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AN IMPROVED MACHINE LEARNING TECHNIQUES FUSION ALGORITHM FOR CONTROLS ADVANCED RESEARCH TURBINE (CART) POWER COEFFICIENT ESTIMATION

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Wind energy is an alternative energy vector that is increasingly attracting the attention of industrialists and scientists. Moreover, the exploitation of this deposit suffers from discontinuity in production due to the instability of the wind and a non-linearity due primarily to wind fluctuations. The stochastic nature of the wind makes difficult the determination of optimal operating points corresponding to the maximal power coefficient and the difference between recorded power coefficient values even if machines are working under the same conditions. As a solution of these problems, this paper proposes a power coefficient real-time estimation based on machine learning techniques fusion based on Ordered Weighted Averaging operator (OWA). statistical analysis is carried out to verify the performance of the proposed algorithm. The reference wind turbine chosen is Controls Advanced Research Turbine (CART) from the National Renewable Energy Laboratory (NREL). Simulations performed on MATLAB software show the efficiency of the proposed approach and its superiority compared to MLP, RBF and ANFIS power coefficient real-time estimators.

Keywords: Power coefficient, Ordered Weighted Averaging (OWA), Data Fusion, Machine Learning, Estimation

1. Introduction

Nowadays, the exploitation of renewable energies, in particular, wind energy has increased considerably [1]. Renewable energy has experienced a meteoric rise in recent years because they are clean and offer a considerable

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economic contribution. This has motivated several countries to consider these inexhaustible sources, including wind energy as an attractive energy vector[2].

Wind turbine is a strongly nonlinear system, because of the stochastic nature of wind as well as the power coefficient. Various analytical models of wind turbine power coefficient $Cp\ (\lambda,\beta)$ can be found in literature, which describes blades aerodynamics' as a function of Tip-speed ratio λ and Pitch angle $\beta(deg)$ [2-6]. [7] Uses a lookup table. It is well established that the nonlinearity of the system is not the only problem to be encountered in wind turbine control, but also the determination of the optimum operating point since it is not the same even if wind turbine has similar characteristics and working under the same conditions [4]. These issues also meet the challenges related to the control of wind turbines and have led many researchers to consider machine learning techniques. Moreover, they are preferred if it is possible to obtain good quality data [8]. For renewable energies, particularly wind energy conversion systems, various techniques have been used, among others, fuzzy logic (FL)[5], Artificial neural networks (ANNs) [1, 9], and adaptive neuro-fuzzy Inference System (ANFIS) [10-12].

In [13] Multi Layers Perceptron Neural Network (MLP) was used to estimate wind speed using a single hidden layer with five tan-sigmoid neurons, in order to compensate power coefficient drift. Despite the effectiveness of the proposed method, the control scheme is very complicated. In [3] a power coefficient $Cp\ (\lambda,\beta)$ optimization based on Lyapunov control strategy has been proposed. Gradient search method has been used in order to ensure the convergence of λ and β to their optimums, which ensures stable and efficient control in second zone[14]. In a major advance in 2013, Petkovic proposed a power coefficient $Cp\ (\lambda,\beta)$ estimation using ANFIS. The results seem innovative and give a good approximation, however, the use of an analytical expression where the coefficients are already estimated harms the estimation and does not allow the expected precision to be achieved[10]. [12] developed a power coefficient $Cp(\lambda,\beta)$ estimation of an offshore wind turbine using ANFIS, the use of bell-shaped MFs gave the best $Cp\ (\lambda,\beta)$ estimation. In [15] a Maximum Power Point Tracking (MPPT) technique based on power coefficient estimation has been proposed, the estimation was done using Recursive least square (RLS), for which a third-order polynomial has been used. In [16] the authors proposed a hierarchical intelligent system for wind turbine power prediction. The fusion of MLP and ANFIS gave a significant reduction in prediction error.

The main objective of this study is to provide a practical and effective-coast intelligent estimator based online data fusion of various machine learning techniques for power coefficient of the Control Advanced Research Turbine (CART) in order to remedy the following problems:

- The traditionally implemented power coefficient lookup table requires a lot of memory.
- The intermediate values of are determined by linear interpolation, while the power coefficient is non-linear.
- The difference between recorded values even when machines are working under the same conditions, which considerably affects the management of wind farms.

2. Wind turbine aerodynamics

CART is a two-blades horizontal axis wind turbine, variable speed and variable pitch operations with a rated energy of 600 kW. Table 1 summarizes the main characteristics of the CART wind turbine.

Table1

Characteristics of CART

Properties	Value	Unit
Rated power	600	(kW)
Hub height	38	(m)
Rotor diameter	43	(m)
Rated rotor speed	4.3646	(rad.s^{-1})
Rated wind speed	13	(m.s^{-1})
Peak power coefficient	0.4292	/
Optimal tip-speed ratio	8.5	/
Optimal pitch angle	1	(deg)

Wind turbine is a complex mechatronic system, designed to produce electrical energy. However wind turbine can extract only a part of the wind kinetic energy given in Eq. 1, the extracted energy does not generally exceed the BETZ limit, this quantity is specific to each turbine and characterized by, $Cp\ (\lambda,\beta)$which expresses the capacity of wind energy extraction [5].

$$P_a = \frac{1}{2}\rho\pi R^2 C_p(\lambda,\beta)v^3 \qquad (1)$$

Where $P_a(W)$ is the wind turbine power, $\rho\ (kg.m^{-3})$, is the air density $R(m)$ is rotor radius , and $v\ (m.s^{-1})$ the wind speed [5, 17].

CART power coefficient $Cp\ (\lambda,\beta)$ with negative values set to zero shown in Fig. 1. It is given by a lookup table developed by NREL. This nonlinear coefficient is function of λ and $\beta(deg)$. The Tip-speed ratio λ refers to the ratio of the tangential speed at the end of the blade and wind speed expressed as follows:

$$\lambda = \frac{\omega_r}{v} R \qquad (2)$$

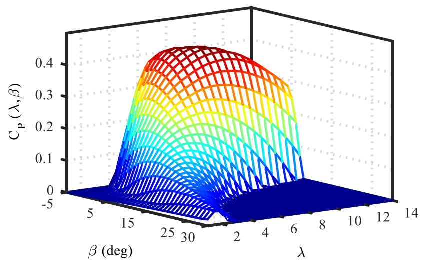

Fig.1 $Cp\ (\lambda,\beta)$ for CART wind turbine

3. Machine learning paradigms

3.1 Artificial Neural Networks (ANNs)

3.1.1 Multi-Layer perceptron neural network (MLP)

The MLP network is a fully interconnected feedforward network.As demonstrated in Fig. 2-a it consists of three or more layers which are input, output and one or more hidden layers hidden expressed by a nonlinear activation function. in this work a sigmoid function given by Eq. 3 is chosen.

$$F_j(x) = \frac{1}{1+e^{-x}} \tag{3}$$

Where F_j denotes the output of the j_{th} hidden neuron .
The mathematical model of a neuron in the i^{th} layer is given by Eq. 4 as follows:

$$O_i = \sum_{j=1}^{n} w_i F_j(x) + b_i \tag{4}$$

Where O_i is the output of i^{th} neuron, w_{ij} denotes the weight between the j_{th} neuron in the hidden layer and the i^{th} neuron in the output layer b_i is the bias of the i_{th} neuron in the output layer.

3.1.2 Radial Basis Function Neural Network (RBF):

RBF neural network illustrated in Fig. 2-b has similar architecture as MLP neural network. However, neurons at the hidden layer are activated by a radial basis function. Were the output of each hidden neuron can be produced as follows:

$$G_j(x) = \exp\left(-\frac{\left\|x-c_i\right\|^2}{\sigma_i^{\,2}}\right) \tag{5}$$

Where c is denotes the center of basis function and σ is the function radius.

The output layer for MLP is RBF is taken linear.

3.2 Adaptive neuro-fuzzy inference system

ANFIS is considered as the most efficient neural system, it was proposed by J S Jang; whose architecture is equivalent to the first order Takagi Sugeno system. ANFIS architecture shown in Fig. 2-c consists of five layers as follows:

a) Fuzzification layer: Is a subset of adaptive neurons$A_i(B_i)$, which makes the transition to the fuzzy domain. [18]. It expresses the membership conditions of each input. The activation function of the neurons i of the first layer is:

$$O_i^1 = U_{A_i}(x) \tag{6}$$

Where (x) denotes node's entry i and A_i is the linguistic label associated with the node i. ANFIS inputs used in this study are the tip speed ratio λ and pitch angle. Both are fuzzified by bell-shaped membership function (MFs), such as:

$$U_{A_i}(x) = \frac{1}{1 + \left[\frac{x - c_i}{a_i}\right]^{b_i}} \tag{7}$$

Where $\{a_i,\ b_i, c_i\}$ are premises parameters.

b) Product Layer: It is a subset of fixed neurons [18]. Each neuron represents the firing strengths of a rule. Its activation function given by Eq. 8.

$$W_i = U_{A_i}(x) \times U_{B_i}(x) \tag{8}$$

c) Normalization layer: It ensures the normalization of the firing strengths of each rule (weight), according to the previous output [18].

$$\bar{W} = \frac{W_i}{W_1 + W_2} \quad for\ i = 1, 2. \tag{9}$$

d) Defuzzification layer: Is a subset of adaptive neurons which receives the normalized weights and calculates the consequent parameters such as:

$$O_i^4 = \bar{W} f_i = \overline{W_i (p_i x + q_i y + r_i)} \tag{10}$$

Where $\bar{W}$ is the normalized weights. The polynomial parameters $\{P_i, q_i, r_i\}$ are called consequent parameters.

e) Output layer: It consists of a single fixed neuron, which deliver the ANFIS output by summing received signals from the defuzzification layer such as:

$$O_i^5 = \sum \bar{W} f_i \tag{11}$$

The training process allows modifiable parameters adaption of the fuzzy inference system (FIS). The hybrid method is a two-step algorithm, using the gradient descent, and the least squares method. Each training iteration includes forward and a backward pass. The least squares method adapts the polynomial consequent parameters during the forward pass, where premise parameters are fixed. While the gradient descent method adjusts the membership function parameters ''premise'' where consequent parameters are fixed. [19].

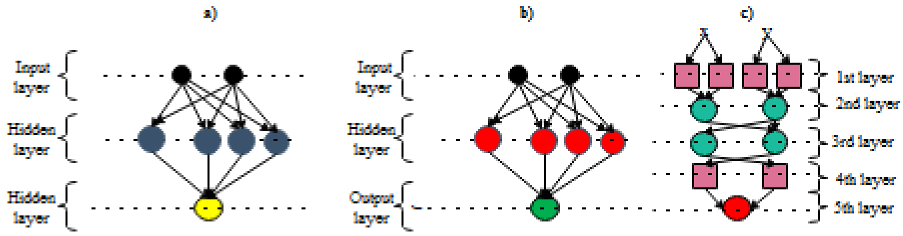

Fig 2. Architectures of the machine learning techniques used for power coefficient estimation. a) MLP, b) RBF, c) ANFIS

3.3 Ordered Weighted Averaging (OWA) operator

The ordered weighted averaging (OWA) operator, initially proposed by Yager [20] is a data fusion technique consisting of amalgamating various homogeneous data sets acquired from several sensors in order to increase its accuracy and consequently provide a better observation compared to the received one. Mathematically, the OWA operator is defined as follows:

Definition 1 [21] **:** An ordered weighted averaging (OWA) operator of dimension n is a mapping $F:\mathbb{R}^n \rightarrow \mathbb{R}$ that has an associated n-vector:

$$\mathbf{W} = \left[w_1, w_2, w_3, \ldots, w_n \right]^T \tag{12}$$

Such that $w_i \in [0,1]\ for\, 1 \le i \le n;$ verifying:

$$\sum_{i=1}^{n} w_i = w_1 + \ldots + w_n = 1 \tag{13}$$

Furthermore:

$$F\left(a_1,\ldots,a_n\right) = \sum_{j=1}^{n} w_j b_j = w_1 b_1 + \ldots + w_n b_n \tag{14}$$

Where b_j is the j_{th} largest element of the collection of objects $\{b_1,\ldots,b_n\}$. The function value $F\left(a_1,\ldots,a_n\right)$ determines the aggregated value of arguments $\{a_1,\ldots,a_n\}$.

As defined in the Eq. 14 the determination of weights is crucial in the data fusion process. In the literature one can find various methods for the determination of weights, among others: the orness measure method proposed by Yager [20]. The orness measure reflects the "andlike" or "orlike" aggregation result of an OWA operator, A number of approaches have also been proposed to obtain the associated OWA operator, namely to quantify the guided aggregation initiated in [20, 22]. Another concept commonly used in the aggregation process is that of fuzzy linguistic quantifiers. It consists in expressing human expertise using a natural language: "most", "many", "at least half", "some" and "few" [23]. . Yager [22, 24] classified fuzzy linguistic quantifiers into three classes: Regularly Increasing Monotone (RIM), Regularly Decreasing Monotone (RDM) and Regular Uni-Modal (RUM). Both RDM and RUM quantifier can be generated from RIM quantifier. He also used the RIM quantifier. In this work the RIM quantifier defined below is chosen to obtain the decision function in the OWA aggregation

Definition 2 [25, 26] **:** A fuzzy subset Q_f of the real line is called a regular increasing monotone (RIM) quantifier, if it satisfies the following conditions:

$$\begin{cases} Q_f(0) = 0 \\ Q_f(1) = 0 \\ Q_f(x) \geq Q_f(x), x \geq y \end{cases} \qquad (15)$$

The RIM quantifiers can be used to express terms like all, most, many and at least α. The commonly used quantifier is Basic linguistic quantifier expressed as follows:

$$Q_r = r^{\alpha} \qquad (16)$$

Where the weights are calculated as follows:

$$w_i = \left(\frac{i}{n}\right)^{\alpha} - \left(\frac{i-1}{n}\right)^{\alpha}, \quad for\, i = 1, \ldots, n \qquad (17)$$

By taking $\alpha > 0$ one can assure that the quantifier is a RIM quantifier [26].

4. Proposed fusion algorithm

In order to improve the accuracy of the power coefficient estimation, a new methodology for fusion of machine learning techniques Fig. 3 is proposed and is detailed in this section.

a) Data collection and preparation.
b) Determination of optimal architectures of machine learning techniques.
c) Data fusion based on Fuzzy Linguistic Quantifier.
d) Statistical analysis of estimators.

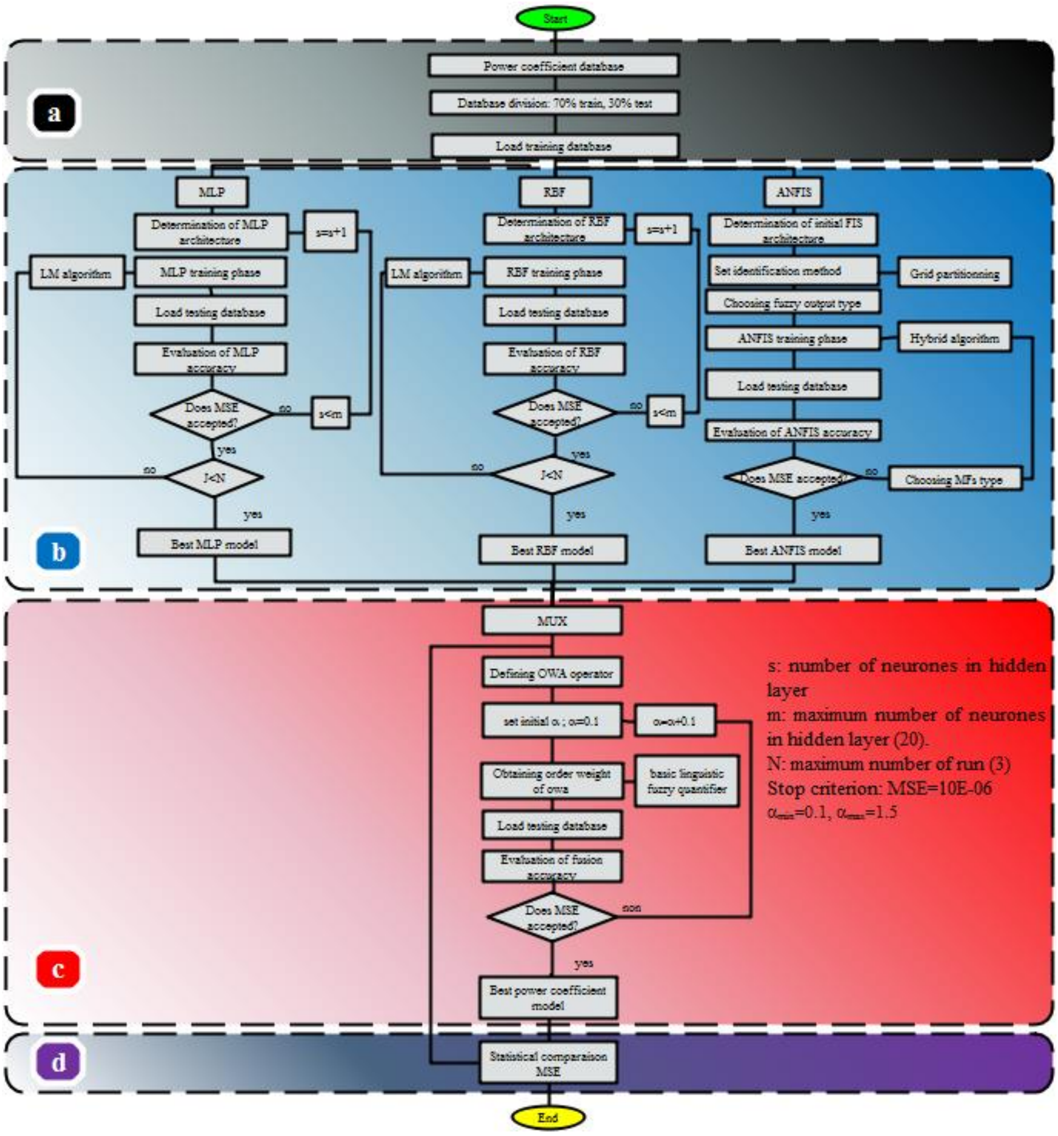

Fig. 3. Chart of the proposed algorithm

As a driven data method, data collection and processing is essential for the construction of power coefficient estimators. For this purpose, lookup table data of the CART wind turbine was used. In this study, the power coefficient $Cp\ (\lambda,\beta)$ is using MLP as well as ANFIS with two inputs and one output, which are tip-speed ratio λ, $\beta\ (deg)$ and $Cp\ (\lambda,\beta)$respectively. The total number of samples forming (input/output) couples is 634. All samples were carefully divided, where 443 (69.87%) are used for training and 191 (30.12%) are used for networks test.

A series of preliminary experiments were performed before implementing the OWA fusion algorithm proposed in this study, in order to determine the boundaries of the architectures of the artificial intelligence techniques proposed in the previous section. The strategy adopted in this phase is to increase the number of elements in the hidden layer (for MLP and RBF based models from 10 to 20, then performing a series of experiments on ANFIS, by varying the type of MFs and the type of fuzzy output whenever necessary. At last and not least optimizing the α until it reaches the value that the OWA operator-based decision making algorithm starts to diverge beyond it.

Once the limits of the proposed algorithm being shown in Fig. 3 are fixed a real-time simulation is performed and the optimal model with the best estimation capability is obtained without overlearning. Finally, the statistical indicator root mean squared error (MSE). expressed in Eq. 18 is used to evaluate the four generated models.

$$MSE = \frac{1}{n}\sum_{n=1}^{n}\left(X_i - Y_i\right)^2 \tag{18}$$

Where n is the number of samples, X_i indicates estimated value and Y_i is the measured value of one data point.

4. Results and discussions

In this section we will discuss the envisaged approach in order to reach the best estimate of the power coefficient. The proposed algorithm has been developed in MATLAB environment, the maximum number of neurons in the hidden layer m=20, 500 epochs. Regarding the OWA-based fusion method α ranges from 0.1 to 1.5 with a step-size of 0.1. In addition, the algorithm repeats the training process 3 times (J=3). The best architecture among J runs is then used for the fusion.

For the estimation of $Cp\ (\lambda,\beta)$ using ANNs, a static architecture of MLP and RBF has been envisaged, The maintained structure Consists of 20 neurons trained based on Livenberg Marquad Algorithm (LM) with an iteration rate equal to 0.25. As illustrated in Fig. 4 a-b, the RBF neural network perform well than MLP. The obtained result mainly depends on the type of transfer function. A test has also been carried out which validates the superiority of RBF over MLP.

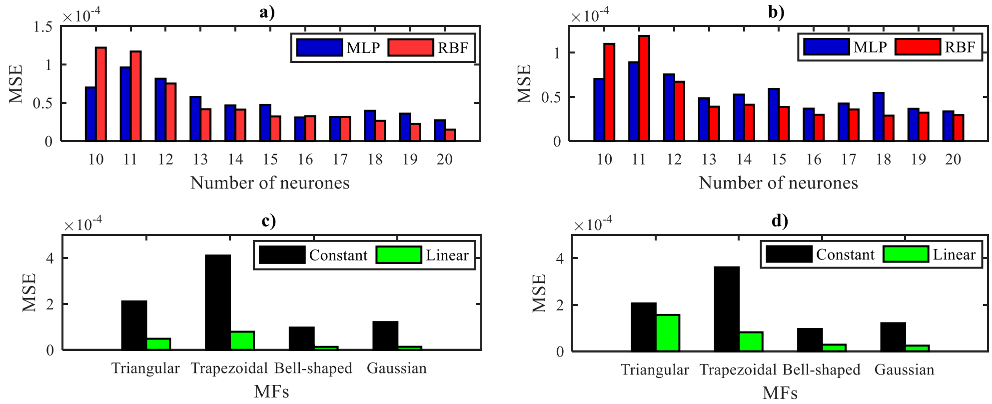

Fig. 4: Recorded MSE. a) MLP and RBF train, b) MLP and RBF test, c) ANFIS train, d) ANFIS test

The construction of ANFIS estimator begins with the construction of an initial FIS. In the present study, the initial FIS system is built using the grid partitioning identification method. The Optimal result giving a minimal error is obtained by using 6 Bell-shaped MFs for both λ and $\beta(deg)$ with linear fuzzy output as demonstrated is Fig. 4 c-d. It is inferred that the fact of increasing the number of MFs is detrimental to the results, which corroborates recommendations given by [18, 19]. It is explained by the influence of the number of modifiable parameters which depends directly on the number and type of MFs. 36 significant rules generated from the system.

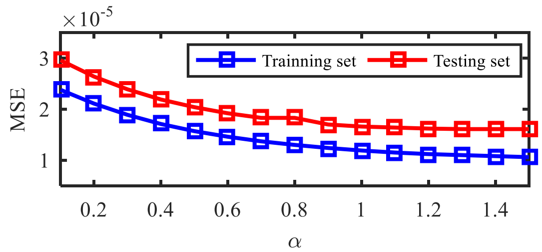

Fig. 5. Influence of α factor on OWA based fusion algorithm

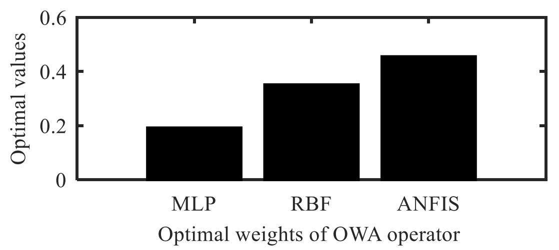

Fig. 6. Optimal weighs of OWA operator

Shown in Fig. 5, the influence of the α factor on the precision of power coefficient estimation. The result shows that the optimal value leading to the minimum error is 1.5. The obtained weight vector $\mathbf{W} = [0.192, 0.352, .456]^T$ shown in Fig. 6, the obtained values are explained by the fact that the most important factor giving which leads to the best decision is the estimation provided by ANFIS as it is more precise compared to MLP and RBF estimators.

To evaluate proposed models' efficiency, the errors produced by MLP and ANFIS estimators in training and testing phases are plotted in Fig.7. It is found that ANFIS estimator provides the best estimation compared to MLP with small and smooth error for both training and testing data sets. Fig. 7-a shows the obtained MLP and ANFIS results against lookup table data in the training phase, while Fig. 7. b, illustrates estimation results obtained in the test.

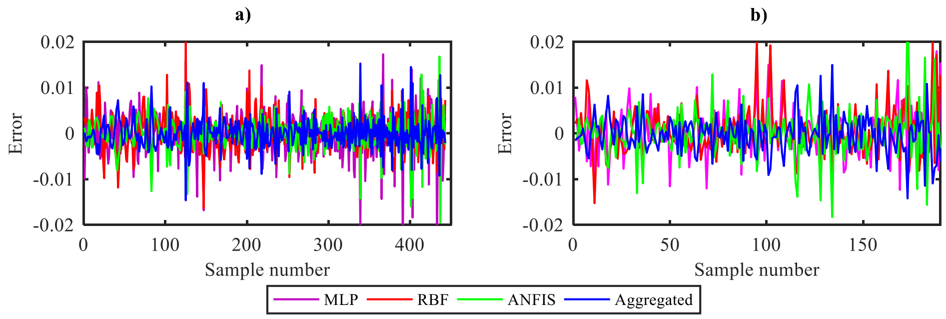

Fig. 7 Estimation errors: a) training error; b) testing error.

The obtained results show that the proposed fusion algorithm based OWA operator gave a spectacular reduction of MSE compared to ANFIS, which reaches the double for training data and oscillates around 61% for the testing set as shown in Table 2. Thus, it clearly proves that the proposed fusion algorithm has more accurate nonlinear mapping capability when compared to other estimators.

Table 2

Comparative statistical analysis

Statistical indicators	**MSE**	
Phase	**Train**	**Test**
MLP	2.72E-05	3.36E-05
RBF	1.49E-05	2.94E-05
ANFIS	1.32E-05	2.85E-05
Aggregated	**6.15E-06**	**1.75E-05**

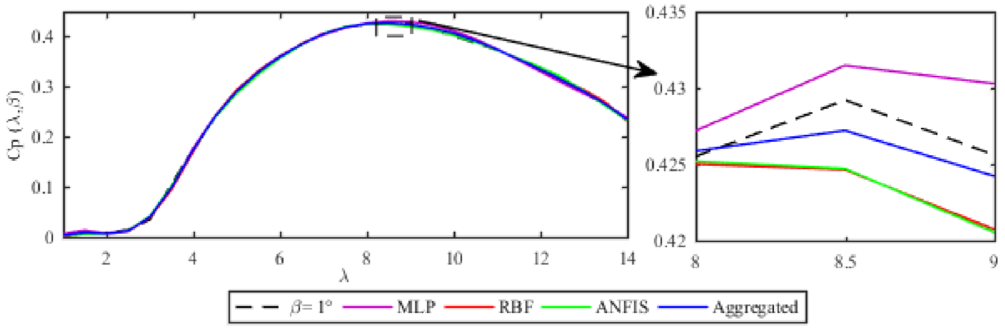

Fig. 8. $Cp\ (\lambda,\beta)$ curve for CART wind turbine

Fig. 8. shows a graphical comparison of power coefficients $Cp\ (\lambda,\beta)$ for optimal pitch angle $\beta = 1(deg)$. Maximum $Cp\ (\lambda,\beta)$ value of the CART wind turbine is 0.4292, however estimated values by MLP, RBF, ANFIS and fusion algorithm, are 0.432, 0.424, 0.425 and 0.426 respectively. Hence, the proposed estimators can be considered as an alternative method for power coefficient determination providing an efficient prediction which can reach the maximum value of the power coefficient $Cp\ (\lambda,\beta)$ and also overcomes the problem of linear interpolation for any intermediate value.

One of the major advantages of using this algorithm is its easy hardware implementation, since the OWA operator is only a set of weights modifying information from different sensors. The proposed algorithm remains a cost-effective solution that can be implemented on FPGA chip, or other commercially available technologies [27]. Moreover, the proposed estimator overcomes the linear interpolation weakness for the intermediate values of the look-up table and can be used to perform serval control strategies of wind turbine.

5. Conclusion

Wind fluctuations, as well as the determination of optimal operating points, represent the main control problems of variable speed wind turbine. In the present paper, a new machine learning techniques fusion based on OWA operator is proposed for power coefficient $Cp\ (\lambda,\beta)$ estimation of the CART wind turbine, and Some properties of the OWA operator based on Fuzzy Linguistic Quantifier are discussed. The proposed algorithm implemented on MATLAB give a good approximation of the power coefficient. The main inferences drawn from the present study are:

- Statistical analysis shows that Fusion based OWA operator provides the best estimation compared to MLP, RBF and ANFIS.

- ANFIS' response does not only depend on the number, type of MFs and the training algorithm but also on the quality of the database.
- ANFIS presents a powerful estimation tool but suffers from training time problem, mainly due to the number and type of MFs. Moreover, MLP remains faster than ANFIS with a satisfactory result.
- The α factor is a crucial factor for weight determination when using a Fuzzy Linguistic Quantifier, therefore the search for its optimal value is essential.

The proposed estimator performs well with the nonlinear nature of the wind turbine and gives an accurate estimate of the power coefficient. As a future work, further real time control strategies need to be conducted to investigate the effect of the proposed power coefficient estimator on variable speed wind turbine.

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