Int. J. Nonlinear Anal. Appl. 13 (2022) 2, 2923–2932
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.27662.3673

Comparison between radial basis neural network improvement method with SALP optimization algorithm (RBF-SSA) with other hybrid optimization algorithms

Mohsen Ahmadnia*, Ahmad Hajipour, Seyed Saeed Bani Fatemi

Faculty of Electrical Engineering and Computer, Hakim Sabzevari University, Sabzevar, Iran

(Communicated by Ehsan Kozegar)

Abstract

In the electricity industry, load forecasting is one of the most important tasks in planning, distribution, operations management, and providing appropriate solutions for power systems. Power consumption plays an important role in the planning and optimal use of power systems. With the existing technology, it is not yet possible to store this energy in large dimensions, so accurate forecasting of consumption can play an important role in the economic use of electricity. The amount of electrical charge consumption is not constant but is complex and nonlinearly a function of several parameters. Due to the variable amount of electrical charge consumption, power companies must anticipate it in different timelines of the information needed to make decisions. In this article, a new method is presented according to the efficiency of short-term load prediction, which can be from the next few hours to a week or a few weeks. Due to the efficiency of evolutionary methods in setting the parameters of forecasting methods, in this paper, the SALP optimization algorithm is used as an algorithm with high convergence accuracy to improve the neural network of the radial base function. Therefore, in this paper, a comparison between the method of improving the neural network of the radial base function with the SALP optimization algorithm for short-term load prediction by considering meteorological factors with other combined methods of optimization algorithms is shown. The results of comparison between predictions in the proposed model (improved neural network with SALP algorithm) compared to other combined methods of load prediction, show that the proposed neural network method improves the radial base function with SALP (RBF-SSA) better. Other combined methods improve the results.

Keywords: Short Term Load Prediction, Radial Base Function Neural Network, SALP Optimization Algorithm
2020 MSC: 68T07

1 Introduction

The economy of the industrial and competitive world today is heavily dependent on electricity. Since electricity cannot be stored and generates more or less than the amount of damage consumed, planning for the amount of electricity production, especially the peak electric charge, is one of the most important scheduling operations for the next day. Irregularities in the electrical industry require accurate load forecasting for electrical load management and

*Corresponding author
Email addresses: mn.ahmadnia@gmail.com (Mohsen Ahmadnia), second.author@email.address (Ahmad Hajipour), third.author@email.address (Seyed Saeed Bani Fatemi)

Received: March 2022 *Accepted:* May 2022

planning strategies. Increasing the complexity and the need for the electric charge by 3 to 7% every year requires high accuracy of prediction. An accurate forecast can minimize the gap between energy supply and demand. Appropriate methods are needed to meet future needs and reduce energy storage pressures. In 1985, it was estimated that a 1% increase in pre-pin error would increase costs by more than 10 million pounds per year in the UK thermal energy system. It can be said that the neural network of the radial base function is a good way to predict short-term load by considering meteorological factors [12]. But this neural network in terms of prediction accuracy will need to adjust the desired values, including 1- Gaussian function centers 2- Gaussian function radius 3- Neural network weights. It has also been proven that evolutionary methods can play a good role in regulating these parameters in optimizing this neural network [2]. On the other hand, the use of an evolutionary algorithm with high search accuracy can help the accuracy of the neural network classification of the radial base function, and the SALP optimization algorithm is one of the algorithms with very high search accuracy [10]. In general, 4 types of electric charge forecasters are used in management systems for operational planning and operation and production in energy systems: (1) Very short-term load forecasters for generating electrical loads Required for a few minutes. (2) Short-term load forecaster to generate the required electrical charge for 1 day to 7 days. (3) Medium-term load forecaster to generate the required electrical charge for more than 7 days to several months. (4) Long-term load forecaster, which is called the time horizon between several months to several years [13]. The short-term load predictor provides an accurate load demand for controlling and scheduling the energy system. Electric charge prediction models can be divided into four categories [5]: (1) Statistical models. (2) Knowledge-based expert systems. (3) Hybrid models. (4) Models based on artificial intelligence.

In the last two decades, a lot of research has been done on the application of artificial intelligence techniques for load prediction. Among these techniques, the models that have attracted the most attention are artificial neural networks, the neural network techniques due to their good ability in nonlinear modeling. It has been widely used in predicting electric charge [4]. Numerous new methods for load forecasting in the past decades have been shown to improve the ability to predict. Due to the sudden and non-linear movement of power systems, the consumption load in different seasons and weather conditions and economic behavior in the problem of predicting the load of electricity consumption has faced challenges [15]. Therefore, in this paper, to predict the short-term load, the use of improved neural networks with the SALP algorithm is proposed.

Short-term load forecasting means forecasting the next few hours to a week, and can be used for operational or planning purposes. Short-term forecasting is a basic process in the operation of power systems. Many operating functions, such as production layout, economic load distribution, and safety assessment, depend on short-term load forecasting.

Neural networks are well used in short-term load prediction. The neural network is a general approximation of the network and includes an input layer, a hidden layer, and an output layer. In this network, weight approximation is performed based on the descending gradient method and has a low convergence rate and easily converges to the local optimal but does not converge to the global optimal and excessive learning causes unknown results. Therefore, it has been shown that the neural network of the radial base function is a suitable method for predicting short-term load by considering meteorological factors.

Therefore, the efficiency of evolutionary algorithms in improving methods, including the use of the SALP optimization algorithm in improving the support vector machine method, has motivated us to use the SALP optimization algorithm to find the appropriate values of the parameters of the neural network method in short-term load prediction. This new method is used to perform short-term load prediction under certain regional climatic conditions and is called the model of the SALP-neural network optimization method of the combined radial base function.

This solution aims to improve the accuracy of short-term load prediction through the model presented in the paper (Combination of radial base function neural network - SALP optimization algorithm) and also to compare the accuracy of short-term load prediction estimation of improved radial base function neural network Finding (RBF-SSA) with other hybrid optimization algorithms, the amount of improvement of which is presented with different optimization algorithms.

2 Reviewing the literature

The methods used in short-term load prediction are mainly divided into two main groups, namely classical methods and methods based on artificial intelligence. Examples of classical methods include regression and the Kalman filter method [6] All of these methods have been used in short-term load prediction, but due to some limitations they cannot be predicted. Achieve the desired. For example, linear regression methods are essentially dependent on background data and cannot solve nonlinear problems. Classical models do not consider other external influencing factors and only make predictions based on past and present data points [16]. To overcome these limitations, researchers have proposed several methods based on artificial intelligence. Some of these methods include artificial neural networks, expert systems, and fuzzy logic. Among these methods, the artificial neural network has been the most common method in the last few years [9]. However, limitations in the ability to generalize and the inability to make full use of the information obtained from a small sample make it easy to get stuck in local optimization [8]. To solve this problem in a classical neural network, a support vector machine (SVM) is used to predict short-term load. Using the principle of structural risk minimization, the backup vector machine achieves better generalizability in the training process [7]. Less sensitivity to local minimums are other benefits of backup vector machines. These interesting features make the backup vector machine the most promising and common method for short-term load prediction [14]. Although the backup vector machine has been used successfully to predict short-term loads, many researchers have proven that the accuracy of the backup vector machine prediction is highly dependent on the choice of values of its parameters [11]. These parameters include C (a parameter that balances the complexity of the model with the training data needed to determine the accuracy of the model), ε (width of the sensitivity error function), and γ (kernel function parameter). The use of a backup vector machines in various studies shows that the correct combination of backup vector machine (SVM) parameters leads to accurate prediction and fast training speed. Therefore, researchers have proposed several hybrid backup machine methods in which different optimization algorithms have been used to find the correct combination of backup vector machine parameters. Hybrid backup vector machine methods are discussed in the next section.

Many algorithms have been proposed in recent years to configure the backup vector machine. Each of these algorithms has played a significant role in better understanding this field. However, these algorithms also have limitations. For example, turbulent ant cumulative optimization algorithms, and genetic algorithms are not the best particle storage mechanism. The particle group algorithm is also a two-step algorithm that requires considerable time to optimize the parameters. There is no optimization method that can solve all optimization problems efficiently. Therefore, under these conditions, it is acceptable to present a new method for determining the parameters of the backup vector machine. In the study [1], a new method called SALP optimization algorithm is proposed to improve the prediction performance of the backup vector machine by determining the appropriate parameters. The SALP collective intelligence algorithm was introduced by Mirjalili [10] and is a nature-inspired random algorithm that mimics the SALP chain behavior for optimization. Compared to other algorithms, the SALP optimization method has unique features, for example, [10]: A: Involvement of all search agents in updating the position of each search agent. B: Pay special attention to initial values to avoid local optimization and better convergence. C: Creating a balance between exploration and extraction. D: No need for gradient information (derivation) search space.

There is a very strong correlation between thermal inertia due to climatic factors (temperature, humidity, wind speed) and demand load (customer behavior). In other words, climatic factors have a huge impact on the amount of load demanded. Therefore, it is important to consider these factors for a correct short-term load prediction model. Temperature consideration is generally accepted and common in the short-term load prediction model. In recent years, researchers have used such models to predict short-term loads in different parts of the world. For example, in [8], the authors applied temperature to models based on artificial neural networks and implemented short-term load predictions in Japan. In [7], the authors consider the temperature in a model based on fuzzy logic and implement short-term load prediction in Jordan. In [14], the authors considered temperature in a regression-based model and implemented short-term load predictions in Serbia. Numerous other studies have been conducted in different parts of the world [11]. In the literature review, it was observed that different prediction models that were improved by evolutionary algorithms were examined. Including a model of locust optimization methods and SALP collective intelligence to improve the support vector machine method [1, 3] in which evolutionary algorithms are used to determine the appropriate parameters of the backup vector machine. SALP Collective Intelligence Algorithm is a one-step algorithm and has unique features such as using all search agents to update the position of each search agent, which gives this algorithm high search power. Three case studies in the study [3] showed findings such as that electricity load demand is influenced by climatic factors and a short-term load forecasting model should include the right climatic factors to predict load demand. It is important to provide a short-term load forecasting model for a specific area because the impact of climatic factors varies in different parts of the world. The findings also show that the prediction accuracy of the improved support vector machine model with locust optimization algorithm compared to the short-term load prediction model using classical methods shows that the proposed model had better prediction in all cases because Satisfies all regional climatic conditions, and in the case of 1 and 2 tested in this study, the error of the proposed model is 5 times less than the classical model. Validation of the proposed model (improved support vector machine with locust optimization algorithm) The results are performed with two other hybrid models, namely genetic algorithm - backup vector machine and particle group algorithm - backup vector machine, and the accuracy of the prediction shows that the proposed model is better than the other two models. The Genetic Algorithm-Support Vector Machine model also performed well in terms of training time, convergence, and search capability. In today's electricity market, short-term load forecasting is a major tool used to predict future scenarios and move towards a profitable policy. The required electricity charge is strongly influenced by the thermal inertia caused by climatic factors. These influencing factors are different in different areas. In this research, load forecasting according to weather factors has been investigated using a neural network model and support vector machine, whose parameters have been improved by evolutionary algorithms such as locust optimization algorithm and leader following algorithm. Also, because in industry, electricity consumption is important for production, and electricity charge forecasting can lead to optimal power consumption management, determination, and planning of production, which in turn improves energy efficiency and production costs, to examine the impact of this pre- The nose is polished in a paper mill. Prediction methods such as multilayer perceptron neural networks and support vector machines have parameters that affect their performance and estimating these parameters increases the performance of these methods in terms of predictive accuracy. These forecasting methods should be selected according to the number of samples because the backup vector machine method, unlike the neural network method, can also have acceptable predictive results in a small number of samples. Studies have shown that evolutionary methods that have high search power, such as the SALP and locust collective intelligence optimization algorithm, lead to proper estimation of the parameters of the detection or prediction method, as well as hybrid optimization methods such as a genetic algorithm. And the particle group algorithm also has a positive effect on learning the prediction method, including the neural network method and the support vector machine. In the meantime, it is important for an algorithm that has a simple setup to use, while having the appropriate search power, that the algorithm follows the leader of this feature.

In summary, the research literature shows that the improvement of support vector machine method or neural networks with evolutionary algorithms such as optimization of SALP collective intelligence and the use of such combined methods in short-term load prediction has improved the predicted results. As a result, it is proven that prediction methods can be improved by evolutionary algorithms.

3 The proposed method

The proposed method for short-term barcode prediction is the neural network function of the radial basis, the parameters of which are improved by the SALP collective intelligence optimization algorithm.

One of the new evolutionary algorithms is SALP's collective intelligence optimization algorithm, which is inspired by SALP's life. Nature-inspired algorithms logically divide the search process into two parts: exploration and exploitation or extraction. In exploration, search agents are encouraged to make random moves while in the exploitation phase they tend to move locally and around their location. These two actions, as well as goal search, are performed naturally by SALP [10].

The steps of the proposed hybrid algorithm are as follows:

1. Select input and output variables by correlation analysis and then raw data is pre-processed.
2. Divide the input and output data sets into training and experimental data sets.
3. Gaussian function centers, Gaussian function radius and neural network weight The radial base function is determined by SALPs. Neural network parameters include number of input layer neurons, number of hidden layer neurons, number of output layer neurons, maximum number of training (1000), neural network convergent value (0.001) and learning rate (0.1).
4. Starts the parameters for the SALP optimization algorithm. Determining the value of the problem parameters such as the lower limit (lb) and the upper limit (ub) of the comfort zone and the maximum number of iterations) The structure of each SALP is an array similar to Figure 1 in which the number of centers of the Gaussian function is the radius of the function. Gaussian and neural network weights are a function of the radial base of the house.

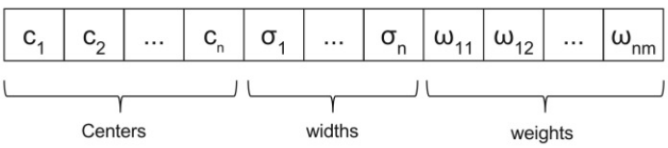

Figure 1: Structure of a SALP in the neural network optimization of the radial base function

5. Train the neural network and calculate the suitability of each SALP.
6. Determining the best SALP (SALP with better fitness) in the variable F
7. Until the termination condition is reached (I <number of iteration):
   (a) Update c_1 with relation (3.1)

$$c_1 = 2e^{-\left(\frac{4I}{L}\right)^2} \tag{3.1}$$

   Where I is the iteration number of the current evolution of the algorithm and L is the final iteration number of the algorithm.
   (b) Updating the first neural network settings according to the best SALP with equation (3.2):

$$x_i^1 = \begin{cases} F_j + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0 \end{cases} \tag{3.2}$$

   x_i^1 the first neural network configuration shown in the form of a SALP similar to the structure in Figure 2, and F is the nearest neural network configuration ever found, which is updated after each iteration according to new paths, ub upper bound and lb The lower bound for each neural network configuration and the parameters c_2 and c_3 are random numbers.

   Update the rest of the SALPs according to the SALPs ahead of themselves with Equation (3.3):

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right) \tag{3.3}$$

   x_j^i For each i is related to the second neural network settings (second SALP) to the last. Each SALP moves backwards according to the number SALP to model the SALP chain behavior. The array structure of each neural network configuration is affected by its current structure as well as the neural network configuration structure shown in the previous SALP.
8. Adding the internal iteration number of the algorithm ($I = I + 1$)
   Figure 2 of the flowchart shows the proposed model:
9. Return the best SALP as the final answer (the best SALP represents the best value for the centers of the Gaussian function, the radius of the Gaussian function, and the neural network weights of the radial base function)
10. Training of neural network of radial base function with Gaussian function centers, Gaussian function radius and optimized weight.
11. Testing the neural network of the radial base function and presenting the result of short-term load prediction.

To evaluate the models, the average percentage of absolute error is calculated from Equation (3.4):

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|A_i - F_i|}{A_i}\right) * 100 \tag{3.4}$$

Which N is the number of hours in the forecast period.

4 Results

The data set used in this research is related to the information of Mashhad Electricity Company for 2019, which has been collected along with meteorological information this year. Specifically, this article deals with the forecast of short-term load per hour on August 7, 2019. For this purpose, the last 46 days, ie from 06.22.2019 to 08.06.2019, have been used for system training. The training data is equivalent to 1104 samples, which include load, temperature, and humidity per hour. The time series of load consumption is shown in Figure 3. In this graph, the vertical axis is the amount of load per megawatt at the scale of 10^1 and the horizontal axis of times per hour per day from July 22 to August 6, 2019, are 1104 samples.

To test the system, the amount of load consumed in 24 hours on August 7, 2019, has been used. Figure 4 shows the time series of the test data. In this diagram, the vertical axis is the amount of load in megawatts at the scale of 10^1 and the horizontal axis of times is the scale of the hour for 24 hours, which is the amount of load from 00:00 to 01:00 as the first example and the amount of load at 23 hours: Shows 00 to 24:00 as the last example.

To test the prediction accuracy, a comparison of radial basis function neural network (RBF) and improved radial basis function neural network with SALP optimization algorithm (RBF-SSA) was used. In the proposed model, first,

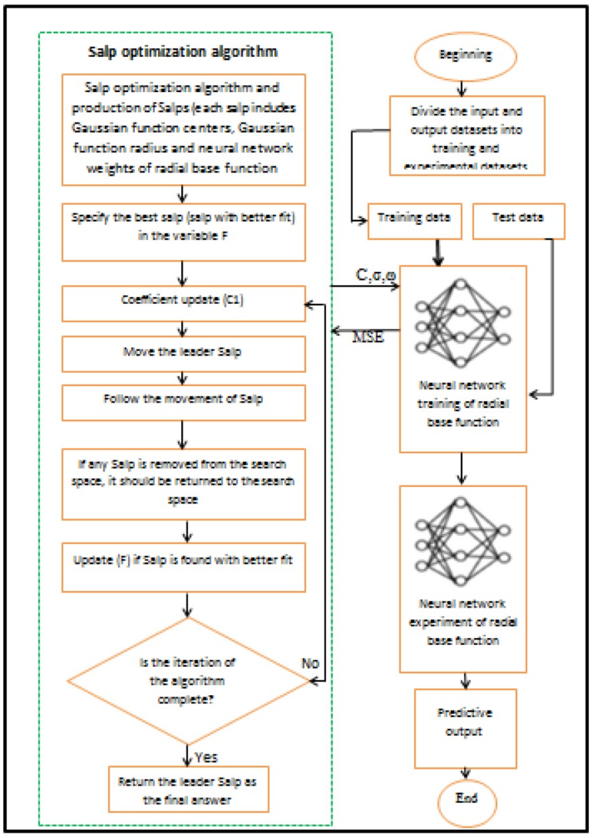

Figure 2: Proposed Model Flowchart (RBF-SSA)

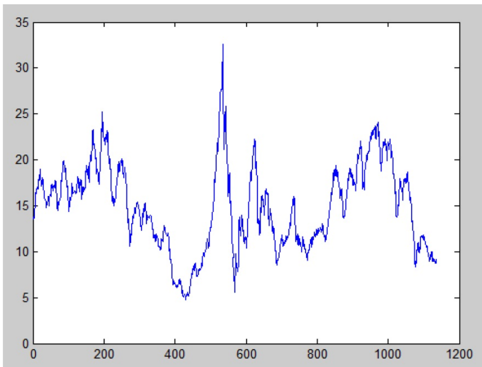

Figure 3: Load data to teach the model in the amount of load consumed

the required data of the educational data set, and the combination of inputs and outputs are specified. Then the objective function is defined which is the degree of accuracy of prediction and the relevant limitations in system modeling are considered. Then, the initial population of SALPs, each of which contains three neural network parameters of the radial base function, is generated. The three neural network parameters of the radial basis function include the number of Gaussian function centers, the Gaussian function radius, and the neural network weights of the radial basis function, which are changed by the operators of the SALP optimization algorithm to achieve the best value for these three parameters. This process is repeated until no improvement in the objective function is seen. The neural network receives the following radial base function:

1. Type of day
2. The amount of load consumed for each hour
3. Temperature for each hour
4. Humidity for each hour

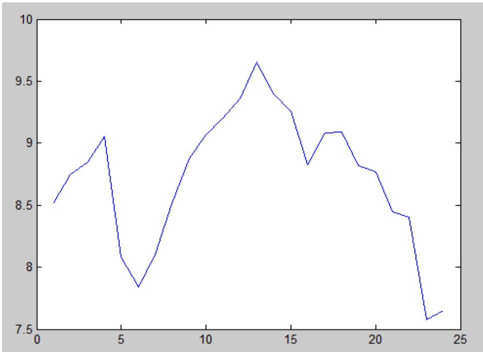

Figure 4: Load data to test the model in the amount of load consumed

RBF is trained using data from the past 46 days and the forecast value is forecast for each hour in a day. A total of 20 SALP (population size) are considered for the simulation, which is considered in 100 replications and it is assumed that no improvement will occur after 100 repetitions.

MAPE error is used to measure the error.

By implementing the SALP optimization algorithm, the best value for Gaussian function centers, Gaussian function radius and neural network weights of the radial base function are determined by the SALP algorithm. Figure 5 shows a prediction of the proposed model.

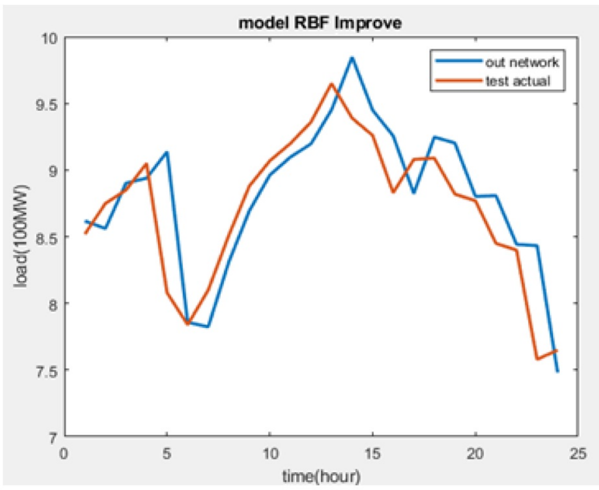

Figure 5: Demonstration of the forecast graph compared to the actual value in the proposed model (RBF-SSA)

Figure 5 shows the forecast diagram compared to the actual value in the proposed model. As it is known, the direction of the chart in the forecasts is well known, but it has not been able to correspond to the time series very accurately.

Table 1: Results of the proposed model (RBF-SSA)

Suggested method	Error rate MAPE(%)
RBF-SSA	4.57

In the proposed method, by optimizing the three parameters of Gaussian function centers, Gaussian function radius and lattice weights, the results are obtained in one optimization.

4.1 Test with other methods

In the following, the simulations of the proposed model are investigated using the support vector machine (SVM) method as a parametric method and the nearest neighbor method as a non-parametric method, and also the multilayer perceptron neural network is tested. Finally, a combined model of support vector machine, perceptron neural network and the proposed method are simulated in a multiple learning model.

To test the nearest neighbor method, the number of different neighbors including 1 to 10 neighbors has been tested.

Table 2: Performance evaluation of KNN method

k	Error rate MAPE(%)
1	87.54
2	82.51
3	82.65
4	79.25
5	78.95
6	77.98
7	71.51
8	72.65
9	70.55
10	71.95

As shown in Table 2, the results of the proposed model with the nearest neighbor method have a high error, and this is due to the lack of training phase in this method and inadequacy in predicting time series.

The following are the simulation results with a support vector machine (SVM) with different cores.

Table 3: Performance evaluation of SVM method with different cores

Core	Error rate MAPE(%)
Sigmoid	12.51
Polynomial	9.54
Gauss	8.44

As shown in Table 3, the results of the proposed model can only have results with the least error with the Gaussian core backup vector machine method.

The results were then tested with a multilayer perceptron neural network method with a number of different latent neurons.

Table 4: Performance evaluation of SVM method with polynomial kernel

Hidden layer neurons	Error rate MAPE(%)
5	14.52
10	17.52
15	12.54
20	9.85
25	10.45
30	12.52
35	13.55
45	9.47
50	10.85
60	12.98

As shown in Table 4, the results of the proposed model in the multilayer perceptron neural network method with the number of hidden layer neurons with 45 neurons have given better results, although this error rate is higher than our proposed method.

But in the hybrid support vector machine model, the perceptron neural network and the proposed method are simulated in a multiple learning model.

As shown in Table 5, the results of the proposed model can only have results with an error of 4.75 with the Gaussian core backup vector machine method. But it still could not be less error-prone than our proposed method.

Table 5:

With SVM Gaussian nucleus	With 45 MLP neurons hidden in the layer	Proposed method RBF-SSA	Error rate MAPE(%)
			4.75

As it is clear from the results of the combined method, the prediction result was not more accurate than the proposed method. Figure 6 also shows a bar chart comparing the best results in this section.

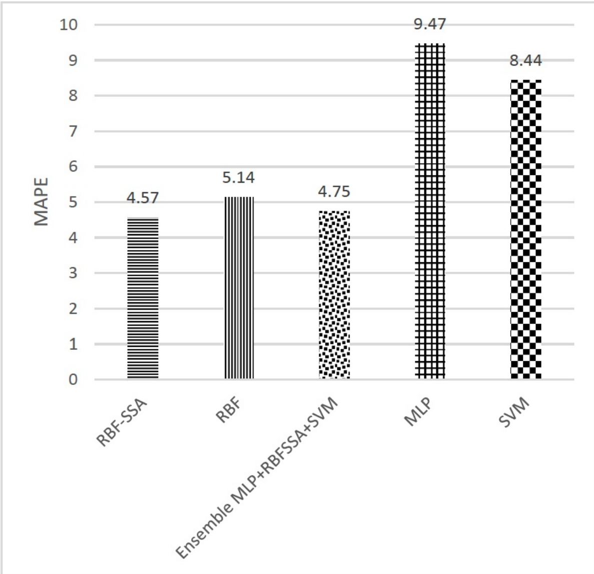

Figure 6: Bar chart comparing the proposed model result (RBF-SSA) with other simulated methods

5 Conclusion

In this paper, in comparison with other methods of artificial intelligence and hybrid algorithms and other studies in short-term load prediction, it was investigated and it was shown that the neural network function of radial basis improved by SALP algorithm (RBF-SSA) is an efficient method in Such are the predictions, it was also shown that the SALP optimization algorithm can work well in short-term load prediction in combination with classification methods such as neural networks. The proposed algorithm has two general advantages over existing algorithms. The proposed algorithm uses the load of the last hour in the network training phase and thus has a higher accuracy of prediction and also uses the SALP optimization algorithm which has shown high convergence power, three main and effective parameters in the neural network The radial base function means the number of centers of the Gaussian function, the radius of the Gaussian function and the weights of the grid is adjusted and the grid can make predictions at its best.

In the proposed model, considering the effect of climate has been one of the forecasting features, so considering the humidity is an additional climatic condition specific to that geographical area that should be applied in the short-term load forecasting model, but the Classic models predict short-term load as the most important factor in increasing or decreasing load consumption, only temperature.

The proposed model is an area-specific method for short-term load prediction that can be applied to any other area with climate restrictions in that area. In the continuation of this article, this study can be expanded by emphasizing the estimation of more detailed relationships between load demand and climatic factors. Such a study could include the following:

1. Consider more influential climatic factors
2. Considering the influential seasonal weather factors
3. In addition, other optimization methods still have the potential to be used to improve the proposed model.

References

[1] A.Z. Ala'M, A.A. Heidari, M. Habib, H. Faris, I. Aljarah and M.A. Hassonah, *SALP chain-based optimization of support vector machines and feature weighting for medical diagnostic information systems*, Evolutionary Machine Learning Techniques, (2020), 11–34.

[2] I. Aljarah, H. Faris, S. Mirjalili and N. Al-Madi, *Training radial basis function networks using biogeography-based optimizer*, Neural Comput. Appl. **29** (2016), no. 7, 529–553.

[3] M. Barman, N.D. Choudhury and S. Sutradhar, *A regional hybrid SSA-SVM model based on similar day approach for short-term load forecasting in Assam, India*, Energy **145** (2018), 710–720.

[4] G. Cervone, L. Clemente-Harding, S. Alessandrini and L. Delle Monache, *Short-term photovoltaic power forecasting using artificial neural networks and an analog ensemble*, Renew. Energy **108** (2017), 274–286.

[5] G.W. Chang, H.J. Lu, Y.R. Chang and Y.D. Lee, *An improved neural network-based approach for short-term wind speed and power forecast*, Renew. Energy **105** (2017), 301–311.

[6] S. Ding, K.W. Hipel and Y.G. Dang, *Forecasting China's electricity consumption using a new grey prediction model*, Energy **149** (2018), 314–328.

[7] Y. Liang, D. Niu and W.C. Hong, *Short term load forecasting based on feature extraction and improved general regression neural network model*, Energy **166** (2019), 653–663.

[8] Y. Liu, W. Wang and N. Ghadimi, *Electricity load forecasting by an improved forecast engine for building level consumers*, Energy **139** (2017), 18–30.

[9] M. Meng, L. Wang and W. Shang, *Decomposition and forecasting analysis of China's household electricity consumption using three-dimensional decomposition and hybrid trend extrapolation models*, Energy **165** (2018), 143–152.

[10] 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*, Adv. Engin. Software **114** (2017), 163–191.

[11] M.Q. Raza, M. Nadarajah, D.Q. Hung and Z. Baharudin, *An intelligent hybrid short-term load forecasting model for smart power grids*, Sustain. Cities Soc. **31** (2017), 264–275.

[12] S.R. Salkuti, *Short-term electrical load forecasting using radial basis function neural networks considering weather factors*, Electr. Eng. **100** (2018), no. 3, 1985–1995.

[13] A. Tarsitano and I.L. Amerise, *Short-term load forecasting using a two-stage sarimax model*, Energy **133** (2017), 108–114.

[14] W. Yang, J. Wang, T. Niu and P. Du, *A hybrid forecasting system based on a dual decomposition strategy and multi-objective optimization for electricity price forecasting*, Appl. Energy **235** (2019), 1205–1225.

[15] W. Yin, Y. Han, H. Zhou, M. Ma, L. Li and H. Zhu, *A novel non-iterative correction method for short-term photovoltaic power forecasting*, Renew. Energy **159** (2020), 23–32.

[16] J. Zhang, Y.M. Wei, D. Li, Z. Tan and J. Zhou, *Short term electricity load forecasting using a hybrid model*, Energy **158** (2018), 774–781.