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An enhanced artificial neural network model for short term load forecasting in smart grid

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ABSTRACT

Accurate short-term load forecasting in the power system may efficiently cut power generating costs while also improving the system's economic and environmental advantages. ARIMA Model, Parameter Regression Model, Kalman Filter Model, and other traditional short-term power demand forecasting methods are examples. Short-term load forecasting of power systems has become commonplace, thanks to the fast advancement of computer technology and the widespread application of AI technologies in the power sector. In this paper, we have designed a short-term load forecasting model using an enhanced ANN. The ANN model is enhanced by determining the optimal weights of it using a hybrid combination of the optimization algorithm. In our work, we have hybrid the firefly and PSO algorithm. The performance analysis of the presented model is done to show its effectiveness over the existing models in MATLAB using various parameters.

Keywords: *Firefly Algorithm, Load Forecasting, Optimization Algorithm, Particle Swarm Optimization Algorithm, Smart Grid.*

1. INTRODUCTION

Due to the emergence of smart electrical grids for information sensing, processing, and transmission, AMI has evolved as a key unit in different energy sectors. This facilitated handling a large volume of metered data and relevant information. Further, accessibility of these huge smart meter data in real-time opens up the opportunities for multiple operations like energy management, load forecasting, power system planning and operation, maintenance scheduling, error mitigation [1].

Load forecasting acts as an indispensable tool for optimum planning and operation in different energy sectors (such as residential, commercial, and industrial sectors). It plays a vital role in decision making, maintaining efficient economic operations in power system and demand-side management (DSM) by motivating customers to modify their electricity demand and the utilities to generate energy as per the requirement. Since electricity demand changes rapidly, it is very difficult for energy sectors to estimate the amount of electricity needed to balance supply and demand in the future. An accurate forecast of electricity pricing is also required for both the producers and the consumers of electric power for taking the energy trading decisions and to avail the minimum possible price of the electricity simultaneously.

Load forecasting methods can be broadly classified into three categories depending on the methodology adopted [2]: (i) based on utilisation side (ii) based on weather information (iii) based on the time horizon. Depending upon the utilisation side, load forecasting can be classified into two categories – (1) Utility-based forecasting, which is used in power generation planning and management, and (2) Consumer-based forecasting, which is applied for the energy optimisation procedures supported by the receiving end-users. The factors affecting load forecasting are the time of the day, day of the week, previous day load, seasonal variations, holidays, weather factors, etc. Depending on the utilisation of weather forecast information, load forecasting can be grouped into two groups namely – (1) Univariate methods, which do not require weather information for forecasting and (2) Multivariate methods, which require weather information for forecasting loads. Depending upon the length of the forecast interval, load forecasting is again classified into four groups – (1) VSTLF (2) STLF (3) MTLF, and (4) LTLF [2].

The main contribution of this paper is to design a STLF model for the SG. To achieve this goal, the most preferred artificial neural network is used, and it is enhanced by determining the optimal weight values of it using hybrid combination of optimization algorithms. In our work, we have hybrid the firefly algorithm with particle swarm optimization (PSO) algorithm. The evaluation of the proposed method is done using various parameters such as RMSE, MAPE, MaxError, and MinError.

The rest of the paper is as follows. Section 2 defines the related work is done in load forecasting. Section 3 explains the preliminaries used to design the proposed method. Section 4 illustrates the proposed method. Section 5 shows the simulation results. In the last, the conclusion and future scope are defined in section 6.

2. RELATED WORK

This section shows the related work is done in the field of load forecasting.

Xie et al. [3], The forecast of short-term power load has a significant impact on the overall functioning of the electric system. It's constantly a study topic to improve the result of power load forecasting. For short-term power load forecasting, this research suggests a system that combines ENN with PSO. To begin, this paper discusses the ENN and PSO algorithms, as well as the performance of a network impacted by ENN settings. The particle swarm optimization approach is then used to find the ENN's ideal learning rate. To test the capabilities of the approach provided in this research, it is applied to the forecasting of short-term power loads, which is a problem that can be handled using ENN. A comparison experiment on this approach (PSO–ENN) with the GRNN, ENN, and the classic BPNN is also provided to demonstrate PSO–efficacy.

Zahra Shafiei and Hossein Afrakhte [4], Power system planning and operating processes rely heavily on electrical load forecasts. For electrical load forecasting, a number of methodologies have been used thus far. Meanwhile, due to their capacity to adjust to the hidden feature of the consuming load, neural-network-based approaches resulted in less prediction mistakes. As a result, the researchers generally agreed with these methodologies. The neural network is then utilised to anticipate the short-term electrical load using these adjusted parameters. A three-layer feedforward neural network trained using the backpropagation technique is employed in this present method, along with an upgraded gbest PSO algorithm. The PSO algorithm cost function is also used to describe the neural network prediction error. MATLAB software was used to evaluate the suggested technique on the Iranian electricity system. The suggested method's performance was assessed using an average of three indicators in addition to graphical data. The simulation results demonstrate the suggested method's ability to properly anticipate the electrical load.

Jankovic et al. [5], This research uses an artificial neural network to present a novel model for optimum comparable days selection and its application in short-term load forecasting. The proposed work is based on a multi-filtering process. It includes the following new features: (1) the use of pre-history; (2) the addition of forecasting factors; (3) an open model with the ability to add additional contribution factors; and (4) PSO for calculating the impact of various contributing factors. Even when it is not clear ahead of time which criteria are the most important, this technique yields optimal comparable day selection. Finally, for short-term load forecasting, an artificial neural network is utilised as a fundamental process. The suggested model was put to the test in Serbia's transmission system, and the results are provided.

Liu et al. [6], Although the load of a power system often exhibits a limited range of nonlinear fluctuations over time, the load characteristics in power systems follow certain laws. As a result, in order to increase load forecasting accuracy, this research provides a FA to optimise the STLF model of ENN. To overcome the shortage of the ENN readily falling into local optimum, the nonlinear optimization ability of the FA is used to optimise the weights and thresholds of the ENN. Then, to improve ENNs fitting ability, utilise the optimised weights and thresholds. Finally, simulation results reveal that the FA-ENN has a greater prediction accuracy than the regular ENN.

3. PRELIMINARIES

Firefly and PSO algorithms are deployed in the ANN model for load forecasting. A detailed description of these algorithms is given below.

3.1 Firefly Algorithm

Without the global information as well as gradient information of the target function, the Firefly Method (FA) has strong resilience, and the algorithm is simple and straightforward to apply [7].

A. Equation for Fluorescein Update

The position of the current firefly and the fluorescein residue from the prior time are used to update the fluorescein. The update formula is as follows:

$$L_i(t) = (1-p)L_i(t-1) + \omega f(X_i(t)) \qquad (1)$$

Where Li (t) and Li (t-1) represent the fluorescein readings at the current and prior times, respectively. f(Xi(t)) is the fitness function value of the current firefly position and can be used to represent the target function value to be solved; (0,1) is the fluorescein volatilization factor.

B. Probability equation for firefly migration Because the brighter a firefly is, the more appealing it is to its neighbours. The following is the technique of calculation:

$$P_{ij}(t) = \frac{L_j(t)-L_i(t)}{\sum_{k\in N_i(t)} L_k(t)-L_i(t)} \quad (2)$$

Where Pij(t) is the likelihood of firefly I approaching firefly j; The firefly neighbour set Ni(t) has a fluorescein level higher than the present firefly i.

C. Equation for updating the location of fireflies

The following is the equation:

$$X_i(t+1) = X_i + s\left|\frac{X_j(t)-X_i(t)}{||X_j(t)-X_i(t)||}\right|, \text{ i=1,2,… } (3)$$

Where Xi(t) and Xi(t+1) are the current and next positions of the firefly, respectively; s is the firefly's moving step length, and its numerical selection will have a direct impact on the algorithm's convergence speed and precision of optimization.

D. Update of the Firefly dynamic decision domain

The following is the equation:

$$r_d^i(t+1) = \min\left(r, \max\{0, r_d^i(t) + \beta(n_i - |N_i(t)|)\}\right) \ (4)$$

Where r is the firefly sensing radius, which represents the firefly's greatest line of sight range; and is the neighborhood's change rate, and denotes the neighborhood's change degree; rd is the dynamic decisionmaking radius of firefly; ni is the neighbourhood threshold, which reflects the threshold of the number of fireflies in the specific neighbourhood set.

3.2 Particle Swarm Optimization (PSO) Algorithm

PSO is a type of swarm-based optimization approach created by Eberhart and Kennedy and motivated by flock behaviour [8]. Each particle in the group has a velocity and seeks to achieve the best velocity based on its own pbest and the gbest of its friends. The simplicity of PSO over other optimization approaches is one of its main advantages. There are just a few settings that need to be tweaked. PSO has been widely employed in a number of applications as a result of this. Allow the particles to be started with locations Xi and velocities Vi in an n-dimensional search space, Xi= (x1, x2, x3,...,xn). The particles are then relocated into new places through the following equations:

$$V_i(i+1) = \omega V_i(i) + C1\varphi 1\left(Pbest - x_i(t)\right) + C21\varphi 2(gbest - x_i(t) \ (5)$$

$$X_i(i+1) = X_i(i) + V_i(i+1) \quad (6)$$

3.3 ANN Model

ANN functions in a similar way to a human brain. A neural network is a widely dispersed, massively parallel processor made up of basic processing units called neurons. This network is made up of several layers, each of which contains neurons as well as weights associated with the connections between them, through which information is transferred in a feed-forward fashion. Figure 1 depicts an artificial neuron model. Weights linking the nodes, the summation function within the node, and the transfer function are the three fundamental components of ANN neurons. This MLP structure has been shown to solve practically any non-linear connection. The data is first sent forward from input to output, and then the weight is modified by back propagation. Learning is the process of adjusting weight and bias using the Levenberg-Marquardt back propagation method [9].

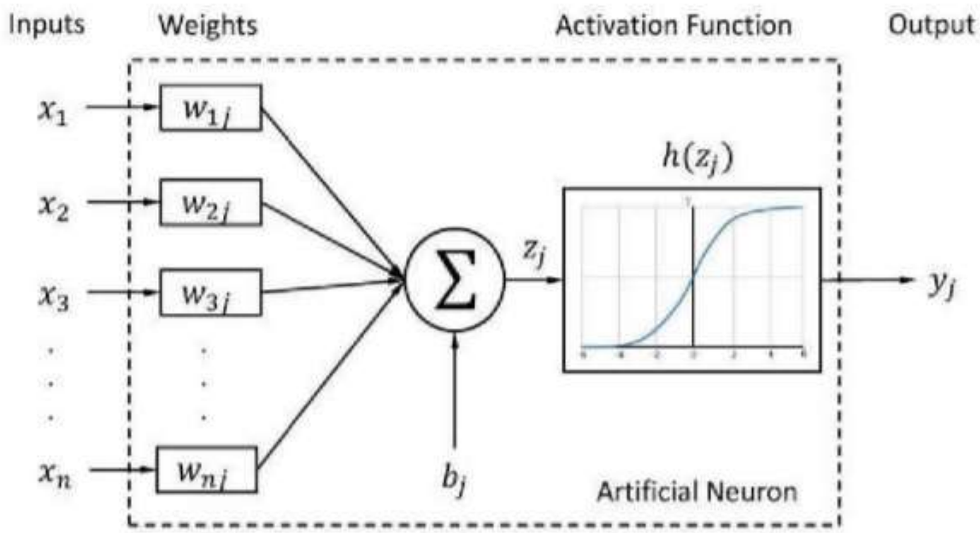


Figure 1 ANN Model [9]

4. Proposed Method

This section explains the proposed method that is designed to predict the load demand based on historical data. The flowchart of the presented algorithm is shown in Figure 2. Next, the proposed methodology is explained for the proposed algorithm.

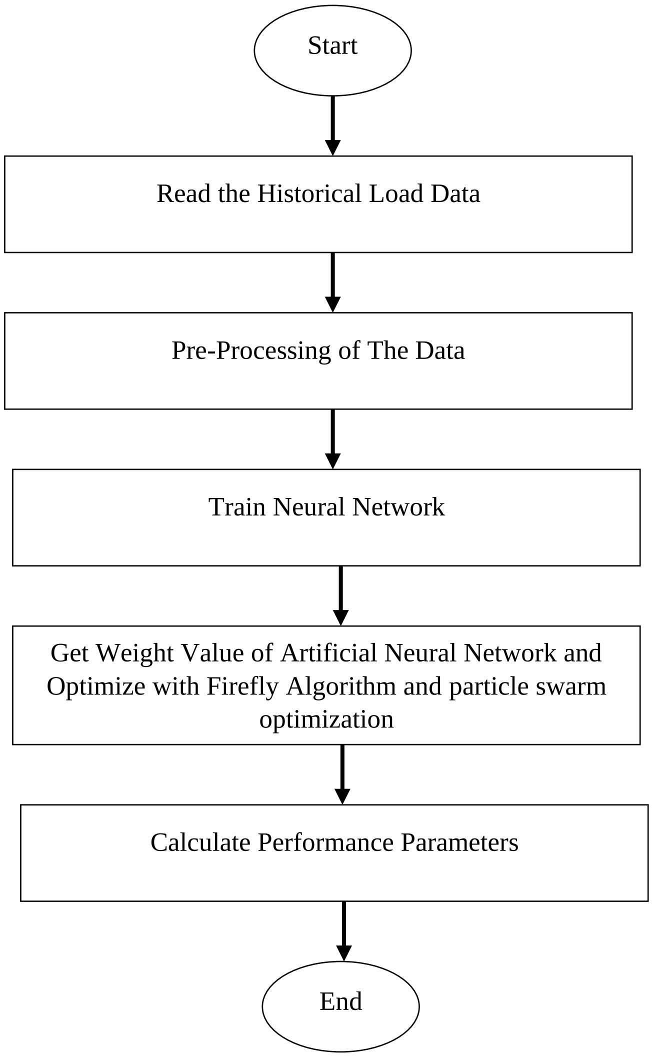


Figure 2 Flowchart of the Proposed Method

Initially, the historical data is read from the excel file in MATLAB. After that, pre-processing of the data is done to determine the most appropriate parameters that are used to train the model. Next, the artificial neural network (ANN) model is trained using appropriate parameters. Further, the ANN model is enhanced by determining the optimal weight values of the network. The optimal weights of the ANN model are determined by a hybrid combination of particle swarm optimization and firefly algorithm. In the testing phase, historical data is input, and performance analysis of the proposed method is done using various parameters such as RMSE, MAPE, MaxError, and MinError.

5. SIMULATION EVALUATION

The proposed method was simulated in MATLAB. The system configurations are an i7 processor, 8GB RAM, 1TB hard disk.

5.1 Performance Analysis Parameters

The performance analysis parameters are explained that are calculated for the proposed method [10].

- RMSE - Root Mean Square Error: The RMSE displays the normal sample variance between the values expected and current values observed. The lesser the RMSE value the greater is the accuracy of the prediction. It is calculated using Eq. (1).

$$RMSE = \sqrt{MSE} \qquad (7)$$

Whereas, MSE denotes the mean square error and it is calculated using Equation (2).

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \qquad (8)$$

Whereas, n represents the total number of the period; e_t represents the residual at some time t;

- MAPE - Mean Absolute Percentage Error: As it tests relative efficiency, it is the most effective way to evaluate predictions for numerous things or goods. It is an accuracy measure widely used in quantitative prediction methods [ref]. If MAPE's value measured is below 10%, it is regarded as an outstanding specific projection, decent provision of 10–20%, good predictions of 20–50%, and bad predictions of over 50%. It is calculated using Eq. (3).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{y_t}100\% \qquad (9)$$

Where, e_t represents the residual at the time t; y_t represents the actual value at some time t; n represents the total number of the period.

- Maximum Error: It measures the maximum error generated between the predicted load and historical data.
- Minimum Error: This parameter measures the minimum error generated between the predicted load and historical data.

5.2 Simulation Setup

The standard dataset was downloaded. The initial parameters are defined for the PSO and Firefly algorithms are defined in Table 1.

Table 1 Initial Parameters for the PSO and Firefly Algorithm

Initial Parameters	Value
Population	10
Iteration	50
C1,C2	2,2
Gamma	1
Beta	2
Alpha	0.2

5.3 Simulation Results

In the simulation, various parameters are calculated for the proposed method, as shown in Table 2.

Table 2 Simulation Results for the Proposed Method

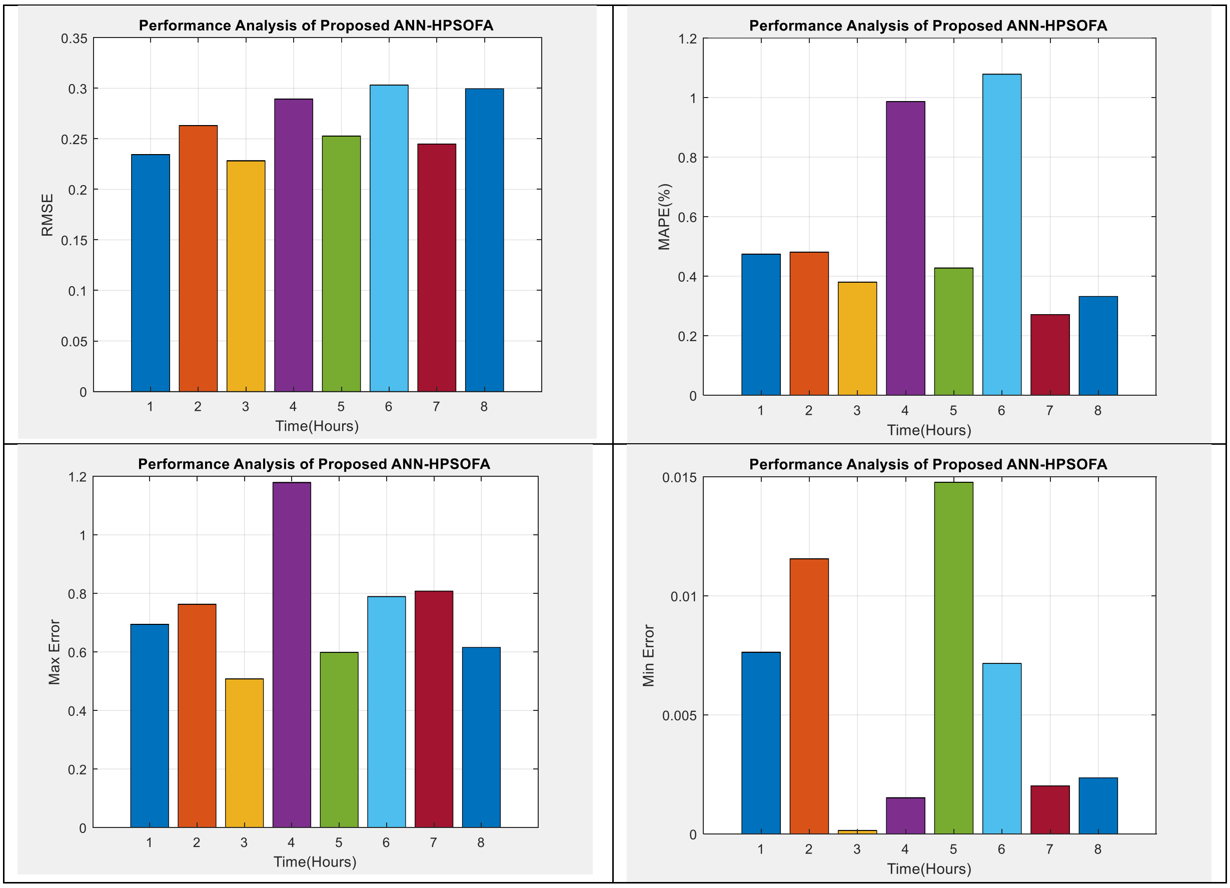
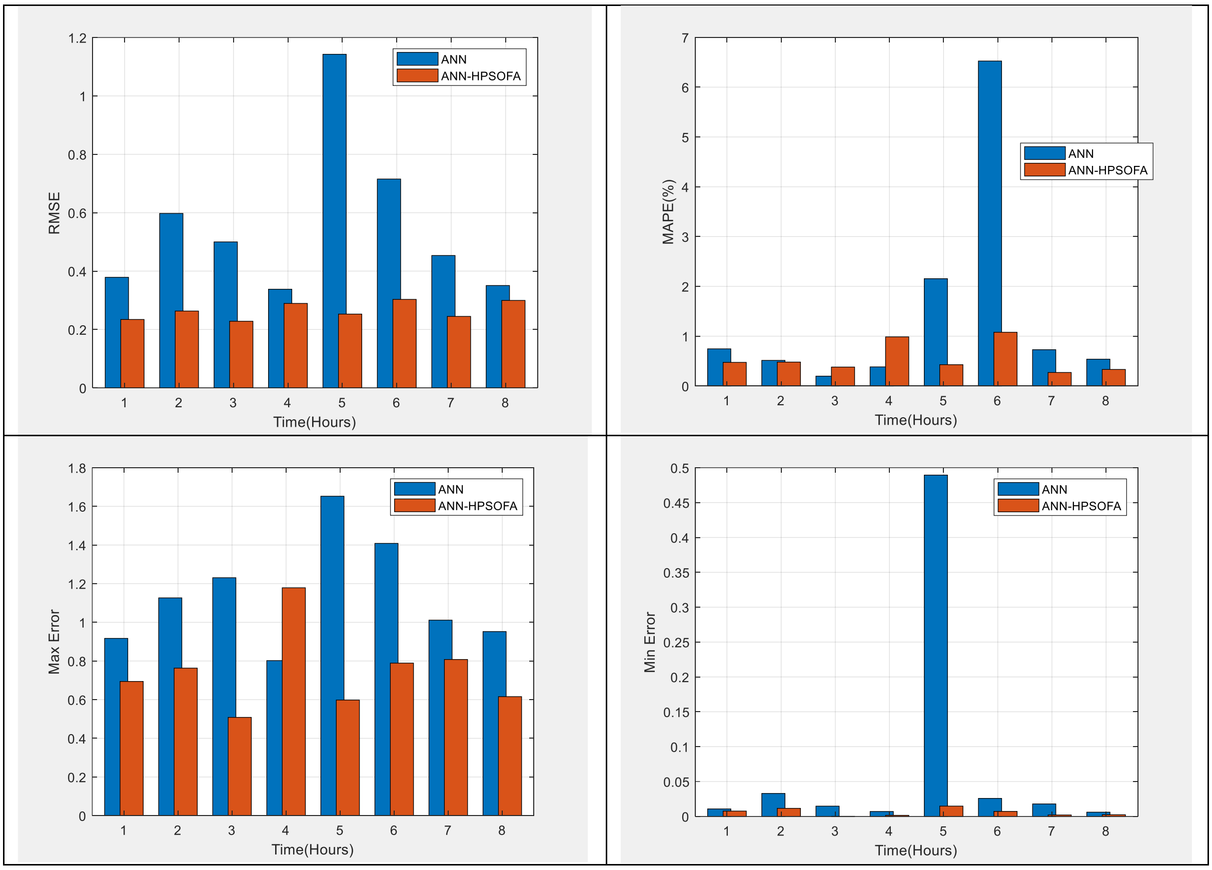


Table 3 shows the comparative analysis of the presented techniques with the ANN based on various parameters. The result represented that the presented method is superior over the ANN method.

Table 3 Comparative Analysis with the ANN Method based on Various Parameters



Next, the presented method is compared and also proposed for load forecasting in Table 4. The result shows that the presented method is superior than ENN, GRNN, BPNN, and PSO-ENN.

Table 4 Comparative Analysis with the Existing Methods [3]

Model	ENN	GRNN	BPNN	PSO-ENN	Proposed Method
RMSE	0.2636	0.4328	0.5445	0.1951	0.2282
MAPE	1.62%	2.72%	2.73%	1.1708%	0.27%
MaxError(MWh)	17.61	26.76	60.04	16.36	0.51
MinError(MWh)	1.32	5.45	1.05	2.30	0.00014

6. CONCLUSION AND FUTURE WORK

In this paper, we have designed a short-term load forecasting method using ANN. The optimal weight values of the ANN algorithm are calculated using a hybrid combination of firefly and PSO algorithms. The simulation is performed in MATLAB. The proposed method provides 0.51 maximum error and 0.00014 minimum error. In the last, the proposed method is compared and found that the presented algorithm is superior to the existing methods. In the future, we will explore other optimization and neural networks to enhance the proposed model performance.

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