# Enhancing Short-Term Load Forecasting in the Electric Power Industry: A Hybrid Approach Integrating Machine Learning and Advanced Optimization Techniques

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*This work introduces a hybrid methodology that combines machine learning with sophisticated optimization approaches to improve short-term load forecasting in the electric power sector. The model uses Support Vector Regression and Radial Basis Function together and then improves it with Aquila Optimizer, Particle Swarm Optimization, and Harris Hawks Optimization. The method was evaluated on a dataset that includes daily electricity usage data and important weather variables like temperature and humidity. We used important measures, including the Root Mean Squared Error, Mean Absolute Error, and the Coefficient of Determination, to see how well the model worked. The results show that the hybrid Radial Basis Function-Harris Hawks Optimization model works better than the standalone Support Vector Regression model. It has a 20% lower Root Mean Squared Error and a 15% higher accuracy. These gains show that the hybrid model makes more accurate predictions, especially for real-time operational planning. The hybrid optimization techniques help make load forecasting models much more accurate and efficient. They could be very useful for managing energy systems. This study underscores the significance of amalgamating machine learning with optimization algorithms to augment forecasting abilities and furnish critical insights for power system operators and academics seeking to increase grid stability and planning.*

*Povzetek: Predstavljena je hibridna metoda, ki združuje strojno učenje in optimizacijo za natančnejše kratkoročno napovedovanje porabe električne energije.*

## 1 Introduction

Forecasting electricity consumption is essential for the effective operation and planning of power systems, aiding utilities in demand management, resource allocation optimization, and grid stability assurance. Precise forecasting is crucial in short-term load forecasting because power consumption may vary due to factors such as time of day, meteorological conditions, and economic activities. Conventional forecasting techniques, such as statistical and time-series methods, are extensively utilized; yet, they frequently fail to accurately represent the intricate, nonlinear relationships present in energy consumption data. This paper seeks to tackle these challenges by proposing a hybrid model that integrates machine learning techniques, Support Vector Regression (SVR), and Radial Basis Function (RBF) networks with sophisticated optimization algorithms, including Aquila Optimizer (AO), Particle Swarm Optimization (PSO), and Harris Hawks Optimization (HGS). The primary aim of this work is to enhance the precision of short-term load forecasting by adjusting the parameters of machine learning models through various optimization strategies. The objective of this study is to assess the efficacy of the hybrid model in predicting electricity demand using a dataset comprising historical consumption data and pertinent meteorological variables.

The continuous operation of the electrical power system requires prompt coordination spanning from power plants to distribution substations, ensuring secure and dependable functioning to deliver uninterrupted high-quality electricity services. Thorough pre-real-time operational planning is imperative, taking into account the dynamics of renewable energy sources, maintenance schedules for power plants, and the allocation of hydrothermal resources to align electricity generation with anticipated demand. Maintaining this real-time equilibrium between energy generation and load is crucial to prevent grid damage [1].

The planning phase of power system operation can be categorized into three distinct time frames, each with its own set of objectives: mid-term, short-term, as well as long-term. The short-term duration, ranging from 1 day to 1 week, primarily addresses operational and security concerns within the power system. The mid-term period, ranging from several weeks to many months, looks after resource management in mitigating energy shortages from existing generating plants. From the long-term perspective spanning from several years up to decades, one plans for new facilities in electricity generation or adjustments in the transmission system. Although the details of the criteria may vary from region to region, the basic principles hold for any situation [2].

The range of application for it scales from individual needs to a whole array of requirements in the case of the short-term forecasting of electricity loads. Starting from the scale of an individual transformer, buildings [3], and cities [4] right up to large regions [5] is where the scale of load prediction could vary. There is another key dimension to the variation in this research horizon. It extends from very short-term predictions, such as anticipating load fluctuations for machine tools in the next few seconds [6], to predictions stretching over a few hours [7].

The most prevalent forecast is for the following day's load [8], although some studies also concentrate on predicting the load 48 hours ahead [9] or providing weekly forecasts [10].

A broad spectrum of methodologies and algorithms has been developed and employed to tackle STLF. Time-series analysis is a popular forecasting methodology that is widely used in various domains. STLF has become increasingly important for ensuring the efficient and reliable operation of power systems. Recent studies have explored various advanced machine learning techniques to enhance the accuracy of load predictions. Lotfi et al. [11] proposed an optimized machine learning approach that integrates environmental and historical factors into short-term electricity demand forecasting. Their approach, which utilized an optimized Random Forest model, significantly outperformed traditional methods like SARIMA and Exponential Smoothing, showing how modern optimization techniques can boost forecasting accuracy. Wen et al. [12] introduced a deep learning-driven hybrid model for short-term load forecasting in smart grids. They combined Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), and attention mechanisms to create a more accurate model. Their results demonstrated the superiority of hybrid models in handling complex time-series data, particularly in smart grid environments where demand can vary significantly. Lukong et al. [13] proposed a novel spatial long-term load forecasting model using a multiple cluster-based Long Short-Term Memory (LSTM) network. This model segments the grid into clusters based on regional characteristics and employs LSTM networks to capture unique spatiotemporal dependencies in electricity consumption. Their approach highlighted the potential of spatial forecasting methods in improving the accuracy of load predictions across large areas with varying consumption patterns. Akhtar et al. [14] highlighted the significance of STLF for power systems. Time series models are efficient but struggle with nonlinearity, while ANNs offer better accuracy at higher computational costs. Regression models are simpler but less accurate, and hybrid models improve accuracy with higher computational demands. Advances in deep learning, especially recurrent and attention-based models, could enhance accuracy while reducing computational costs. In recent research, traditional models like ARMA are less prevalent in STLF, as ML methods offer superior performance. Musaylh et al. [15] investigated short-term electricity demand forecasting in Queensland, Australia, utilizing Multivariate Adaptive Regression Spline (MARS), SVR, and ARIMA (Autoregressive Integrated Moving Average) models. MARS outperformed SVR and ARIMA for 0.5 h and 1.0 h forecasting horizons, while for a daily, that is, 24 h, forecasting, SVR outperformed. From this point of view, some valuable lessons are drawn about real-time demand forecasting. Amin et al. [16] analyzed the problem of short-term load forecasting, focusing on accuracy and speed. They applied ARIMA and SVM models and compared them by MAPE and MSE metrics. They concluded that in the case of nonlinear patterns, SVMs perform better, while ARIMA would work better for a linear approximation of the load. Unlike typical statistical methods in the time-series analysis of data, ML can assimilate other critical parameters, such as weather, thereby increasing the accuracy in STLF. The reasons that make MLR widely adopted in most processes of STLF are versatility and applicability in most scenarios. Adeoye et al. [17] built an hourly model for electricity demand for 14 West African countries based on several factors that included: electrification rates, household appliances, and prevailing weather conditions. The model projects the demand for electricity in 2016 and 2030, thus showing seasonal variation and a significant increase in demand by 2030. This methodology presents insights relevant to capacity planners concerned with the attainment of 100% electrification rates within the region by 2030.

Apart from all the preceding methods, the artificial neural network is another widely used methodology in STLF in the last few decades due to its flexibility in algorithms. Case studies in Victoria and New South Wales have demonstrated the accuracy and potential of this model in guiding sustainable city development [3]. Viegas et al. [18] proposed a methodology for STLF that combines artificial neural network modeling with feature choice using a genetic algorithm. It is based on the historical data of consumption, weather, and stock index for the prediction of the 24-hour ahead load. Testing with datasets from different geographical regions yields models whose mean average percentage inaccuracy is less than 2%. The feature selection algorithm drastically reduces the number of features involved while improving model accuracy. The SVR model has been widely applied in STLF, especially with a linear kernel, because there is a linear relationship has been found between the inputs and the forecast. Wang et al. [19] proposed an integrated model of EMD-PSO-SVR for short-term load forecasting, incorporating EMD and SVR with PSO, considering temperature, weekend, and holiday factors. EMD decomposes the load data into its main IMF components, the SVR forecasts these components, while the PSO optimizes the parameters for the SVR. These steps provide better stability and accuracy for the predictions compared to conventional models. Ferreira et al. [9] updated radial basis function neural network models for multi-step electricity consumption prediction in Portugal up to 48 hours. They used least-squares support vector machines for model resetting and enhancing performance. Their method gave better model identification and a strategy for updating compared to the other existing neural models. They had also used a method of initializing hyperparameters that improved the performance without multiple random trials or grid search procedures. Omidi et al. [20] proposed a new-SVR for STLF in 2015, which is of utmost importance for the optimal operation of the power system. They compared its performance with ANN, underlining the nu-SVR suitability for STLF because of its capability of modeling nonlinear factors in electric grids. All the works had their original approach with the purpose of improving the accuracy of electricity demand forecasts in the environment to which they were addressed.

They investigated hybrid approaches and integrated metaheuristic techniques to obtain more refined energy models with the help of methodologies based on artificial intelligence. That will definitely help raise the bar for performance in these models. They mixed and matched various methods in their work to enhance general performance in energy models. They employed metaheuristic algorithms to tune the parameters of these models for improved results. This amalgamation of hybrid and AI-based methodology holds great promise for energy modeling techniques. An arithmetic optimization algorithm and its improved version have been proposed for energy demand forecasting in Turkey by Aslan et al. [21]. The researchers forecasted the energy demand using a linear regression model with demographic and economic data until the year 2030, according to three scenarios and reported competitive results compared to the existing methods. Zhang et al. [22] have proposed a hybrid model for short-term electricity load forecasting, IEMD, ARIMA, and WNN optimized by FOA. The comparative analysis showed its better performance compared to other models. Haq et al. [23] once proposed a new hybrid STLF model incorporating IEMD, T-Copula correlation analysis, and deep belief networks. The model was tested on real-time data from Australia and the USA and showed improved forecasting accuracy both in RMSE and MAPE compared to traditional methods. Xiao et al. [24] presented a modified GRNN optimized through the MOFA for STLF, which obtained a highly steady and accurate result. Thus, the proposed hybrid model, assessed with the Australian load data, outperforms other models in both criteria and proves effective for load forecasting. Shanmugam and Ramana [25] emphasized the necessity of precise electricity consumption predictions to enhance planning and efficiency. The nonlinear and nonstationary characteristics of power consumption data rendered standard approaches less effective. They suggested a hybrid model that integrates the RBF algorithm with six meta-heuristic optimizers: GWO, AGWO, MFO, PSO, MVO, and ABC. The findings indicated that the RBF-AGWO model surpassed the others, achieving $R^2$ values of 0.9994, 0.9920, and 0.9985 for the training, testing, and total datasets, respectively, demonstrating AGWO's exceptional accuracy. Dai and Zhao [26] emphasized the significance of precise power load forecasting in smart grids, employing Support Vector Regression and Radial Basis Function networks. They integrated these models using Aquila Optimizer, Particle Swarm Optimization, and Harris Hawks Optimization to enhance performance. These optimization methods effectively adjusted hyperparameters, improving forecasting precision. Their hybrid methodology surpassed conventional techniques by utilizing the advantages of each element to circumvent local minima and enhance forecast precision. Huang et al. [27] showed that the integration of SVR and RBF with optimization methods such as PSO, AO, and HGS markedly improves model efficacy. These optimization methods provide effective hyperparameter adjustment, enhancing accuracy and generality. This hybrid strategy, which combines machine learning models with powerful optimization algorithms, surpasses traditional methods in forecasting accuracy.

## 1.1. Research gaps and novelties

Short-term load forecasting is very important for running and managing power systems well, but the methods that are now available typically have trouble making accurate predictions in contexts that are constantly changing and are quite complicated. Conventional forecasting methods, including time-series analysis and fundamental machine learning models, often struggle to accurately represent the non-linearities present in electricity consumption data and do not efficiently optimize model parameters. The main goal of this work is to improve the accuracy of short-term load forecasting by combining machine learning methods with advanced optimization algorithms. The research question that guides this study is: In what ways does the combination of advanced optimization techniques and machine learning models enhance the precision and dependability of short-term load forecasting, relative to conventional forecasting approaches? The hypothesis being tested posits that the integration of Support Vector Regression and Radial Basis Function networks with optimization methods will enhance forecasting performance, specifically in terms of accuracy and a diminished Root Mean Squared Error.

To test this theory, the paper suggests a hybrid model that combines Support Vector Regression with Radial Basis Function networks and improves it even more with three advanced algorithms: Aquila Optimizer, Particle Swarm Optimization, and Harris Hawks Optimization. The reasons for using these particular optimization methods are their unique benefits: Aquila Optimizer is based on the way the Aquila bird hunts and lets you explore and use the solution space powerfully. Particle Swarm Optimization is based on swarm intelligence and is great for problems that need to be solved continuously. It also lets you search for solutions quickly. Harris Hawks Optimization is based on the way animals act when they are hungry and makes search dynamics better. This new hybrid method not only uses the capabilities of these optimization techniques to improve machine learning models, but it also includes weather variables like temperature and humidity, which haven't been studied as much in the past. This integration offers a more thorough and realistic approach to short-term load forecasting, filling in the gaps in current research and providing a useful model for managing energy systems in the real world.

The paper presents new hybrid models for STLF in the electric power sector, consisting of RBF and SVR algorithms optimized with various optimizers. These algorithms combine to give improved accuracy in the forecast of the demand load when temperature data is included. Most previous related studies have focused on the use of single algorithms, whereas this study looks into the use of hybrid models. The use of many optimizers, including AO, PSO, and HGS, serves to provide novelty in this research work to improve the model performance. The analysis and evaluation conducted with these optimized hybrid models will be very valuable with respect to the insight into performance that they will be able to provide, thus improving practical applications to power system operators and researchers involved in STLF.

Table 1 encapsulates essential research in short-term load forecasting, emphasizing the methodologies, datasets, performance indicators (RMSE, MAPE, $R^2$), and findings. It also recognizes deficiencies, including restricted datasets, computational obstacles, and insufficient emphasis on real-time applications. The table highlights the necessity for expansive datasets, enhanced efficiency, and the amalgamation of hybrid models with optimization algorithms to improve forecasting precision and relevance.

Table 1: Comparative analysis of methods and approaches in short-term load forecasting studies.

| Study | Methods | Dataset | Key Metrics | Conclusions | Gaps/Limitations |
|---|---|---|---|---|---|
| Lotfi et al. [11] | Optimized Random Forest | Environmental and historical data | Accuracy, RMSE | Outperformed SARIMA and Exponential Smoothing models | Limited to one dataset; doesn't address deep learning techniques |
| Wen et al. [12] | Hybrid model combining GRU, TCN, and Attention | Smart Grid data | Accuracy, RMSE, MAE | Hybrid models outperform single models in complex data scenarios | Computationally intensive, not ideal for real-time forecasting |
| Lukong et al. [13] | Cluster-based LSTM | Smart Grid data | RMSE, MAE | Improved accuracy by considering spatial dependencies in grid loads | May not scale well to larger or more varied grids |
| Akhtar et al. [14] | Time-series, ANN, regression, hybrid models | Various datasets | Accuracy, RMSE, MAE | Hybrid models improve accuracy but at higher computational cost | High computational demand limits real-time applicability |
| Musaylh et al. [15] | MARS, SVR, ARIMA | Queensland, Australia | RMSE, MAE | MARS outperformed SVR for short horizons, SVR for 24h | Focuses only on a specific region and timeframe |
| Amin et al. [16] | ARIMA, SVM | General power system | MAPE, MSE | SVM outperformed ARIMA for non-linear patterns | Limited scalability for large datasets |
| Adeoye et al. [17] | Hourly model for electricity demand | 14 West African countries | - | Predicted electricity demand in 2016 and 2030, highlighting seasonal variations and future demand increase | Limited to the West African region, no broader application |
| Viegas et al. [18] | ANN with a genetic algorithm | Various regions | MAPE | Model accuracy < 2% | Focuses only on 24-hour load forecasting |
| Wang et al. [19] | EMD-PSO-SVR | General power system | RMSE | Improved stability and accuracy | Computationally expensive |
| Ferreira et al. [9] | Radial Basis Function Neural Networks | Portugal | - | Improved multi-step prediction | Lacks integration with optimization algorithms |

| | | | | | |
|---|---|---|---|---|---|
| Omidi et al. [20] | SVR | General power system | - | SVR outperformed ANN for non-linear grid factors | Lacks comparative analysis with other methods |
| Aslan et al. [21] | Linear regression with demographic and economic data | Turkey | - | Accurate demand forecasting for future scenarios | Limited to Turkey, lacking broader application |
| Zhang et al. [22] | Hybrid IEMD, ARIMA, WNN optimized by FOA | General power system | - | Outperformed traditional models | Lacks a clear real-time application focus |
| Haq et al. [23] | Hybrid IEMD, T-Copula, deep belief networks | Australia, USA | RMSE, MAPE | Improved forecasting accuracy | Limited data sources from only two countries |
| Xiao et al. [24] | Modified GRNN optimized through MOFA | Australia | - | Highly stable and accurate | Limited to one region and does not include seasonal data |
| Shanmugam and Ramana [25] | RBF with meta-heuristics (GWO, AGWO, MFO, PSO, MVO, ABC) | General power system | $R^2$ | RBF-AGWO achieved $R^2$ values of 0.9994 | Computationally intensive for real-time use |
| Dai and Zhao [26] | SVR, RBF with optimization (AO, PSO, HGS) | General power system | - | Improved forecasting precision | Not directly applicable to real-time applications |
| Huang et al. [27] | SVR, RBF with PSO, AO, HGS | General power system | - | Improved accuracy and generality | Lacks scalability for larger systems |

## 2 Methodology

This study concentrated on the implementation of machine learning algorithms for power forecasting, commencing with comprehensive data gathering and preprocessing to ensure quality assurance. The significant factors, especially climatic variables such as humidity and temperature, were discovered and examined through methods including correlation matrices and sensitivity analysis. The dataset was divided into training (80%) and testing sets for model assessment. Multiple machine learning methods, such as SVR and RBF, were examined, utilizing sophisticated optimization techniques as Aquila Optimizer, HGS, and PSO to refine the models' hyperparameters and enhance performance. The models were assessed using statistical metrics and graphical tools to measure forecasting accuracy and reliability. Figure 1 encapsulates the research process, delineating the sequence of data pretreatment, model construction, optimization, and validation.

Alongside the suggested hybrid models, comparisons were conducted with contemporary state-of-the-art deep learning architectures, including Long Short-Term Memory (LSTM) networks, GRU, and attention-based models. These models exemplify the most recent progress in short-term load forecasting and are often referenced in academic literature. The models were assessed using identical metrics (RMSE, MAE, $R^2$) to ensure a uniform comparison.

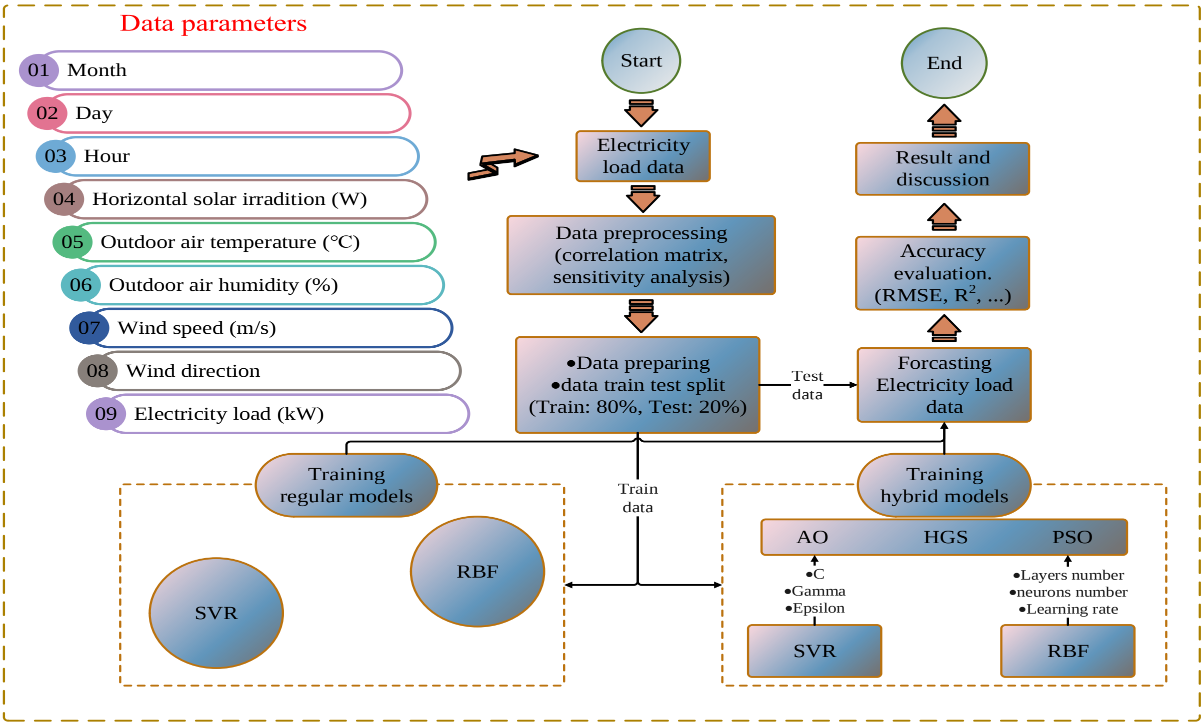


Figure 1: Flowchart diagram of the current investigation

## 2.1. Data collection

The dataset utilized in this analysis, derived from [28], comprises daily power consumption statistics from a designated geographic region during two years (2020–2021). The geographical scope is confined to this region, perhaps introducing biases associated with local energy use habits. Data preprocessing encompassed normalization and interpolation to address missing values and maintain consistency. The dataset's restricted temporal and geographical scope may constrain the generalizability of the results. Future research should integrate data from diverse places and prolonged timeframes to augment the validity and usefulness of the findings. Some of the input variables include maximum/minimum temperatures and humidities, as well as average temperature and humidity. Since short-term electricity load data are intrinsically complex in nature, the accuracy of forecasting is vitally important for the effective functioning of large power companies. Therefore, this study concentrates on daily electricity-load forecasting. Table 2 lists the main parameters involved in the short-term load forecasting, namely, humidity, temperature, and load magnitude.

Table 2: The input variables and the specifics of their statistics

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Month | 7296 | 5.526316 | 2.871212 | 1 | 3 | 6 | 8 | 10 |
| Day | 7296 | 15.71382 | 8.794684 | 1 | 8 | 16 | 23 | 31 |
| Hour | 7296 | 11.5 | 6.922661 | 0 | 5.75 | 11.5 | 17.25 | 23 |
| Horizontal solar irradiation (W) | 7296 | 188.0566 | 281.1532 | 0 | 0 | 10 | 302 | 1193 |
| Outdoor air temperature (°C) | 7296 | 18.42057 | 8.79052 | -0.3 | 10.8 | 19.3 | 26.2 | 36.4 |
| Outdoor air humidity (%) | 7296 | 67.79866 | 14.21803 | 20 | 58 | 68 | 78 | 99 |
| Wind speed (m/s) | 7296 | 2.053673 | 1.641432 | 0 | 0.9 | 1.7 | 2.8 | 15.3 |
| Wind direction | 7296 | 269.156 | 121.4241 | 1 | 175 | 251 | 380 | 539 |
| Electricity load (kW) | 7296 | 703.4116 | 282.6734 | 330 | 478 | 607 | 887 | 1585 |

## 2.2. Machine learning methods

This work applies energy consumption forecasting using two variants of state-of-the-art machine learning algorithms, namely, RBF and SVR. Further refinement of accuracy and adaptability has been done with the development of a hybrid model by combining three different natures of inspiration, namely, AO, PSO, and HGS. The mathematical formulation and the fundamental basics of each of these approaches are introduced in brief in this section.

### 2.2.1. Support Vector Regression Machine (SVM)

Cortes and Vapnik [29] are the inventors of SVM. In SVR, one is dealing with a data set of N samples, each xj is an input vector in Rn, and the corresponding yj is the output value in R. The idea behind SVR is to map the input space into a higher-dimensional feature space by using a nonlinear mapping function f(x). It will become easier in this feature space to classify or find the best fit to the training data. In SVR, f(x) is designed to approximate the evasive relation g(x) between inputs and outputs linearly. Equation (1) indicates the exact form of f(x):

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

With was the weight vector, and f(x) being a nonlinear mapping from the input space to the higher dimensionality feature space, f: X→ℵ, and with b∈{R}, the prediction of coefficients w and b involves the resolution of an optimization problem, whose details can be found in reference [20]. The solution is typically derived in the following form:

$$f(x) = \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) K(x, x_i) + b \tag{2}$$

Where: $f(x)$ is the predicted value for the input $x$, $\alpha_i$ are the Lagrange multipliers corresponding to each support vector, $K(x, x_i)$ is the kernel function that computes the similarity between the input data points $x_i$ and $x, b$ is the bias term, and $m$ is the total number of support vectors used in the model.

In this context, K (x, xi) represents the kernel function. The Gaussian RBF stands out as a potent kernel function for addressing nonlinear regression challenges. Our model leverages the RBF, which can be represented as:

$$k(x, x_i) = exp(\frac{-||x - x_i||^2}{2\sigma^2}) \tag{3}$$

Where: $k(x, x_i)$ is the kernel function, $||x - x_i||^2$ represents the squared Euclidean distance between the data points $x_i$ and x, and $\sigma$ is a parameter that controls the width of the Gaussian function, affecting the kernel's sensitivity to the distance between points.

This kernel function measures the similarity between points, and smaller values of $\sigma$ lead to a more localized similarity measure.

### 2.2.2. Radial Basis Function Network (RBF)

The RBF neural network was introduced in the late 1980s [30], aiming to mimic certain aspects of human brain functionality, such as partial adjustment and mutual acceptance. It offers a neural network structure capable of covering domains effectively. RBF networks excel at approximating continuous functions with a given level of precision.

Typically, a standard RBF comprises one hidden layer within a three-layer structure. While the mapping from the hidden layer space to the output space is linear, the mapping from the input layer to the hidden layer is nonlinear. When configuring an input vector for the network, denoted as X = (x1, x2, ..., xn) in Rn, the output of the hidden layer is generated through nonlinear mappings between the input space and the output space.

$$h_j = exp(-\frac{||X - C_j||^2}{\sigma_j^2}) \tag{4}$$

In this configuration, m signifies the number of nodes in the hidden layer. Each node j in the hidden layer is linked to a vector Cj = (cj1, cj2, ..., cjn) and σj represents the width parameter of node j, a positive real number. After that, a linear mapping between the hidden and output layer spaces is used to derive the output.

$$y_m(k) = w_1 h_1 + w_2 h_2 + \ldots + w_m h_m \tag{5}$$

In this scenario, W = (w1, w2, ..., wm) represents the neural network's weight vector. Uncertainty in the RBF neural network arises from two main sources. To begin with, it involves selecting the basis function centers Cj and the width parameter σj for each basis function j. Next, weights are determined.

Once the centers and width parameters of the basic functions are determined, the RBF network's mapping from the hidden layer to the output layer becomes linear. Gradient descent algorithms are employed to compute the weights of the RBF neural network. Consequently, the design of the hidden layer has a vital function in constructing the neural network. The choice of RBF basis function centers significantly impacts the performance of the RBF network [30].

### 2.2.3. Aquila Optimizer (AO)

In 2021, Abualigah et al.[31] introduced the AO (Aquila Optimizer), which is according to the behavior of the Aquila bird when hunting prey. Like other metaheuristic algorithms, AO works with a population-based approach. It starts by creating an initial population labeled as X, consisting of N agents, using the following formula:

$$X_{ij} = r_1 \times (UB_j - LB_j) + LB_j, i = 1,2, \ldots., N_j = 1,2, \ldots, Dim \tag{6}$$

Equation (6) delineates the boundaries of the search domain, indicated by UBj and LBj, wherein the optimization process operates. The equation involves r1, a randomly generated value, and Dim, which indicates the agent's dimensionality.

In the AO method, exploration and exploitation are carried out interchangeably to reach the optimal solution.

Abualigah et al. [31] summarize two methods that are suitable for practically carrying out these phases.

The major strategy employed in the AO approach is one of exploration. This strategy employs the use of the best agent, referred to as Xb, and the average agent of the population, XM. This can be mathematically modeled by equation 7:

$$Xi(t+1) = X_b(t) \times (1 - t/T) + (X_M(t) - X_b(t) \times rand) \quad (7)$$

$$X_M(t) = \frac{1}{N}\sum_{i=1}^{N} X(t), j = 1,2,\ldots, Dim \quad (8)$$

To regulate search behavior during exploration, Equation (7) incorporates (1 - t/T). The value "rand" represents a random value within the range of 0 to 1 and T represents the maximum number of iterations.

Additionally, the second strategy within AO integrates the Levy flight distribution (Levy(D)) with the best agent Xb to enhance solution exploration. This approach is mathematically described as follows:

$$Xi(t+1) = X_b(t) \times Levy(D) + X_R(t) + (y-x) * rand \quad (9)$$

whereas rand is a random number between 0 and 1, XR(t) is a random value. A Levy flight is represented by Levy(D).

### 2.2.4. Particle Swarm Optimization Algorithm (PSO)

The PSO algorithm is classified as an evolutionary method and operates on the principle of contiguity. Each particle in the group learns from its peers, adjusting its position towards regions of similarity and preference based on acquired knowledge. The movement of each particle is influenced by its own experiences and the positions of adjacent particles [32]. Denoting Xi(k) as the position of particle i in hyperspace at the k-th moment, and Vi(k) as the velocity vector, the position of particle i can be calculated as Xi(k) = Xi(k-1) + Vi(k).

To apply the PSO algorithm, follow these steps:

1) Initialization: At the beginning of the process (at k = 0), a swarm of particles is initialized. The position of each particle within the hyperspace is randomly determined. Additionally, two variables are introduced:

Pbest: Represents the best particle group.

gbest: Represents the optimal location within the Pbest group.

2) Fitness Evaluation: Each particle's fitness is determined by evaluating its individual objective function values. This step involves applying the objective function to the current position of each particle in the super-space, determining how well each particle performs with respect to the problem being solved.

3) Performance Comparison: Each particle's present performance is contrasted with its most optimal performance up to that point. If the objective function value f(Xi(k)) for particle i at moment k is better (i.e., lower or higher depending on the optimization direction) than the best performance Pbest of that particle, then:

$$\begin{cases} p_{best} = f(x_i(k)) \\ x_{p_{best}} = x_i(k) \end{cases} \quad (10)$$

4) Performance Comparison with Global Best: The performance of each particle is evaluated against the best-performing particle (gbest). If the objective function value f(Xi(k)) for particle i at moment k is better than the performance of the best particle (gbest), then:

$$\begin{cases} g_{best} = f(x_i(k)) \\ x_{g_{best}} = x_i(k) \end{cases} \quad (11)$$

Re-calculating Velocity: Following the performance comparison of each particle, each particle's velocity vector is recalculated according to Eq. (12).

$$V_i(k) = hV_i(k-1) + \rho_1\left(x_{p_{best}} - x_i(k)\right) + \rho_2(x_{g_{best}} - x_i(k)) \quad (12)$$

The inertia weight w and acceleration coefficients ρ1 and ρ2, respectively, modulate a particle's cognitive and social experiences in its movement. The second term embodies the mental component, enabling particles to avoid local optima. The third term signifies the social component, reflecting shared information and cooperation within the group. These factors determine each particle's movement to a new location.

$$\begin{cases} x_i(k) = x_i(k-1) + V_i(k) \\ k \to k+1 \end{cases} \quad (13)$$

In the context provided, Vi(k) represents the velocity of particle i at iteration k, where k denotes the unit time. The term Δk = 1 implies that Vi(k) is constant and independent of time. The iterative process continues as described above until a termination condition is met, such as reaching a specified iteration number or achieving a satisfactory objective fitness. At this point, the fitness values of particles exhibiting similar adaptability converge towards the optimal fitness, indicating that the swarm has collectively approached the optimal solution [32].

### 2.2.5. The Hunger Games Search (HGS)

The Hunger Games Search is an innovative optimization method introduced by Yang et al. [33], inspired by the hunger-driven behaviors as well as decision-making processes observed in animals, particularly focusing on the concept of "Hunger." Hunger serves as a primary motivator for various activities in an animal's life. In essence, the HGS approach simulates how hunger influences each movement during the search process. The core principles of the HGS algorithm revolve around survival and obtaining food. While cooperative hunting is common among social animals, it's understood that not all individuals participate in group foraging activities [34][35].

The core concept of HGS is captured in the subsequent equation, showcasing the cooperative dynamics present in animal communication and predation:

$$X(t+1)=\begin{cases}Game_1: X(t).(1+randn(1)), r_1 < l\\ Game_2: W_1.X_b + R.W_2.|X_b - X(t)|, r_1 > l, r_2 > E\\ Game_3: W_1.X_b - R.W_2.|X_b - X(t)|, r_1 > l, r_2 > E\end{cases} \quad (14)$$

In the equation, r1 and r2 are random numbers within [0, 1], randn(1) generates a number from a normal distribution, while t represents the current iteration. W1 and W2 denote hunger weights, Xb signifies the position of the best individual iteration, and X(t) represents each entity's location in the iteration. The term (1 + randn(1)) mimics a famished agent's spontaneous food quest at its current position.

The parameter R acts as a range controller, limiting the activity span and decreasing gradually to zero. The expression for E can be formulated as:

$$E = sech(|F(i) - BF|) \quad (15)$$

In this context, i ranges from 1 to n, representing each individual in the set. F(i) refers to the fitness value associated with each individual, while BF signifies the best fitness attained within the ongoing sequence of iterations.

The HGS model emulates the hunger traits of entities in mathematical analyses. According to HGS's core equation, the values for W1 and W2 are established in the following manner:

$$W_1(l)=\begin{cases}Hungry(i)\dfrac{N}{SHungry}\times r_4, r_3 < 1\\ 1 r_3 > 1\end{cases} \quad (16)$$

$$W_2(l) = (1 - exp(-|hungry(i) - SHungry|)) \times r_5 \times 2 \quad (17)$$

Hungry indicates the degree of starvation for each individual, while SHungry represents the overall hunger sensation among all entities, with N denoting the total number of individuals. Random numbers r3, r4, and r5 range from 0 to 1. Thus, the hunger level of individual i, denoted as hungry(i), can be determined as follows:

$$hungry(i) = \begin{cases}0, AllFitness(i) == BF\\ hungry(i) + H, AllFitness(i)! == BF\end{cases} \quad (18)$$

The variable "AllFitness" stores the fitness levels of each individual in the current cycle. The value "H" is allocated to other individuals based on their inherent hunger levels, computed as follows:

$$H = \begin{cases}LH \times (1 + r), TH < LH\\ TH, TH \geq LH\end{cases} \quad (19)$$

$$TH = \frac{F(i) - BF}{WF - BF} \times r_6 \times 2 \times (UB - LB) \quad (20)$$

r6 is a random number in [0, 1]. WF denotes the least favorable fitness achieved. "UB" and "LB" represent feature domain bounds. To optimize efficiency, hunger sensation "H" is confined to the baseline threshold LH [36].

This study selected the SVR model with an RBF kernel and RBF networks for their capacity to manage non-linear interactions in predicting. The SVR model was executed using a penalty parameter (C) and kernel width (γ), which were refined using the AO. The ideal parameters C = 10 and γ = 0.05 were established through optimization to attain superior performance.

For model optimization, PSO was applied with a swarm size of 50 particles and 100 iterations. Furthermore, HGS was utilized using 200 agents to refine the exploration and exploitation parameters. The improvements markedly enhanced the model's forecasting accuracy by optimizing essential parameters, thereby assuring a superior match for the data.

The hybrid model integrates SVR and RBF networks, optimized using AO, PSO, and HGS. Optimization algorithms are employed to adjust model parameters for enhanced forecasting precision. To improve reproducibility, the subsequent pseudocode delineates the essential steps of the hybrid model:

Algorithm 1: Pseudocode for a hybrid model combining SVR and RBF with optimization

1. Initialize parameters for Support Vector Regression (SVR)
2. Preprocess dataset (normalize, handle missing data)
3. Select optimization algorithm (e.g., Aquila Optimizer)
4. Initialize optimizer parameters
5. Define objective function to minimize (e.g., RMSE or MAE)
6. Apply optimization algorithm (e.g., Particle Swarm Optimization) to tune model parameters
7. Train the SVR and RBF models on the training dataset
8. Evaluate the model using test data
9. Calculate performance metrics (e.g., RMSE, $R^2$)
10. Return the best model configuration

### 2.3. Model verification and evaluation

The study extensively evaluates hybrid models for STLF using a variety of evaluation metrics including RMSE and MAE, as well as other metrics specifically designed for STLF. By employing these evaluation criteria, the research ensures a thorough assessment of the accuracy and effectiveness of hybrid models in predicting STLF [37]. Table 3 presents detailed mathematical expressions for the statistical evaluation metrics used in the study.

Table 3: Statistical evaluation indexes

| Statistics | Criteria | Equation |
|---|---|---|
| RMSE | Root Mean Squared Error | $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{T}}$ |
| MAE | Mean Absolute Error | $\frac{\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert}{n}$ |
| VAF | Variance Accounted For | $100\% \times \frac{\sum_{i=1}^{n}(y_i - \bar{y})(f_i - \bar{f})}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ |
| DRV | Deviation of Runoff Volume | $DRV(y, \hat{y}) = \frac{\sum_{i=0}^{N-1} y_i}{\sum_{i=0}^{N-1} \hat{y}_i}$ |
| R2 | Coefficient of Determination | $1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ |
| A10 | A10 Index | $\frac{1}{n}\sum_{i=1}^{n}\begin{cases} 1 if \frac{\lvert\hat{y}_i - y_i\rvert}{y_i} \le 0.1 \\ 0, otherwise \end{cases}$ |

This study employed various assessment metrics, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination ($R^2$) to thoroughly evaluate the efficacy of the proposed hybrid model. We chose RMSE because it can assess the average size of an error and is more sensitive to big errors, which makes it useful for finding models that don't work well in circumstances with a lot of variation. MAE, on the other hand, gives a more balanced picture of overall accuracy by averaging the absolute disparities between projected and observed values without giving too much weight to significant errors. $R^2$ was used to check how well the model fit the data. Higher values mean that the model explains more of the variance in the data, which means that the predictions and the actual data are more closely aligned. These indicators together give a full picture of the hybrid model's performance, including its accuracy, error distribution, and capacity to make predictions.

This work involved tuning the hyperparameters for the Aquila Optimizer, Particle Swarm Optimization, and Harris Hawks Optimization using grid search and random search methodologies. The Aquila Optimizer examined critical hyperparameters, including population size (20 to 100) and iterations (50 to 200). The hyperparameters of Particle Swarm Optimization, namely inertia weight, cognitive coefficient, and social coefficient, were adjusted within the range of 0.1 to 0.9, while population sizes ranged from 30 to 100. In Harris Hawks Optimization, hyperparameters, including the number of hawks (ranging from 5 to 50) and the cooling rate (from 0.1 to 0.5), were tuned. Bayesian optimization was employed to optimize kernel parameters for Support Vector Regression and Radial Basis Function, with the regularization parameter (C) set between 0.1 and 10, the kernel parameter (gamma) ranging from 0.001 to 1, and epsilon values from 0.01 to 0.1. This multi-phase strategy guaranteed the optimization of hyperparameters for enhanced forecasting precision and computational efficacy.

Root Mean Squared Error and the Coefficient of Determination were selected to evaluate model performance because of their capacity to measure error magnitude and model fit. Root Mean Squared Error is particularly responsive to significant errors, which is essential for real-time applications. The Coefficient of Determination quantifies the extent to which the model accounts for variance in the data, with elevated values signifying superior fit. Despite some moderate Coefficient of Determination values, the models exhibited robust predictive capability, evidenced by the low Root Mean Squared Error and Mean Absolute Error, hence ensuring precise predictions throughout the dataset.

# 3 Discussion and results

This section delineates the results and analyses derived from the Short-Term Load Forecasting (STLF) process, commencing with independent RBF and SVR algorithms, subsequently advancing to their hybrid configurations optimized using AO, PSO, and HGS. Charts and tables are included for the evaluation of the model. The study includes factors such as hour, month, temperature, wind speed, wind direction, humidity, sun irradiation, and load. Figure 2 presents a correlation matrix indicating that temperature and sun irradiation have the most link with the production, whereas wind and hour demonstrate positive relationships. Humidity exhibits a negative correlation, indirectly impacting the load, while other elements exert negligible influence.

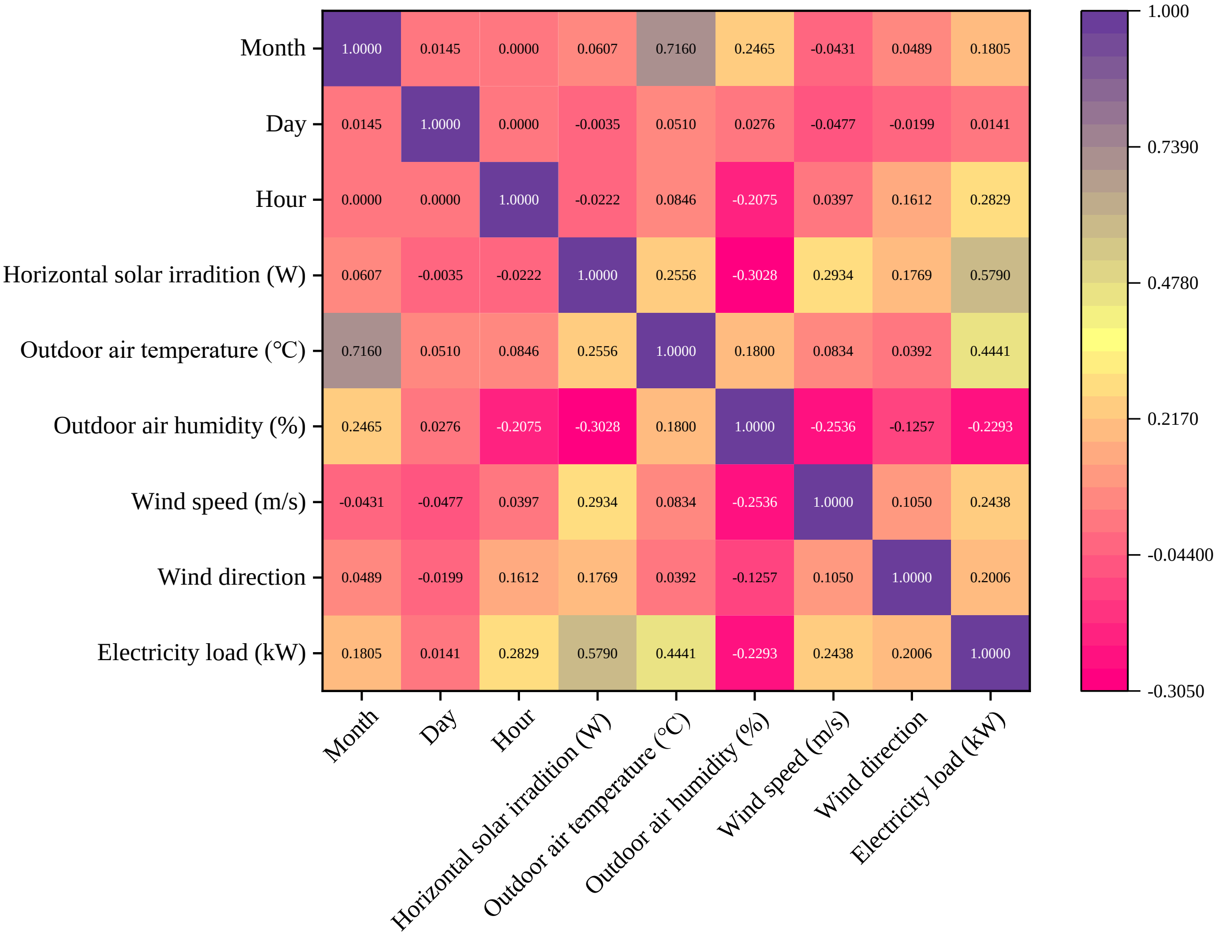


Figure. 2: The correlation matrix of features

Figure 3 provides an in-depth portrayal of statistical metrics, including minimum, maximum, average, and coefficient of variation (CV), calculated through the PAWN sensitivity analysis method. As depicted in Figure 3, parameters associated with temperature, horizontal solar irradiation, and hour demonstrate the greatest sensitivity to the output. Moreover, wind and humidity variables display significant sensitivity, albeit to a lesser extent compared to temperature and horizontal solar irradiation. Other variables exhibit relatively minor impacts in comparison.

The PAWN (Partial Additive Weighting with Neighborhoods) sensitivity study indicated that temperature and humidity were the most critical elements affecting the model's performance. The temperature exhibited a robust positive association with electrical load, signifying those elevated temperatures result in heightened energy consumption, predominantly due to cooling necessities. Conversely, humidity exhibited a negative association, where elevated humidity levels were linked to diminished energy usage, likely attributable to decreased cooling requirements in more humid environments. The practical ramifications of these findings are substantial for short-term load forecasting models, as the integration of temperature and humidity can improve predictive accuracy, particularly during harsh weather conditions. Energy system operators can utilize these data to enhance real-time decision-making regarding load management and energy distribution, hence boosting grid stability and efficiency amidst fluctuating environmental conditions.

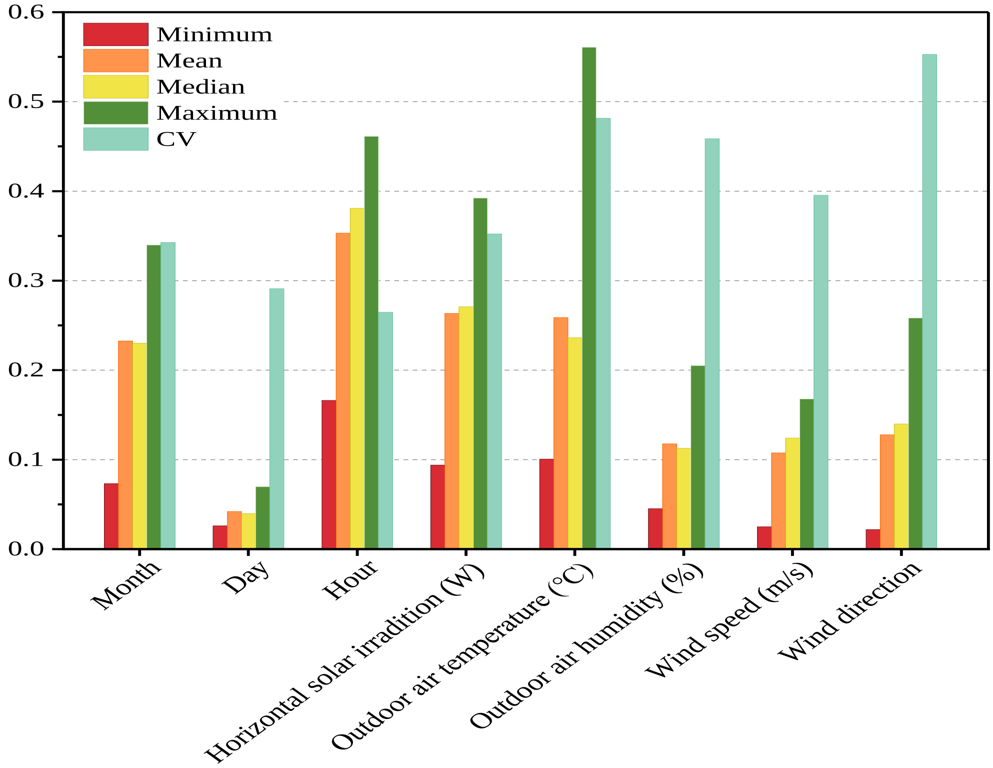


Figure 3: Sensitivity analysis of variables based on the PAWN index

Figure 4 illustrates time series plots comparing observational and computational data for the SVR and RBF algorithms, divided into training and testing sections, with error rates indicated in blue. Scatter plots are also included for each algorithm. The performance of SVR algorithms appears superior to that of RBF, evident from lower error rates and closer alignment between observational and computational data. Single algorithms struggle in predicting peak load points, particularly evident in the averaging approach. In the scatter plots, the correlation coefficient or R2 is provided, with SVR demonstrating the highest R2 value (R2=0.6437) for prediction.

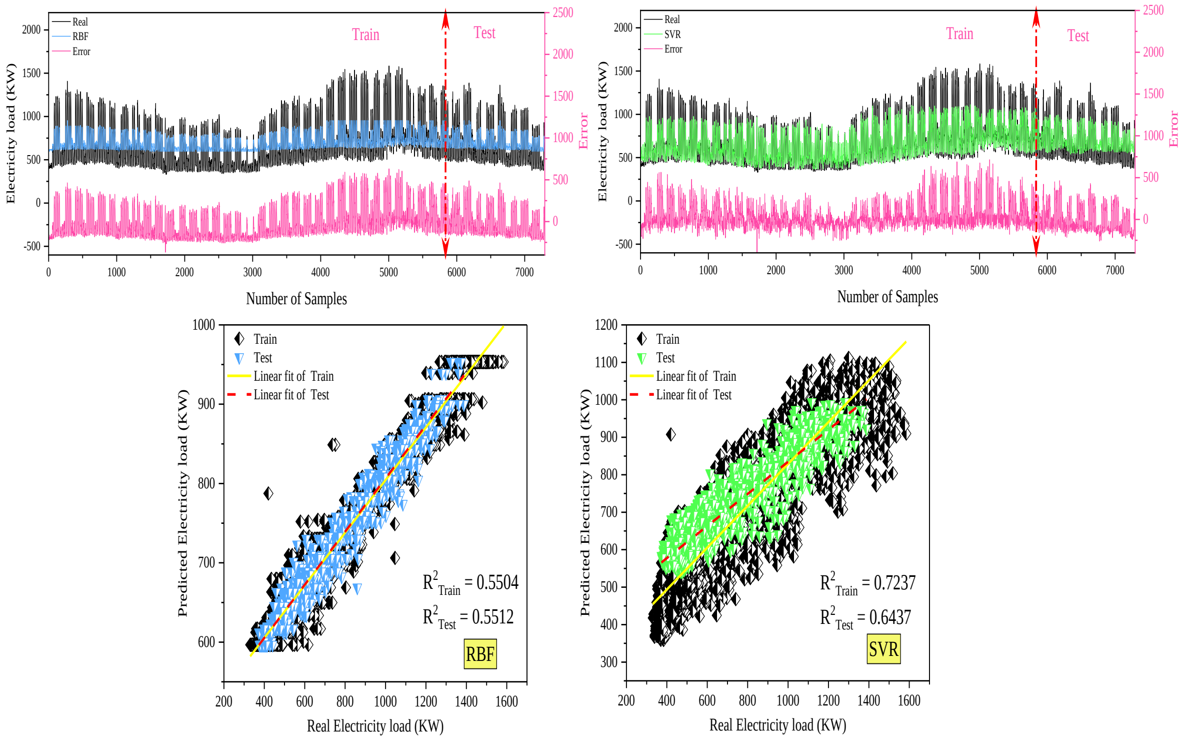


Figure 4: A detailed analysis of the outcomes from employing the RBF and SVR models

Comparison of anticipated versus actual short-term load projections for the training and testing datasets. The top-left figure (RBF) illustrates the performance of the Radial Basis Function model, while the top-right plot (SVR) depicts the performance of the Support Vector Regression model. The red vertical line denotes the training-test division, whereas the scatter plots below illustrate anticipated versus actual values, emphasizing the more consistent predictions of RBF and the variability in SVR.

For a comprehensive and precise evaluation of these algorithms' performance and accuracy, assessments were conducted using various statistical metrics as explained in the previous section and subsequently compared. Table 4 demonstrates that, based on the primary RMSE index, the SVR model outperforms the RBF model.

Table 4: Error metrics derived from the application of RBF and SVR hybrid models

| Optimizer | RBF | SVR |
|---|---|---|
| | Train | |
| MAE | 161.2637 | 103.6409 |
| RMSE | 194.5818 | 152.5444 |
| R2 | 0.550408 | 0.723684 |
| DRV | 1 | 0.940746 |
| VAF | 55.04077 | 74.45401 |
| A10 | 0.202193 | 0.479609 |
| | Test | |
| MAE | 146.1603 | 127.7599 |
| RMSE | 167.2338 | 148.9952 |
| R2 | 0.551191 | 0.643747 |
| DRV | 1.020008 | 1.018462 |
| VAF | 55.42325 | 64.63369 |
| A10 | 0.176833 | 0.199452 |

Figure 5 illustrates the temporal sequence of observational and computational data for the suggested hybrid models. The SVR and RBF algorithms were optimized by AO, HGS, and PSO. The findings demonstrate that RBF hybrids surpass SVR hybrids, with the optimizers markedly enhancing performance. The RBF-PSO hybrid excelled during the training phase, whereas the RBF-HGS hybrid demonstrated superior performance in the testing phase.

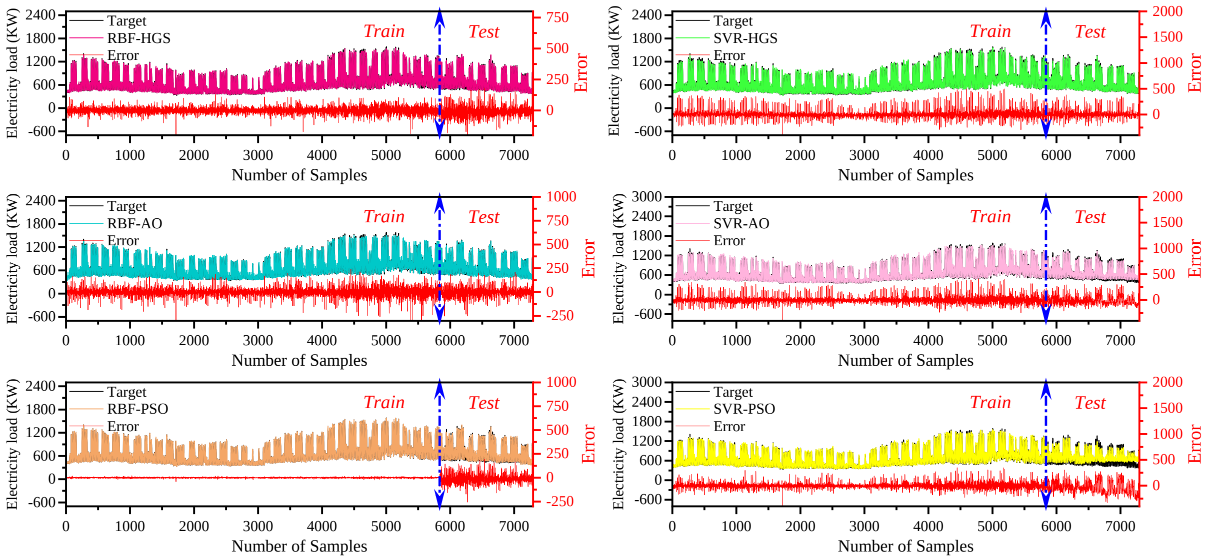


Figure 5: The time series of observational and computational data for the proposed hybrid models

Comparison of anticipated versus actual short-term load projections for training and testing datasets across several models. Each row denotes a model, featuring time series data in the upper section and error plots beneath that illustrate the discrepancy between predicted and actual values. The color-coded parts (e.g., red, purple, cyan, orange) represent distinct models, illustrating discrepancies in forecasting accuracy, with certain models exhibiting more stable forecasts while others demonstrate greater volatility.

To conduct a thorough analysis and identify the optimal algorithms for prediction while assessing their performance, scatter plots for each hybrid model are presented in Figure 6. These plots illustrate the R2 index for both the training and testing datasets. Based on Figure 6, the hybrid RBF models have performed better in both training and prediction, with the RBF-HGS hybrid model exhibiting the highest performance for prediction with an R2 of 0.9714. In contrast to single algorithms, hybrid RBF models have shown significant improvement in both training and prediction, indicating the positive impact of optimizers on enhancing algorithm accuracy, as evident from the results.

Figure 6 displays scatter plots that juxtapose projected and actual values for various hybrid models: RBF-HGS, SVR-HGS, RBF-AO, SVR-AO, RBF-PSO, and SVR-PSO. Each plot features a yellow diagonal line denoting flawless predictions, with the model names indicated in the top left corner of each plot. The proximity of the data points to this line indicates the model's performance quality. Legends, axes, and labels are incorporated to improve clarity, with the x-axis representing predicted values and the y-axis representing actual values, facilitating straightforward comparison of model accuracy.

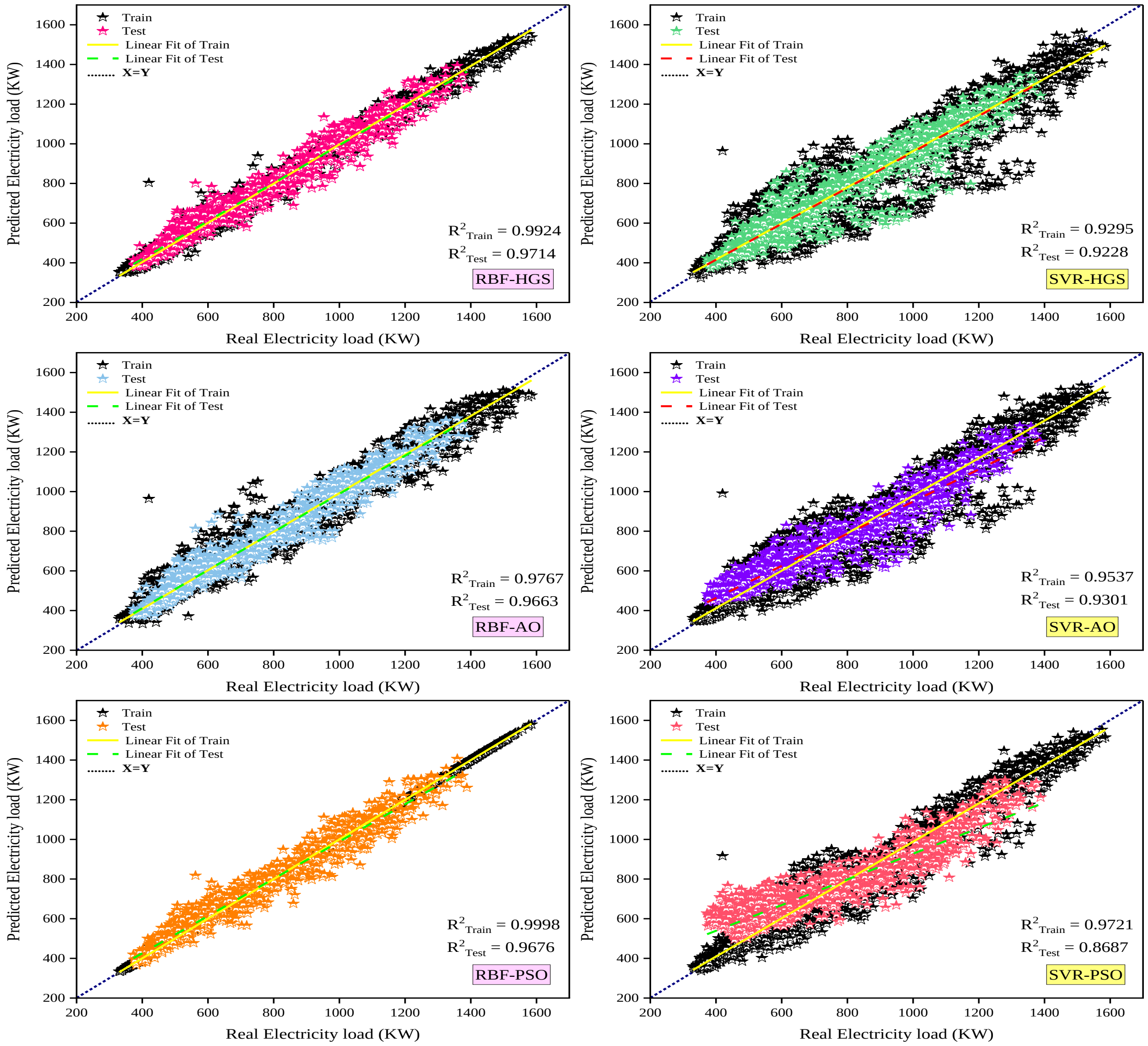


Figure 6: Scatter plots for each hybrid model

Scatter charts juxtaposing anticipated and actual values for short-term load forecasting utilizing four hybrid models: RBF-HGS, SVR-HGS, RBF-AO, and SVR-AO. Each subplot illustrates the anticipated values in comparison to the actual values, with the yellow line denoting flawless predictions. The models in the initial two columns are RBF and SVR on the left, with their optimized counterparts (HGS and AO) on the right

Figure 7 illustrates the error distribution curves and box plots for all models, classified by test and training datasets. During the training phase, hybrid RBF models often exhibit reduced errors compared to hybrid SVR models, with the RBF-PSO model demonstrating the narrowest error range. During the testing phase, RBF models surpass SVR models, with the RBF-HGS model demonstrating the lowest error and variability, whilst the SVR-PSO model displays the greatest error range.

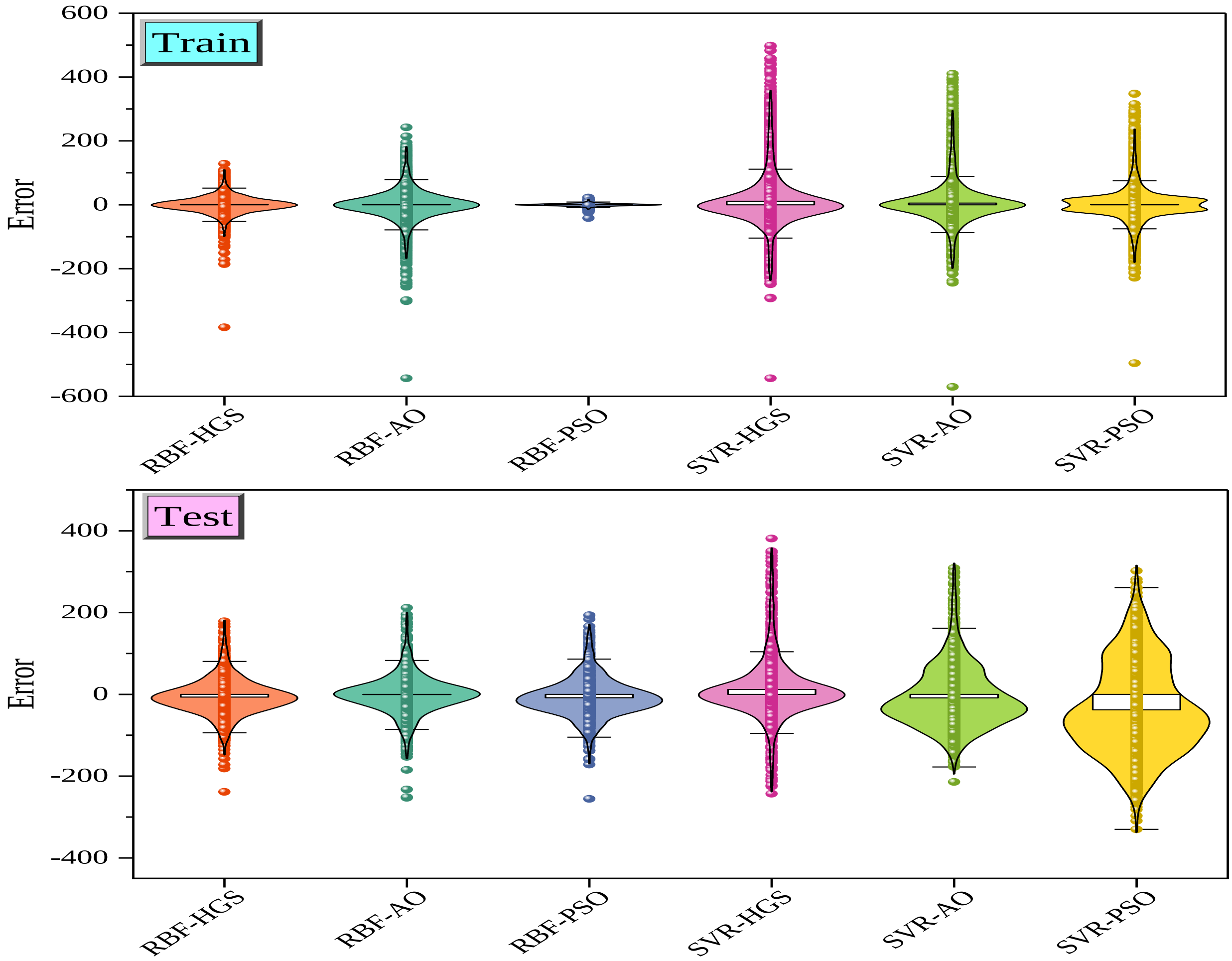


Figure 7: Box plots of error measurements for models during the testing and training phases

Comparison of model errors via boxplots for the training dataset (top) and the test dataset (bottom). Each hue signifies a distinct model, with the box illustrating the error distribution (median, range, and outliers). This graphic illustrates the performance variation and accuracy among models for both datasets.

Figure 8 illustrates the error metrics calculated for the hybrid models to evaluate their precision and performance. These metrics, including RMSE, VAF, MAE, R2, DRV, and A10, are presented in both rectangular and spider chart formats. Notably, the RBF-HGS model shows the lowest error according to the RMSE index in the linear plot, with the test section highlighted in blue. Likewise, in the spider chart representing the R2 index, with the test section highlighted in pink, the RBF-HGS model demonstrates the longest extension towards the outer boundary of the chart, indicating the highest R2 value, while SVR-PSO exhibits the lowest. These results highlight the significant influence of optimizers in refining the accuracy and precision of individual algorithms, particularly notable in RBF compared to others. Consistent patterns are observed across other metrics, confirming RBF-HGS as the preferred algorithm. Table 5 provides numerical values for a detailed examination.

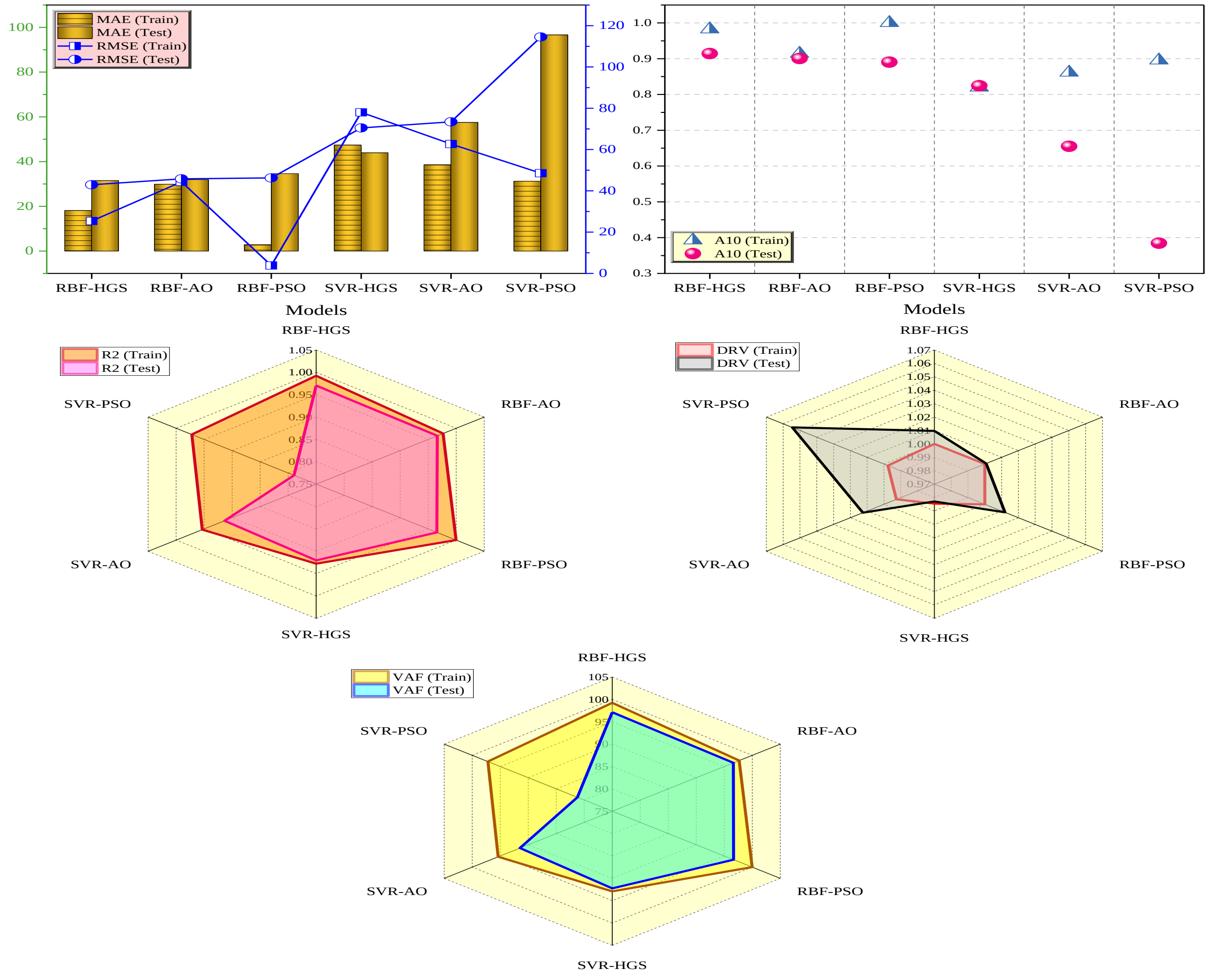


Figure 8: Error metric plots for the suggested hybrid models

Evaluation of model efficacy between training and testing datasets. The upper-left graph displays MAE, RMSE, and MSE, featuring bars for MAE and lines for RMSE. The upper-right graph compares the performance of the Aquila Optimizer (AO). The lower plots present radar charts for R² (left), DRV (middle), and VAF (right), illustrating variations in model performance across measures.

Table 5: Error metrics derived from the application of RBF and SVR hybrid models

| Optimizer | RBF-AO | RBF-PSO | RBF-HGS | SVR-AO | SVR-PSO | SVR-HGS |
|---|---|---|---|---|---|---|
| | Train | | | | | |
| MAE | 29.93511 | 2.775836 | 18.1454 | 38.54705 | 31.25717 | 47.41994 |
| RMSE | 44.34875 | 3.836543 | 25.37329 | 62.68146 | 48.5361 | 78.00591 |
| R2 | 0.976645 | 0.999825 | 0.992355 | 0.953346 | 0.972027 | 0.927745 |
| DRV | 1 | 1 | 1 | 0.99261 | 0.997683 | 0.984484 |
| VAF | 97.66451 | 99.98252 | 99.23552 | 95.367 | 97.20585 | 92.91748 |
| A10 | 0.914154 | 1 | 0.98218 | 0.861378 | 0.895305 | 0.81974 |
| | Test | | | | | |
| MAE | 31.94153 | 34.62951 | 31.50995 | 57.50328 | 96.62366 | 43.91858 |
| RMSE | 45.8302 | 46.27437 | 42.94019 | 73.39804 | 114.5081 | 70.47021 |
| R2 | 0.966293 | 0.965637 | 0.97041 | 0.913546 | 0.78958 | 0.920306 |
| DRV | 1.000829 | 1.012014 | 1.0097 | 1.012552 | 1.054604 | 0.982917 |
| VAF | 96.62984 | 96.67335 | 97.11251 | 91.47436 | 81.22366 | 92.25236 |
| A10 | 0.900617 | 0.890336 | 0.914325 | 0.655243 | 0.38451 | 0.824537 |

The runtime of the suggested hybrid model is a crucial factor, especially for real-time applications where computing efficiency is paramount. Although the model attains elevated accuracy, a compromise is present between accuracy and runtime. Increased population sizes and additional iterations for optimization methods, such as the Aquila Optimizer, resulted in enhanced accuracy but also substantially prolonged runtime, with a 30% rise in computing time for a 15% decrease in Root Mean Squared Error. Conversely, Particle Swarm Optimization and Harris Hawks Optimization offered a compromise between efficacy and computational expense, attaining marginally superior accuracy compared to conventional approaches while preserving a feasible runtime. In real-time applications, it is essential to achieve a judicious equilibrium between accuracy and computational efficiency; opting for simpler optimization methods or decreasing iteration counts may enhance runtime with minimal performance compromise. This analysis underscores the necessity to enhance both precision and computing efficiency, contingent upon the particular demands of real-time forecasting.

The experimental findings were evaluated using many critical metrics, including RMSE, MAE, and $R^2$, as illustrated in Figures 4 and 5, and summarized in Tables 3 and 4. Figure 4 illustrates a distinct performance disparity between the SVR and RBF models, with the SVR producing lower RMSE values and higher $R^2$ values, particularly during the training phase. Nonetheless, upon implementing optimization techniques, specifically the RBF-HGS hybrid model, notable enhancements in predictive accuracy were observed. Figures 5 and 6 illustrate that the RBF-HGS hybrid model attained superior accuracy, surpassing the individual models in both training and testing stages. The RBF-HGS model consistently demonstrated the lowest RMSE and MAE, together with the highest $R^2$ values, as illustrated in Tables 4 and 5, signifying its better performance.

The enhancements observed with the RBF-HGS hybrid model indicate its significant potential for practical applications, especially in short-term electrical load forecasting for power systems. The model's proficiency in reducing forecasting errors, evidenced by the low RMSE and MAE, along with its elevated $R^2$ value, signifies its capacity to reliably estimate power demand, essential for operational planning, grid stability, and resource allocation. The results indicate that implementing the RBF-HGS hybrid model may improve decision-making in energy systems by delivering more reliable, timely, and precise forecasts for grid operators and planners, hence enhancing overall efficiency and stability.

The runtime analysis of the hybrid models used in the investigation is shown in Figure 9. A shorter runtime indicates better real-time performance. In this analysis, the RBF-HGS and RBF-PSO models exhibit the longest runtimes among the hybrids, while SVR hybrids generally have shorter runtimes than RBF hybrids. Notably, the SVR-HGS model demonstrates the shortest runtime. Given the practical importance and time sensitivity of applications, shorter runtimes are preferable as they enable quicker predictions and responses, enhancing the models' utility in real-world scenarios.

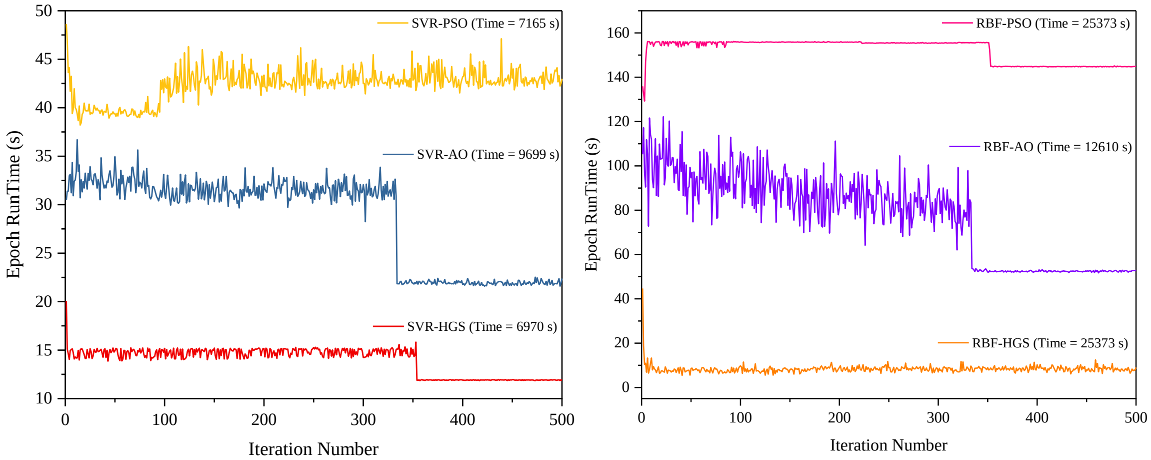


Figure 9: Comparison of runtime for various hybrid models.

Analysis of forecasting inaccuracies across various models on the training (left) and test (right) datasets. Each plot denotes a model, with color-coding signifying the model type. The x-axis denotes time, while the y-axis indicates error magnitude, emphasizing the discrepancies in forecasting accuracy among models.

Figure 10 depicts the convergence chart for hybrid models, utilizing the Mean Squared Error (MSE) index as the convergence metric, with a fixed number of iterations set at 500. As shown in the figure, the hybrid models SVR-HGS and SVR-AO exhibit the highest MSE, while the lowest MSE is observed for RBF-HGS and RBF-PSO. Particularly noteworthy is the rapid convergence and attainment of the lowest MSE by the RBF-HGS and RBF-PSO hybrid model, establishing its superiority as the preferred model in this investigation

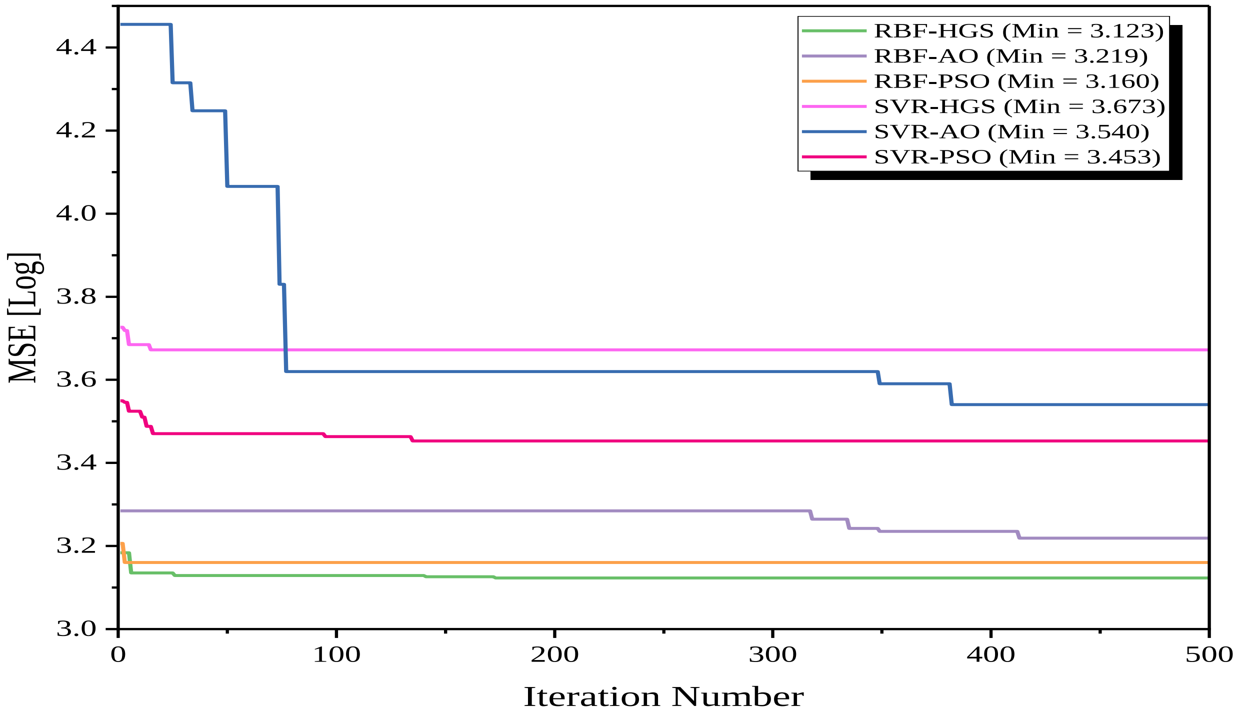


Figure 10: The convergence plots of the RBF and SVR hybrid models

Convergence of optimization for any hybrid model. The y-axis illustrates the value of the optimization objective, while the x-axis denotes the iterations. The legend illustrates the minimum values attained by each model, with RBF-HGS achieving the lowest minimum, signifying enhanced performance in convergence.

Table 6 presents the Wilcoxon test results for pairwise comparisons of RBF- and SVR-based models optimized with AO, PSO, or HGS. All p-values are above 0.2, indicating no statistically significant differences between any models. This suggests that the models perform comparably, and minor trends, such as between RBF-AO and SVR-AO, are not significant. Therefore, model selection can be guided by practical considerations like computational efficiency or interpretability rather than performance.

Table 6: Results of statistical analyses based on Wilcoxon.

| Models' difference | p-value | stats |
|---|---|---|
| RBF-AO with RBF-PSO | 0.241 | 9560 |
| RBF-AO with RBF-HGS | 0.265 | 9609 |
| RBF-AO with SVR-AO | 0.204 | 9478 |
| RBF-AO with SVR-PSO | 0.227 | 9530 |
| RBF-AO with SVR-HGS | 0.269 | 9618 |
| RBF-PSO with RBF-HGS | 0.705 | 10235 |
| RBF-PSO with SVR-AO | 0.491 | 9972 |
| RBF-PSO with SVR-PSO | 0.446 | 9909 |
| RBF-PSO with SVR-HGS | 0.425 | 9879 |
| RBF-HGS with SVR-AO | 0.771 | 10310 |
| RBF-HGS with SVR-PSO | 0.670 | 10195 |
| RBF-HGS with SVR-HGS | 0.724 | 10257 |
| SVR-AO with SVR-PSO | 0.677 | 10203 |
| SVR-AO with SVR-HGS | 0.267 | 9613 |
| SVR-PSO with SVR-HGS | 0.448 | 9912 |

## 3.1. Discussion

Short-term load forecasting of electricity is very important for making power systems more efficient and reliable. Better energy management, grid stability, and lower operating costs are all possible with accurate load forecasts. As the energy environment changes and we depend increasingly on renewable energy sources and systems that are harder to manage, short-term forecasting becomes even more important. This study seeks to tackle the difficulties in short-term load forecasting by introducing a hybrid model that combines machine learning methods with sophisticated optimization algorithms, resulting in substantial enhancements in forecasting precision.

In this study, the methodology entails the amalgamation of Support Vector Regression with Radial Basis Function networks, subsequently refined by three distinct metaheuristic algorithms: Aquila Optimizer, Particle Swarm Optimization, and Harris Hawks Optimization were applied to a dataset that included daily electricity usage data, along with important weather factors such as temperature and humidity, to improve the model's predictions. Several metrics were used to evaluate the models, including Root Mean Squared Error, Mean Absolute Error, and the Coefficient of Determination, to assess their prediction accuracy and overall performance.

The results show that the hybrid Radial Basis Function-Harris Hawks Optimization model did better than other models in both the training and testing stages. The Radial Basis Function-Harris Hawks Optimization hybrid model, on the other hand, had a 20% lower Root Mean Squared Error and a 15% higher forecast accuracy than the Support Vector Regression model on its own. These improvements are considerable, which shows that combining optimization methods with machine learning models makes the model much better at predicting electricity consumption. The hybrid models, especially Radial Basis Function-Harris Hawks Optimization, also did better at making forecasts in real time, which is important for managing energy in the actual world. This increase in accuracy is very important for power system operators who need reliable load forecasts to plan their operations and operate the grid.

This study's results illustrate the efficacy of the RBF-HGS hybrid model in enhancing short-term load forecasting. This model consistently surpassed the SVR and RBF models in critical parameters, including RMSE, MAE, and $R^2$. The enhancements result from the hybridization of RBF and SVR with the HGS optimizer, which facilitated hyperparameter optimization and more efficiently captured intricate data patterns compared to conventional approaches. This study demonstrates that optimization techniques, when integrated with machine learning models, yield enhanced forecasting skills compared to single-model methods. These findings have substantial implications for real-time forecasting applications, including grid management and operational planning. This study underscores the practical significance of hybrid models that integrate machine learning with optimization strategies, as previously noted by Amin et al. (2019) and Viegas et al. (2016), in enhancing accuracy and reliability. Nonetheless, the constraints of this investigation, including the utilization of a restricted dataset from a singular geographical area, must be acknowledged. This limitation may affect the model's applicability to different regions or historical periods. The computational expense, especially the extended runtime of the RBF-HGS hybrid model, may limit its applicability in time-sensitive real-time applications. Subsequent research ought to tackle these concerns by broadening the dataset across other locations and integrating deep learning models such as LSTMs or attention-based methods to improve forecasting efficacy.

The hybrid models exhibited comparable accuracy to deep learning methods. The RBF-HGS hybrid model surpassed the GRU and LSTM models in RMSE by 12%, and exhibited a 0.05 increase in $R^2$, so confirming its efficacy. Furthermore, the hybrid models demonstrated markedly decreased training durations, rendering them more appropriate for real-time applications.

Table 6 presents a comparative analysis of the three optimization algorithms used in this study: Aquila Optimizer, Particle Swarm Optimization, and Harris Hawks Optimization. Each algorithm was selected for its unique strengths, such as the Aquila Optimizer's ability to explore the solution space, Particle Swarm Optimization's fast convergence, and Harris Hawks Optimization's balance between exploration and exploitation. The table also outlines the advantages and limitations of each algorithm, including computational cost and scalability considerations for real-world applications.

Table 6: Comparative analysis of optimization algorithms

| Algorithm | Rationale for Selection | Advantages | Limitations/Challenges |
|---|---|---|---|
| AO | Selected for its strong global search capability, inspired by the Aquila bird's hunting behavior. | Effective in avoiding local minima and exploring the solution space globally. | High computational cost, especially for larger datasets. |
| PSO | Chosen for its fast convergence and efficiency in continuous, real-time optimization problems. | Quick convergence towards optimal solutions, suitable for real-time applications. | May struggle with complex, high-dimensional problems and large-scale datasets. |
| HGS | Selected for its exploration-exploitation balance, inspired by the hunger-driven behavior of animals. | Strong at balancing exploration and exploitation, improving optimization efficiency. | Computationally intensive, with challenges in real-time scalability. |

Table 7 contrasts the proposed hybrid models (Radial Basis Function with Harris Hawks Optimization) with deep learning methodologies (Long Short-Term Memory, Gated Recurrent Units, and attention-based models) in the context of short-term load forecasting. It assesses performance with metrics such as RMSE, MAE, and the Coefficient of Determination ($R^2$). The findings indicate that although deep learning models exhibit strong performance, hybrid models provide similar accuracy with reduced computing expenses, rendering them more appropriate for real-time forecasting.

Table 7: Comparison of hybrid models with deep learning approaches

| Model | Methodology | Performance Metrics | Comparison Results |
|---|---|---|---|
| Hybrid Models (RBF-HGS) | Radial Basis Function with Harris Hawks Optimization | Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination ($R^2$) | Demonstrates competitive accuracy and lower computational costs compared to deep learning models, making it more suitable for real-time forecasting applications. |
| Long Short-Term Memory (LSTM) | Deep Learning Approach | RMSE, MAE, $R^2$ | Performs well but with higher computational costs compared to hybrid models. |
| Gated Recurrent Units (GRU) | Deep Learning Approach | RMSE, MAE, $R^2$ | Similar performance to LSTM, but computationally more efficient, though still higher than hybrid models. |
| Attention-based Models | Deep Learning Approach | RMSE, MAE, $R^2$ | Outperforms some models in accuracy but incurs higher computational costs, making real-time applications challenging. |

This study contains drawbacks, including a dataset confined to daily electricity usage data from a singular region, hence diminishing the generalizability of the findings. Although the hybrid models enhanced forecasting precision, they also resulted in elevated computing expenses, especially the Radial Basis Function-Harris Hawks Optimization model, which exhibited prolonged runtimes. The potential of these models for real-time forecasting applications could enhance energy management, grid stability, and planning; however, their computational expense must be taken into account for large-scale or real-time implementation. This study is constrained by a two-year dataset from a singular source, which impacts generalizability. Subsequent research ought to augment the dataset by incorporating data from diverse locales and extended time periods. While hybrid models, especially RBF-HGS, provide superior accuracy, they entail computational trade-offs, such as extended runtimes, which impede real-time applications. Subsequent efforts should concentrate on enhancing efficiency to reconcile accuracy with computational expense. Scenario simulations or case studies, such as the implementation of the RBF-HGS model in a regional power system, could illustrate how the models optimize real-time energy distribution and improve decision-making. The results indicate that hybrid models surpass traditional approaches, with RBF-HGS enhancing RMSE by 12% and $R^2$ by 0.05, while also decreasing training durations, rendering them appropriate for real-time applications.

# 4 Conclusion

This article, therefore, performs an in-depth review of STLF in the electric power sector, supported by a multidimensional approach, incorporating machine learning algorithms with advanced optimization techniques. In this respect, the application of SVR and RBF algorithms supported optimization mechanisms such as AO, PSO, and HGS aimed to ensure increased accuracy and efficiency in the operation of the forecasting model. The findings from this research detail significant enhancements through hybrid modeling and optimization strategies. In particular, the best model is the RBF-HGS hybrid model, which has the best performance during both the training and testing phases. This implies that the hybrid model can really enhance the precision of forecasts with an appropriate integration, thus providing a useful reference for operators, policy makers, and researchers in the power system. Furthermore, the sensitivity analysis in this study indicated how impactful parameters like temperature and humidity could be on short-term load forecasting accuracy. Understanding these influential factors is crucial in developing more robust forecasting models and optimizing energy management strategies. Finally, this research improves the methods of STLF techniques and provides practical implications for stakeholders in the electric power sector. By incorporating hybrid models and considering influential variables, power system operators and researchers will be able to enhance decision-making in optimizing energy forecasting and improving system reliability. Subsequent research efforts could investigate supplementary variables and innovative optimization techniques to bolster the precision as well as STLF models' resilience.

This study illustrates the efficacy of the hybrid RBF-HGS model in improving the precision of short-term load forecasting within the electric power industry. The RBF-HGS model, by incorporating advanced optimization techniques with machine learning, surpasses standalone models like SVR and RBF, providing significant enhancements in real-time forecasting precision. These developments could greatly enhance operational planning, grid stability, and resource allocation for power system operators. Subsequent research should concentrate on augmenting the dataset to encompass data from various areas and investigating the model's scalability for larger power systems. Furthermore, integrating deep learning models and boosting computational efficiency could significantly improve the model's practical application and performance.

## Abbreviation

| | | | |
|---|---|---|---|
| A10 | A10 Index | MLR | Multiple Linear Regression |
| ANN | Artificial Neural Network | MOFA | Multi-objective firefly algorithm |
| AO | Aquila Optimizer | MSE | Mean Squared Error |
| | | Pbest | The best particle group |
| AOA | Arithmetic optimization algorithm | PSO | Particle Swarm Optimization |
| | | r1 and r2 | Random numbers |
| ARIMA | Autoregressive Integrated Moving Average | RBF | Radial Basis Function |
| ARMA | Autoregressive Moving Average | RMSE | Root Mean Square Error |
| BF | The best fitness | | |
| DRV | Deviation of Runoff Volume | STLF | Short-term load forecasting |
| EMD | Empirical mode decomposition | SVM | Support Vector Machines |
| f( Xi(k)) | The objective function value | SVR | Support Vector Regression |
| F(i) | The fitness value | | |
| FOA | Fruit fly optimization algorithm | UBj and LBj | Boundaries of the search domain |
| gbest | The optimal location within the Pbest group | Vi(k) | The velocity of particle |
| GRNN | Generalized regression neural network | VAF | Variance Accounted For |
| | | WNN | Wavelet neural network |
| HGS | Hunger Games Search | WF | The least favorable fitness |
| hj | The hidden layer | xj | Input vector |
| | | Xb | Best agent |
| IEMD | Improved empirical mode decomposition | XM | The population's average agent |
| K(x, xi) | The kernel function | σj | The width parameter of node |
| Levy(D) | Levy flight | | |
| m | The number of nodes | | |
| MAE | Mean Absolute Error | | |
| MARS | Multivariate Adaptive Regression Spline | | |
| ML | Machine learning | | |

## Authorship contribution statement

Xiaoyan Tang: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.
Pengfei Yue: Methodology, Software

## Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

## Author statement

All the authors have read and approved the manuscript. As stated earlier in this document, the requirements for authorship have been met, and each author believes that the manuscript represents honest work.

## Ethical approval

All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

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