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A Hybrid Prediction Model for Short-Term Load Forecasting in Power Systems

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ABSTRACT

Short-term load forecasting (STLF) plays a vital role in effective power system management by assisting power dispatch centers in developing generation plans and ensuring smooth system operation. This study introduces a novel hybrid prediction model called iSSA-LSSVM to tackle the STLF challenge. By integrating the Salp Swarm Algorithm (SSA) with Least Squares Support Vector Machines (LSSVM), the iSSA-LSSVM model significantly improves LSSVM's prediction accuracy. One of the key contributions is the model's ability to autonomously fine-tune LSSVM hyperparameters, eliminating the need for manual adjustments and optimizing performance. Modifying the SSA within iSSA-LSSVM enhances the original algorithm's exploration and exploitation capabilities, ensuring better search efficiency and precision. Using a dataset with four independent variables as input and electrical power output as the target variable, the model demonstrates superior predictive performance. Comparative analysis with three other models shows that iSSA-LSSVM achieves a lower Mean Square Error (MSE) and faster convergence. This improvement in accuracy and efficiency enhances STLF, allowing power dispatch centers to develop more precise generation plans and ensure more reliable power system operation.

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1. INTRODUCTION

The power system is an intricate network where challenges emerge throughout planning, execution, commissioning, and ongoing maintenance, spanning from generation and transmission to distribution. Integrating renewable energy sources into these existing networks introduces significant concerns, including voltage fluctuations, power imbalances, and a notable increase in power losses. One of the most exciting topics in power system planning is forecasting the electricity load. This particularly crucial because the power system, characterized by its complexity and challenges across various stages from generation to distribution, faces issues such as voltage fluctuations, power imbalances, and increased power losses, especially in integrating renewable energy sources.

Electricity load forecasting, predominantly in the context of short-term predictions, holds substantial academic importance due to its pivotal role in enhancing the operational efficiency of power systems and aiding participants in the electricity market. Load prediction entails forecasting future energy demand by analyzing historical energy consumption records in a time series format [1]. The accuracy of forecasts for renewable energy efficiency plays a crucial role in the effective management and operation of energy systems. [2]. More precise predictions reduced risk and enhanced stability and reliability of the network [3, 4]. Precise load forecasting outcomes offer valuable insights for crafting power generation strategies and facilitating informed decision-making among market stakeholders. As a consequence, this is a key factor in ensuring the stability and economic viability of the power system. Historical demand data combined with piecewise interpolation, an electricity demand forecasting methodology, has been proposed in [5].

Short-Term Load Forecasting (STLF) is essential

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for evaluating and planning power grid needs, as it allows for predicting future electricity demand from customers [6]. This forecasting process employs different scoring methods to determine the accuracy of load predictions across various time horizons. Depending on the timeframe of the prediction, load forecasting can be categorized into several groups. Very STLF (VSTLF), which operates on timescales from one minute to ten minutes, focuses on achieving economic control and managing load frequency fluctuations. STLF, spanning from minutes or hours to weeks [7, 8], is instrumental in balancing the supply and demand of electricity. Medium-Term Load Forecasting (MTLF), covering periods from one day to a year, aids in scheduling power outages and planning maintenance activities. MTLF offers a theoretical foundation for optimizing the maintenance of grid equipment [9]. Lastly, Long-Term Load Forecasting, extending beyond a year, plays a crucial role in the strategic planning of infrastructure development within the power grid domain [10].

Electric load forecasting relies on three primary types of models: statistical models, conventional models, and hybrid models. Traditionally, statistical models and machine learning (ML) techniques have been vital in forecasting electric load demand. The field has witnessed extensive utilization of both methods. Moreover, achieving improved forecasting results typically involves combining various techniques or models. Hybrid approaches, for instance, may include integrating time series analysis with ML or combining multiple ML models to optimize predictions.

ML techniques have demonstrated significant efficiency across diverse fields, such as the study in [11], which evaluated Sift-SVM for defect detection in smartphone camera modules. Meanwhile, a study in [12] presented a lightweight model that leverages optical flow and RGB data to detect violence in video streams, achieving high accuracy in categorizing violent behaviors. The study highlights the potential of machine learning models to enhance real-time decision-making, similar to their application in STLF.

Load forecasting remains a significant subject of interest, as evidenced by numerous published studies in literature, spanning from the past to the present. Numerous techniques, whether single or hybrid, have been proposed to enhance the precision of load forecasting, with the goal of improving overall accuracy in predicting future electrical demands. Load forecasting and operation strategy for distributed energy systems (DES) based on utility reformation has been discussed in [13]. In the study conducted by [10], two distinct techniques were presented for STLF, namely Auto-Regressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN). The efficacy of these proposed techniques was evaluated using actual daily electricity consumption data from 707 individual households in Ireland, spanning for a 18-month duration. In the study, the evaluation criterion used was the Mean Absolute Percentage Error (MAPE), which indicated a preference for the ANN approach in terms of forecasting accuracy. The preference for the ANN approach arises from the fact that ARIMA is unsuitable for handling these datasets due to its limitations in capturing non-linear characteristics. Additionally, ARIMA outcomes are highly influenced by observation frequency and measurement errors [14]. This assertion is further substantiated in [15]. The application of ANN can also be observed in [16], where it demonstrates the utilization of ANN in conjunction with an improved Markov chain, while another ANN-based method is [17]. In the study, an error-correction module inspired by the concept of meta-learning is incorporated into the model to capture the nonstationary pattern of the grid load. On the other hand, the study in [18], the ANN is applied to a large-scale power system. Nonetheless, it is worth noting that ANN is sensitive to hyperparameters, requiring careful tuning to achieve good results. Besides, it also involves longer training time. As a result, hybrid models have been proposed, such as those discussed in [19], which combine ANN with Invasive Weed Optimization and Differential Evolution methods. The primary objective of the study is to utilize meta-heuristic approaches for training the neural network to enhance the precision of the perceptron neural network. The findings indicate that the algorithm put forward leads to increased convergence with neural network coefficients compared to existing algorithms. Nevertheless, the suggested approach also resulted in a decrease in prediction errors within the neural network.

Empirical Wavelet Transform (EWT) and Autoformer time series prediction model for Time series analysis model in forecasting have been proposed in [20]. Meanwhile, in [1], a hybrid technique for residential loads using Empirical Mode Decomposition (EMD) and Extreme Learning Machines (ELM) is presented, which is validated using real-time residential intelligent meter data. The approach presented in [1] is similar to the models [21-23], which also utilized ELM-based techniques for predicting of the case of interest. A refined version of ELM is presented in [24], where the ELM is in hybrid with Particle Swarm Optimization (PSO) to attain optimal parameter values. Even with the hybrid model, the ELM may be exposed to its limited adaptability to dynamic environments and changing data patterns, which require further improvement.

The study in [25] utilized a hybrid model combining Manta-Ray Foraging Optimization to optimize the Support Vector Regressor (SVR). The evaluation also considers other hybrid techniques, such as SVR optimized by the Slime Mould Algorithm (SMA) [26], Moth Flame Optimization (MFO) [27], and a few others. When tested on real-world case data, these proposed hybrid techniques have shown the ability to mitigate the weaknesses of a single method. Other hybrid techniques between ML and optimization techniques also can be seen in [28-30]. In [30], the study optimized the use of Deep Learning (DL) for short-term multivariate time series load forecasting at low voltage levels by incorporating Adaptive Wind-Driven Optimization (AWDO). This optimization technique has significantly improved the performance of the proposed technique.

Another hybrid DL approach for load forecasting is demonstrated in [31]. In this study, features are selected using Pearson correlation coefficients, and subsequently, the hybrid DL model is constructed by combining BiLSTM and Random Forest. When evaluated using the MAPE, the proposed model demonstrated lower error rates compared to benchmark models, including the single Random Forest and single BiLSTM models. In [32], a mathematical model is developed for predicting energy output using both the Sequential API and Functional API within ANN, specifically with a single hidden layer for each approach. The successful training and testing of all models demonstrated their strong compatibility in predicting the energy output of a Combined Cycle Power Plant (CCPP). Works in [33] employed similar data as in [34].

Previously, in 2017, an STLF model that combines singular spectrum analysis and Support Vector Machines (SVM), and fine-tuned using the Cuckoo Search (CS) algorithm was developed [35]. SVM is a supervised learning algorithm used for classification and regression tasks [36]. Before the forecasting process, the CS algorithm was employed to address the shortcomings associated with manually chosen parameters. Experimental results showcased that the suggested model surpassed the performance of individual SVM, Seasonal Autoregressive Integrated Moving Average (SARIMA), and Back Propagation Neural Network (BPNN). An alternative hybrid SVM incorporating optimization techniques has been documented in [37, 38], where the SVM was automatically fine-tuned using the Grasshopper Optimization Algorithm (GOA) and Firefly Algorithm (FA), respectively.

The study centered on developing a prediction model for the full-load electrical power output of a base power plant. To achieve this objective, a hybrid model is introduced that combines an improved version of the Salp-Swarm Algorithm (iSSA) with the Least Squares Support Vector Machine (LSSVM) [39], referred to as the iSSA-LSSVM. The SSA is chosen as an optimizer for LSSVM due to its encouraging performance, which has been proven in numerous published studies [40-42].

The primary contributions of this study are as follows:

1. Automatic Hyper-Parameter Tuning for LSSVM: This study introduces a novel approach for automatic hyper-parameter tuning specifically designed for LSSVM. This method significantly reduces the need for manual intervention and enhances the model performance and generalization capabilities.
2. Enhancement of the Standard Salp Swarm Algorithm (SSA): Significant improvements to the standard SSA are proposed, focusing on refining both the exploitation and exploration phases (see Section 3.2). These enhancements lead to a more efficient and effective search process, resulting in better optimization outcomes.
3. Application of iSSA-LSSVM for Predicting Power Plant Output: The iSSA-LSSVM is implemented to predict the full load of electrical power output of a base power plant. This application illustrates the practical usefulness and higher predictive accuracy of the proposed method when applied to real-world situations.

This paper is organized as follows: Section 1 discusses the importance of time series prediction, mainly using ML-based algorithms. The existing works related to the research topic are also presented in this section. Sections 2 and 3 provide a concise overview of the chosen machine learning technique, LSSVM, and the optimization tool, SSA, respectively. The implemented methodology is described in Section 4, while the obtained results are discussed in Section 5. Finally, Section 6 concludes the paper.

2. LEAST SQUARES SUPPORT VECTOR MACHINES

Least Squares Support Vector Machines (LSSVM) [39] is a noteworthy machine learning technique derived from the conventional SVM [43]. The expression for the LSSVM regression model is as follows:

$$y(x) = \sum\nolimits_{i=1} aiK(x, xi) + b \tag{1}$$

This expression represents the kernel functions, with b denoting the ith support vector, Lagrange multipliers, and bias parameters, respectively. Compared to other available kernels, such as linear, polynomial, and multilayer perceptron, the Radial Basis Function (RBF) kernel has demonstrated its superiority in delivering outstanding performance. Hence, the RBF kernel was employed in this study and is defined as follows:

$$K(xi, xj) = exp\left(\frac{\|xi - xj\|^2}{2\sigma^2}\right) \tag{2}$$

3. OPTIMIZATION BASED ON THE SALP-SWARM ALGORITHM

This section discusses the characteristics of the SSA as found in nature, along with its mathematical model. A detailed explanation of the algorithm can be discovered in [44].

3.1 Formulation of Salp-swarm Algorithm

The salp population is first divided into two groups: the leaders and the followers. The leader is situated at the forefront of the salp chain, while the remaining salps make up the followers. The leader is responsible for guiding the salp swarm, while the followers follow each other (including the leader directly or indirectly). The Salp Swarm Algorithm (SSA) [44] is controlled by only one parameter. Salp positions are defined in an n-dimensional space, where n represents the number of variables for the specific problem being addressed, as follows:

$$x_j^i = \begin{cases} F_j + c_1[(ub_j - lb_j)c_2 + lb_j]c_3 & \geq 0 \\ [F_j + c_1[ub_j - lb_j]c_2 + lb_j]c_3 & < 0 \end{cases} \tag{3}$$

where;

F_j = food source position in the jth dimension

x_j^i = the position of the first salp i.e., the leader

c_1, c_2 and c_3 = random numbers

ub_j and lb_j = upper and lower bound of jth dimension, respectively

Equation (3) defines how the position of x_j^i, the first salp or leader, is updated based on the position of the food source F_j. This equation updates only the leader's position in relation to the food source. However, the second step, responsible for balancing both the exploitation and exploration processes, requires a more sophisticated approach. The random number c_1 plays a crucial role in achieving this balance between the two processes. Equation (4) defines c_1, which is essential in ensuring optimal results for the Salp Swarm Algorithm, as follows:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{4}$$

Equation (5) defines how the position of followers is updated. In this equation, the position of each follower is adjusted according to the positions of both the leader and the other followers. The variables l and L represent the current iteration and the maximum number of iterations, respectively. Additionally, the parameters c_2 and c_3 are random numbers uniformly generated within the interval of [0, 1]. They dictate whether the following positions in the jth dimension should be towards positive infinity or negative, as well as the step size.

$$x_j^i = \frac{1}{2}at^2 + v_0 t \tag{5}$$

where

$i \geq 2$

x_j^i = position of ith follower salp in jth dimension

t = time

v_0 =initial speed

$a = \frac{v_{final}}{v_0}$, where $v = \frac{x - x_0}{t}$

In optimization, the measure of time is typically the number of iterations. Thus, the difference between iterations is usually one. When $v_0 = 0$, this can be defined using equation (6):

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{6}$$

x_j^i = position of ith follower salp in jth dimension

The salp chain simulation can be implemented using equations (3) to (6). A pseudocode for the Salp Swarm Algorithm is provided in Figure 1.

Algorithm 1: SSA

```
Start
Initialize the salp population xi (i =1, 2, …, N), considering ub and lb
While (end condition is not satisfied) do
   Calculate fitness function of each agent (salp)
   F=the best search agent
   Update ci using (4)
   For xi (each salp)
     If(i==1)
       Update the position of the leading salp by (3)
     Else
       Update the position of the follower salp by (5)
     End
   End
Update the salps based on ub and lb
Return F
```

Fig.1: *SSA Pseudo Code.*

3.2 Improved Salp-swarm Algorithm

In this study, two specific enhancements to the traditional SSA has been introduced to improve its performance in optimization tasks:

a. The traditional SSA can be less effective during the exploitation phase, especially when the search space is enormous. To improve this, equation (3) has been revised by eliminating the lower bound, enabling a more aggressive search for optimal solutions. The updated equation is:

$$\boldsymbol{x_j^1} = \begin{cases} \boldsymbol{F_j + c_1\left((ub_j - lb_j)c_2\right), c_3} & \boldsymbol{\geq r} \\ \boldsymbol{F_j - c_1\left((ub_j - lb_j)c_2\right), c_3} & \boldsymbol{< r} \end{cases} \tag{7}$$

Where r is a uniformly distributed random number between 0 and 1. The modification enhances the algorithm's ability to focus on promising areas in the search space, thereby improving exploitation.

b. Improved Exploration: To enhance the exploration capability, particularly at the followers' level, a new term has been introduced incorporating the distance between the follower's current position and the leader's position. This term, combined with random parameters p and $q = (1 - p)$, increases diversity in the search process. The updated position update equation for followers is:

$$\boldsymbol{x_j^i} = \left(\boldsymbol{p x_{ij}} + \boldsymbol{q x_j^{i-1}}\right), \boldsymbol{i} \geq \mathbf{2} \tag{8}$$

This addition promotes a more diverse search pattern and prevents premature convergence by encouraging followers to explore new areas around the leader.

These modifications, detailed in Equations (7) and (8), are designed to enhance both the exploitation and exploration capabilities of the SSA. Consequently, the iSSA demonstrates better performance in locating optimal solutions. The iSSA is then hybridized with LSSVM, resulting in a more robust model for predictive applications, as discussed in Section 5. The improvement of iSSA is similar that observed in [45]. Subsequently, the iSSA was hybridized with LSSVM for predictive applications.

4. RESULT AND DISCUSSION

This section describes the methodology implemented for this study, which includes details about the employed dataset, the proposed iSSA-LSSVM prediction model, the parameter settings, and the metric used for evaluation.

4.1 Dataset Description

The dataset used in this study was the same as the one used in a previous study [34]. The dataset includes four independent parameters: AT, which represents ambient temperature; AP, indicating atmospheric pressure; RH, denoting relative humidity; and V, which refers to exhaust steam pressure. One dependent parameter, labeled PE, corresponds to the total electrical power output. The dataset spans a six-year period from 2006 to 2011 and contains 9,568 instances. The AT is recorded in whole degrees Celsius ($\circ$C) with values ranging from 1.81 to 37.11$\circ$C. AP, is collected in milli bars unit with values varying from 992.89 to 1033.30 mbar. Meanwhile, the RH is measured in percentage with collected values ranging from 25.56-100.16%. The value of V is measured in cm Hg and ranges from 25.36-81.56 cm Hg, while the dependent output variable, PE, is measured in Megawatt (MW) with a range of 420.26-495.76 MW. It is important to note that the prediction approach used in this study differs slightly from the one used in [34].

The selected input variables for this study are based on their direct influence on power plant performance and overall energy output. AT affects the efficiency of the plant's cooling systems and, consequently, its production. AP influences air density, which is critical for combustion and turbine performance. RH plays a role in the cooling process and energy transfer efficiency, while V is a crucial factor in the efficiency of steam turbines, directly affecting the plant's power generation. Together, these four independent variables provide a comprehensive representation of environmental and operational conditions, allowing for a more accurate prediction of the PE.

To prevent overfitting and to ensure the applicability of the proposed hybrid model for future power output prediction of combined cycle power plant (CCPP), the 9568 data points are divided into 70% for training, 15% for validation, and 15% for testing. The specifications of the input-output model can be found in Table 1.

Table 1: *Training, Validation and Testing Data.*

Input	Training Data	Output	Validation Data	Testing Data
AT	1-6700 instances (70%)	P_E	6701-8134 instances (15%)	8135-9568 instances (15%)
AP				
RH				
V				

The mentioned dataset was normalized using zero mean normalization. The purpose is to provide the same range of values for each input in the prediction model. Correctly selecting input variables is essential in predicting the full load electrical power output because it directly affects the accuracy of the prediction model. Determining which input variables significantly influence the prediction results is a crucial component of this task. These parameters, which are related to ambient conditions and exhaust steam pressure, serve as the input variables within the dataset utilized in this study.

4.2 iSSA-LSSVM Prediction Model

In the proposed iSSA-LSSVM, the improved Salp Swarm Algorithm (iSSA) is utilized to fine-tune the hyperparameters γ and σ^2 of the LSSVM automatically. These hyperparameters significantly influence the model's performance, as they determine the trade-off between the regularization term and the kernel function's spread. Manual tuning of these parameters is often labor-intensive and prone to suboptimal results, mainly when dealing with complex datasets. The iSSA algorithm, as detailed in Section 3.2, automates this tuning process by efficiently exploring the solution space, enhancing both exploration and exploitation capabilities. This automation ensures that the model consistently identifies the optimal hyper-parameter values without requiring extensive trial-and-error methods. By integrating iSSA, the proposed model navigates the hyper-parameter space more effectively, adjusting γ and σ^2 in response to the dataset's characteristics. The flowchart in Figure 2 visualizes the complete tuning process, illustrating how iSSA iteratively searches for the optimal hyper-parameters within the defined maximum number of iterations.

Once these optimal values are identified, they

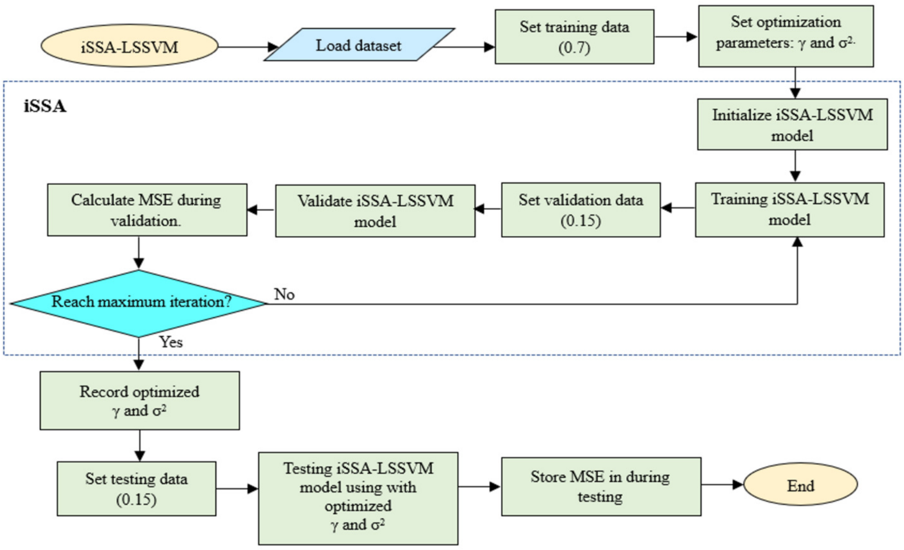

Fig.2: *iSSA-LSSVM flowchart.*

are directly applied to the LSSVM, leading to enhanced predictive performance, as shown in the testing phase. This automatic hyper-parameter tuning approach provides significant benefits by reducing the computational effort required for manual tuning and improving the overall reliability of the LSSVM model. As a result, the iSSA-LSSVM model delivers improved prediction accuracy and robustness, providing a more practical and scalable solution for real-world applications.

4.3 Comparison Hybrid Algorithms

For comparison, the proposed iSSA-LSSVM will be tested against three other hybrid methods: SSA-LSSVM, PSO-LSSVM, and CV-LSSVM. Brief descriptions of PSO and CV are provided below:

4.3.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) [46], a meta-heuristic optimization algorithm, is inspired by the social behavior of bird flocks or fish schools. It involves a population of potential solutions, called particles, that move through the search space, guided by their own best-known position and the global best-known position in the swarm. Each particle's position represents a potential solution, and the algorithm continuously refines these solutions until a satisfactory one is identified. At each iteration, the particles update their velocities and positions based on their previous velocity, best-known position, and the global best-known position in the swarm. In PSO, the velocity update rule is influenced by the particle's tendency to move towards its own best-known position (exploitation) and its tendency to move towards the global best-known position (exploration). PSO has gained widespread popularity because of several key advantages: its computational efficiency and straightforward implementation, its ability to adapt to different types of problems, its flexibility in handling various constraints, its rapid convergence toward optimal solutions[47], and the fact that it requires tuning relatively few parameter values [48].

4.3.2 Cross Validation

K-fold cross-validation is a commonly used technique for assessing the performance of a ML model. The method involves partitioning the available data into k equal-sized subsets or folds, and then repeatedly training the model on $k-1$ of these folds while using the remaining. This process is carried out k times, with each fold being the validation set once. The model performance is then averaged over all k iterations, which yields a more reliable estimate of the model's performance.

4.4 Parameters Setting

Before training the dataset, parameters settings for all identified algorithms, namely iSSA-LSSVM, LSSVM optimized by Particle Swarm Optimization (PSO-LSSVM), original SSA (SSA-LSSVM), and Cross Validation (CV-LSSVM) are established as shown in Table 2. The proposed iSSA-LSSVM algorithm, and the selected approaches, was used to determine the optimal hyper-parameters settings, with the maximum iteration required for achieving the best mean squared error (MSE) being governed as 10 through a series of experiments. Increasing the maximum number of iterations did not lead to better results. Meanwhile, the size of the population, lower bound, and upper bound values were determined based on a trial-and-error approach.

Table 2: *Parameters Setting.*

	iSSA-LSSVM	SSA-LSSVM	PSO-LSSVM	CV-LSSVM
Maximum iteration	10	10	10	10
Population size	10	10	10	-
The lower bound of γ and σ^2	1	1	1	1
The upper bound of γ and σ^2	1000	1000	1000	1000

4.5 Prediction Evaluation Metrics

The performance of the prediction models is evaluated using the following metrics:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{9}$$

Where n represents the number of data points, Y_i denotes Observed values while $\hat{Y}_i$ is the predicted values. This means that if a prediction model performs better, the metrics used to evaluate its performance would have smaller values.

5. RESULTS

Experiments were conducted using the parameter setting outlined in section 4.4. The goal was to compare the performance of iSSA-LSSVM with other algorithms, including SSA-LSSVM, PSO-LSSVM, and CV-LSSVM, in predicting power output.

The results obtained are presented in Table 3. The table demonstrates that the iSSA-LSSVM outperformed other hybrid algorithms, achieving the lowest MSE of 14.4322, marked in bold. This result indicates a higher accuracy and efficiency than the different models. The optimal hyper-parameters for iSSA-LSSVM $\gamma = 707.0735$ and $\sigma^2 = 1$, reflecting the best balance of model complexity and performance. In contrast, SSA-LSSVM, while close in performance, showed an MSE that was slightly higher by 0.0066, with $\gamma = 748.6146$ and $\sigma^2 = 1$. Though the difference is marginal, it demonstrates the refinement achieved through the improved optimization in iSSA-LSSVM.

PSO-LSSVM, which has an MSE of 16.8418, and CV-LSSVM, with the highest MSE of 17.1841, lag in accuracy and efficiency. The significant difference in MSE for CV-LSSVM, which uses $\gamma = 14.2488$ and $\sigma^2 = 35.3795$, indicates that this algorithm struggled to optimize the hyper-parameters effectively, resulting in a lower performance. This analysis highlights the superior performance of iSSA-LSSVM in terms of accuracy (lower MSE) and efficiency (optimized hyper-parameters), thereby reinforcing its potential in the application domain.

Table 3: *Optimal Results Obtained by All Hybrid Algorithms.*

	iSSA-LSSVM	SSA-LSSVM	PSO-LSSVM	CV-LSSVM
γ	707.0735	748.6146	829.8137	14.2488
σ^2	1	1	45.1214	35.3795
MSE	**14.4322**	14.4388	16.8418	17.1841

Furthermore, Figure 3 compares the performance of iSSA-LSSVM with different hybrid algorithms. The blue line defined iSSA-LSSVM, while the orange line represents SSA-LSSVM. The other algorithms, including PSO-LSSVM, CV-LSSVM, and actual values, are represented by the yellow, purple, and green lines, respectively. The figure shows that iSSA-LSSVM generated prediction values that are closest

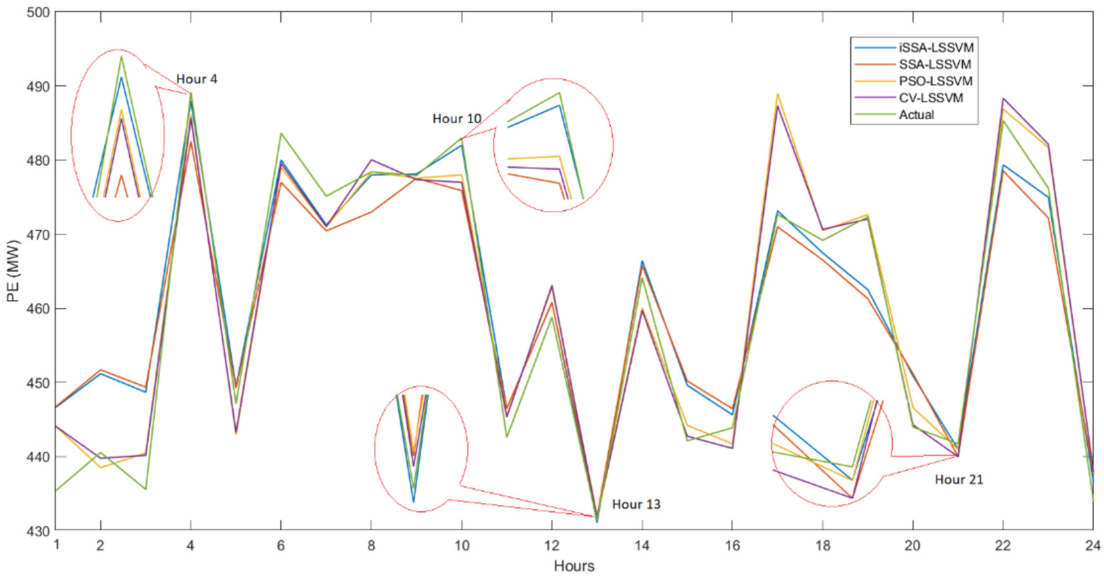

Fig.3: *Comparison of Predicted power output for 24 hours by all identified hybrid methods.*

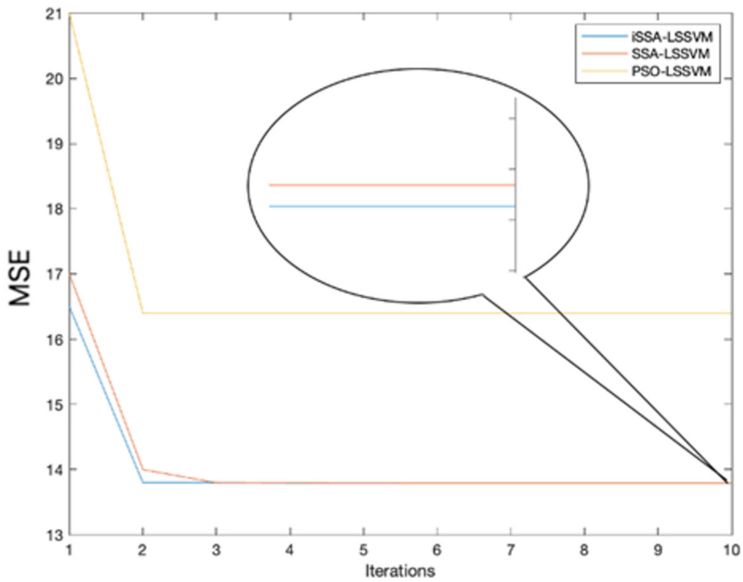

Fig.4: *Comparison of Convergence Curve.*

to the actual values compared to the other hybrid algorithms. Even during sudden spikes in hour 4, the proposed iSSA-LSSVM could still to learn the pattern and produce the closest values. Additionally, during hours 10, 13, and 21, iSSA-LSSVM yielded the closest values. It is also noteworthy that during hour 13, all algorithms could to produce almost precise outputs.

Figure 4 compares the convergence rate performance of iSSA-LSSVM, SSA-LSSVM, and PSO-LSSVM. The graph indicates that iSSA-LSSVM has a faster convergence rate than SSA-LSSVM, as the line for iSSA-LSSVM falls below the line for SSA-LSSVM. This improvement is attributed to the introduced enhancement that supports the algorithm's exploration and exploitation process, which ultimately enables it to attain global optimal rather than local optimal.

The results presented in Figure 4 provide compelling evidence of the superiority of the iSSA-LSSVM over SSA-LSSVM and PSO-LSSVM in terms of convergence rate for time series prediction. The introduced improvement contributed to the faster convergence rate achieved by iSSA-LSSVM, effectively supporting both the exploitation and exploration processes. By striking a balance between exploitation and exploration, iSSA-LSSVM avoids being trapped in local optima and converges more rapidly towards the global optimum. This feature is beneficial for time series prediction tasks, where it is essential to accurately capture the patterns and dynamics of the data.

It is worth noting that while SSA-LSSVM eventually converges, the results indicate a saturation point at a higher MSE value. This finding suggests that SSA may encounter challenges handling specific datasets or prediction tasks, leading to suboptimal outcomes or longer convergence times. The iSSA-LSSVM, on the other hand, exhibits a more favorable convergence behavior, demonstrating its potential to overcome such limitations and deliver improved performance in various scenarios. However, it can struggle with specific data sets or prediction tasks, leading to suboptimal results or longer convergence times. Regarding computational efficiency, all the algorithms evaluated in this study, namely iSSA-LSSVM, SSA-LSSVM, CV-LSSVM, and PSO-LSSVM, demonstrated highly efficient performance, with computation times consistently under one minute.

The differences in computational times between the algorithms were minimal, indicating that each method can provide predictions within an acceptable time frame for real-time applications such as STLF. The overall time efficiency was comparable across all algorithms, ensuring that the choice of method does not impose a significant computational burden in practical settings. Therefore, computational time is not a limiting factor when selecting these methods for STLF tasks.

Overall, the results provide valuable insights into the effectiveness of different hybrid algorithms for predicting power output from generators. The superior performance of iSSA-LSSVM could suggest that combining different optimization techniques can lead to better results than using only a single optimization method. However, more research is needed to validate these findings and determine the optimal parameter settings for different data sets and prediction tasks. The enhanced exploration and exploitation process of iSSA-LSSVM contributed to its faster convergence rate and ability to attain global optimal. These findings can inform future research in the field of power output prediction and provide a basis for devoloping of more effective hybrid algorithms.

6. CONCLUSION

This study introduces the iSSA-LSSVM hybrid method to enhance the generalization capabilities of LSSVM in time series prediction of full-load electrical power output. By optimizing LSSVM hyper-parameters through improved SSA, the approach aims to improve overall performance by avoiding local optima. This study focuses on two main objectives: automatic optimization of critical LSSVM hyper-parameters using the advantages of the SSA algorithm and enhancing the SSA algorithm itself. The iSSA-LSSVM method shows promising outcomes, especially regarding convergence rate, suggesting efficiency in finding optimal solutions. For future work, the proposed method will be evaluated on a broader range of time series data. Additionally, hybrid approaches will be explored, explicitly integrating iSSA-LSSVM with various deep learning architectures, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), to enhance time series prediction accuracy further. The focus will be on investigating how these hybrid models can improve performance in short-term and long-term forecasting scenarios.

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AUTHOR CONTRIBUTIONS

Conceptualization, methodology, validation, formal analysis, investigation, data curation, and writing—original draft preparation, Z.M.; writing—review, editing, and visualization, M.H.S. All authors have read and agreed to the published version of the manuscript.

References

[1] S. M. Sulaiman, P. A. Jeyanthy, D. Devaraj and K. V. Shihabudheen, "A novel hybrid short-term electricity forecasting technique for residential loads using Empirical Mode Decomposition and Extreme Learning Machines," *Computers & Electrical Engineering*, vol. 98, p. 107663, 2022.

[2] X. He, W. Zhao, Z. Gao, Q. Zhang and W. Wang, "A hybrid prediction interval model for short-term electric load forecast using Holt-Winters and Gate Recurrent Unit," *Sustainable Energy, Grids and Networks*, vol. 38, p. 101343, 2024.

[3] R. Wazirali, E. Yaghoubi, M. S. S. Abujazar, R. Ahmad and A. H. Vakili, "State-of-the-art review on energy and load forecasting in microgrids using artificial neural networks, machine learning, and deep learning techniques," *Electric Power Systems Research*, vol. 225, p. 109792, 2023.

[4] Y. Wang, S. Sun, G. Fathi and M. Eslami, "Improving the Method of Short-term Forecasting of Electric Load in Distribution Networks using Wavelet transform combined with Ridgelet Neural Network Optimized by Self-adapted Kho-Kho Optimization Algorithm," *Heliyon*, vol. 10, no. 7, p. e28381, 2024.

[5] S. Williams and M. Short, "Electricity demand forecasting for decentralised energy management," *Energy and Built Environment*, vol. 1, no. 2, pp. 178-186, 2020.

[6] S. Nazir, H. Hamdoun, O. Al-Azubi and J. Alzubi, "Cyber Attack Challenges and Resilience for Smart Grids," *European Journal of Scientific Research*, vol. 134, no. 1, pp. 111-120, 2015.

[7] A. Jahani, K. Zare, and L. M. Khanli, "Short-term load forecasting for microgrid energy management system using hybrid SPM-LSTM," *Sustainable Cities and Society*, vol. 98, p. 104775, 2023.

[8] H. Wang, K. A. Alattas, A. Mohammadzadeh, M. H. Sabzalian, A. A. Aly and A. Mosavi, "Comprehensive review of load forecasting with emphasis on intelligent computing approaches," *Energy Reports*, vol. 8, pp. 13189-13198, 2022.

[9] S. Zhang, R. Chen, J. Cao, and J. Tan, "A CNN and LSTM-based multi-task learning architecture for short and medium-term electricity load forecasting," *Electric Power Systems Research*, vol. 222, p. 109507, 2023.

[10] C. Tarmanini, N. Sarma, C. Gezegin and O. Ozgonenel, "Short term load forecasting based on ARIMA and ANN approaches," *Energy Reports*, vol. 9, pp. 550-557, 2023.

[11] H. A. Phan *et al.*, "Development of an Autonomous Component Testing System with Reliability Improvement Using Computer Vision and Machine Learning," *ECTI Transactions on Computer and Information Technology (ECTI-CIT)*, vol. 18, no. 1, pp. 64 - 75, 2024.

[12] A. Dey, S. Biswas and L. Abualigah, "Efficient Violence Recognition in Video Streams using ResDLCNN-GRU Attention Network," *ECTI Transactions on Computer and Information Technology (ECTI-CIT)*, vol. 18, no. 3, pp. 329-341, 2024.

[13] C. Li, Z. Li, H. Zhu, Z. Tian, and W. Feng, "Study on operation strategy and load forecasting for distributed energy system based on Chinese supply-side power grid reform," Energy and Built Environment, vol. 3, no. 1, pp. 113-127, 2022.

[14] G.-F. Fan, Y.-Y. Han, J.-W. Li, L.-L. Peng, Y.-

H. Yeh and W.-C. Hong, "A hybrid model for deep learning short-term power load forecasting based on feature extraction statistics techniques," *Expert Systems with Applications*, vol. 238, p. 122012, 2024.
[15] M. Zhang et al., "Accurate ultra-short-term load forecasting based on load characteristic decomposition and convolutional neural network with bidirectional long short-term memory model," *Sustainable Energy, Grids and Networks*, vol. 35, p. 101129, 2023.
[16] A. Alhendi, A. S. Al-Sumaiti, M. Marzband, R. Kumar and A. A. Z. Diab, "Short-term load and price forecasting using artificial neural network with enhanced Markov chain for ISO New England," *Energy Reports*, vol. 9, pp. 4799-4815, 2023.
[17] X. Xiao, H. Mo, Y. Zhang and G. Shan, "Meta-ANN – A dynamic artificial neural network refined by meta-learning for Short-Term Load Forecasting," *Energy*, vol. 246, p. 123418, 2022.
[18] L. B. S. Morais, G. Aquila, V. A. D. de Faria, L. M. M. Lima, J. W. M. Lima and A. R. de Queiroz, "Short-term load forecasting using neural networks and global climate models: An application to a large-scale electrical power system," *Applied Energy*, vol. 348, p. 121439, 2023.
[19] A. A. Movassagh, A. Alzubi, Jafar,, M. Gheisari, M. Rahimi, M. S. Kumar, A. A. Abbasi and N. Nabipour, "Artificial neural networks training algorithm integrating invasive weed optimization with diferential evolutionary model," *Journal of Ambient Intelligence Humanized Computing*, vol. 14, pp. 6017-6025, 2023.
[20] D. Liu and H. Wang, "Time series analysis model for forecasting unsteady electric load in buildings," *Energy and Built Environment*, vol. 5, no. 6, pp. 900-910, 2023.
[21] J. Yuan, L. Wang, Y. Qiu, J. Wang, H. Zhang and Y. Liao, "Short-term electric load forecasting based on improved Extreme Learning Machine Mode," *Energy Reports*, vol. 7, pp. 1563-1573, 2021.
[22] S. Li, L. Goel and P. Wang, "An ensemble approach for short-term load forecasting by extreme learning machine," *Applied Energy*, vol. 170, pp. 22-29, 2016.
[23] C. Chupong and B. Plangklang, "Incremental Learning Model for Load Forecasting without Training Sample," *Computers, Materials & Continua*, vol. 72, no. 3, pp. 5415-5427, 2022.
[24] N. Zeng, H. Zhang, W. Liu, J. Liang and F. E. Alsaadi, "A switching delayed PSO optimized extreme learning machine for short-term load forecasting," *Neurocomputing*, vol. 240, pp. 175-182, 2017.
[25] S. Li *et al.*, "Short-term electrical load forecasting using hybrid model of manta ray foraging optimization and support vector regression," *Journal of Cleaner Production*, vol. 388, p. 135856, 2023.
[26] S. Li, H. Chen, M. Wang, A. A. Heidari and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," *Future Generation Computer Systems*, vol. 111, pp. 300-323, 2020.
[27] S. Mirjalili, "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm," *Knowledge-Based Systems*, vol. 89, pp. 228-249, 2015.
[28] M. Zulfiqar, M. Kamran, M. B. Rasheed, T. Alquthami and A. H. Milyani, "Hyperparameter optimization of support vector machine using adaptive differential evolution for electricity load forecasting," *Energy Reports*, vol. 8, pp. 13333-13352, 2022.
[29] X. Han, Y. Shi, R. Tong, S. Wang and Y. Zhang, "Research on short-term load forecasting of power system based on IWOA-KELM," *Energy Reports*, vol. 9, pp. 238-246, 2023.
[30] I. A. Ibrahim and M. J. Hossain, "Short-term multivariate time series load data forecasting at low-voltage level using optimised deep-ensemble learning-based models," *Energy Conversion and Management*, vol. 296, p. 117663, 2023.
[31] H. Xu, G. Fan, G. Kuang, and Y. Song, "Construction and Application of Short-Term and Mid-Term Power System Load Forecasting Model Based on Hybrid Deep Learning," *IEEE Access*, vol. 11, pp. 37494-37507, 2023.
[32] C. A. Saleel, "Forecasting the energy output from a combined cycle thermal power plant using deep learning models," *Case Studies in Thermal Engineering*, vol. 28, p. 101693, 2021.
[33] T. Danesh, R. Ouaret, P. Floquet, and S. Negny, "Hybridization of model-specific and model-agnostic methods for interpretability of Neural network predictions: Application to a power plant," *Computers & Chemical Engineering*, vol. 176, p. 108306, 2023.
[34] P. Tüfekci, "Prediction of full load electrical power output of a base load operated combined cycle power plant using machine learning methods," *International Journal of Electrical Power & Energy Systems*, vol. 60, pp. 126-140, 2014.
[35] X. Zhang, J. Wang and K. Zhang, "Short-term electric load forecasting based on singular spectrum analysis and support vector machine optimized by Cuckoo search algorithm," *Electric Power Systems Research*, vol. 146, pp. 270-285, 2017.
[36] H. A. Phan *et al.*, "Development of an Autonomous Component Testing System with Reliability Improvement using Computer Vision and Machine Learning," *ECTI Transactions on Computer and Information Technology*, vol. 18,

no. 1, pp. 64-75, 2024.
[37] M. Barman, N. B. Dev Choudhury and S. Sutradhar, "A regional hybrid GOA-SVM model based on similar day approach for short-term load forecasting in Assam, India," *Energy*, vol. 145, pp. 710-720, 2018.
[38] M. Barman and N. B. Dev Choudhury, "Season specific approach for short-term load forecasting based on hybrid FA-SVM and similarity concept," *Energy*, vol. 174, pp. 886-896, 2019.
[39] B. Beiranvand and T. Rajaee, "Application of artificial intelligence-based single and hybrid models in predicting seepage and pore water pressure of dams: A state-of-the-art review," *Advances in Engineering Software*, vol. 173, p. 103268, 2022.
[40] S. Samantaray, S. Sawan Das, A. Sahoo and D. Prakash Satapathy, "Monthly runoff prediction at Baitarani river basin by support vector machine based on Salp swarm algorithm," *Ain Shams Engineering Journal*, Vol. 13, no. 5, p. 101732, 2022.
[41] J. Lu, J. Yue, L. Zhu, D. Wang and G. Li, "An improved variational mode decomposition method based on the optimization of salp swarm algorithm used for denoising of natural gas pipeline leakage signal," *Measurement*, vol. 185, p. 110107, 2021.
[42] S. Zhao, P. Wang, A. A. Heidari, H. Chen, W. He and S. Xu, "Performance optimization of salp swarm algorithm for multi-threshold image segmentation: Comprehensive study of breast cancer microscopy," *Computers in Biology and Medicine*, vol. 139, p. 105015, 2021.
[43] J. Cervantes, F. Garcia-Lamont, L. Rodríguez-Mazahua and A. Lopez, "A comprehensive survey on support vector machine classification: Applications, challenges and trends," *Neurocomputing*, vol. 408, pp. 189-215, 2020.
[44] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris and S. M. Mirjalili, "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems," Advances in Engineering Software, vol. 114, pp. 163-191, 2017.
[45] M. H. Sulaiman and Z. Mustaffa, "An application of improved salp swarm algorithm for optimal power flow solution considering stochastic solar power generation," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 5, p. 100195, 2023.
[46] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh and S. Mirjalili, "Particle Swarm Optimization: A Comprehensive Survey," in *IEEE Access*, vol. 10, pp. 10031-10061, 2022.
[47] A. Huong, K. G. Tay, N. A. Jumadi, W. M. H. W. Mahmud and X. Ngu, "DFU Infection and Ischemia Classification: PSO-Optimized Deep Learning Networks," —em Applications of Modelling and Simulation, vol. 7, no. 2023, pp. 111-121, 2023.
[48] A. Hamdan, S. S. Nah, G. S. Leng, C. K. Leng and T. W. King, "Recent Evolutionary Algorithm Variants for Combinatorial Optimization Problem," *Applications of Modelling and Simulation*, vol. 7, no. 2023, pp. 214-238, 2023.

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