Renewable Energy Forecasting with Hybrid Nonlinear Model (ANFIS): Case Study of Wind Speed in Thailand

Anupong Banjongkan*, Nittaya Kerdprasop and Kittisak Kerdprasop
School of Computer Engineering, Suranaree University of Technology, Nakhon Ratchasima, 30000, Thailand.

*Correspondence. banjongkan@gmail.com(A.B.)
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Abstract: Renewable energy has been a hot topic recently, especially wind power which has grown considerably in the past decade. The forecast of wind speed in advance is important information for wind power plant management. In this paper, a high-efficiency time series model for forecasting wind speed day-ahead is proposed, developed from the nonlinear hybrid model called Adaptive Neuro-Fuzzy Inference System (ANFIS). It brings together the advantages of fuzzy and neural network learning. In addition, a comparative study was done with Autoregressive Integrated Moving Average (ARIMA) and other nonlinear time series models including Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) models. The realistic data from the meteorological data of Chaiyaphum province, Thailand were used in this research. The dataset was split into learning and testing data in the ratio of 75% and 25%, respectively. The result shows that the forecasting performance of the ANFIS model was comparable to the ARIMA model. Both models achieve high accuracy than other neural network models. The proposed model achieves high efficiency at 22.89 MAPE and 0.41 of R^2. Interestingly, the ANFIS model has a learning time faster than ANN and LSTM models by at least 100 times.

Key words: ANFIS, fuzzy, neural network, renewable energy, time series

1. Introduction

Due to the shortage of main energy resources like petroleum, the price of fuel energy has risen as well as the often control through resource-rich countries in the Middle East. Alternative energy sources with unlimited supply called renewable energy such as wind power, solar radiation, and sea wave power have been receiving continuous attention over the past decade, especially wind power. The growth of wind power plants or wind turbine farms is widespread in each country around the world.

According to [1] reported, in 2021 there is a growth in wind power plants worldwide. It has a total electricity generation capacity of 874 Gigawatt, 13% more than the previous year. The total electricity capacity from wind power plants worldwide in 2022 is expected to reach 955 Gigawatt. Forecasting information in advance is an important part of management and planning. It makes maximized efficiency in managing wind power plants such as planning for the installation of the new wind turbine node and planning for maintenance. The hardware-based wind speed forecasting tools known as physical models have limitations in the setup process and forecasting accuracy [2–3] because the nature of wind speed is random and chaotic. The wind speed records are time series data, which means the value of wind speed depends on time. It says today's value depends on past values. As explained in [4], the components of time series can be defined in terms of correlation of the time series data as shown in Eq. (1)

$$y_t = Linear_t + Nonlinear_t + e_t \tag{1}$$

where y_t is the actual time series value, $Linear_t$ is linear correlation part, $Nonlinear_t$ is nonlinear correlation part, and e_t is the error part. So, many researchers have developed tools for forecasting wind speed through machine learning with various time series modeling techniques.

The models developed through a neural network proposed by [5] were time series model to be used for forecasting wind energy with ANN technique using feed-forward back-propagation networks with Radial Basis Function (RBF), and Adaptive Linear Element networks were tested with wind data from two sources in the state of North Dakota, USA. Such research found that the time series model RBF neural networks performed well on the site Kulm dataset. The backpropagation network performed well on the site Hann dataset. The research work of [6] presented the improvement of ANN time series models for wind power forecasting based on an optimization technique. Two methods, namely ANN-LM (Levenberg Marquardt) and ANN-PSO (Particle Swarm Optimization) were tested on the collected wind datasets from the IST-University of Lisbon automatic weather station. The multivariate data (wind speed, temperature, humidity, and pressure) were processed in their research. The results showed that the ANN-LM model achieved the best forecasting results. In papers [7–9] the authors used the hybrid technique via a statistical ARIMA model working with the neural network (ANN) model. The results of those work reported that the hybrid models can achieve high accuracy in wind speed forecasting. The statistical model studied by [10] performed well in forecasting long-term wind speed in the Zhangye area with ES-ARMA and ES-GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, in which ES is Eliminating the Seasonal technique. The results of that research showed that the ES-GARCH time series model gave better long-term wind energy forecasting efficiency than ES-ARMA, with ES-GARCH giving the lowest MAE of 0.30 of the winter data and ES-ARMA also providing the lowest MAE of 0.34 for the winter dataset. The work proposed in [11] also used a hybrid nonlinear model with optimization techniques including the PSO, Genetic Algorithm (GA), and Differential Evolution (DE) to forecast the wind speed of different locations in Malaysia. The overall result showed that the proposed method with PSO and GA outperformed ANFIS standalone and ANFIS-DE. The work of [12] used the regional atmospheric modeling system (RAMS) to simulate 168-h low-level wind forecasts over some areas of Thailand. The results showed good forecasting but consume much computing power.

This research proposed the nonlinear hybrid time series model for forecasting wind speed. Machine learning technique with the ANFIS algorithm is the key to this research sharing the same research scheme as adopted in [11]. However, this research uses a different architecture and fuzzy rule base creation method. Especially, this research focuses on the dataset of Thailand. The comparative study with other time series models are also presented in this research.

The rest of the paper is organized as follows: section2 presents the methods used in the research. The dataset, experiment setup, and testing technique were discussed in section3. The last two sections (4 and 5) are discussing the experimental results and concluding the research, respectively.

2. Methodology

2.1. ARIMA–linear time aeries model

ARIMA is a statistical model developed from the auto-regressive (AR) and moving average (MA) models by adjusting the time series data to stationary. The letter I (Integrate) in the ARIMA model was used for processing the data with the differencing technique. This time series model is parametric. The values of parameters p, d, and q are shown in Eq. (2). The order of an ARIMA model can be determined by using the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF), proposed by Box and

Jenkins [13].

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j e_{t-j} + \varepsilon_t \tag{2}$$

where α_i is ith autoregressive parameter, β_j is jth moving average parameter, and ε_t is the error at time t.

2.2. ANN–nonlinear time series model

ANN is a basic neural network with the concept of imitating the working process of the human brain to apply to learn information through the machine learning process. The basic ANN is called a Multi-layer Perceptron (MLP), which uses the back-propagation process to learn the data, presented by Rumelhart in 1985 [14]. Fig. 1 shows the simple structure of MLP such that there are three layers of the network structure. The first layer is the input layer, which is responsible for receiving input data. The second layer is the hidden layer, which is the data processing layer that can be modified to contain more than one layer. Finally, is an output layer where each neural node of the hidden and output layer will be processed through Eq. (3).

$$y_i = f(x_i W_i + B_i) \tag{3}$$

where y_i, x_i, W_i, B_i, and $f()$ are the output, input, weight, bias, and activation function of neural node i, respectively.

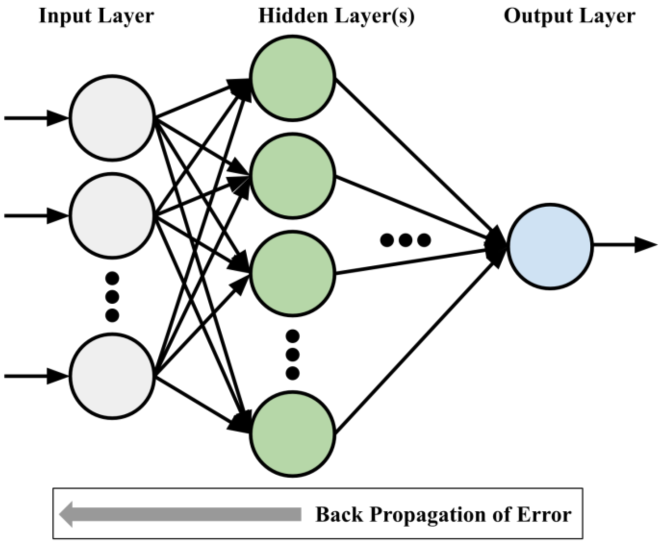


Fig. 1. The multilayer perceptron topology.

2.3. LSTM–nonlinear deep learning model

LSTM is a deep learning neural network improved from the recurrent neural network (RNN). It was proposed by S. Hochreiter and J. Schmidhuber in 1997 [15]. The LSTM was developed to have the ability to memorize and selectively forget some correlations of a time series. Such ability enables the LSTM to capture important patterns of long-term correlation.

An important mechanism that makes LSTM work well with time series data is the “cell state” instead of symbol C in Fig. 2, which is an important part of finding long-term patterns. Due to the complexity of the LSTM structure, it requires high computing power and takes a lot of time to learn the data.

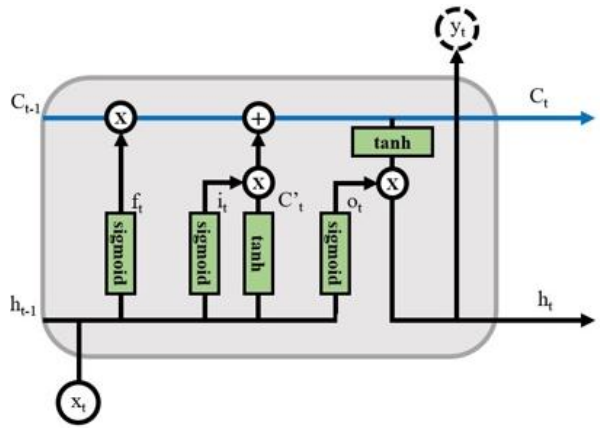


Fig. 2. Show the component inside the LSTM neural node.

2.4. ANFIS–nonlinear hybrid time series model

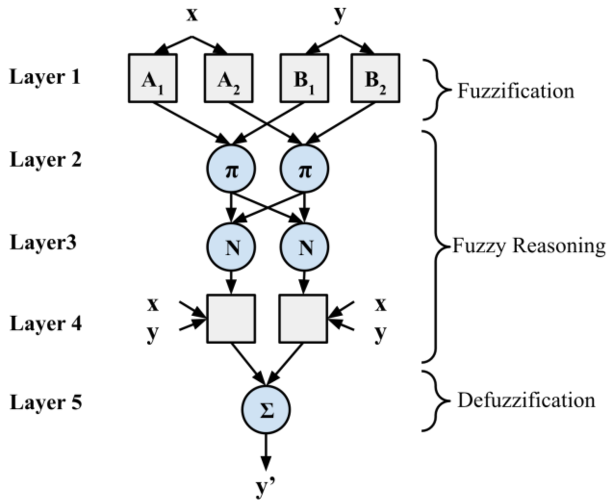


Fig. 3. The adaptive neuro-fuzzy inference system topology.

ANFIS is a nonlinear hybrid model that is a combination of neural networks and fuzzy inference systems proposed by J. S. R. Jang [16]. The advantages of fuzzy inference systems are that they can interpret information by mapping input space to output space through the fuzzy if-then rule as illustrated in Eqs. (4) and (5). The ANFIS takes less time in its learning process than other network models. Moreover, ANFIS brings the capabilities of the neural network to the learning process, making ANFIS robust to the uncertainty of data.

Fig. 3 shows the working process of the ANFIS model that is composed of five layers. ANFIS can learn from data like a general neural network. It uses back-propagation to calculate the error to optimize parameters. The parameter after the "If" condition is called the antecedent parameters (a, b, and c) which are parameters of the membership function, and the parameter after "Then" is called the consequence parameters (p, q, and r) which are the parameters of the output equation.

$$If\ x\ is\ A_1\ and\ y\ is\ B_1, Then\ f_1 = p_1x + q_1y + r_1, \tag{4}$$
$$If\ x\ is\ A_2\ and\ y\ is\ B_2, Then\ f_2 = p_2x + q_2y + r_2 \tag{5}$$

For the fuzzy If-then rules generation process [17], three algorithms can be used including Fuzzy C-mean Clustering (FCM), Grid Partitioning (GP), and Subtractive Clustering (SC).

2.5. Model assessment

Performance evaluation of the time series model for this research adopts five measurement metrics: MAE, MAPE, RMSE, %RMSE, and R^2 [18]. If y_t is the observed value at a time t and y_t' is the forecasted value at the same time t, then the error (e_t) of forecasting is defined as Eq. (6). The Mean Absolute Error (MAE) can be calculated as shown in Eq. (7). The Mean Absolute Percentage Error (MAPE) can be computed as in Eq. (8). The Root Mean Square Error (RMSE) computation is shown in Eq. (9). The Percentage of Root Mean Square Error (%RMSE) can also be computed as in Eq. (10). These four metrics assess errors of forecasting. The coefficient of determination (R^2) as shown in Eq. (11) is used to compare the performance of the time series models.

$$e_t = y_t - y'_t \tag{6}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{7}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100 \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(e_t)^2} \tag{9}$$

$$\%\mathrm{RMSE} = \frac{RMSE}{\bar{y}} \times 100 \tag{10}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{t=1}^{n}(e_t)^2}{\sum_{t=1}^{n}(y_t-\bar{y})^2} \tag{11}$$

3. Experimentation

3.1. Dataset

This research uses the meteorological data collected from the open data of the Thailand Meteorological Department. This is a realistic data recorded from the weather ground-base station, which is located in Chaiyaphum province, Thailand. Chaiyaphum is the area that has large private wind turbine farms. This research uses only wind speed data, which are recorded as the average daily wind speed. We used the data from the years 2017-2020 by selecting the data from 2017-2019 for learning and the rest in the year 2020 for model testing. Fig. 4 shows the wind speed data of Chaiyaphum, used in this research.

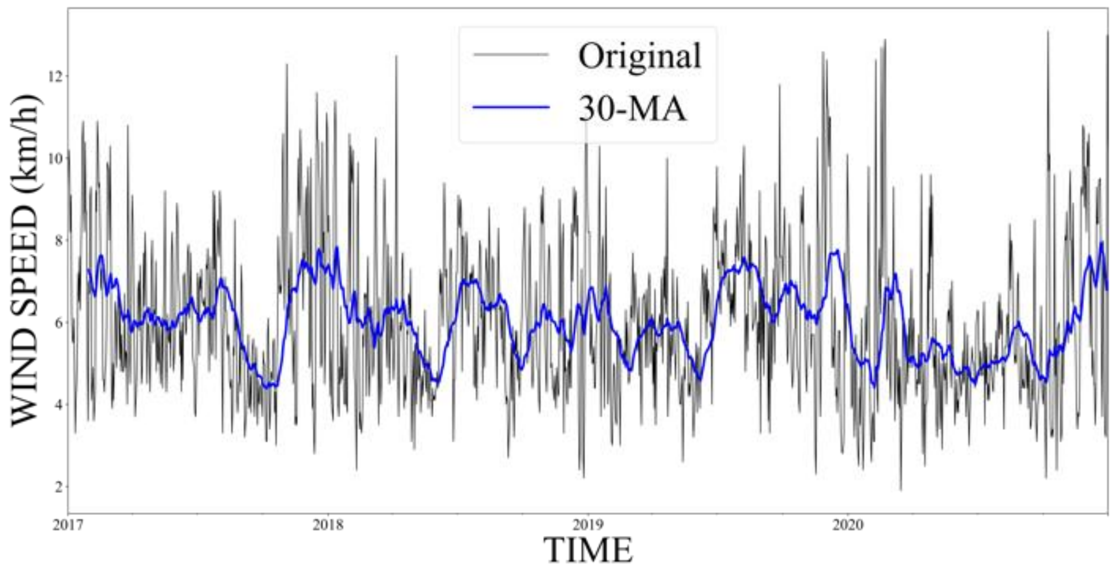


Fig. 4. Wind speed of CHAIYAPHUM site during 2017-2020 (raw and 30 days moving average values represented by gray and blue, respectively).

3.2. Research workflow

The research process is shown in Fig. 5. Firstly, it is the data preparation phase to perform data collection to extract meteorological data of the Chaiyaphum weather station. The second step is to select only the wind speed feature from 2017 to 2020. The Last Observation Carried Forward (LOCF) data imputation technique [19] has been used to complete the dataset. Finally, the dataset has been split into 75% for model training and 25% for testing. That is using data from 2017 to 2019 as a training set, while data in the year 2020 are used as a test set.

The next step of the research workflow is model building. This research develops a highly efficient time series model for forecasting wind speed. This research presents model development through machine learning techniques using the nonlinear hybrid model ANFIS algorithm. The univariate technique has been used. ANFIS time series modeling determines the input using the lag times of the wind speed time series data. We use lag time at y_{t-1}, y_{t-2}, and y_{t-3}, which are predictors and y'_t is the output. While the number and type of membership along with the fuzzy rule define via the subtractive clustering algorithm.

After that, ARIMA, ANN, and LSTM time series modeling have been constructed as a model for performance comparison against the proposed time series model. The ARIMA model is a statistical model which is known as parametric modeling in the sense that it requires three parameter variables including p, d, and q. This research uses the “auto_arima” function in the "pmdarma" library of python to find the p, d, and q values automatically, where the values of the parameters in the ARIMA model are p = 2, d = 0, and q = 1. For the time series modeling of the neural networks group (ANN and LSTM), this research defines the structure of the ANN and LSTM based on the performance of the computer used to execute the models as well as using a trial-and-error manner to decide the suitable neural network structure for this research. The structure of the time series model of the ANN is that there are three inputs (y_{t-1}, y_{t-2}, y_{t-3}) with two hidden layers, each layer with 128 neural nodes, and one output node (y'_t). The LSTM structure is defined to have the same three inputs as well as one output as the ANN model, and the number of LSTM neural nodes is 128.

Optimizing the non-parametric parameter values of the ANN and LSTM models is done through the back-propagation process with a gradient descent algorithm. The activation function of neural nodes of both models is the Rectified Linear Unit (ReLU) function.

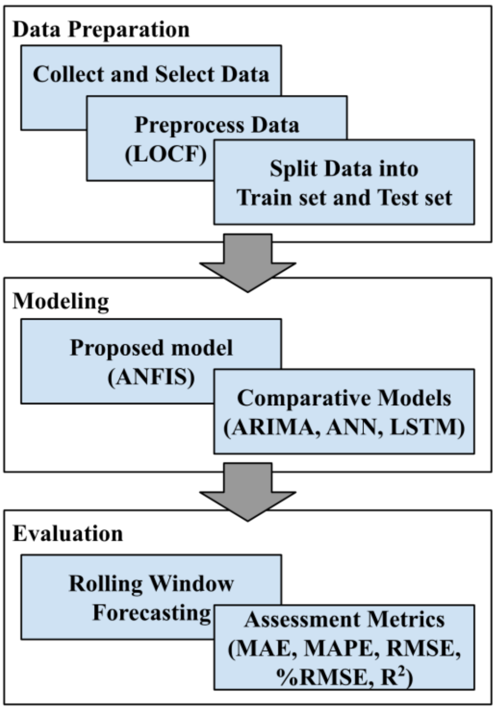


Fig. 5. The research workflow.

The final step of the research is a process to test the efficiency of the nonlinear hybrid model. The unseen data (test set) has been used with the sliding windows technique [20] to feed the input of the model. Five metrics (namely MAE, MAPE, RMSE, %RMSE, and R^2) have been used to evaluate the forecasting performance of the time series model. The comparative time series models (ARIMA, ANN, and LSTM) have been evaluated with the same procedure as the proposed model.

4. Results and Discussion

4.1. The results

The assessment of developing a time series model for forecasting wind speed in Chaiyaphum Province, Thailand, is the performance evaluation of the proposed time series nonlinear hybrid model: ANFIS against other three time series model: ARIMA, ANN, and LSTM based on five measurement metrics. Table 1 shows the results of model evaluation assessed with the training dataset. The results show that the ARIMA model yields MAE, MAPE, RMSE, %RMSE, and R^2 efficiency of 1.06, 18.76, 1.40, 22.67, and 0.42, respectively. While the time series model of ANN gives the forecasting performance as follows: MAE = 1.02, MAPE = 17.81, RMSE = 1.34, %RMSE = 21.77, and R^2 = 0.46. The forecasting performance of LSTM is MAE = 0.88, MAPE = 15.71, RMSE = 1.16, %RMSE = 18.82, and R^2 = 0.60. Lastly, the results of the proposed ANFIS model return the MAE, MAPE, RMSE, %RMSE, and R^2 values as 1.0477, 18.5201, 1.3791, 22.3598, and 0.4359, respectively.

Table 1. The forecasting performance of the trainset

	MAE	MAPE	RMSE	%RMSE	R-Square
ARIMA	1.0668	18.7673	1.4006	22.6709	0.4228
ANN	1.0206	17.8113	1.3428	21.7704	0.4653
LSTM	0.8860	15.7191	1.16092	18.8212	0.6003
ANFIS	**1.0477**	**18.5201**	**1.3791**	**22.3598**	**0.4359**

The results of performance evaluation on the test dataset (Table 2) are that the ARIMA model shows MAE, MAPE, RMSE, %RMSE, and R^2 efficiency of 1.14, 22.43, 1.55, 27.80, and 0.41, respectively. While the time series model of ANN gives the set of results performance MAE = 1.19, MAPE = 23.54, RMSE = 1.59, %RMSE = 28.56, and R^2 = 0.37. The LSTM model gives the set of results performance as MAE = 1.37, MAPE = 28.04, RMSE = 2.02, %RMSE = 36.14, and R^2 = 0.008. Lastly, the results of the proposed ANFIS model return the MAE, MAPE, RMSE, %RMSE, and R^2 values as 1.15, 22.89, 1.55, 27.81, and 0.41, respectively.

Table 2. The forecasting performance of the test set

	MAE	MAPE	RMSE	%RMSE	R-Square
ARIMA	1.1463	22.4311	1.5561	27.8098	0.4119
ANN	1.1904	23.5462	1.5981	28.5605	0.3797
LSTM	1.3790	28.0452	2.0202	36.1047	0.0088
ANFIS	**1.1516**	**22.8986**	**1.5566**	**27.8182**	**0.4115**

4.2. Discussion

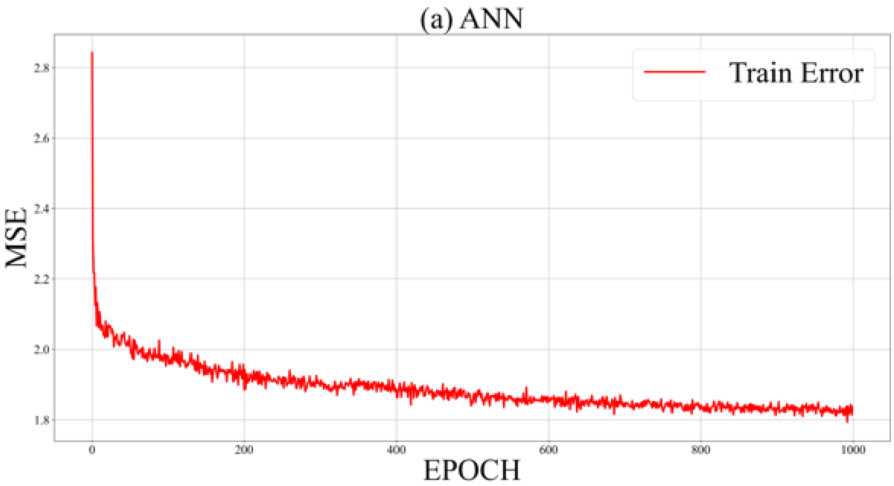
From the performance testing results of wind speed forecasting of the proposed ANFIS time series model and other three comparative models. We found that the proposed ANFIS model shows its forecasting efficiency comparable to the statistical ARIMA time series model, and more efficient than both neural network models (ANN and LSTM). The proposed ANFIS model shows robustness to uncertain data better than the ARIMA model. This is because the ARIMA model needs to define the parameters p, d, and q appropriately before running the model.

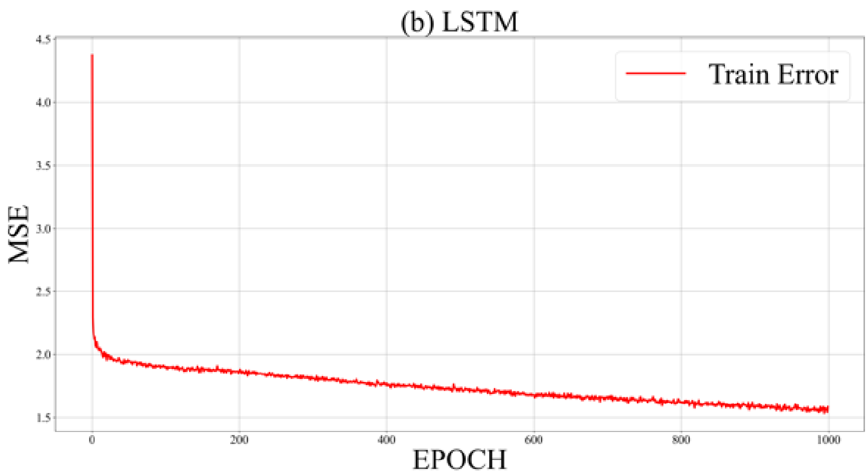
The results show that the forecast within the training set (seen data) of the model in the neural network group performs better than the statistical model. While performing with the test set (unseen data), the neural network models show lower forecasting performance than the statistical time series model, which means the neural network models tend to be over-fitting. This can be obviously seen in the LSTM model that its coefficient of determination value of 0.0088 in the unseen data.

To consider in the aspect of the learning process of the proposed nonlinear hybrid model (ANFIS), and the comparative model in the neural network group. The result in Table 3 shows that the proposed model has a learning efficiency of about 100 times faster than other neural network models because of the less complex neural structure of ANFIS. Fig. 6 shows the learning performance of the ANFIS model and comparative models. The ANFIS model achieves stable learning error because the ANFIS has initialized hyperparameters through the fuzzy rule that is built on subtractive clustering algorithm in the fuzzy reasoning process. The forecasting of four models compared to the actual observed values is graphically shown in Fig. 7.

Table 3. The number of tuning parameters and time consumption of the neural time series model

	Number of Parameters	Number of Neural Nodes	Time Consumption (Seconds)
ANN	17,153	256	1106.2978
LSTM	66,689	128	1901.3514
ANFIS	**20 with 2 fuzzy rules**	**22**	**9.4320**





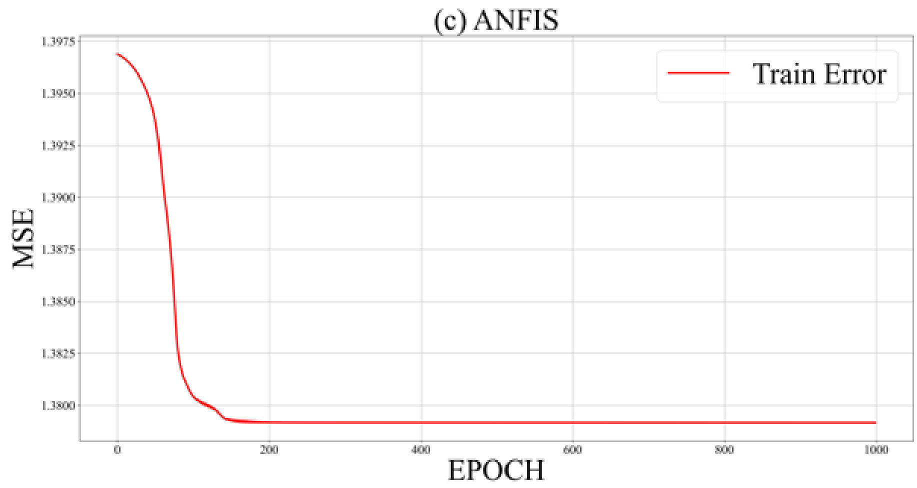


Fig. 6. The graphs showing training errors of (a) ANN, (b) LSTM, and (c) ANFIS.

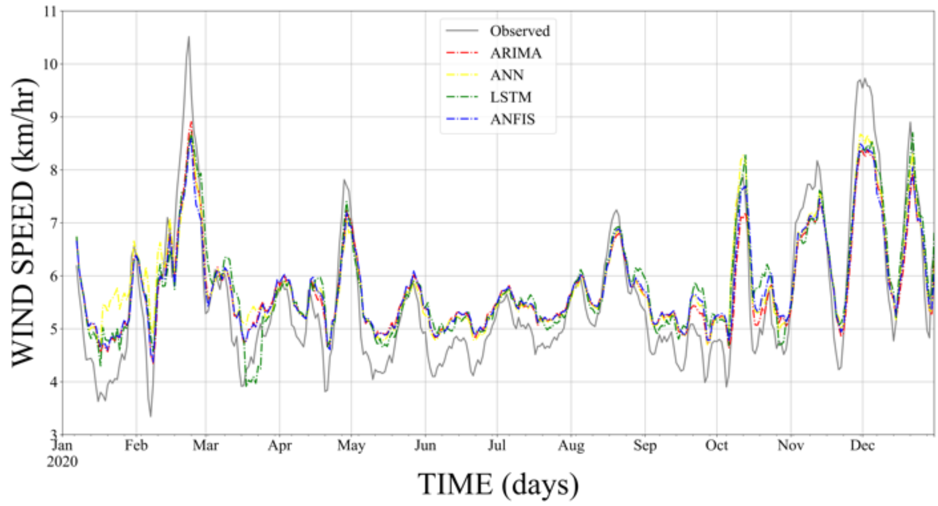


Fig. 7. The results of wind speed forecasting day ahead of the test set.

5. Conclusion

This research presents a time series model for forecasting wind speed using machine learning with the nonlinear hybrid algorithm (ANFIS). The meteorological data used the experimentation are the open data available from the Thai Meteorological Department. The dataset is partitioned into a training set and a test set at a ratio of 75% and 25%, respectively. For performance comparison, ARIMA statistical time series model and ANN and LSTM neural network models have also been developed to compare against the proposed ANFIS model.

For efficiency evaluation of the time series model proposed in this research, the assessment has been done in two aspects. First, the efficiency of forecasting is estimated from MAE, MAPE, RMSE %RMSE, and R2. Then, the structure and the learning speed of the models are considered to reflect the complexity of the model. The results of the model performance evaluation reveal that the proposed ANFIS time series model is slightly better than the neural network model (ANN and LSTM) and the accuracy in wind speed forecasting of ANFIS is similar to the ARIMA model. Efficiency in terms of model building time of ANFIS is the best among neural network models, with at least 100 times better learning speed when measured in seconds.

The results of performance comparisons in this research show that the proposed nonlinear hybrid time series model performs well for wind speed forecasting. It is useful for wind power plants. Our future work is the improvement of the ANFIS model based on the hyper-parameter tuning of the nonparametric model using global optimization techniques.

Conflict of Interest

The authors declare that they have no conflicts of interest.

Author Contributions

A.B. is responsible for the design, the model development, the data analysis as well as the manuscript preparation. N.K. helps proving the research framework and revising the manuscript. K.K. provides critical feedback and helps proving the algorithms and discussing the experimental results. All authors had approved the final version.

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