Short-term load and spinning reserve prediction based on LSTM and ANFIS with PSO algorithm

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Abstract

In this paper, Short-term predicting of load and spinning reserve is first performed using a combination of ANFIS and meta-heuristic algorithms including Differential Evolution (DE), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The ANFIS-PSO combination is selected as the best ANFIS combination in load and spinning reserve prediction with a lower error criterion than other methods. As a DL method, LSTM network can provide good accuracy for load and spinning reserve forecasting. In the optimal ANFIS-PSO method, the average error value is low, but the error variance is high, on the contrary, in the LSTM method, the average error value is high, and the error variance is low. Therefore, we use the combination of ANFIS-PSO and LSTM to reduce the average error and error variance to an acceptable level. The weighted average method is as follows: the accuracy of each Method is obtained in the training step, then the predicted value for each data in the test step is calculated in each Method, then they are multiplied, and after that added together, finally will be divided to the total accuracy of two methods. The results obtained from the weighted average Method show the success of the proposed Method.

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Short-term load and spinning reserve prediction based on LSTM and ANFIS with PSO algorithm

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Abstract: In this paper, Short-term predicting of load and spinning reserve is first performed using a combination of ANFIS and meta-heuristic algorithms including Differential Evolution (DE), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The ANFIS-PSO combination is selected as the best ANFIS combination in load and spinning reserve prediction with a lower error criterion than other methods. As a DL method, LSTM network can provide good accuracy for load and spinning reserve forecasting. In the optimal ANFIS-PSO method, the average error value is low, but the error variance is high, on the contrary, in the LSTM method, the average error value is high, and the error variance is low. Therefore, we use the combination of ANFIS-PSO and LSTM to reduce the average error and error variance to an acceptable level. The weighted average method is as follows: first, the accuracy of each Method is obtained in the training step, then the predicted value for each data in the test step is calculated in each Method, then they are multiplied, and after that added together, finally will be divided to the total accuracy of two methods. The results obtained from the weighted average Method show the success of the proposed Method.

1. Introduction

Load modeling is a challenging task due to fluctuating electricity consumption levels and changing weather conditions. Load forecasting is necessary to improve consumption performance, infrastructure, and coordination between residential electricity. With the increase in population and growth of industrial societies, changes in load consumption in power networks are inevitable, and it is necessary to predict the amount of load required by the power system in the short term. Short-term load predicting is an essential criterion in power system planning and operation. Determining the maximum loading time and advance preparation for critical network times, load distribution studies, system reliability studies and even economic operation of generation and transmission networks all depend on short-term and medium-term hourly load predicting. Since load predicting from the present to the next few days is of particular importance. Due to the variable amount of electric load consumption, electricity generating companies must obtain the information needed for their decisions in the power system by predicting the load in different schedules. Spinning Reserve is also one of the side services that are very important for ISO and helps it to establish justice in the electricity market. The correct timing of the spinning reserve helps the system to overcome problems, such as the emergency exit of the generator or significant load forecasting errors, without exiting the load. Spinning reserve is provided by production units synchronous with the network. The spinning reserve capacity allocated to the units must be accessible within a maximum period of 10 minutes [2]. In most restructured electricity systems, such as California, New York, PJM, and New England, the provision of secondary services is the responsibility of ISO. There are various methods and models for securing reservations in the competitive environment of the electricity industry. ISO can set up a market with the Pool model to provide the reserve required by the system or purchase this amount of reserve under the influence of bilateral contracts with producers. Nowadays, providing spinning reserve service as well as other ancillary services is considered through competitive market, because competition can help to increase the profitability and productivity of goods, price transparency, and producer and consumer satisfaction [2]. The purpose of reservation prediction is to help better planning for the system. The purpose of planning and using reservation capacity is to create system security and reduce other related costs. Providing a spinning reserve has a cost, because the production units must produce less than the optimal output. Traditionally, there are three solutions to determine the amount of spinning reserve needed, one is equal to the capacity of the largest unit in the circuit and the other is a fraction of the load or a combination of both previous solutions. Although this is an easy way, the natural probabilities of the system's behavior, component defects, and economic issues are not considered. The short-term and daily forecast of the required spinning reserve helps the ISO to make effective and timely decisions based on the most minor power outages in the network. Also, based on the forecasted information, the market participants can choose the best offer for the daily spinning reserve market [3-4]. Although it is difficult to predict the amount of reserve for the installed capacity for many years ahead, it is easier to roughly predict the required and available reserve for the next moment or part of the future hours [4].

In [5], a hybrid technique using a Convolutional Neural Network (CNN) and a Multi-Layer Bi-Directional LSTM (M-BLSTM) for energy consumption prediction is proposed in three levels. Level 1 involves effective preprocessing to Confirmation, Screening, and adjust data. Level 2 involves a CNN with an M-BLSTM network that earns the input in sequence form and procedures. This method has a much better performance than other methods and obtained the lowest value for Mean Squared Error (MSE). To increase the prediction accuracy for the heat load, the spatiotemporal-LSTM attention model, which is new and combined, is considered in the reference [6]. The spatial-temporal attention LSTM model, by combining time and place, attention mechanism, and internal composition, it can focus on the most sensitive features of the data and also learn that feature and increase the prediction accuracy significantly. In [7], a novel deep Neural Network (NN) that merges the hidden specifications of the CNN and LSTM models is considered to elevate the prediction accuracy. In [8], two different models, including ANFIS with Fuzzy-C-Means (FCM), and LSTM network, are utilized to apply one-day ahead short-term renewable electricity generation predicting. The results of LSTM and ANFIS methods were almost the same. In [9], multi-layer LSTM networks are suggested, which have a powerful ability of forecasting fluctuating load information. The presented method by using different structures of LSTM meta-parameters for a specific time series by the well-known network search model, proposes a robust prediction method. It can obtain nonlinear patterns in data related to time series, while considering the intrinsic properties of non-fixed time series information. To demonstrate the efficiency of the mentioned method, it is compared with Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Recursive Neural Network (RNN) and monolayer LSTM. In reference [10], the LSTM network is proposed. It performs better than other algorithms used for short-term forecasting of residential loads. In reference [11], a new hybrid Artificial Intelligence (AI) and DL for predicting demand are proposed. The demand prediction is conducted by a hybrid AI/DL. In reference [12], a comprehensive evaluation of the DL algorithm is presented by performing load prediction at different levels of the power system. The proposed deep network improves the prediction accuracy in terms of average absolute percentage error, up to 23% at the aggregation level and, root mean square error, up to 5% at the dissociated level, compared to the shallow NN. In the reference [13], a model of a CNN based on LSTM is presented. The proposed approach solves nonlinear and uncertainty problems with many linear and nonlinear approaches to determine the best features, time series models, and the number of layers to integrate the LSTM approach. In [14], a novel demand forecasting approach due to deep multi-task learning is proposed. Novelty in this paper is including (a) considering the high-dimensional temporal and spatial specifications; (b) realizing the forecasting needs of different loads; (c) considering the coupling communications; (d) meeting the sharing of learning results of various networks. In [15], a novel forecasting approach for small-size demand prediction is presented. The proposed approach is due to an enhanced version of experimental mode decomposition. In [16], a new multi-objective fuzzy model can perform the interval prediction for short-term electrical demand. Also, a data-driven model is proposed for distributed interval fuzzy model. In [17], a residential electrical demand anomaly detection framework includes a hybrid one-step-ahead demand predictor and a rule-engine-based demand anomaly detector. In [18], a new short-term heating demand forecasting model based on a feature fusion LSTM method is presented to achieve high predictive accuracy of intelligent district heating systems and increase the ability to specify on a multi-time scale. In [19], a two-step model for forecasting residential demand is proposed, which includes two steps: in the first step, the raw data of electricity consumption are refined for useful training; and the second level comprises a hybrid approach with the integration of CNN and multilayer bidirectional gated recurrent unit. In the reference [20], a combination of CNN and LSTM is presented. The proposed CNN-LSTM method, which is a hybrid method, uses CNN layers to extract features from input information with LSTM layers. In the reference [21], two different methods based on different data, including ANFIS with fuzzy c mean (FCM) and LSTM network, have been used to predict the short-term one-day REG. Short-term forecasts for hydropower (HEG), geothermal electricity (GEG), and bioenergy (BEG) were also made using the mentioned methods. Measurement criteria are: root mean square error (RMSE), correlation coefficient (R), mean absolute error percentage (MAPE) and mean absolute error (MAE). Then, by measuring the error criterion, a comparison was made between the actual values and the values predicted by ANFIS-FCM and LSTM models. According to the obtained results based on the error measurement criterion (MAPE), the best estimate was obtained for the REG model. For REG, HEG, GEG, and BEG estimates, the minimum error values (MAPE) were 7.20, 7.46, 1.63, and 2.46 percent, respectively. According to the results, it can be seen that both ANFIS and LSTM models provide good performance for daily REG forecasting, and AN-FIS and LSTM models provide almost identical results. In the reference [22], a load prediction method based on multilayer LSTM networks is proposed. The proposed network search method selects the most suitable forecasting model according to different combinations of LSTM meta-parameters for a specific time series. It can record nonlinear patterns in time series data while considering the intrinsic properties of non-static time series data. The proposed Method is compared with several well-known time series forecasting methods from statistical and computational methods using load data related to the furniture company. The methods include ARIMA, ETS, ANN, KNN, RNN, SVM, and Single Layer LSTM. Experimental results show that the proposed method has better performance in terms of comparison criteria than previously tested methods. In this reference, a multi-layer LSTM network is proposed for load forecasting, which can effectively model time series patterns. Statistical tests have been chosen to compare the performance of the proposed method in comparison with other methods. The results show that the proposed method is superior to other compression methods. In addition, experiments on the main load time series show that the proposed method has the best performance in terms of RMSE and SMAPE, followed by SVM and ANN. This shows that computational intelligence techniques are highly capable of patterning actual time series data. Experimental results show that traditional statistical methods such as ETS and ARIMA have poor performance compared to SVM, ANN, and LSTM. The resulting model can be used to predict future demand, such as predicting future customer behavior. Other DL methods, such as attention-based NNs, can also be used to predict time series for future studies. In [23], this reference addresses the problem of predicting short-term loads for single-dwelling households. First, the difference in electric charge at the single subscriber level and the distribution substation level is explained. Although daily consumption patterns are always present after loading at the distribution substation level, for an individual household, energy consumption is usually volatile. A density-based clustering method,compares differences and measurements between aggregated and individual loads. Essentially, residents' lifestyles, no matter how inconsistent, are reflected as repetitive patterns in energy consumption. Consequently, this reference proposes a load prediction framework based on the LSTM recursive NN to predict the individual residential load, it is very challenging because it has been proven that LSTM learns long-term communication. Multiple criteria are extensively tested and compared with the LSTM method for load prediction in real datasets. Many load predicting methods that are powerful for substation-level load predicting seem to have difficulty predicting individual loads. The proposed LSTM network shows powerful performance in predicting load data. Although the accuracy of individual load predicting is low, the aggregation of all individual forecasts yields higher accuracy than the conventional direct load forecasting strategy. Inconsistencies in daily load consumption profiles generally affect customer predictability. The greater this inconsistency, the more LSTM can help improve prognosis compared to simple ANN. For future research, methods for adjusting parameters to increase prediction accuracy for different types of customers are being developed. In reference [24], a load prediction system at the level of distribution voltage, by DL algorithm and also a new AI network, is introduced. This system was used to present and evaluate an advanced hybrid AI technique and an OPELM and LSTM technique in predicting the load of SA distribution networks, respectively. For a case study of two case studies, Actual electricity consumption data for South African distribution subscribers were used. The first case for testing (a) included a substation with a voltage of 11.88 kV and a power of 80 MVA, which included two transformers with a capacity of 40 MVA. The second case for testing (b) consists of a consumer fed by a switching substation with a voltage level of 132 kV. Also, in this study, the effect of temperature on the efficiency of the new combination of AI technique and DL technique was investigated. In both case studies, ANFIS and OP-ELM achieved higher accuracy in developing their models regardless of temperature. But in the case of LSTM, the opposite is true because LSTM models have the least errors in their development, including temperature. The lowest error in load predicting by LSTM model was related to case study A, MAPE was 6.35%, MAE was 4.78%, and RMSE was 6.33%. The highest efficiency of LSTM network was related to case study B with MAPE 11.54%, MAE 8.96% and RMSE 14.07%. LSTM has lower prediction error than ANFIS system. Removing some data to eliminate dents and bumps, caused the accuracy of all models related to technique A to decrease. In the second case for testing (b), it is exactly the opposite. In order to predict the load of the South African distribution network when using DL techniques, the effect of other weather parameters such as wind, humidity, density, etc., should be further investigated. The temperature variable is considered as one of the inputs. This research shows that a combination of a new AI technique and a DL algorithm can be used to predict South Africa's distribution load. These methods can be tested to predict the load of distribution networks at medium voltage (MV) level, large power supplies, and high power consumers. As South Africa is still struggling to adopt smart-capable meters, the integration of smart meters should be a priority to improve load predicting in the distribution system for future work. The effect of consumer behavior on the performance of load predicting by combined techniques of AI and DL is very important, which should include the integration of smart meter data. In the reference [25], a new prediction model is presented, including the combined distance with the KNN combination optimized by NSGA-II, the self-adaptive core density estimation based on the boundary core, and the deep belief network. Five data sets are used confirm the robustness and high performance of this model. The findings indicate that the displayed distance prediction model has higher flexibility and reliability, and at the same time, it does not have complexity in the prediction process. The results are: First, NSGA-II-KNN-DBN in multi-stage prediction and at different confidence intervals can produce very stable prediction results. Second, the interval predicting model can significantly drop the predicting error by classifying the raw time series compared to other common traditional forecasting techniques. This indicates that the DL approach is more robust than traditional predicting methods. Third, to achieve NSGA-II reliability, comparisons are made with other optimization algorithms, especially density and probability-based algorithms. The results indicate that NSGA-II performance is higher due to more successful optimization performance and greater search accuracy. They can be used in practical applications in electrical load, and experimental achievements show that the use of DL approaches is essential. DL methods for predicting electric charge distances are of great value in future research.

In this research, a new solution for short-term load and spinning reserve predicting by using the combination of ANFIS-PSO and LSTM network is presented. First, preprocessing is performed on the Consumption load and spinning reserve data. Then the short-term load and spinning reserve prediction are performed by using ANFIS-DE, ANFIS-GA and, ANFIS-PSO. Finally, they are compared with each other based on different evaluation criteria. According to the MSE and RMSE error comparison criteria, the ANFIS-PSO method is selected as the best method and is used to combine with the LSTM network by the weighted average method. The simulation results obtained from combining two methods by using Heuristic weighted average method show that the proposed Method is successful.

The rest of this paper is organized as follows. The formulation of the propsed problem is presented in Section 2. In Section 3, the numerical results are tested. Finally, Section 4 includes the conclusion and results analysis.

2. Methodology

2.1. ANFIS

Based on the relationship between NNs and fuzzy logic, various types of systems have been created. Many believe that the word Neuro-fuzzy does not apply to all compounds; because some of these components are complementary to each other, and instead, each of these components can be replaced by other systems such as decision trees, evolutionary algorithms, and the like. The goal in the fuzzy neural system is to automatically determine rules that are fuzzy or membership functions that are related to fuzzy sets, which is done by the NN. Unlike the Neuro-fuzzy system, there is a fuzzy-NN where fuzzy logic helps to improve the efficiency or to add the concept of uncertainty to the NN. The appropriate structure of ANFIS technique is selected according to the input data, membership degree, input and output membership functions, and rules. In the training step, by changing the degree of membership of the parameters, the predicted value becomes closer to the real value, considering that the error is within the permissible limit. The ANFIS method uses NN and fuzzy logic for nonlinear mapping between input and output and has good training, construction and classification capabilities. Its learning rule is based on the error Back Propagation (BP) algorithm to minimize the MSE between the network output and the actual.

The ANFIS technique was first presented by Jang in 1993 and is an adaptive and training network. Neural fuzzy modeling of a system describes the behavior of a system with the laws of fuzzy logic in the structure of the NN. Figure 1 indicates the overview of ANFIS structure. In this figure, five layers are observed. The first layer is called the fuzzy layer, which uses membership functions to determine the degree of membership of each variable and creates a fuzzy system. The second layer is the inference layer, and extracts the weight of each function. The third layer is called the normalization layer, and then in the fourth layer, the normalized weights from the third layer are applied, and finally, in the fifth layer, they are added together. Nodes have functions with adjustable or fixed parameters.

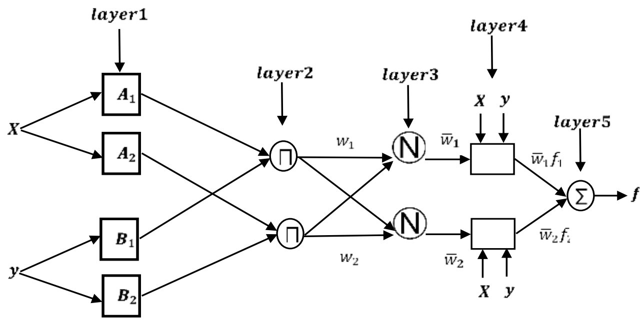

Fig. 1 *Overview of ANFIS structure [8]*

Output layers:
Layer 1: The inputs of the whole system pass through the membership functions in the first layer.

$$\begin{cases} Q_{1,i} = \mu A_i(x), & for\ i = 1,2 \\ Q_{1,i} = \mu B_i(x), & for\ i = 3,4 \end{cases} \tag{1}$$

$$\mu A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{2}$$

Membership functions are often chosen as Gaussian functions. The parameters of this layer are the initial parameters of the system.

Layer 2: The product of the input signals is equal to the output of this layer.

$$Q_{2,i} = w_i = \mu A_i(x)\mu B_i(y), \quad i = 1,2 \tag{3}$$

Layer 3: The output of this layer is the normalization of the previous layer.

$$Q_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{4}$$

Layer 4:

$$Q_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \tag{5}$$

Layer 5: The total output of the system is equal to the output of the fifth layer:

$$Q_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

2.2. LSTM

The LSTM network was first introduced by Hoch Reiter and Schmid Huber in 1997 and is a particular type of RNN network that solves its long-term memory problem. Unlike traditional Recurrent NNs, where content is rewritten at each stage, intuitively, if at the elementary level the LSTM network distinguishes important information in the input, it can send this information without delay for a long time, so it can preserve such long-term potential dependencies. The LSTM network has two inputs and two outputs. One of the inputs called C_{t-1}, connects directly to the output called C_t, which this connection continues from the beginning to the end of the sequence. Cell-State means long-term memory, which is a critical component in LSTM and has two important and interesting properties: 1- The information in it can be deleted, which means forgetfulness. 2- There is the ability to add information to the Cell-State, which means to remember.

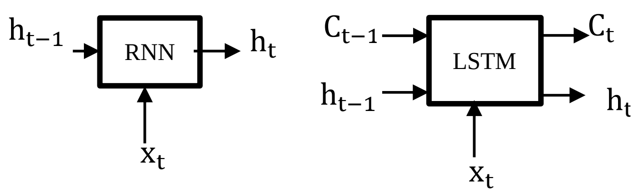

Fig. 2 *RNN network and LSTM network [9]*

Unlike the traditional RNN that receives a balanced sum of input signals and then gives it to an activator function, each LSTM uses a memory called cell state at each moment [26]. The activation section (h_t) corresponding to LSTM is represented in equation 7. In this equation, Γ_0 is called the output gate and monitors the amount of memory content and calculated according to Equation 8, where σ is the sigmoid activation function, and W_0 is a diagonal matrix [27]. The memory cell (C_t) is also updated by relatively regardless of the current memory and adding new memory content as $\hat{C}_t$ according to Equation 9 [28]. The amount of current memory that does not matter and is to forgotten is governed by the forget gate. The update gate controls the new content to be added to the memory cell [29]. These operations are performed according to the following equations:

$$h_t = \Gamma_0 * \tanh(c_t) \tag{7}$$
$$\Gamma_0 = \sigma(W_0[h_{t-1}, X_t] + b_0) \tag{8}$$
$$C_t = (\Gamma_f * C_{t-1}) + (\Gamma_u . \hat{C}_t) \tag{9}$$
$$\hat{C}_t = \tanh(W_c[h_{t-1}, X_t] + b_c) \tag{10}$$
$$\Gamma_f = \sigma(W_f[h_{t-1}, X_t] + b_f) \tag{11}$$
$$\Gamma_u = \sigma(W_u[h_{t-1}, X_t] + b_u) \tag{12}$$

The LSTM network has internal mechanisms called gates. These gates control the flow of information. They also specify what data is important in the sequence and should be retained and what data should be deleted; In this way, the network passes essential information along the sequence chain to get the desired output.

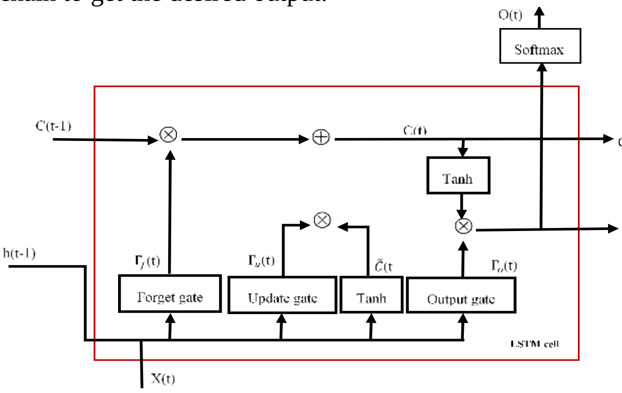

Fig. 3 *LSTM network overview [7]*

2.3. Proposed evolutionary algorithms

2.3.1. DE algorithm

This algorithm was presented by Storn and Price in 1996. The main difference between this algorithm and other algorithms is its unique method of generating new answers. Unlike evolutionary algorithms, where the crossover operation is performed first and then the mutation operation, in the DE algorithm, temporary response is generated first using the mutation operator, and then a new and definite response is generated using the crossover operator. In this algorithm, unlike other evolutionary algorithms that use a known probability distribution to sample and create mutation steps, the difference between the answers we have reached so far is used to generate new answers and mutation operations. The DE algorithm emphasizes distance between members of the population because it contains helpful information about the objective function and the optimization problem, which can increase the exploration property and better results.

2.3.2. GA algorithm

GA is a particular type of evolutionary algorithms that was introduced by John Holland in the early 1970s. First, the data are randomly distributed in space and the initial population is generated, then by selection methods, the cost or fitness value of each data is determined based on the objective function, and the desired data are selected, which are the parents of the first generation. Then, through crossover and mutation operations, children are created from the parents. After the formation of the first generation, the selection operation is performed. Among the parents and children of the first generation, the best ones are introduced as new parents to go to the second generation. Thus, the second-generation data is the best parents and children of the first generation, plus some random data. Suppose random information is not added in the new generation, the probability of getting stuck in local optimal point's increases. In each generation, we select the best data with the deterministic selection method and send it to the next generation, which is called elitism, so we always keep the best, which increases the speed of the GA.

2.3.3. PSO algorithm

The PSO algorithm was presented in 1995 by two scientists, James Kennedy (psychologist) and Russell Eberhart (electrical engineer). At first, they decided to use existing social interactions to create a kind of computing intelligence that lacks specific individual skills. Their efforts Cause to the development of an optimization algorithm named PSO, is adapted from the collective behaviour of groups of animals such as birds and fish. Because it solves the problem with the most minor information, it is one of the metaheuristic algorithms. Also, since it has an iterative recovery mechanism, it is also one of the evolutionary algorithms. The PSO algorithm belongs to the group of collective intelligence algorithms and is based on the sharing of information and experiences. In the PSO algorithm, there is a set of particles. Each of the particles has a position in the search space that is described as a number or vector and has a proposal for solving the optimization problem. All particles in their motion use their previous experiences and the whole group. In each position of the space in which the particle is located, the value of the objective function is calculated. Then it chooses the direction of movement using a combination of information including its current location, the best location it has been in before, and information about the location of the best particle. Each particle has five properties: 1- Particle position 2- Objective function corresponding to the particle position 3- Particle velocity 4- Best experienced particle position 5- Amount of cost or fitness function commensurate with the best experienced position.

2.4. Proposed Method

First, preprocessing is done to remove incomplete and abnormal data from the database, which will be done in different ways, including thresholding and averaging. First, load and spinning reserve forecasting will be done by the ANFIS system optimized with meta-heuristic DE, GA, and PSO algorithms. Then load and spinning reserve forecasting will be done by the LSTM network alone to compare with the weighted average heuristic method. Finally, by combining the two methods of AN-FIS-PSO and LSTM, load forecasting and spinning reserve are done using the innovative weighted average method. To show the power of the innovative method, the evaluation criteria of MSE, RMSE, MEAN, and STD are calculated for each method according to the predicted output values and the actual value. The suggested flowchart for load forecasting is as follows:

3. Numerical results

3.1. Information of studied system

The actual values of the input load and spinning reserve for forecasting in different Method are shown in Figures 5a and 5b, respectively: The input load data from the NEPOOL region from 2004 to 2007 are selected by ISO New England, which includes 35,000 data for four years, and 70% of the data are selected for training and 30% for testing. The spinning reserve data was drawn hourly from the PJM electricity market in January 2013 for one week, which includes 200 data. 90% of the total information is used to train the network and the remaining 10% is used to test the network.

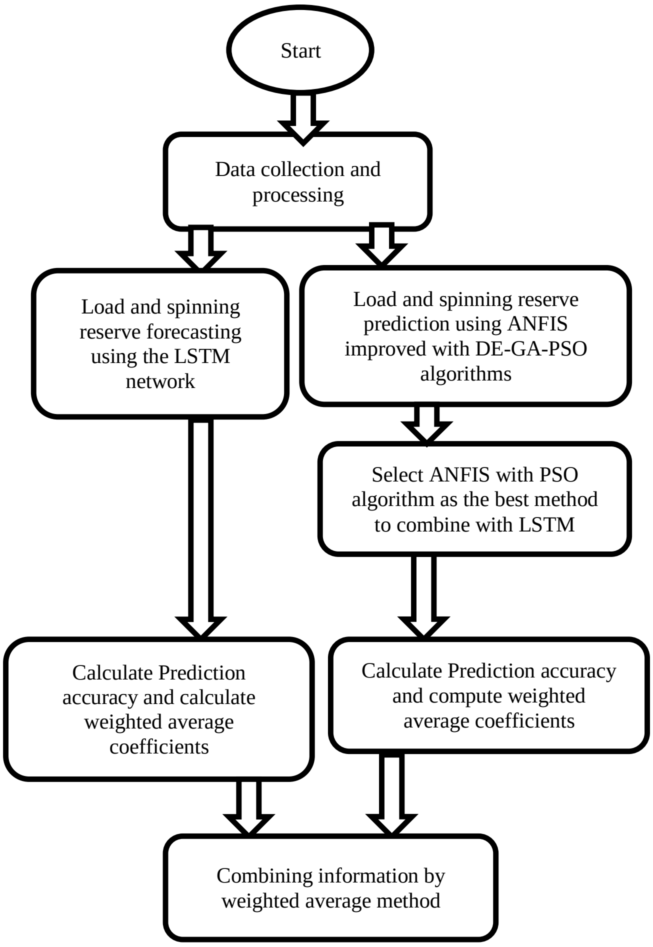

Fig. 4 Proposed flowchart

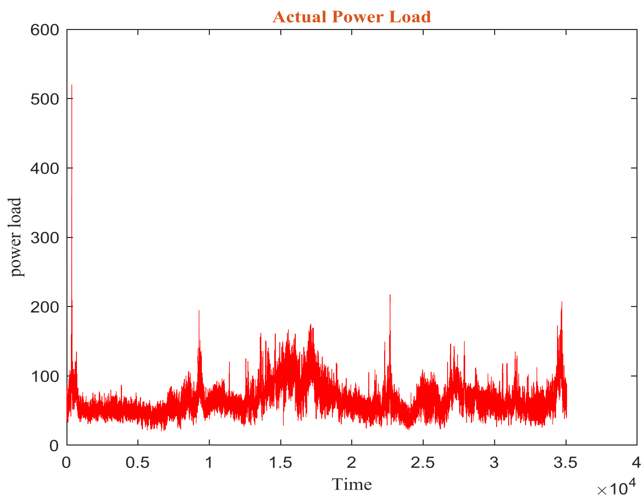

Fig. 5 (a) *Actual values of input load [7]*

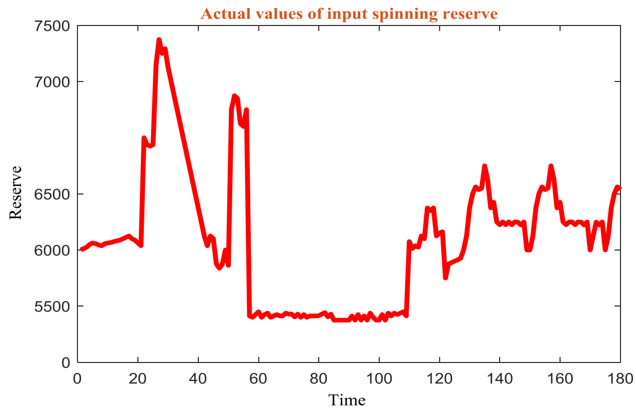

Fig. 5 (b) *Actual values of input spinning reserve [7]*

The number and time of iteration of each algorithm will be determined according to the damping of the algorithm. The rules of the Neuro-Fuzzy systems with the PSO algorithm between input and output are shown in Figure 6.

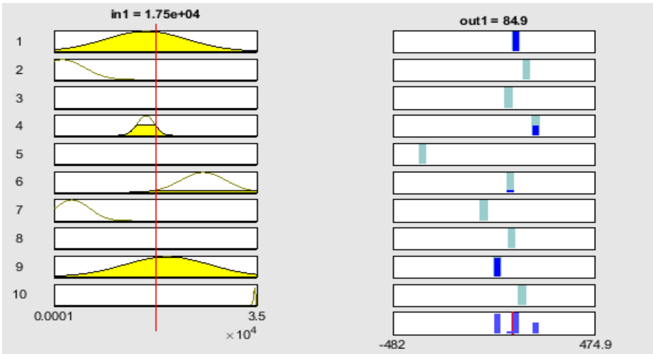

Fig. 6 *Fuzzy system rules*

The Neuro-Fuzzy system improved by the PSO algorithm is as follows:

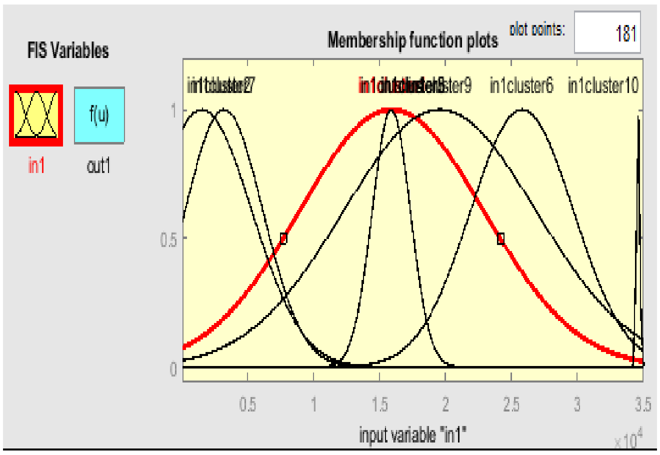

Fig. 7 *The input of Neural Fuzzy Inference System with PSO*

3.2. Numerical results

Simulations are performed in MATLAB software, and the results for load and spinning reserve prediction using ANFIS optimized with different algorithms are considered as follows. In the upper part of Figures 8 to 12, are the predicted and actual load and spinning reserve values. In the lower left position, the amount of prediction error according to the number of samples, and also, at the bottom right, a histogram of the forecast error is shown.

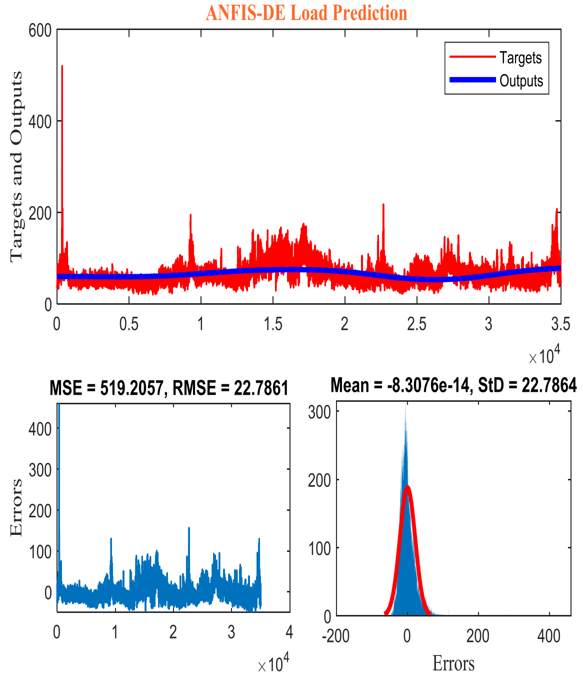

Fig. 8 (a) *Load prediction by ANFIS-DE combination*

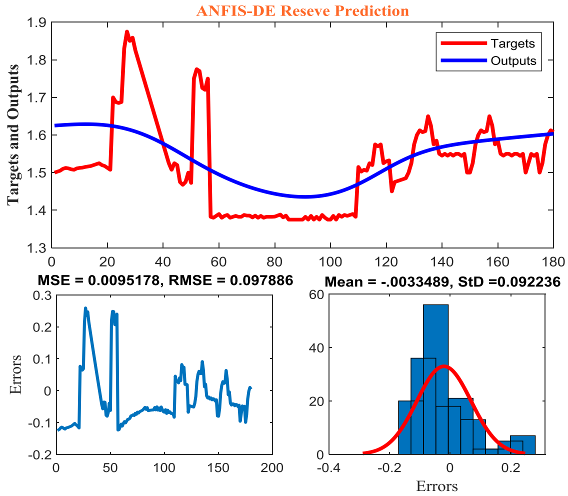

Fig. 8 (b) *Spinning reserve prediction by ANFIS-DE combination*

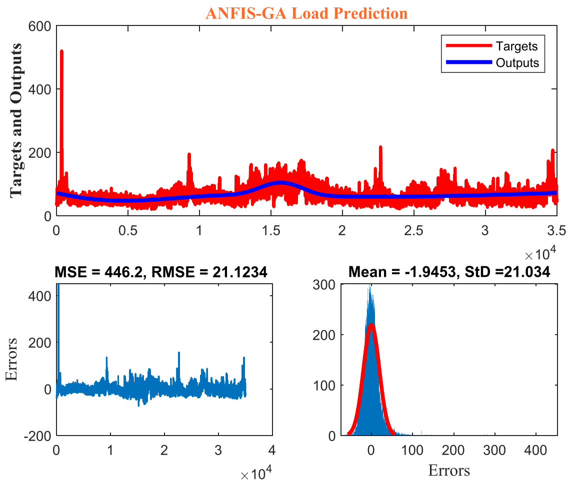

Fig. 9 (a) *Load prediction by ANFIS-GA combination*

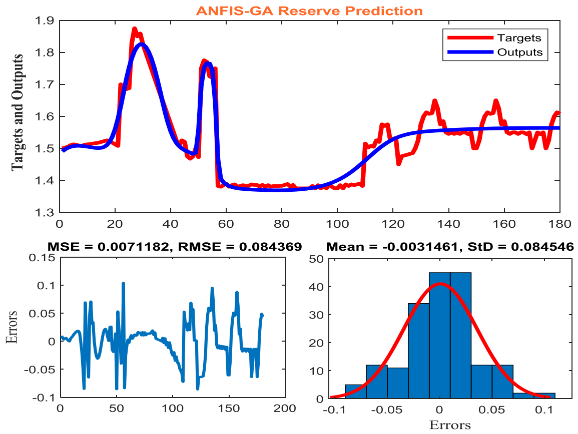

Fig. 9 (b) *Spinning reserve prediction by ANFIS-GA combination*

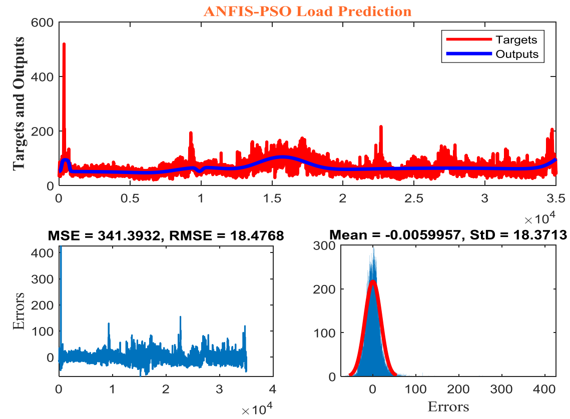

Fig. 10 (a) *Load prediction by ANFIS-PSO combination*

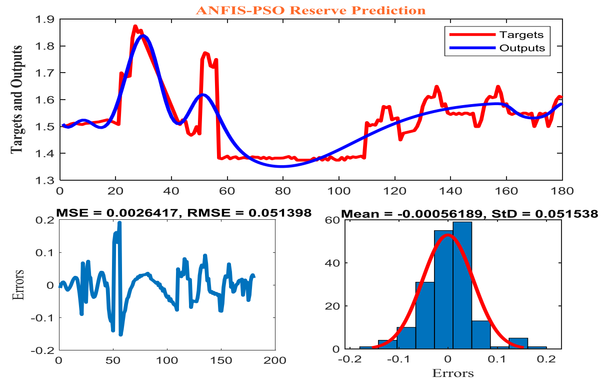

Fig. 10 (b) *Spinning reserve prediction by ANFIS-PSO combination*

Comparing Figures 8 to 10, it can be inferred that the ANFIS-PSO algorithm performs better than other algorithms. Based on the error evaluation criteria according to Table 1.a and 1.b, the PSO algorithm has higher efficiency and accuracy for optimizing the fuzzy neural system, and the error values in the ANFIS-PSO combination have a significant reduction compared to the ANFIS combination with other algorithms.

Figure 7 shows the belonging functions for the input of the fuzzy neural system, which this input contains 10 clusters that have been clustered using the FCM algorithm. The ANFIS network intercepts the range of input data, and the figure above is the input of a fuzzy system improved by the PSO algorithm.

Table 1 (a) Comparison of ANFIS performance evaluation criteria optimized with different algorithms for load forecasting.

Study network	STD	MEAN	RMSE	MSE
ANFIS with DE	22.7864	-8.3076e-14	22.7861	519.2057
ANFIS with GA	21.034	-1.9453	21.1234	446.2
ANFIS with PSO	18.4771	-0.005995	18.4768	341.3932

Table 1 (b) Comparison of ANFIS performance evaluation criteria optimized with different algorithms for spinning reserve forecasting

Study network	STD	MEAN	RMSE	MSE
ANFIS with DE	0.09223	-.0033489	0.09788	0.009517
ANFIS with GA	0.08454	- 0.0031461	0.08436	0.007118
ANFIS with PSO	0.0515	- 0.0005618	0.05139	0.002641

Since the purpose of this article is to predict the load and spinning reserve using the combination of fuzzy neural system and DL method, LSTM network is used, which is one of the DL methods.

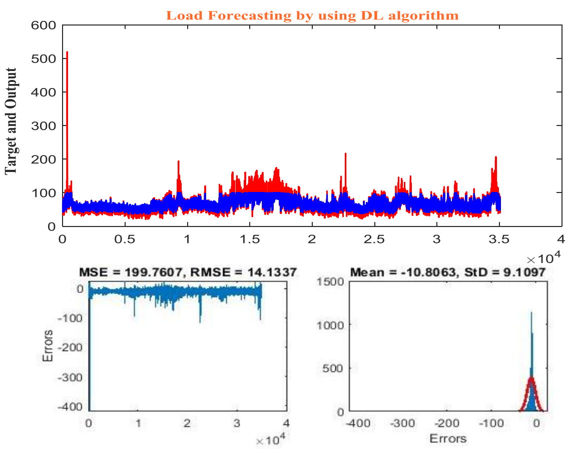

Fig. 11 (a) Load forecasting by using DL algorithm.

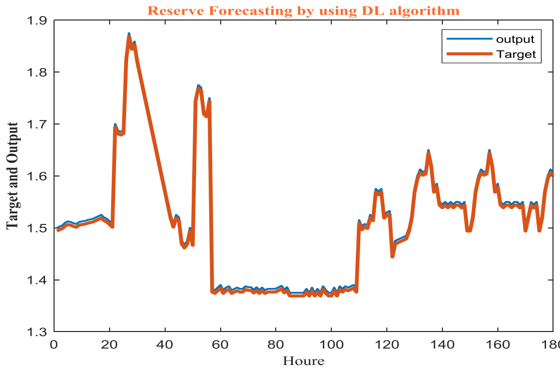

Fig. 11 (b) spinning reserve forecasting by using DL algorithm.

The results obtained from the DL method, it shows the high accuracy and efficiency of this method compared to optimized neural fuzzy methods. As seen in Table 2, according to MSE and RMSE evaluation criteria, the LSTM network has higher accuracy and efficiency than the best combination of fuzzy neural systems.

Table 2 (a) Evaluation criteria in load forecasting by LSTM network.

Study network	STD	MEAN	RMSE	MSE
LSTM	9.1097	-10.8063	14.1337	199.7607

Table 2 (b) Evaluation criteria in spinning reserve forecasting by LSTM network

Study network	STD	MEAN	RMSE	MSE
LSTM	0.009734	-0.00145	0.049576	0.0022124

3.3. The reason for combining ANFIS-PSO and LSTM network

In the ANFIS-PSO method, the average error value is lower than the LSTM network, but the standard deviation is higher than the LSTM method and vice versa. Therefore, to reduce the average error and standard deviation to an acceptable level, the combination of the two methods is used with the help of the heuristic weighted average method. The simulation results confirm the combination of the proposed LSTM network with ANFIS-based methods.

3.4. Weighted average method (WAM)

First, in the training phase, based on the training data, the accuracy of each of the ANFIS-PSO and LSTM methods is calculated, then in the testing phase, based on the test data, the predicted value is obtained for each data. In the system of combining information, the weights of each method are entered in the calculations based on the accuracy of that method. In the proposed method, based on the accuracy obtained from each method in the training step, the amount of weight gained for the combination as a weighted average is determined. Then normalization is performed according to the weights. The higher the accuracy of the data in each method, the more weight it will have in the weighted average method.

Steps of combining information by the weighted average method:

In the first step, the training data is given to the ANFIS-PSO intelligent system in the form of a 6-hour package to predict the load and spinning reserve for the next hour.

In the second step, the sum of all training errors for all training data is calculated in the ANFIS_PSO method.

In the third step, the accuracy of the ANFIS_PSO method will be calculated according to formula 14 and then normalized.

In the fourth step, the training data is given to the LSTM network in the form of a 12-hour package to predict the load and spinning reserve for the next hour.

In the fifth step, the sum of all training errors is calculated for all training data in the LSTM method.

In the sixth step, the accuracy of the LSTM method will be calculated according to formula 14 and then normalized.

In the seventh step, 6-hour test data is given to the trained ANFIS_PSO system, and the predicted value is calculated for each data.

In the eighth step, 12-hour test data is given to the trained LSTM network and the predicted value is calculated for each data.

In the ninth step, according to formula 13, we combine all the steps using the weighted average method.

$$\text{WAM} = \frac{w_A * \mu_A + w_L * \mu_L}{w_A + w_L} \quad (13)$$

$$accuracy = \frac{\text{predicted value}}{\text{actual value}} \qquad 0 < accuracy < 1 \quad (14)$$

w_A :the ANFIS-PSO accuracy in the training step

μ_A :value predicted by the ANFIS-PSO in the testing step

w_L :the LSTM accuracy in the training step

μ_L :value predicted by the LSTM in the testing step

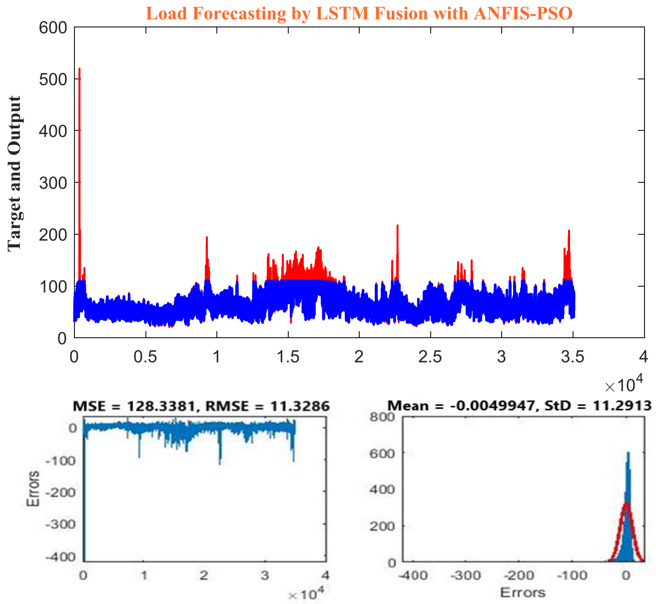

Fig. 12 (a) Load prediction by the weighted average method.

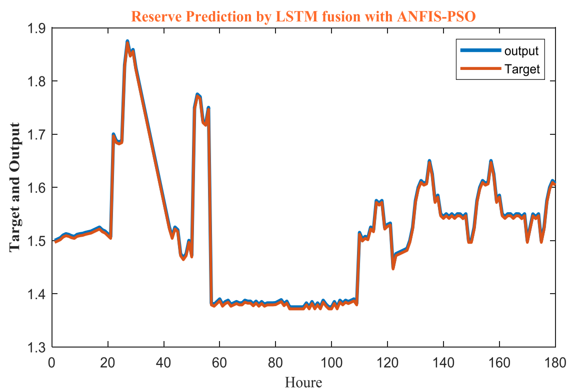

Fig. 12 (b) Spinning reserve prediction by the weighted average method.

Table 3 (a) Evaluation criteria of the weighted average method for load forecasting

Study network	STD	MEAN	RMSE	MSE
Proposed method	11.2913	-0.00499	11.3286	128.3381

Table 3 (b) Evaluation criteria of the weighted average method for spinning reserve forecasting.

Study network	STD	MEAN	RMSE	MSE
Proposed method	0.00771	-0.00045	0.03843	0.001135

4. Conclusion

In this paper, first, preprocessing load and spinning reserve data is performed. Then using the ANFIS system optimized by DE, GA, and PSO algorithms, short-term load, and spinning reserve forecasting will be done. According to all the error evaluation criteria, the ANFIS-PSO combination has less error than other ANFIS combinations. Therefore, it will be selected as the selected method to combine with the LSTM network using the innovative weighted average method. Then, load and spinning reserve prediction are performed by the LSTM network alone to compare with the innovative weighted average method. As a result, based on the error evaluation criteria such as MSE, RMSE, MEAN, and STD, the superiority of the weighted average method over the ANFIS-PSO and the LSTM methods is proven. Because this method has been able to significantly improve the results compared to these two methods according to all error evaluation criteria. To predict the load and spinning reserve based on the RMSE evaluation criteria, the innovative weighted average method has improved by 38.7%, and 25%, respectively, compared to the ANFIS-PSO method and by 19.8%, and 22.5%, respectively, compared to the LSTM method. To predict the load and spinning reserve based on the MSE evaluation criteria, the innovative weighted average method has improved by 62.4% and 57%, respectively, compared to the ANFIS-PSO method and by 35.7% and 48.6%, respectively, compared to the LSTM method. To predict the load and spinning reserve based on the MEAN evaluation criteria, the innovative weighted average method has improved by 16.7% and 19.3%, respectively, compared to the ANFIS-PSO method and by 91.5% and 22%, respectively, compared to the LSTM method. To predict the load and spinning reserve based on the STD evaluation criteria, the innovative weighted average method has improved by 39.8% and 85%, respectively, compared to the ANFIS-PSO method and by 19.3% and 20.7%, respectively, compared to the LSTM method.

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