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Performance Comparison of Hybrid Neuro-Fuzzy Models using Meta-Heuristic Algorithms for Short-Term Wind Speed Forecasting

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ABSTRACT

In this paper, short-term wind speed forecasting models have been developed using neuro-fuzzy systems. The optimal neuro-fuzzy model has been investigated in detail. In addition, meta-heuristic algorithms, such as artificial bee colony differential evolution genetic algorithm and particle swarm optimization for training adaptive neuro-fuzzy inference systems parameters have been used in this study. This is a novel study, as four different meta-heuristic approaches are used to determine the appropriate adaptive neuro-fuzzy inference systems model parameters for short-term wind speed estimation, and analyzed comparatively. To validate the effectiveness of the proposed approach, wind speed series collected from a wind observation station located in Turkey are used in the short-term wind speed forecasting. In the first step, the results of analysis for finding the accurate model revealed that the optimal model that is proposed is adaptive neuro-fuzzy inference systems$_{7\text{-}1}$ architecture. The meta-heuristic algorithms used in the optimization of adaptive neuro-fuzzy inference systems model parameters are then independently run 10 times, and the performance results are calculated statistically for the training and test phases of the adaptive neuro-fuzzy inference systems model. The results of the study clearly show that the adaptive neuro-fuzzy inference systems-particle swarm optimization hybrid model has the best performance in the training aspect, but it is observed that the ANFIS-differential evolution hybrid model gives better results than the others in the test step.
***Index Terms*—**Artificial intelligence, forecasting, neuro-fuzzy, meta-heuristic algorithms, wind energy.

I. INTRODUCTION

In today's globalized world, energy is an indispensable part of human life, in parallel with industrial development and socio-economic progress. The alarming changes in climate and the increasing population have led to growing demands to gradually reduce emissions from energy generation processes, from the environmental perspective. The production of electrical energy from renewable energy sources offers a way for significant reduction of these emissions.

Wind energy, one of the most important renewable energy sources, has great interest worldwide. According to the Global Wind Energy Council (GWEC), total installations of global wind power in 2017 were 52.492 MW, bringing the global total to 539.123 MW [1]. As of the end of 2017, Asia and Europe have the highest total installed capacity, with 228.684 MW and 177.506 MW, respectively. In terms of countries, China and the United States constitute approximately 52% of the total installed wind power in the world. In 2017, Turkey was placed in the top 10 countries in the world with the new installed wind energy conversion systems. In the first half of 2018, the total cumulative installation of wind energy reached 7,012.75 MW in Turkey. According to July 2018 data, wind energy conversion systems of 885.27 MW capacity are under construction. The official wind energy vision and goal of Turkey are to reach a scenario with 20 GW of wind power capacity installation, by the year 2023 [2].

In the light of all these assessments, wind power plants around the world have become one of the most important sources of electricity supply for many countries. Due to the increasing

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importance of wind energy in the whole power generation system, determining the power to be obtained from this energy source is of great importance in terms of production planning and integration of the wind power plant into the grid.

Wind speed is one of the most effective factors in determining the wind energy potential. Wind power estimation becomes difficult due to the discontinuous, asymmetric, and chaotic nature of wind speed, and this prevents accurate prediction of energy production. Accurate estimation of wind speed and power is also important for the following reasons:

- determination of the location of the wind farms;
- determination of energy unit costs in advance;
- efficient management of wind farms;
- effective and efficient marketing of energy;
- prediction of the need and costs of technical service;
- minimization of risk of overload in substations; and
- reliable integration of the wind turbine into the power system.

Currently, prediction of wind speed over both the short-term (e.g., hourly) and the long-term (e.g., monthly or seasonal) continues to attract the attention of researchers [3]. Several methods have been proposed by researchers to estimate the wind speed and power [4-6], such as numerical weather prediction (NWP), statistical approaches, and hybrid methods. Numerical weather forecasts are defined as generation of estimates through time integration of a comprehensive set of mathematical equations defining almost all dynamic and physical processes in the atmosphere, using numerical procedures. These models are based on mathematical models of fluid mechanics that can predict wind changes through a range of climatic and physical input parameters. The major disadvantage of this method is the required measurement of different parameters such as temperature, pressure, and humidity, with the steps in the process being long and costly.

In the researches on wind speed estimation, it can be seen that using different methods together, more accurate approaches and predictions can be realized in a hybrid structure [7-9]. Using hybrid structures with different decomposition methods or optimization techniques of both time series analysis and intelligent heuristic approaches are important to establish more accurate models. In hybrid approaches on wind speed estimation, it is also seen that using decomposition techniques such as empirical mode decomposition and wavelet transform, the original signals are decomposed for hybrid structure with intelligent approaches [10-12]. Other hybrid approaches are artificial neural networks (ANN) trained by heuristic algorithms, and ANFIS or multilayer perceptron (MLP) systems optimized by different heuristic methods.

Hybrid use of neuro-fuzzy approaches with different optimization techniques for forecasting models in some fields is among the popular topics of today [13,14]. However, it has been observed that optimal design for using a large number of inputs, outputs, and membership functions (MFs) have not been investigated using different architectures for neuro-fuzzy models in wind power forecasting. Therefore, hybrid approaches are suggested as being advantageous in creating more accurate models, after creating different multi-step prediction models for different input, output, and MF values, in order to fill this gap in the literature. In addition to these, it is seen that the use of meta-heuristic approaches in hybrid models is among the popular topics in wind energy studies and other research topics [15,16].

In this paper, the originality and novelty of the proposed hybrid methods can be explained as follows: (a) optimization of ANFIS model parameters by using meta-heuristic algorithms for the short-term wind speed forecasting has been discussed. In the framework of the proposed hybrid estimation method, ABC, DE, GA and PSO algorithms have been used to optimize ANFIS model parameters. (b) In the ANFIS model, nine different structures (ANFIS1-9) have been created according to the number of the input and output, and these models have been evaluated for the ABC, DE, GA, PSO and back propagation methods. Afterwards, an optimum ANFIS model has been obtained by means of changing the MF and the number of rules of this structure. (c) The optimum ANFIS model and ANN model in [17] for the short-term wind speed forecasting have been compared by performance metrics, which are root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

The rest of this paper is organized as follows: Section 2 presents the basic ANFIS structure, and in Section 3, the meta-heuristic algorithms (ABC-DE-GA-PSO) used in this study are given briefly. Section 4 presents how the ANFIS training procedure is realized using meta-heuristic algorithms. In Section 5, the different ANFIS variants are evaluated and the optimal architecture of ANFIS is determined for short-term wind speed forecasting, and then the comparison results are presented between meta-heuristic algorithms. Finally, this paper ends with concluding remarks.

A. ANFIS

ANFIS, which was presented by Jang in 1993 [18], is a graphical network representation of Sugeno-type fuzzy systems with neural learning capabilities. This network consists of nodes with specific functions collected in layers, as shown in Fig. 1.

ANFIS normally consists of five layers of neurons, and the neurons in the same layer are of the same function family. All layers of ANFIS are given in the following equations:

$$\mu_{A_i}(x) = e^{\left(\frac{-(x-c_i)^2}{2\sigma_i^2}\right)}, i=1,2$$

$$\mu_{B_i}(y) = e^{\left(\frac{-(y-c_i)^2}{2\sigma_i^2}\right)}, i=1,2$$

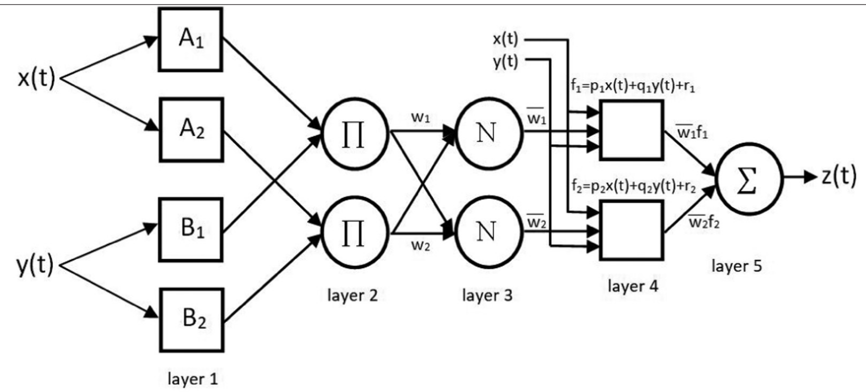

Fig. 1. ANFIS Structure with two inputs and one output.

$$w_i = \mu_{A_i}(x)\mu_{B_i}(y), i = 1,2$$

$$\bar{w}_i = \frac{w_i}{\sum_i w_i}, i = 1,2$$

$$f_i = p_i x + q_i y + r_i, i = 1,2$$

$$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), i = 1,2$$

$$z = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

c_i and σ_i represent the antecedent parameters, μ denotes the membership function in (1) and (2) for the first layer of ANFIS. In the second layer, the rule premise results are evaluated as given in (3). The average premise results ($\bar{w}_i$) are calculated in the third layer's output. The parameters p_i, q_i, r_i given in (5) are defined as the consequent parameters, and f_i represents the rules in a Sugeno-type fuzzy system. Evaluation of the implication and rule consequences is presented in the last layer's output.

B. Meta-Heuristic Algorithms

In this section, the artificial bee colony (ABC) algorithm, differential evolution (DE) algorithm, genetic algorithm (GA), and particle swarm optimization (PSO) algorithm, which are well-known meta-heuristic algorithms, are briefly outlined.

1) Ant bee colony algorithm

The ABC algorithm which was introduced by Karaboga in 2005 [19] is a swarm-based meta-heuristic algorithm. This algorithm is inspired by the behavior of honey bees. In the ABC algorithm, an ABC consists of employed bees, onlooker bees and scout bees. The first half of the colony includes the employed bees and the second half consists of the onlooker bees [20]. The main aim of some artificial bees (employed and onlooker bees) in the colony is to discover the food sources with high nectar in a search space depending on their own experience. Scout bees randomly search for food sources, unlike other bees. The ABC algorithm has got three parameters: the colony size, limit value, and the value of maximum number of cycles [19-21]. The main steps of the ABC algorithm are as follows:

Initialization Phase;
WHILE
Employed Bees Phase;
    Onlooker Bees Phase;
    Scout Bees Phase;
    Save the best solution achieved so far;
ENDWHILE;

2) Differential evolution algorithm

The DE algorithm which is a class of the evolutionary algorithms was proposed by Storn and Price [22,23]. It includes three basic operations: recombination, evaluation, and selection. In the recombination procedure, new candidate solutions are basically generated by the weighted difference between two selected population members added to a third population member in the population [23-25]. This procedure is based on mutation and crossover operations like GA. There are several versions of mutation, which form the several corresponding DE strategies. In the evaluation procedure, cost values of new candidate solutions are calculated. For the next iteration, the better candidates are selected according to the cost values between original and updated population in the selection procedure. The DE algorithm has three parameters: scaling factor, crossover probability, and population size [25].

The pseudocode of the DE algorithm is given below:

Initialization Phase;
WHILE
    Recombination Phase (mutation & crossover);
    Evaluation Phase (calculate the new cost);
    Selection Phase (select better candidate);
    Save the best solution achieved so far;
ENDWHILE;

3) Genetic algorithm

GA is an evolutionary-based heuristic algorithm which is inspired by the theory of natural evolution [26]. GA is based on two operators, known as crossover and mutation mechanisms. This algorithm starts with a randomly determined population. The offspring which inherit the characteristics of the parents are generated by crossover and mutation operators. For these offspring, their cost values are calculated, and then the population members are determined for the next generation by the selection operator (roulette wheel, tournament method, etc.). In the selection process, if parents have better fitness than other members in the population, their offspring can be better than the parents and they have a better opportunity for the next generation [27,28]. There are three basic parameters of GA are crossover probability, mutation probability, and population size [29].

The pseudo code of the GA is given below:

Initialization Phase;
WHILE
    Crossover Phase;
    Mutation Phase;
    Fitness Phase (calculate costs);
    Selection Phase (Roulette or Tournament method);
    Save the best solution achieved so far;
ENDWHILE;

4) Particle swarm opwtimization algorithm

The PSO algorithm is a population-based meta-heuristic algorithm developed by Dr. Eberhart and Dr. Kennedy in 1995 [29]. The PSO algorithm simulates the behaviors of bird flocking. In this algorithm, a group of birds randomly search to find food source in the space. The birds are called as particles in the PSO mechanism. All the particles/birds have cost values, calculated using the fitness function and the velocities directing the flight [30]. In each iteration, the particle is updated by personal best and global best values. The personal best denotes the best solution achieved so far for each particle. The global best represents the best solution obtained so far by any particle in the population. There are some parameters to be tuned in the PSO algorithm before optimization. These are the number of particles and learning factors (c1 and c2). The main steps of the PSO algorithm are given below:

Initialization Phase;
WHILE
    Update Velocity Phase;
    Update Position Phase;
    Evaluation Phase (calculate fitness);
    Update Personal Best Phase;
    Update Global Best Phase;
ENDWHILE;

C. Short-term wind speed forecasting using hybrid ANFIS models

This section describes how to optimize ANFIS parameters with meta-heuristic algorithms. ANFIS consists of two parameters to be updated by the training process: premise and consequent parameters. Premise parameters denote the parameters of Gauss membership function, given as $\{c_i, \sigma_i\}$ in (1–2). Consequent parameters represent the parameters in the defuzzification layer, given as $\{p_i, q_i, r_i\}$ in (5). In the optimization process, one of the important criteria is the problem dimension. The sum of the premise and the consequent parameters of ANFIS gives the dimension of the optimization problem, as given in (8) below:

$$Nv = Np + Nc \rightarrow Np = Ni \times Nm \times 2, Nc = Nr \times (Ni + 1)$$

where Nv denotes the number of variables or problem dimension, Np represents the number of premise parameters of ANFIS, and Nc represents the number of consequent parameters of ANFIS.

Ni stands for the number of ANFIS inputs, Nm denotes the number of membership functions for each input, and Nr represents the number of rules in the defuzzification layer of ANFIS. Fig. 2 shows the flowchart of ANFIS training and test using meta-heuristic algorithms. As can be seen from this flowchart, RMSE is used as a fitness function.

In training of ANFIS parameters, RMSE values are calculated by using (9), given below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(y_i - \breve{y}_i\right)^2}{N}}$$

where $\breve{y}_i$ denotes the output of ANFIS model, y_i represents the actual data of the wind speed, and N stands for the size of the training data. The training and test dataset selection procedure for short-term hourly wind speed forecasting are shown in Fig. 3. This illustration belongs to the one-step prediction ANFIS model with dataset for instant windspeed and windspeed of the three previous hours.

II. RESULTS AND DISCUSSION

In this paper, hybrid ANFIS models are proposed to predict the short-term wind speed. To optimize the ANFIS parameters, the well-known meta-heuristic algorithms (ABC, DE, GA, and PSO) are used. For training and test ANFIS models, the short-term wind speed dataset used is the monthly data taken in Turkey, which includes 744 hours of wind speed data. The first 521 datasets are determined as the training data for ANFIS models and the remaining 223 datasets are used as the test data. For training the ANFIS model, the termination criteria in the meta-heuristic algorithms used in this study are to reach the maximum number of iterations.

The size of search agent population is determined as 10 times the problem dimension (number of variables). The parameters of the meta-heuristic algorithms are given in Table I.

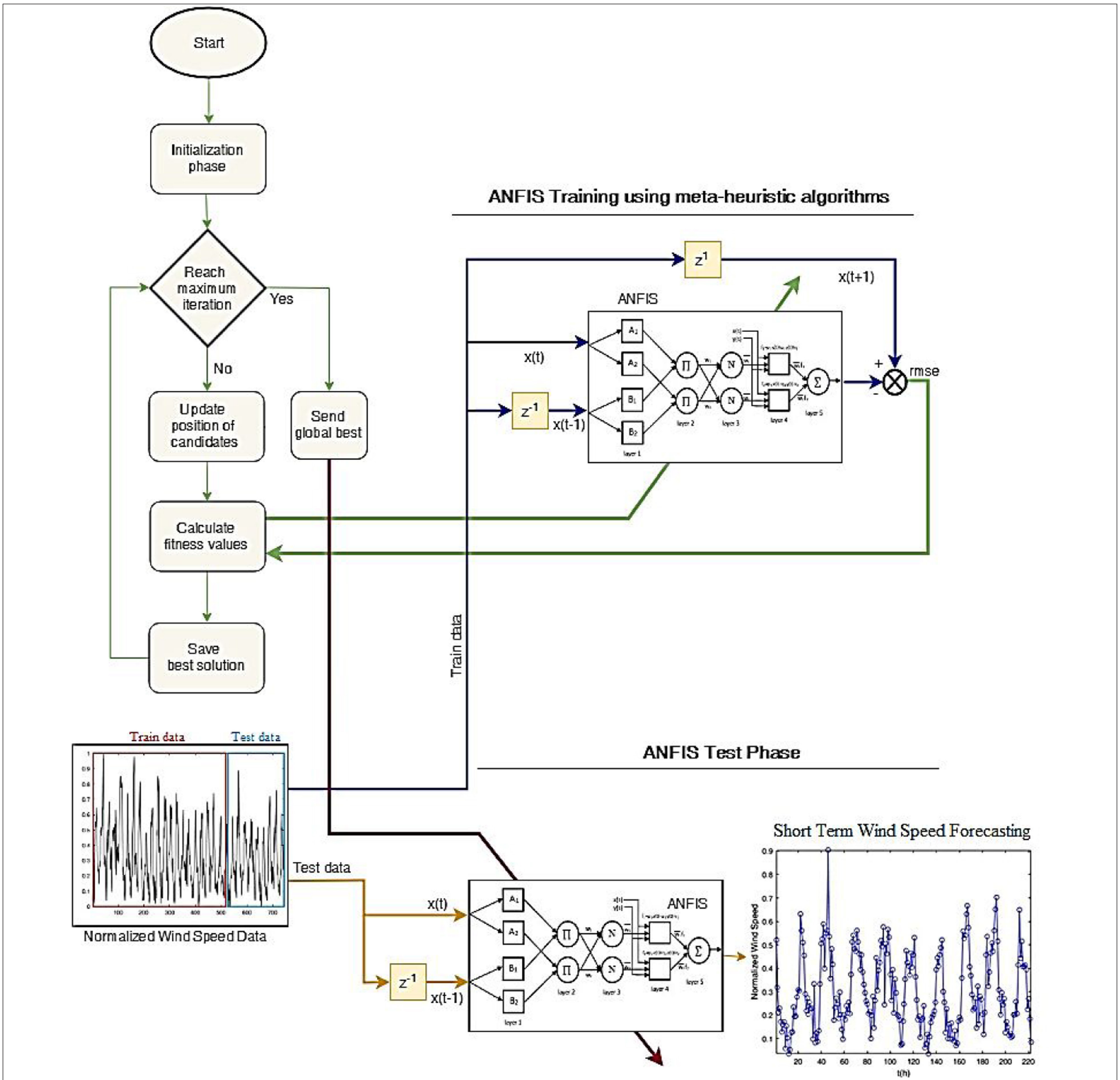

Fig. 2. Flowchart of the ANFIS training and test using meta-heuristic algorithms.

A. Analysis of Different ANFIS Variants

To estimate the short-term wind speed, different ANFIS variants are first considered according to the inputs and outputs. The main purpose is to determine the most suitable ANFIS model here. The specifications of the nine different ANFIS models are summarized in Table II.

For all models, the number of MFs and the number of rules are the same. The outputs of ANFIS variants were determined as 1-, 2-, and 3-hour-ahead wind speed forecasting. As inputs, the dataset of instant wind speed and of the previous hours were used. In Fig. 4, $ANFIS_{1-3}$ architecture is shown.

The MSE and RMSE metrics are presented in Tables III and IV for training and test results of ANFIS variants. The best result of each ANFIS variant is emphasized in boldface. According to the training results, the best ANFIS architecture is the $ANFIS_7$ model consisting of four inputs with dataset of the previous three hours and of instant wind speed, and 1-hour-ahead wind speed forecasting. As can be seen from the test results, ANFIS models with 1-hour-ahead wind speed forecasting ($ANFIS_1$, $ANFIS_4$, and $ANFIS_7$) have better performances than those of the others. The best MSE and RMSE scores belong to the $ANFIS_7$ model trained by the DE algorithm. Hence, according to the training results, the $ANFIS_7$ models for short-term wind speed forecasting were selected.

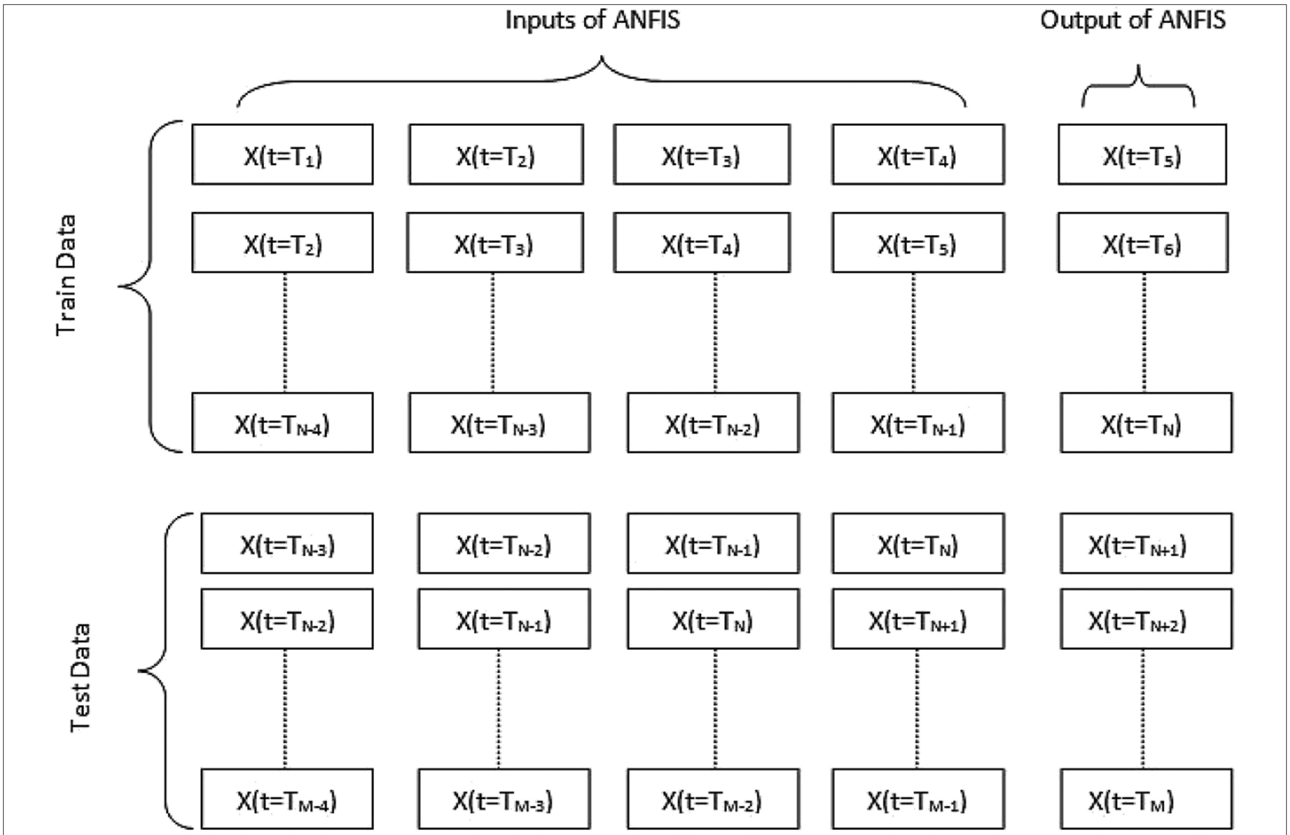

Fig. 3. Training and test dataset selection procedure.

Fig. 5 shows the training and test results of the $ANFIS_7$ variant for wind speed estimation by the well-known meta-heuristic algorithms (ABC, DE, GA, and PSO) and back propagation method (BP). The convergence curves of meta-heuristic algorithms obtained in training processes of nine ANFIS variants are illustrated in Fig. 6. It is evident from these figures that GA and PSO algorithms have better convergence than DE and ABC algorithms for all ANFIS variants. According to the numbers of the MFs and the rules, the different $ANFIS_{7,x}$ variants have been discussed, to find the most suitable ANFIS architecture. In the next section, the multiple run performances of the meta-heuristic algorithms have been analyzed in detail.

TABLE I. PARAMETERS OF META-HEURISTIC ALGORITHMS USED FOR TRAINING ANFIS

Algorithm	Parameters
ABC	Abandonment Limit Parameter : 0.6 × *n*Var × *n*Pop Population Size : 10 × *n*Var
DE	Scale Weighting Factor: 0.8 Crossover Constant : 0.5 Strategy: DE/rand/1/bin Population Size : 10 × *n*Var
GA	Crossover Coefficient : 0.4 Mutation Coefficient : 0.7 Population Size : 10 × *n*Var
PSO	Inertia Weight : 1.0 Damping Ratio : 0.99 Personal Learning Coefficient : 1.0 Global Learning Coefficient : 2.0 Population Size : 10 × *n*Var

nVar, Number of variable; nPop, Number of population.

There are four different $ANFIS_{7,x}$ models to determine the most suitable architecture, and these models' specifications are summarized in Table V. In these $ANFIS_7$ variants, the same number of MFs and the rules from two to five are used.

The training and test results of $ANFIS_7$ variants are given in Tables VI and VII. These results include the MSE and RMSE values obtained for $ANFIS_7$ variants trained by ABC, DE, GA, and PSO algorithms. In the training and test results, the $ANFIS_{7,1}$ model for training results and the $ANFIS_{7,3}$ model for test results are the best models in terms of MSE and RMSE metrics. For the $ANFIS_{7,1}$ model, the dimension of the optimization problem is 26, but the number of variables in the $ANFIS_{7,3}$ model is double of that of the $ANFIS_{7,1}$ model. The number of variables is one of the important factors affecting the optimization of the run time.Therefore, choosing the ANFIS model with a low number of variables gives us an advantage for ANFIS training. Hence, we decided to use $ANFIS_{7,1}$ for short-term wind speed forecasting.

TABLE II. SPECIFICATIONS OF ANFIS VARIANTS

ANFIS Model	Inputs	Output	Number of MFs	Number of Rules	Number of Variables
$ANFIS_1$	x(t), x(t-1)	x(t+1)	4	4	28
$ANFIS_2$	x(t), x(t-1)	x(t+2)	4	4	28
$ANFIS_3$	x(t), x(t-1)	x(t+3)	4	4	28
$ANFIS_4$	x(t), x(t-1), x(t-2)	x(t+1)	4	4	40
$ANFIS_5$	x(t), x(t-1), x(t-2)	x(t+2)	4	4	40
$ANFIS_6$	x(t), x(t-1), x(t-2)	x(t+3)	4	4	40
$ANFIS_7$	x(t), x(t-1), x(t-2), x(t-3)	x(t+1)	4	4	52
$ANFIS_8$	x(t), x(t-1), x(t-2), x(t-3)	x(t+2)	4	4	52
$ANFIS_9$	x(t), x(t-1), x(t-2), x(t-3)	x(t+3)	4	4	52

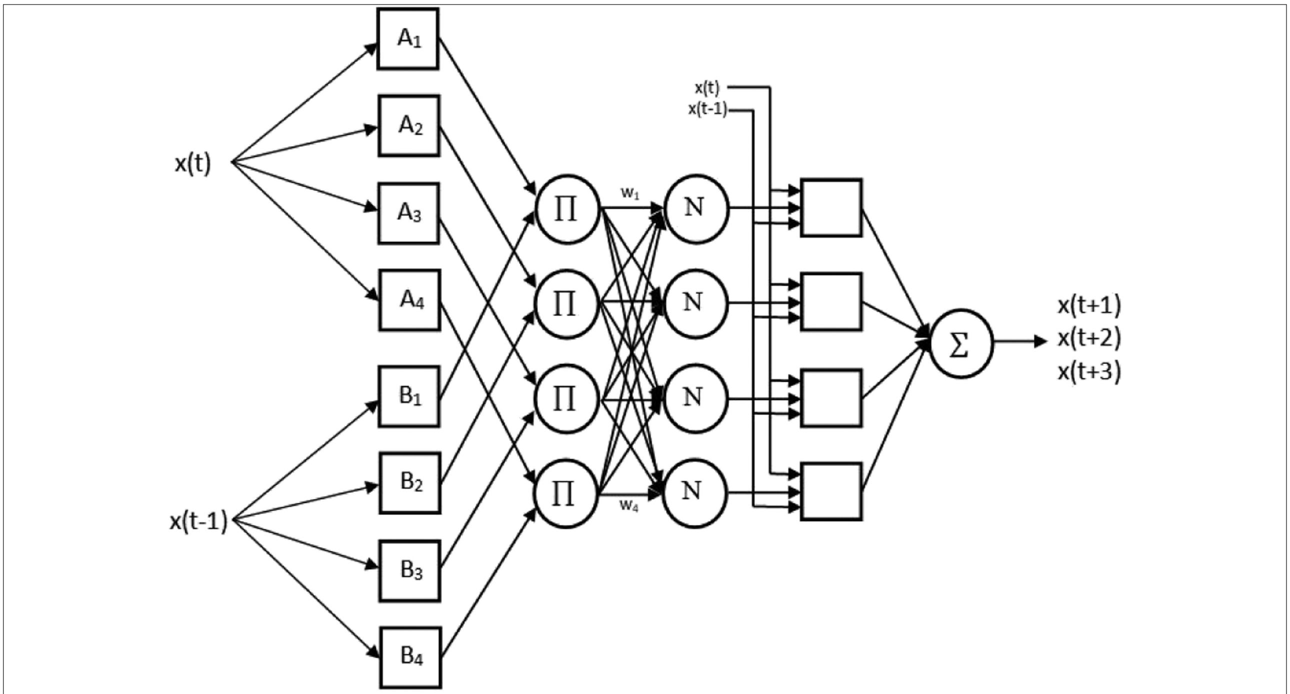

Fig. 4. $ANFIS_{1\text{-}3}$ architecture.

Fig. 7 shows the convergence curves obtained by training $ANFIS_7$ variants using ABC, DE, GA, and PSO algorithms. The structure of the $ANFIS_{7,1}$ model is shown in Fig. 8.

B. Wind Speed Forecasting Results of ANFIS with Meta-Heuristic Algorithms

In order to evaluate the performance of the proposed hybrid ANFIS models, four forecasting models (ANFIS-ABC, ANFIS-DE, ANFIS-GA, and ANFIS-PSO) are used in the one-step short-term wind speed forecasting. We have used some error metrics to show the forecasting performances of the proposed models, such as RMSE (in Eq. 9), MSE, MAE, and MAPE, given as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \check{y}_i\right)^2$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \check{y}_i\right|$$

TABLE III. TRAINING RESULTS OF ANFIS VARIANTS

ANFIS Model	ABC		DE		GA		PSO		BP	
	MSE	RMSE	MSE	RMSE	MSE	RMSE	MSE	RMSE	MSE	RMSE
$ANFIS_1$	8.88e−03	9.42e−02	9.03e−03	9.50e−02	8.42e−03	9.17e−02	8.47e−03	9.20e−02	8.82e−03	9.39e−02
$ANFIS_2$	1.91e−02	1.38e−01	1.91e−02	1.38e−01	1.82e−02	1.35e−01	1.83e−02	1.35e−01	1.83e−02	1.35e−01
$ANFIS_3$	2.78e−02	1.67e−01	2.75e−02	1.66e−01	2.60e−02	1.61e−01	2.63e−02	1.62e−01	2.66e−02	1.63e−01
$ANFIS_4$	8.85e−03	9.41e−02	8.95e−03	9.46e−02	7.94e−03	8.91e−02	8.20e−03	9.05e−02	8.46e−03	9.20e−02
$ANFIS_5$	1.91e−02	1.38e−01	1.90e−02	1.38e−01	1.76e−02	1.33e−01	1.73e−02	1.31e−01	1.79e−02	1.34e−01
$ANFIS_6$	2.70e−02	1.64e−01	2.71e−02	1.65e−01	2.54e−02	1.59e−01	2.49e−02	1.58e−01	2.46e−02	1.57e−01
$ANFIS_7$	**8.76e−03**	**9.36e−02**	**8.82e−03**	**9.39e−02**	**7.86e−03**	**8.87e−02**	**7.70e−03**	**8.78e−02**	**8.37e−03**	**9.15e−02**
$ANFIS_8$	1.86e−02	1.36e−01	1.89e−02	1.38e−01	1.68e−02	1.30e−01	1.62e−02	1.27e−01	1.73e−02	1.31e−01
$ANFIS_9$	2.58e−02	1.61e−01	2.66e−02	1.63e−01	2.36e−02	1.53e−01	2.24e−02	1.50e−01	2.41e−02	1.55e−01

TABLE IV. TEST RESULTS OF ANFIS VARIANTS

ANFIS Model	ABC		DE		GA		PSO		BP	
	MSE	RMSE	MSE	RMSE	MSE	MSE	MSE	RMSE	MSE	RMSE
$ANFIS_1$	8.42e−03	9.18e−02	8.40e−03	9.16e−02	**8.53e−03**	**9.23e−02**	8.74e−03	9.35e−02	**8.53e−03**	**9.24e−02**
$ANFIS_2$	1.62e−02	1.27e−01	1.61e−02	1.27e−01	1.58e−02	1.26e−01	1.57e−02	1.25e−01	1.62e−02	1.27e−01
$ANFIS_3$	2.23e−02	1.49e−01	2.22e−02	1.49e−01	2.25e−02	1.50e−01	2.43e−02	1.56e−01	2.26e−02	1.50e−01
$ANFIS_4$	**8.33e−03**	**9.13e−02**	8.52e−03	9.23e−02	9.26e−03	9.62e−02	**8.58e−03**	**9.26e−02**	8.57e−03	9.26e−02
$ANFIS_5$	1.63e−02	1.28e−01	1.62e−02	1.27e−01	1.67e−02	1.29e−01	1.59e−02	1.26e−01	1.63e−02	1.28e−01
$ANFIS_6$	2.17e−02	1.47e−01	2.21e−02	1.49e−01	2.15e−02	1.47e−01	2.19e−02	1.48e−01	2.24e−02	1.50e−01
$ANFIS_7$	8.85e−03	9.40e−02	**8.15e−03**	**9.03e−02**	8.54e−03	9.24e−02	8.69e−03	9.32e−02	8.65e−03	9.30e−02
$ANFIS_8$	1.57e−02	1.25e−01	1.55e−02	1.24e−01	1.57e−02	1.25e−01	1.53e−02	1.24e−01	1.62e−02	1.27e−01
$ANFIS_9$	2.09e−02	1.45e−01	2.12e−02	1.46e−01	2.19e−02	1.48e−01	2.04e−02	1.43e−01	2.13e−02	1.46e−01

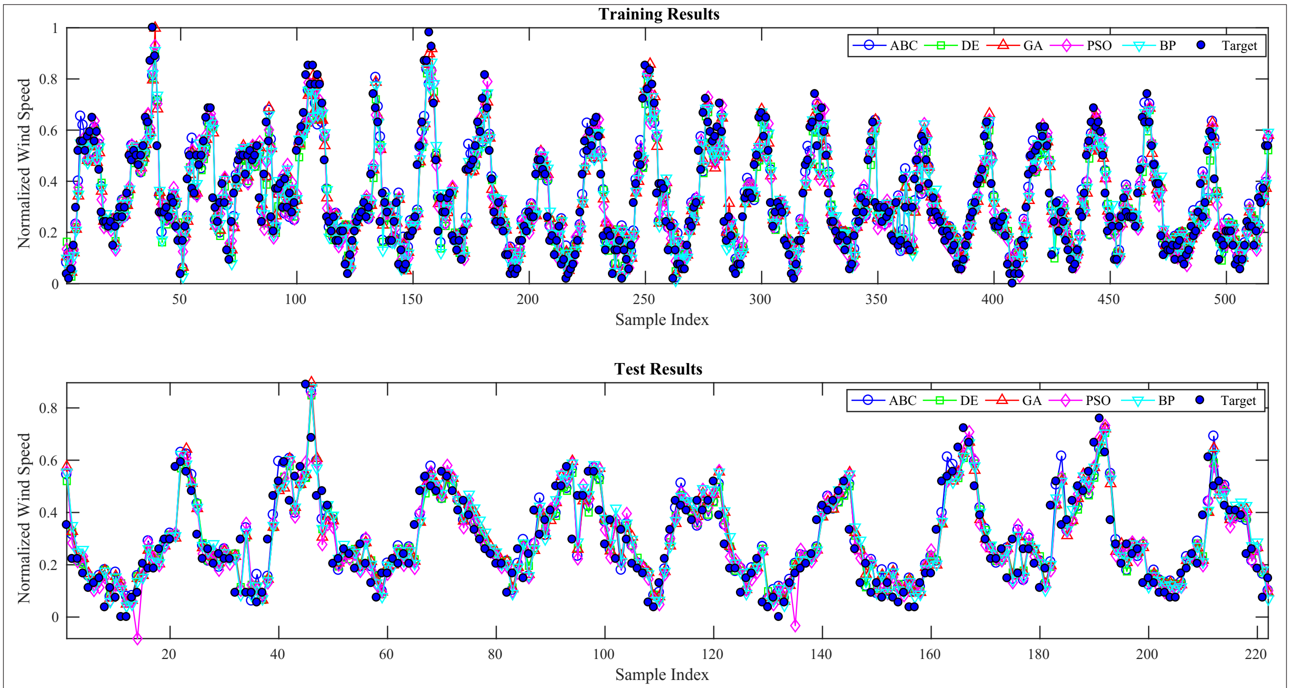

Fig. 5. Training and test results for $ANFIS_7$ (ABC, DE, GA, PSO, and BP).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \check{y}_i}{y_i}\right| \times 100$$

where y_i and $\check{y}_i$ represent observed value and predictive value of the wind speed, *N* is the total number of datasets used for performance evaluation and comparison. MAE is average absolute forecast error of i times forecast results. MAPE is a measure of the accuracy of prediction method for performance evaluation and comparison in statistics. The physical basis for using RMSE/MAE is that they express the overall error in wind speed for the entire test set [5].

Table VIII summarizes the ANFIS training and test results with 10 independent runs for well-known meta-heuristic algorithms (ABC, DE, GA, and PSO algorithms). In addition, the statistical results of performance metrics for the ANN model in [17] are calculated for comparison with 10 runs. The best result of each metric is emphasized in boldface here. In this table, four statistical metrics are used for repetitive results: best, worst, mean, and standard deviation.It can be seen from this table that the proposed meta-heuristic algorithms have competitive results for ANFIS training and test. ANFIS training results show that the PSO algorithm has the best error metric values. For the test phase, the DE algorithm has the best performance, according to most of the error and statistical metrics. In general, the proposed hybrid models give better results than the ANN model, as seen from the results in the table.

At the end of the training process, the premise and consequent parameters of the ANFIS model are updated. Hence, Gauss membership functions are adjusted for each input of the ANFIS model. In Fig. 9, the input Gauss membership functions of hybrid ANFIS models updated by meta-heuristic algorithms are represented.

Fig. 10 shows the statistical results of the error metrics (MSE, RMSE, MAE, and MAPE) for the meta-heuristic algorithms (ABC, DE, GA, and PSO) used in this study. These boxplots are the optimization results obtained with 10 runs for the ANFIS training phase. In Fig. 11, the statistical results of tests of hybrid ANFIS models are shown, according to the meta-heuristic algorithms.

Fig. 12 shows the hybrid ANFIS models' results for the training phase of the short-term wind speed forecasting. In Fig. 13, the forecasting results of test data for 1-hour prediction are represented. As can be seen from these figures, the test and training results show that the proposed hybrid ANFIS models are close in performance and can be used as alternatives to each other.

The error values of wind speed sampling points are shown in Fig.14(a) for each meta-heuristic algorithm. Fig.14(b) shows the convergence curves of ABC, DE, GA, and PSO algorithms for training of ANFIS parameters. These curves come from the RMSE values obtained for the best solutions found by meta-heuristic algorithms. It is clearly observed that the PSO algorithm is more successful than the others, according to the convergence curves.

III. CONCLUSION

Wind speed is one of the most important parameters that determine the amount of electrical power to be obtained

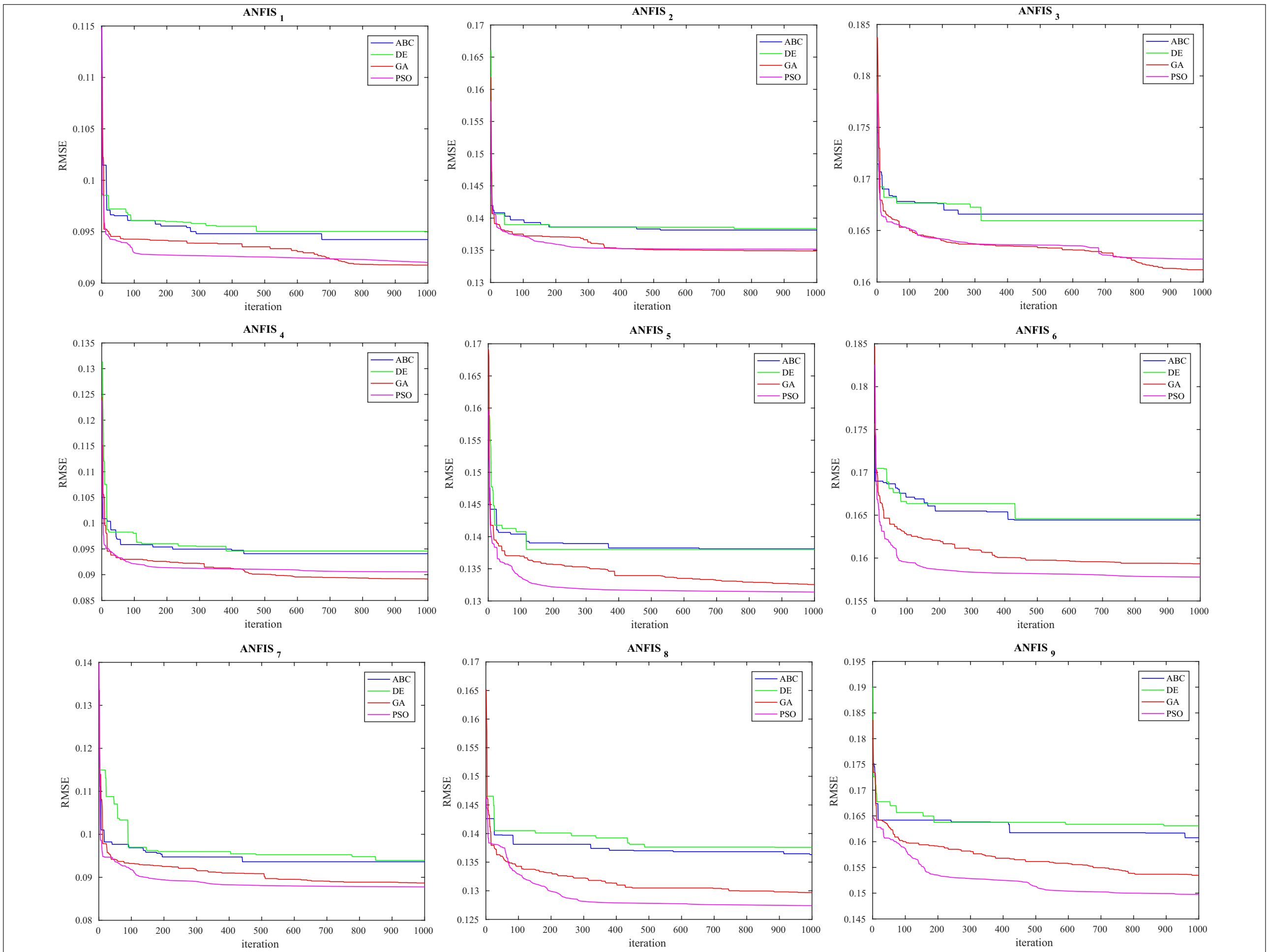

Fig. 6. Convergence curves obtained by ABC, DE, GA, and PSO algorithms during training all ANFIS structures.

TABLE V. SETTING THE NUMBER OF MFS AND RULES FOR ANFIS$_7$ MODEL

ANFIS Model	Inputs	Output	Number of MFs	Number of Rules	Number of Variables
ANFIS$_{7,1}$	x(t), x(t-1), x(t-2), x(t-3)	x(t+1)	2	2	26
ANFIS$_{7,2}$	x(t), x(t-1), x(t-2), x(t-3)	x(t+1)	3	3	39
ANFIS$_{7,3}$	x(t), x(t-1), x(t-2), x(t-3)	x(t+1)	4	4	52
ANFIS$_{7,4}$	x(t), x(t-1), x(t-2), x(t-3)	x(t+1)	5	5	65

TABLE VI. TRAINING RESULTS OF ANFIS$_7$ VARIANTS FOR DIFFERENT NUMBERS OF MFS AND RULES

ANFIS Model	ABC		DE		GA		PSO	
	MSE	RMSE	MSE	RMSE	MSE	RMSE	MSE	RMSE
ANFIS$_{7,1}$	**8.58e−03**	**9.26e−02**	**8.56e−03**	**9.25e−02**	8.16e−03	9.03e−02	8.35e−03	9.14e−02
ANFIS$_{7,2}$	8.62e−03	9.29e−02	8.73e−03	9.34e−02	7.99e−03	8.94e−02	7.84e−03	8.86e−02
ANFIS$_{7,3}$	8.76e−03	9.36e−02	8.82e−03	9.39e−02	**7.86e−03**	**8.87e−02**	7.70e−03	8.78e−02
ANFIS$_{7,4}$	8.87e−03	9.42e−02	9.26e−03	9.62e−02	7.99e−03	8.94e−02	**7.41e−03**	**8.61e−02**

TABLE VII. TEST RESULTS OF ANFIS$_7$ VARIANTS FOR DIFFERENT NUMBERS OF MFS AND RULES

ANFIS Model	ABC		DE		GA		PSO	
	MSE	RMSE	MSE	RMSE	MSE	RMSE	MSE	RMSE
ANFIS$_{7,1}$	8.89e−03	9.43e−02	8.60e−03	9.27e−02	8.56e−03	9.25e−02	**8.42e−03**	**9.18e−02**
ANFIS$_{7,2}$	8.77e−03	9.37e−02	8.36e−03	9.14e−02	8.79e−03	9.38e−02	8.50e−03	9.22e−02
ANFIS$_{7,3}$	8.85e−03	9.40e−02	**8.15e−03**	**9.03e−02**	**8.54e−03**	**9.24e−02**	8.69e−03	9.32e−02
ANFIS$_{7,4}$	**8.25e−03**	**9.08e−02**	8.77e−03	9.36e−02	8.61e−03	9.28e−02	8.57e−03	9.26e−02

from wind energy systems. Hence, wind speed forecasting is critical in the integration of systems that convert wind energy to the grid, in parallel with the increasing energy need. Wind speed is characteristically asymmetric and chaotic, making it difficult to forecast wind power and to predict energy production. Therefore, many different approaches such as numerical weather prediction (NWP), statistical, and hybrid methods are proposed in wind speed forecasting studies, and it is aimed to develop more accurate models in this regard.

In this paper, four different hybrid ANFIS models are proposed for short-term wind speed forecasting. The proposed hybrid structures consist of well-known meta-heuristic algorithms, fuzzy logic, and artificial neural network models. In this study, well-known meta-heuristic algorithms (ABC, DE, GA, and PSO) are used for training two important parameter values—the premise and the consequent—of the ANFIS model. Firstly, nine ANFIS models with the same membership function and rule number for different input and output combinations are

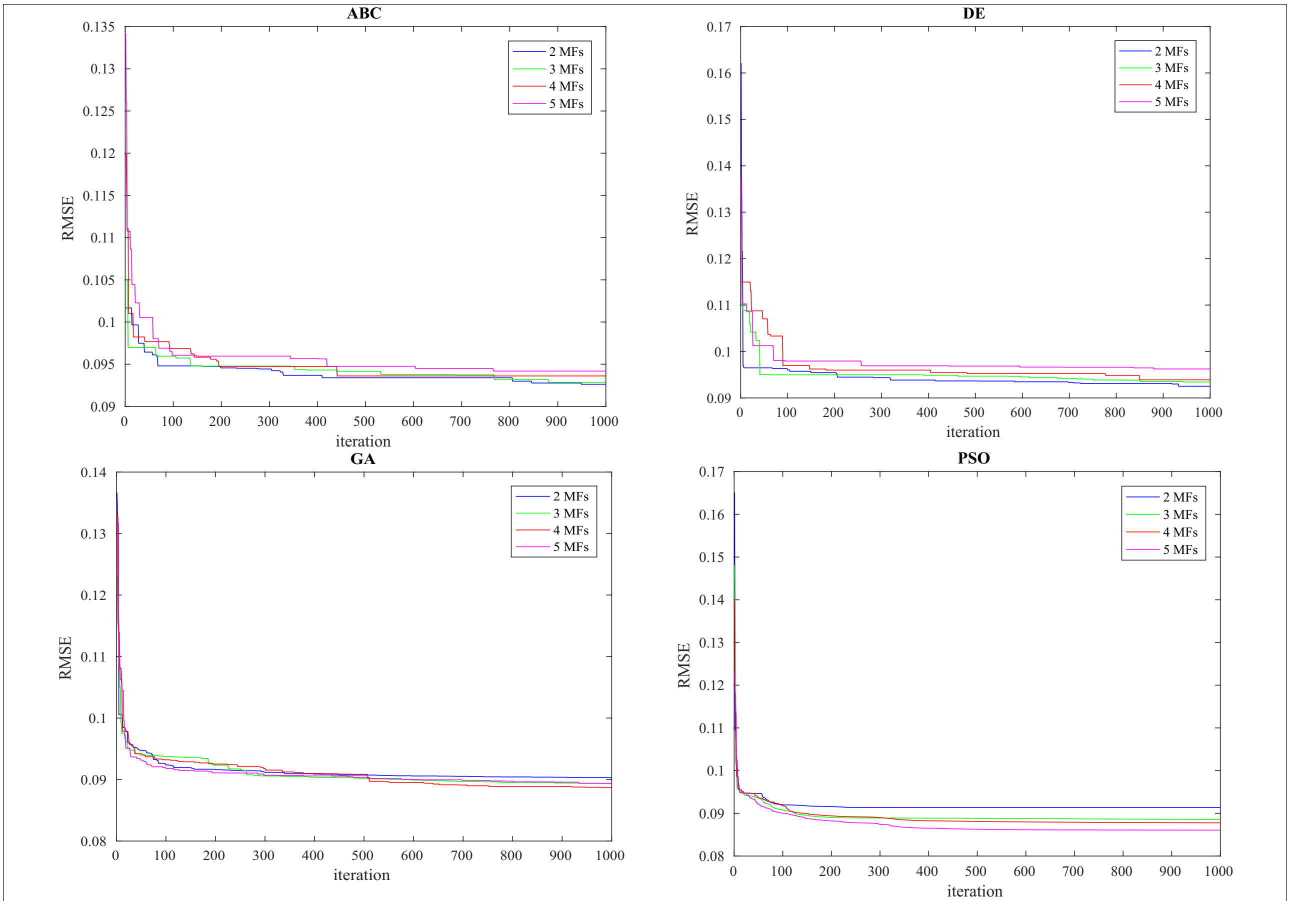

Fig. 7. Convergence curves obtained by ABC, DE, GA, and PSO algorithms for training ANFIS$_7$ variants with different numbers of MFs and rules.

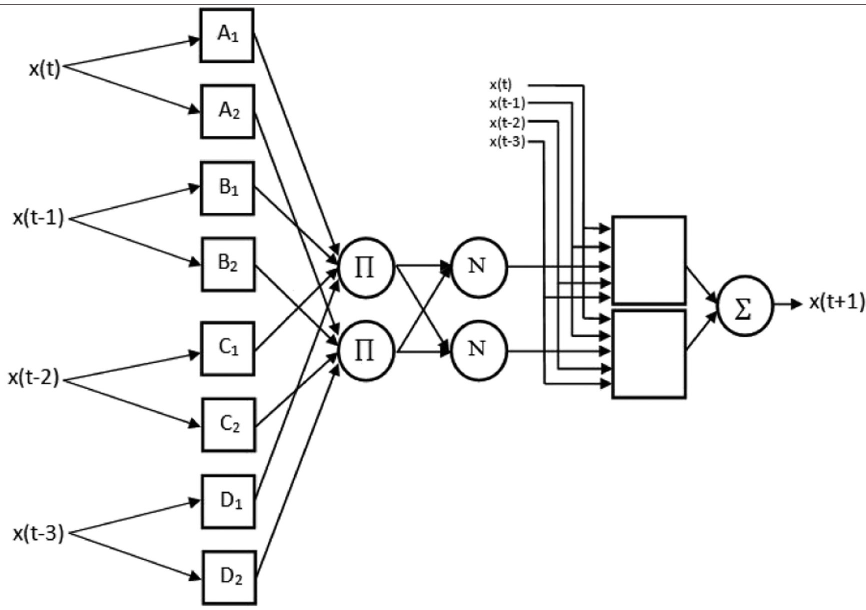

Fig. 8. Optimal ANFIS architecture ($ANFIS_{7\text{-}1}$) selected for this study.

TABLE VIII. COMPARISON OF ANFIS TRAINING AND TEST RESULTS WITH 10 INDEPENDENT RUNS

		Training Results				Test Results			
		MSE	RMSE	MAE	MAPE (%)	MSE	RMSE	MAE	MAPE (%)
ANFIS-ABC	*best*	8.56e−03	9.25e−02	7.04e−02	25.75	8.31e−03	9.12e−02	7.11e−02	27.90
	worst	8.71e−03	9.33e−02	7.19e−02	27.13	9.15e−03	9.56e−02	7.27e−02	31.97
	mean	8.64e−03	9.30e−02	7.14e−02	26.47	8.52e−03	9.23e−02	7.16e−02	28.87
	Std	4.91e−05	2.64e−04	4.44e−04	0.51	2.31e−04	1.23e−03	4.55e−04	1.25
ANFIS-DE	*best*	8.52e−03	9.23e−02	7.02e−02	25.67	8.22e−03	9.07e−02	7.03e−02	27.87
	worst	8.73e−03	9.34e−02	7.17e−02	27.01	8.93e−03	9.45e−02	7.32e−02	29.58
	mean	8.60e−03	9.27e−02	7.12e−02	26.14	8.47e−03	9.20e−02	7.15e−02	28.32
	Std	6.28e−05	3.38e−04	4.87e−04	0.45	1.91e−04	1.03e−03	7.35e−04	0.52
ANFIS-GA	*best*	8.21e−03	9.06e−02	6.89e−02	25.44	8.12e−03	9.01e−02	6.85e−02	28.29
	worst	8.75e−03	9.36e−02	7.14e−02	27.25	2.92e−02	1.71e−01	8.06e−02	45.91
	mean	8.50e−03	9.22e−02	7.04e−02	26.39	1.05e−02	9.99e−02	7.19e−02	30.71
	Std	2.15e−04	1.17e−03	1.03e−03	0.69	6.56e−03	2.50e−02	3.30e−03	5.37
ANFIS-PSO	*best*	7.92e−03	8.90e−02	6.81e−02	25.21	8.23e−03	9.07e−02	6.92e−02	28.25
	worst	8.96e−03	9.46e−02	7.24e−02	27.05	5.98e−02	2.45e−01	8.63e−02	34.96
	mean	8.59e−03	9.27e−02	7.08e−02	26.47	1.51e−02	1.14e−01	7.41e−02	29.46
	Std	3.42e−04	1.86e−03	1.33e−03	0.66	1.63e−02	4.93e−02	5.08e−03	2.00
ANN	*best*	8.59e−03	9.27e−02	7.08e−02	25.97	8.22e−03	9.06e−02	6.96e−02	27.69
	worst	9.13e−03	9.56e−02	7.35e−02	27.53	8.84e−03	9.40e−02	7.36e−02	30.53
	mean	8.84e−03	9.40e−02	7.19e−02	26.79	8.48e−03	9.21e−02	7.14e−02	28.81
	Std	1.97e−04	1.05e−03	8.45e−04	0.43	1.90e−04	1.04e−03	1.17e−03	0.80

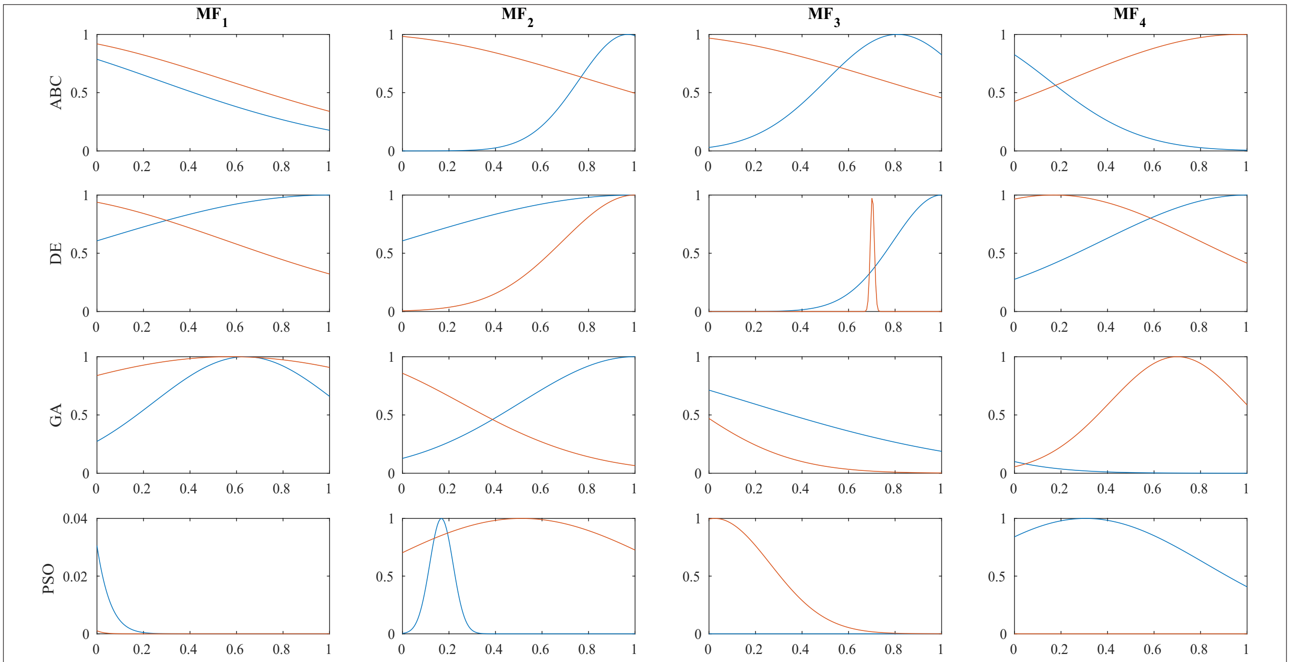

Fig. 9. Input MFs of hybrid ANFIS models for best fitness values.

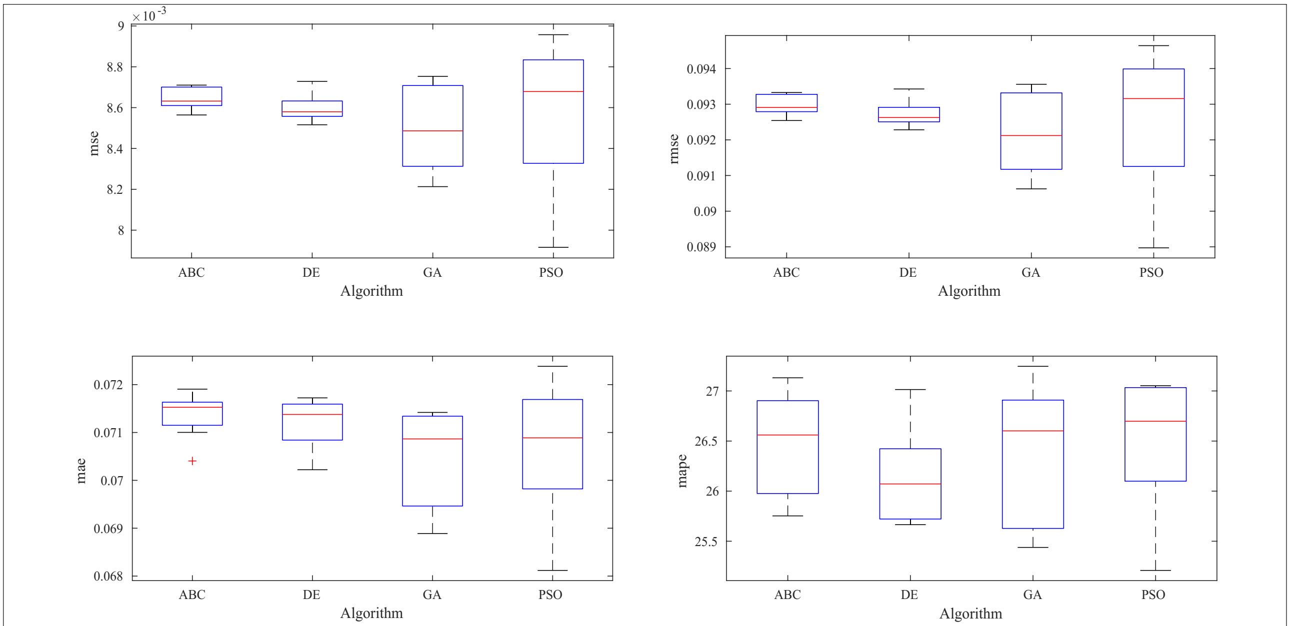

Fig. 10. Statistical results of meta-heuristic algorithms with 10 runs for ANFIS training phase.

analyzed for ABC, DE, GA, and PSO algorithms. As seen from Table III and IV, the $ANFIS_7$ model is chosen as the most suitable model according to the error performance criteria (MSE and RMSE) of the resulting training and test data. In the next step, four different models are discussed by changing the membership function (MF) and rule numbers for the $ANFIS_7$ model. $ANFIS_{7,1}$ which has four inputs, one output, two MFs, and two rules is found to be the most suitable model due to the low number of variables, RMSE, and MSE values, as seen in the results.

As seen from Table VIII, the training of model parameters of $ANFIS_{7,1}$ are performed with 10 runs for four meta-heuristic algorithms, and the well-known error metrics—RMSE, MSE,

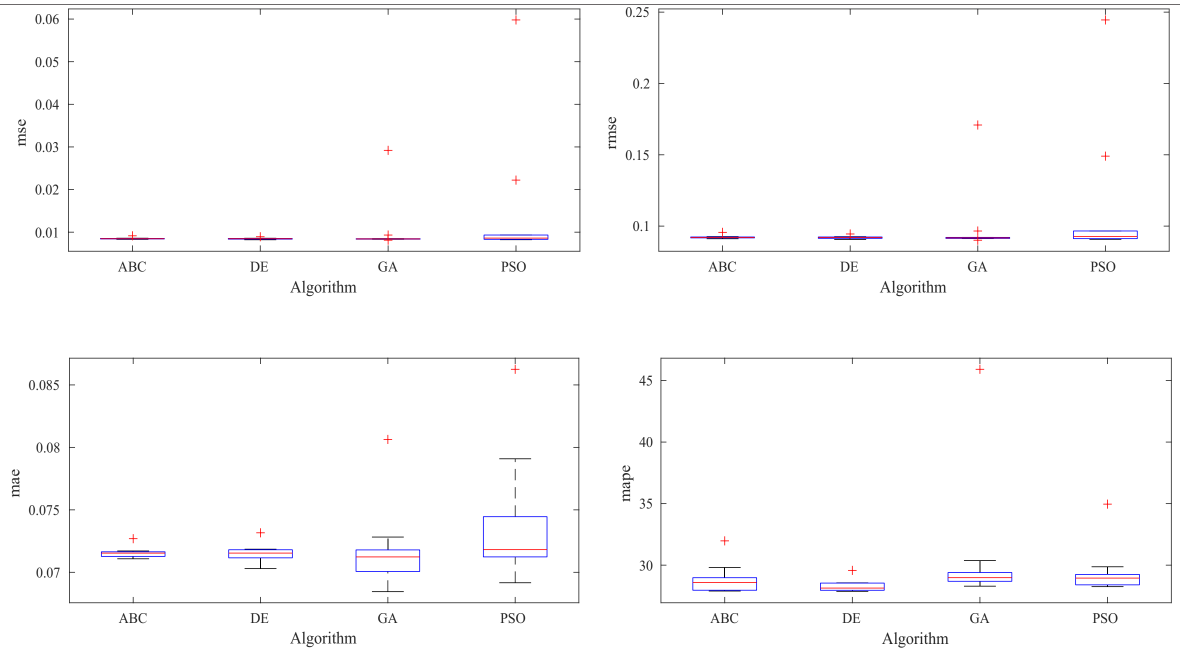

Fig. 11. Statistical results of meta-heuristic algorithms with 10 runs for ANFIS test phase.

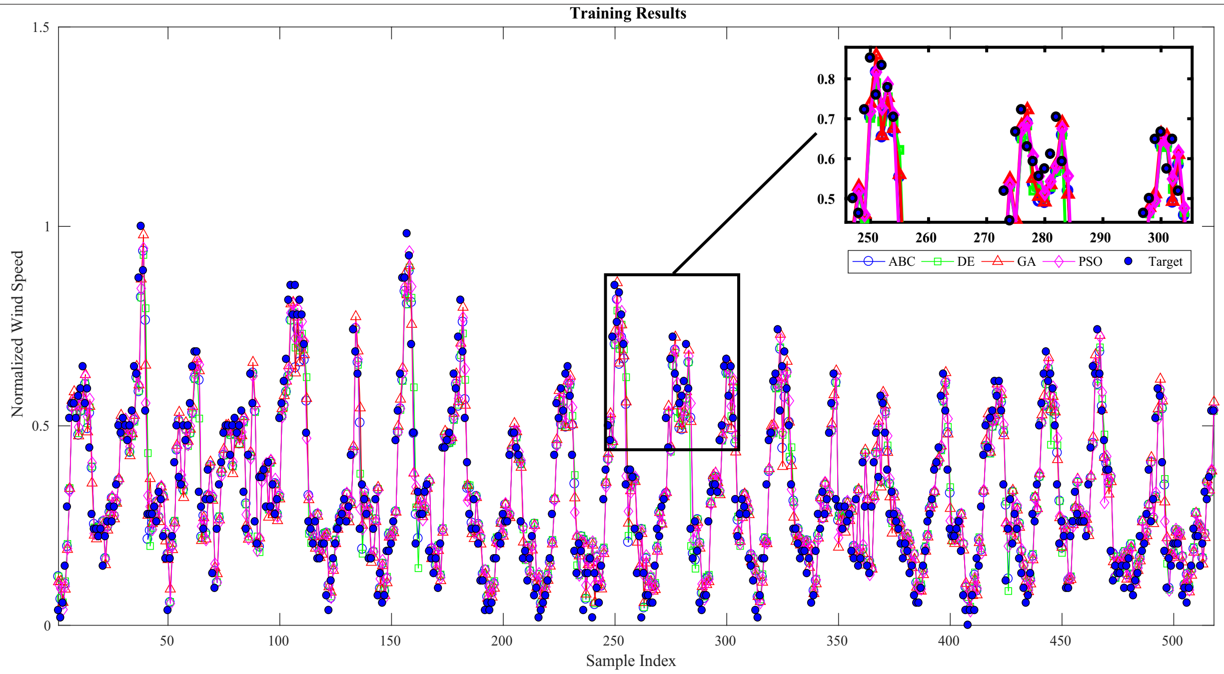

Fig. 12. Best training results of hybrid ANFIS models with 10 independent runs.

MAE, and MAPE—are calculated statistically for short-term wind forecasting. Although the ANFIS-PSO model is successful in the training section, it is observed that the ANFIS-DE model gives better results in the test step. In addition, the proposed hybrid models are also compared with the well-known ANN model in the literature.

The results show us that the hybrid ANFIS models trained by meta-heuristic algorithms for short-term wind speed forecasting are better than the ANN model, but the obtained error performance criteria of the meta-heuristic algorithms are close, which shows that the proposed hybrid ANFIS models can be used as alternatives to each other.

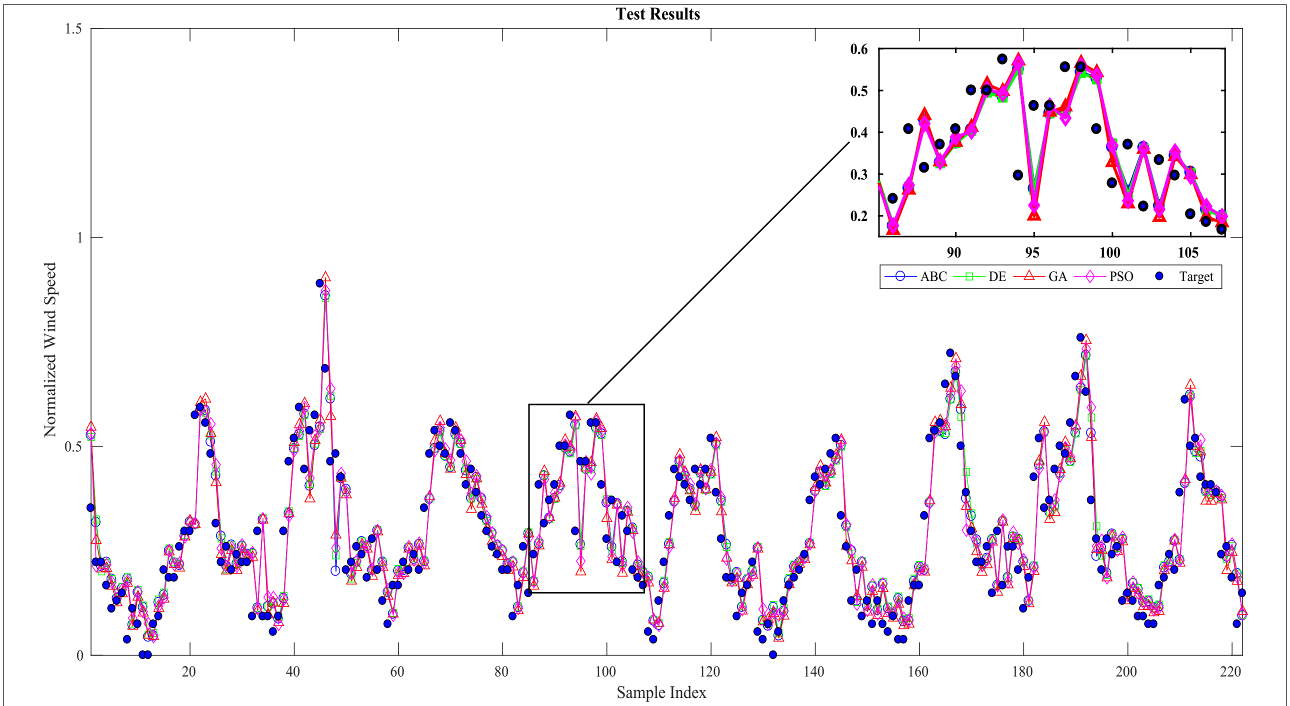

Fig. 13. One-step short-term wind speed forecasting test results by hybrid ANFIS models.

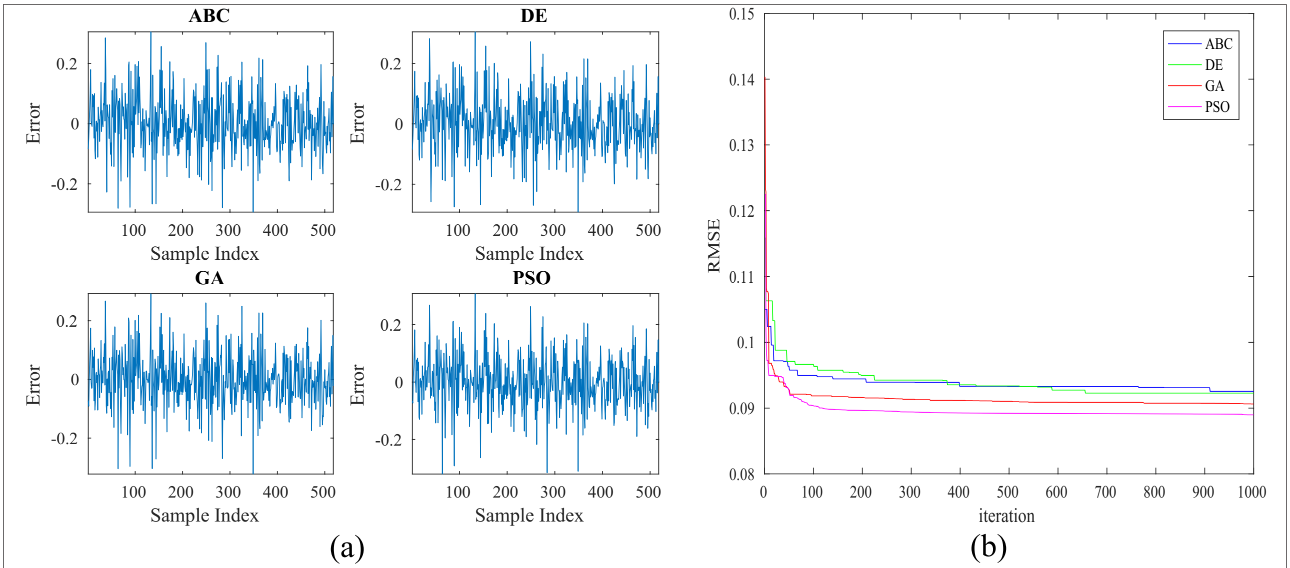

Fig. 14. Best error variations (a) and best convergence curves (b) obtained by ABC, DE, GA, and PSO algorithms for optimization of ANFIS model parameters.

Future studies are expected to generate more precise hybrid models using different intelligent heuristic approaches. In addition, with the help of the new generation decomposition algorithms such as ensemble empirical mode decomposition (EEMD), and swarm decomposition (SWD), the performance of the model can be further improved by taking hybrid models into consideration. The disadvantage of the hybrid models is that the computation time is relatively high, mainly due the large amout of calculation involved in parallel computation of the hybrid structures. Therefore, it is thought that the learning algorithms such as meta-extreme learning machine (Meta-ELM) will provide advantages in hybrid structures in terms of computation time.

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