Short-Term Load Forecasting of Mosul Governorate Using the LSSVM Model Based on Meteorological Factors Effect

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Abstract—**Reliable data-driven methods, utilizing validated predictive models of electricity consumption, offer substantial promise to effectively manage energy in densely populated electrical grids, especially in urban areas like Mosul City. This research presents a model for forecasting the hourly electrical load for Mosul City, taking into account meteorological variables such as temperature, humidity, wind speed, cloud cover, and the type of day (holiday or working day). It explores two distinct scenarios: the first one examines the influence of weather elements on predictions of electrical load, and the second one employs the Least Squares Support Machine (LSSVM) model to forecast electricity consumption in Mosul City using historical load data and meteorological information. Two optimization algorithms, the Particle Swarm Optimization algorithm (PSO) and the Whale Optimization Algorithm (WOA), are employed to improve model accuracy and adjust the parameters of the LSSVM. In addition, the performance of the models in this research is evaluated using the Mean Absolute Percentage Error (MAPE). The results demonstrate the superiority of the LSSVM+PSO model over the LSSVM+WOA model and the basic LSSVM model in terms of accuracy and error reduction, while according to execution time, the LSSVM+PSO model takes a little longer than the LSSVM+WOA model. Consequently, the LSSVM+PSO model is deemed suitable for forecasting hourly electricity consumption in the city of Mosul.**

Index Terms—**Least Squares Support Machine (LSSVM), mosul, particle swarm, short-term forecasting, whale**

I. INTRODUCTION

Load forecasting is crucial for efficient power system planning, scheduling, and operation. It plays a critical role in cost reduction and the optimization of electric power production dispatching, while also guaranteeing consistent, dependable, and safe access to electricity [1].

Electric load prediction can be categorized into three types based on the time horizon. More specifically, long-term electric load predictions span from one year to ten years, medium-term electric load predictions cover a range of one week to one year, and short-term electric load predictions encompass a period of one hour to one week [2].

Each framework in question is focused on specific tasks. For instance, long-term load predictions are utilized for planning purposes, such as capacity expansion and station infrastructure development. These predictions take into account factors such as population growth, economic trends, and technological advancements. On the other hand, medium-term load predictions are commonly employed for operational planning and resource allocation. These forecasts are based on seasonal changes, economic conditions, and historical load data. Lastly, short-term load forecasting plays a crucial role in real-time operations, power system planning, and grid management. This particular type of forecast heavily relies on various short-term factors, including weather conditions, time of day, day of the week, holidays, and other aspects that impact energy consumption in the short run [3].

Short-term load prediction plays a crucial role in power planning models, offering benefits such as optimizing power plant operations, enhancing system stability, cutting costs, and boosting financial returns for utilities and energy providers. However, inaccurate forecasts can result in substantial power losses. Therefore, there is a pressing need for the development of a precise and efficient short-term electrical load prediction system to satisfy load forecasting criteria [4].

There are three categories of techniques for electric load forecasting: conventional, unconventional, and hybrid optimization techniques. These techniques are classified based on their complexity. Conventional techniques refer to simple methods that rely on fundamental equations and technologies to forecast the load. These techniques, such as the Kalman Filter (KF), Multiple Linear Regression (MLR), exponential smoothing, regression, and time series methods, can easily identify a single optimal solution and are straightforward to implement [5].

Unconventional techniques include artificial intelligence-based methods and modern computing, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVM), and fuzzy models. Hybrid technologies integrate optimal AI technologies in a coordinated manner

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to achieve the best results in short-term load forecasting [6].

To construct prediction models, it is necessary to establish the definition of inputs and outputs. The accuracy of the prediction relies on the precision of the input factors, which are influenced by the characteristics of the load. The resulting output is a daily load forecast for the upcoming 24 hours. Many factors can affect electric load prediction, including meteorological factors (temperature, humidity, wind speed, and cloud cover.), and the type of day (working or holidays) [7].

The primary aim of the research is to develop a proficient predictive model for hourly electricity load forecasting in Mosul City, integrating historical load data, meteorological factors, and factors like the type of day (holiday or working day). The research seeks to explore the impact of weather elements on electricity consumption and evaluate the effectiveness of the Least Square Support Vector Machine (LSSVM) model combined with optimization algorithms Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) in enhancing forecast accuracy.

An overview of important studies conducted in the field of electrical load forecasting showed the importance of continuous research and development in this field to improve forecast accuracy and improve power system operations. Several research have been done to solve the power system forecasting.

Ziel [8] introduced the “Post-COVID Paradigm”, which is an inventive concept involving the combination of multiple point prediction models to create an online forecast where this model on Day-Ahead electricity demand forecasting. Chen *et al.* [9] developed an evolutionary load prediction technique in response to the global COVID-19 pandemic. This model was designed to provide timely solutions to the challenges posed by load forecasting during this crisis, significantly reducing the disparity between predicted and actual load values.

While, the revolution in the world of smart algorithms and their applications is one of the most applied and promising topics in power engineering, such as PSO) Genetic Algorithm (GA), Grey Wolves Optimization (GWO), Garra Rufa Optimization (GRO), and Ant Colony Optimization Algorithm (ACO) [10–14]. Reddy [15] introduced an innovative method for predicting short-term load. His proposal involved incorporating back propagation and the Bat algorithm, while also considering environmental factors like temperature and humidity. Salkuti [16] proposed an innovative method that utilizes Radial Basis Function Neural Networks (RBFNNs) to address short-term load forecasting and takes into account external variables like temperature and humidity into the forecasting process. Tudosev *et al*. [17] proposed a convolutional neural network (CNN) model that integrates traditional external factors and incorporates data related to the COVID-19 pandemic. This model was used to address short-term load forecasting for the total electricity load in the Romanian power system. To innovation of several hybrid models for short-term load forecasting, Yadav *et al.* [18] combined various techniques, including wavelet decomposition, fuzzy clustering, Support Vector Regression (SVR), and Deep Learning Networks (DLN). Through case studies, these hybrid models were evaluated for accuracy and compared with traditional methods and deep learning techniques. The findings demonstrated that hybrid models outperformed conventional approaches and deep learning methods, show casing their effectiveness in load forecasting. Jaber *et al.* [19, 20] employed a hybrid model that combined the SVM model with the PSO algorithm and the Firefly Algorithm (FA) in two separated papers to optimize the SVM parameters, thereby enhancing the accuracy of short-term load predictions. Barman *et al*. [21] proposed a novel hybrid season-specific model for short-term load forecasting that incorporates seasonality effects, they used a Season Specific Similarity Concept (SSSC) to identify season-specific effective meteorological variables and used them into the forecasting process. By combining FA, SVM, and SSSC, the model integrated traditional methods by integrating season-specific effective meteorological variables and considering cloud cover and wind speed in addition to temperature, leading to improved forecasting accuracy for different seasons. Qiang *et al.* [22] recommended the use of the LSSVM model to analyze the factors influencing load forecasting. Their approach relied on historical load data and meteorological information specific to particular locations. Mustaffa *et al.* [23] introduced a novel hybrid method, which combines the marriage in Moth-Flame Optimization (MFO) algorithm with the LSSVM model termed MFO-LSSVM and proved its effectiveness in addressing a wide range of optimization challenges. Khwaja *et al.* [24] introduced a model to improve short-term electrical load forecasting through an ensemble machine learning method based on the ANNs model, showing a reduction in bias and variation in comparison to current load prediction methods. Liu *et al*. [25] put forth a short-term hybrid prediction model comprising three key modules: parameter optimization, data preprocessing, and forecasting. By mitigating the limitations of traditional models, the hybrid model achieved commendable predictive performance. A unique hybrid method, developed by Yang *et al.* [26] hinged on the LSSVM model and leveraged the GWO and Cross-Validation (CV) algorithms to optimize Auto Correlation Function (ACF) and LSSVM regression. To address the issue of inefficiency, Ma *et al*. [27] offered a short-term load prediction model based on the PSO algorithm which is used to optimize the LSSVM model. Liu [28] introduced a short-term power load forecasting method that integrates the SVM model, CNN, and Random Forest (RF). This model leverages RF for input variable optimization, CNN for feature extraction, and an SVM model for prediction. The evaluation of this method on Singaporean power load data used an improved forecast accuracy compared to alternative models. Since several electric load models were applied effectively under particular circumstances, Duan *et al.* [29] suggested a library to keep a collection of electric load models on hand and to select the top model each day to address the electrical load forecasting issues.

Despite their potential benefits, all of the aforementioned methods possess a number of significant drawbacks that need to be taken into consideration. For example, the RBF model suffers from over fitting and a low convergence rate and requires a large amount of historical data for prediction [19]. The RF model encounters challenges when faced with highly variable data, exhibits sensitivity in the selection of input features, and may involve high computational costs [30]. The ANNs are vulnerable to adversary attacks, and the ANNs typically need many labeled training data to learn effectively [31]. SVM suffers from sensitive to outliers and lacks flexibility in handling large feature spaces [32]. Addressing these drawbacks often involves careful model selection, preprocessing of data, and optimization of hyper parameters.

This study explores two distinct scenarios aimed at enhancing the accuracy of electrical load forecasting. In the first scenario, the study investigates the influence of meteorological factors on electricity usage. Utilizing the correlation coefficient, the connection between weather elements and electrical loads is analyzed. Results indicate that temperature and humidity exhibit a stronger impact on electrical load compared to wind speed and cloud cover. In the second scenario, the LSSVM model is employed to predict electricity consumption in Mosul, Iraq, based on historical load data and meteorological information. The LSSVM model is trained using this data set, enabling future electrical load predictions. To further improve forecast accuracy, the WOA and the PSO algorithms are applied. These algorithms optimize the kernel function and regularization parameters of the LSSVM model. The findings demonstrate that the LSSVM model combined with PSO achieves superior performance compared to other scenarios, including LSSVM combined with WOA or LSSVM alone. This model yields the lowest error rate and accurately predicts the electrical load for Mosul city.

This research is distinguished by its meticulous analysis of meteorological factors and the application of mathematical methods to understand their interaction with electrical loads. The utilization of the WOA algorithm for short-term load forecasting in Iraqi electrical power system data analysis represents a novel contribution to the field. Overall, this study offers precise results with minimal effort, contributing significantly to the improvement of short-term load forecasting accuracy.

II. Methodology

A. Least Squares Support Vector Machine

LSSVM is a supervised machine learning method, serving as an extension of the SVM technique. It significantly expedites solution times by transforming the quadratic programming (QP) problem arising from the classic SVM's constraint conditions into a linear equation problem. This reformulation simplifies computation, thereby facilitating and accelerating the training process [23]. $\{(x_k, y_k), k = 1, 2, \hat{} \ , n\}$ is the training set, with $xk \in Rn$ being the input data and $y_k \in \mathbf{R}_n$ being the output data. The samples are transferred into a significantly higher dimensional feature space (x_k) using a nonlinear mapping function called $(\cdot)$. The best decision function should be established in the high-dimensional feature space:

$$y(x) = \boldsymbol{\omega}^T \boldsymbol{\phi}(x) + b \tag{1}$$

where $\boldsymbol{\omega}^{\boldsymbol{T}}$ is an m-dimensional vector, b is a bias, and $\boldsymbol{\phi}(x)$ is a nonlinear function that converts the input space into the feature space. In LSSVM, the optimization problem is defined in order to solve the objective function thus:

$$\begin{cases} \min\limits_{\omega,b,e} J_2(\boldsymbol{\omega}, b, \xi) = \frac{1}{2}(\boldsymbol{\omega}^T\boldsymbol{\omega}) + \gamma \frac{1}{2}\sum_{i=1}^{n} \xi_k^2 \\ y_k[\boldsymbol{\omega}^T \boldsymbol{\phi}(x_k) + b] = 1 - \xi_k, k = 1, \cdots, n \end{cases} \tag{2}$$

where the regularization factor γ, also known as the penalty factor, reduces the impact of the maximum margin and the minimum regression error, and where ξ is the slack variable required to accommodate regression error. The related Lagrange dual issue is:

$$L(\boldsymbol{\omega}, b, \xi; \alpha) =$$

$$J_2(\boldsymbol{\omega}, b, \xi) - \sum_{k=1}^{n} \alpha_k\{y_k(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{\phi}(x) + b) - 1 + \xi_k\} \tag{3}$$

where $\alpha_i (i = 1,2, \cdots, n)$ is the Lagrange multiplier. According to Karush-Kuhn-Tucker (KKT) conditions:

$$\begin{cases} \frac{\partial L}{\partial \omega} = 0 \to \boldsymbol{\omega} = \sum_{k=1}^{n} \alpha_k y_k \boldsymbol{\phi}(x_k) \\ \frac{\partial L}{\partial b} = 0 \to \sum_{k=1}^{n} \alpha_k y_k = 0 \\ \frac{\partial L}{\partial \xi_k} = 0 \to \alpha_k = \gamma_k \\ \frac{\partial L}{\partial \alpha_k} = 0 \to y_k[\boldsymbol{\omega}^T\boldsymbol{\phi}(x_k) + b] - 1 + \xi_k = 0 \end{cases} \tag{4}$$

The above equations can be written as the solution to the following set linear equations

$$\begin{bmatrix} 0 & -y^{\mathrm{T}} \\ y & \Omega + \gamma^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \bar{1} \end{bmatrix} \tag{5}$$

where $\mathbf{y} = [y_1, \cdots y_n]^T$, $\bar{\mathbf{1}} = [1, \cdots 1]^T$, $\boldsymbol{\alpha} = [\alpha_1, \cdots \alpha_n]^T$, $\boldsymbol{\Omega} = \mathbf{Z}\mathbf{Z}^T$, $\mathbf{Z}[\boldsymbol{\phi}(x_1)^T y_1, \cdots, \boldsymbol{\phi}(x_n)^T y_n]$. Each matrix element in the matrix has the following form:

$$\Omega_{i,j} = y_i y_j \boldsymbol{\phi}(x_i)^{\mathrm{T}} \boldsymbol{\phi}(x_j) = y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \tag{6}$$

The kernel function is defined as $K(x_i, x_j)$. The kernel function $K(x_i, x_j) = \boldsymbol{\phi}(x_i)^T \boldsymbol{\phi}(x_j)$. As a value equal to the inner product of two vectors $\mathbf{x}_i$ and $\mathbf{x}_j$ in the feature space $\boldsymbol{\phi}(x_i)$ and $\boldsymbol{\phi}$. Radius basis function (RBF) kernels and polynomial kernels are examples of kernel functions:

$$\text{Polynomial: } K(x, x_k) = (x_k^T x + 1)^d, d = 1, \cdots, n \tag{7}$$

$$\text{RBF: } K(x, x_k) = \exp\left(-\frac{\|x - x_k\|^2}{2\sigma^2}\right) \tag{8}$$

where (σ^2) is a tuning parameter that is related to the radial basis function.

The LSSVM model for regression is as follows:

$$y(x) = \sum_{k=1}^{n} \alpha_k K(x, x_k) + b \tag{9}$$

The basic outline of the the LSVM model can be summarized in the following steps: as shown in Fig. 1.

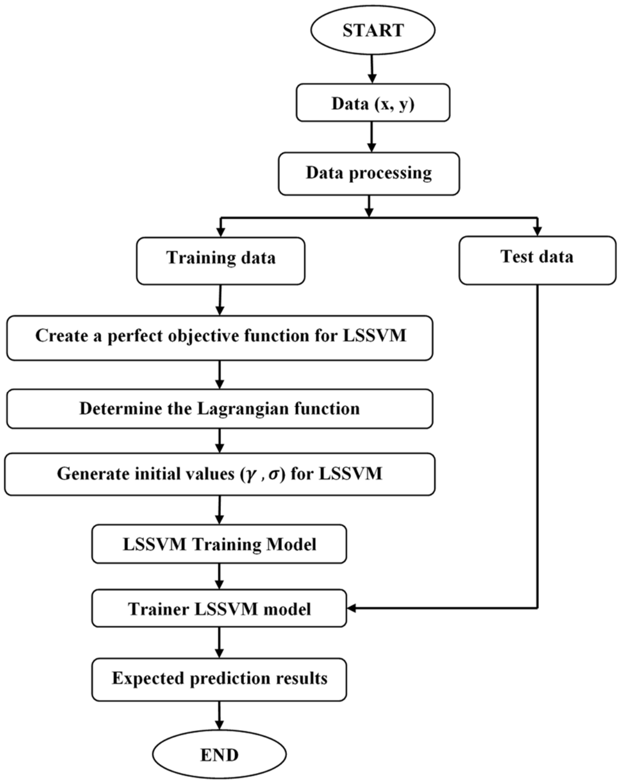

Fig. 1. Flowchart of least squares support vector machine.

Step 1: Prepare and preprocess the required data. In this step, the data is processed, missing values are handled, and outliers are processed to ensure data quality and reliability.

Step 2: Separate the data into test and training sets. This step is crucial for evaluating the model's performance and generalizing it to unseen data.

Step 3: Construct an objective function that aims to find the hyperplane that maximally separates the data while minimizing the errors between the expected and actual values. The excellent objective function of LSSVM ensures that the model is globally optimal, meaning that it finds the best possible solution given the training data.

Step 4: Define the Lagrangian function, a critical component of LSSVM. It provides a way to formulate an optimization problem and transform it into a more efficient dual problem. This transformation allows kernel functions to handle nonlinear relationships between input features and the target variable.

Step 5: Specify the LSSVM model parameters, such as kernel parameters and regularization parameters. These parameters play a significant role in model performance and need to be carefully selected.

Step 6: Train the LSSVM model using the training data after choosing appropriate hyper-parameters. LSSVM defines model parameters through an optimization problem that seeks to minimize the objective function.

Step 7: Utilize validation data to evaluate the trained model's performance. Depending on the specific task, select an appropriate evaluation measure, such as mean absolute percentage error for regression tasks or classification accuracy for classification tasks.

Step 8: Improve the model's performance by adjusting its parameters based on the evaluation results. This iterative process continues until the desired level of performance is achieved, ensuring the model's effectiveness in making predictions or classifications.

Step 9: Iterative optimization: Iterate through training and validation steps and adjust model parameters to improve model predictions. Continuously evaluate whether the required model performance has been achieved.

B. Particle Swarm Algorithm

In 1995, Kennedy and Eberhart introduced the PSO as a global search technique inspired by the foraging behavior of birds. This algorithm has gained popularity as an optimization method [33]. The fundamental benefit of PSO is its capacity to quickly reach convergence in a variety of challenging optimization situations. PSO also provides several appealing benefits, such as simplicity by using fewer mathematical equations and having fewer implementation factors [34]. In a PSO algorithm, there are a swarm of particles, each representing a potential solution in an m-dimensional search space. Each particle is defined by its current position, denoted as $x_i = (x_{i1}, x_{i2}, \dots, x_{im})$, and its velocity, denoted as $v_1 = (v_{i1}, v_{i2}, \dots, v_{\mathrm{im}})$. Each particle keeps track of its best-known position, referred to as pbest t_i =(pbest$_{i1}$, pbest$_{i2}$, ..., pbest$_{im}$). This represents the best solution the particle the particle has currently discovered. The entire swarm keeps track of the global best position, referred to as gbest t_i= (gbest$_{i1}$, gbest$_{i2}$ ..., gbest$_{im}$, which represents the best solution found by any particle in the entire swarm. PSO uses an iterative process to update the velocity and position of each particle. The velocity update Eq. (10) calculates the new velocity v_i^{k+1} for particle i in the k+1 iteration. It depends on the previous velocity v_i^k, the particle's personal best pbest t_i, and the global best gbest t_i. It also includes random factors (r_1 and r_2) and acceleration coefficients (c_1 and c_2).

$$v_i^{k+1} = wv_i^k + c_1 r_1(\text{pbest } t_i^k - x_i^k) + c_2 r_2(\text{gbest } t_i^k - x_i^k) \tag{10}$$

The position update Eq. (11) calculates the new position x_i^{k+1} for particle i based on its current position x_i^k and velocity v_i^k.

$$x_i^{k+1} = x_i^k + \alpha v_i^k \tag{11}$$

The factor w is known as the inertia weight. r_1 and r_2 are random variables sampled from the range [0, 1]. c_1 and c_2 are acceleration coefficients: These coefficients determine the influence of the particle's personal best (pbest t_i) and the global best (gbest t_i) on its velocity update. $v_{\max}$ sets a limit on the maximum velocity, controlling the global exploration capability of the PSO algorithm.

These steps describe the basic process of using the PSO algorithm to optimize the parameters of the LSSVM model for electricity demand forecasting, as shown in Fig. 2.

Initially, the necessary data is input and prepared. This involves eliminating any missing values, dealing with outliers to maintain data accuracy, and dividing the data into a training set and a testing set. The training dataset is used to train the LSSVM+PSO model, while the testing dataset is reserved to evaluate its performance. The LSSVM parameters are then specified, and these parameters may include kernel parameters and regularization parameters. The PSO algorithm is used to optimize the LSSVM parameters. The PSO will iteratively search for the best set of parameters that minimizes the predefined objective function. Once the PSO algorithm optimizes the LSSVM parameters, use the resulting LSSVM+PSO model to forecast electricity demand. To evaluate the performance of the LSSVM+PSO model, use appropriate evaluation metrics. By adhering to these procedures, an effective and precise forecasting model can be developed for applications such as predicting electricity demand. This involves enhancing the LSSVM parameters through the utilization of the PSO algorithm to attain enhanced operational efficacy.

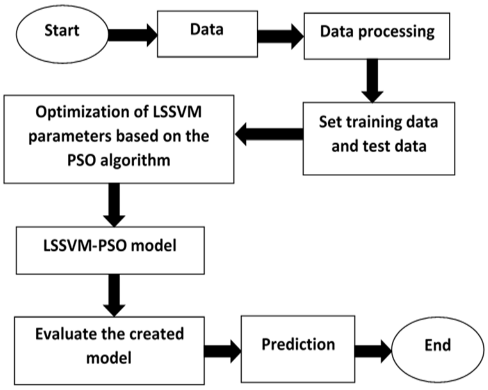

Fig. 2. Flowchart of least squares support vector machine with particle swarm optimization.

C. Whale Optimization Algorithm

WOA is a nature-inspired optimization method proposed by Mirjalili and Lewis in 2016. It is widely used in engineering and optimization tasks due to its simplicity, effectiveness, and relatively few parameters [35]. The algorithm is inspired by the hunting behavior of humpback whales and is designed to strike a balance between global and local search capabilities [36]. WOA consists of three main steps: Surrounding Prey, Bubble-Net Technique, and Chasing the Prey [35].

Surrounding Prey: In this step, the algorithm simulates how humpback whales locate and encircle their prey. The ideal candidate solution is expected to be the target or very near it because the exact location of the optimal solution in the search space is initially uncertain.

$$\begin{aligned} X(t+1) &= X^*(t) - AD, \\ D &= |CX^*(t) - X(t)| \end{aligned} \tag{12}$$

Eq. (12) describes the behavior, where $X(t)$ represents the current location of the prey (candidate solution), $X^*(t)$ is the current optimal solution, D is the distance between a whale's location and the global optimal location, and A and C are coefficient vectors.

$$A = 2a\mathrm{r} - a, \;\; C = 2\mathrm{r} \tag{13}$$

$$a = 2 - \frac{2t}{T_{\max}} \tag{14}$$

Eqs. (13) and (14) are used to calculate the values of A and C, with a decreasing linearly from 2 to 0 over the iterations, and r being a random scalar variable between [0, 1]. Where $T_{\max}$ is the maximum number of iterations.

Bubble-Net Technique: This step describes how humpback whales use a bubble-net method to capture prey. Two methods are introduced:

Shrinking Encircle Mechanism: Here, the value of a is decreased, and a random A between 01 and 1 is inserted to find the new position.

Spiral Position Updated: Eq. (15) is used to describe how whales move in a helix-shaped pattern, which helps them in their hunting.

$$X(t+1) = De^{\mathrm{bt}}\cos(2\pi l) + X^*(t) \tag{15}$$

Eq. (16) determines the path that individuals take to progress toward the population's overall ideal location, and each whale randomly chooses one of the two updating mechanisms based on a probability p.

$$X(t+1) = \begin{cases} X^*(t) - AD & \text{if } p < 0.5 \\ De^{\mathrm{bt}}\cos(2\pi l) + X^*(t) & \text{if } p \geq 0.5 \end{cases} \tag{16}$$

Chasing the Prey: In this step, the agent's location is updated with a randomly chosen value to replace the best match. This random update improves the search ability of the algorithm, ultimately enhancing its performance. Eq. (17) describes this process,

$$\begin{aligned} X(t+1) &= X_{\mathrm{rand}} - AD, \\ D &= |CX_{\mathrm{rand}} - X(t)| \end{aligned} \tag{17}$$

where $\vec{X}_{\mathrm{raud}}$ is the randomly generated location of the in whale. The ideal solution is chosen when$|\vec{A}| < 1$; an agent is picked at random if$|\vec{A}| > 1$. When the WOA meets the termination criteria, it is terminated.

The fundamental schema of LSSVM using WOA involves several stages, as shown in Fig. 3. Firstly, input and prepare the required data, followed by processing the data to address missing values and outliers to uphold data quality. Subsequently, split the data into two sets: the training data set and the test data set. After that, initialize the LSSVM model parameters, such as kernel parameters and regularization parameters, then utilize the WOA algorithm to optimize these LSSVM parameters. WOA iteratively searches for the optimal set of parameters by minimizing a predefined objective function. After the WOA algorithm optimizes the LSSVM parameters, an LSSVM+WOA model is generated. The LSSVM+WOA model is applied to perform forecasts or forecasting tasks, such as electricity demand forecasting. In order to evaluate the performance of the LSSVM+WOA model, appropriate evaluation metrics are used. Depending on the specific problem, select relevant metrics, such as Mean Absolute Percentage Error (MAPE). By adhering to these steps, one can create a proficient predictive model for various applications, such as electricity demand forecasting. The optimization of LSSVM parameters using the WOA algorithm can significantly improve the model's predictive performance.

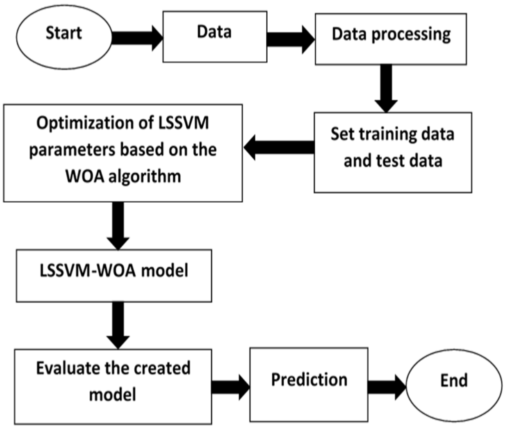

Fig. 3. Flowchart of least squares support vector machine with whale optimization algorithm.

III. Model Performance Evaluation

Some pointers should be made to comprehensively understand the characteristics of the model and thus verify the effectiveness of the proposed model. The indicator MAPE is introduced as a widely used measure for evaluating the accuracy of predictions. It measures the average absolute percentage difference between expected and actual values. This indicator can reveal the performance of the model from different angles. MAPE provides a clear understanding of how well the predictive model is performing in terms of the magnitude and direction of errors. The formula to calculate MAPE is as follows:

$$\text{MAPE} = \frac{1}{L}\sum_{t=1}^{L}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \times 100 \qquad (18)$$

where L is the length of the time series, which is utilized to verify the hybrid method, y_t represents the true data at time t, and $\hat{y}_t$ denotes the forecasting data at the corresponding time.

IV. Results and Discussion

This work comprises two distinct scenarios related to meteorological factor analysis and short-term electrical load prediction. In this first scenario, the primary objective is to analyze meteorological factors, which include (temperature, humidity, wind speed, and cloud cover). The goal is to assess the impact of these meteorological factors on short-term electrical load prediction. Correlation coefficients are employed to quantify the strength of the relationships between weather conditions and fluctuations in electrical demand. Data for this analysis is sourced from the Iraqi Meteorological Organization and Seismology. In the second scenario, the primary focus is on short-term electrical load prediction. The prediction model used is the LSSVM model. LSSVM utilizes historical electrical load data from previous years and relevant weather data (temperature, humidity, wind speed, cloud cover, and day type) as input features. The historical electrical load data serves as a training dataset for the LSSVM model. To enhance the model accuracy, optimization algorithms, namely the WOA and the PSO, with the LSSVM model, are integrated to fine-tune the LSSVM model's kernel functions and regularization parameters. These optimization algorithms help the model capture underlying data patterns more effectively, leading to more accurate load predictions.

A. Analysis of Influencing Factors

In the first scenario, the work is devoted to analyzing the effect of weather factors on the electrical load by using correlation coefficients as indicators of the strength of their relationships. These coefficients, which lie within the range of 01 to +1, allow a quantitative assessment of the degree of correlation between electrical load patterns and the values of different meteorological variables. A coefficient of +1 indicates a strong positive correlation, 0 indicates no correlation, and -1 indicates a strong negative correlation. To approximate these correlations, a fourth-degree linear polynomial equation is used. To calculate correlation coefficients, meteorological data is collected from the Iraqi meteorological organization and seismology, while electrical load data are obtained from the Training and Development Center of the Iraqi Ministry of Electricity. This data collection process extends over the summer and winter seasons of the city of Mosul for 2022 and 2023. It reveals the complex relationships that exist between meteorological conditions and fluctuations in electrical loads. This correlation coefficient allows measuring the extent to which meteorological factors influence electrical load, providing valuable insights into the relationship between weather conditions and electricity consumption.

Table I shows the correlation coefficient values between electrical load variables and various weather factors for the 2022 summer season in Mosul.

TABLE I: Correlation Factor between Variables and Electrical Load in Summer

Variable	Correlation coefficient value between variables and electrical load in summer
Temperature	0.7793
Humidity	0.4695
Wind Speed	0.05495
Cloud Cover	0.05029

A strong correlation coefficient of (0.7793) indicates a robust relationship between temperature and electrical load during the summer. As temperatures rise, the electrical load also rises significantly, indicating that rising temperatures lead to increased electricity consumption in the summer. With a correlation coefficient of (0.4695), there is a moderate relationship between humidity and electrical load during the summer. Although not as strong as the temperature relationship, this suggests that high humidity levels contribute to electrical overload, likely due to the relationship between humidity and temperature. The weak correlation coefficient of (0.05495) indicates that there is no relationship between wind speed and electrical load during the summer. Wind speed does not affect load consumption. The correlation coefficient of (0.05029) also indicates that there is no relationship between cloud cover and electrical load during the summer. Cloud cover has almost no effect on electricity consumption in Mosul during the summer. Based on the values of the correlation coefficient, temperature and humidity are considered the fundamental factors that drive electrical loads during the summer season in Mosul in 2022. Wind speed and cloud cover have almost no effect on electricity consumption. These results highlight the importance of considering temperature and humidity when forecasting and managing electrical loads during the summer season in Mosul.

This relationship between the variables can be illustrated in the following figures: Fig. 4 shows that high temperatures have a very strong and significant effect on the electrical load. This indicates that electrical energy consumption increases as temperatures rise. Fig. 5 shows a relationship between humidity and electrical load. High temperatures lead to increased humidity levels, which in turn contributes to electrical load consumption. According to the very weak value of the correlation coefficient, Fig. 6 shows that wind speed does not affect load consumption during different periods of the summer season. Fig. 7 shows that the relationship between cloud cover and electrical load is weak.

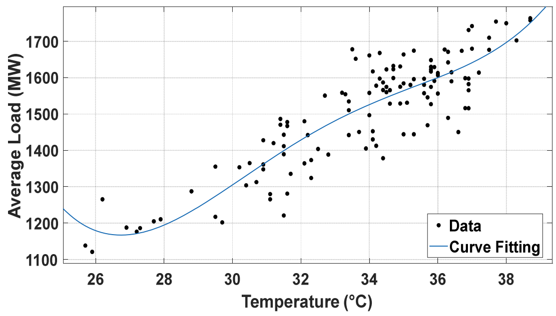

Fig. 4. Correlation factor between temperature and electrical load.

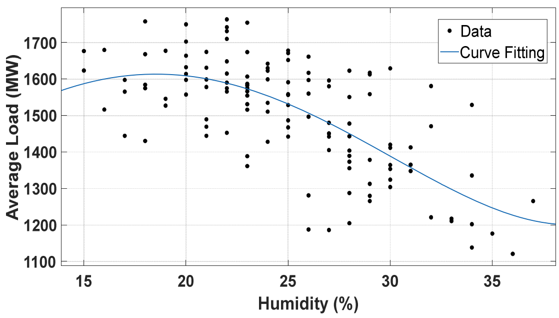

Fig. 5. Correlation factor between humidity and electrical load.

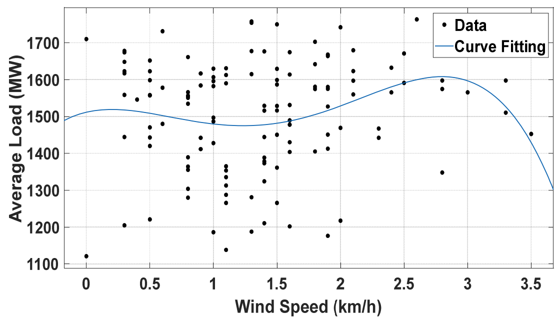

Fig. 6. Correlation factor between wind speed and electrical load.

Cloud cover does not have any significant impact on electricity consumption in Mosul during the summer. These figures reveal that high temperatures have the largest and most important impact on the electrical load during the summer of Mosul in 2022. Humidity also plays a role, although to a lesser extent. Wind speed and cloud cover do not affect electricity consumption. These results emphasize the importance of considering temperature and humidity factors when forecasting and managing electrical loads during the summer in Mosul.

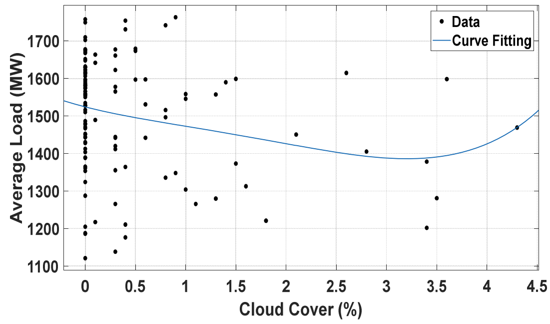

Fig. 7. Correlation factor between cloud cover and electrical load.

TABLE II: CORRELATION FACTOR BETWEEN VARIABLES AND ELECTRICAL LOAD IN WINTER

Variable	Correlation coefficient value between variables and electrical load in winter
Temperature	0.8305
Humidity	0.2613
Cloud Cover	0.05551
Wind Speed	0.008299

Table II presents the correlation coefficient values between electrical load variables and various weather factors for the winter season of the year 2023 in Mosul. These correlation coefficients offer valuable insights into the relationships between weather conditions and electrical load. The strong positive correlation coefficient of (0.8305) indicates a robust relationship between temperature and electrical load during the winter season. As temperature decreases, there is a tendency for electrical load to increase. This suggests that colder temperatures drive higher electricity consumption. A correlation coefficient of (0.2613) suggests a simple relationship between humidity and electrical load during the winter season. While this correlation is not as strong as temperature, it still signifies that humidity levels in the air have a moderate impact on electrical load. The small correlation coefficient of (0.05551) indicates a very weak relationship between cloud cover and electrical load during winter. Cloud cover appears to have only a modest effect on the electrical load during the winter. A correlation coefficient of (0.008299) indicates that there is no relationship between wind speed and the electrical load during the winter. Wind speed appears to have not a minimal impact on electrical load. These correlation coefficients reveal the relative effects of these weather factors on the electrical load during the winter. Temperature is the primary factor that has the most significant impact on load demand in an unquestionable manner. Although humidity affects load consumption, it plays a secondary role compared to temperature. Cloud cover and wind speed do not show significant relationships with the electrical load during this season. These findings provide valuable insights for energy management and demand forecasting during the winter months in Mosul.

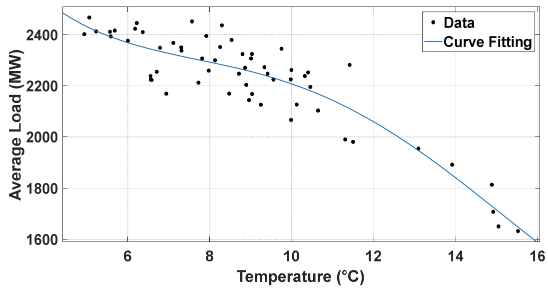

Fig. 8. Correlation factor between temperature and electrical load.

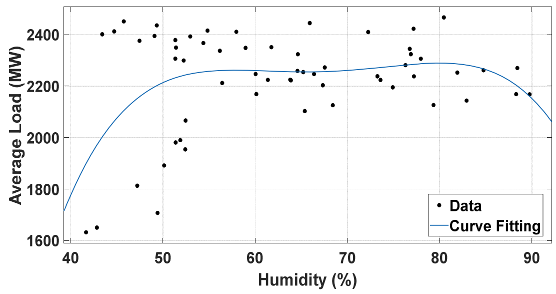

Fig. 9. Correlation factor between humidity and electrical load.

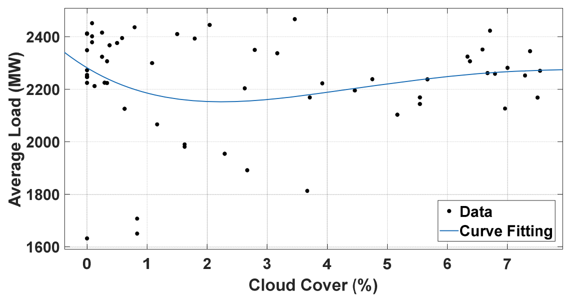

Fig. 10. Correlation factor between cloud cover and electrical load.

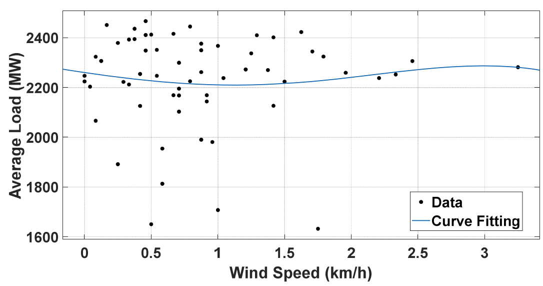

Fig. 11. Correlation factor between wind speed and electrical load.

This relationship between the variables can be illustrated in the following figures: Fig. 8 shows that electrical energy consumption reaches its highest levels when the temperature drops. As temperatures decrease, there is a noticeable increase in electricity consumption. Temperature exhibits the highest value of the correlation coefficient and the strongest correlation with electrical load. Fig. 9 elucidates the effect of humidity on electrical load due to its direct relationship with temperature. As the weather becomes colder, humidity levels tend to rise, leading to increased electrical energy consumption. This indicates that humidity contributes to increased electricity use during the winter. Fig. 10, representing cloud cover, indicates a very weak relationship between cloud cover and electrical load. The effect of cloud cover on electrical energy consumption during the winter is minimal. Fig. 11, shows that a relationship between wind speed and electrical load is very weak. That is, Wind speed has little effect on electrical energy consumption during the winter. These results underscore the significance of temperature and humidity as the primary factors influencing electrical load during the winter in Mosul in 2023. Cloud cover and wind speed do not show significant relationships with the electrical load during this season. These findings emphasize the importance of considering temperature and humidity when forecasting and managing electrical loads during the winter in Mosul.

B. Load Forecasting

The second scenario involves the utilization of a MATLAB simulation environment to carry out the task. The input data for load forecasting is collected from the city of Mosul, covering the period from 2019 to 2023. This dataset includes various datasets, such as daily electricity demand, daily temperature, humidity, wind speed, cloud cover, and day type. The primary objective is to predict the electrical load data for the next day. To evaluate the accuracy of these predictions, the MAPE is employed as a measure of performance.

Table III provides an assessment of the percentage error of forecast models for predicting short-term electrical load in Mosul on August 20, 2022. The mean absolute percentage error is being utilized to evaluate the accuracy of these methods. Two optimization algorithms, the WOA and the PSO, are employed to optimize the parameters of the LSSVM model used for prediction. The results indicate that both the LSSVM+WOA and LSSVM+PSO models outperform the basic LSSVM model in terms of the percentage error of short-term electrical load predictions. However, the LSSVM+PSO model stands out as the most accurate and least percentage error among the three models assessed. These models take into consideration meteorological factors such as temperature, humidity, wind speed, cloud cover, and the type of day (holiday or work). It is worth noting that the accuracy of the model results is influenced more by temperature and humidity than by wind speed and cloud cover. This observation aligns with the findings of the correlation factor analysis, which also emphasizes the substantial impact of temperature and humidity on short-term electrical load. Table IV provides a comprehensive assessment of the forecast model's percentage error in predicting the conductor's short-term electrical load for week during the summer of 2022.

TABLE III: MAPE OF LOAD FORECASTING FOR SUMMER AUGUST 20, 2022

Method	Factors		
	Temperature with humidity	Temperature, humidity, and wind speed	Temperature , humidity, and cloud cover
LSSVM+PSO	0.48%	0.50%	1.65%
LSSVM+WOA	0.66%	0.74%	1.85%
LSSVM	1.41%	1.77%	2.15%

TABLE IV: MEAN ABSOLUTE PERCENTAGE ERROR OF LOAD FORECASTING MODELS FOR MOSUL CITY IN SUMMER 2022

City	Season	Date	MAPE		
			LSSVM (base)	LSSVM +PSO	LSSVM +WOA
		8/1/2022	3.15%	0.86%	0.88%
		8/2/2022	3.88%	1.50%	1.62%
		8/3/2022	0.46%	0.30%	0.33%
Mosul	Summer	8/4/2022	4.53%	2.92%	2.94%
		8/5/2022	3.55%	0.64%	1.00%
		8/6/2022	2.43%	0.30%	0.37%
		8/7/2022	5.99%	1.23%	1.25%

The relationship between the actual values and the real values can be illustrated in the following figures: Fig. 12, Fig. 13, and Fig. 14 show the closeness of the results obtained from the models used to predict short-term electrical loads under the influence of weather and type of day (holiday or working days), presented in the form of curves. Among these models, the curve corresponding to the LSSVM+PSO model is the closest to the actual values of electrical loads, followed by the LSSVM+WOA model, which is close to the actual values of electrical loads. These curves illustrate the percentage error of the model and depict the peak times of demand on the electric load, which occur in the middle and at the end of the day. These figures confirm that the LSSVM+PSO model is more accurate and reliable for short-term electrical load prediction than the LSSVM+WOA and basic LSSVM models. This suggests that the integration of the PSO algorithm into the LSSVM model enhances its predictive capabilities.

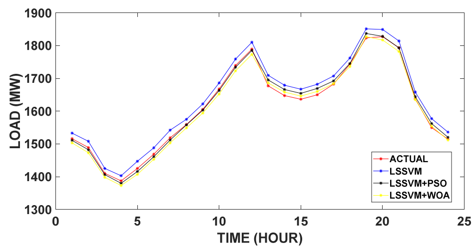

Fig. 12. Electrical load forecast for August 20, 2022 using temperature and humidity.

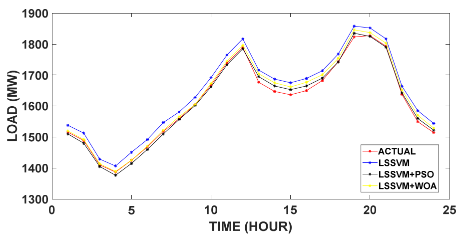

Fig. 13. Electrical load forecast for August 20, 2022 using temperature, humidity and wind speed.

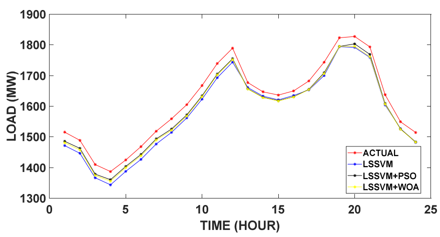

Fig. 14. Electrical load forecast for August 20, 2022 using temperature, humidity and cloud cover.

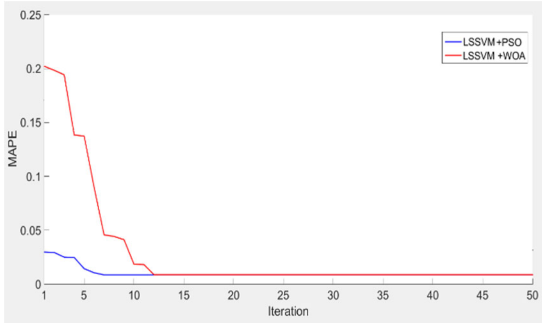

Fig. 15. Optimization convergence for load forecasting on 8/1/2022.

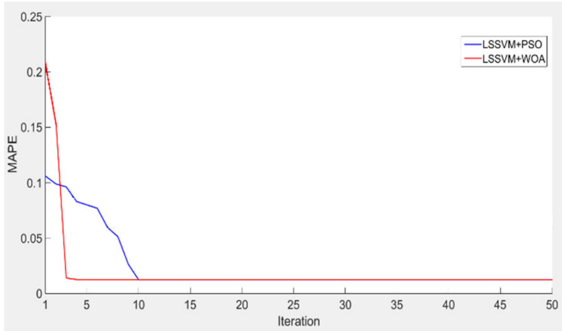

Fig. 16. Optimization convergence for load forecasting on 8/7/2022.

Additionally, the convergence of the optimization algorithms in Fig. 15, and Fig. 16 provide further insights into their performance. These figures depict how the algorithms converge towards optimal solutions over the first 50 iterations. By analyzing these convergence figures alongside the percentage error assessments presented in Table IV, can gain a comprehensive understanding of the effectiveness and efficiency of each integrated method in predicting short-term electrical load accurately. Furthermore, convergence figures offer valuable visualizations to compare the convergence speed and efficiency of the PSO, and the WOA when integrated with the LSSVM model to reach optimal solutions. Fig. 15 and Fig. 16 show that the LSSVM+PSO model has faster convergence than the LSSVM+WOA model to reach optimal solutions.

Table V assesses the percentage error of error between the predicted values and the actual values for short-term electrical load forecasts for January 23, 2023, in Mosul city. The MAPE is employed to gauge the accuracy of these methods. These results demonstrate that integrating optimization algorithms, specifically the PSO and the WOA algorithms, with the LSSVM model enhances the accuracy of short-term electrical load predictions compared to using the LSSVM model. Among the three models evaluated, the LSSVM+PSO model exhibits the lowest percentage error, followed by the LSSVM+WOA model. This improvement in accuracy is especially notable when considering the influence of meteorological factors such as temperature, humidity, and the type of day (holiday or work) compared to the influence of wind speed and cloud cover. This finding aligns with the results of the correlation analysis, which highlights the significant impact of temperature and humidity on short-term electrical load. The results indicate that the LSSVM+PSO model achieves the lowest error rate, delivers the most precise predictions, and closely approximates the actual values of short-term electrical load. This underscores the effectiveness of integrating PSO optimization into the LSSVM model for enhancing the accuracy of load forecasts in Mosul city.

TABLE V: MAPE OF LOAD FORECASTING FOR WINTER JANUARY 23, 2023

Method	Factors		
	Temperature with humidity	Temperature , humidity, and cloud cover	Temperature, humidity, and wind speed
LSSVM+PSO	0.30%	0.84%	1.34%
LSSVM+WOA	0.52%	0.86%	1.62%
LSSVM	1.24%	1.82%	3.15%

TABLE VI: MEAN ABSOLUTE PERCENTAGE ERROR OF LOAD FORECASTING MODELS FOR MOSUL CITY IN WINTER 2023

City	Season	Date	MAPE		
			LSSVM (base)	LSSVM +PSO	LSSVM+WOA
		1/1/2023	4.77%	0.40%	0.55%
		1/2/2023	6.99%	3.33%	3.36%
		1/3/2023	2.79%	0.79%	0.86%
Mosul	Winter	1/4/2023	5.21%	0.76%	0.91%
		1/5/2023	3.43%	1.37%	1.38%
		1/6/2023	1.27%	0.55%	0.56%
		1/7/2023	8.17%	4.77%	4.84%

Table VI provides a comprehensive assessment of the percentage between the predicted values and the actual values of the forecast model in predicting the short-term electrical load of the conductor for a week during the winter of 2023.

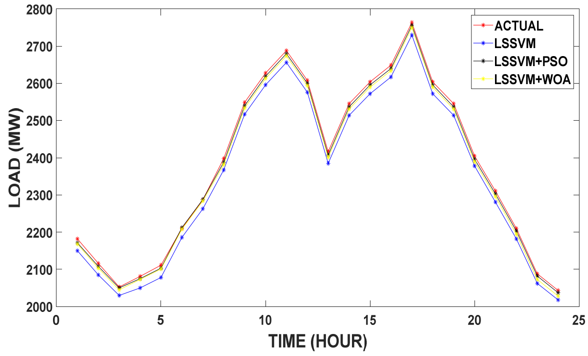

Fig. 17. Electrical load forecasts for January 23, 2023 using temperatures and humidity.

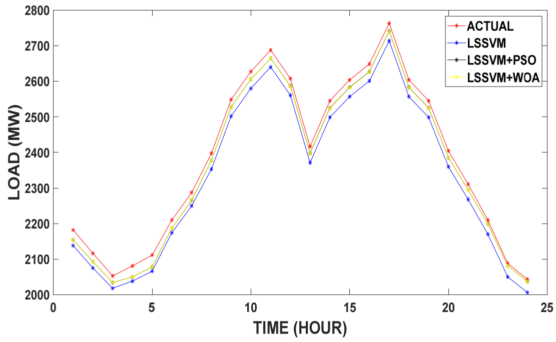

Fig. 18. Electrical load forecasts for January 23, 2023 temperature, humidity and cloud cover.

The relationship between the actual values and the real values can be illustrated in the following figures: Fig. 17, Fig. 18, and Fig. 19 illustrate the proximity of the results obtained from the models used for short-term load prediction, taking into account the influence of weather and type of day (holiday or working days). These figures depict the curves generated by the models, with a particular focus on the LSSVM+PSO model. It is worth noting that the curve corresponding to the LSSVM+PSO model closely aligns with the actual values of electrical loads, indicating a high level of accuracy and reliability in short-term electrical load prediction. Following closely behind is the LSSVM+WOA model curve, which also exhibits a close alignment with the actual load values. In contrast, the curve associated with the LSSVM models deviates more from the actual load values, confirming the superior performance of the LSSVM+PSO model in capturing load patterns and providing accurate predictions.

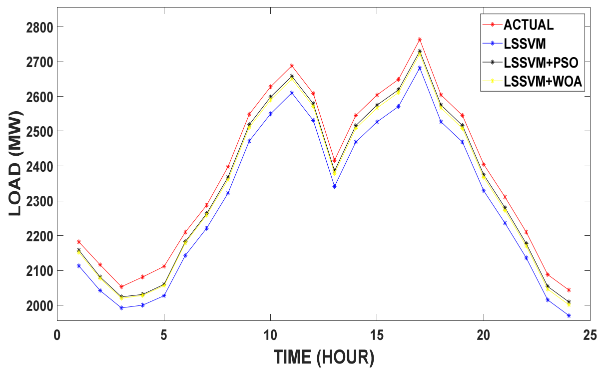

Fig. 19. Electrical load forecasts for January 23, 2023 temperature, humidity and wind speed.

Additionally, the convergence of the optimization algorithms in Fig. 20 and Fig. 21 provide further insights into their performance. These figures depict how the algorithms converge towards optimal solutions over the first 50 iterations. By analyzing these convergence figures alongside the percentage error assessments presented in Table VI, can gain a comprehensive understanding of the effectiveness and efficiency of each integrated method in predicting short-term electrical load accurately. Furthermore, convergence figures offer valuable visualizations to compare the convergence speed and efficiency of optimization algorithms the PSO, and the

WOA when integrated with the LSSVM model to reach optimal solutions. Fig. 20 and Fig. 21 show that the LSSVM+PSO model has faster convergence than the LSSVM+WOA model to reach optimal solutions.

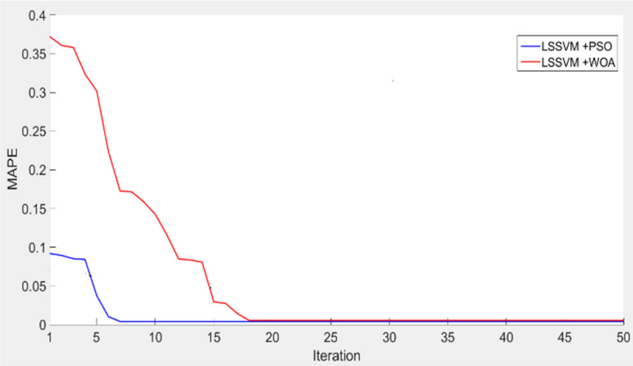

Fig. 20. Optimization convergence for load forecasting on 1/1/2023.

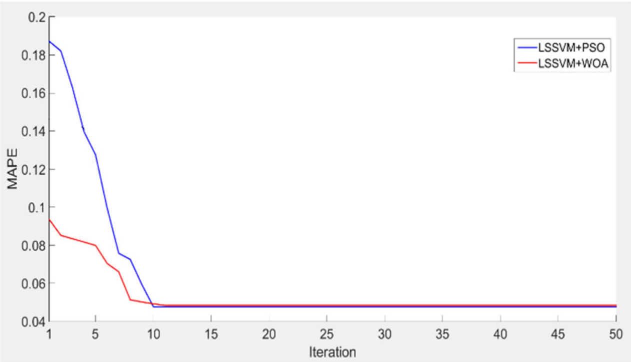

Fig. 21. Optimization convergence for load forecasting on 1/7/2023.

V. Conclusions

The work presents two distinct scenarios. In the first scenario, it focuses on analyzing weather factors and their impact on electrical load using correlation coefficients. In the second scenario, the focus is on enhancing the accuracy of short-term energy consumption forecasts using the LSSVM model. Historical load data is obtained from the Iraqi National Dispatch Center, while meteorological data is sourced from the Iraqi Meteorological Organization and Seismology in the city of Mosul. To improve the LSSVM model's performance, two different optimization algorithms are employed, namely the PSO and the WOA. The research findings indicate that the enhanced LSSVM model using the PSO algorithm outperforms the WOA algorithm, albeit by a slight margin, in providing reliable predictions of electrical loads. The work concludes that temperature and humidity, along with the type of day, have a more significant and positive impact on electrical load forecasting compared to wind speed and cloud cover. Furthermore, it is noted that both the LSSVM+PSO model and the LSSVM+WOA model achieve better accuracy in electrical load prediction results than the basic LSSVM model. Based on these results, it is inferred that the proposed method, particularly the LSSVM+PSO model, can be effectively utilized for accurate and reliable load prediction, while according to execution time, the LSSVM+PSO model takes a little longer than the LSSVM+WOA model. Future work also suggests the possibility of extending this method by incorporating additional factors to further enhance its predictive capabilities.

Conflict of Interest

The authors declare no conflicts of interest.

Author Contributions

The author, Taha Abbas Sadiq, conducted the research, created the optimization algorithms, and wrote the paper; the author, Balasim Mohammed Hussein, analyzed the data and all authors approved the final version.

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