International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 1
DOI: https://doi.org/10.17762/ijritcc.v11i1.5987
***Article Received**: 16 November 2022 **Revised**: 18 December 2022 **Accepted**: 30 December 2022*

Context-Aware Clustering and the Optimized Whale Optimization Algorithm: An Effective Predictive Model for the Smart Grid

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Abstract — For customers to participate in key peak pricing, period-of-use fees, and individualized responsiveness to demand programmes taken from multi-dimensional data flows, energy use projection and analysis must be done well. However, it is a difficult study topic to ascertain the knowledge of use of electricity as recorded in the electricity records' Multi-Dimensional Data Streams (MDDS). Context-Aware Clustering (CAC) and the Optimized Whale Optimization Algorithm were suggested by researchers as a fresh power usage knowledge finding model from the multi-dimensional data streams (MDDS) to resolve issue (OWOA). The proposed CAC-OWOA framework first performs the data cleaning to handle the noisy and null elements. The predictive features are extracted from the novel context-aware group formation algorithm using the statistical context parameters from the pre-processed MDDS electricity logs. To perform the energy consumption prediction, researchers have proposed the novel Artificial Neural Network (ANN) predictive algorithm using the bio-inspired optimization algorithm called OWOA. The OWOA is the modified algorithm of the existing WOA to overcome the problems of slow convergence speed and easily falling into the local optimal solutions. The ANN training method is used in conjunction with the suggested bio-inspired OWOA algorithm to lower error rates and boost overall prediction accuracy. The efficiency of the CAC-OWOA framework is evaluated using the publicly available smart grid electricity consumption logs. The experimental results demonstrate the effectiveness of the CAC-OWOA framework in terms of forecasting accuracy, precision, recall, and duration when compared to underlying approaches.

Keywords —Knowledge Discovery, Context Aware Clustering, Electricity Monitoring, Artificial Neural Network, Bio-Inspired Optimization, and Whale Optimization

I. INTRODUCTION

Extraction of meaningful information or patterns from large data stores is known as data mining [1]. The three steps of data mining are pre-processing, data mining, and post-processing. Knowledge discovery in databases (KDD) has become popular as database data has risen. KDD is a nontrivial approach for identifying a valuable, consistent, and previously found pattern in massive datasets. Pre-processing is used before data mining techniques are matched with trustworthy data. Included are purification, amalgamation, picking, and evolution. The data mining steps of knowledge discovery in databases employs a numerous of techniques to unearth hidden knowledge. The final phase calculates mining results, user needs, and domain knowledge. Data mining is vital. It's the process of synthesizing information from several sources. Data mining software analyses data systematically. It lets people view data from several angles to categorize and assess linkages. Data mining uses hundreds of variables to find patterns in huge relational datasets [2]. Data mining evaluates large datasets. It also includes the necessary tools. Information from marketing, communications, and health is used in data mining.

Data streams are necessary for programmes that make decisions, such as power utilisation. Discovering power usage patterns from such data sources involves data mining. Data streams reflect information flow. Multi-Dimensional Data Streams (MDDS) are made up of data feeds from sensors, call centres, networks, and other sources [3]. Data mining is challenging because of the volume and velocity. Feature evolution, indefinite length, constrained labelled data, idea evolution, concept drift, and other characteristics are all present in data streams [4–7]. Data streams experience idea drift when their primary notion changes [8] [9]. Streaming courses evolve concepts. Feature evolution is when data stream features change. Data streams lack labels since it's difficult to manually categorize all the data pieces. Each complicates data stream mining. Researchers have concentrated on discovering knowledge from MDDS's electrical data for power applications. Electric consumption statistics can help policymakers and property possessors understand consumers' demand-usage tendencies [10-12]. For consumer involvement in period-of-Use fees, crucial high costing, and individualized responsiveness to demand, precise

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power utilization estimates leveraging multidimensional data streams are essential. Accurate consumption forecasting improves grid operations and power system planning, and it also has major repercussions on the environment and the economy, like diminishing power dissipate and hastening the decarbonization of the power precinct. Despite established models, estimating residential electric consumption is difficult owing to tenants' unpredictability [13][14]. The pursuit of a model that can deliver precise energy forecasts is ongoing.

Researchers must overcome a number of challenges, including as erroneous projections, scalability, and efficiency, in order to extract knowledge from the MDDS. There are numerous documented data mining strategies for efficiently extracting information from multi-stream power datasets. Energy utilisation has been estimated using optimization techniques, clustering techniques, machine learning techniques, and more recently [15]. Effective electricity prediction requires both electrical features that take context into account and accurate prediction models [16]. This research article concentrates on the energy consumption forecast model for smart grid systems. Pre-processing, predictive feature extraction and prediction models are common components of a prediction model. The prediction model is a vital phase in which researchers may employ classifiers such as Support Vector Machines, Artificial Neural Networks, and so on. However, using these classifiers in their original form is not optimal because the authors had incorrect training and testing results. As a result, it is critical to optimize such classifiers using algorithms that are inspired by biology or nature. Researchers have paid close attention to bio-inspired or nature-inspired algorithms in recent years. One of the most popular categories of nature inspired algorithms is the swarm intelligence algorithm. SI algorithms are created by mimicking animal or plant behavior. Ant Colony Optimization (ACO) [17], Particle Swarm Optimization (PSO) [18], Grey Wolf Optimization (GWO) [19], Artificial Bee Colony (ABC) [20], Brain Storm Optimization (BSO) [21] [22], and Whale Optimization Algorithm (WOA) [23] are some of the most extensively utilized SI algorithms.

The researchers selected WOA to enhance the ANN among these SI techniques in this research article. Whales' hunting tactics, specifically how they identify and attack their food utilising a bubble-net feeding technique, served as the inspiration for the well-known, successful, and competitive algorithm WOA. WOA has been demonstrated to outperform PSO, ACO, BSO, ABC, and other algorithms in terms of optimization performance [24]. When solving high-dimensional large-scale optimization problems, it still has issues with low solution accuracy, delayed convergence, and easily falling into regionally optimal solutions. In order to increase performance, substantial work has been done to optimise the WOA algorithm. Accordingly, researchers adopted the Optimized WOA (OWOA) algorithm in this research article to overcome the challenges of existing WOA while applying it to ANN training. Using OWOA, authors have proposed a novel predictive model called Context-Aware Clustering (CAC)-OWOA. The proposed CAC-OWOA consists of the below contributions.

- The integrated CAC-OWOA predictive framework for energy consumption prediction for smart grid systems employing various electricity records using context-aware clustering and OWOA-based ANN has been proposed by researchers in this research publication.
- Researchers have developed a novel CAC in this study that is based on the idea of supervised by-self grouping, where the context related information is assessed through monitoring to create groups.
- Context-aware clustering enhances prediction accuracy by taking into consideration commodity dependencies at a higher contextual level. The predictive feature vector created by the CAC served as the predictive model's input.
- In order to reduce error rates and increase overall prediction accuracy, researchers have presented an effective ANN predictive model employing the OWOA bio-inspired algorithm in this study article.
- Researchers offer an experimental examination for CAC-OWOA paradigm utilising the publicly available power usage data to show the efficacy of the proposed predictive paradigm for the smart grid system.

The sections that make up the rest of the research article are listed below. The investigation of relevant works is presented in Section 2 along with an appraisal of the research gaps. Section 3 presents the approach of the CAC-OWOA paradigm. Section 4 presents the simulation outcome, and Section 5 presents the conclusion.

II. Related Studies

Monitoring energy use with effective prediction models is essential for improving smart grid performance. Through the use of various mining techniques, several systems for calculating energy demand have recently been created. To learn about load forecasting or energy consumption forecasting, these strategies refers multi-dimensional power data flows as an input. Researchers reviewed the recently proposed energy forecasting methods and improved WOA strategies.

A. Energy Forecasting Methods

The K-means clustering and Fuzzy C-Mean techniques are used in the short-term energy load forecast model for electricity users that is presented in [25]. The authors employed K-means clustering to divide their clients into two groups based on their

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electrical usage parameters. Then, comparable data was filtered out using the Fuzzy C-Mean technique. The statistics analysis algorithms to extract the device's energy status from its flowing power usage data were proposed by the authors in [26]. For non-intrusive load monitoring, the authors combined a multitarget classification algorithm with a distinctive data learning model to create the system. In [27] author examined existing methods and suggested machine learning. The authors used the ANN approach with the Genetic Algorithm (GA) SI method. The authors tested their prediction model on a real-world testbed. In [28], the authors have investigated a novel incremental learning technique for estimating building energy usage. The swarm decision table methodology was created by the authors, who contrasted it with the traditional decision tree methodology. Trials were run on multidimensional data flows with real-time IoT. The spatial and temporal ensemble forecasting model was created in [29] with the purpose of predicting short-term electricity usage. Utilising the k-means method and group analysis, the authors looked at power use profiles at the apartment level. Long Short-Term Memory Unit (LSTM) and Gated Recurrent Unit, two deep learning paradigms, were used together in the ensemble predicting paradigm by the authors (GRU). The Microsoft Azure Cloud-based technique's energy consumption projection model was put forth in [30]. Classifiers like KNN, ANN, and SVM are referred for the forecasting paradigm. The occupantbehavior-sensitive prediction paradigm, another new endeavour, was created in [31] to forecast building energy demand. Different techniques of ML like ANN, DNN, Ensemble Bagging Trees (EBT), and Classification and Regression Trees have been created by authors (CART). Using machine learning techniques, the power consumption estimation model was recently demonstrated in [32] for Agartala (India). A forecasting system has been created by the authors to predict the burden for subsequent 1 day, 1 week, and 1 month. Machine learning methods like XGBoost classifiers and random forest (RF) classifiers have been developed by authors. In [33], the authors present a blend ML technique for forecasting peak demand and device’s power use. Authors advocated the faster k-medoids clustering approach, SVM, and ANN for forecasting appliance energy use and consumer peak demand. The distributed clustering algorithm with two layers (DCA), was introduced in [34], another modern clustering technique for energy forecasting that employs affinity propagation and k-means clustering algorithms. The authors covered user-side DR flexibility and incentive Demand Response (DR). As a technique for metaheuristic improvement, the dragonfly algorithm (DA) was introduced in [35]. The authors have created an algorithm to deal with the practical issue of electricity observation in one and more advanced houses. The appliances have been divided into shiftable and nonshiftable categories by authors. The authors of [36] developed a new approach for forecasting the power usage of each consumer appliance from a collection of linked consumers' digital loads. Authors first gather and save the most recent data for individual piece of equipment with varying burden for digital applications. The authors then computed individual power usage. The Artificial Bee Colony (ABC) technique, a search-based optimization strategy, was developed by authors to forecast the power consumption of specific customers. In [37], the use of ensemble techniques to improve the execution of ANN models for home energy forecasting had investigated. A home in Portugal features a Home Energy Management System (HEMS), batteries, and solar panels. The value reported in [38] for the maximum mutual knowledge quantum for monthly power use. The elements with the highest reciprocal information coefficient have been selected. Datasets with high relevance parameters were pooled. Finally, the prediction of power usage had conducted using the random forest. In order to calculate how much electricity had been used over time, the clustering technique K-means was combined with a well-known deep learning transformer in [39]. The K-means clustering approach was employed to improve the predictability of the transformer paradigm, which was used to forecast power utilization in the hour that would follow.

B. *Improving* WOA Methods

As improving the conventional ANN classifier using the optimized bio-inspired algorithm WOA is the key contribution of this paper, researchers have reviewed some recent research articles [40-47] on improved WOA in this section. [40] presented the idea of a leader to direct the populace toward the ideal solution area and quicken WOA convergence. The two most successful methods for enhancing WOA are chaotic sequences and Opposition-Based Learning (OBL), according to the authors in [41]. In order to enhance the standard WOA, two strategies were employed in [42]: (1) adaptive double weights to balance the algorithm's early spatial search ability and later local spatial tuning ability, and (2) random replacement of poorer agents with better ones to improve the algorithm's solution convergence speed. The first significant improvement in [43] is optimising the beginning population by means of a chaotic sequence. Following that, Gaussian variation had applied to maintain the population's diversity level. Finally, a "reduced" technique was utilized to find the best answer. In [44], the quantum behavior in the conventional WOA proposed replicating humpback whales' hunting activity to improve the algorithm's search capabilities. To enhance the WOA, a modified WOA with single-dimensional swimming (SWWOA) had presented in [45]. To optimize searchability, the initialized population had generated using a tent map. Second, after each cycle, quasi-opposition learning had used to increase searchability even further. Third, a special nonlinearly controlled parameter factor built on the logarithm function had been provided to strike a balance between exploration and exploitation. In [46], four primary operators were proposed to

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improve WOA's search performance called Improved WOA (IWOA). The operators included density peak clustering, opposition-based learning, nonlinear parameter design, and differential evolution. Modified whale optimization algorithm (M-WOA), a novel variation of WOA, was proposed in [47] to address the issue of delayed convergence and to strike a balance between exploration and exploitation. In M-WOA, the choice of a roulette wheel had been combined with WOA to speed up convergence. The M-WOA was used to improve the performance of the ANN training phase.

C. Research Gaps Analysis

In the MDDS for energy forecasting models, clustering techniques, ML approach, and swarn intelligence are some of the commonly utilised tools to uncover patterns. According to the findings of these recent studies and the proposed CAC-OWOA model, researchers have discovered the following study essentials in this article.

- In some recent energy forecasting strategies reported in research articles [25] [29] [33] [34], context information regarding energy usage was disregarded in favour of using traditional clustering techniques for group creation. It leads to a flawed strategy for the smart grid's electricity forecasting.
- The energy forecasting methods in the research articles [25-39] utilized conventional prediction models such as ANN, SVM, etc. These classifiers, however, experience an incorrect training phase, become trapped in local optima, and converge slowly to the best answers.
- The optimization algorithms were utilized in research articles [35] [36] for improving the energy forecasting model but still suffered from a lack of context-aware predictive feature formation for accurate forecasting. Also, the conventional optimization algorithms failed to overcome the challenges of slow convergence and quickly into local optima for the MDDS dataset.
- The improved bio-inspired algorithm WOA had been proposed in research articles [40-47], but none of these methods have been applied to the energy consumption forecasting domain. Except for the research article [47], none of the improved WOA techniques were applied to machine learning algorithms.

This research article proposes the CAC-OWOA predictive model to overcome the above research challenge. The context-aware efficient clustering algorithm is proposed to build the efficient predictive features vector for accurate energy consumption forecasting. The conventional ANN algorithm is improved by applying the OWOA algorithm at the training phase to reduce errors, slow convergence, and misclassifications while working on MDDS datasets.

III. CAC-OWOA METHODOLOGY

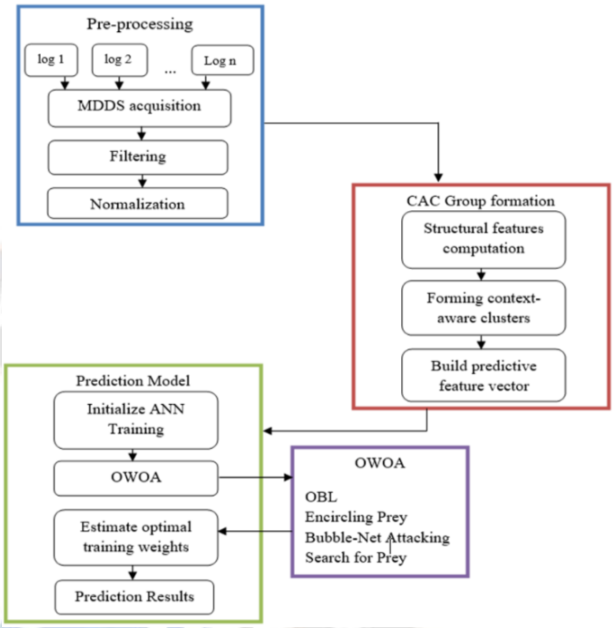

Figure 1. The architecture of the proposed smart grid system's energy consumption prediction model

Figure 1 shows the outline of the proposed CAC-OWOA model for efficient energy consumption forecasting considering the smart grid application. To the best of our knowledge, CAC-OWOA is the first integrated approach in the smart grid power forecasting domain. Figure 1 depicts the three primary phases of CAC-OWOA: pre-processing, CAC, and the prediction model. During the pre-processing step, the electric consumption logs (log 1, log 2, ..., log n) are gathered from the household residence into one MDDS log. As each log is gathered from each home in the residential complexes, its contents may be unfinished and disorganised, which could result in incorrect information discovery. As a result, researchers have initially used a filtering mechanism to suppress the noisy and messy data from the input MDDS. Then, researchers perform the data normalization to scale the energy consumption parameters. Researchers applied the suggested CAC group creation approach, which estimates context-aware structural characteristics using distance similarity measures, after preprocessing the input electrical MDDS data. Researchers sorted and built groups based on estimated predictive features. One of four power usage patterns is used to identify each cluster (for instance, periodic, irregular, smooth, and regular). It is the method of creating a predictive feature vector for subsequent processing to anticipate energy usage. The suggested OWOA-based ANN algorithm will be used to educate as well as assess the input

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prediction qualities in the suggested architecture. The OWOA method lowers the overall MSE rate and raises the ANN training process's prediction accuracy. The OWOA approach optimizes weight based on current fitness ratings. Table 1 shows the mathematical notations and their significance.

TABLE 1. MATHEMATICAL NOTATIONS AND SIGNIFICANCE

Notations	Significance
DT	Data on electricity use
M	Incorrect data parameters
N	Standardised dataset
G	Set of groups/clusters
c	Number of groups/clusters
GM	Group Members
r	Number of GMs in each group
C	Groups with centroids
P	Context-aware groups with labels as predictive feature vector
D	Dimensional space for WOA
L	Coefficient vector in WOA
Q	Coefficient vector in WOA
t	Current iteration number
X	Current solution in the population
X^*	Best solution in the population
b	Logarithmic spiral
l	Random value in the range [1, 1]
p	Selection parameter
X_{rand}	Randomly generated solution in population
q	Exponential function
GT	Maximum number of iterations
P^{train}	Pre-processed training data

A. *Data Pre-processing*

For some metrics, the data may contain a variety of noise, including inaccurate, missing, or insufficient information. To solve these issues, researchers have offered a simple strategy based on messy data management approaches and Natural Language Processing (NLP). In some cases, attributes in particular tuples created by real-time IoT applications may contain messed-up or missing data, such as Inf, Null, or NaN values instead the original values. These values could result in inaccurate knowledge discovery and forecasting. Such chaotic input log data must therefore be suppressed or sanitised. Algorithm 1 illustrates the suggested pre-processing and data normalisation method. First, using NLP, researchers have detected and eliminated stop words (SW), URLs, and special characters (SC), such as #, @, and complicated characters (CC), such as a+, B-, and others. After that, researchers located any untidy data (Inf, Null, or NaN) and replaced it with an average value for that parameter. By removing the inconsistent values, function mean (.) determines the mean value for whole column. It guarantees the removal of such data from sources with many dimensions.

First algorithm: Pre-processing of raw data

Input

DT: Data on electricity use

M←{Inf,NaN,Null}: Incorrect data parameters

Output

N: Standardised dataset

a. Gathering of MSSD data DT
b. [m,n]←size(DT)
c. N←zeros (m,n)
d. For each i=1:m
e. For each j=1:n
f. If (DT(i,j)≠SC || DT(i,j)≠ URL || DT(i,j)≠CC||DT(i,j)≠SW)
g. N(i,j)←DT(i,j)
    i. Else
h. N(i,j)←mean(:,j)
    i. End If
    ii. If (DT(i,j)==M)
i. N(i,j)←mean(:,j)
    i. Else
j. N(i,j)←DT(i,j)
    i. End If
k. End For
l. End For
m. Return (N)

B. *CAC-based Predictive Features*

Contextual group construction of the pre-processed energy data as input seeks to create accurate and effective predictions based on consumption patterns in comparison to previous methods. The proposed CAC group formation technique's design is presented in this section. The complete functionality of the suggested clustering technique is depicted in Figure 2. The CAC approach takes input N as normalized electricity data. Researchers first used k-means clustering to get the centroids after pre-processing. Researchers created the first groupings and then improved them to achieve context-aware clustering of incoming data. To do context-aware clustering, researchers retrieved two characteristics contexts from individual power history such as absorbed power and velocity. The distance between two rows is measured in terms of velocity and power consumption using a well-known Euclidean distance. Researchers ordered the group members in ascending order after estimating their distances. Finally, the groups are re-formed based on the sorted scores. This strategy decreases data loss while also raising prediction accuracy.

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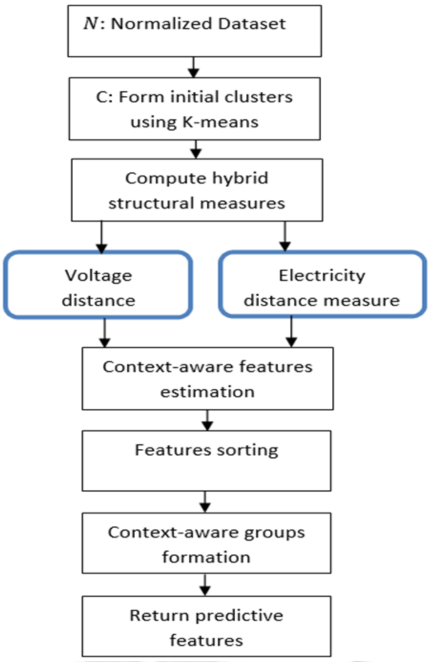

Figure 2. CAC's architecture for grouping power data.

The k-means clustering cluster receives the normalised electricity data N and uses it to compute the centroids and the members of each group (GMs). Computing the clusters G and its centroid entails:

$$G = \text{kmeans}\,(N, c) \qquad (1)$$

Where, G refers for the groups created using the k-means clustering approach on the data N, and c denotes the group numbers (in this work, the researchers set c=4). Every group $G^i, i \in c$has a minimum r GMs. Each cluster has a different value for r, meaning that there may be different numbers of GMs in each cluster. As previously noted, the traditional group creation approach has significant knowledge acquisition and forecasting challenges. Finally, researchers have proposed a mechanism for optimizing the originally generated clusters using a context-aware method. The CAC algorithm demonstrates the full capability of the proposed group-building approach. By employing two parameters—velocity and electricity—to calculate the resemblance score of individual power history in individual group, the groups are optimised. Researchers have initialised the output grouping vector H with m+2 and n sizes, as displayed in Second algorithm. In order to include the recently determined unified predictive feature utilising the function hybridScore (.) and accompanying as a group number, a predictive label, two more columns are introduced. The function hybridScore (.) calculates the degree of resemblance allying the centroid of the current cluster $C^i_{centroid}$ and current GM log. Every number of records n in the database 'N' over the number of groups 'c', the present record/log and its contextual value 'h' are iteratively stored into the 'H' vector for each cluster. The entries in vector H are then presented in sorted order as ascending into 'S' vector according to the appropriate value of 'h'. In order to record the optimised groups together with their labels, researchers initialised the Predictive vector P after initialising vector H. All of the entries in S are sorted into groups with group numbers in the output P based on the context-aware score. The constraint (n/c), where 'n' is the total number of logs and 'c' is groups number, should be satisfied by the number of logs (GMs) in individual group.

Researchers have calculated the Euclidean distance between the centroid of the group to which the current CM log belongs and the velocity attributed and power usage attributes of the current CM log using the function hybridScore (.). The calculations are described in detail below.

$$v^i_j = \text{dist}\left(\log^j.\text{Velocity}, C^i_{centroid}.\text{Velocity}, '\text{euclidean}'\right) \qquad (2)$$

Where, using its centroid $C^i_{centroid}$, v^i_j indicates the Euclidean distance for the j^{th} log $\log^j$ belonging to the i^{th} cluster.

$$e^i_j = \text{dist}\left(\log^j.\text{Electricity}, C^i_{centroid}.\text{Electricity}, '\text{euclidean}'\right) \quad (3)$$

Where, using the centroid $C^i_{centroid}$, , e^i_j denotes the Euclidean distance for the j^{th} log $\log^j$ belonging to the i^{th} cluster.

The weight-based method is then used to compute the integrated blend contextual or structural resemblance score. The following formulas are used to calculate the hybrid score $h_j$for j^{th} log $\log^j$:

$$h_j = \left(a^1 \times v^i_j\right) + \left(a^2 \times e^i_j\right) \qquad (4)$$

where weights for each structural metric are represented by a^1 and a^1 . $a^1 + a^2 = 1$ is the sum of the two weight parameters. In this study, the velocity and power attributes are both given identical weight, $a^1 = 0.5 \;\&\; a^2 = 0.5$ .. The predictive features vector P with its numeric labels is the phase's output.

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Second algorithm: CAC (Context Aware Clustering)

Input

C: groups with centroids

c: total groups

N: pre − processed dataset

n: number of logs/rows in N

m: number of column in each row/log

Output

P: Context aware groups with labels as predictive

```
Initialize: H ← ones(n, m + 2)
t = 1, t ∈ n
for i = 1:c
    for j = 1: size (C^i)
log ← CM^i(j)
h ← hybridScore(log, C^i_centroid)
H(t, 1:m) ← log
H(t, m + 1) ← h
t ← t + 1
    end For
end For
S ← getSort(H(:, m + 1), "ascending")
Initialize: P ← ones(n, m + 2)
for i = 1: lenght (S)
    for j = 1:c
        if (lenght(C^j) ≤ |n/c|)
C^j ← add (S(i, :))
P ← S(i, :)
P(i, m + 2) ← j, assign label
        end if
    end for
end for
Return (P)
```

C. OWOA-Based ANN Predictive Model

The next phase of the CAC-OWOA is the predictive model, which is applied to the predictive features vector P. Before applying the OWOA-based ANN algorithm, researchers partition the P into training called P^{train}(90 %, 80 %, and 70 %) and testing calledP^{test} (10 %, 20 %, and 30 %) samples. The P^{train} dataset is then fed as input to an OWOA-based ANN classifier. ANNs are frequently employed as classifiers in machine learning because of their effectiveness and simplicity. It has also been used in intrusion detection models for power systems. The work of training for the ANN is still difficult. Local optima, delayed convergence, and greater error rates are challenges for traditional ANN training algorithms. Therefore, to optimize the ANN training process, researchers applied to OWOA bio-inspired algorithm. The OWOA approach is applied to discover the optimal weights and biases to address local optima problems, slow convergence, and higher error rates. As the existing WOA algorithm suffered from slow convergence and easily resulted in local optima, researchers introduced the OWOA as the modified bio-inspired algorithm. Before presenting the algorithm of OWOA-based ANN, researchers first describe the functionality of WOA and OWOA to highlight modifications.

1. WOA

A population-based meta-heuristic method of this type is WOA. The WOA replicates the encircling of prey, the bubble-net attack method, and exploration (search for prey) that humpback whales engage in.

Encircling Prey: WOA assumes that the prey is the optimal option with the best fitness in the present population. All of the other alternatives will encircle the prey and update themselves in the direction of the best solution. The following is the mathematical model of encircling behavior:

$$D = |L.X^{*}(t) - X(t)| \tag{5}$$

$$X(t+1) = X^{*}(t) - Q.D \tag{6}$$

Where, t represents the current iteration number, X and X* represents the current and best solution in the population, and L and Q represent the coefficient vectors computed by:

$$L = 2r \tag{7}$$

$$Q = 2q.r - q \tag{8}$$

Where, q is linearly reduced from 2 to 0 over the iterations and r represents the random vector of range [0, 1].

Bubble-Net Attacking Technique: The next phase of WOA is to simulate the bubble-net attacking method. It is performed in two steps: the shrinking encircling approach and the spiral updating position. The mathematical representation of the shrinking encircling approach is similar to Eq. (5) and Eq. (6). With a random step, the existing solution can update itself toward the optimal solution. In the spiral update position step, the new position for the current solution is updated at each iteration. The best solution takes the place of the current solution in the new position in the spiral update position step.

$$D' = |X^*(t) - X(t)| \quad (9)$$

$$X(t+1) = D'.e^{bl}.\cos(2\pi l) + X^* \quad (10)$$

where b is a constant used to define the logarithmic spiral and l is a random value in the range [1, 1]. A selection parameter p is established to balance the two models. In WOA, the selection parameter p is 0.5; there is a 50% chance of selecting either the decreasing encircling mechanism or the spiral updating position mode, as shown in Eq. (11). The value of p is generated randomly.

$$X(t+1) = \begin{cases} X^*(t) - Q.D & \text{if } p < 0.5 \\ D'.e^{bl}.\cos(2\pi l) + X^*(t), & \text{if } p \geq 0.5 \end{cases} \quad (11)$$

Exploration Phase: In the wild, whales randomly drift apart and hunt for fresh prey. A random search operation is employed in the exploration phase to replicate the search behavior when $|Q| \geq 1$. The current solution will be updated with a random solution drawn from the current population rather than the best solution. This step is mathematically represented by:

$$D = |L.X_{rand}(t) - X(t)| \quad (12)$$

$$X(t+1) = X_{rand}(t) - Q.D \quad (13)$$

where X_{rand} denotes the solution that was produced randomly in the current iteration of the problem. Up until the convergence criteria (halting criteria) are met, the aforementioned stages are repeated.

2. *OWOA*

As the existing WOA technique suffered from two major problems, such as slow convergence and easily falling into local optima, researchers have optimized the WOA to address such problems in this paper. Researchers adopted Opposition Based Learning (OBL) to avoid trapping into local optima solutions. The technique of Nonlinear Parameter Design (NPD) is then applied to achieve the balance between the exploitation and exploration phase. It results in fast convergence. The functionality of OWOA is presented in algorithm 3. As shown in Algorithm 3, researchers have highlighted the modifications in the existing WOA in bold font. These changes are concerning with OBL and NPD mechanisms.

OBL: The OBL technique is suggested for preventing trapping into local optimum solutions.At the end of each iteration, OBL is employed in the initialization and solution update steps. During the initialization phase, OBL might develop a new solution on the opposing side, increasing the search space's variety. At the end of each iteration, during the solution update phase, OBL might develop a new solution on the opposing side and pick the best solution between the new and old solutions. OBL can assist WOA in improving search performance and identifying local best solutions. It is mathematically represented below. The solution X_i in d-dimensional search space is represented by $X_i^* = \{X_{i,1}, X_{i,2}, \dots, X_{i,d}\}$. The opposition point X_i^* of X_i is given by:

$$X'_{i,j} = (X_{lb,j} + X_{ub,j}) - X_{i,j} \quad (14)$$

$X_{lb,j}$&$X_{ub,j}$ denotes the lower and upper bound of j^{th} dimension.

NPD: The NPD approach introduces the fast convergence in the OWOA algorithm by balancing the exploitation and exploration phases. The redesigned WOA (i.e., OWOA) now includes an exponential function q. The percentage of exploitation and exploration phases is determined by the value of the coefficient vector Q. The NPD is mathematically represented by:

$$q = q_{min} + (q_{max} - q_{min}) \times e^{-2t/GT} \quad (15)$$

Where, q_{max} and q_{min} represent maximum and minimum value q, GT represents the maximum iterations, and t is the current iteration. A high value of q makes a large step size during the exploitation phase, which helps speed up the search. For the exploration phase, a modest step size with a small value of q might be useful.

The pseudo code in algorithm 3 for the proposed OWOA model shows the optimized mechanism to estimate the optimal solutions. Rather than the conventional population initialization mechanism, researchers utilized OBL for the same in lines 1-6 of algorithm 3. The rand value is generated between 0 to 1 to produce the new solution during the initialization step to achieve the global optima and prevent local optima. The OBL is then applied during the solution update phase to estimate the opposition solutions (represented by lines 29-36 of algorithm 3). The optimal solution is identified after calculating the fitness of each population-level solution (represented by lines 7-8 of Algorithm 3). Furthermore, the exponential function q of the coefficient vector Q is updated using the NPD mechanism, as shown in line 10 of algorithm 3. The NPD of q achieves the balance among exploitation and exploration phases, resulting in fast convergence compared to the conventional WOA mechanism. Other steps in algorithm 3 represent the functionality of the WOA approach. Lines 16-17 employ the encircling prey, lines 19-21 use the hunt for prey (exploration), and lines 25-26 use the spiral updating position.

International Journal on Recent and Innovation Trends in Computing and Communication
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Algorithm 3: OWOA

Inputs

N: $Population\ size$

HC: $Halting\ criterion$

GT: $Maximum\ number\ of\ iterations$

t: $current\ iteration$

Output

X^*: $Best\ solution$

1. Produce initial population $X_i, i \in 1, 2, \dots, N$
2. For $\mathrm{i} = 1{:}\,\mathrm{N}$
3. If ($\mathrm{rand} < 0.6$)
4. Produce the new solution using OBL
5. End If
6. End For
7. Compute fitness value for X_i
8. Discover the best solution X^* with optimal fitness value
9. While ($\neq HC$)
10. Update q using NPD according to Eq. (15)
11. For $i = 1{:}\,N$
12. Update $Q, L, l, \&\ p$
13. For $t = 1{:}\,GT$
14. If ($p < 0.5$)
15. If ($|Q| < 1$)
16. $D = |L.X^*(t) - X_i(t)|$
17. $X_i(t) = X^*(t) - Q.D$
18. Else If ($|A| \geq 1$)
19. Choose random solution X_{rand}
20. $D = |L.X_{rand}(t) - X_i(t)|$
21. $X_i(t) = X_{rand}(t) - Q.D$
22. End If
23. End If
24. If ($p \geq 0.5$)
25. $D' = |X^*(t) - X_i(t)|$
26. $X_i(t) = D'.e^{bl}.\cos(2\pi l) + X^*(t)$
27. End If
28. End For
29. For $i = 1{:}\,N$
30. If ($rand < 0.6$)
31. X_i^{OBL}:Produce new solution using OBL
32. If ($X_i^{OBL} > X_i$)
33. $X_i \leftarrow X_i^{OBL}$
34. End If
35. End If
36. End For
37. End For
38. Discover best solution X^*
39. End While

3. Modified ANN Model

Researchers proposed the OWOA-based ANN electricity forecasting prediction model for higher accuracy and minimal computing efficiency. Feed-forward, feed-backward, and self arranged maps are the 3 different ANN architectures and their corresponding neuron layouts. A multilayer perceptron is a feed-forward neural network that uses the hidden layer to translate inputs into outputs. To solve the issues associated with ANN learning, researchers have used a proposed OWOA (algorithm 3) as a trainer for a feed-forward neural network. Because it is a gradient-free and flexible machine capable of local-optima avoidance, it has been proved that this technique can address many optimization problems and outperform other current algorithms in training MLPs.

The effectiveness of the suggested OWOA-based ANN training strategy is shown in Figure 3. Wherein it uses $\mathrm{P}^{\mathrm{train}}$ vector as an input, which is the predictive feature vector. The OWOA includes procedures like population initialization, fitness computation of each population for an ideal solution, encircling prey, spiral updating position, prey exploration, and updating and finding an ideal solution for each population utilising OBL. All these steps are performed according to proposed algorithm 3 for the ANN training phase. In OWOA-based ANN training, every whale searcher is initially configured to optimise a potential neural network (NN). Weight and bias vectors in an MLP network show the connections between the hidden layers and inputs along with outputs layer and hidden. The sum of biases and weights (WB) attribute fusions in network like MLP that will be enhanced by Whale Optimisation Algorithm (WOA) is shown in Eq. (16).

$$\mathrm{WB} = \mathrm{n.q} + 2.\mathrm{n} + 1 \qquad (16)$$

Where q is the total number of neurons in the hidden layer and n is the total number of input nodes ($\mathrm{P}^{\mathrm{train}}$ - entire number of records in input vector).

Each population uses the mean suare error (MSE) of the multilayer perceptron network, which essentially serves like fitness function, to determine how much actual and expected classes A differ from each other. The MSE for k samples is calculated using:

$$\mathrm{mse} = \frac{\sum_{\mathrm{x}=1}^{\mathrm{k}} (\mathrm{A_x} - \bar{\mathrm{A}}_{\mathrm{x}})^2}{\mathrm{k}} \qquad (17)$$

The quantity of feature vectors is calculated from the vector $\mathrm{P}^{\mathrm{train}}$ steps prior to the OWOA-ANN training and classification phases. Ratios for training and testing are randomly assigned to these feature vectors.

International Journal on Recent and Innovation Trends in Computing and Communication
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Article Received: 16 November 2022 Revised: 18 December 2022 Accepted: 30 December 2022

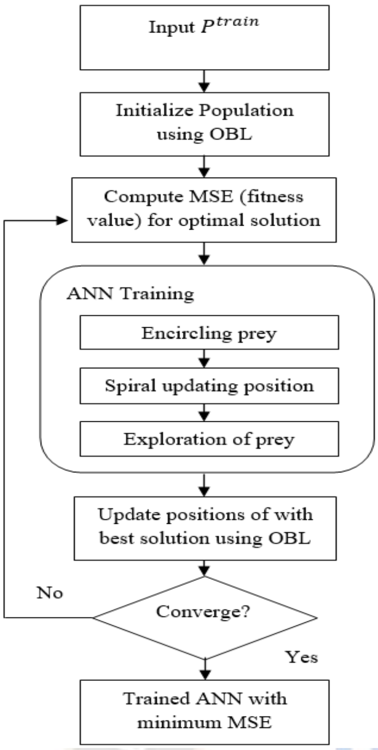

Figure 3. Architecture of OWOA-based ANN training algorithm

IV. EXPERIMENTAL RESULTS

Windows machine with Python 3.11.0 with an Intel I3 processor, eight gigabyte RAM, and Nvidia graphics is used to implement and analyse the suggested model. The MDDS electrical logs were taken from a research dataset that was made available to the public [48]. The data includes electricity use data of tall residential structures of Indian Institute of Technology, Bombay campus between Dec’ 2018 to Jan’ 2021. A digital metre that keep track of data for interval of five to eight seconds is placed in every sixty units in the building that are designated as 3RHK (3 rooms, hall, and kitchen). The voltage phase-I, voltage phase-II, voltage phase-III, phase-I power usage, and phase-II power usage fields are all listed after the date at the beginning of each item in the dataset. Researchers receive a dataset with two new entries after using procedures 1 and 2: an incorporated predictive feature and an related cluster number (one, two, three, or four). The suggested OWOA-based ANN (OWOA-ANN) model's performance has been compared, as previously said, to the performance of various classifiers, including WOA-ANN, KNN, ANN and SVM All of the above mentioned classifiers received the anticipated feature vector (FV) with tag from the researchers. The outcomes for training mean square error, training precision, testing precision, testing precision, and testing recall are studied for power usage prediction. Section B compares the performance of the suggested paradigm to cutting-edge techniques with respect to prediction time, recall and precision. The following table lists the formulas for accuracy, precision, recall, and MSE.

$$\text{accuracy} = \frac{\text{TN+TP}}{\text{TN+TP+FN+FP}} \quad (18)$$

$$\text{recall} = \frac{\text{TP}}{\text{FN+TP}} \quad (19)$$

$$\text{precsion} = \frac{\text{TP}}{\text{FP+TP}} \quad (20)$$

$$\text{mse} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (21)$$

Where, TP refers to true +ve, TN refers to true -ve, FN refers to false -ve, and FP refers to false +ve. In MSE formula, n represents number of samples, Y_i represents the observed value, and $\hat{Y}_i$ represents the predicted value.

A. Investigating Training Performance of Classifiers

As the proposed model CAC-OWOA is mainly based on CAC and OWOA mechanisms for the efficient energy consumption forecasting for smart grid, researchers investigate the performance of the CAC predictive feature extraction approach using the different classifiers, including the proposed OWOA-based ANN. Prediction models like ANN, SVM, KNN, WOA-ANN, and the planned OWOA-ANN are combined with the CAC model. As the ANN training process is modified using existing WOA and the proposed OWOA bio-inspired algorithms in WOA-ANN and OWOA-ANN, researchers have measured the performances for training as well as testing for each classifier. Researchers investigated the WOA-ANN model to show the impact of using OWOA in place of WOA with ANN. Researchers assessed the training accuracy, training MSE, testing precision, testing accuracy, and testing recall for each testing scenario (10%, 20%, and 30%) for each prediction algorithm.

Researchers begin by looking at the CAC training outcomes for each classifier in figures 4–8. Figures 4, 5, and 6 show the training MSE for ten percent, twenty percent, and thirty percent of the testing data samples, with a predicting duration of 200 minutes. Researchers found that when forecasting span increases, training error decreases because there is more historical data available. Additionally, it implies that training with small data samples may increase errors. Consequently, factual MDDS is crucial for precise forecasting. The other conclusion drawn based on the data as depicted in figures 4, 5 and 6 is that test sample size has an impact. The less test data

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***Article Received**: 16 November 2022 **Revised**: 18 December 2022 **Accepted**: 30 December 2022*

samples provided the lowest mean square error since there were more training data for the classification.

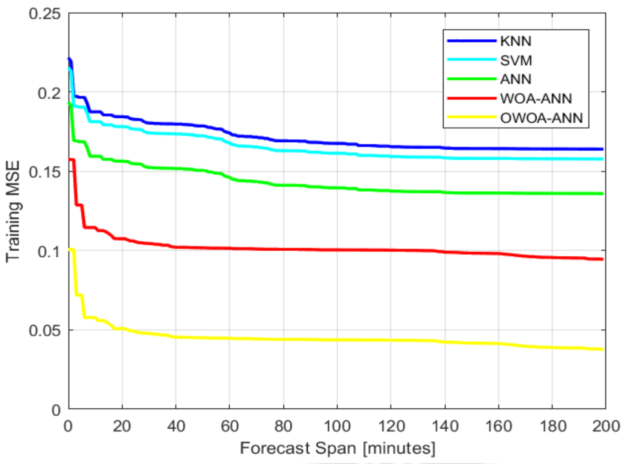

Figure 4. Examination of the training MSE for the 10% test samples

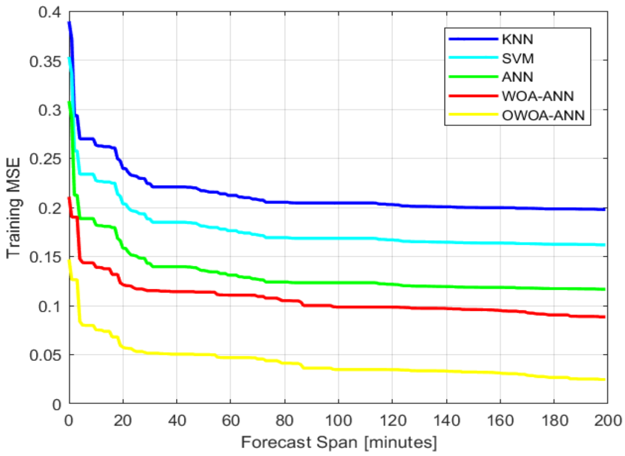

Figure 5. Examination of the training MSE for the 20% test samples

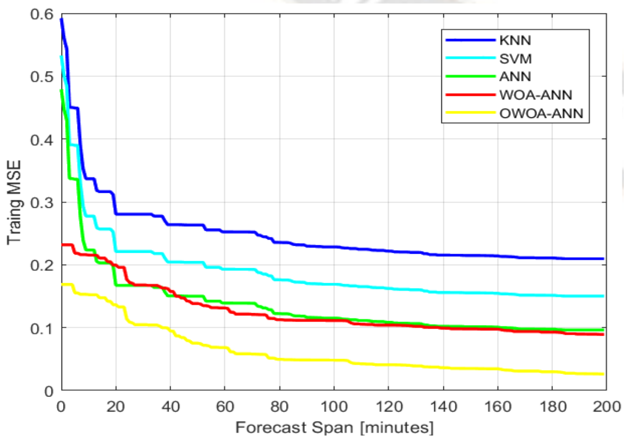

Figure 6. Examination of the training MSE for the 30% test samples

From figures 4-6, the training MSE rate performance of the proposed OWOA-ANN model shows efficiency compared to conventional classifiers SVM, ANN, KNN, and WOA-ANN. The use of WOA for ANN training significantly affects the reduction of MSE or training error performance compared to all conventional classifiers. The WOA optimized the ANN training process that overcomes the problems of higher training errors by selecting the optimizing weights and biases. Therefore, WOA reduces the MSE while ANN training improves the forecasting accuracy. Even if the existing WOA improved the ANN performance, it suffered from the serious problems of slow convergence and being trapped easily into local optima. The proposed OWOA model overcomes these problems of WOA. The OWOA-based ANN delivered a further reduction in training MSE compared to WOA-ANN. The main reasons for improving the performances using the OWOA mechanism are: (1) The OBL-based population initialization and position updates with the best solution phases result in the answer for trapping into local optima. (2) Also, the NPD mechanism is used to compute the exponential function such that the balance between exploitation and exploration phases is achieved. It results in fast convergence with higher accuracy compared to WOA-ANN. For the 10 % and 20 % test samples scenario, the performance of WOA-ANN is efficient for MSE compared to ANN, SVM, and KNN. But in figure 6 (30% test samples), the MSE performance of WOA-ANN is close to or overlaps with ANN performances. The shortcomings of WOA affect the MSE performance for the small training samples scenario. The OWOA addresses these shortcomings. And hence it reduces the MSE performance in all test cases scenario.

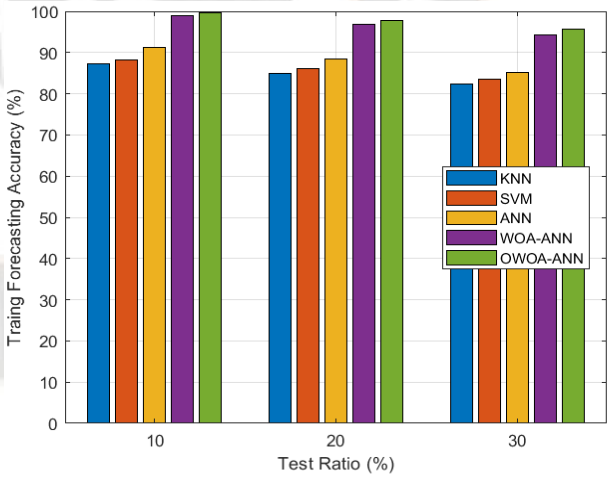

Figure 7. Analysis of training accuracy performance

Figure 7 shows each prediction algorithm's overall training accuracy performance for different test case scenarios. The average results of training the MSE are shown in Figure 8 for each test ratio scenario. The reduction in training MSE leads to the accuracy improvement using the proposed OWOA-ANN

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model compared to conventional classifiers and the WOA-ANN classifier. The ANN classifier using WOA and OWOA training mechanisms shows a significant accuracy improvement compared to SVM, ANN, and KNN training performances. In this research article, the shortcomings of WOA are addressed by the proposed OWOA model, which is reflected in the training MSE and accuracy performances. The other reasons for performance improvement using the OWOA-ANN model compared to existing methods are explored in the above paragraphs.

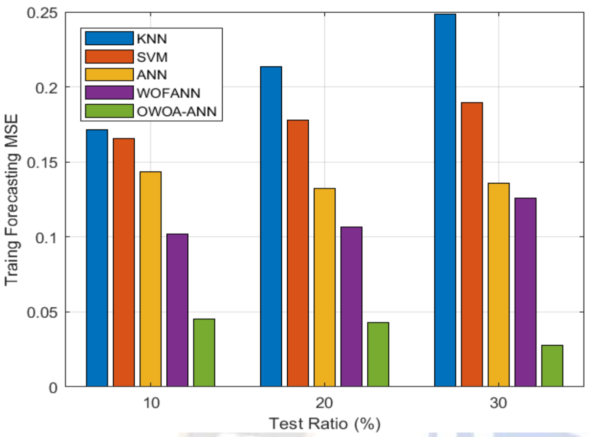

Figure 8. Analysis of training MSE performance

B. Investigating Testing Performance of Classifiers

In the above section, researchers have investigated the training accuracy and MSE performances for 90 %, 80 %, and 70 % training samples. After the training process, the next step is to forecast the energy consumption patterns for 10 %, 20 %, and 30 % test samples by utilizing the 90 %, 80 %, and 70 % trained models, respectively. Figures 9, 10, and 11 show, accordingly, the prediction outcomes for each testdata sample situation according to accuracy, precision, and recall parameters. Figures 9–11 demonstrate that when test sample numbers increase, overall forecasting accuracy, precision, and recall rates decrease as a result of less training sample numbers. In comparison to KNN, SVM, ANN, and WOA-ANN approaches, the suggested CAC along with OWOA-based ANN prediction paradigm showed greater forecasting rates for precision, accuracy, and recall. From these outcomes, it is revealed that CAC-based predictive feature vectors are not sufficient to improve forecasting performances. The optimized ANN classifiers using WOA and OWOA delivered the best performances compared to conventional classifiers. The OWOA-ANN was introduced to address the problems of the WOA-ANN model in this paper, and the results of training and testing justified the efficiency of the proposed OWOA-ANN compared to all other mechanisms. Table 2 demonstrates the average training accuracy, training MSE, testing accuracy, testing precision, and testing recall parameters. The KNN, SVM, and ANN outcomes are very poor compared to WOA-ANN and OWOA-ANN methods. Among WOA-ANN and OWOA-ANN, the OWOA-ANN has improved the parameters of training accuracy, accuracy, precision, and recalls approximately by 1+ %, but reduced the training MSE/error rate (0.0387) significantly with fast convergence for optimal solutions.

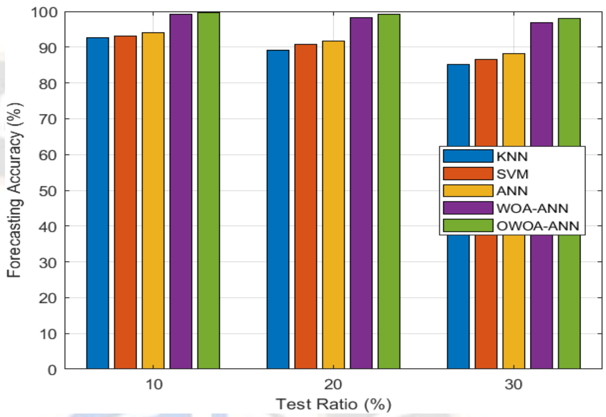

Figure 9. Test samples forecasting accuracy analysis

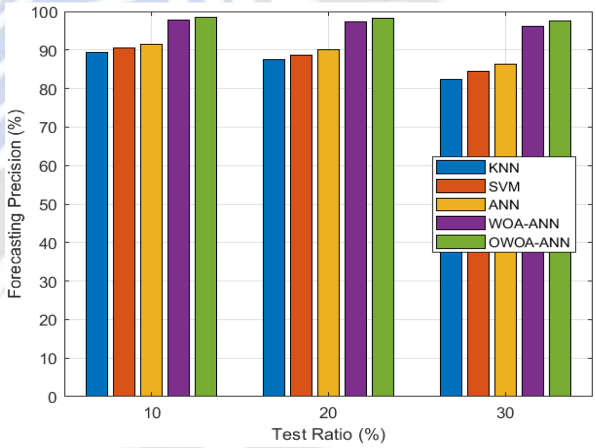

Figure 10. Test samples forecasting precision analysis

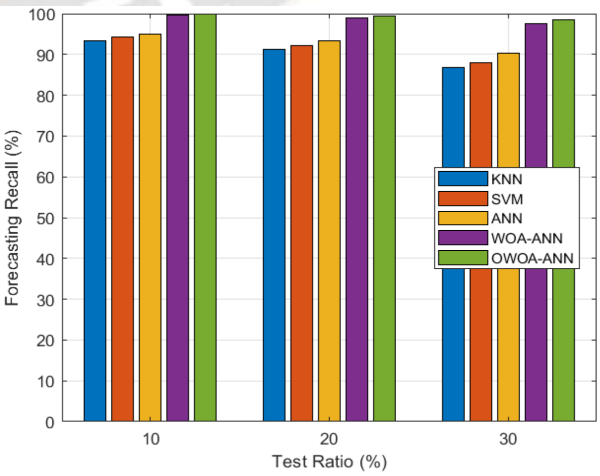

Figure 11. Test samples forecasting recall analysis

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TABLE 2. AVERAGE PERFORMANCE ANALYSIS

	Training Accuracy (%)	Training MSE	Accuracy (%)	Precision (%)	Recall (%)
KNN	84.93	0.2114	89.03	86.39	90.51
SVM	85.92	0.1775	90.17	87.85	91.42
ANN	88.27	0.1373	91.33	89.23	92.84
WOA-ANN	96.58	0.1113	98.06	97.15	98.69
OWOA-ANN	97.71	0.0387	98.97	98.08	99.29

C. State-of-the-art Analysis

In this section, researchers have contrasted the proposed model CAC-OWOA with current energy consumption forecasting models that employ various approaches. In comparison to several modern methods created by authors in article [35], [36], [37], and [38], researchers assessed the performance of the suggested CAC-OWOA model. The creators of these methods have used DA and GA in [35], artificial bee optimization in [36], ensemble prediction model in [37], and random forest method in [38] to predict power usage, which makes them similar to the proposed methodology. For the comparison investigation in this work, researchers used these methods along with the data and other examination conditions indicated above. Average findings for accuracy, precision, recall, and forecasting time are displayed in Table 3. These projections are based on ten applications of each approach for 70% (training) and 30% of the time (testing). Table 3 demonstrates that, in comparison to existing approaches, the proposed CAC-OWOA technique significantly enhanced overall knowledge discovery from MDDS and prediction performance. Performance is improved by optimising groups using contextual group generation with structural resemblance measures and improved artificial neural network utilizing the OWOA method. As discussed earlier, the limitations of existing methods are addressed by the CAC-OWOA concerning the context-aware predictive features extraction and efficient prediction model. The proposed CAC algorithm and modified ANN using the OWOA mechanism result in significant performance improvement compared to underlying solutions.

TABLE 3. COMPARATIVE ANALYSIS OF DIFFERENT KNOWLEDGE DISCOVERY AND FORECASTING TECHNIQUES

Methods	Hussain et. al [35]	Ghosh et. al [36]	Bot et. al [37]	Pang et.al [38]	CAC-WOA
Accuracy (%)	95.72	94.32	94.12	93.21	98.31
Precision (%)]	93.74	93.23	93.02	92.43	97.87
Recall (%)	96.32	95.37	95.06	94.73	99.71
Forecastin g Time (Seconds)	1.99	1.64	1.57	1.53	1.31

Researchers have also compared the proposed OWOA approach with recently proposed improved WOA techniques. Researchers have analyzed the performance of OWOA with basic WOA, SWWOA [45], IWOA [46], and M-WOA [47] models. All these models are evaluated regarding convergence time, training accuracy, and MSE rate for the 70 % training sample. Table 4 shows the average outcomes of 10 executions of each method. All methods, WOA, SWWOA, IWOA, and M-WOA, were implemented to perform the ANN training to measure the performances shown in table 4. The OWOA model shows a significant reduction in convergence time and error (MSE) rate with higher training accuracy due to the simple yet effective mechanism of OBL and NDP mechanisms.

TABLE 4. COMPARATIVE STUDY OF DIFFERENT VARIANTS OF WOA

Methods	Convergence Time (Seconds)	Training Accuracy (%)	MSE
WOA	211	94.66	1.32
SWWOA [45]	173	94.92	1.01
IWOA [46]	178	95.26	0.92
M-WOA [47]	164	95.77	0.85
OWOA	145	96.73	0.31

V. CONCLUSION AND FUTURE WORKS

For effective exploration from multi-dimensional power usage data history, the novel CAC-OWOA framework was proposed. These findings were created to forecast energy use for sophisticated electricity monitoring systems. The suggested model uses the CAC technique, an ANN based on OWOA, and data pre-processing. The data pre-processing technique enhanced the quality of raw electricity records, which increased forecasting reliability and efficiency. Researchers overcome the constraints of existing clustering algorithms in the CAC approach by creating groups based on the dataset's context information. It resulted in the efficient development of predictive features and suitable predictive classes. The upgraded bio-inspired algorithm OWOA overcame the limitations of ANN. The suggested OWOA method increased the performance of ANN training in terms of training accuracy and MSE with fast convergence. The experimental outcomes revealed that the proposed CAC-OWOA framework for the smart grid system had improved the overall performance compared to underlying methods. The prediction accuracy, precision, and recall of the proposed model have improved by 4%, 4.7%, and 4.34%, respectively. Comparing the overall forecasting duration to the underlying approaches, a reduction of 22.02% has been achieved. Investigating other domain datasets with the suggested model is the path in which this work will go in the future.

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***Article Received**: 16 November 2022 **Revised**: 18 December 2022 **Accepted**: 30 December 2022*

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