Power Curve Modelling for Wind Turbine Using Artificial Intelligence Tools and Pre-established Inference Criteria

Jonata C. de Albuquerque, Ronaldo R. B. de Aquino, Otoni Nóbrega Neto, Milde M. S. Lira, Aida A. Ferreira, and Manoel Afonso de Carvalho Jr.

***Abstract*—We propose a new way to develop non-parametric models of power curves using artificial intelligence tools. One parametric model and eight non-parametric models are developed to emulate the behavior described by the power curve of the wind farms. A comparison between the power curve models based on artificial neural networks (ANNs) and those based on fuzzy logic are also proposed. Some of the power curve models based on ANNs and fuzzy inference systems (FISs) are used as well as two new FISs with the proposed new heuristic. An initial pre-training is proposed, resulting from the characteristics derived from the expert inference followed by a transformation of a fuzzy Mamdani system into a fuzzy Sugeno system. Although the presented values by the error indicators are comparable, the results show that the new pre-trained FIS models have better precision compared with the ANN and FIS models. The comparative study is conducted in two wind farms located in northeastern Brazil. The proposed method is a relevant alternative to improve power curve approximation based on an FIS.**

***Index Terms*—Wind turbine, pre-training, artificial intelligence, artificial neural network (ANN), fuzzy inference system (FIS).**

I. Introduction

THE modelling of power curves is a crucial factor in wind power operation, which contributes to different aspects of the operation, e. g., control and performance improvement of a wind turbine or a wind farm [1], [2]. There are currently several techniques to adjust the modelling of power curves. The methods can be either parametric or non-parametric. The non-parametric models create a heuristic method based on the dataset to represent the behaviors and features of wind farms or wind turbines.

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J. C. de Albuquerque, R. R. B. de Aquino (corresponding author), O. N. Neto, M. M. S. Lira, and M. A. de Carvalho Jr. are with the Department of Electrical Engineering, Federal University of Pernambuco, Recife, Brazil (e-mail: jonata. albuquerque@ufpe. br; rrbaquino@gmail. com; otoni. nobrega@ufpe. br; milde@ufpe.br; macj@ufpe.br).

A. A. Ferreira is with DASE, Federal Institute of Pernambuco, Recife, Brazil (e-mail: aidaferreira@recife.ifpe.edu.br).

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In [3], a data-driven method for the performance analysis of wind turbines was presented. In [4], three different operation curves were used to monitor the performance of a wind farm: the power curve, the rotor curve, and the blade tilt curve. Five years of historical data were used. Using wind speed as an input variable, a database was established to construct the wind power reference curves, rotor speed, and tilt angle of the blade. In [5], parametric and non-parametric models of power curves in wind turbines were developed. The parametric models used four to five expressions of logistic parameters. The parameters were defined using the genetic algorithm (GA), evolutionary programming (EP), particle swarm optimization (PSO), and differential evolution (DE).

In [6], an equivalent wind power model was developed for forecasting. A summary of the available data, methodology, and validation of results was included. In [7], to determine nominal wind speeds, wind turbines were continuously operated at their maximum power coefficient to maximize the annual energy production (AEP).

In [8], a new method called the alternative moment method (AMM) was introduced to estimate the parameters of the Weibull distribution. In [9], a model based on data partition centers was developed, and data mining was proposed to construct the model. In [10], a control model that considered the losses related to the tread effect in the performance of a maximum power point tracking (MPPT) model was developed using a power curve.

In [11], the power uncertainty was estimated for a wind turbine operating between the cut-in speed and the nominal wind speed. In [12], the probabilistic interconnection between speed and power was demonstrated, which allowed for a performance comparison of two plants, and it can be used to simulate plant operations through sampling.

In [13], the impact of large offshore wind farms was modelled on a large power system using realistic wind power prediction errors and a complete model of unit commitment, economic dispatch, and energy flow. In [14], a review of the state-of-the-art technologies monitoring wind turbines was conducted, including descriptions of different maintenance strategies. In [15], an extensive review was presented in short, medium, and long terms. In [16], a dynamic method was introduced for determinating power curves for wind turbines.

Recently, the substantial growth of the Brazilian load demand is inevitable. Wind energy is one of the solutions. However, wind speed variability introduces a random profile in the energy matrix. Thus, over the years, heuristics and applications that seek to achieve the optimality of the control and operation have been increasingly developed. The concepts and techniques of artificial intelligence are applied to wind forecasting in order to improve the adaptation of wind farms and wind turbines under varying conditions.

One important element of wind power forecasting is a model that attempts to reproduce the power curve of a wind farm or machine under a given load condition when connected to an electrical network. This is the motivation for developing the models of power curves that optimally match wind turbine performance and enhance the reliability of power system.

II. Power Curves

Power curves of wind turbines represent the physical relationship between the electric power generated by the wind turbine and the wind speed incidence at the height of the rotor hub. According to the International Energy Agency (IEA), a power curve is the functional identity of a wind turbine and is defined as a performance certificate guaranteed by the manufacturer.

A typical power curve is modeled based on three basic characteristics: the cut-in speed, the range of wind speed constituting the region of effective operation, and the cut-out speed. These aspects are defined for a given height of the rotor hub in the steady state without turbulence.

These three features delimit the power curve of any turbine. The operation range of the turbine is established and the minimum and maximum operation values of the average speed and average power are defined. A schematic diagram of a power curve can be found in Fig. SA1 of Supplement A [1].

According to [17], power curve is more important. Coupled with the average wind speed and statistical distributions such as the Rayleigh distribution, the power curve provides the information which is indispensable in predicting the annual energy yield.

Using the power curve to control a wind farm is another generalized method, which considers the limitations of machine construction. Generally, for a wind farm, the measurements are taken over a specific period. The average of the variables is then calculated and aggregated to the wind speed period. The average values should be appropriate according to the local or global control analysis of the wind incidence on a single wind turbine or on several wind turbines in the wind farm.

Figure 1 shows the average power curve for a wind farm, which represents the average range of speeds versus the average power range for all wind turbines in the wind farm.

The available wind energy that crosses the rotor of a wind turbine can be obtained as:

$$P_w(v) = \frac{1}{2}\rho A v^3 \tag{1}$$

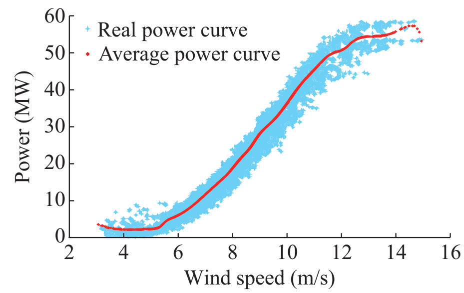

Fig. 1. Average speed versus average power for a wind farm.

where $P_w(v)$ is the power linked to a wind speed v; A is the surface area of the turbine rotor; and ρ is the air density (a typical value is 1225 kg/m³ [18]). P_e is the power generated by a wind turbine by means of the power coefficient and efficiency extracted from the wind generators:

$$P_e = \eta C_p P_w \tag{2}$$

where C_p is the non-dimensional power coefficient, which represents the theoretical amount of mechanical force that can be extracted by the turbine rotor; and η is the efficiency of the wind turbine [19]. C_p is an expression that relates the blade tip speed of the turbine λ and the blade inclination angle θ [20]. The theoretical maximum mechanical energy extracted by wind turbines is 0.5926, which is known as Betz's limit [21].

III. Fuzzy Inference System (FIS)

A. Mamdani FIS

The Mamdani inference model is one of the first systems using fuzzy set theory [22]. The semantic rule which is traditionally used to process inferences with the Mamdani model is called the maximum and minimum inference. Union and intersection operations are used between sets of the same form [22]. The production rules in a Mamdani model have fuzzy relations between in antecedents and their consequents.

Considering that a fuzzy system is composed of n rules with one of the rules represented as: if $X_1 = A_1$, $X_2 = A_2$, ..., $X_p = A_p$, then $Y_1 = B_i$, where X_i are the system inputs; $A_1, A_2, ..., A_j$ are the linguistic variables defined by the input relevance function; Y_1 is the output; and B_i is a linguistic variable defined by the output relevance function.

B. Sugeno FIS

Fuzzy Takagi-Sugeno-Kang (TSK) inference [23] is similar to Mamdani inference in many aspects, since the two initial stages of inference, which are the fuzzification of the inputs and the application of the fuzzy operator, are the same in both systems. The difference lies in the output. In a TSK system, a tendency toward a constant or linear character can be assumed.

We develop a new heuristic that uses the pre-established inference for training and parameterizing the models of power curves. The proposed heuristic consists of an initial training that uses fuzzy inference, which is a starting point for the parameterization of the model. This stage is performed on fuzzy Mamdani models and is called the pre-set. The second stage consists of the transformation of the Mamdani model into a Sugeno model with similar parameters as in the previous model, which is necessary to reinforce the learning process. In the third stage, an adaptive neuro-fuzzy inference system (ANFIS) is used to optimize the parameters of FIS Sugeno block with a less complex starting point than the initial point.

In the process of secondary learning, ANFIS is used to establish the best parameters of the resulting FIS through neural networks. Examples of parameters include the number of membership functions, the types of membership functions (Gaussian), the best arrangement at each specific interval, the range of inference, and the number of clusters used in the learning. The pre-trained FIS can be considered as a less entropic set, i. e., with a better-defined clustering, than the starting point of the system without defining the parameters. The proposed method significantly improves learning the models of power curves, which is verified by evaluation indices.

IV. Data Arrangement

A comparative study is conducted on two wind farms in the coastal region of northeastern Brazil based on the historical data of supervisory control and data acquisition (SCADA). The data are provided by the Brazilian electric system operator.

Wind farm 1 has 28 Suzlon model S88 aerogenerators of 2100 kW and 60 Hz with a rotor diameter of 88 m. They are installed in the towers with a height of 80 m for a total installed capacity of 70.56 MW. Wind farm 2 has 60 Suzlon model S88 aerogenerators of 2100 kW and 60 Hz with a rotor diameter of 88 m. They are installed in towers with a height of 80 m for a total installed capacity of 126 MW.

The databases are inserted into the models through the construction of conditioning patterns with two basic sets. First, the learning set is used to train the models, and second, the simulation set is used to compare the efficiency between the models. The learning set is divided into smaller subsets called the training, testing and validation sets with 60%, 20%, and 20% of the data, respectively. The learning set covers approximately two years in wind farm 1 and three years in wind farm 2. The simulation is carried out over one year for both wind farms.

After defining the learning and simulation sets, the training phase starts to train the models in order to ensure a good approximation of the power curves for each wind farm. The effectiveness of the learning process is verified in the simulation phase. The dataset arrangement and number of patterns are provided in Table I.

TABLE I
Dataset Arrangement and Number of Pattern

Wind farm	Duration of learning (hour)	No. of patterns (learning)	Duration of simulation (hour)	No. of patterns (simulation)
Wind farm 1	14-22	2064	23-9	3664
Wind farm 2	10-23	3950	23-0	1390

V. Power Curve Models of Wind Turbine

Although the power curve provided by a manufacturer describes the relationship between the wind speed and power generated for a specific air density, it does not consider the installation site or wear of the wind turbine. Therefore, it is important to develop the models of power curves for wind farms in operation.

In [24], no discrepancies are found between the power curves at low wind speeds and high wind speeds. Another important point is that due to wind speed variability, the power curve provided by a manufacturer is an unsuitable model to estimate the generated power since it ignores dynamic wind trends [25].

In [26], based on the slope method and monotonic spline regression, two non-parametric techniques are presented to construct power curves of wind turbines that preserve monotonicity. The results show that monotonic spline regression has the best performance because its power curve is more similar to the theoretical one.

In [27], three advanced models of power curves for aerogenerators are evaluated based on the techniques such as the Gaussian process (GP), random forest (RF), and support vector machine (SVM). The performance of the developed models of power curves is then compared using appropriate precision metrics. The power curve based on a GP has the highest tuning accuracy, while the SVM has the lowest accuracy, although it produces acceptable results with a narrow range of wind speed.

Considering various parameters in power estimation by incident winds, we develop nine models of power curves forwind turbine: two with artificial neutral networks (ANNs), two with FIS (Mamdani), two with FIS (Sugeno), two with FIS (Sugeno) by ANFIS, and one with the latest fuzzy models. Note that the data range is chosen to better adapt the models of power curves with actual operation of the wind farms, which focuses on the effective region of the power curves between the cut-in and cut-out speeds.

A. Average Power Curve (Reference Model)

The parametric model of the average power curve is mainly based on the average power curve of wind farms 1 and 2. Thus, to ensure a good approximation of the trend, a polynomial function is constructed to suit the characteristics of the average power curve. The average power curve consists of a parametric model that determines a polynomial function, establishing the approximate average relation of the power curve based on the given database.

The polynomial function is composed of specific, well-known sections in the power curve. In this paper, medium curve models are operation models, and the region is of effective operation, i. e., after the cut-in region and before the cut-out region. Therefore, the polyfit function in MATLAB is used to generate the medium curves. Four polynomial regions are considered in each wind farm dataset, as shown in Fig. 2. To approximate each region, we use a suitable polynomial degree: degree 3 for the first 3 regions and degree 0 for the region of constant power.

The polynomial forms for each region are expressed as follows. The equations include polynomial coefficients that create a best fit approximation. The region names characterize the relationship between the points, which is specified according to a distinctive polynomial for both wind farms.

1) Cubic region 1 of wind farm 1 is described as $P_{c11}(v)=$

$-0.02v^3-0.89v^2+4.82v-0.05$.

2) Cubic region 1 of wind farm 2 is described as $P_{c12}(v)= -0.09v^3+0.68v^2-0.17v+0.02$.

3) Cubic region 2 of wind farm 1 is described as $P_{c21}(v)= -0.11v^3+3.22v^2-22.67v+49.48$.

4) Cubic region 2 of wind farm 2 is described as $P_{c22}(v)= -0.09v^3+3.02v^2-20.37v+43.36$.

5) Cubic region 3 of wind farm 1 is described as $P_{c31}(v)= 1.63v^3-64.48v^2+851.52v-3696.9$.

6) Cubic region 3 of wind farm 2 is described as $P_{c32}(v)= 0.29v^3-13.94v^2+222.17v-1083.8$.

7) Constant region of wind farm 1 is described as $P_{c41}(v)= 51.63$.

8) Constant region of wind farm 2 is described as $P_{c42}(v)= 98.64$.

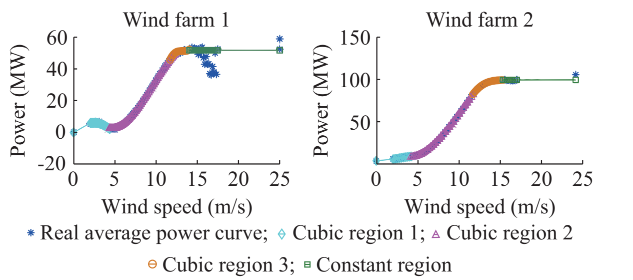

Fig. 2. Polynomial approximations relative to average power curves in wind farms 1 and 2.

B. Non-parametric Models of Power Curves Using ANNs

ANNs are applied in the structure of two models of power curves, and the choice of their input variables is made due to their close correlation with wind speed. More than one hidden layer is used in the architectures, which enhances the approximation precision. The Levenberg Marquardt learning algorithm is applied in ANN models, and the hyperbolic tangent is used as the activation function in each layer [1].

1) PC1-ANN Model

The PC1-ANN model consists of a multi-layer perception (MLP) neural network with the average wind speed as the input and the average wind power as the output. The PC1-ANN architectures and characteristics for wind farms 1and 2 are shown in Figs. SA2-4 of Supplement A.

2) PC2-ANN Model

The PC2-ANN model consists of an MLP neural network with two inputs: the average wind speed (output) and the average wind direction. The architectures of PC2-ANN [1] for wind farms 1 and 2 are shown in Figs. SA5-6 of Supplement A, respectively. The approximation characteristics of the networks for both wind farms are shown in Fig. SA7 of Supplement A.

C. Non-parametric Models of Power Curves Using Fuzzy Logic

In this paper, we use the models based on three distinct types of fuzzy systems: Mamdani inference, TSK inference, and an ANFIS neuro-fuzzy system.

1) PC1-fuzzy (Mamdani) Model

The PC1-fuzzy model consists of an FIS with the average wind speed as the input and the average wind power as the output [1]. For the learning phase, the PC1-fuzzy (Mamdani) model is manually constructed by trial and error to describe the appropriate position for the pertinence function in an established range and compare the obtained and expected values. PC1-fuzzy has one input and one output, each of which has five logistic sigmoidal member functions derived from the distribution of the speed in relation to the power.

The architecture of PC1-fuzzy is shown in Fig. SA8 of Supplement A. PC1-fuzzy resulting from the learning process related to wind farms 1 and 2 is shown in Fig. 3.

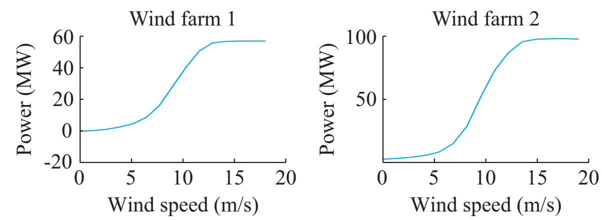

Fig. 3. PC1-fuzzy resulting from learning process related to wind farms 1 and 2.

2) PC2-fuzzy (Mamdani) Model

The PC2-fuzzy model is a Mamdani FIS with two inputs: the average wind speed and the average wind direction. The output is the average wind power. The learning stage of the PC2-fuzzy (Mamdani) model is manually constructed by trial and error to describe the appropriate position for the pertinence function in an established range and to compare the obtained and expected values. Five logistic sigmoid functions are used for the speeds and seven Gaussian member functions are used for the direction. The same criterion of the five logistic sigmoid functions is used by the output inference. The architecture of PC2-fuzzy is shown in Fig. SA9 of Supplement A. Figure 4 shows the PC2-fuzzy surfaces resulting from the learning process. The same heuristic is used for both wind farms.

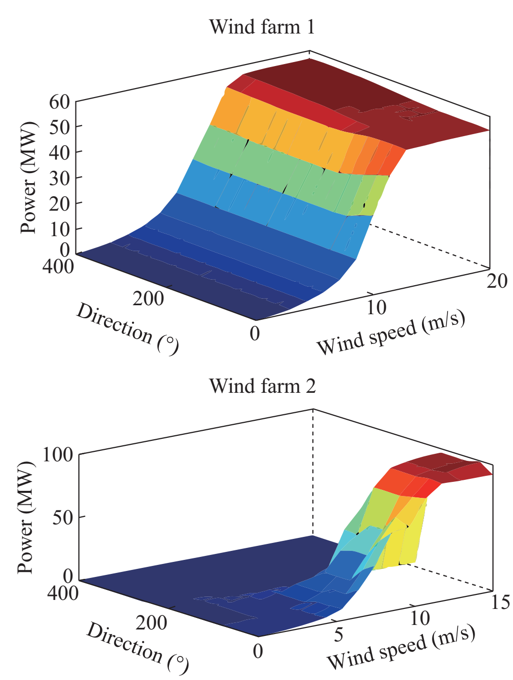

Fig. 4. PC2-fuzzy surface resulting from learning process related to wind farms 1 and 2.

3) PC1-fuzzy (Sugeno) Model and PC1-fuzzy (Sugeno-ANFIS) Model

PC1-fuzzy (Sugeno) and PC1-fuzzy (Sugeno-ANFIS) apply the wind speed as the input and the average wind power as the output with TSK as the inference. The output is discriminated by ranges. And each range obeys a specific inference function, either constant or linear.

To convert the characteristics of a Mamdani FIS into a Sugeno FIS, the "mam2sug" transformation function in MATLAB is applied. The transformation converts a Mamdani FIS, where the inference is given by the criterion of the maximum and minimum range, to a Sugeno FIS, whose inference or output function is given by linear or constant functions related to each range. The main difference between the traditional Sugeno models and the models developed in this paper is the pre-training, resulting from the use of the "mam2sug" transformation.

After the transformation, the input data clustering becomes better defined, i.e., more classes of data per range of input variables are formed. The increasing number of classes increases the amount of information per track, which improves the performance of the PC1-fuzzy (Sugeno-ANFIS) model and makes it more accurate than a TSK system with standard initialization without pre-training. After the pre-training, PC1-fuzzy (Sugeno) model is obtained without using ANFIS.

The routine for creating the fuzzy PC (Sugeno-ANFIS) is as:

1) Creation of FIS (Mamdani)

a) The learning database is initialized in FIS, and the inputs and outputs are loaded into it.

b) The numbers of intervals of the respective inputs and outputs are selected by successive tests.

c) The type of member function inferred in each interval is chosen through the correlation trend between the input and output variables.

d) The best arrangement of the member functions in each interval is manually adjusted by trial and error until the value of the output reaches a satisfactory approximation level.

2) Creation of pre-established inference (pre-training)

a) The "mam2sug" transformation is used, converting the FIS (Mamdani) into the FIS (Sugeno).

b) The learning database is started in ANFIS.

c) A satisfactory sampling radius is defined on ANFIS.

d) With the value of the sample ray, the grid partition function is chosen. It automatically adjusts the best arrangement of the member functions by interval.

e) FIS is created (Sugeno-ANFIS).

The architecture of the PC1-fuzzy (Sugeno-ANFIS) model and the trend curve resulting from the new learning process for both wind farms are shown in Figs. 5 and 6, respectively.

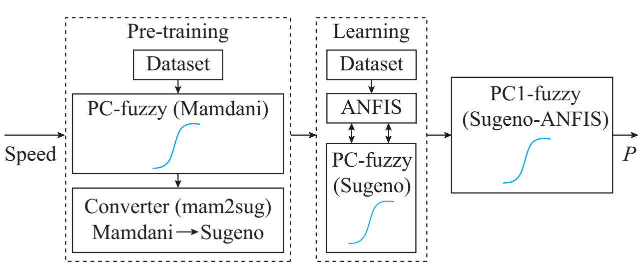

Fig. 5. PC1-fuzzy (Sugeno-ANFIS) resulting from learning process related to wind farms 1 and 2.

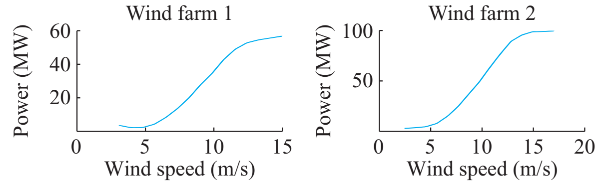

Fig. 6. Trend curve resulting from learning process related to wind farms 1 and 2.

4) PC2-fuzzy (Sugeno) model and PC2-fuzzy (Sugeno-ANFIS) model

PC2-fuzzy (Sugeno-ANFIS) has similar characteristics compared with those of PC1-fuzzy (Sugeno-ANFIS), differing only in its architecture. The average wind speed and the average wind direction are the inputs and the average wind power is the output. The heuristic and the methods used to define the main parameters of this power approximation block are similar to those described in the previous fuzzy block. Besides, after the pre-training, PC2-fuzzy (Sugeno) model is obtained without using ANFIS. PC2-fuzzy (Sugeno-ANFIS) and the trend surfaces resulting from the learning process are shown in Figs. 7 and 8, respectively. The same heuristic is used for both wind farms 1 and 2.

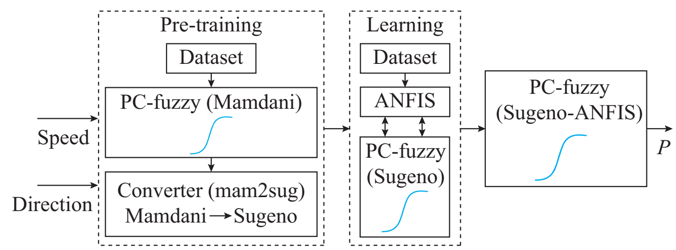

Fig. 7. PC2-fuzzy (Sugeno-ANFIS) resulting from learning process related to wind farms 1 and 2.

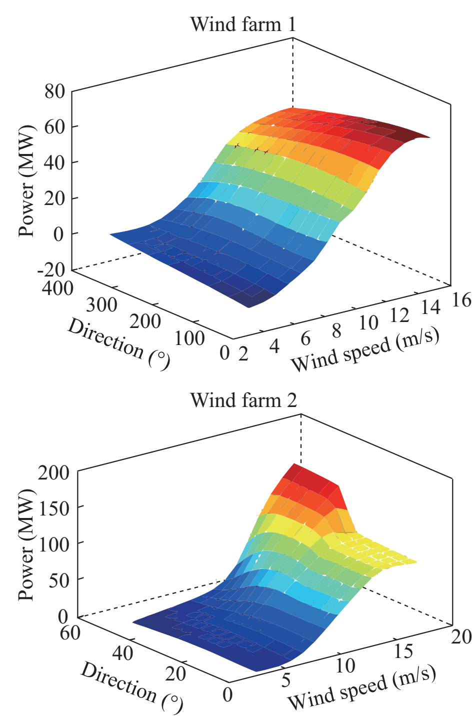

Fig. 8. Trend surfaces resulting from learning process related to wind farms1 and 2.

Figure 8 shows that there is a variation in the behavior when there is a variation in the direction. The behavior is also evident in the Mamdani FIS models. It can thus be concluded that when there is an inherent variation in the speed and direction, the Sugeno-ANFIS model is more suitable than the Mamdani model.

VI. Model Evaluation and Result Analysis

A. Format for Tables

The polynomial model of the average power curve is used as a reference in the approximation. The mean absolute error (MAE), normalized mean absolute error (NMAE), and root mean square error (RMSE) between the approximate power values are calculated for the curves and their respective real values according to the database of wind farms 1 and 2.

The power predict error $e_P(k)$, the mean absolute power prediction error $MAE_P(k)$, the normalized mean absolute power prediction error $NMAE_P(k)$, and the root mean square power prediction error $RMSE_P(k)$, are calculated in (3)-(6), which is based on the installed capacity of the wind farm $P_{total}^{\max}$ and RMSE:

$$e_P(k) = P(k) - \overline{P}(k) \tag{3}$$

$$MAE_P(k) = mean\left(\left| e_P(k) \right|\right) \tag{4}$$

$$NMAE_P(k) = \frac{1}{P_{instal}^{\max}} mean\left(\left| e_P(k) \right|\right) \tag{5}$$

$$RMSE_P(k) = \sqrt{mean\left(\left| e_P{}^2(k) \right|\right)} \tag{6}$$

where $P(k)$ and $\overline{P}(k)$ are the actual and desired outputs of the network, respectively. The gain of the respective power curve model is calculated in (7) when it is compared with the reference model. In this case, the polynomial parametric model of the average power curve is:

$$G_{ref,CA}(k) = 100 \frac{CA_{ref} - CA(k)}{CA_{ref}(k)} \tag{7}$$

where CA_{ref} is the evaluation criterion of the reference model; and $CA(k)$ is the evaluation criterion of the proposed model. MAE, NMAE, and RMSE can be used as the evaluation criteria.

The performance indices MAE, NMAE and RMSE are presented in Table II, which are relative to the approximations for both wind farms. Based on the results in Tables II and III for wind farms 1 and 2, the PC2-fuzzy model (Sugeno-ANFIS) has a considerable advantage over the other models. Besides, the ANN models with two inputs have the second best performance, which is due to the close correlation of average wind direction with average wind speed.

In the proposed method, a second variable along with wind speed is applied as the input to the models of power curves. Two hidden layers are used in the ANN models, which enhances the learning performance of these models.

The significant difference between the error indicators for wind farms 1 and 2 is important to be noted, which indicates that the behavior of most of the algorithms on the same dataset is similar. When a dataset can be easily explained by the models, all of the error indicators are low as shown in Table II. However, when the dataset is difficult to be explained, all of the error indicators are high as shown in Table III, regardless of the algorithm used.

TABLE II
Performance of Models of Power Curves in Wind Farm 1

Model	MAE (MW)	NMAE (%)	RMSE (MW)
PC1-ANN	1.84	2.61	3.58
PC2-ANN	1.59	2.26	2.09
PC1-fuzzy (Mamdani)	1.73	2.45	2.21
PC2-fuzzy (Mamdani)	1.87	2.65	2.37
PC1-fuzzy (Sugeno)	2.02	2.86	2.47
PC2-fuzzy (Sugeno)	1.82	2.58	2.31
PC1-fuzzy (Sugeno-ANFIS)	1.67	2.37	2.11
PC2-fuzzy (Sugeno-ANFIS)	1.57	2.22	2.00
Average power curve (reference model)	3.18	4.51	3.76

TABLE III
Performance of Models of Power Curves in Wind Farm 2

Model	MAE (MW)	NMAE (%)	RMSE (MW)
PC1-ANN	3.28	2.60	4.27
PC2-ANN	3.34	2.65	4.37
PC1-fuzzy (Mamdani)	3.79	3.01	5.18
PC2-fuzzy (Mamdani)	3.59	2.85	4.67
PC1-fuzzy (Sugeno)	3.57	2.83	4.76
PC2-fuzzy (Sugeno)	3.54	2.81	4.66
PC1-fuzzy (Sugeno-ANFIS)	3.27	2.59	4.26
PC2-fuzzy (Sugeno-ANFIS)	3.19	2.49	4.13
Average power curve (reference model)	3.37	2.67	4.34

Similar behavior occurs for the Sugeno-ANFIS models since ANFIS is responsible for deep learning by defining the best parameters of the pre-trained FIS. The optimal search accomplishes the influence of neuro-fuzzy inferences in the training process, thus the performances of these models are improved.

Figures 9, 10, and 11 are the bar diagrams that clearly express MAE, NMAE, and RMSE of the models for the inferred power curves of both wind farms. Tables IV and V present the gains of the proposed models of power curves over the polynomial model of the average power curve. The results represents the clear advantage of the pre-established inference models, i. e., the PC2-fuzzy (Sugeno-ANFIS) and PC1-fuzzy (Sugeno ANFIS) models.

These gains are described by MAE, NMAE, and RMSE indices of 50.65%, 50.65%, and 46.68%, respectively. For wind farm 2, the PC1-fuzzy (Sugeno-ANFIS) and PC2-fuzzy (Sugeno-ANFIS) models have the best results, as indicated by the MAE, NMAE, and RMSE of 5.26%, 6.78%, and 4.70%, respectively.

Another relevant result is the advantage of the models with two correlated inputs, which is expected due to the greater amount of information provided to the fuzzy block. The presence of some negative gains indicates lower performance in relation to the reference model.

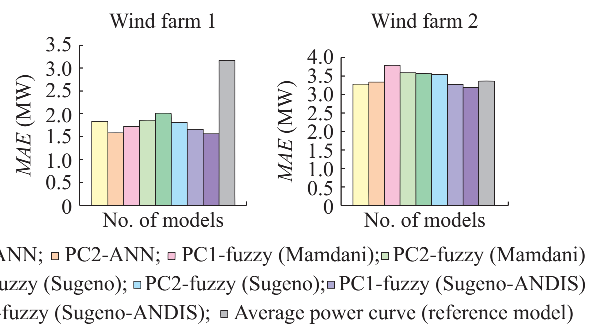

Fig. 9. MAE of simulation set for models of active power curves in wind farms 1 and 2.

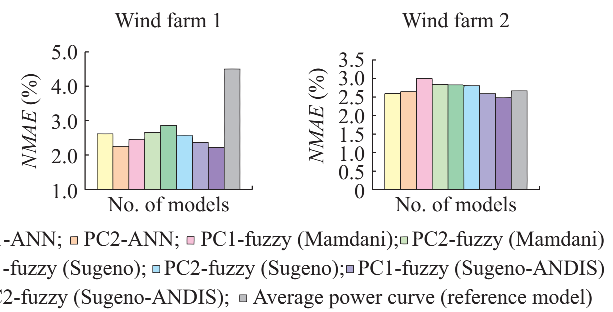

Fig. 10. NMAE of simulation set for models of active power curves in wind farms 1 and 2.

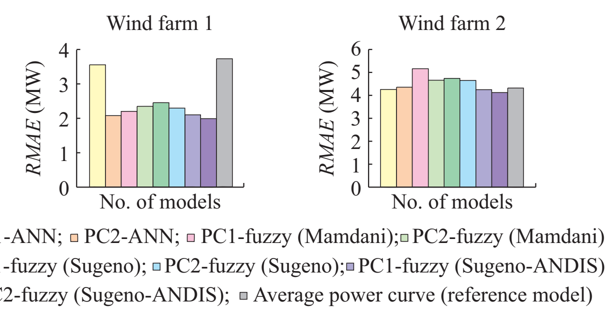

Fig. 11. RMSE of simulation set for models of active power curves in wind farms 1 and 2.

TABLE IV
GAINS IN RELATION TO REFERENCE MODEL WIND FARM 1

Model	Gain MAE (%)	Gain-NMAE (%)	Gain-RMSE (MW)
PC1-ANN	42.03	42.03	4.71
PC2-ANN	49.95	49.95	44.27
PC1-fuzzy (Mamdani)	45.69	45.69	41.07
PC2-fuzzy (Mamdani)	42.76	42.76	38.44
PC1-fuzzy (Sugeno)	36.51	36.51	34.28
PC2-fuzzy (Sugeno)	42.76	42.76	38.44
PC1-fuzzy (Sugeno-ANFIS)	47.47	47.47	43.73
PC2-fuzzy (Sugeno-ANFIS)	50.65	50.65	46.68

The performance of the models of power curves on the simulation dataset is shown in the power responses according to Tables IV and V. The simulated power curves for wind farms 1 and 2 are shown for all models except the fuzzy Sugeno models, due to their low performance as shown in Fig. 12.

TABLE V
GAINS IN RELATION TO REFERENCE MODEL WIND FARM 2

Model	Gain MAE (%)	Gain-NMAE (%)	Gain-RMSE (MW)
PC1-ANN	2.67	2.67	1.59
PC2-ANN	0.87	0.87	–0.83
PC1-fuzzy (Mamdani)	–12.56	–12.56	–19.39
PC2-fuzzy (Mamdani)	–5.10	–5.10	–7.56
PC1-fuzzy (Sugeno)	–6.01	–6.01	–9.69
PC2-fuzzy (Sugeno)	–5.10	–5.10	–7.56
PC1-fuzzy (Sugeno-ANFIS)	2.86	2.86	1.74
PC2-fuzzy (Sugeno-ANFIS)	5.26	6.78	4.70

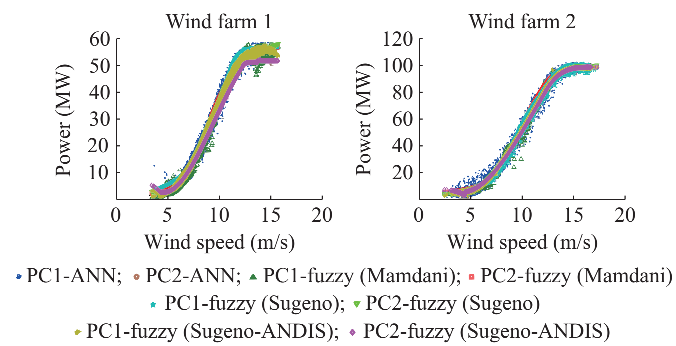

Fig. 12. Responses of power curves for entries of simulation dataset.

The small and similar errors are achieved in the developed models. Small differences may have an impact on the power forecasting, the generation dispatching from other sources, the cost of the generator system, and the finances of the wind farm owner. The energy quantity saved by the proposed methods is shown in Tables II and III. The best model saves 0.02 MW (in MAE) more than the second best model in wind farm 1 and 0.08 MW (in MAE) in wind farm 2.

VII. CONCLUSION

In this paper, a new method is proposed to improve the performance of approximation models of power curves. Pre-established inference is applied, resulting from the conversion of a Mamdani FIS into a Sugeno FIS.

The results indicate that the pre-training is effective in terms of improving the power curves because it selects the clusters with a pre-defined organization tendency. And the result database has less data entropy, which is a decisive factor in obtaining satisfactory results in the learning process.

Two wind farms are studied. The reference model is a polynomial parametric model of the average power curve. The performance evaluation shows that the proposed fuzzy model outperforms the others. The pre-inference criteria improves the performance of the fuzzy models in this paper compared with that of other models. Moreover, the models presenting the best performance are those with two inputs: the average wind speed and the average wind direction. The choice of these variables is based on the study on correlation.

The gains obtained by the new models in relation to the average power curve (the reference model) are particularly satisfactory for wind farm 1, where the gains in MAE, NMAE, and RMSE indices of the highest pre-established inference models are 50.65%, 50.65%, and 46.68%, respectively.

For wind farm 2, due to better wind speed and direction data, the pre-established inference models also have positive gains in MAE, NMAE, and RMSE indices, which are 5.26%, 6.78%, and 4.70%, respectively. However, they are much more modest in relation to the gains for wind farm 1.

The proposed models exhibits better performance compared with those in [12] and [10]. NMAE can be approximated in the range of 2.9% to 5.5% in [10] and 1.0% to 14% in [12], whereas the models developed are in the range of 2.2% to 4.5% for wind farm 1, and 2.3% to 3.0% for wind farm 2. In [12] and [10], the models address the power in kW. While in this paper, the models address the power in MW. The results are quite satisfactory when considering the installed capacity of the wind farms.

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Jonata C. de Albuquerque received the bachelor and master degrees in electrical engineering from the Federal University of Pernambuco, Recife, Brazil, in 2012 and 2015, respectively. Currently, he is a Ph.D. student from the Federal University of Pernambuco. His research interests include wind power prediction, power curve evaluation, artificial intelligence, neural networks, and fuzzy logic.

Ronaldo R. B. de Aquino received the bachelor and master degrees in electrical engineering from the Federal University of Pernambuco, Recife, Brazil, in 1983 and 1995, respectively, and Ph.D. degree in electrical engineering from the Federal University of Paraíba, Recife, Brazil, in 2001. He is currently a Full Professor and is the Head of Department of Electrical Engineering in Federal University of Pernambuco. His research interests include power generation dispatch, load forecasting, wind speed and power forecasting.

Otoni Nóbrega Neto received the bachelor, master and Ph. D. degrees in electrical engineering from the Federal University of Pernambuco, Recife, Brazil, in 2004, 2006 and 2010, respectively. He is currently an Associate Professor of Department of Electrical Engineering in Federal University of Pernambuco. His research interests include load forecasting and optimum dispatch of electric power generation.

Milde M. S. Lira received the bachelor, master and Ph.D. degrees in electric engineering from Federal University of Pernambuco, Recife, Brazil, in 1989, 1999 and 2004, respectively. She is currently an Associate Professor in Federal University of Pernambuco. Her research interests include transmission of electric energy, distribution of electric energy, neural networks, fuzzy logic, artificial intelligence, wind, load, flow prediction, wavelets and electrical electric power quality.

Aida A. Ferreira received the bachelor degree from Catholic University of Pernambuco, Recife, Brazil, in 1989, and master and Ph.D. degrees in Computer Science from the Federal University of Pernambuco, Recife, Brazil, in 2004 and 2011, respectively. He is a Full Professor at the Federal Institute of Pernambuco, Recife, Brazil, since 2004. His research interests include artificial neural networks, wind power forecasting, load forecasting, time series forecasting, reservoir computing and development of geographic information systems, and software engineering disciplines.

Manoel Afonso de Carvalho Jr. received the bachelor degree in electric engineering from Federal University, Recife, Brazil, in 1973, and Ph.D. degree from the Victoria University of Manchester, Manchester, UK, in 1983. He is currently a Full Professor of Department of Electrical Engineering, Federal University of Pernambuco, Recife, Brazil. His research interests include neural networks, artificial intelligence, saturated reactor, power systems and voltage stability.