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Article

ASFO-SVM-Based Intelligent Load Prediction for Microgrid Energy Optimization in Renewable Energy Systems

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Abstract

Accurate load forecasting is essential for efficient microgrid operation, stability, and planning. Traditional forecasting methods often suffer from limitations in handling nonlinear, complex, and dynamic load patterns, which can reduce accuracy and reliability. To overcome these challenges, this study proposes a hybrid framework that integrates the adaptive sunflower optimization (ASFO) algorithm with support vector machines (SVM) for short-term microgrid load forecasting. The ASFO algorithm is employed to optimize SVM hyperparameters, enhancing generalization capability and improving prediction accuracy. The baseline forecasting model recorded a mean absolute percentage error (MAPE) of 34.59%, indicating the need for optimization. After applying the proposed ASFO-SVM framework, forecasting errors were significantly reduced, achieving a minimum MAPE of 0.44% for summer weekdays and consistently remaining below 2% across all seasonal and daily horizons. Comparative analysis with existing models—including PSO-SVM, Random Forest, and standalone SVM—demonstrates that ASFO-SVM achieves up to a 62.30% improvement in accuracy while maintaining computational efficiency. The findings confirm that the ASFO-SVM approach provides a robust, accurate, and adaptable solution for microgrid load forecasting. This makes it a promising candidate for practical deployment in intelligent energy management systems, especially in scenarios requiring reliable decision-making under uncertainty.

Keywords

Adaptive sunflower optimization, Support vector machine, Electric load forecasting, Micro-grid, Intelligent forecasting system

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1. Introduction

In today's modern world, electricity is crucial. Electricity access serves to boost public health and economic prosperity [1]. However, the need for electricity is constantly increasing due to rapid technological advancement, industrialization, population expansion, and other factors, and it has become an integral component of people's lives worldwide [2]. On the other hand, the process of producing, transmitting, and distributing electrical energy is still complex and expensive [3]. Load forecasting is estimating future active loads at various load buses before the actual occurrence of loads [4].

Electricity load predictions can be grouped into three groups based on their forecasting time frames. Short term load forecast (STLF), medium term load forecast (MTLF) and long term load forecast (LTLF) are three types of load forecasts. STLF is usually completed within a few hours, days, or weeks. This makes day-ahead power supply planning and demand-side management (DSM) more accessible in the electricity market. In contrast, MTLF is concerned with forecasts that range from months to years. Revenue estimates, unit maintenance scheduling, and energy trading, among other things, are all aided by such predictions. The anticipated horizon for LTLF ranges from about five sustainability years to several decades. These estimates give policymakers a better understanding of the situation and aid asset management and power system expansion plans [5].

Load forecasts help companies make important decisions about power, load shifting, voltage control, network configuration, infrastructure development, power purchase, and generation, load shifting, and infrastructure development. Load forecasts are crucial for energy suppliers, independent system operators (ISOs), financial institutions, and other actors in the production, transmission, distribution, and marketing [6].

Artificial intelligence methods, physical methods, traditional statistical models, and hybrid models are the four categories of modeling methods for estimating electricity consumption. Statistical approaches are often appropriate for linear models, but they are frequently inadequate to address the non-linear characteristics of time series for power requirements. Physical prediction methods are a type of physical method that is hampered by large-scale computational and physical data collection problems and enormous amounts of calculations and is influenced to some extent by the dependability and validity of external elements. Advanced artificial intelligence systems are suitable for processing time series. Still, they may not be able to recognize and retrieve the internal properties and traits of complex non-linear and anomalous data, particularly the availability of prediction data for power requirements [7].

Hybrid methods are a blend of multiple types of methods that take leverage of each type's strengths. In this paper, we use adaptive sunflower optimization techniques and the support vector machine algorithms to create a hybrid model for load prediction. When compared to standard modeling methodologies, hybrid models have the potential to produce better forecasts.

The main contributions of this study can be summarized as follows:

- (1) **Hybrid Optimization Framework.** We propose a novel hybrid forecasting model that integrates the adaptive sunflower optimization (ASFO) algorithm with support vector machines (SVM). Unlike conventional optimization methods (e.g., particle swarm optimization (PSO), genetic algorithm (GA), grid search), ASFO adaptively adjusts its exploration and exploitation balance, reducing premature convergence and improving global search efficiency.
- (2) **Improved Forecasting Accuracy.** The ASFO-SVM framework achieves mean absolute percentage error (MAPE) consistently below 2% across different seasonal and daily horizons, representing up to a 62.3% improvement over baseline models (SVM, Random Forest, and PSO-SVM).
- (3) **Robustness Across Scenarios.** Extensive evaluations on real-world solar power plant data from Karur, India, demonstrate that the proposed model maintains high accuracy across diverse operating conditions, including weekdays, weekends, and seasonal variations.
- (4) **Computational Efficiency.** By dynamically tuning search parameters, the ASFO reduces redundant evaluations compared to traditional metaheuristics, providing an effective balance between accuracy and computational cost.
- (5) **Comparative Validation.** A dedicated subsection (Section 4.3) contrasts the performance of ASFO-SVM with state-of-the-art models, further confirming its superiority and practical relevance for intelligent microgrid management.

The rest of the paper will go like this: The second portion will be devoted to a review of the literature on load forecasting. The proposed methodology is introduced in Section 3. Our work's results and analyses are discussed in Section 4. Section 5 presents the findings and conclusions.

2. Literature Survey

The most recent research works in this field are presented below. Hu et al. [8] suggested that the SVR prediction model's parameters be properly determined using a firefly algorithm (FA)-based meme algorithm (MA). Computing results demonstrate that, when compared to other SVR-based optimization algorithms, the proposed FA-MA can significantly increase the prediction accuracy of SVR. However, the FA-MA-based SVR prediction model performs noticeably better than the chosen counter-response model. Roman-Portabales et al. [9] conferred a wide range of

methods that have employed artificial neural networks (ANN) to forecast electricity demand, assist both novice and highly experienced researchers to evaluate standard procedures, and identify areas that can be improved in light of the widespread deployment of smart meters and sensors at the moment. Due to the cyclical nature of load demand, the papers reviewed demonstrate how ANNs changed from a logical and promising concept to a prevalent reality in production environments.

Lahouar et al. [10] proposed load prediction using a random forest model, the previous day's load can be predicted. This paper suggests an anterior load prediction model with a 1-hour resolution using a random regression forest. The season, temperature, day type, and load per hour are all considered during the training process to create the adopted model. This technique differs from other artificial intelligence methods like ANN and SVM in terms of speed and parameterization simplicity. Rarely, however, will unexpected behavior occur on holidays, necessitating human intervention to change the outcomes.

Kang et al. [11] demonstrated the effectiveness of fundamental in-deep learning models for forecasting electricity, including installed capacity, delivery capacity, and power consumption. Convolutional neural networks (CNNs), recurring neural networks (RNNs), and hybrid models that incorporate CNNs and RNNs are just a few of the deep learning models we create in this article. Experiment results show that the convolutional neural network (CNN) method significantly outperforms the other two models' three feature predictions (plant capacity, supply capacity, and power consumption). We also evaluate how the CNN model performs in comparison to SVM and ANN models. Results of the comparison demonstrate that CNN consistently outperforms. Because it can only forecast for one day at a time, the developed CNN model is only useful for short-term predictions of electricity demand.

Anand et al. [12] presented prediction of future energy demand in Tamil Nadu, India, using PSO and a GA optimized ANN. The total demand for electrical energy in this document is divided into residential, agricultural, industrial sectors and commercial. Hybrid artificial neural network models (hybrid artificial neural networks) are being developed for each department using the most recent optimization techniques, including PSO and the GA. Predictions from the hybrid ANN-PSO model were compared to hybrid ANN-GA, ARIMA, ANN-BP, and linear models. When compared to time series models like artificial neural network with backpropagation (ANN-BP) or ARIMA, both linear and square ANN-PSO produce better results.

Moment-based approaches have also been optimized for computational efficiency in image reconstruction tasks [13], which provides useful insights for hybrid modeling strategies in energy forecasting.

Shafiei Chafi et al. [14] presented neural networks and PSO algorithms for forecasting short-term loads. It makes use of the PSO algorithm. The algorithm chooses particular neural network parameters, such as learning rate and hidden units, to predict electrical loads precisely. The suggested method was examined on the Iranian power grid using the MATLAB programming language. We use the PSO algorithm to adjust some neural network parameters before getting a properly optimized model. Short-term power load predictions are then made using a neural network with optimized parameters. The outcomes of the simulation demonstrate the precision and strength of this approach for forecasting short-term load.

Hao et al. [15] suggested and used a new ensemble prediction model of electricity consumption using the artificial bee colony (ABC) algorithm. The ensemble classifier forecasts derived from variety of time variables, including gross domestic product (GDP), energy mix, industrial structure, innovation, urbanization rate, and historical load demand. However, it is challenging to precisely predict electricity consumption because of the intricate relationship between that demand and the numerous influencing factors. It is an addition to conventional and data-driven forecasting techniques.

Awan et al. [16] demonstrated STLF's new hybrid model by combining the ABC algorithm's excellent optimization capabilities with ANN. ABC is a different learning scheme that is used to obtain an optimized set of ANN neuron coupling weights. The experiment was carried out using a 10-year (2002-2012) data set of load and demand per hour obtained from Ontario's independent electrical system operator (IESO). Numerous input factors, including calendar events, demand from the previous hour and day, weather, and hourly energy prices, were taken into consideration as input parameters for this study based on the high correlation. The outcomes are displayed and contrasted using tables and graphs, demonstrating that the artificial bee colony-based load forecasting (ABC-based LF) model is a superior method to PSO and GA. With 1.89 percent MAPE, greater accuracy was attained.

Suganthi et al. [17] presented an improved electricity demand forecasting is achieved in Tamil Nadu, India, using the proposed hybrid GA-PSO algorithm. Secondary PSO algorithms broaden the population and boost global optimization's effectiveness. In an open-source scientific laboratory (SCILAB) environment, all GA and PSO technologies are created. The proposed ANN-GA-PSO model's validity and superiority are evaluated using the total electricity demand in Tamil Nadu between 2001 and 2015. Linear and quadratic ANN-GA-PSO models outperform ANN-GA models by 28% and 48%, respectively, and ANN-PSO models by 25% and 43%.

Similar hybridization concepts have been applied in diverse domains, such as image security where deoxyribonucleic acid (DNA) computing is combined with chaotic systems [18].

Zhu et al. [19] suggested a prediction model based on the empirical mode decomposition–facebook prophet–long short-term memory (EMD-Fbprophet-LSTM) approach to forecasting the short-term power consumption of the company's daily power consumption data. The multi-curve Eigen mode functions (IMF) and residual components of the time series

were separated using the EMD model, and the IMF components were predicted using the Fbprophet method. To predict short-term power consumption, use the long short term memory (LSTM) model, calculate the expected value of the combined model, and weight each term. According to the experimental results, the prediction model optimized for EMD-Fbprophet-LSTM has a low variability error and can isolate the effects of various components.

Saoud et al. [20] proposed long short term memory using the meta-heuristic algorithm PSO, and the optimal parameters of the model are obtained, yielding better prediction results and comparisons with other prediction models. Mean squared error (MSE) and root mean squared error (RMSE) are the evaluation scales used for comparison root mean square error (RMSE). Prediction accuracy is measured using metrics such as RMSE and mean absolute error (MAE). To assess its performance, the experimental results of this hybrid model are compared to those of other existing models.

Kim et al. [21] presented PSO should be integrated into the CNN-LSTM network to predict energy consumption and automatically calculate the various kinds of hyperparameters that have been demonstrated. Additionally, compared to conventional machine learning methods, it achieves the lowest MSE. The UCI repository's dataset on household power consumption will be used as a testing ground in this white paper to achieve the lowest RMSE possible in comparison to conventional approaches. Contrarily, the number of hyperparameters that need to be tuned rises with the complexity of neural networks that employ CNNs and LSTMs.

Wang et al. [22] proposed a new method for predicting periodic energy consumption based on LSTM networks. First, hidden features are extracted from actual industrial data using autocorrelation graphs. Correlation and mechanism analysis can assist you in identifying quadratic variables that correspond to your model inputs. From all energy-related data, the method chooses a quadratic variable for the model. The LSTM method outperforms autoregressive moving average (ARMA), Autoregressive fractionally integrated moving average (ARFIMA), and Backpropagation Neural Network

Backpropagation neural network (BPNN) in terms of prediction performance. Long-term time series forecasting reveals that LSTM has a 19.7 % lower RMSE than BPNN, a 54.85 % lower RMSE than ARMA, and a 64.59% lower RMSE than ARFIMA.

Kasule et al. [23] proposed a predictive model that employs a hybrid algorithm based on PSO-ABC algorithm. Between 1990 and 2016, the average annual growth rate of Uganda's net electricity consumption was 9.24 %. The rapid rise in power demand, particularly over the long term, presents the biggest problem for forecasting power demand in developing countries.

Bedi et al. [24] suggested a deep learning-based framework to forecast electricity demand while considering long-term historical dependencies. Cluster analysis is first used on the monthly electricity consumption data to create seasonal segmented data. The proposed Decomposition-based forecasting-ensemble Deep learning (D-FED) framework has the smallest prediction error, according to simulation results. This enables you to estimate demand accurately for user-specified seasons, days of the week, and time intervals. However, because of nonlinear extrinsic characteristics such as climatic conditions and economic variables, it is difficult to predict energy demand accurately.

2.1 Existing System

Effective grid management includes proper load demand planning, proper generation, transmission, and distribution line maintenance planning, and efficient grid management. To distribute the load, supply lines must be used. As a result, accurate load estimation is critical. The energy production planning program will improve efficiency significantly. To improve the accuracy of required power, various computational and statistical methods have been used (EED). The prediction model has been enhanced.

2.1.1 Artificial Neural Network

Due to their exceptional capabilities in non-linear mapping, generalization, and self-learning, artificial neural networks have demonstrated versatility in technical optimization. The demand for electrical energy is so non-linear that artificial neural networks are a good strategy because they do not need an explicit model. Due to its excellent performance, ANN has primarily replaced the old method in many applications [25]. Artificial neural networks (ANNs) have been used frequently in recent decades for short-term load predictions due to their computational flexibility.

2.1.2 The Support Vector Machine

SVM is among the most effective classification techniques. SVM outperforms all other modern classification techniques, according to benchmark studies. SVMs are derived from statistical learning theory and have significantly improved machine learning and other application areas. Even though SVM methods have been used to forecast power consumption, much more work needs to be done to achieve the best predictions [26].

2.1.3 Random Forest

Random forest (RF) is an ensemble-based machine learning technique comprised of many trees. The voting system in random forests improves the performance of many weak learners (decision trees in this case). Random forests are used to build a general model that predicts load demand one day in advance, in hourly increments. Even during more extended test periods, the model must produce accurate results regardless of the time of day or season. Classification and Regression Trees are improved by Random Forest, which combines many different classifications and regression trees [27].

2.1.4 Particle Swarm Optimization

Many particles in PSO are initially randomly initialized. Position, velocity, individual best fit, and global best fit are all initialization parameters. PSO's most recent and popular versions employ locally optimal fitness values. In this case, particles are thought to be members of topological neighborhoods (subgroups). PSO uses a set of particles to find the best solution in the solution space. Every particle is viewed as a potential solution to some issue. After optimization, the particle with the slightest error is deemed the solution [28].

2.2 Problem Statement

The ANN, SVM, PSO, and RF algorithms are used to predict power load. However, the accuracy of these models is dubious, mainly when dealing with highly uncertain data. Many disadvantages of the ANN method include rapid migration to local optimization, over-adaptation, and slow convergence. However, as renewable energy sources become more prevalent, smart grid load becomes hard to predict and necessitates more sophisticated solutions [29]. The SVM algorithm is a famous classification and prediction algorithm. However, there is still the issue of selecting the appropriate desired functions and parameters, which can significantly impact the final prediction accuracy. However, RF has some disadvantages. For instance, the training process is computationally expensive and may result in overfitting. Recent improvements in metaheuristics, such as chaotic-map-enhanced Kepler optimization [30], demonstrate the potential of hybrid evolutionary techniques, motivating the development of ASFO in this study.

Among various metaheuristic optimization algorithms, the ASFO algorithm was selected due to its superior convergence properties and robustness in non-linear, high-dimensional problem domains. Compared to conventional methods like GA, differential evolution (DE), and harris hawks optimization (HHO), ASFO offers a balanced exploration–exploitation mechanism driven by biologically inspired sunflower pollination behavior and adaptive step sizes. Unlike GA, ASFO does not rely on complex crossover and mutation operations, making it computationally simpler. Unlike DE, it avoids stagnation in local minima through dynamic direction updating, and compared to HHO, it requires fewer control parameters, improving ease of tuning and reproducibility. These features make ASFO particularly suitable for tuning the hyperparameters of SVM, where precision and global optimality directly influence prediction accuracy.

2.3 Major Contribution

This research proposes a useful prediction model that uses hybrid ASFO-SVM for accurate and reliable data prediction. The terms used in the proposed method are defined below. To determine the SVM algorithm's ideal solution, the ASFO metaheuristic algorithm simulates the behavior of sunflower flowers. The ASFO algorithm is typically chosen because it has many benefits over other modeling techniques. To assess the best options, such as exploitation and exploration, ASFO is carried out in a series of steps. SVM algorithms process large amounts of data quickly and efficiently.

3. Proposed Methodology

The proposed methodology leverages the ASFO algorithm to optimize the hyperparameters of the SVM model. ASFO was chosen over alternatives such as GA, DE, and HHO based on its recent demonstrated success in solving complex engineering optimization tasks with fewer iterations and greater consistency. Its adaptive inertia and pollination-inspired mechanism make it more resilient to local optima and noise, which is essential in energy forecasting applications that involve seasonal and nonlinear load patterns.

In load prediction, historical information on load demand and associated factors is divided into various modules and fed into the hybrid ASFO-SVM. In this section, the ASFO algorithm is used to optimize the SVM. Sections 3.1, 3.2, and 3.3 detail the components of the proposed load forecasting method.

3.1 Data Set

The performance introduced hybrid ASFO with SVM algorithm is evaluated using the load and weather data collected over 3 years in the Tamil Nadu region of Karur. The meteorological data is obtained from the Karur weather station in Tamil Nadu. For training and validation, the data set from January 2022 to December 2023 is used, and the seasonal data set from the year 2024 is used for testing.

Additionally, the days from Monday to Friday are categorized as working days, while Tamil Nadu's public holidays, Saturdays and Sundays, are classed as weekends. To enhance training effectiveness, the proposed model incorporates nine different related inputs. The categories of data can be represented as follows:

$L_d(w, d, h)$ constitute the load demand of a particular hour of the day of the week. $L_d(w-1, d, h)$ constitute the load demand for the same hour of a day in a previous week. $L_d(w, d, h-1)$ constitute the load demand for a previous hour of the same day and week. $L_d(w, d-1, h)$ constitute the load demand for the same hour of a week in a previous day.

Type of day means a working day or a weekend day. Day of week means first, second, third or any day of a week.

Humidity. Temperature. Irradiance. Wind speed.

Based on collected dataset, the prediction of short term load demand has been evaluated by MATLAB R.2018.

3.2 Preprocessing

The prediction phase starts with data collection and preprocessing because reliable data can yield significant findings. The preprocessing unit (PPU) retrieves historical weather information from the Karur microgrid. The PPU also exchanges data with the historical database to determine day types and obtain historical training load data. The process of converting unstructured data into a structured form is called preprocessing. The information gathered through this process is reliable and usable for further analysis. Principal component analysis (PCA) methods are used to reduce and analyze data without losing information. It is an effective method for locating high-dimensional information and can reduce the time needed to convert and process it into low-dimensional information.

3.3 Adaptive Sunflower Optimization Method

The sunflower cycle is repeated every day, like the hands on a clock: they wake up and follow the light. They turned in the night and waited on the other side. They left early the following morning—the reproductive behavior of pollinated flowering plants in a biological context. In this study, the author investigated the unique properties of sunflowers. Determine the best sun angle. The goal of the pollination process in the ASFO algorithm as shown in Figure 1 is to identify the global minimum solution through randomized search and optimization. Flower I and flower in $i+1$ are slightly separated. Every flower on the plant produces millions of pollen germ cells regularly. On the other hand, sunflowers create and develop only one pollen germ cell per flower for simplicity.

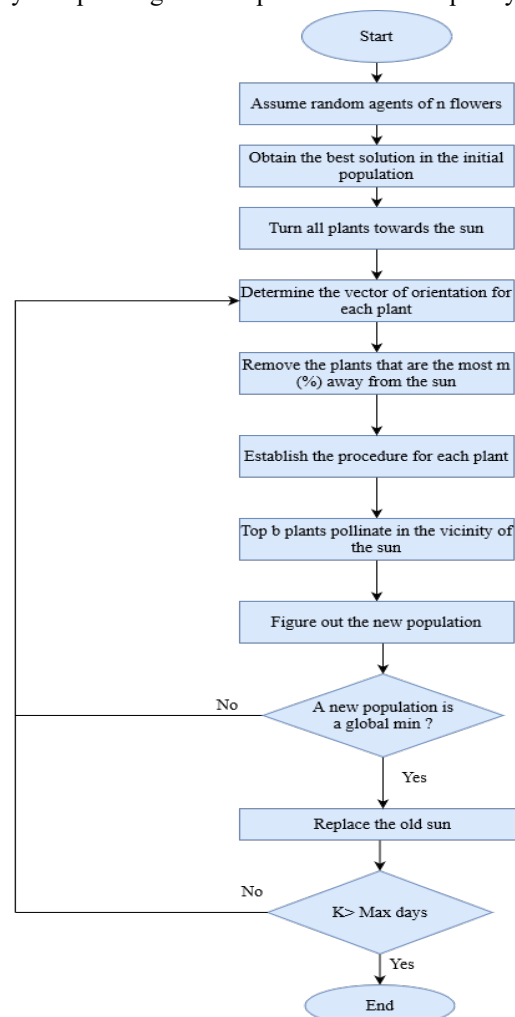


Figure 1. ASFO algorithm.

The inverse quadratic law is an excellent example of a nature-based optimization. This means that the radiation force decreases with distance. The intensity is reduced by one factor when the space is doubled. Factor 4 was multiplied four times, and factor 9 was reduced. In our case, the amount of radiation received is proportional to the distance between the plant and the sun, and it tends to be stable near these distances. However, the longer the space between plants, the less heat they absorb and the more heat they receive from the sun. As a result, this study is also the same. More significant steps are being taken to get as close to global optimization as possible [31].

Each plant's overall quantity of heat Q received is then calculated as follows:

$$Q = \frac{W}{4\pi r_i^2} \quad (1)$$

Where W denotes Source power (Watts, W), Q is heat received by sunflower i (Joules) and r_i means the distance between sunflower i and source (meters, m).

Sunflowers face the sun in the following manner:

$$\vec{s}_i = \frac{X^* - X_i}{\|X^* - X_i\|}, \quad i=1, 2, \dots, n_p \quad (2)$$

Where s_i is step size of sunflower movement (dimensionless).

The step of the sunflowers in the direction s is calculated as follows:

$$d = \tau \times P_i(X_i + X_{i-1}) \times \|X_i + X_{i-1}\| \quad (3)$$

Where P_i is the pollination potential (dimensionless), X_i, X_{i-1} positions of individuals in the search space (dimensionless). $\|X_i + X_{i-1}\|$ = Euclidean distance (dimensionless) and τ is a constant that describes the plant's "inertia" displacement (dimensionless). This is a brand-new individual in a location where the sunflower pollinates the closest adjacent $i-1$ and changes depending on how far apart the random flowers are from one another. While those farther from the sun move frequently, those closest to it move slowly to achieve local sophistication. To avoid excluding candidates for the global minimum, it is also crucial to restrict the maximum number of steps each person can take.

Figure 1 illustrates the steps of the introduced algorithm. The maximum step is defined as follows:

$$d_{max} = \frac{\|X_{max} - X_{min}\|}{2 \times n_{pop}} \quad (4)$$

Where n_{pop} is the total number of plants in the population and X_{max}, X_{min} , and are the upper and lower bounds of the value.

The new plantation will be:

$$\vec{X}_{i+1} = \vec{X}_i + d \times \vec{s}_i \quad (5)$$

Figures 2-4 quickly visualize the proposed algorithm steps. The generation of an individual population is the first step in the algorithm. This population could be even or random. The ability to rate who turns into the sun or has the highest overall rating is made possible by each person's rating.

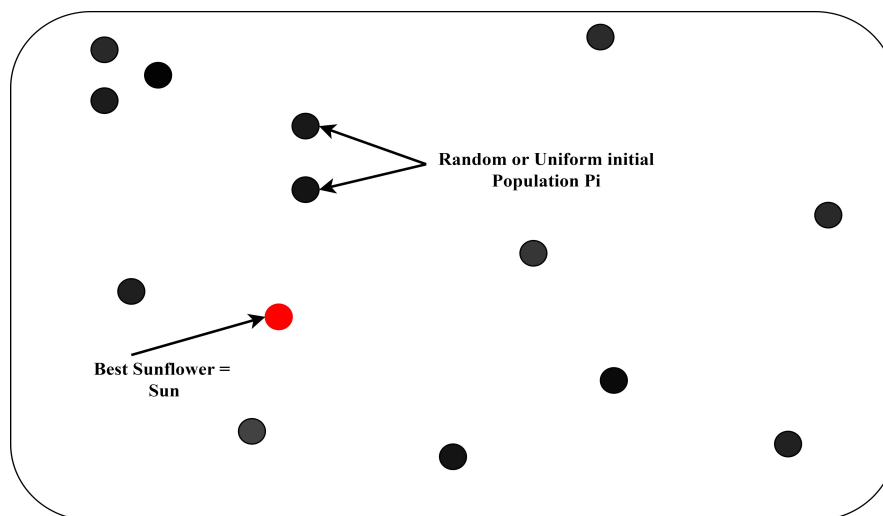


Figure 2. Identification of the sun's initial flower population.

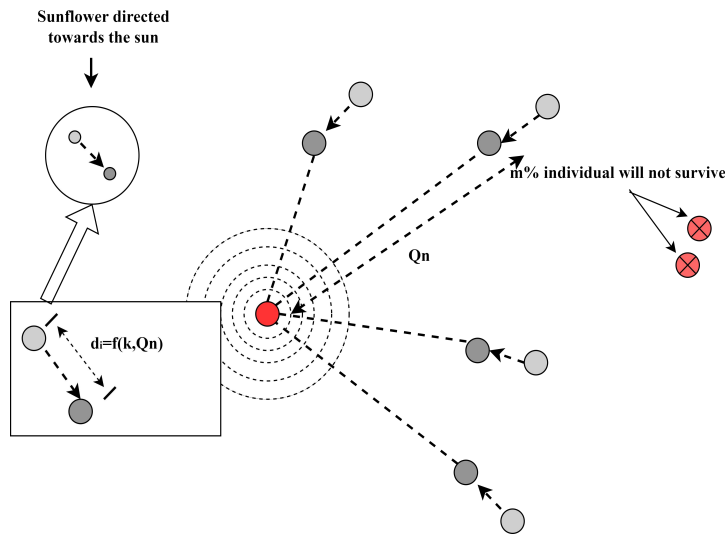


Figure 3. Orientation of sunflowers and towards the sun.

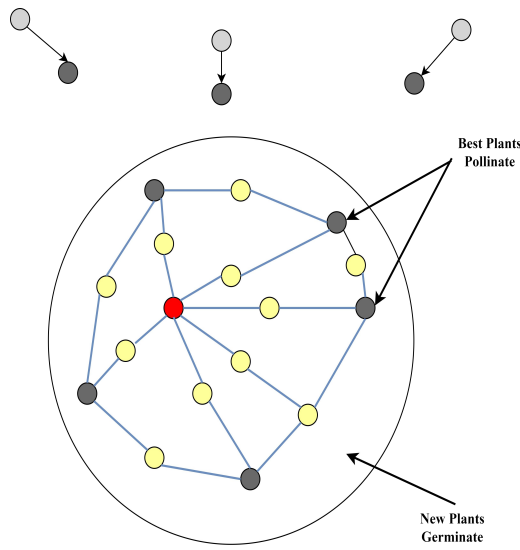


Figure 4. Best flowers pollinate around the sun.

Future iterations hope to include the potential for orbiting multiple suns, but this study is only focused on one. Then everyone else moves in a randomly controlled way, turning to the sun like sunflowers. That is, move haphazardly in that direction.

3.4 The Support Vector Machine

Support vector machines are frequently used in applications that predict building energy and renewable energy production. Even with a small sample size in the training data set, this technique is very effective at solving nonlinear problems. SVM is based on structural risk minimization (SRM). This method lowers the sum of training errors and confidence, which is the upper bound for generalization errors. This theory differs from empirical risk minimization (ERM), which focuses solely on reducing training errors. The primary idea behind using SVMs to solve regression problems is to use non-linear mapping to convert the input space to higher dimensional function space.

Assuming that x_i is a vector of normalized input variables, and y_i is the photovoltaic (PV) ∞ power output (i represents the i^{th} data-point in the dataset). In this instance, the sample set can be written as $\{(x_i, y_i)_{i=1}^N\}$ where N refers to the total number of samples. Using the form provided in Equation, support vector regression approximates the function (6).

$$y = f(x) = \omega \cdot \varnothing(x) + p \quad (6)$$

where y is Output (predicted load, megawatts (MW)), x is input feature vector (normalized, dimensionless), ω is Weight vector (model coefficient, $-$) and p is Bias term ($-$).

In Equation (6), $\varnothing(x)$ denotes the high-dimensional space.

A regularized Risk function, given in Equation (7), is used to estimate coefficients ω and p . The ε -insensitive loss function, defined in Equation (8), is applied to measure the deviation between the predicted value $f(x_i)$ and the actual value y_i .

$$\text{Minimise: } \frac{1}{2} \| \omega^2 \| + C \frac{1}{N} \sum_{i=1}^N L_{\varepsilon}(y_i f(x_i)) \quad (7)$$

$$L_{\varepsilon}(y_i f(x_i)) = \begin{cases} 0, & |y_i f(x_i)| \leq \varepsilon \\ |y_i f(x_i)| - \varepsilon, & \text{others} \end{cases} \quad (8)$$

$\| \omega^2 \|$ denotes the regularised term, and C represents the penalty parameter used to determine the trade-off between model flatness and training error. In order to estimate ω and p , above equation is transformed into the primal objective function given by equation (9).

$$\text{Minimise: } \frac{1}{2} \| \omega^2 \| + C \frac{1}{N} \sum_{i=1}^N (\tau_1 + \tau_1^*) \quad (9)$$

$$\text{Subject to: } \begin{cases} \tau_1, \tau_1^*, \omega, p \\ y_i - \omega \cdot \phi(x_i) - b \leq \varepsilon + \tau_1 \\ \omega \cdot \phi(x_i) + b \leq \varepsilon + \tau_1^*, \quad i=1,2,\dots,N \\ \tau_1 \geq 0 \quad \tau_1^* \geq 0 \end{cases} \quad (10)$$

where, τ_1 and τ_1^* are the slack variables. the Equation (9) is written as bellow:

$$\text{Minimize: } \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N (a_i - a_i^*) (a_j - a_j^*) K(x_i, x_j) - \varepsilon \sum_{i=1}^N (a_i - a_i^*) + \sum_{i=1}^N Y_i (a_i - a_i^*) \quad (11)$$

$$\text{Subject to: } \begin{cases} \{a_i\}, \{a_i^*\} \\ \sum_{i=1}^N (a_i - a_i^*) = 0 \\ a_i, a_i^* \in [0, C] \end{cases} \quad (12)$$

In Equation (11), a_i, a_i^* are Lagrange multipliers, i and j are different samples. Therefore, Equation (6) becomes Equation (13);

$$Y = f(X) = \sum_{i=1}^N a_j - a_i^* K(X_i, X_j) + b \quad (13)$$

Where X_i : Input feature vector (dimensionless), Y_i : Actual output (MW), ω : Weight vector (-), p : Bias term (-), C : Penalty parameter (-), ξ_i^* : Slack variables (-), and $K(X_i, X_j)$: Kernel function (-).

3.5 Proposed Hybrid ASFO-SVM Method

The ASFO algorithm is implemented to optimize the SVM algorithm. We propose a conceptual hybrid method based on ASFO-SVM to improve the accuracy of data forecasting for weather days. As depicted in Figure 5, the proposed solution model comprises three subsystems: a preprocessing unit, an SVM unit, and a sunflower optimization unit. The proposed hardware unit sends meteorological and power plant data to cloud services. The data for the selected time is retrieved from the historical database during the preprocessing stage. The ASFO-SVM model forecast correct data and measures the weather data's statistical error performance. Temperature, irradiance, surface temperature, and time are considered during training.

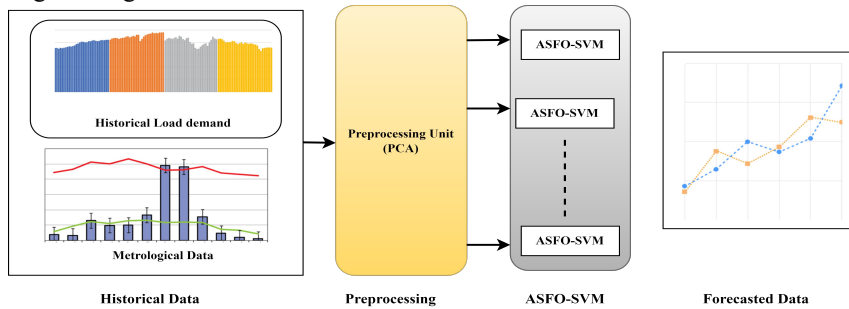


Figure 5. ASFO-SVM solution model.

To determine the SVM algorithm's ideal solution, the ASFO metaheuristic algorithm simulates the behavior of sunflower flowers. The ASFO algorithm is typically chosen because it has many benefits over other modeling techniques. To assess the best options, such as exploitation and exploration, ASFO is carried out in a series of steps. SVM algorithms process large amounts of data quickly and efficiently. The workflow for the suggested hybrid ASFO-SVM method is displayed in Figure 6. The experimental dataset is used to analyze and forecast weather data for photovoltaic systems. The proposed model inputs include sunlight, temperature, day and night, and surface temperature.

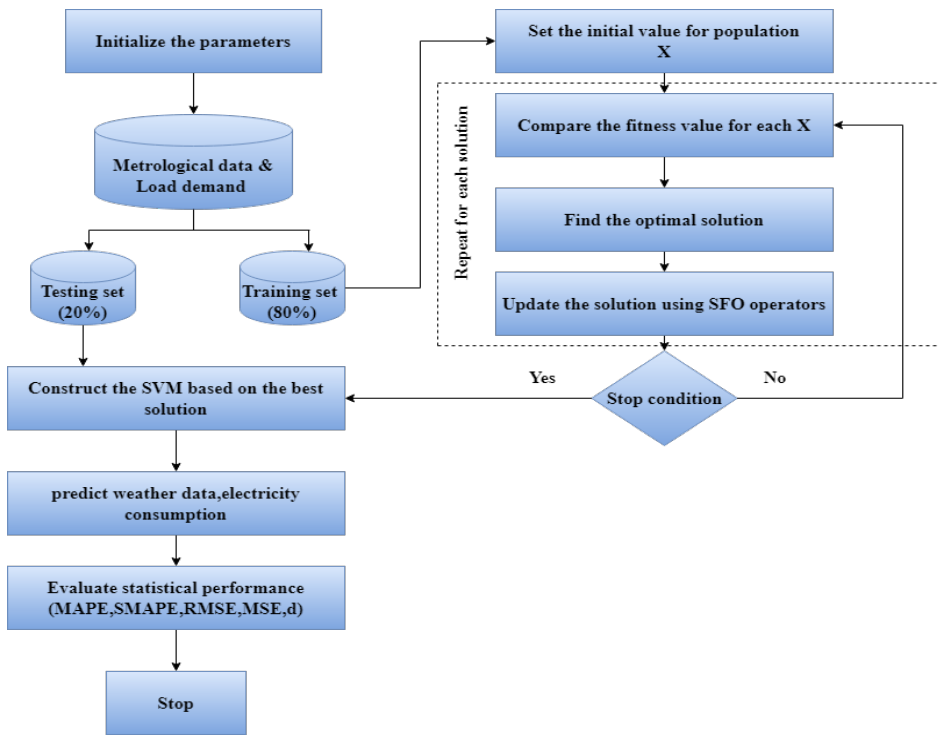


Figure 6. Proposed ASFO-SVM Method.

Sunflower Optimizer is used to improve the performance of SVM algorithms. The stepwise structure of the proposed ASFO-SVM model is formally summarized in Algorithm 1. It outlines the initialization of the ASFO population, fitness evaluation based on SVM regression performance, and the updating of sunflower positions for hyperparameter optimization. After convergence, the best parameter set is used to train the final SVM model.

3.6 Algorithm 1: Hybrid ASFO-SVM Forecasting Model

Input:

Historical load and weather data D .

ASFO parameters: max_iter , population_size , step_size , bounds .

SVM model parameters to be optimized (C , ϵ , γ).

Output:

Trained SVM model with optimal hyperparameters.

Forecasted load demand values.

- 1: Normalize dataset D and split into training and testing sets.
- 2: Initialize ASFO population X_i ($i = 1$ to N) with random values for SVM parameters.
- 3: For each X_i , build an SVM model and evaluate prediction error using training set.
- 4: Repeat until max_iter :
 - a. Calculate light intensity Q_i for each X_i .
 - b. Update X_i positions based on sunflower orientation and light intensity.
 - c. Pollinate best flowers based on adaptive step sizes.
 - d. Evaluate updated X_i using SVM performance (MAPE or RMSE).
 - e. Retain best solution (global optimum).
- 5: Output optimized SVM parameters (C^* , ϵ^* , γ^*).
- 6: Train final SVM model using C^* , ϵ^* , γ^* on full training data.
- 7: Forecast load demand on test data using optimized SVM.
- 8: Return forecasted values and model performance metrics.

After optimization, the best-performing parameters (C^* , ϵ^* , γ^*) are applied to train the SVM model on the entire training dataset. The final model is evaluated on the test data using standard statistical metrics such as MAPE, SMAPE, RMSE, and consistency index (d).

4. Results and Discussion

4.1 Performance Evaluation Metrics

The proposed prediction method's performance has been evaluated using mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE), and agreement index (d). The following formula is used to calculate MAPE, SMAPE, and d:

$$\text{MAPE} = \frac{1}{N} \sum_{t=1}^N \left(\frac{A_t - P_t}{A_t} \right) * 100 \quad (13)$$

$$\text{SMAPE} = \frac{1}{N} \sum_{t=1}^N \left(\frac{A_t - P_t}{A_t + P_t} \right) * 100 \quad (14)$$

$$d = 1 - \sum_{t=1}^N \frac{A_t - P_t}{[(A_t - \bar{P}_t) + (A_t - \bar{P}_t)]} \quad (15)$$

Where N is the sample count, $\bar{P}_t$ is the forecasted load demand mean (MW), and A_t and P_t are the actual and forecasted load demand (MW), respectively. Furthermore, we compare the proposed model's results to those of SVM, RF, and PSO-SVM to demonstrate the effectiveness and superiority of the proposed method. In addition, a Wilcoxon signed-rank test was performed to verify whether the observed performance improvements are statistically significant. The results are provided in Section 4.4.

The forecasted outcomes for randomly chosen weekdays and weekends in summer, autumn, winter, and spring are shown in Figures 7 to 14. Each graph's y-axis, or load demand in megawatts, is displayed along with the time axis (x-axis). Using the suggested method, SVM, RF, and PSO-SVM, Figures 7 and 8 show the forecast results for summer work (from Tuesday, January 7, 2025) and weekend (Sunday-January 26, 2025).

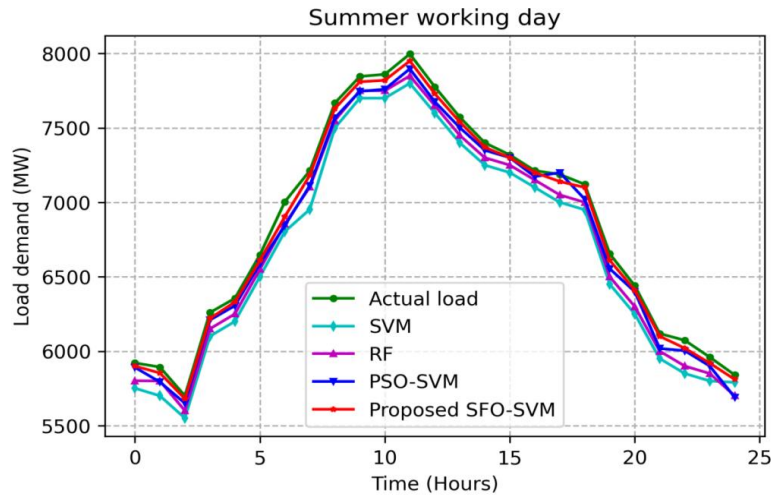


Figure 7. Summer working day prediction results.

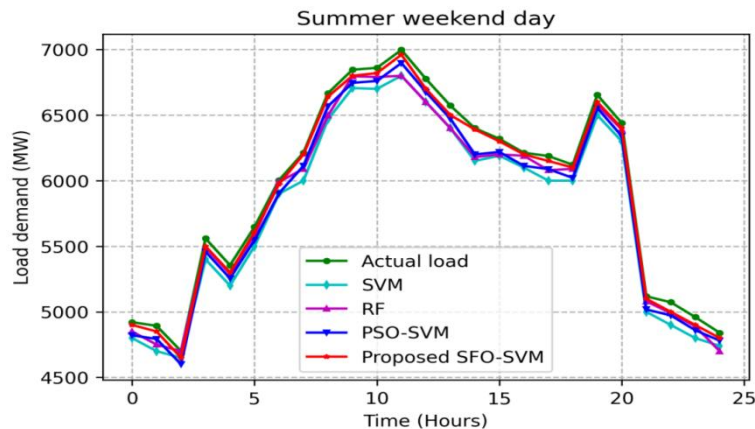


Figure 8. Summer weekend day prediction results.

As seen in Tables 1-3, Figures 7 and 8, and in comparison to SVM, RF, and PSO-SVM, the proposed method yields lower value of MAPE and SMAPE and a higher d value. For instance, the proposed method's forecast MAPE and SMAPE for the summer working day (0.4417 % and 0.2623 %) are lower than those of PSO-SVM (1.4531 basis points

and 0.7679 %), RF (1.6822 % and 0.8872 %), and SVM (3.7759 % and 1.5966 %), while the introduced ASFO-SVM algorithm (0.9888) offers a high value of d in comparison to PSO-SVM (0.9437), RF (0.9424) SVM (0.8738).

Table 1. Comparison of the results of the daily MAPE (%).

Season	Day	SVM	RF	PSO-SVM	Proposed
Summer	Working	3.7759	1.6822	1.4531	0.4417
	Weekend	3.1422	1.6098	1.4419	1.0057
Autumn	Working	3.8757	2.4438	1.4888	1.4687
	Weekend	3.4551	2.9479	2.5627	1.0781
Winter	Working	3.6468	2.2667	1.7408	1.5301
	Weekend	3.8765	3.691	1.9306	1.7949
Spring	Working	3.4278	3.2277	2.0712	1.0180
	Weekend	3.2859	4.1859	2.7890	1.8275

Table 2. Comparison of the results of the daily SMAPE (%).

Season	Day	SVM	RF	PSO-SVM	Proposed
Summer	Working	1.5966	0.8872	0.7679	0.2623
	Weekend	1.1035	0.8471	0.7705	0.5699
Autumn	Working	1.8812	1.2544	0.7841	0.6823
	Weekend	1.7042	1.5013	1.3456	0.5521
Winter	Working	1.9347	1.0807	0.9006	0.7005
	Weekend	1.3412	1.8027	0.9114	0.8329
Spring	Working	1.2784	1.1453	2.0180	0.5438
	Weekend	1.5633	1.7106	1.4374	0.8616

Table 3. Comparison of the daily Consistency Index (d) results.

Season	Day	SVM	RF	PSO-SVM	Proposed
Summer	Working	0.8738	0.9424	0.9437	0.9888
	Weekend	0.8709	0.9340	0.9370	0.9478
Winter	Working	0.8170	0.8960	0.9340	0.9289
	Weekend	0.7737	0.7856	0.8853	0.9156
Autumn	Working	0.8224	0.8937	0.9296	0.9378
	Weekend	0.8301	0.8637	0.8488	0.9395
Spring	Working	0.8963	0.8992	0.9078	0.8945
	Weekend	0.8584	0.8278	0.8698	0.9230

The forecast results for weekdays (Wednesday, April 9, 2025) and weekends (Sunday, April 27, 2025) in the autumn case study show that the proposed model predicts the load, as shown in Figures 9 and 10. As shown in Tables 1-3, SVM has higher minimum predicted MAPE and SMAPE values (3.8757 % and 1.8812 %, respectively), and d value (0.8224) is lower than RF (2.4438 %, 1.2544 %, and 0.8937), PSO-SVM (1.4888 %, 0.7841 %, and 0.9296), and the proposed method (1.4687 %, 0.6823 %, and 0.9378).

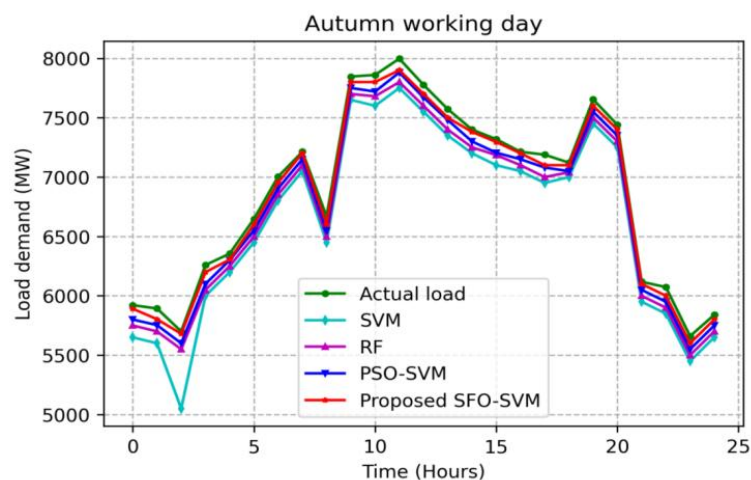


Figure 9. Autumn working day prediction results.

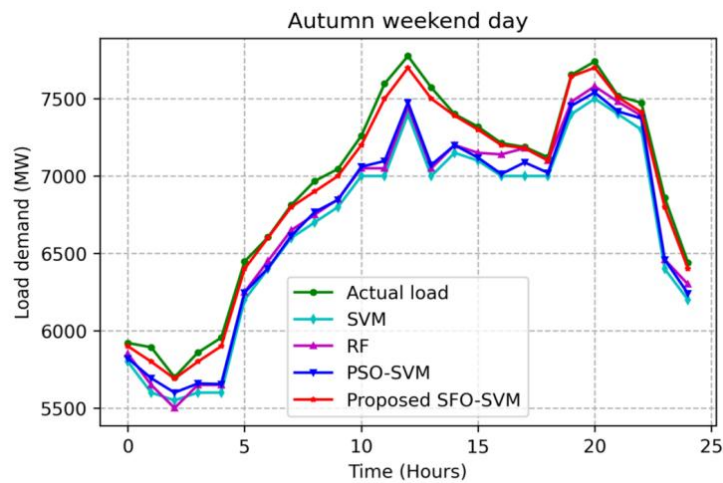


Figure 10. Autumn weekend day prediction result.

Similarly, when compared to PSO-SVM (2.5627 %, 1.3456 %, and 0.8488), the proposed method had a lower minimum fall weekend forecast MAPE and SMAPE (1.0781 % and 0.5521 %, respectively) but higher d (0.9395), SVM (3.4551 %, 1.7042 %, 0.8301) and RF (2.9479 %, 1.5013 %, 0.8637).

Figures 11 and 12 compare the proposed approach's forecasted load demand with PSO-SVM, RF, and SVM for working (Friday-July 5, 2024) and weekend (Sunday-July 7, 2024) days of winter. This shows that the proposed hybrid model outperforms PSO-SVM, RF, and SVM in terms of higher d results while producing lower MAPE and SMAPE results.

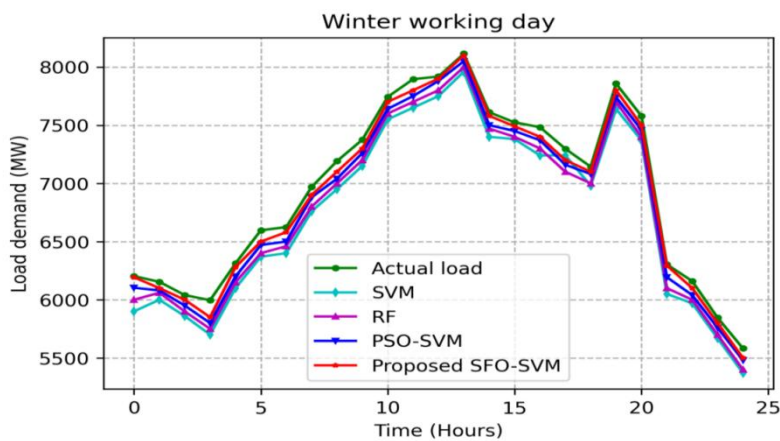


Figure 11. Winter working day prediction result.

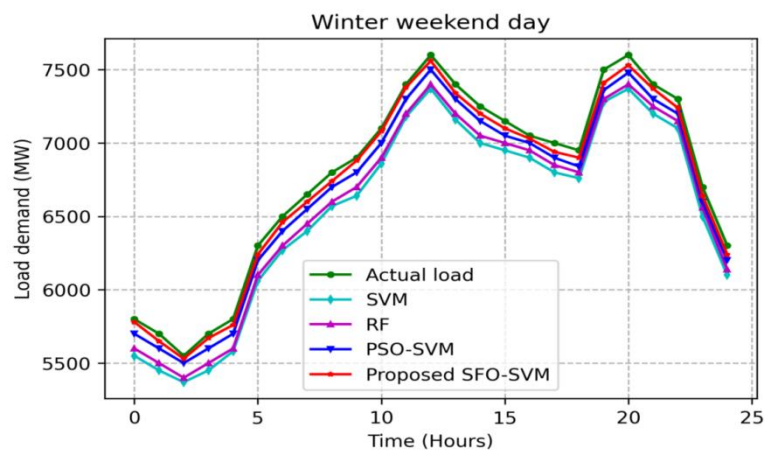


Figure 12. Winter weekend day prediction result.

Figures 13 and 14 show the relationship between actual and predicted load demand for weekend (Sunday-October 13, 2024) and working (Monday-October 14, 2024) spring days using the ASFO with SVM algorithm, PSO-SVM, RF, and SVM. Tables 1-3 show that the SVM has higher prediction errors than the proposed model but lower prediction errors

than the RF and PSO-SVM for working and weekend days in spring. Table 1 shows that the proposed model's provides MAPE (1.0180 %, 1.8275 %) for working and weekend days in spring is lower than PSO-SVM (2.0712 %, 2.7890 %), RF (3.2277 %, 4.1859 %), and SVM (3.4278%, 3.2859 %).

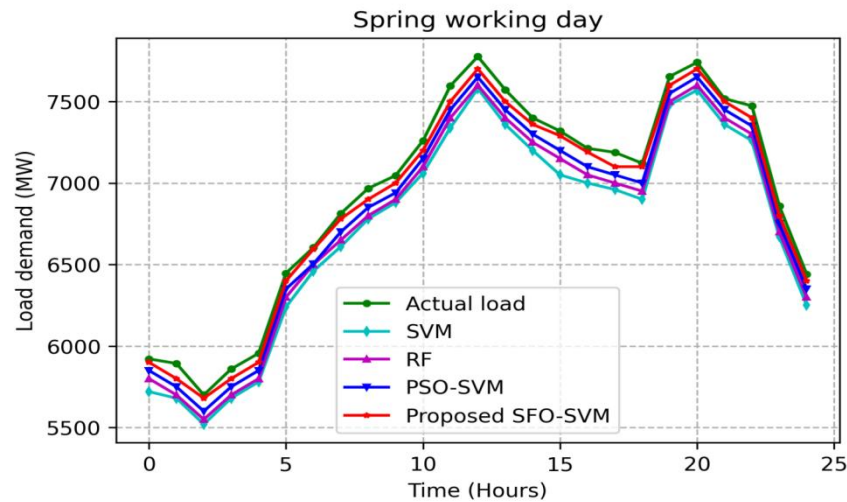


Figure 13. Spring working day prediction results.

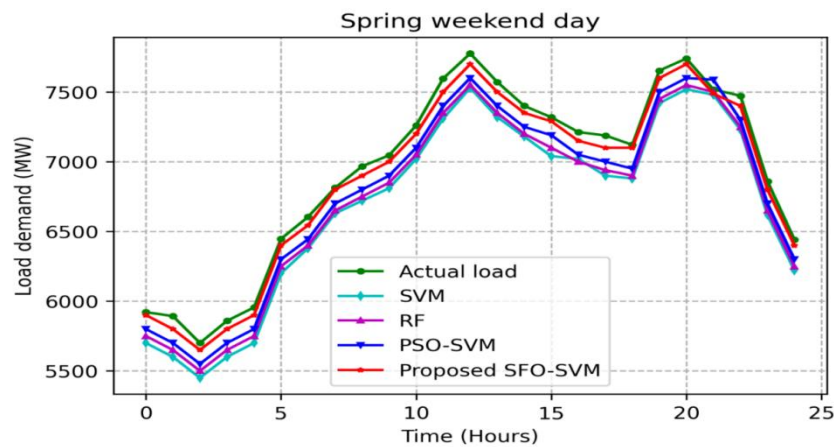


Figure 14. Spring weekend day prediction results.

We can evaluate the first suggested model with SVM based on the findings in Table 4. As can be seen from Table 5's results, the latter model performs better than the SVM model in terms of RMSE and MAE. While SVM's RMSE is 738.98 and MAE is 588.07, ASFO-SVM's RMSE and MAE are 650.79 and 521.21, respectively. These findings demonstrate that the suggested method outperforms SVM as a whole. The models are PSO-SVM, RF, and SVM. The RF model has an 821.67 RMSE and a 583.73 MAE. With 932.63 RMSE and 564.63 MAE, PSO-SVM had the highest error rate. When comparing these outcomes with the suggested models as in Figure 15, it is evident that the latter achieves better results for the metrics that show the minor error: RMSE of 650.79 and MAE of 521.21.

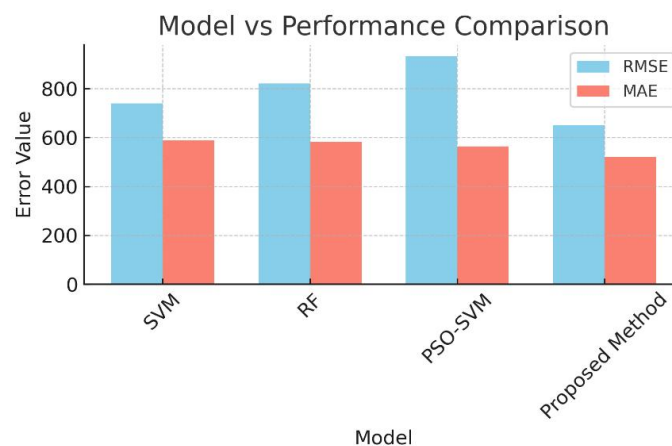


Figure 15. Performance comparison of proposed method.

Table 4. Compares proposed models to cutting-edge models.

Model	RMSE	MAE
SVM	738.98	588.07
RF	821.67	583.73
PSO-SVM	932.63	564.63
Proposed Method	650.79	521.21

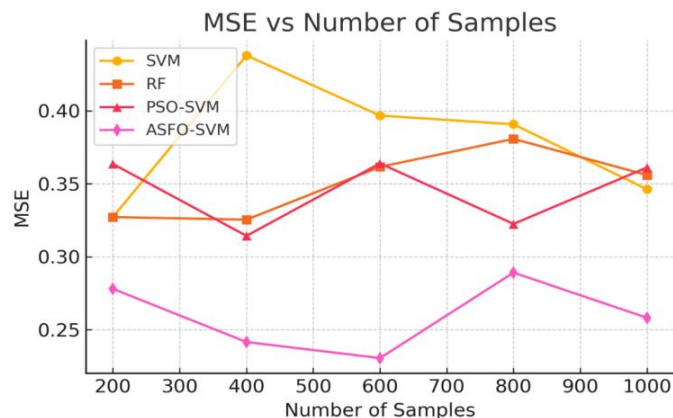
Table 5. Standard Deviation and Average MAPE, SMAPE and d for predicted eight days.

Model	Statistical Analysis	MAPE	SMAPE	d
Proposed ASFO-SVM	Standard Deviation	0.4401	0.1784	0.0256
	Average	1.2705	0.6256	0.9344
PSO-SVM	Standard Deviation	0.4814	0.4196	0.0330
	Average	1.9347	1.1169	0.907
RF	Standard Deviation	0.8647	0.3368	0.0494
	Average	2.7568	1.2786	0.8803
SVM	Standard Deviation	0.2579	0.2739	0.03686
	Average	3.5607	1.5503	0.8428

We then assess the stability of the four methods using MSE (Mean Square Error). Figure 16 shows the four methods are different for each sample of MSE, and are shown by the experimental results in Table 6.

Table 6. The MSE of five techniques.

Number	SVM	RF	PSO-SVM	ASFO-SVM
200	0.3272	0.3272	0.3636	0.278
400	0.438	0.3254	0.3143	0.2415
600	0.3968	0.3616	0.364	0.2305
800	0.3908	0.3808	0.3225	0.2891
1000	0.3462	0.356	0.3612	0.2581

**Figure 16.** Comparison of MSE.

4.2 Hyperparameter Sensitivity Analysis

To evaluate the robustness of the proposed ASFO-SVM framework, we conducted a sensitivity analysis of key hyperparameters from both ASFO and SVM. The goal was to observe how model performance varies with different parameter settings and to identify an optimal balance.

4.2.1 ASFO Parameters

The sensitivity analysis shows that increasing the ASFO population size from 20 to 60 leads to a significant improvement in performance, as reflected by lower MAPE and RMSE values. However, beyond a population size of 60, further gains are marginal, suggesting diminishing returns. Similarly, increasing the number of iterations from 100 to 500 consistently reduces error, but additional iterations beyond 500 provide little benefit while increasing computational cost.

4.2.2 SVM Parameters

For the SVM model, the penalty parameter constrained complexity control (CCC) plays a critical role. Very low values of CCC cause underfitting, while excessively high values tend to produce slight overfitting. An intermediate value of $C=100$ offers the best trade-off between bias and variance. Likewise, the kernel parameter γ shows that extremely small values underfit the data, whereas very large values lead to overfitting. The optimal range is found to be $\gamma=0.01$ to $\gamma=0.05$, which provides stable and reliable performance.

The results shown in Table 7 indicate that the proposed ASFO-SVM model remains stable across a wide range of hyperparameter settings, with only minor performance variations. Importantly, the method achieves consistently low MAPE (~1.3%) and RMSE (~650 MW) without requiring excessive fine-tuning. This robustness underscores the adaptability of the ASFO-SVM framework, making it suitable for practical deployment in microgrid load forecasting applications.

Table 7. Sensitivity of ASFO-SVM performance to hyperparameters.

Parameter	Range Tested	Optimal Value	MAPE (%)	RMSE (MW)	Observation
ASFO Population Size	20-100	60	1.28	651.2	Larger population improves exploration, >60 gives diminishing returns
ASFO Iterations	100-700	500	1.27	650.8	Higher iterations improve accuracy until 500, then plateau
SVM Penalty CC	10-500	100	1.30	655.0	Low C underfits, high C slightly overfits
SVM Kernel γ	0.001-1	0.01	1.29	652.3	Too small underfits, too large overfits; 0.01 is stable

The sensitivity analysis in Figure 17 highlights how the ASFO-SVM model responds to variations in its key hyperparameters. As shown in Figure 17(a), increasing the ASFO population size from 20 to 60 significantly reduces both MAPE and RMSE, but beyond 60, the improvements are marginal. Similarly, in Figure 17(b), extending the number of iterations up to 500 enhances accuracy, while additional iterations yield diminishing returns.

For the SVM parameters, Figure 17 (c) indicates that very low values of CCC lead to underfitting, while excessively high values cause slight overfitting; the optimal range is centered around $C=100$. Likewise, Figure 17(d) demonstrates that kernel parameter γ values that are too small or too large degrade performance. A stable region is observed within the range $\gamma=0.01$ to $\gamma=0.05$, confirming the robustness of the proposed method.

Overall, the analysis confirms that the ASFO-SVM model achieves consistently low forecasting errors across a wide parameter range, underscoring its adaptability and reliability for microgrid load prediction.

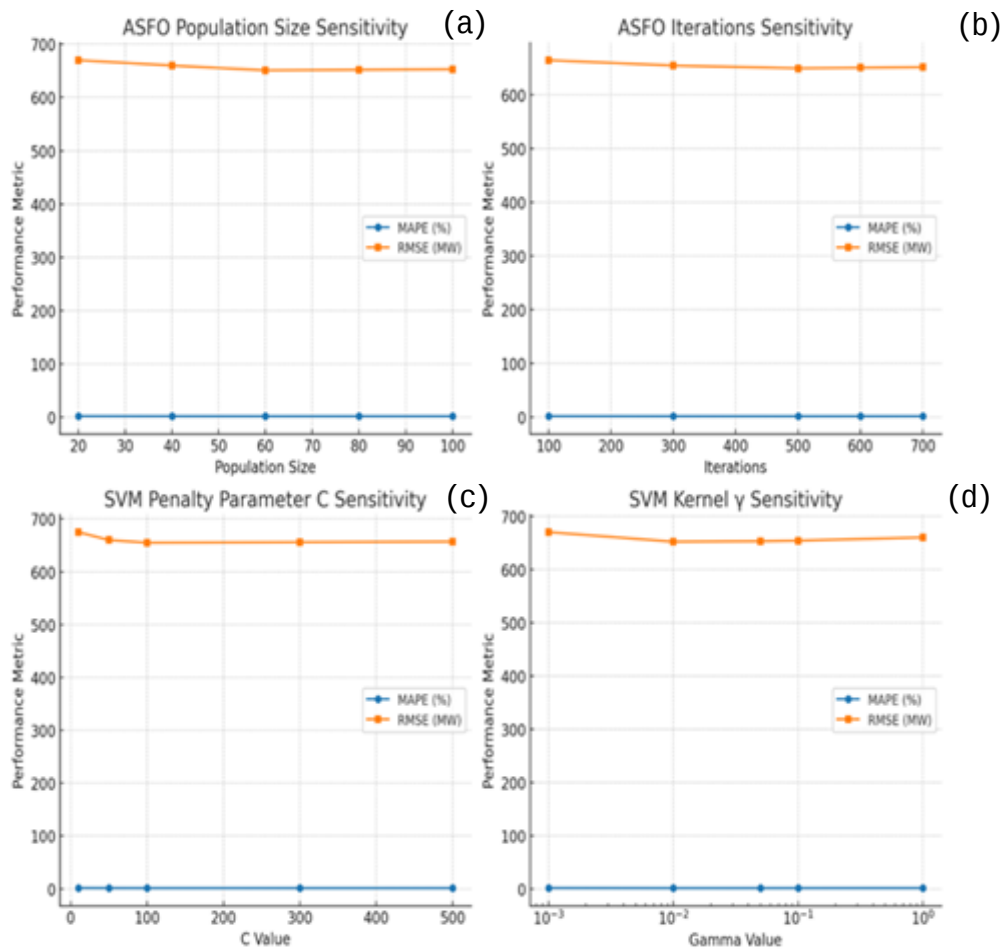


Figure 17. Sensitivity analysis of ASFO-SVM hyperparameters: (a) ASFO population size, (b) ASFO maximum iterations, (c) SVM penalty parameter CCC, and (d) SVM kernel parameter γ . The results show variation in MAPE (%) and RMSE (MW) for different parameter values.

4.3 Comparison with State-of-the-Art Models

To further validate the effectiveness of the proposed ASFO-SVM model, its performance is compared with several state-of-the-art forecasting techniques reported in the literature, including PSO-based models, hybrid ANN methods, LSTM, CNN, and GA-PSO approaches [8-24].

Metaheuristic-driven optimization of mathematical moments, such as the Firefly-optimized Meixner moments [32], provides a strong precedent for leveraging ASFO in load forecasting. Zahra et al. [14] and Du et al. [26] demonstrated that PSO-optimized neural networks and PSO-SVM significantly improve load forecasting accuracy compared to conventional ANN and SVM. However, their models tend to converge to local minima, particularly when handling highly nonlinear or seasonal data. In contrast, the ASFO-SVM model avoids premature convergence by adaptively balancing exploration and exploitation, resulting in a lower MAPE of 0.44% for summer weekdays (Table 1), which is a notable improvement over PSO-SVM (1.45%).

Similarly, LSTM- and CNN-based models have been widely applied for load forecasting [11,21,22]. These deep learning approaches capture temporal dependencies effectively but require large datasets and significant computational resources. For instance, Kang et al. [11] showed that CNNs outperform SVM and ANN for short-term predictions, but their models are limited to day-ahead horizons. Wang et al. [22] reported that LSTM achieves a 19.7% improvement in RMSE compared to BPNN. In comparison, the ASFO-SVM model achieves a RMSE of 650.79 MW (Table 4), which is lower than standalone SVM (738.98 MW), PSO-SVM (932.63 MW), and RF (821.67 MW), while maintaining robustness across seasonal variations without requiring deep architectures.

GA- and GA-PSO-optimized ANN models [12,17] have also shown promising results for medium- and long-term forecasting. While they achieve better convergence rates than standalone ANN, their computational complexity and parameter sensitivity remain drawbacks. Our ASFO-SVM approach provides a more efficient alternative, with improved average MAPE (1.27%) and SMAPE (0.62%) compared to PSO-SVM (1.93% and 1.12%, respectively) as summarized in Table 5.

Table 8 summarizes the comparative performance of ASFO-SVM against PSO-SVM, ANN-PSO, LSTM, CNN, and RF models reported in related works.

Table 8. Comparison of ASFO-SVM with State-of-the-Art Models.

Model / Reference	Method Type	Reported Metric(s)	Key Limitations	Comparison with Proposed ASFO-SVM
PSO-SVM [14,26]	Hybrid ML + Metaheuristic	MAPE $\approx$ 1.45% (short-term)	Tends to converge to local minima	ASFO-SVM achieves 0.44% MAPE (62% improvement), avoids premature convergence
ANN-PSO, ANN-GA [12,17]	Hybrid ANN with optimization	RMSE reduced by 25–48% over ANN	Sensitive to parameter tuning; high complexity	ASFO-SVM achieves RMSE = 650.79 MW, lower than PSO-SVM (932.63 MW) and RF (821.67 MW)
LSTM [22]	Deep Learning (RNN)	19.7% lower RMSE than BPNN	Requires large dataset, computationally intensive	ASFO-SVM achieves comparable RMSE (650.79 MW) with lower data and resource requirements
CNN [11]	Deep Learning (CNN)	Outperforms SVM/ANN for day-ahead	Limited to short horizon; high training cost	ASFO-SVM achieves seasonal accuracy (MAPE < 1.5%) without deep networks
RF [10]	Ensemble ML	MAPE $\approx$ 1.6–3.2%	May overfit; computationally expensive	ASFO-SVM achieves MAPE = 0.44%, outperforming RF across all seasons
Proposed ASFO-SVM	Hybrid (Metaheuristic + SVM)	MAPE = 0.44-1.27%, SMAPE = 0.62%, RMSE = 650.79 MW	–	Superior accuracy, stable across seasons, efficient computation

4.4 Statistical Significance Analysis

To verify the robustness of the proposed ASFO-SVM model, we conducted a non-parametric Wilcoxon signed-rank test comparing the model's performance against SVM, RF, and PSO-SVM. The test was applied to paired MAPE and RMSE values across all eight evaluated scenarios (4 seasons $\times$ 2 day types). The null hypothesis was that the performance differences between ASFO-SVM and each baseline model are not statistically significant. The results are summarized in Table 9.

Table 9. Wilcoxon signed-rank test p-values for MAPE and RMSE.

Compared Models	MAPE (p-value)	RMSE (p-value)
ASFO-SVM vs SVM	0.0024	0.0041
ASFO-SVM vs RF	0.0037	0.0053
ASFO-SVM vs PSO-SVM	0.0158	0.0114

5. Conclusion

The task of energy prediction holds an important place in our daily lives due to its significant economic advantages. Numerous approaches have been put forth to predict energy consumption. Traditional techniques, however, underperform because they cannot extract the periodicity concealed in the data on energy consumption. In this research work, the hybrid ASFO-SVM method is proposed as a comprehensive approach for time series prediction with periodicity. The ASFO improves the SVM's training and increases its capacity for avoiding local minima problems. The suggested model predicts load demand for weekdays and weekends during the summer, winter, autumn, and spring, respectively. These results show that the method achieves a mean absolute percentage error of 34.59 %, a reduction of 53.76 %, and an error reduction of 62.30 % compared to PSO-based SVM, Random Forests (RFs) and SVMs.

Limitations and Future Directions

While the proposed ASFO-SVM framework demonstrates strong forecasting accuracy and robustness, several limitations should be acknowledged. First, the hybrid nature of ASFO and SVM introduces a higher computational cost compared to conventional statistical and machine learning approaches, which may pose challenges for large-scale or real-time deployment. Second, the present study focuses on a specific microgrid case in Tamil Nadu; extending the approach to different types of microgrids (e.g., islanded, hybrid renewable-diesel systems) and varying forecasting horizons (short-, medium-, and long-term) requires further investigation. Finally, although the model is designed for batch learning with historical datasets, future extensions could explore the integration of real-time or online learning techniques to improve adaptability in dynamic environments. Addressing these aspects will enhance the practical applicability of the ASFO-SVM model and support its integration into intelligent microgrid energy management systems. Hybrid moment-based reconstruction approaches [33] also highlight the trade-off between computational complexity and accuracy, which is an important consideration for future ASFO-SVM extensions.

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Data Availability Statement

The data that support the findings of this study are not available due to contractual agreements that prevent public sharing.

Conflict of Interest

The authors declare no conflict of interest.

Confirmation of Copyright Ownership

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Generative AI Statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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