and a peak energy load reduction of 0.66%. However, the same sample period (60 minutes) is used for fairness compared to the prior research.

Based on the findings from the proposed schedule, the peak load drops to 4.2 kW (the overall peak is lowered by 30%), and the total cost is lowered to 30.7848$ (the whole bills are reduced by 40.74% through the DR). with an end-user inconvenience of 19 slots. Considering that the same utility income is assumed for all methods, the suggested method delivers a larger decrease in expenses and peak demand than the previous work.

Table 5. Comparison results

References	Before Scheduling			After Scheduling					
	Total energy (kWh)	**Peak load (kW)**	**Total cost ($)**	**Total energy (kWh)**	**Peak load (kW)**	**Total cost ($)**	**INCON**	**Cost saving %**	**Peak saving %**
[31]	80.28	6	51.95	80.28	5.5	38.59	------	25.71	8.3
Proposed method (60 minutes)	80.28	6	51.95	80.28	4.2	30.78	19	40.74	30
Proposed method (30 minutes)	80.28	6	51.95	80.28	4.76	29.786	50	42.66	20.66

6. Conclusions

The MOPOA-CRITIC-ELECTRE optimization algorithms provide a multi-objective home load scheduling method that provides optimum load scheduling, which lowers peak load demand for utility companies and assists end customers in reducing their energy bills.

For a fair and comparative evaluation of the proposed load scheduling method, analyses were carried out with both 60-minute and 30-minute samples since the previous study utilized a 60-minute sampling period. A 30-minute sample duration was added to test if a shorter interval might enhance scheduling results. The results revealed a cost reduction of 40.74%, a peak load reduction of 30% within 60 minutes, a cost decrease of 42.66%, and a peak reduction of 20.66% within 30 minutes. Reducing the sample duration from 60 to 30 minutes substantially enhanced the solutions. These methods' advantages coincide with end-user economic objectives and overall resilience and efficiency by limiting load demand oscillations.

The drawback of our proposal is the potential for data privacy concerns, especially when collecting and utilizing sensitive user data for optimization purposes. We will address this issue by outlining safeguards for user privacy, such as anonymization techniques.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Author Contribution Statement

Hiba Haider Taha and Haider Tarish Haider were responsible for Conceptualization, data curation, formal analysis, investigation methodology, validation, writing—original draft preparation, writing—review and editing,

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