A Short Term Wind Speed Forecasting Model Using Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System Models

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Abstract. Future power systems encourage the use of renewable energy resources, among them wind power is of great interest, but its power output is intermittent in nature which can affect the stability of the power system and increase the risk of blackouts. Therefore, a forecasting model of the wind speed is essential for the optimal operation of a power supply with an important share of wind energy conversion systems. In this paper, two wind speed forecasting models based on multiple meteorological measurements of wind speed and temperature are proposed and compared according to their mean squared error (MSE) value. The first model concerns the artificial intelligence based on neural network (ANN) where several network configurations are proposed to achieve the most suitable structure of the problem, while the other model concerned the Adaptive Neuro-Fuzzy Inference System (ANFIS). To enhance the results accuracy, the invalid input samples are filtered. According to the computational results of the two models, the ANFIS has delivered more accurate outputs characterized by a reduced mean squared error value compared to the ANN-based model.

Keywords: Artificial Neural Network · Adaptive Neuro-Fuzzy Inference System · Wind speed · Temperature · Mean Square Error

1 Introduction

The deployment of renewable energy sources (RES) such as wind power generation systems has gained significant attention in many countries following the objective established by the European Union (EU) to confront climate change in the framework for action on climate and energy for the period of 2021–2030 [1]. Wind is an abundant and non-polluting source, considered as one of the most requested approaches in generation to ensure a sustainable energy supply and

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a key element of micro-grids for the implementation of a smart grid infrastructure [2]. Therefore, wind power generation forecasting is essential for the optimal operation of a power system with a high level penetration of wind energy conversion systems but the latter encounters several challenges due to the intermittent effect of the wind [3].

The uncertainties associated with wind power may endanger system reliability and power quality, as a consequence a grid integration challenges, such as balance management and reserve capacity [4].

Because of weather pressure difference, air density, topography and other factors, wind speed is considered one of the hardest meteorological parameters to predict. As a result, the power delivered by the wind turbine will be quite difficult to predict [5]. Therefore, the prediction model will mostly be non-linear and should respect the accuracy rules as much as possible. Consequently, remarkable progress has been achieved in the improvement of wind speed and/or power prediction methods. In the literature, multiple prediction methods have been proposed and performed, each employing a different technology and giving good results with a different forecasting horizon. The recent studies in the context of wind prediction have focused on short-term wind predictions, ranging from a few minutes to a few days, in view to the relevance of these data for power systems that require a day ahead scheduling operations, as the case of the power flows circulating in micro-grids systems. Nevertheless, it is usually very difficult to make a long-term prediction because strategies designed for long-term prediction horizons are less effective in the short term [6].

In the latest years, with the increasing computation speed of computers, researchers have proposed a number of power prediction models for wind speeds based on complex statistics and artificial intelligence techniques [7]. The AI-based models that rely on a large number of historical data for constructing an input/output mapping function are widely adopted, the new methods are also based on the adaptive neuro-fuzzy inference system (ANFIS), fuzzy logic methods, support vector machine (SVM), neuro-fuzzy network and evolutionary optimization algorithms [8]. For instance, in [9], Saeed et al. have devloped an ANN model based on Multiple Layer Perceptron (MLP) architecture with three layers (input, hidden, and output) on the basis of the input data concerning previous recorded wind speed, air pressure, air humidity and air temperature obtained by local meteorological station. In [10], the authors proposed a new two-step hybrid approach based on the association of Artificial Neural Network (ANN), Genetic Algorithm (GA), and Hilbert-Huang transforms (HHT), for day-to-day wind energy forecasting, the concept is focused on two steps: the first one employs Numerical Weather Prediction (NWP) to forecast the wind speed at the wind farm site. The second step maps actual wind speed versus power characteristics recorded by SCADA (system control and data acquisition) system. Then, the future day wind velocity predicted from the first step is incorporated into the following step to predict the prospective day's wind power. Other methods based on ANN have been developed on [11,12]. Yang et al. [13], developed an ANFIS method for intercepting the incomplete and incorrect wind data. The performance trials are proved by twelve sets of real wind data collected from North China wind farms, respectively interpolated and evaluated. The computational results demonstrated the performance of the ANFIS method. The authors in [14] had shown an SVM-based strategy for wind energy prediction, indeed, the computational analysis is performed by using real measurement of wind velocity, the results prove that the proposed SVM method is more effective than the persistence model. Jursa and Rohrig have published a novel approach to short-term forecasting based on evolutionary optimization methods for neural network automated specification and nearest neighbor search. The computational results proved that the wind speed forecasting error can be reduced using the proposed automated specification method. Moreover, there are other hybrid methods, as suggested by [16], where the authors had proposed a hybrid approach, based on the combination of ANN with wavelet transform, for short-term wind power forecasting in Portugal.

According to the growing use of wind power in the electricity system, the accurate prediction of wind speed becomes increasingly important, as indicated above, many researchers have done developments on wind power prediction. In this work, the wind speed is predicted accurately using multiple local meteorological measurements for each five minutes concerning the previously recorded wind speed and temperature measured at laboratory level of Polytechnic Institute of Bragança, Portugal. The input data set is composed of 103104 samples. The contribution of this paper represents a comparative study in term of accuracy between two wind speed forecasting models, one based on the artificial neural network intelligence (ANN), in which several configurations are proposed by changing the: training, testing and validation samples, while the other is based on Adaptive Neuro-Fuzzy Inference System (ANFIS) model. The two approaches are compared regarding to their Mean Squared Error (MSE) value. Furthermore, in order to achieve an increase accuracy stage for the two models, it is proposed to introduce a filtering system on the initial data set devoted to eliminating the out-of-valid samples, then, the filtered list of data set will be used as a new input for the learning process of the two models.

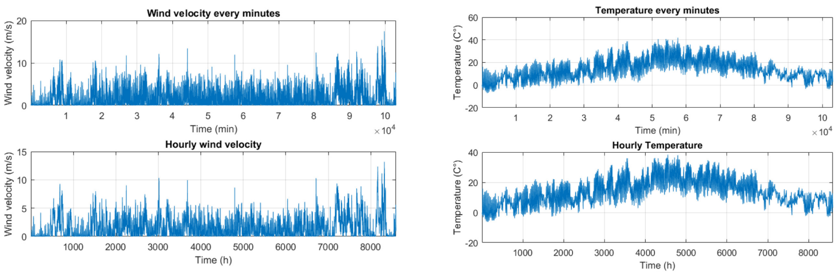
The remaining parts of the paper are organized as follows: Sect. 2 illustrates the study data used in the prediction models regarding wind and temperature samples, in Sect. 3 the forecasting models including the Artificial Intelligence of Neural Network (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) are explained. The computational results of the two forecasting models are presented, compared and discussed in Sect. 4. Finally, Sect. 5 concludes the study and proposes guidelines for future works.

2 Study Data

In this study, a real meteorological measurements were collected using a data monitoring system composed of an *anemometer* placed at 10 m from the ground to record the wind speed values and a *K-type thermocouple* to measure the temperature data. The monitoring system can record the sensors' measurements with an interval of five minutes. The data are measured by the meteorological station of the laboratory of the Polytechnic Institute of Bragança in Portugal (latitude: 41° 47′52, 5876° ″ N - longitude: 6° 45′55, 692° ″ W) as shown in Fig. 1, for the length of time from January 1, 2019 to December 31, 2019.

Fig. 1. Satellite view of the study area.

The input samples represent a set of measurements quantified at 103104 values recorded each five minutes for both wind speed and temperature data. Figure 2a and 2b show the wind speed and temperature data respectively measured each five minutes and their average value for each hour.



(a) Pattern of wind speed data.

(b) Pattern of temperature.

Fig. 2. Study data in 5 min' interval in Polytechnic Institute of Bragança.

3 Artificial Intelligence Proposed Models

Wind speed prediction is a widely discussed topic, several models have already been proposed in the literature as defined in Sect. 1. In this paper to develop a wind speed prediction system with two Artificial Intelligence (AI) techniques, an ANFIS and ANN based-models are used. The wind speed is predicted accurately using multiple local meteorological measurements. The proposed models uses the previously recorded wind speed V_i and temperature T_i together to predict the future value of wind speed V_{i+1}, where i is the discrete sampling taken for a step of 5 min and 60 min. The principle of the two AI models are explained in the following.

3.1 Artificial Neural Network

The structure of the ANN based on a feed-forward network is composed of three layers: an input layer, an output layer, and a hidden layer as illustrated in Fig. 3.

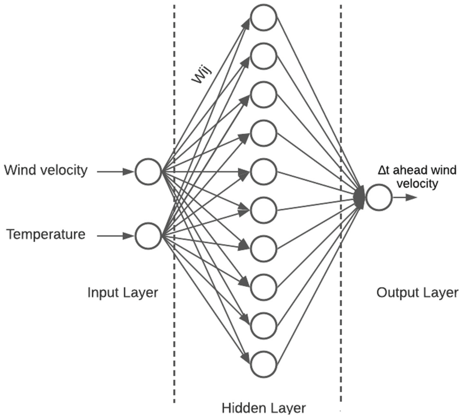


Fig. 3. Structure of the ANN model.

The neural network is initially trained while employing the initial weights. Following the back-propagation principle, for the error correction, the inputs including wind speed V_i and temperature T_i are weighted together by W_{ij} via the Levenberg-Marquardt algorithm that is chosen for its fast convergence, hence, the neural network weights are updated to achieve a more consistent level of prediction following the Eq. (1) [17]:

$$W_{ij} = W_{(i-1)j} + \eta \times \left[V_i^d - V_i^p\right] \times X \tag{1}$$

where W_{new} and W_{old} are respectively the new and the currently updated weights. η is the network learning rate equal to 1%. V_i^d and V_i^p are the desired and predicted outputs respectively. X is the current input at which the network made false predictions.

The activation function $f(s)$ used for the output layer neuron is taken in a sigmoid as following [17]:

$$f(S) = \frac{1}{1 - e^{-S}} \tag{2}$$

where S represents the sum of the products between the inputs data V_i and T_i respectively with their corresponding weights W_{ij} written as:

$$S = V_i(t) \times W_{i1} + T_i(t) \times W_{i2} + b \tag{3}$$

where b is the bias.

Then, the output of the activation function will represent the predicted output V_i^p, However, The performances of the prediction model are measured using the mean square error (MSE) value as [18]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(V_i^d - V_i^p)^2 \tag{4}$$

where n is the number of periods.

Therefore, The feed-forward network with a back-propagation principle assures the adjusting of weights which is determined at the offline training as described in Fig. 4.

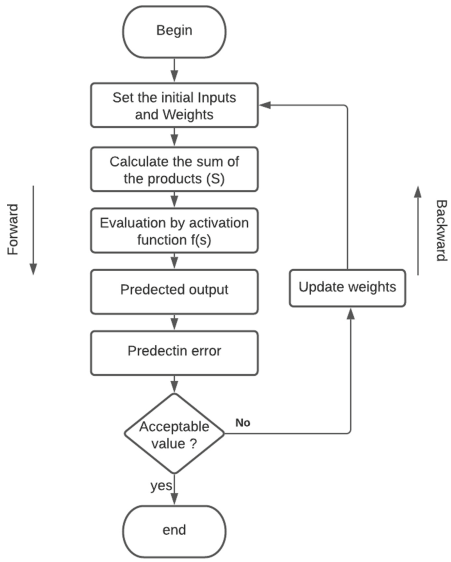


Fig. 4. Back-propagation learning process.

In this work, there are 103104 pairs of input samples, to achieve an accurate model, it is proposed to train the neural network with the most persistent values by eliminating the invalid samples, to do this, the latter are excluded from the data set through a data filter. The filter returns a logical array whose elements are true when an outlier or invalid value is detected in the corresponding element of the data set. An outlier is defined as a value that deviates by more than three median absolute deviations (MAD) from the median [19]. The adopted learning process is described in the flowchart of Fig. 5.

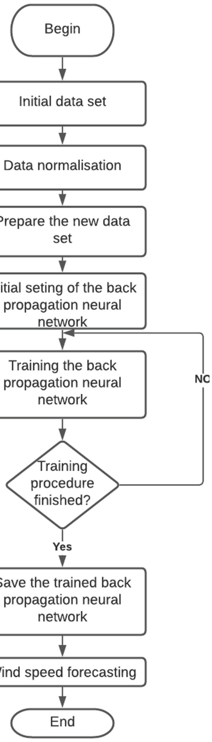


Fig. 5. The adopted learning process.

3.2 Adaptive Neuro-Fuzzy Inference System

The second AI model adopted in this study is the ANFIS framed by combining two intelligent models: the fuzzy inference system (FIS) and the neural network (NN). It has the potential to capture the benefits of both in a single framework. Moreover, the adopted inference system is based on the Sugeno fuzzy model corresponding to a set of fuzzy if-then rules that have the learning capability to approximate non-linear functions [20].

The proposed model includes five layers [21], comprised of two types of nodes: fixed and adaptable as illustrated in Fig. 6.

The first layer commonly called fuzzification, takes the input values including the previously recorded data of temperature $T_i(t)$ and wind velocity $V_i(t)$ to determine the membership function belong to them. The membership degrees of each function are computed by using the premise parameter set, namely

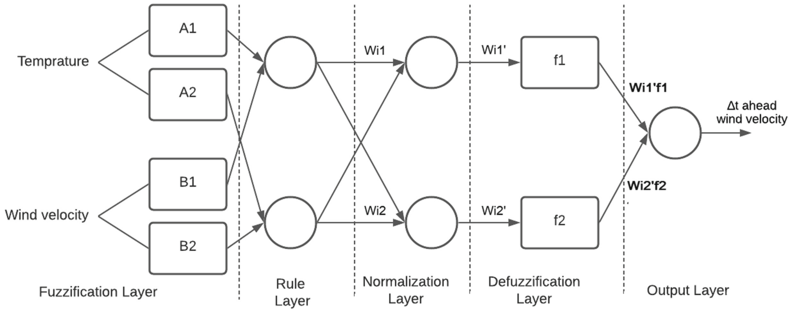


Fig. 6. Structure of the ANFIS model.

$\{A, B, C\}$. In order to firing the fuzzy rules, the rule layer is responsible for generating the firing strengths for the rules, as indicated before, the ANFIS is based on sugeno fuzzy model responsible for generating two principal rules [22]:

– *Rule 01*: if $T_i(t)$ is A1 and $V_i(t)$ is B1 then, $f_1 = P_1 T_i(t) + Q_1 V_i(t) + r_1$

– *Rule 02*: if $T_i(t)$ is A2 and $V_i(t)$ is B2 then, $f_1 = P_2 T_i(t) + Q_2 V_i(t) + r_2$

Where, $\{A_1, A_2, B_1, B_2\}$ are the fuzzy membership functions and $\{P_1, P_2, Q_1, Q_2, r_1, r_2\}$ are the linear parameters of consequent part of the rule. As result, the output of each node is the product of all incoming signals. The third layer is intended for normalizing the computed firing strengths by dividing each value for the total firing strength as follow:

$$W_{i1}^{'} = \frac{W_{i1}}{W_{i1} + W_{i2}} \tag{5}$$

$$W_{i2}^{'} = \frac{W_{i2}}{W_{i1} + W_{i2}} \tag{6}$$

The fourth layer takes as input the normalized values and the consequence parameter set$\{P_\alpha, Q_\alpha, r_\alpha\}$ with $\alpha = \{1, 2\}$ as demonstrated above, in this inference system, the output of each rule is a linear combination of the input variables added by a constant term, the output returned by this layer follows the defuzzification process as [23]:

$$O_4^1 = W_{i1}^{'} \times f_1 = W_{i1}^{'} \times (P_1 T_i(t) + Q_1 V_i(t) + r_1) \tag{7}$$

$$O_4^2 = W_{i2}^{'} \times f_2 = W_{i2}^{'} \times (P_2 T_i(t) + Q_2 V_i(t) + r_2) \tag{8}$$

Those values are then passed to the last layer to return the final output which is the weighted average of the output for each rule denoted by the sum of the two equations (7) and (8). Figure 7 represent the schematic diagram of fuzzy based inference system.

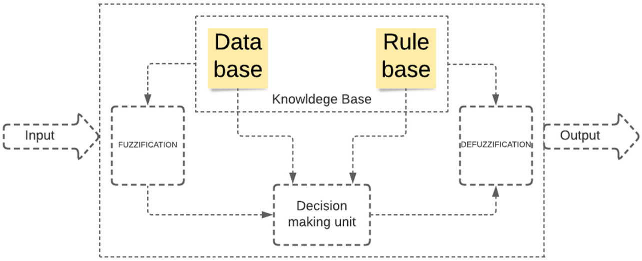


Fig. 7. The schematic diagram of fuzzy based inference system.

4 Results and Discussions

4.1 ANN Model

The multi-layer neural network proposed is being trained with the predefined function "nntool" in *MatLab*. The feed-forward network based on a back-propagation algorithm ensures the adjustment of the weights which is identified in the offline training following the mechanism explained above in Fig. 4.

In order to investigate multiple local meteorological data type effect, two data sets are provided, the first one consists of using as inputs: the samples of wind speed and temperature taken in a time interval of 5 min between each measurement and the second one consists in taking them in 60 min interval, therefore the predicted values will track the character of the inputs values.

Furthermore, to evaluate the performance of the ANN wind speed prediction model. It is proposed to test it with several configurations by changing the number of training, validation, and testing samples as indicated in Tables 1 and 2 of the MSE values. Five successive tests have been executed for each configuration, the results are evaluated by the best, worst and average values of the resulting mean square error.

The neural network model involves randomly dividing the available measured set of samples into three parts, a training set, a testing set, and a validation set or hold-out set. The model is fitted on the training set. Then a test dataset independent of the training dataset follows the same distribution behavior as the training dataset, this later is used only to assess the performance. The fitted model is used to predict the future wind velocity for the observations in the validation set according to the input sample types. Finally, the resulting validation set error rate is assessed using Mean Square Error (MSE) since the problem concerns a quantitative response.

According to the computation results of Tables 1 and 2, it is noticeable that the error value for an interval measurement of ($\Delta t = 60$ min) are less significant than the one of ($\Delta t = 5$ min). The results can be justified by the large number of data sets involved in the training of the second model.

Table 1. MSE results for different learning configurations of the ANN model considering 5 min interval time data.

	$\Delta t = 5$ min		
Configuration	MSE cases		
	Best	Worst	Average
Training = 70%, Testing = 15% Validation = 15%	0.51	0.52	0.51
Training = 80%, Testing = 10% Validation = 10%	0.49	0.52	0.50
Training = 85%, Testing = 5% Validation = 10%	0.49	0.51	0.49
Training = 50%, Testing =25% Validation = 25%	0.52	0.58	0.54
Training = 85%, Testing = 10 % Validation = 5%	0.52	0.62	0.54
Training = 90%, Testing = 5% Validation = 5%	**0.46**	**0.53**	**0.50**
Training = 40%, Testing = 35% Validation = 25%	0.50	0.51	0.50
Training = 40%, Testing = 25% Validation = 35%	0.50	0.51	0.50

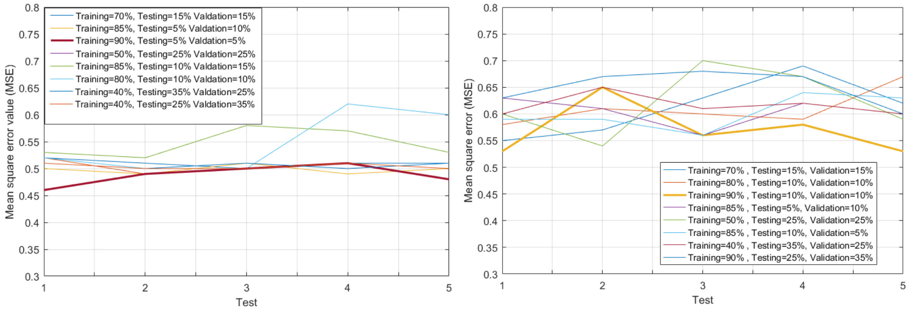
Table 2. MSE results for different learning configurations of the ANN model considering 60 min interval time data.

	$\Delta t = 60$ min		
Configuration	MSE cases		
	Best	Worst	Average
Training = 70%, Testing = 15% Validation = 15%	0.55	0.69	0.61
Training = 80%, Testing = 10% Validation = 10%	0.58	0.67	0.61
Training = 85%, Testing = 5% Validation = 10%	0.58	0.65	0.57
Training = 50%, Testing = 25% Validation = 25%	0.56	0.62	0.60
Training = 85%, Testing = 10 % Validation = 5%	0.54	0.70	0.62
Training = 90%, Testing = 5% Validation = 5%	**0.59**	**0.64**	**0.60**
Training = 40%, Testing = 35% Validation = 25%	0.60	0.65	0.61
Training = 40%, Testing = 25% Validation = 35%	0.63	0.68	0.65

Figure 8 shows the mean square error results for five successive tests considering different training configurations of the ANN based-model.

The results provided more pertinent MSE values in terms of precision by selecting a training configuration composed of samples (Training = 90%, Testing = 5% Validation = 5%) adaptable to the five successive tests considering both types of input data as shown in Fig. 9.

In addition to adjusting the weights by the back-propagation algorithm for precision improvement, it is proposed to further reduce the mean square error value by filtering out the most non-conforming training input values deleting the outliers values, as illustrated above in Fig. 5.



(a) $\varDelta t = 5\,min$. (b) $\varDelta t = 60\,min$.

Fig. 8. MSE values for each configuration after five successive tests.

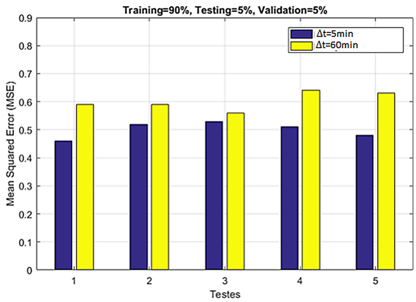
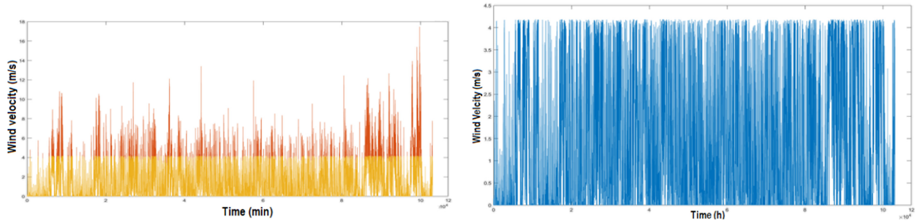


Fig. 9. MSE results for five successive tests considering the combination: Training = 90%, Testing = 5% Validation = 5%.

Figures 10 and 11 represent the filtered data results for measurement interval of 5 min and 60 min respectively.

By adopting this approach, according to Figs. 12, 13 and Tables 3 and 4, the mean square error results experienced an interesting improvement either for 5 min or 60 min interval time measurement. This comes back to the nature of the input data. Likewise, the elimination of invalid pairs (wind speed - temperature) allowed model training with more persistent data.

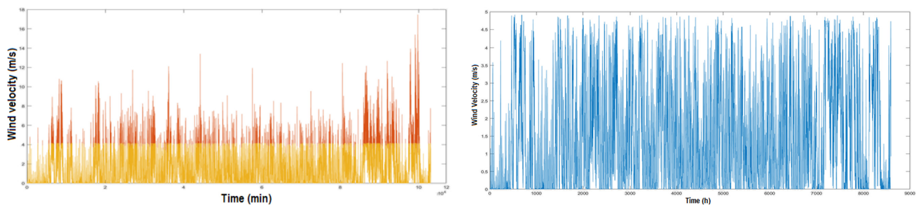
To evaluate the first part of the results based on the artificial neural network model, the best wind speed forecasting model would be to establish a network configuration considering the input learning samples for a measurement interval of $\varDelta t = 5$ min divided by 90% for training, 10% for testing, and 10% for validation as well as considering the exclusion of invalid or outliers values.



(a) The pattern of wind speed data in 5 min' interval with outlier values.

(b) The pattern of temperature data in 5 min' interval without outlier values.

Fig. 10. Data filtration for 5 min' interval time.



(a) The pattern of wind speed data in 60 min' interval with outlier values.

(b) The pattern of temperature data in 60 min' interval without outlier values.

Fig. 11. Data filtration for 60 min' interval time.

4.2 ANFIS Model

As another forecasting approach, an ANFIS model based on both ANN and Fuzzy Inference Systems (FIS) Sugeno-based was designed to forecast the wind speed in horizon of one day with a time-step of five minutes. The variants of the algorithm used in the study are two input membership functions tuned using the training data including the two processing parameters, namely the wind speed and the temperature that was generated from the set of filtered data deleting the outliers values.

The filtered dataset used as ANFIS inputs in the training, testing, and validation phases are taken with the same sampling configuration as the best one achieved on the ANN model, in like manner, the experiments samples were divided into three groups: for training: 90%, testing = 5%, and validation = 5% of ANFIS.

The mean squared error value is used to compare predicted and actual values of wind speed for model validation and further conclude its effectiveness. The reduced number of input membership functions brings a simple ANFIS network structure. for that, the results had shown an interesting convergence to the target. According to the Fig. 14 describing the variation of the value of the MSE according to the epochs reflecting the number of times that the learning algorithm was working through the entire dataset knowing that in each epoch the samples in the dataset has the opportunity to update the internal model

Table 3. MSE values with and without outlier data for 5 min interval considering the samples combination: Training = 90%, Testing = 5% Validation = 5%.

MSE	Cases		
	With outlier	Without outlier	Deviation
Best	0.46	0.20	56.52%
Worst	0.53	0.28	47.16%
Average	0.50	0.24	52%

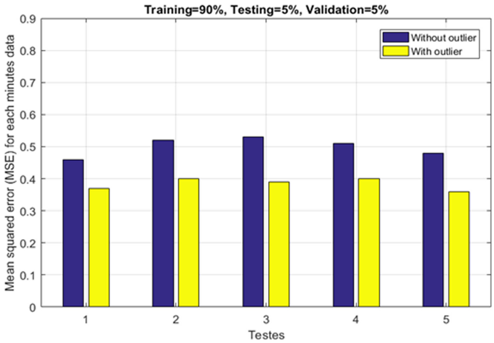


Fig. 12. MSE values for five successive tests considering with and without outlier data for 5 min interval time.

parameters. Furthermore, the fuzzy system is assigned to the epoch for which the least learning error is reached. If two epochs are equal in terms of learning error, the fuzzy system of the preceding epoch is returned. The learning algorithm had run through 1000 epoch until the MSE from the model has been sufficiently minimized to 0.11. The results of the ANFIS model have shown the effectiveness of the latter comparing with the ANN model as shown in Table 5, With well-chosen set samples of ANN configurations, and fully compliant data, the ANFIS has resulted in an 90% accurate forecasting model.

Table 4. MSE values with and without outlier data for 60 min interval considering the samples combination: Training = 90%, Testing = 5% Validation = 5%.

MSE	Cases		
	With outlier	Without outlier	Deviation
Best	0.59	0.42	28.8%
Worst	0.64	0.56	12.5%
Average	0.60	0.47	21.66%

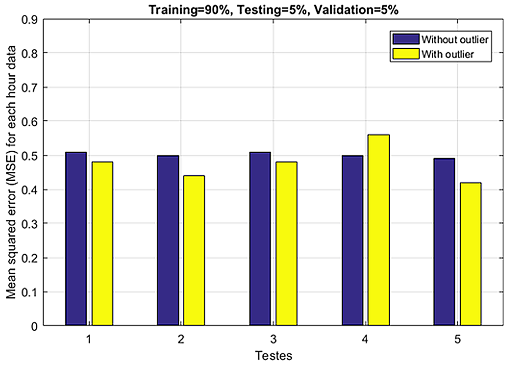


Fig. 13. MSE values for five successive tests considering with and without outlier data for 60 min interval time.

Table 5. Comparison of MSE between ANN and ANFIS models.

Model	Adaptive Neuro Fuzzy Inference System	Artificial Neural Network
Mean Square Error	0.11	0.24

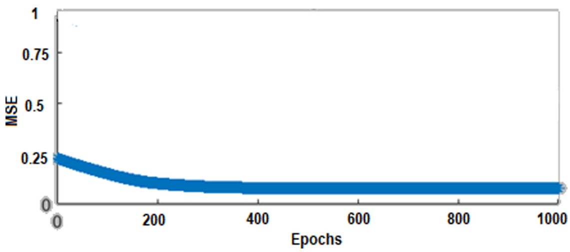


Fig. 14. Learning error curve of the adaptive neuro-fuzzy inference system.

5 Conclusions and Future Work

The wind speed prediction is very important for the electricity trades, strategic scheduling, commitment decision and wind farm investigations for all perspectives. In this paper, the previously recorded wind speed and temperature were used to forecast the future wind speed values in the horizon of one day with a time-step of five minutes and sixty minutes respectively. For this purpose two artificial intelligence models have been proposed, the first one was the artificial intelligence of the neural network (ANN) based on the back-propagation algorithm and the second one concerned Adaptive Neuro-Fuzzy Inference System (ANFIS) sugeno-based. To improve the accuracy of computational results for both models, the input set of training data was filtered to achieve a set without outlier values. Several configurations were proposed for the model learning, after five successive tests for each one, the best configuration was to opt for a sampling of 90% training, 5% testing and 5% validation. Comparing the the Mean Square Error (MSE) values resulting from the two models, the ANFIS has outperformed the ANN model in term of accuracy. As continuation of this work it is envisaged to combine different learning mechanisms with optimization methods to obtain accurate results effective in short and especially long term prediction.

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