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Efficient power management optimization based on whale optimization algorithm and enhanced differential evolution

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ABSTRACT

Daily increases in electricity prices accompany daily increases in energy consumption and use. An effective load-balancing scheduling system is necessary for the lowest cost of use and the lowest cost. Despite these devices having a significant capacity for power consumption, they must find a means to balance the load at a low price. Even if lowering the voltage is challenging, it is possible to do it at the lowest cost. Hybrid Whale Differential Evolution (HWDE) is a new optimization method that combines the well-known approaches of the Whale Optimization Algorithm (WOA) and Enhanced Differential Evolution (EDE). By balancing the required Real-Time Price (RTP) and Critical Peak Price (CPP) loads, WOA and EDE capabilities can save costs and ensure the device receives sufficient voltage. The three most recent performance indicators are kWh per charge, energy usage, and the maximum-average ratio. Existing models are evaluated according to their expenses (in rupees), energy consumption, cost per kilowatt-hour, and total cost. All simulation results indicate that HWDE is the optimal solution in every circumstance. In MATLAB simulations, HWDE consistently outperforms its rivals.

1. Introduction

Energy is becoming an increasingly important part of human life. Electricity is a major source of energy. Power is a necessity for human survival in the modern world. Before the invention of electricity, life was much simpler. Physical labor is a major part of the job description. Existence as a human is filled with difficulties, such as the need for enough illumination, food storage, preparation of meals, and cleaning up after oneself. It was not until Benjamin Franklin that electricity was made widely available to the public. Benjamin Franklin's discoveries on lightning and electricity in the middle of the 18th century provided the groundwork for future scientists. In the late 1800s, Michael Faraday revealed the fundamentals of electricity production. Finally, with the help of Thomas Edison, clients could now access energy via new industrialization and innovations [1]. In the late 19th century, the first electrical network was created. Multiple power grids had been established in various places by the end of the twentieth century due to the rapid development of the concept of the power grid. We began by producing and providing electricity to customers before expanding into other businesses. The power plant is the name given to the structure. There are numerous methods for generating power. The creation of power necessitates that it be made available to customers. The power grid is responsible for all electricity generation, transmission, and distribution [2].

To reduce expenses and Peak Average Ratio (PAR), smart appliances can be programmed to shift load from peak to off-peak hours [3]. The CSUA (Candidate Solution Update Algorithm) algorithm was developed by merging some aspects of the JA (Java Algorithm) and the BAT (BA) approach. By using Energy Management Controller (EMC) in BA, JA, and CSUA, it is possible to convert Demand Management Strategy (DMS) peak load to actual load. They compared these scheduling methods

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Nomenclature

AMI	Advanced Metering Infrastructure
BA	Bat Algorithm
CC	Consumer Comfort
CPP	Critical Peak Price
CSUA	Candidate Solution Updating Algorithm
DAP	Day Ahead Pricing
DR	Demand Response
DSM	Demand Side Management
EDE	Enhanced Differential Evolution
EHEMC	Efficient Home Energy Management Control
GWD	Genetic Wind Driven
GWO	Gray Wolf Optimization
HEMS	Home Energy Management System
HWDE	Hybrid Whale Differential Evolution
IBR	Inclined Block Rate
JA	Jaya Algorithm
LST	Least Slack Time
PAR	Peak to Average Ratio
RTP	Real-Time Price
SG	Smart Grid
SSM	Supply Side Management
TG	Traditional Grid
WOA	Whale Optimization Algorithm

using a variety of Secure Household (SH) device algorithms. Using the CPP and Time to Use Pricing (ToUP) home energy management systems based on robots, load-matching and scheduling algorithms have been developed to reduce energy losses and utility costs [4]. Load balancing is utilized to keep SH's power consumption rise within a preset maximum. The Least Slack Time (LST) technique is used to configure smart devices that are aware of Direct Current (DC). When designing intelligent devices with LST, the primary focus should be maximizing DC. Multi-SH control through enhanced LST multiprocessor scheduling approach.

Population-based Whale Optimization Algorithm (WOA) can avoid local optima and get a globally optimal solution. These advantages cause WOA to be an appropriate algorithm for solving different constrained or unconstrained optimization problems for practical applications without a structural reformation in the algorithm. The WOA is one of the recent meta-heuristic algorithms. WOA has advantages such as an exploration mechanism leading towards the global optimum, a suitable balance between exploration and exploitation that avoids the local optimum, and a good exploitation capability. It works by starting with a set of random solutions. At each iteration, search agents update their positions concerning either a randomly chosen search agent or the best solution obtained so far. Contrasting with the other optimization algorithms, it uses different techniques to test and evaluate combinations of hyper-parameters to find the optimal configurations for model performance. The algorithm can often be used within the model itself to improve its effectiveness in light of its target function.

In this work, demand-side management and device scheduling have been successfully combined as the core idea. The residential sector accounts for more than 80 % of the increase in electricity demand (see). Energy can be wasted if the equipment is mishandled or used unanticipatedly. When it comes to balancing electricity output and consumption, this shows how difficult it is. There is a focus on how electricity is used and managed. Efforts to maximize energy use need the application of optimization strategies. An incentive-based strategy, Demand Response (DR), is expected to be particularly effective at enticing customers. Utilities use a range of pricing schemes, including DSM, to reduce peak load and power consumption as an optimization problem and a metaheuristic technique.

Regarding power supply, it's well worth investigating how to design electronics. The Sharma and Saxena models [5] and EDE [6] have all been offered as power optimization strategies in this context as differential evolution of hybrid grey wolves [7]. These solutions, however, are not inexpensive. This research aims to develop a WOA- and EDE-optimized method for cost-effective energy management. Combining EDE with WOA algorithms yields an optimum hybrid whale differential evolution method (HWDE). To save energy, lower the PAR, and improve user comfort, this technology takes it a step further by grouping intelligent appliances based on their use and power.

- An improved planning method for energy management and efficiency is provided by merging EDE and the WOA.
- A DMS that transfers transferable peak load to actual load should be proposed and implemented to reduce PAR.
- Perform an energy consumption, Kilo Watt Hour (kWh) load, and power factor analysis on the proposed strategy

The benefit of the WOA is that it is a new optimization technique for solving optimization problems. This algorithm includes three operators to simulate the search for prey, encircling prey, and bubble-net foraging behavior of humpback whales. An optimization algorithm is a procedure executed iteratively by comparing various solutions until an optimum or satisfactory solution is found. Optimization has become part of computer-aided design activities with the advent of computers. The WOA is a swarm intelligence based Search-Algorithm while browsing for an optimal solution. However, it suffers from the poor & inconsistent exploration problem that causes the trapping of local optima in randomly deployed nodes that fail to guarantee network coverage. Hence, the WOA can also be utilized for computer networks and other Artificial Intelligence (AI) applications. The applications and other benefits of the WOA which differ from others are its unique characteristics and high response time, and it takes less time to execute while operating. It is not accurate to say that the WOA is definitively the "best" optimization algorithm, as the choice of the most suitable optimization algorithm often depends on the specific problem being addressed and the resources available. However, WOA is a relatively recent and promising optimization algorithm that performs well on certain problems. The WOA is a metaheuristic algorithm inspired by the hunting behavior of humpback whales. It is particularly useful for solving optimization problems involving many variables and complex, nonlinear functions. WOA maintains a population of candidate solutions, which are iteratively refined through search and update operations. One of the strengths of WOA is its ability to balance exploration (i.e., searching the solution space broadly for potentially promising regions) and exploitation (i.e., intensively searching areas that are likely to contain the optimal solution). This is accomplished through a combination of random and adaptive search, which helps prevent the algorithm from becoming stuck in local optima. WOA has also effectively handled constrained optimization problems, where one or more constraints restrict the feasible solution space. The algorithm achieves this by dynamically adjusting the search space based on the constraints so that candidate solutions are always feasible. In summary, WOA is a promising optimization algorithm that has performed well on certain problems. However, as with any optimization algorithm, its suitability depends on the specific problem being addressed, and further research is needed to evaluate its effectiveness compared to other algorithms fully.

The remainder of the article is as follows; Section 1 serves as an introduction and setting. The 2nd Section provides a theoretical examination of the relevant article. Section 3 explains how to investigate.

While Section 4 focuses on the facts and comments. Finally, Section 5 concludes the paper.

2. Related work

An Efficient Home Energy Management Controller (EHEMC) based on the Genetic Harmony Search Algorithm (GHSA) was developed by [8], which was designed to maximize PAR and Critical Controller (CC) while keeping costs down GHSA. They are masters in single and multiple extension CPP and RTP procedures. The device's power consumption over a range of operating hours reveals how well it will perform in the various types of homes for which it has been designed. The problem of energy optimization was tackled using a variety of heuristics. This method displays high search efficiency and the ability to solve problems quickly. In addition to higher PAR and CC, the data show significant cost savings.

Authors of [9] name of the town HEMS and SH were created to replicate smart home appliances more realistically. The DC, PAR, and energy expenses can all be reduced with simple adjustments made between SH devices. Use the RTP and Day Ahead Pricing (DAP) protocol suites for your needs. Peak and trough expenditures might be used as a fitness measure. As a result, delay is minimized, and device health may be more easily assessed. The author uses dynamic programming to solve the challenge of managing the weight of a backpack. Based on simulation findings, the proposed optimization technique has a 95 percent confidence interval. For example, authors of [10] presented a Glow Worm Optimization Genetic Algorithm (GWO/GA) hybrid to lower the energy consumption of PAR and SH. Multiple timings were supplied by executing algorithms on some SH. As a result, the price of PAR and power have both decreased. Authors of [11] have proposed techniques for prioritizing dynamic SH mode load. They suggest a four-premised evolutive ease-of-value technique for determining time-adjusted tables' temporal and device-based attributes (EACA). Design ideal power consumption patterns and limit your electricity consumption to the range of peak demand to better adhere to your planned budgets. The DE approach proposed by authors of [12] uses crossover and mutation procedures more extensively. A detailed timetable has been created using the most up-to-date DE algorithms.

Authors of [13] proposed QBPSO (Quad-Binary Particle Swarm Optimization) to address technical optimization challenges based on home consumer-based Particle Swarm Optimization (PSO). The author first introduces a user-friendly family taxation model into the Critical Peak Average (CPA). User-centric programming is a major focus of their products. They want to cut costs and the time it takes to complete a task by using technologies that search for or show data near the source. Second, PSO has been renamed QBPSO, and this is the result of a merger. The PSO's binary engineering optimization problem is to blame for this. They created a second-order transfer function that targets devices that have been interrupted. The results show a decrease in resistance when the DC is only slightly impacted. In The Beyond, the housing market is discussed [14]. The DSM was treated as an optimization issue for cost and performance reasons. Hybrid Gray Wolf Differential Evolution (HGWDE) is a hybrid of Extended Differential Evolution (EDE) and Gray Wolf Optimization (GWO), which uses CPP and RTP as the two main elements.

In [15], the system includes WOA, Determined Energy (DE), GWO, Anti-Defiant Challenge Differential Evolution (QODE), and Anti-Defiant Challenge Gray Wolf Optimization (QOGWO) algorithms. Two devices are used for reactive power planning: the Thyristor Controlled Series Compensator (TCSC) and the Static Supply Vector Compensator (SVC). Humpback whale hunters use a cutting-edge algorithm called WOA. Natural metaheuristics are usually referred to as this. Optimization is carried out using a genetic algorithm known as DE. The genetic features of mutations and crosses are exploited as genuine optimization parameters. As a result, GWO is built on the principles of natural metaheuristics. Using grey wolf hunting habits is like WOA. Use IEEE30 and IEEE57 bus test systems to evaluate the algorithm. Power flow analysis was used to locate the TCSC, and the voltage collapse proximity display (VCPI) approach was used to locate the SVC. It employs WOA, GWO, DE, QODE, and QOGWO algorithms to determine the optimal course of action for control variables such as TCSC, SVC, and serial to reduce further the system's dynamic power consumption and running expenses.

This study was done by [16]. Home Energy Management System (HEMS) is an automatic switching mechanism and load balancing system that we developed to reduce needless energy use. With their method of load balancing, they keep household spending in check. They design the device to the user's comfort and apply the Least Slack Time (LST) method to program it. They performed simulations to compare the projected scenario to the current energy management situation. Using an automatic switching method, they found large cost increases and PAR.

Authors in [17] coupled the Tabu Search Algorithm (TS) with the Bacterial Forging Algorithm (BFA) to train devices with variable duty cycles (BFA). To reduce power consumption and equipment latency, they increased the CC of the Hybrid Bacterial Forging Taboo Search (BFTS) algorithm that employs Real Time Pricing (RTP) to determine power consumption. The results of BFA and TS were compared to those of BFTS in this study. According to the findings, the proposed program has proven extraordinarily beneficial.

Authors of [18] suggested particle swarm optimization (PSO) based on home energy consumption-based technologies and the engineering optimization issue of particle swarm optimization secondary binary particles (QBPSO). To begin with, the author introduces a user-friendly family taxation model for the CPA to adopt. They tailor their strategies to fit the needs of the target audience. They aim to reduce the load by reducing expenses and PAR by displaying or searching for data at the source of the demand. Second, QBPSO has brought PSO up to date. This is because of the PSO's binary engineering optimization problem's performance limits. Second-order transfer function interrupted devices are the focus of the suggested technique. The results reveal a decrease in resistance when the DC is slightly altered.

Authors of [19] aimed to reduce residential electricity use. The expansion of household gadgets needs a growing fuel supply. The author asserts that domestic areas are more adaptable than industrial or commercial ones. Their solution is the Candidates Solution Update Algorithm (CSUA), which combines components of the JA and BAT algorithms to obtain the desired result. In high school, they used ToU and CPP in addition to fifteen smart devices for their experiment. They discovered that changing loads from peak to off-peak hours can cut electricity bills. Authors of [20] presented two heuristics to lower the PAR. Due to the 2-Dimensional (2D) packing issue, these techniques are known as G-MinPeak and Level Match. Each method has been evaluated in the actual world using a specific set of facts. Both tactics have been demonstrated to be effective in reducing PAR. In addition, they present five novel applications that utilize these tactics to lower PAR.

Authors of [21] established a Microgrid (MG) technology alongside Hybrid Power Control (PFM) for Hybrid Renewable Energy (HRES). The approach proposed combines the Supply Source Airier (SSA) and WOA algorithms. The proposed project name was Supply State Analytical Worm Optimization (SSAWO). An SSA measures the supply-to-load voltage differential, which is subsequently used to generate a drive regulation signal. Multifunctional functions include the networks required to generate effective and efficient energy from available sources. The WOA approach ensures online control signals that use the same motion for various active and potent forces. The control model generates power control parameters based on the supplied flow type. The proposed method controls the MG system based on the PFM source and parameter distribution. Current technologies usually rely on renewable energy sources and storage to meet the grid's energy demands.

Authors of [22] used a comprehensive Demand-Side Management strategy; markers of indoor comfort, including thermal comfort, air quality, humidity, and visual comfort, can all be enhanced DSM. As a solution, they propose identifying and resolving scheduling issues before building a new cluster-based, flexible WOA paradigm with many restarting alternatives. Work with the Map to modify crucial WOA settings using various implementation strategies. Consider minimizing the number of testing and monitoring programs, and evaluate the suggested approach based on its well-established properties. A way to optimize your time through appointment scheduling. This strategy is expected to expedite metaheuristic integration.

Authors of [23] estimated modeling of DSM with the force transfer approach from the day before is a little issue. Adaptive Moth Flame (AMF), or adaptable moth ignition processes, are a solution to the apparent optimization issue with DSM. The proposed inquiry studied residential, commercial, and industrial energy usage. Utilizing an AMF optimization technique may minimize peak loads and operational expenses simultaneously. Comparing the outcomes of the commercial, residential, and industrial sectors employs multiagent and evolutionary techniques. Residentially and commercially, AMF-based DSM technology has surpassed multi-agent and evolutionary approaches. The particle sampling method is more cost-effective than the suggested method [24–27].

Authors of [28] implement an Enhanced Whale Optimization Algorithm (IWOA) in Mega Grids (MGs) to handle optimal energy trading concerns and save operating costs. This ideal transaction is realizable using Incentive-Based Demand Response (IBDR) and considering the volatility of renewable energy, taxes, and market clearing prices. Various probability distribution functions and scenario generation and reduction strategies represent these uncertainties. The applicability and effectiveness of the recommended strategy were evaluated by recreating the MG test procedure. This strategy will improve MG's performance regarding the most effective solution and company operations. IBDR significantly affects the power system and provides the biggest end-user benefits with more robust incentives than price reductions.

Authors of [29] the above-ground whale optimization technique developed by Zhengfei is based on four perspectives: dimension selection, reconnaissance control, enhanced environment rendering, and solution selection. Using this assignment as a test bed, we will use the whale optimization technique to determine the capacitance and inductance of single- and three-phase unit lengths with varying amounts of bundled conductors. Beginning with 23 standard benchmarks, the algorithm's ability to find the optimal solution was evaluated against various other development strategies. Determine the proper transmission line parameters above phases 1 and 3, considering the various combinations of inductors and conductors in the capacitor body, using the proposed method. Based on the findings, it is possible to conclude that the Mega Worm Optimization Algorithm (MWOA) method is more accurate and trustworthy for optimizing global or near-global flexibility management settings. In addition, the results demonstrate that the proposed strategy can compete with more sophisticated methods and solve real-world problems.

Authors of [30] developed an interactive model incorporating user demand forecasts, energy supply estimates, and operational collaboration optimization. Regional Climate Simulation (RCS), Demand Forecasting (DF), instrument output calculation (Mechanism Modeling), and Collaborative Processing Optimization (CPO) are all possible within an integrated framework. Included are the following: As a result of climate change, we are utilizing the PRESIS model to predict temperature and radiation changes and the TRNSYS software to predict future hospital patient needs. A simulation model has determined how much power a gas turbine mechanism can generate in various climates. Using this dynamic interaction model, each connection is considered in the operation and management of the supply system, thereby enhancing the system's cost-effectiveness and adaptability. Most of the study focuses on the problem's broader context and the underlying structure of the model.

Authors in [31,32] proposed some novel schemas for efficient power optimization based on the optimization algorithms to effectively balance the load of power appliances. The home energy management system (HEMS) based on the advanced Internet of Things (IoT) Technology has attracted the special attention of engineers in the field of smart grid (SG), Which has the task of demand side management (DSM) and helps to control the equality Between demand and electricity supply. The authors introduced the optimal control of a DC motor based on a proportional-integral-derivative (PID) controller. In this study, an improved version of the whale optimization algorithm has been adopted for the optimal selection of the PID controller parameters for optimal DC motor speed control and minimum Settling time.

Authors in [33,34,35,36,37,38,39] suggested that WOA is a prominent problem solver broadly applied to solve NP-hard problems such as feature selection. However, it and most variants suffer from low population diversity and poor search strategy. Introducing efficient strategies is highly demanded to mitigate these core drawbacks of WOA, particularly for dealing with the feature selection problem. The squeezing of surrounding rock can be described as the large time-dependent deformation during tunnel excavation, which appears in special geological conditions, such as weak rock masses and high in situ stress. Several problems, such as budget increases and construction period extension, can be caused by squeezing in the rock mass. It is significant to propose a model for accurate prediction of rock squeezing. In this research, the support vector machine (SVM) as a machine learning model was optimized by the WOA.

The overall evaluation of the related work is discussed in Table 1.

3. Research methodology

Fig. 1 displays the general organizational framework of the suggested paradigm. In addition to the chosen instrument, the proposed method requires one SH. Each piece of equipment possesses a unique set of qualities. Design and development of a product in compliance with a set of requirements. The HEM protocol governs communication between the service provider and the client. The utility uses all of these signals to

Table 1
Tabular Summary of the Literature Review.

Study.	Year.	Limitations and Suggestions
[8]	2017	Only the energy efficiency is optimized and suggested to deploy in real-time applications
[9]	2022	Authors approached to introduce optimization schema for the limited supply of power.
[10]	2013	Only the load is decreased.
[11]	2007	Load decreased.
[12]	2018	Billing and load decreased.
[13]	2011	Load balancing is achieved.
[14]	2017	Load decreased.
[15]	2019	Electric supply chain minimized.
[16]	2017	Billing and load are balanced.
[17]	2018	Focused on load differ from real-time.
[18]	2018	Energy optimized to balance home appliances.
[19]	2018	Energy harvesting is minimized.
[20]	2018	Balancing property is achieved by deploying the optimization quickly to calculate the impact in real-time.
[21]	2014	Load is balanced
[22]	2008	The load is balanced.
[23]	2018	The load is balanced.
[28]	2022	Energy and load are balanced.
[29]	2018	Consumption of power is optimized.
[30]	2021	Consumption of power is optimized.
[31]	2020	Consumption of power is optimized.
[32]	2022	The workload is measured in real-time
[33]	2022	Load is balanced
[34]	2019	Load is balanced
[35]	2022	Load is balanced
[36]	2022	Energy and its consumption are minimized with an optimization approach by applying EDE
[37]	2022	Load is balanced
[38]	2022	Applied WOA to control the consumption of power and supply
[39]	2021	The energy level is balanced by focusing on load balancing

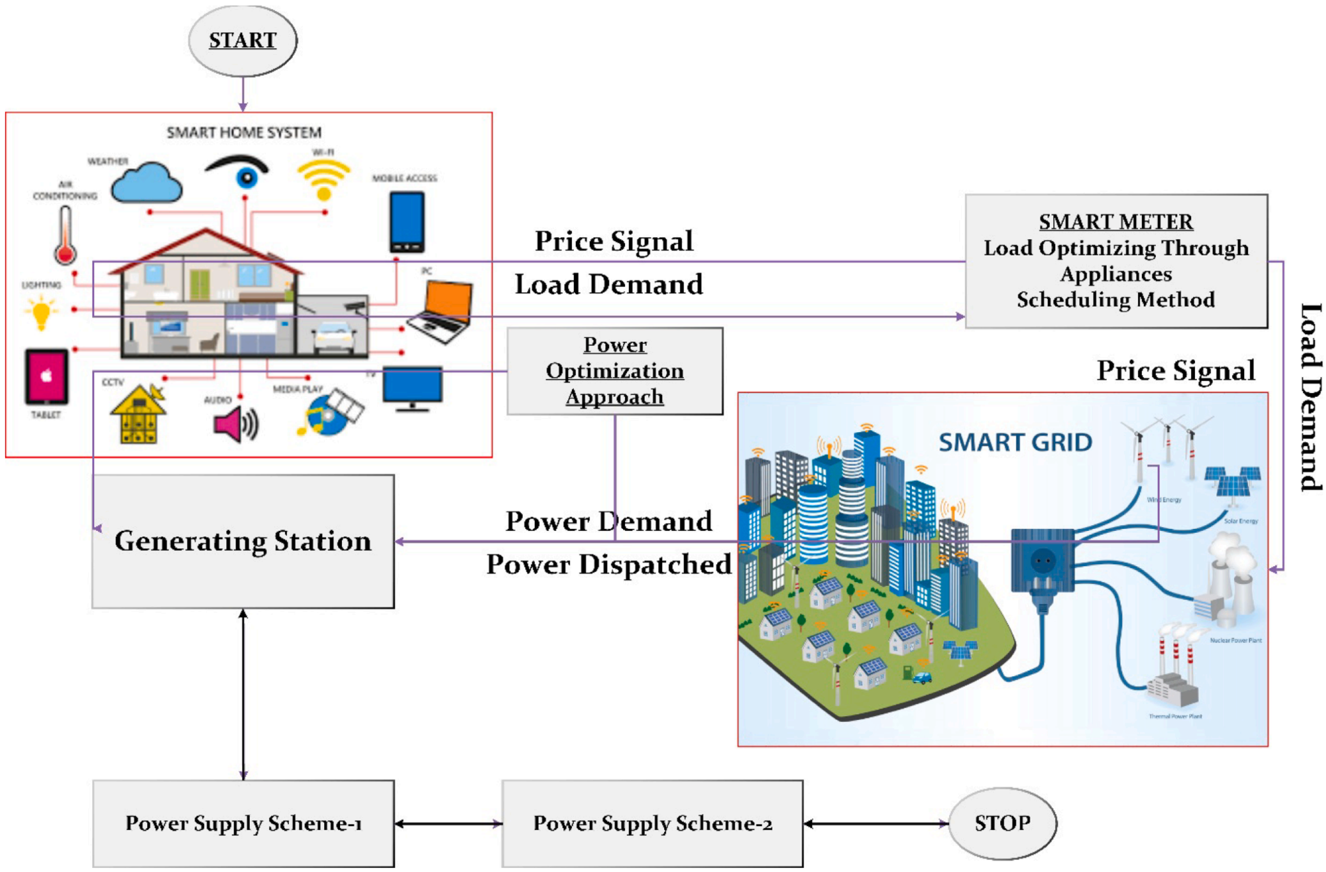

Fig. 1. Proposed Scheme Model.

measure the water flow. RTP is one of the most popular protocols. When a business is busy, customers' weight requirements are the best indicator of their values. During peak hours, electricity is more expensive than at other times of the day or night.

The model incorporates two-way communication. Initially, customers split the electricity bill in half. The amount of available electricity decides which devices are powered on. During peak hours, power-hungry appliances are prohibited. Modify the EMC to automate and reduce energy usage. After receiving the load demand through SMS from the client, the power company returns the electricity to the user. Various devices are graded based on the amount of electricity they consume daily. The load on each device is optimized by assigning power levels following the proposed strategy. Load management is based on achieving the best possible results. The following parameters were solved using the MATLAB simulation tool to validate the suggested scheme:

- The unit cost is presented in real-time.
- Electricity consumption by planned and unplanned loads
- Reduce the overall amount of planned and unanticipated tax expenses.

Simulation parameters for the proposed work are illustrated in tabular form in Table 1.

The parameters were applied to the evaluation of our proposed plan. Watts (W) or kilowatts (kW) can be used to measure power if the load on the equipment is sufficient (kW). Using RTP, the price per kilowatt-hour of electricity is determined (kWh). The energy consumption of each device is calculated based on anticipated and unanticipated demand. Additionally, utility providers must charge customers as little as possible for fees connected with anticipated and unanticipated usage.

3.1. Flow chart for proposed scheme

The WOA scheme has been applied for the load balancing and balancing of the properties among the home appliances and the expenditures of these. The key concept has been deployed in the given Fig. 2, which demonstrates the methodology concept. The core methodology lies in the major flowchart, which expresses how the load balancing of the electricity and home appliances has been handled. It is clear from the flowchart that this terminology has been exploited to be fully functional. The core system model deployment phases have been included in the major methodology.

After that, the flowchart and explanation for the second suggested way are provided. Detailed and sequential instructions on how to install the application are provided. Following is an illustration of the proposed algorithm or pseudocode.

Algorithm-1: Pseudo Code for Proposed System

1. $Input\ =\ 1-cost\ of\ electricity$
2. $Input\ =\ 2-load\ in\ KWh\ (Kilowatts)$
3. $Input\ =\ 3-PAR$
4. $Required\ =\ EDE,\ WOA,\ DSM$
5. $Output\ =\ Scheduled\ Procedure$
6. $Start;$
7. $Initialization;$
8. $h(hours\ =1):\ p(rand\ numb)\ =[0,1]:\ g(distance\ from\ prey):\ V(mutant\ vector:\ V^{*}\ = updated\ vector:\ H\ = max\ hours;$
9. IF
10. $h <= H\ True;$
11. $Proceed\ to\ the next\ step;$
12. $Else$
13. $Proceed\ to$ the $final\ step\ End;$
14. $ENDIF;$
15. $Calculate\ mutant\ vector\ v;$
16. $Iteration\ t\ =1;$

(continued on next page)

(*continued*)

Algorithm-1: Pseudo Code for Proposed System

17. *IF*
18. $t <= max\ t$;
19. *Proceed to thenext step*;
20. *Else*
21. *Go back to step* 4 *with* $h = h + 1$;
22. *ENDIF*;
23. *IF*
24. $p < 0.5$;
25. *Proceed to thenext step*;
26. *Else*
27. *Proceed with* $p >= 0.5$;
28. *Update V using current position* $-II$;
29. *Compare* V^* *with thetarget vector*;
30. *ENDIF*;
31. *IF*
32. $IgI < 1$;
33. *Proceed to* the *next step*;
34. *Update V using current position* $-I$;
35. *Go to step* 16;
36. *Else*
37. *Update V using current position* $-II$;
38. *Go to step* 16;
39. *ENDIF*;
40. *IF*
41. $V^* < V$;
42. *Proceed to Update thevalue of* the *V step*;
43. *Else*
44. *Go to step* 9 *with* $t = t + 1$;
45. *ENDIF*;
46. *IF*
47. *Step* 24 does *not satisfy the condition*;
48. *Go to step* 9 *with* $t = t + 1$ *same as* 25;
49. *ENDIF*;
50. *End*;

The overhead occurs when the implementation of the actual job and the bandwidth, like the paving of the target machine or device, is not operable and calculable. With the proposed work, the overhead can occur when the simulation or the required data exceeds the limit. The proposed algorithm has been placed in the controlled environment setup. The overhead of algorithm 1 will have occurred if the load and balancing of the WOA exceed the defined limit. In most cases, the overhead of an algorithm refers to the additional computational resources, such as time or memory, that are required by the algorithm beyond the basic requirements of the problem being solved. Overhead can occur for various reasons, such as maintaining data structures, additional operations, or calculations required by the algorithm. Here are some examples of overhead in algorithms such as Sorting algorithms, Search algorithms, Dynamic programming algorithms, and Genetic algorithms. In general, the overhead of an algorithm is a trade-off between the complexity of the problem being solved and the resources required by the algorithm. Efficient algorithms aim to minimize the overhead while providing accurate and reliable results. The overhead denotes the worst, average and best-case scenario of the algorithm.

3.2. System model formulation

Multiple mathematical formulas represent the mathematical model of the proposed system, each represented by an equation.

- *Initialization with V phase:* EDE is an evaluation of specific families utilizing a variety of instruments and methods. Organize the devices into discrete sections depending on their relative efficacy and optimize the schedule. Their plan moves the peak load to the genuine load, yielding significant cost and PAR reductions. EDE is an improved version of DE. The initial population for the population-based EDE method is produced at random. Four separate phases make up the EDE algorithm. It involves the production of populations, mutation, hybridization, and selection. The following formulae generate random populations: (8–10).
- *EDE detection.*
- The detection phase of the EDE has been deployed and implemented with the other WOA and HWDE approaches. Accordingly, each approach has been illustrated and expressed in Eqs. (1)–(3).
- *WOA detection:* The combination of EDE and WOA results in HWDE, as seen in the following equations.

The WOA detection refers to the CoE, which denotes the cost of electricity. The three approaches in combined methodology fashion have performed the major detection.

$$Avg_{rate}(EDE) = \sum_{i=1}^{n} xi - CoE_{ini} \tag{1}$$

$$Avg_{rate}(WOA) = \sum_{i=1}^{n} xi - PAR_{ini} \tag{2}$$

$$Avg_{rate}(HWDE) = \sum_{i=1}^{n} xi - LiKWh_{ini} \tag{3}$$

- *Supply of Maximum Volt Phase:* At first, the electricity voltage needs to be balanced and supplied as required by the home appliances. For this aspect, the supply of maximum volt phase is implemented, which can deliver the obligatory voltage and increase appliance utilization.

For the maximum voltage, given Eq. (4) illustrates as,

$$Elec_{max} = max(220 - 240) \tag{4}$$

In Eq. (4), the voltage is given from 220v to 240; the lowest voltage is 220 and the highest voltage is 240.

- *Time t and Vector v phase*: The time and vector phase here demonstrates that both depend on each other and possess the properties of the variables that change with the passage of time. Here the t and v implement the key concept of the three approaches by the given expression.

The time and vector of the three approaches are given in Eq. (5);

$$t_{t-v} = max\left(t_{EDE} + t_{WOA} = t_{HWDE}\right) \tag{5}$$

While for transition in which vector is superior to time is given in Eq. (6) as;

$$t_{v-t} = max\left(t_{HWDE} = t_{WOA} + t_{EDE}\right) \tag{6}$$

In Eq. (6), the vectors and times of each model are considered. Both the word and the vector convey information regarding the duration of time and the flow direction at a given time point.

- *Vector V* Updating:* For updating the v phase in this terminology, the three approaches have been implemented, and a hybrid approach HWDE has resulted, which here can update the average of the v accordingly

Where the proposed method is given as;

$$t_{HWDE} = t_{HWDE} \times a_{average} \times v^{*}a_{vector^{*}average} \tag{7}$$

Equation (7) illustrates the update of the vector with the multiplication of another vector in which the update takes place by increasing the amount of processing.

- Applying EDE: For the proposed model, the hybrid approach is given with three different approaches in which the value has been started

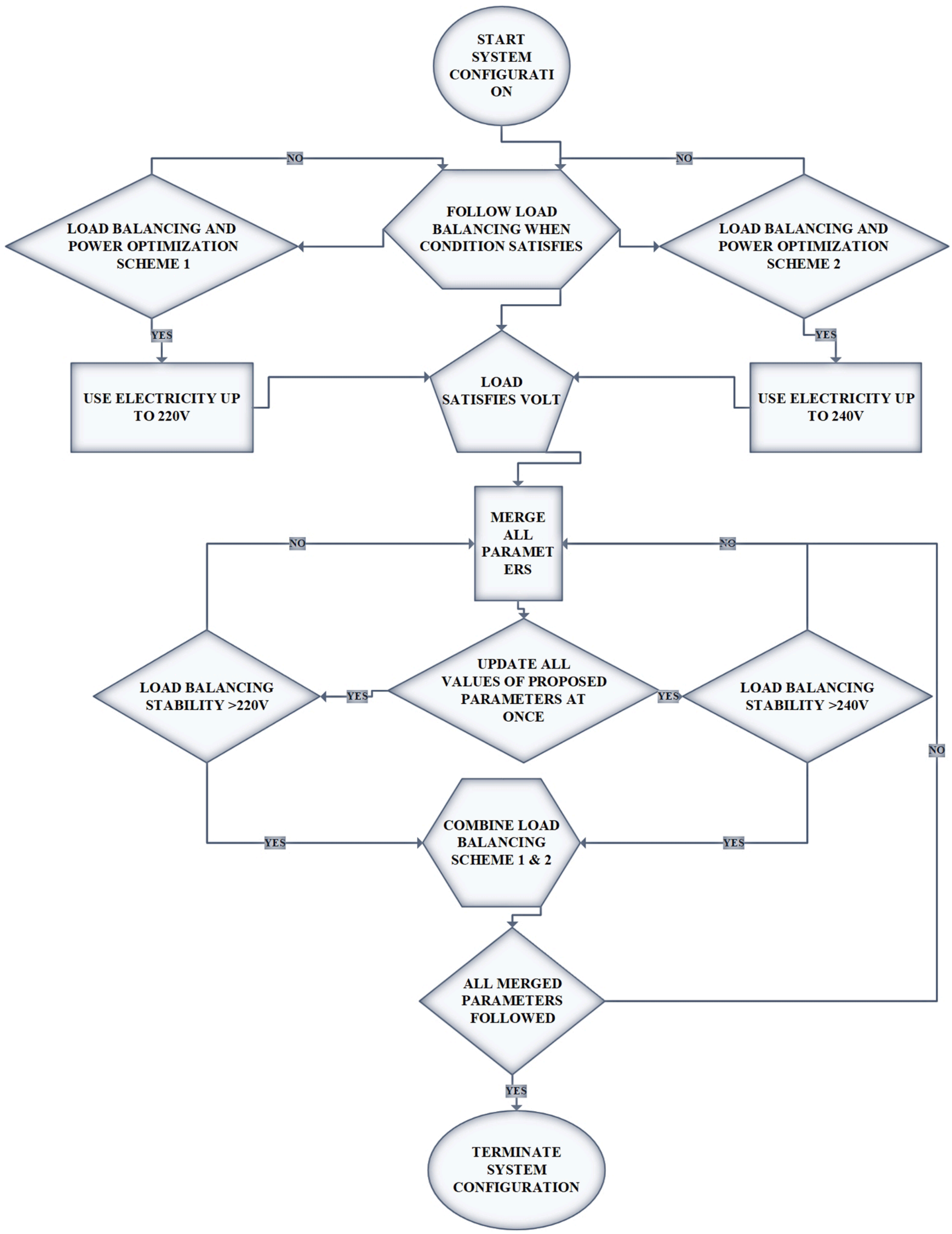

Fig. 2. The Proposed Work's Flow Chart.

from 0.3, 0.6, and 0.9 [30]. If the values are less than or equal to the given statement with random prey, proceed with Equation (8) [31].

In this case, the three conceptual implementations have taken place by calculating the three random values, which are three balanced values. They hence are applied and implemented by using these expressions.

$$H_{b,a,D+1} = \begin{cases} Z_{b,a,D+1} if random b(b) \leq 0.3 \\ y_{b,a,D} otherwise \end{cases} \quad (8)$$

Similarly, if the value is less than or equal to 0.6, proceed with this method using Equation (9).

Then two more vectors are created using Equations (9) and (10), pronounced as fourth and fifth train vectors.

$$H_{b,a,D+1} = \begin{cases} Z_{b,a,D+1} if random b(b) \leq 0.6 \\ y_{b,a,D} otherwise \end{cases} \quad (9)$$

If the value is less than or equal to 0.9, use the expression in Equation (10) [31].

$$H_{b,a,D+1} = \begin{cases} Z_{b,a,D+1} if randomb(b) \leq 0.9 \\ y_{b,a,D} otherwise \end{cases} \tag{10}$$

The crossover ratio is denoted by H, with values of 0.3, 0.6, and 0.9. Multiple H, Z, and Y denote mutant, trial, and target vectors. Equations (8), 9, and 10 illustrate the conditional aspects of the values generating the threshold voltage with three $\times$, y, and z.

- Applying WOA

The WOA works on three methods which are given below with mathematical models.

- Exploration Phase

$$\vec{D} = \left(\overrightarrow{CX_{rand}} - \vec{X}\right) \tag{11}$$

$$X(t+1) = X_{rand} - AD \tag{12}$$

denotes a random position of I and II [30]. The distance vector is illustrated in this scenario in which the D and X bars represent two different ordering of the exploration phase.

- Exploitation Phase

$$\mathrm{X}(\mathrm{t}+1) = \mathrm{D}\,\mathrm{e}^{\mathrm{bt}}\cos(2\pi\mathrm{t}) + \mathrm{X}^{*}(\mathrm{t}) \tag{13}$$

$$\mathrm{X}(\mathrm{t}+1)\begin{cases} X(\mathrm{t}) - ADp < 0.3 \\ D\mathrm{e}^{\mathrm{bt}}\cos(2\pi\mathrm{t}) + X(\mathrm{t})p \geq 0.6 \end{cases} \tag{14}$$

In Eqs. (13) and (14), the term shows the distance of the initial i^{th} values from the whale to the prey [32].

- Attack on Prey

$$\mathrm{D} = \mathrm{C}.\mathrm{X}_{\mathrm{p}}(\mathrm{t}) - \mathrm{X}(\mathrm{t}) \tag{15}$$

$$\mathrm{X}(\mathrm{t}+1) = \mathrm{X}_{\mathrm{p}}(\mathrm{t}) - \mathrm{AD} \tag{16}$$

In Eqs. (15) and (16), the coefficient vectors A and C and the position vector Xp are depicted [33]. The initial iteration of the vector is represented by an independent X whale's position [34].

The overall performance of the proposed approach has been implemented by using the major mathematical model to balance and optimize the key aspects of the methodology.

4. Performance evaluation

This section provides the simulation results in graphs and tables, and the findings are explained and understood. The three suggested parameters have been thoroughly examined and demonstrated. Continually, the simulated scenario is displayed. In this context, each property's applicability is separate. The three evaluation criteria are summarized in the table below.

- *Cost of Electricity:* The item's power consumption is broken down to reveal anticipated and unanticipated expenditures.
- *Load in KWh (Kilowatts):* The total electrical load per kilowatt-hour can be determined by calculating the cost per kilowatt-hour and multiplying it by the kilowatt-hour. Calculating the load and 24-hour electricity usage
- *Peak to Average Ratio (PAR):* This statistic demonstrates the average ratio of simulation values to the initial twenty-four hours of simulation. In this instance, the peak ratio is seen well, although the lowest value is deemed undesirable in other instances. In addition, table and graph data are provided for each indicator in the section presented.

4.1. Electricity cost (in Rupees)

There are four ways to compute your electricity bill in rupees. Beginning with the first hour, the simulation might last up to twenty-four hours. Fig. 4 displays the individual values for each approach. It is unclear which method is which in the following table and diagram (proposed model). The simulation cost is 0.61, the EDE is 0.39, the WOA is 0.89, the HGWDE is 0.21, and the HWDE cost of the suggested model is 0.18. The unexpected expenses for EDE, WOA, and HGWDE in the second hour of the simulation are \$0.62, \$0.39, \$0.89, and \$0.22, respectively. While all other models cost at least one-tenth as much as the HWDE model (0.18), two options are available: divide the full simulation time into 24 equal sections totaling 24 h, as depicted in Fig. 3, or evaluate the duration of each phase differently. During the simulation's peak time, HWDE was determined to be the model with the best overall performance. In all time frames, from one hour to twenty-four hours, HWDE is the most cost-effective and least expensive alternative. Reasons why energy is necessary: In this instance, it is shown that the proposed method is more effective than existing models. As simulation execution time increases, so do costs. The proposed plan is founded on models that could aid an optimization technique, resulting in energy savings and improved output. Due to a variety of reasons, one model may fail, while the proposed model may handle the problem effectively. Hopefully, this will prove useful. They occasionally work together to attain the same objective. As a result, astonishing accomplishments will be accomplished.

4.2. Energy consumption (KWh)

Regarding energy consumption, it is advised to utilize the least amount possible. Across four models, the cost value can range from one hour to twenty-four hours. HWDE has the best overall performance and uses the least energy in this circumstance. Employing WOE, HGWDE, and EDE to construct and assess the suggested model is essential. The promise of additional time also promotes utilization; however, the proposed HWDE technique can maintain performance while reducing consumption in all circumstances while maintaining performance. Fig. 4 Demonstration of Simulated durations for various plots ranging from one hour to twenty-four hours. The unit of measurement for energy usage is the kilowatt. The suggested model value begins at 1 h 132 K-Wh, while the unplanned value is 400.9, the EDE cost is 909.05, the WOA cost is 537, and the HGWDE cost is 180. A simulation demonstrates that, even though the proposed model spends more energy, this HWDE consumes the least energy in total power usage (time). The essential elements are constant maintenance and a small operating budget. This model is the most popular on the market. HWDE has the highest average and total expenses, notwithstanding the success of other departments.

Due to its improved performance and lower energy consumption, the proposed model is preferable to all others (measured in dollars and rupees). Several models have tracked and analyzed the overall average cost of HWDE. Reasons why energy is necessary: According to current models, the performance of the suggested work is superior. As the simulation continues, the costs also increase. The proposed plan is founded on models that could aid an optimization technique, resulting in energy savings and improved output. Due to a variety of reasons, one model may fail, while the proposed model may handle the problem effectively. Hopefully, this will prove useful. They occasionally work together to attain the same objective. As a result, astonishing accomplishments will be accomplished.

4.3. Cost in (\$/KWh)

Considering RTP and Critical Peak Price (CPP), we evaluated the four models presented in the preceding sections (CPP). These two standards are utilized when calculating and measuring energy costs. The RTP is recorded as real-time pricing, and the price volume is sorted to replicate

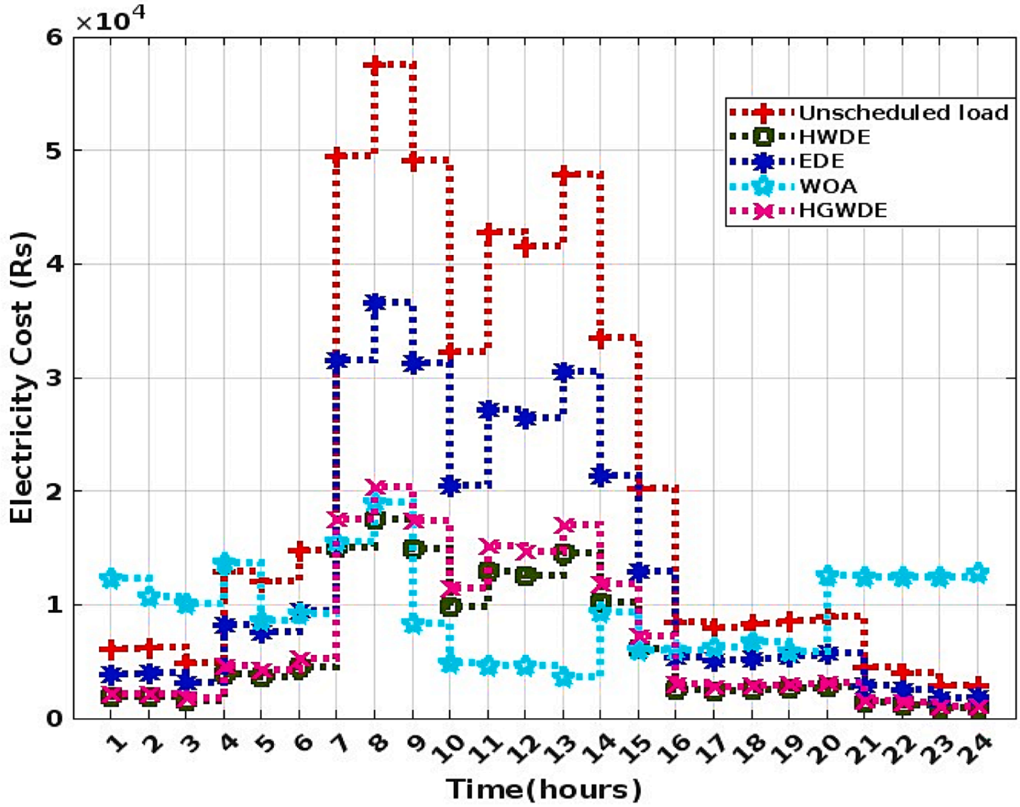

Fig. 3. Electricity Cost (Rs) vs Time (Hours).

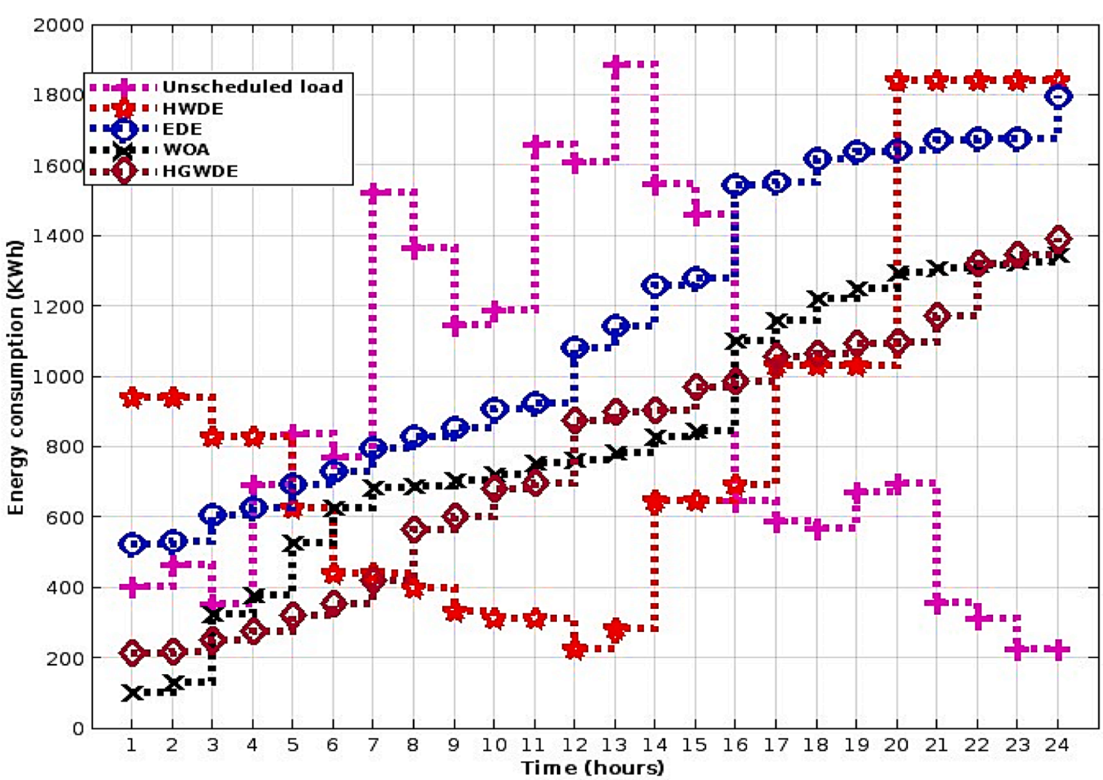

Fig. 4. Energy Consumption (KWh) vs Time (Hours).

the actual activity during one to twenty-four hours. Fig. 5 illustrates the circumstance. RTP, unlike CPP, can analyze and identify the value of normal to extremely high-power consumption in the presence of a processing environment. Certain crucial computations can only be performed during crucial simulations in which CPP plays a crucial role. Several measurements of RTP and CPP were utilized to calculate the overall average cost of RTP ($/KWh) and the cost of CPP ($/KWh), and the results indicated that they increased from the first simulation to the last by 13,52208 and 14,84458 respectively A.

Eight per kilowatt-hour; in the following paragraphs, we will explain how pricing is determined. Compared to other modern models, our described method performs far better. Cost per kilowatt-hour rises as simulation duration increases. The proposed plan is founded on models that could aid an optimization technique, resulting in energy savings and improved output. Due to a variety of reasons, one model may fail, while the proposed model may handle the problem effectively. Hopefully, this will prove useful. They occasionally work together to attain the same objective. As a result, astonishing accomplishments will be accomplished.

4.4. Total cost ($)

The four models' total power costs (in US dollars) are estimated and documented. The least expensive technique is the most cost-effective. During the simulation, unexpected expenditures of $3.21 arose, with EDE's costs at $3.11, HGWDE's at $2.63, and WOAs at $2.57. The WOA performance schedule was superior. The suggested HWDE model has two fees, which is uncommon for models. A strategy centered on the energy planning process, a variable tax rate for rupee and US dollar costs and expenditures, and the strictest RTP and CPP standards are urged. This statement is an integral part of the recommended maintenance work. RTP and CPP are utilized to limit the strain on mobile and stationary devices.

The proposed method is more energy-efficient than current practices and justifies the total energy use. According to the given R and projected USD, the cost of the simulation increases proportionally with its duration. It can vary significantly Depending on the technology and algorithm employed. The proposed plan is founded on models that could aid an optimization technique, resulting in energy savings and improved output. Combining two existing models has the benefit that if one model fails, the other model takes care of the problem and continues to function properly, etc., which is advantageous if both models strive toward the same objective. Advantageous if both models fail. And the ultimate result will be magnificent.

Regarding cost ($), RTP, and CPP, Fig. 6 suggested model outperformed all other options. As stated in Table 2, all RTP and CPP costs were determined from the general average of power prices. Fig. 7 indicates that unscheduled loads are the most expensive. The HWDE model provides the highest quality while remaining more cost-effective than previous methods.

Each model is documented after a thorough reading and assessment of valid grounds. The previous section documents and discusses the outcomes. Fig. 6 depicts five distinct models for your consideration. Specifically, the average electricity use, the average electricity cost, and the average power consumption. Fig. 6 and Fig. 7 also display the average RTP and CPP values. In this case, the four performance measures utilize RTP and CPP. All these components are necessary to maintain a suitable transmission load at a low cost and with little energy use. Fig. 8a, 8b and 8 are three examples of Table 2 from Table 3. (c).

This section contains four models that explain various situations where the greatest and worst performance are recorded. It was determined that power consumption, power consumption, load per KWh,

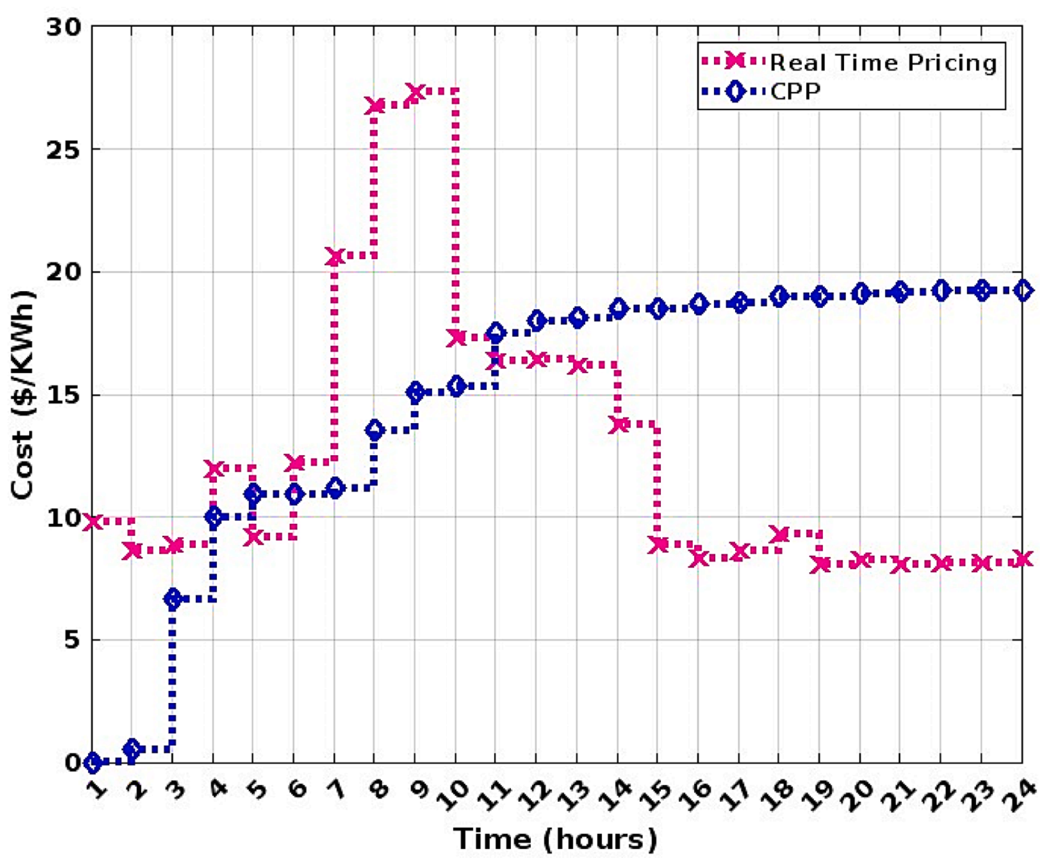

Fig. 5. RTP and CPP Cost ($/KWh) vs. Time (Hours).

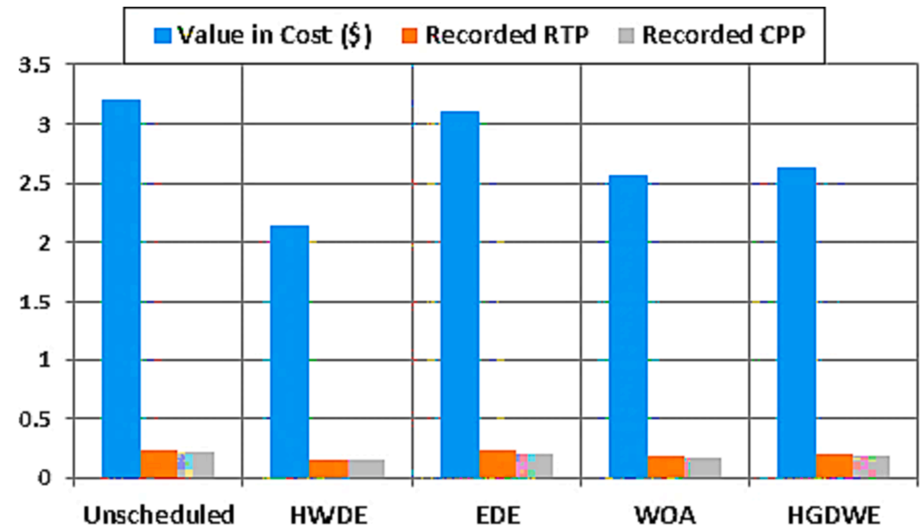

Fig. 6. Value of cost ($), Recorded RTP, and CPP.

Table 2
Simulation Setup.

Parameter	Value
Simulator	MATLAB R2021a
Performance Metrics	Cost of ElectricityLoad in Kwh (Kilowatts) Peak to Average Ratio (PAR)
Additional Evaluation Parameters	Heat (J/goC) Joules Per Gram Per Degree Initial CostAnnual Cost Saving
Proposed Values For Scheduling	0.3 0.60.9
Simulation Time	24 Hours
Optimization Methods	WOA DSMEDE
Simulation Plot Size	600 m*600 *m*
Existing Approaches	EDEWOA
Proposed Approach	Hybrid Whale Differential Evolution (HWDE)
Maximum Voltage	220–240 V
Electricity Cost and Scheduling	Shiftable Appliances Controllable AppliancesNon-shiftable Appliances

peak-average ratios EDE and WOA, and four proposed performance metrics were studied. It is also important to note that the anticipated load positively influences electricity usage and costs. HWDE is an outstanding simulator for both removable and non-removable devices. This technique loads the scheduling mechanism while maintaining a regulated RTP and CPP environment.

The four performance evaluation parameters have been introduced and deployed with proper implementation and justification for the proposed work. The main focus of these parameters is to generally balance the performance of the electricity and other home appliances. The key concept of these regarding their implementation in the algorithm is these are the sole parameters that can find out or via which it can be seen and measured that in previous works, how much was the utilization and consumption and how much is with the current WOA schema. To calculate the cost in Rs and $, with the kilowatts and total cost, the mentioned parameters have performed their duties well. Concluding it, the parameters are the measurement values that can be regarded as the sole objects in the implementation and testing of the proposed work.

4.5. Performance evaluation using additional parameters

For analysis and evaluation, the proposed HWDE model has been evaluated with additional parameters which are given as under;

- Heat (J/goC) Joules Per Gram Per Degree
- Initial Cost
- Annual Cost Saving (12 Months)

The performance has been achieved and evaluated with the heat, initial cost, and annual cost. Each parameter has been tested with the unscheduled model and is compared with the proposed model. The heat parameter has been evaluated in terms of joules shown in Fig. 9. The joules per gram per degree is the measurement values which has been witnessed that the proposed model can perform better compared with the unbiased and unscheduled one. Likewise, other parameters have also achieved the best performance with the proposed model shown in Figs. 10 and 11 respectively. The kay factor is that the scheduled model has the ability to perform better. The WOA and EDO models of optimization can achieve the best performance when combined in a single scheme.

4.6. Statistical analysis

The variable time_slots is quantitative in nature. While the regressors (independent) variables are of binary nature (qualitative). Linear regression model is run on data. The output suggests that average value of regression model when regressors are zero is 8.44 min. That means in case of no dryer, dish washer and washing machine average time slot is 8.44 min. For dish water the regression coefficient is 4.750 that shows that one-unit increase in dish washer will raise the time slot by 4.75. Similarly, regression coefficient for washing machine is −3.44. That shows decrease in dependent variable time_slot by 3.44 for one-unit increase in washing machine. The p value shows no significance for regressors. That may be due to nature of data because all the independent variables are measured on binary scale. Figs. 12, 13, 14, 15, 16, and 17 illustrates differently the statistical analysis of the proposed model with each electric home appliances.

This is scatter plot for the fitted model. Which shows that plot is reasonable. However, individual scatter plot of time_slot with dish_washer, drayer and washing_machine are not very convincing because of the nature of said independent variables.

4.7. Correlation analysis

Figs. 18 and 19 represents the analysis of the proposed model w.r.t the correlation. The correlation analysis has been implemented. Here, each appliance denotes differently each correlation with the direct and

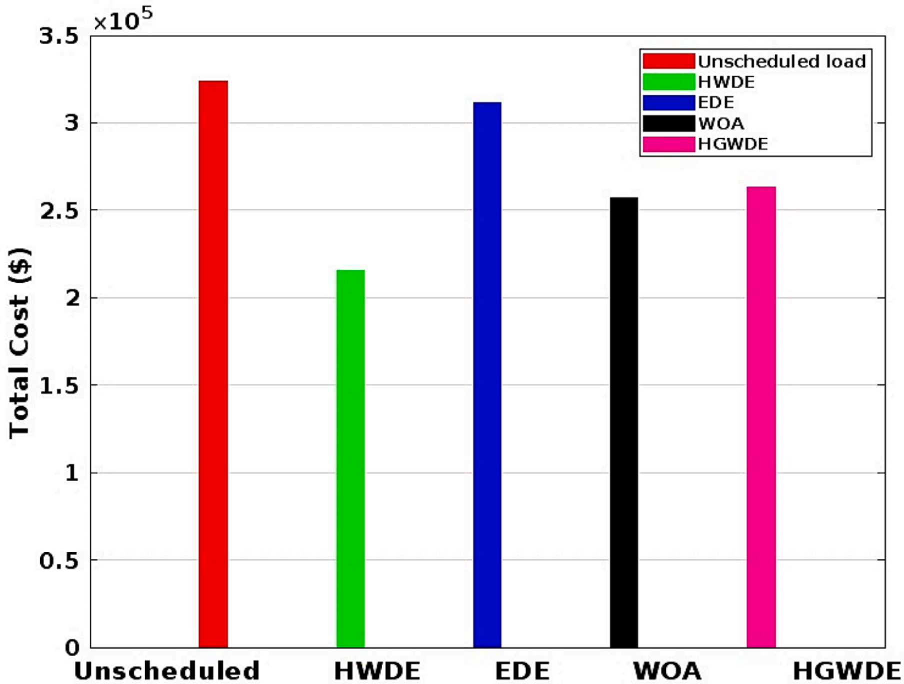

Fig. 7. Total Cost ($) vs. Time (Hours).

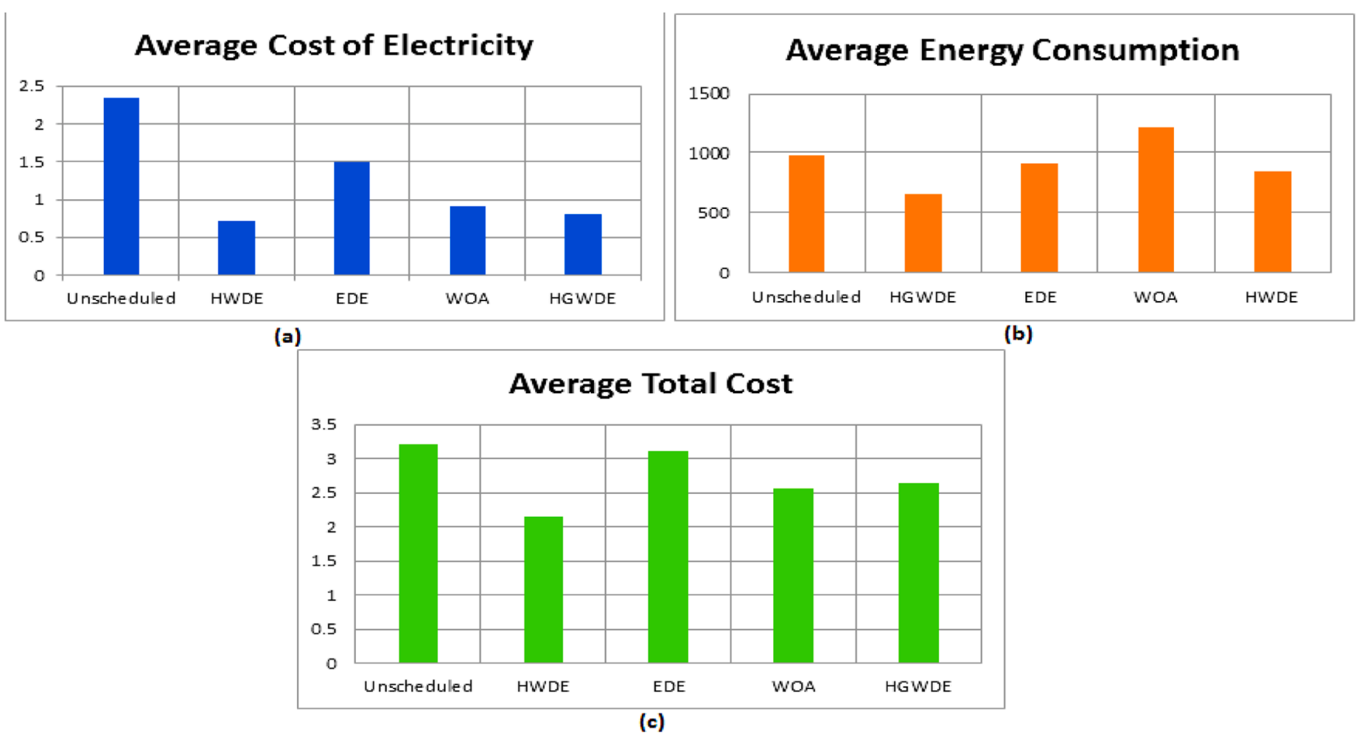

Fig. 8. (a) Average Cost of Electricity, (b) Average Energy Consumption, and (c) Average Total Cost.

indirect relation.

4.8. Sensitivity analysis of the proposed HWDE model

The proposed model has focused on the optimization and load balancing of the cost, heat, energy, and cost of annual demand, cost in units, and cost in dollars. The values of these parameters have been taken form the Meta heuristic analysis based on the performance and the type of electricity. Based on the household usage of the daily electricity the proposed work parameters have been taken into consideration to evaluate effectively with the unscheduled approaches. The values have been derived from the simulation readings. Each cycle and round has been measured and calculated in the MATLAB environments.

Table 3
Average Results of Proposed Model with Existing Models.

Model Name	Average Cost of Electricity	Average Energy Consumption	Average Total Cost
Unscheduled	2.3429	1.11	3.21
HWDE	0.7192	658.3417	0.14
EDE	1.4883	911.62	3.11
WOA	0.9129	1212.3	2.57
HGWDE	0.8046	840.25	2.63
Average RTP	13.52208		
Average CPP	14.84458		

4.9. Scalability and applicability of the proposed HWDE model

There are a lot of advantages from which the proposed work can be benefited. The proposed work can be effectively utilized in the environment where the load of electricity can cause a serious issue. Some of the key points of scalability and applicability of our proposed work are as follows;

- To effectively functionalized the proposed model.
- To enhance the quality of the appliances.
- To enhance the lifetime of the appliances by utilizing the proposed model.
- By expanding the nature and usage of the appliances and to maximize the utilization and reduce the energy consumption.
- To deliver a best way of load balancing and to reduce the risk and danger.
- To consume less energy, less heat, less cost, and less optimization time and to deliver the best performance based WOA and EDE model.

5. Conclusions

The cost of electricity has been proven to be proportional to the average daily electricity usage rate. To maximize resource utilization and cost savings, it is essential to have a system capable of balancing and

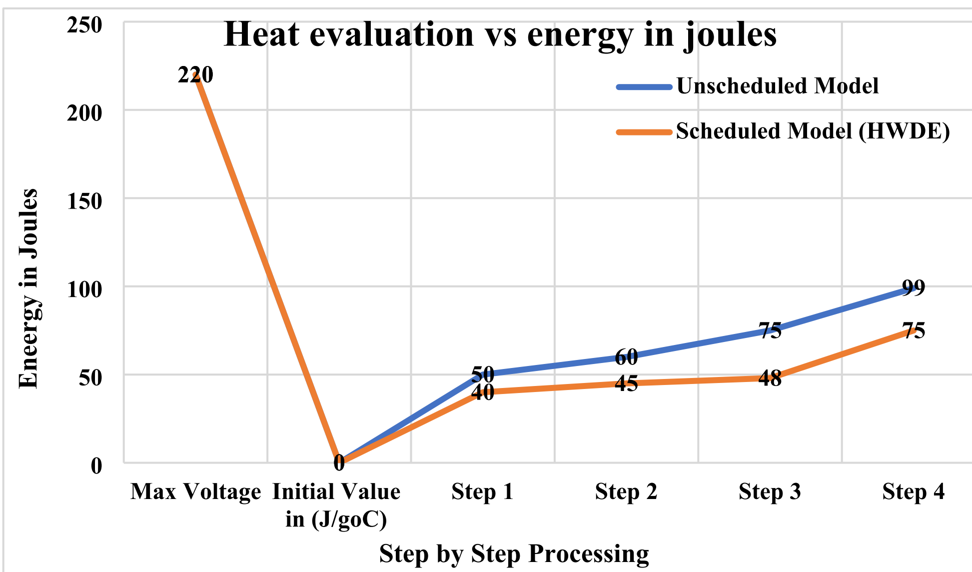

Fig. 9. Evaluation of the step by step process of HWDE vs unscheduled Model.

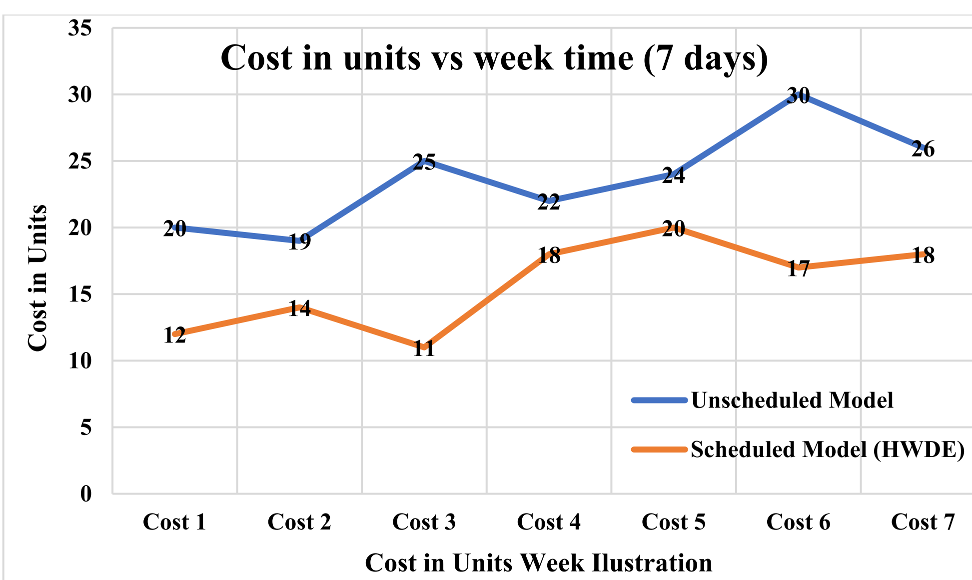

Fig. 10. Weekly Evaluation of the Cost in Units.

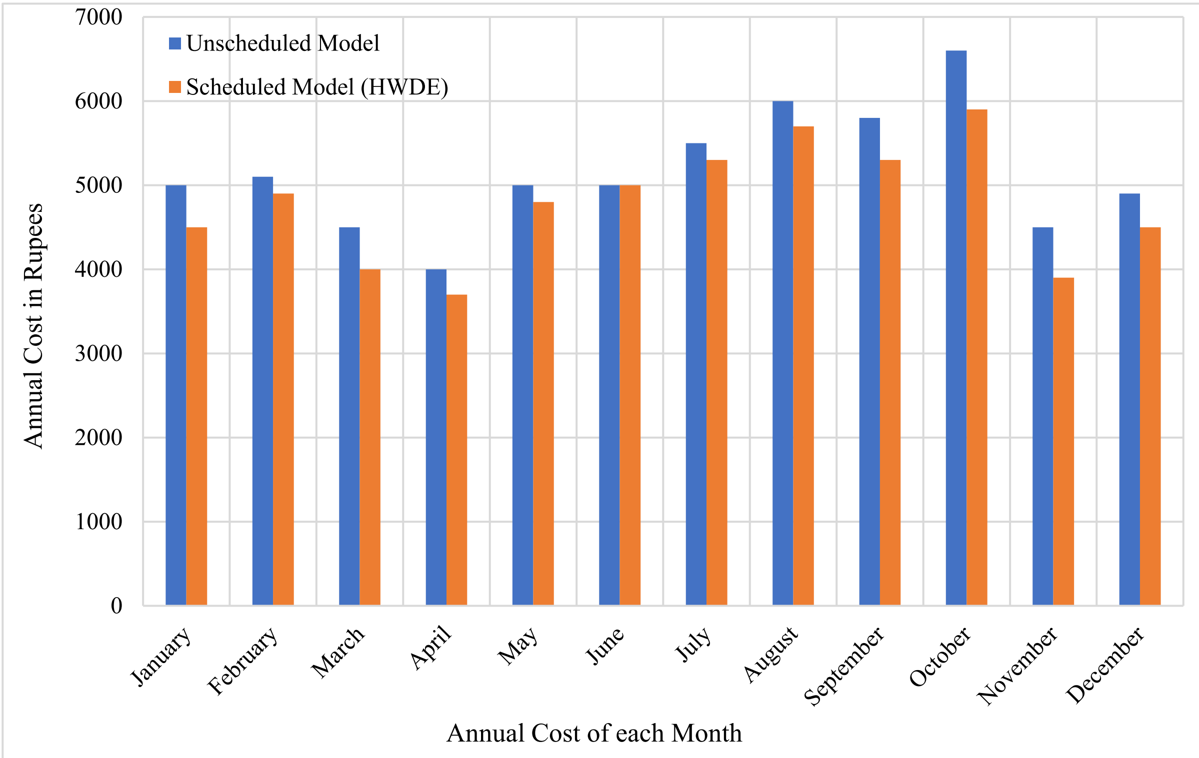

Fig. 11. Annual Cost Evaluation in Rupees vs Each Month.

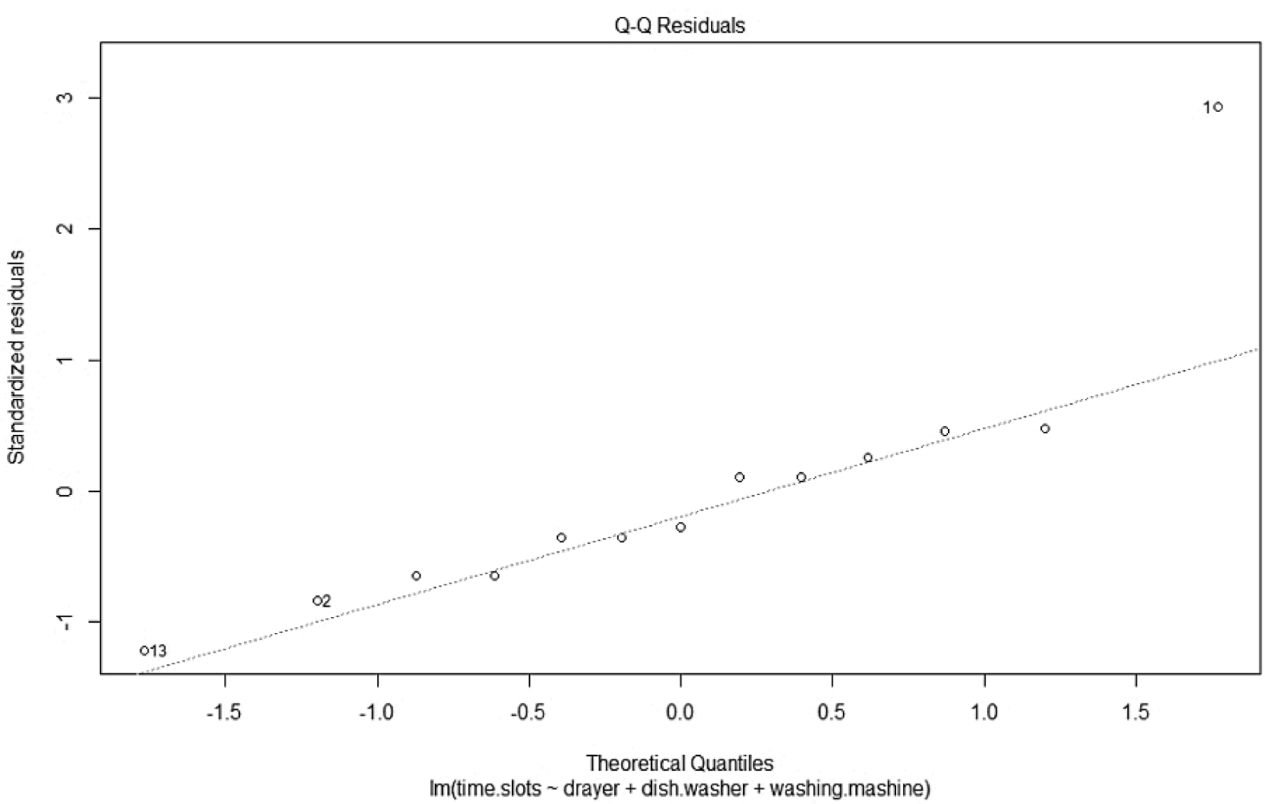

Fig. 12. Statistical Analysis of the Proposed Model vs Residual Comparison.

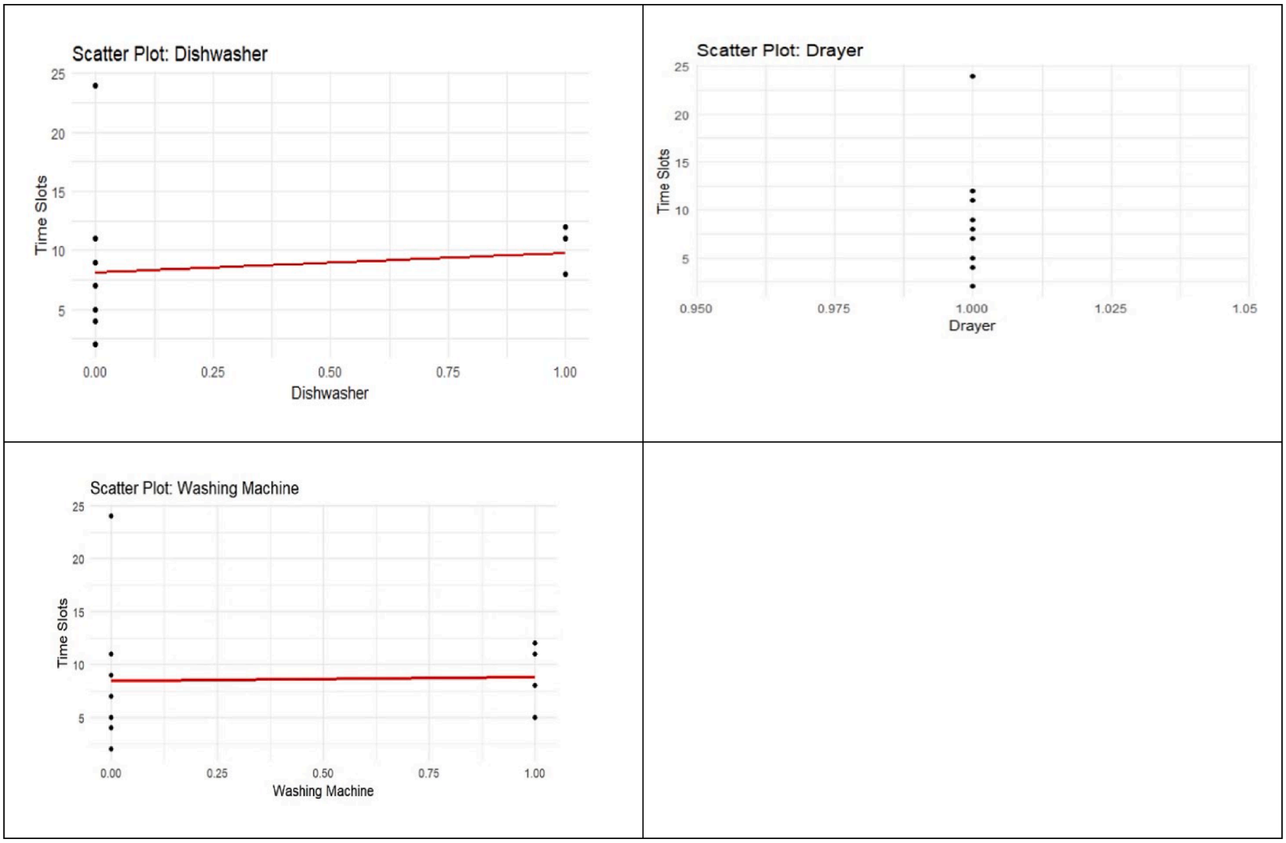

Fig. 13. Statistical Analysis of the Proposed Model vs Each Appliances.

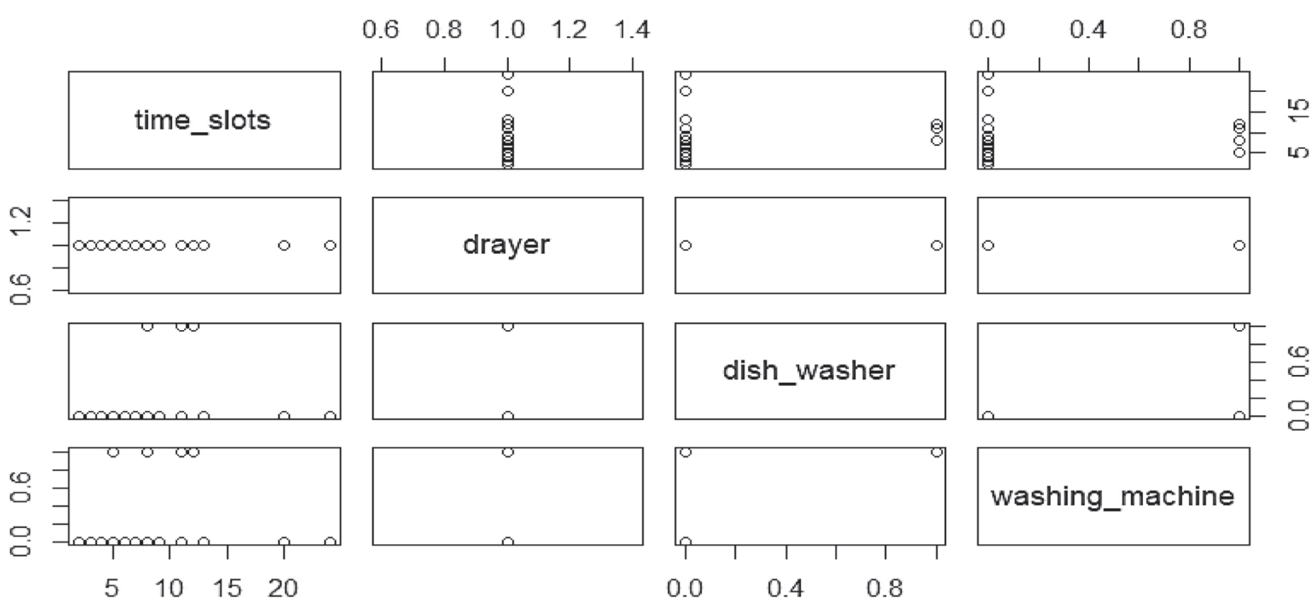

Fig. 14. Statistical Analysis of the Proposed Model vs Each Time_Slot with Appliances.

scheduling loads effectively. These devices can still utilize the necessary amount of power, but they must do so while incurring as little load-balancing expense as is humanly possible. Even though lowering the voltage is challenging, it is still possible to provide adequate voltage at the lowest possible cost. This is true despite the complexity of reducing the voltage. During this investigation, the existing WOA and EDE optimization strategies were integrated to create a novel model called HWDE. The name of this model was derived from the combination of two optimization procedures. It is the offspring of two separate species that were interbred. Load balancing utilizing WOA, HGWDE, and EDE components consumes much energy; this is required for RTP and CPP cost savings. There is a cost involved with this, however. The device's overall costs and expenditures must be decreased while remaining at the same level. The power supply introduces three unique metrics: the

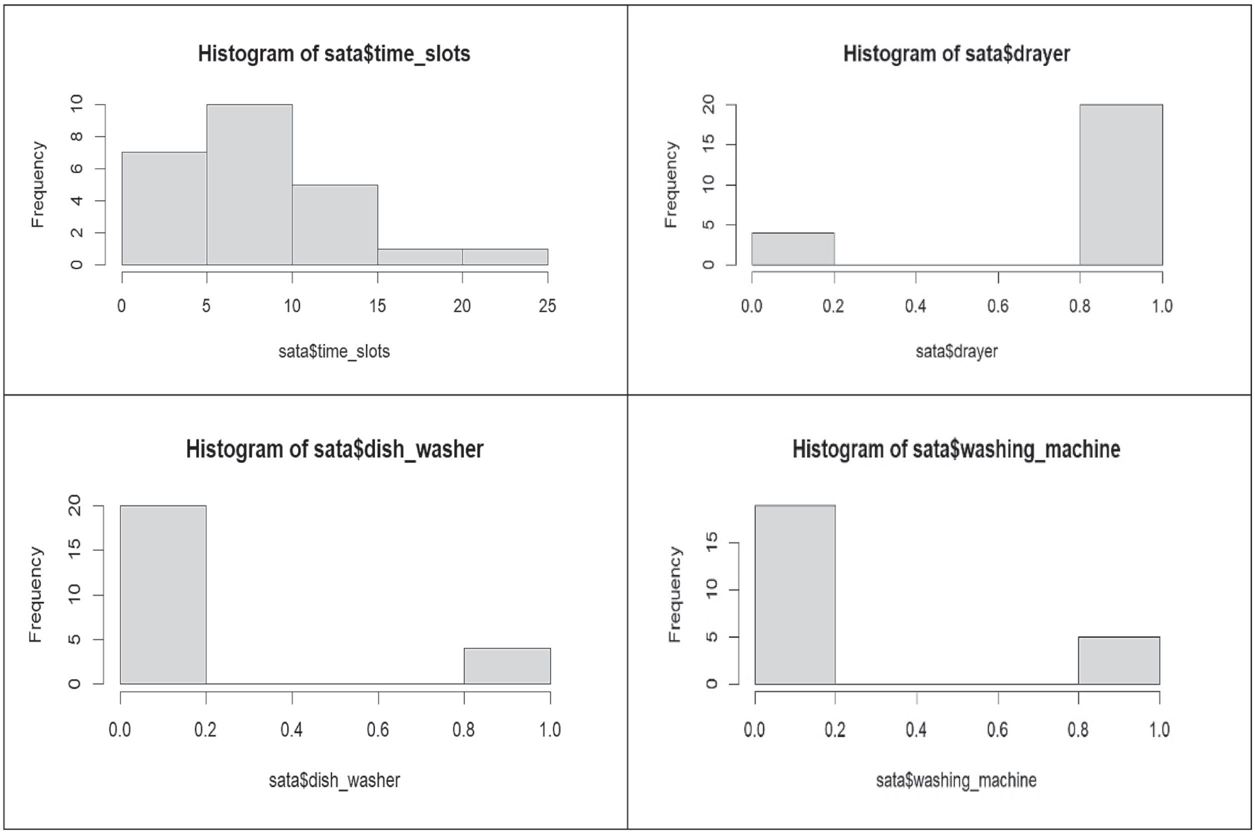

Fig. 15. Statistical Analysis of the Proposed Model vs Histogram Comparison with Time_Slot.

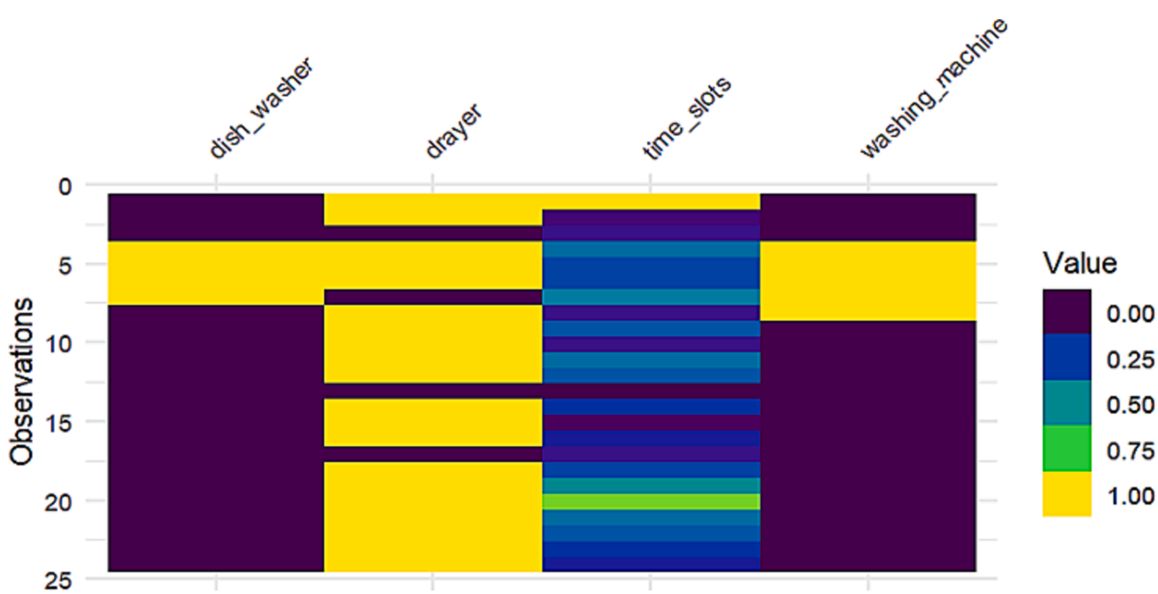

Fig. 16. Statistical Analysis of the Proposed Model vs Observations.

maximum average ratio, the load per kWh, and the total power consumption.

Existing models are analyzed to evaluate their energy costs ($/KWh), energy consumption, price ($/Rs), and total costs. HWDE consistently achieved the best results across all MATLAB-modeled scenarios. Before the establishment of the tax, the EDE was 1.4883, the EDE, WOA, HGWDE, and HGWDE were all 0.8046, and the HGWDE was 0.7192. The average electricity rate was 2.3429, while the WOA was 0.9129. The WOA had a value of 0.9128. The average amounts of energy consumed by unscheduled loads were comparable to the average amounts of energy consumed by scheduled loads: 981.11 kWh, 911.62 kWh, 1212.3 kWh, 658.3417 kWh, and 840.25 kWh. A shipment could range from $3.21 to $4.00, depending on size and weight.

- Features and Limitations

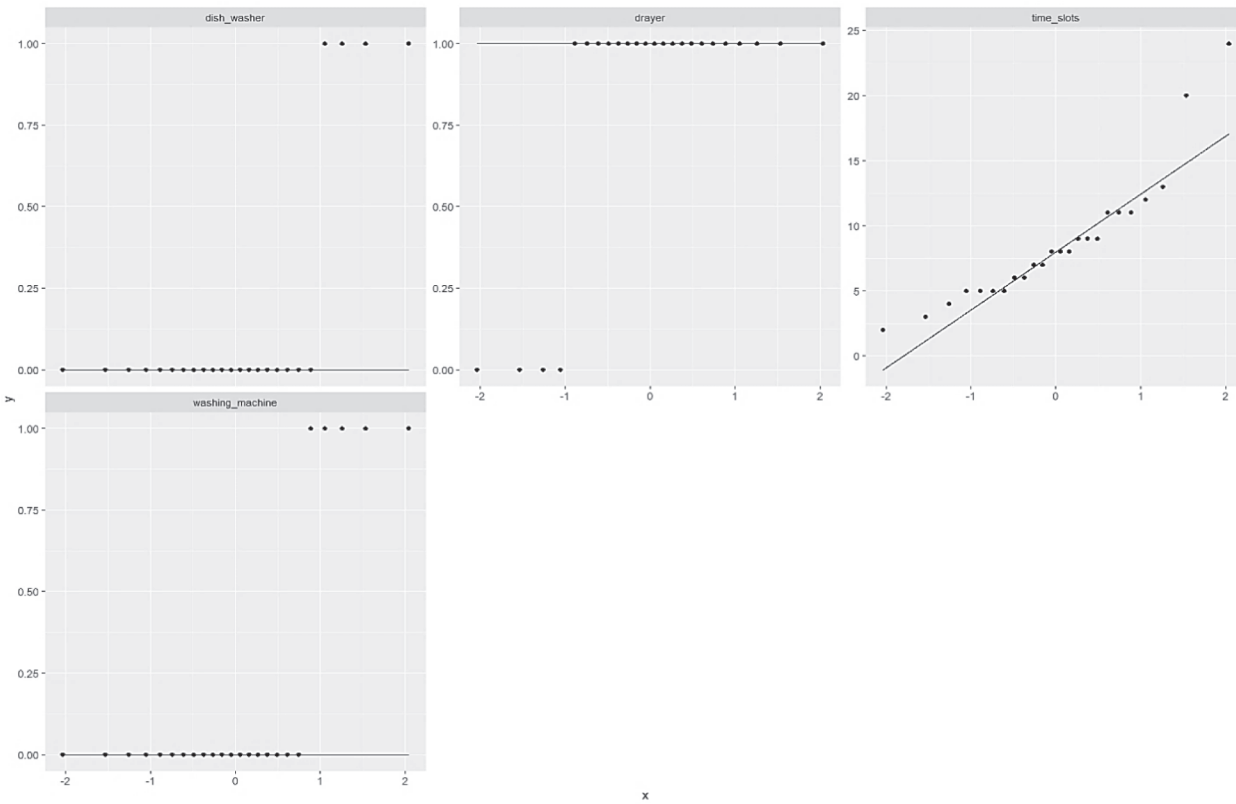

Fig. 17. Statistical Analysis of the Proposed Model vs Each Electricity Appliances.

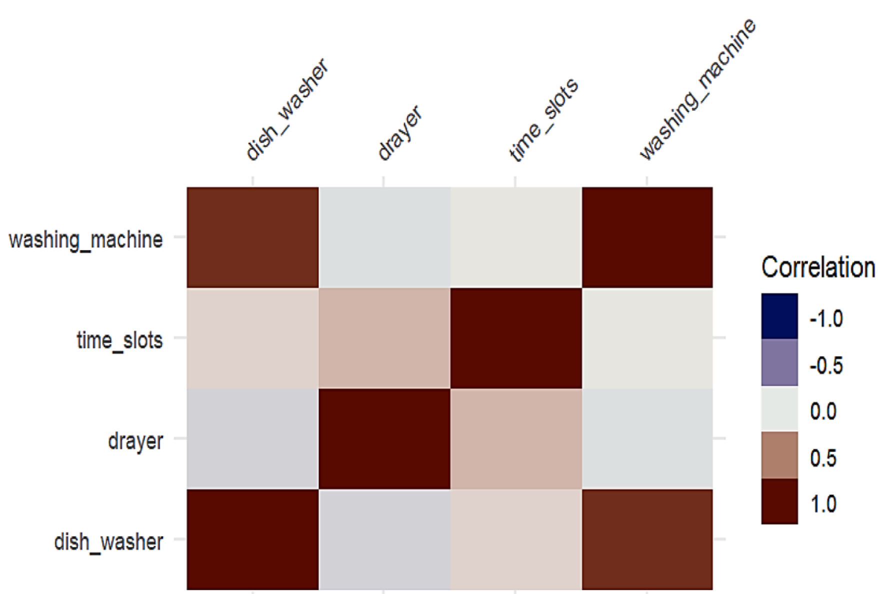

Fig. 18. Correlation Analysis of the Proposed Model vs Confusion Matrix.

Effective for complex, nonlinear optimization problems: WOA has been shown to be particularly effective for optimization problems involving many variables and complex, nonlinear functions.

Balances exploration and exploitation: WOA uses a combination of random search and adaptive search, which helps to balance exploration and exploitation, preventing the algorithm from getting stuck in local optima. Handles constrained optimization problems: WOA effectively handles constrained optimization problems, where one or more constraints restrict the feasible solution space. Easy implementation: The algorithm is relatively simple and can be applied to various optimization problems.

Not guaranteed to find the global optimum: Like all metaheuristic algorithms, WOA does not guarantee that the global optimum will be found. The algorithm may get trapped in local optima, especially for highly complex optimization problems. Requires fine-tuning of parameters: The performance of WOA can depend on the choice of several

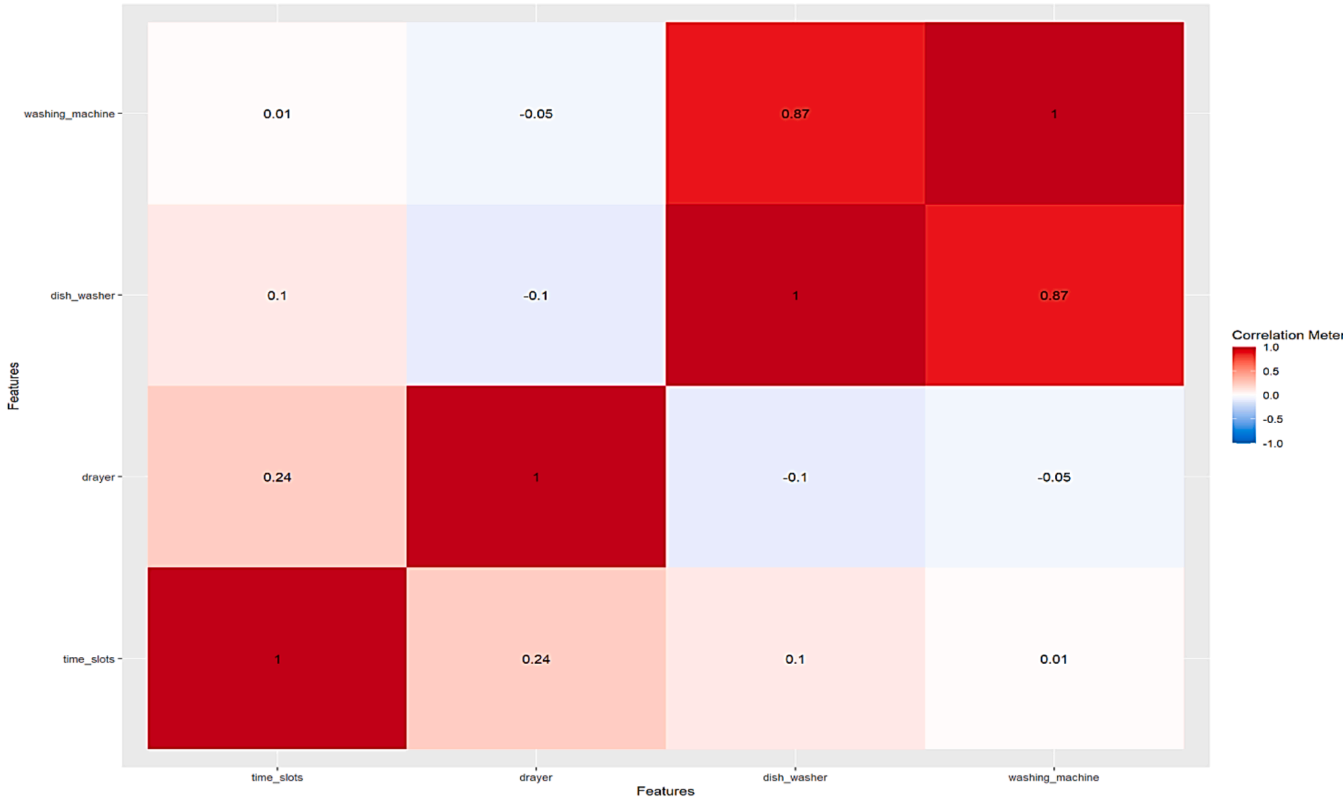

Fig. 19. Correlation Analysis of the Proposed Model vs Correlation Meter Illustration.

parameters, such as the population size, search range, and crossover rate. Fine-tuning of these parameters can be time-consuming and requires expertise. High computational complexity: WOA can be computationally expensive, especially for large-scale optimization problems, as it requires many iterations and evaluations of the objective function. Sensitivity to initial conditions: WOA can be sensitive to the initial conditions, and different initializations may result in different solutions. Therefore, multiple runs with different initial conditions may require a more robust solution.

- Future Work

In the future, these evaluation and optimization algorithms can also be tested under diverse simulations and other home appliance setup settings. The idea of the optimizations can be expanded and enhanced by using hybrid optimization algorithms, which can possess the features and positive aspects of the advanced optimization schemes. This idea can be effectively deployed with the new parameters and other new statistical implementations.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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