# AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM APPROACH FOR PREDICTION OF POWER FACTOR IN WIND TURBINES

**Raşit ATA**

Celal Bayar University Department of Electrics,
45700, Kırkağaç, Manisa, Turkey

E-mail: rasit.ata@bayar.edu.tr

## ABSTRACT

*This paper introduces an adaptive neuro-fuzzy inference system (ANFIS) model for predicting the power factor of a wind turbine. This model based on the parameters involved for NACA 4415 and LS-1 profile types with 3 and 4 blades. In model development, profile type, blade number, Schmitz coefficient, end loss, profile type loss, and blade number loss were taken as input variables, while the power factor was taken as output variable. After a successful learning and training process the proposed model produced reasonable mean errors. The results on a testing data indicate that the ANFIS model is found to be more successful than the ANN approach in estimating the power factor.*

*Keywords: Energy, wind turbine, power factor, ANFIS*

## 1. INTRODUCTION

Utilization of wind energy as an energy source has been growing rapidly in the whole world due to environmental pollution, consumption of the limited fossil fuels and global warming. Wind energy conversion systems appear as an attractive alternative for electricity generation. At the end of 2007, worldwide capacity of wind-powered generators was 94.1 gigawatts [1]. Although wind currently produces just over 1% of world-wide electricity use,[2] it accounts for approximately 19% of electricity production in Denmark, 9% in Spain and Portugal, and 6% in Germany and the Republic of Ireland (2007 data). Globally, wind power generation increased more than fivefold between 2000 and 2007 [1].

The major components of a typical wind energy conversion system include a wind turbine, a generator, interconnection apparatus, and control systems. Therefore, the design of a wind energy conversion system has been receiving much more attention than ever before. The most important part of a wind energy conversion system is the wind turbine, which transforms the wind kinetic energy into mechanical or electric energy. The system basically comprises a blade, a mechanical part and an electric engine coupled to each other. The kinematical energy of wind is the function of wind speed, the specific mass of air, the area of air space where the wind is captured and the height at which the rotor is placed. Since the wind energy is proportional to the third power of the wind speed, it is the most important factor that affects the wind energy [3].

The power generated by each wind turbine depends on parameters such as turbine type, the number of blades and the power factor. The power factor is also called blade yield and can be obtained from blade and wind properties. In this study, power factor o wind turbine is predicted using Adaptıve Neuro-Fuzzy Inference System (ANFIS) from seven input variables. For training process is used the parameters involved for NACA 4415 and LS-1 profile types with 3 and 4 blades. Characteristic values of the two profiles are given in previous study [4]. After a successful learning and training process the proposed model produced reasonable mean errors. The results on a testing data are compared with the ANN and the conventional approach in estimating the power factor. ANFIS have been used in renewable energy systems as for in many other disciplines. Regarding the use of wind energy, there are several applications of ANFIS such as wind speed prediction [5-7] and wind power forecasting [8-9]. The other renewable energy applications of ANFIS are solar energy [10-11] and wave prediction [12].

## 2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Fuzzy systems and neural networks are natural complementary tools in building intelligent systems. While neural networks are low-level computational structures that perform well when dealing with raw data, fuzzy logic deals with reasoning on a higher level. However, fuzzy systems lack the ability to learn and cannot adjust themselves. A neuro-fuzzy system is, in fact, a neural network that is functionally equivalent to a fuzzy inference model. For example an *Adaptive Neuro-Fuzzy Inference System* (ANFIS) proposed by Roger Jang [13] is a five-layer feed-forward neural network, which includes fuzzification layer, rule layer, normalization layer, defuzzification layer and a single summation neuron. An ANFIS uses a hybrid learning algorithm that combines the least-squares estimator and the gradient descent method [13-15].
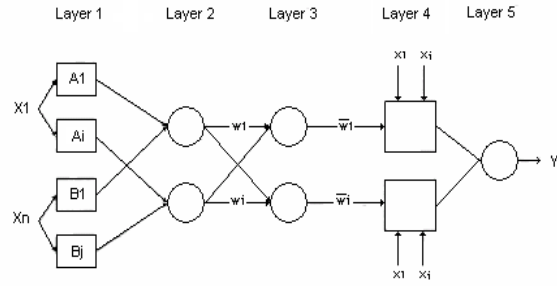


**Figure 1.** ANFIS Architecture.

An ANFIS system (Fig. 1) can incorporate fuzzy if-then rules and also, provide fine-tuning of the membership function according to a desired input output data pair [13,14]. A first order Sugeno fuzzy model is used as a means of modeling fuzzy rules into desired outputs.

$$if\ X_1 = A_i\ and X_n = B_j then f_i = p_i X_1 + q_i X_n + r_i \qquad (1)$$

Where $X_1$ and $X_n$ are the inputs, $A_i$ and $B_j$ are the fuzzy sets, $f_i$ are the outputs within the fuzzy region specified by the fuzzy rule and $p_i$, $_i r$, $q_i$ are the design parameters that are determined during the training process.. Each neuron in the first layer corresponds to a linguistic label and the output equals the membership function of this linguistic label.

$$OL1_i = \mu_{Ai}(X_1) \qquad (2)$$

where $\mu_{A_i}(X_1)$ is membership grade function. Each node in layer 2 estimates the firing strength of a rule, which is found from the multiplication of the incoming signals.

$$OL2_i = \mu_{Ai}(X_1) * \mu_{Bj}(X_n) \qquad (3)$$

Each node in layer 3 estimates the ratio ($w_i$) of the $i$th rule's firing strength to sum of the firing strength of all rules, j.

$$OL3_i = \overline{w}_i = \frac{w_i}{\sum_{j=1}^{i} w_i} \qquad (4)$$

The output of layer 4 is the product of the previously found relative firing strength of the *ith* rule and the rule.

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$$OL4_i = \overline{w}_i f_i = \overline{w}_i (p_i X_1 + q_i X_n + r_i) \quad (5)$$

The final layer computes the overall output as the summation of all incoming signals from layer 4.

$$OL5_i = \sum_{i=1}^{j} \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

The results are then defuzzified using a weighted average procedure. A back-propagation training method is employed to find the optimum value for the parameters of the membership functions and a least squares procedure for the linear parameters on the fuzzy rules, in such a way as to minimize the error between the input and the output pairs [8].

The forward pass adjusts the neuron consequents, layer-by-layer, to minimize the error. Once it has reached the output of the last layer, the backward pass begins and the antecedents are updated as the consequents are held constant. However, the difference (between the ANFIS and an ANN) that needs to be considered when creating a prediction system is in the selection of model parameters.

To use the ANFIS model in Matlab, the user defines the number of inputs; the number of membership functions (MFs) and their type/shape; and the number of training epochs. Changing even one of these parameters by just a small amount can be the difference between a system that appears to be not working at all and a system that produces desired results [16-17].

The specific advantages of ANFIS over the two parts of this hybrid system are:
• ANFIS uses the neural network's ability to classify data and find patterns.
• It then develop a a fuzzy expert system that is more transparent to the user and also less likely to produce memorization errors than a neural network.
• Furthermore, ANFIS keeps the advantages of a fuzzy expert system, while removing (or at least reducing) the need for an expert.
However, the problem with the ANFIS design is that a large amount of training data is required to develop an accurate system.

# 3. INPUT VARIABLE SELECTION

One of the most important tasks in developing a successful the power factor forecasting model is the selection of the input variables, which determines the architecture of the model.
Considering the losses in a wind turbine, power factor can be expressed as;

$$C_p = [\ A,\ \lambda_A,\ C_{pschmitz}, \eta_{end3},\ \eta_{end4},\ \eta_{profile1},\ \eta_{profile2}] \quad (7)$$

where A is an integer number representing the type of profile, 1 for LS-1 and 2 for NACA4415; $\lambda_A$ is the tip speed ratio, $C_{pschmitz}$ is the schmitz coefficient, $\eta_{end}$ represents the end losses for 3 and 4 blade turbines, $\eta_{profile}$ is the profile type losses for the type of profiles considered, LS-1 and NACA4415.

As seen from Eqn. (7), the assessment of power factor is a quite cumbersome for which an effective procedure is needed. The procedure is designed to power factor for 3-blade and 4-blade turbines. The profile types considered are LS-1 and NACA4415. The properties of these profiles are presented in Figs. 2 and 3 [4]. The input parameters are taken as those included in Eq. (7). The blade number losses are not directly taken us an input parameter but considered during the preparation of training data. The design procedure for such a network is described in the next section.

# 4. ANFIS MODEL APPLICATION

As compared to conventional methods, fuzzy logic (FL) has 2 important advantages in data analysis. First, it reduces possible difficulties in the modeling and analysis of complex data. Second, it is appropriate for incorporating the qualitative aspects of human experience within its mapping rules, which provide a way of catching information. Artificial neural networks (ANNs) have also been used to identify models of complex systems. For the same purpose, ANNs and FL are combined, referred to as ANFIS, to take advantage of the learning capabilities of ANNs and modeling superiority of FL [5].
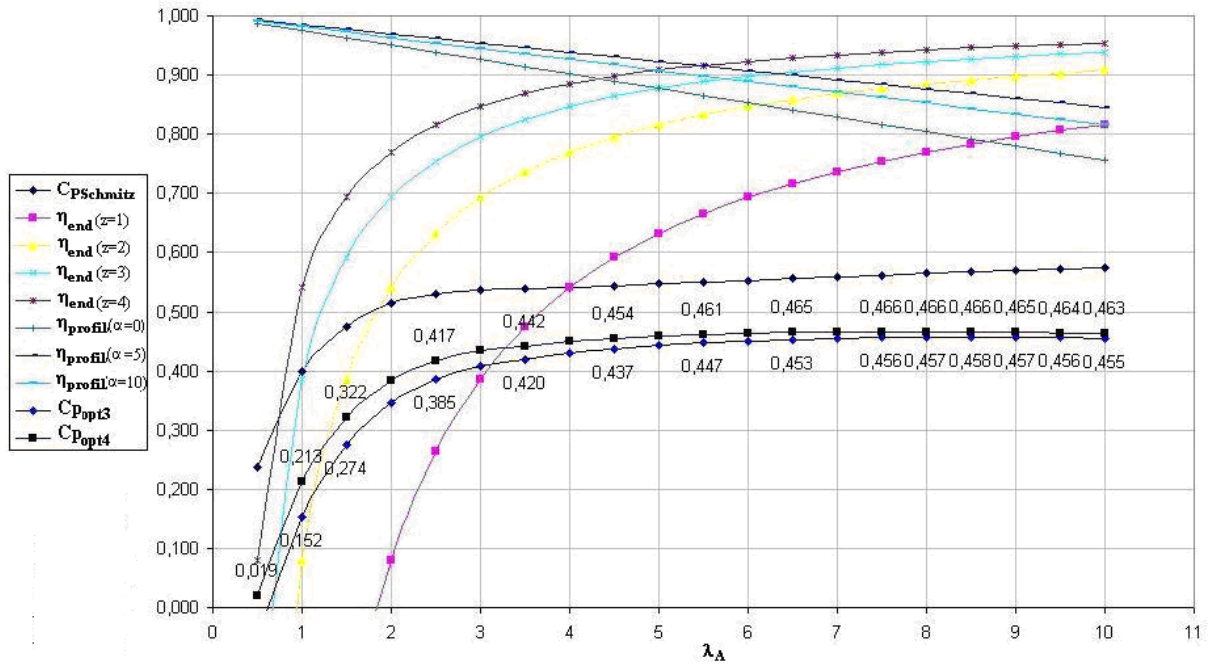
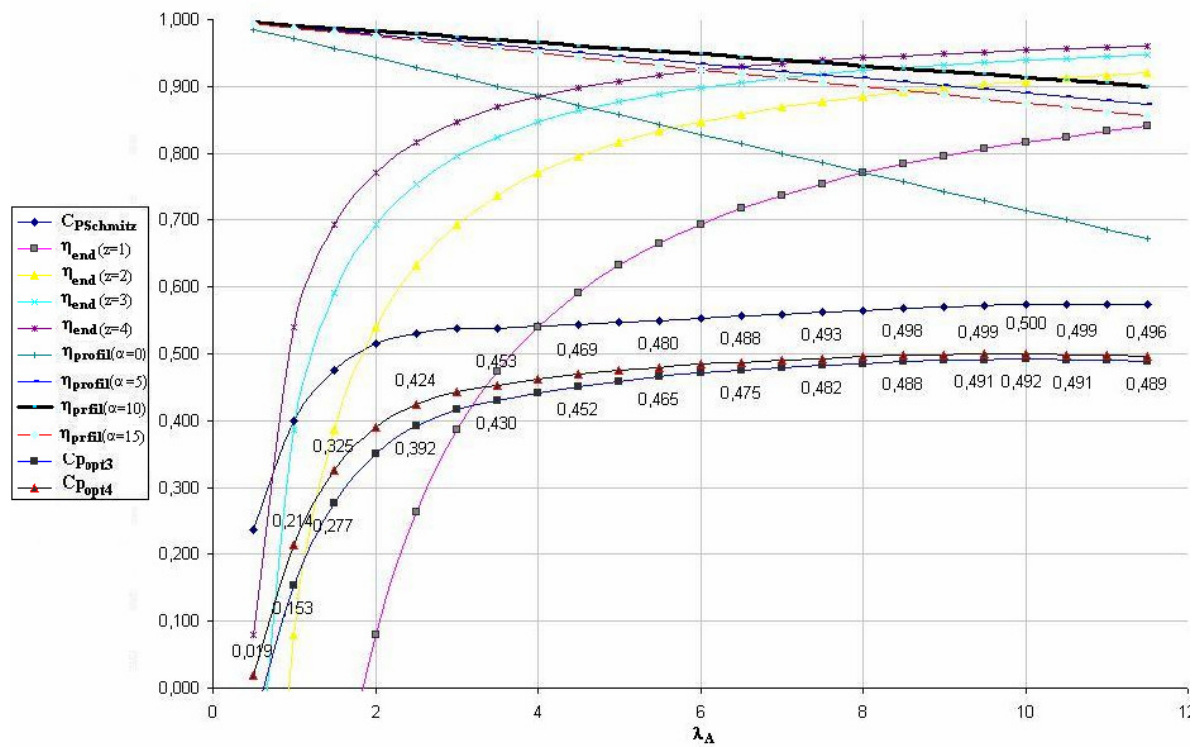**Figure 2.** Plot of the values of the profile type NACA 4415.



**Figure 3.** Plot of the values of the profile type LS-1.

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In the current study, the following steps, in summary, are used in the development of the proposed model:

i. the input and output data were divided into 2 groups for training and testing;
ii. a fuzzy model was created using the ANFIS editor and data training was carried out;
iii. the test data were utilized for the validation of the model.

A hybrid ANFIS algorithm based on the Sugeno system improved by Jang [13] was used for acquiring optimal output data in the study. The algorithm consists of the least-squares method and the back-propagation algorithm. The first method was used for optimizing the consequent parameters, while the second method in relation to fuzzy sets was employed to arrange the premise parameters [18].

In the model application, the type of profile, the Schmitz coefficient, the end losses, the profile type losses for the type of profiles considered were taken as input variables, while power factor value was taken as output variables for 2 different profile

types characteristics, LS-1 and NACA4415. ANFIS model with seven input variables was developed and tested. Data used for ANFIS model training and testing were formed from the characteristic values given in Figs 2 and 3 for the two profile types considered. In previous study [4], the same data set used for ANN training was used for ANFIS learning process in this study.

The membership function of the model outputs was selected to be Gaussian (gaussmf). Using this membership function was developed ANFIS model. A separate data set, not included in the training set, was employed for verifying the ANFIS model generalization capabilities.

## 5. RESULTS AND DISCUSSION

The trained ANFIS model, with seven input variables, were developed and tested. The testing process was carried out using nine different (from the training samples) samples and the outputs are presented in Table 1. As seen from Table 1, ANFIS Model' performance is satisfactory with small deviations from the values obtained from the curves given in Figs. 2 and 3. The conventional values given in Table 1 and Table 2 are obtained from Figs. 2 and 3. Table 2 obtained in previous study [4] is included ANN predicted values. As shown in Table 1, the relative errors of the two output parameters were all within±0.33% and within±0.20% for majority of testing data.

Fig. 4 summarized the evaluation results for ANN, ANFIS, and Conventional models. Results in Fig. 4 show that for ANFIS models error values, for power factor, were small relative to their target values (conventional values).

The results indicate that both ANN and ANFIS models can give good predictions of the power factor. However, the ANFIS model performs better than ANN model.
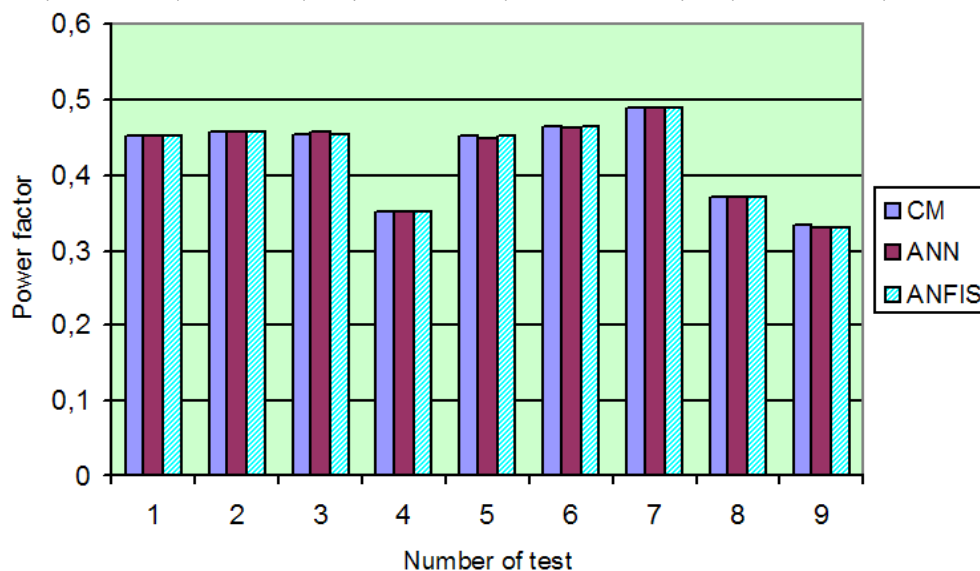
**Table 1**. Comparison of power factor obtained by ANFIS and Conventional method (CM).

| Test No | ANFIS | | | Conventional method | | | Error (%) | |
|---|---|---|---|---|---|---|---|---|
| | $C_{popt3}$ | $C_{popt4}$ | | $C_{popt3}$ | $C_{popt4}$ | | | |
| 1 | 0.4530 | 0.4650 | | 0.4528 | 0.4646 | | -0.04 | -0.08 |
| 2 | 0.4576 | 0.4665 | | 0.4576 | 0.4665 | | 0.00 | 0.00 |
| 3 | 0.4550 | 0.4630 | | 0.4553 | 0.4627 | | -0.06 | -0.06 |
| 4 | 0.3515 | 0.3893 | | 0.3510 | 0.3900 | | -0.14 | 0.17 |
| 5 | 0.4520 | 0.4690 | | 0.4520 | 0.4690 | | 0.00 | 0.00 |
| 6 | 0.4641 | 0.4800 | | 0.4650 | 0.4800 | | 0.19 | 0.00 |
| 7 | 0.4895 | 0.4970 | | 0.4890 | 0.4960 | | 0.01 | -0.20 |
| 8 | 0.3695 | 0.3896 | | 0.3700 | 0.3890 | | 0.13 | -0.15 |
| 9 | 0.3309 | 0.3381 | | 0.3320 | 0.3390 | | 0.33 | 0.26 |

performance faster and deliver better results in many test values.

**Table 2**. Comparison of power factor obtained by ANN and Conventional Method (CM).

| Test No | ANN | | | Conventional method | | | Error (%) | |
|---|---|---|---|---|---|---|---|---|
| | $C_{popt3}$ | $C_{popt4}$ | | $C_{popt3}$ | $C_{popt4}$ | | | |
| 1 | 0.4531 | 0.4664 | | 0.4528 | 0.4646 | | -0.06 | -0.38 |
| 2 | 0.4576 | 0.4676 | | 0.4576 | 0.4665 | | 0.00 | -0.23 |
| 3 | 0.4566 | 0.4649 | | 0.4553 | 0.4627 | | -0.28 | -0.47 |
| 4 | 0.3525 | 0.3888 | | 0.3510 | 0.3900 | | -0.42 | 0.30 |
| 5 | 0.4505 | 0.4702 | | 0.4520 | 0.4690 | | 0.33 | -0.25 |
| 6 | 0.4637 | 0.4808 | | 0.4650 | 0.4800 | | 0.27 | -0.16 |
| 7 | 0.4890 | 0.4991 | | 0.4890 | 0.4960 | | 0.00 | -0.62 |
| 8 | 0.3689 | 0.3916 | | 0.3700 | 0.3890 | | 0.29 | -0.66 |



**Figure 4**. Comparison of power factor(for $C_{popt3}$) obtained by ANN, ANFIS and Conventional models.

## 6. CONCLUSION

An ANFIS model was developed for use in predicting power factor in wind turbines. The evaluation of the model results indicated that the proposed model is more successful than ANN and conventional method. In comparison to the conventional models the ANN and ANFIS model are able to predict and optimize system performance faster and deliver better results in many test values.

The proposed approach is illustrated in the paper by using selected blade profile types of wind turbine (NACA 4415 and LS-1). Test results have demonstrated that the ANFIS model can accurately predict power factor for different profile types. The further applications to the other mostly used profile types such as Clark Y, NACA 2412, RAF-15, C-80, Göttingen 398, and

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M-6 can be achieved in the same manner as introduced in this paper.

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**Rasit Ata** was born in Manisa, Turkey on May 8, 1968. He received B.S., M. S. and Ph. D. degrees in Electrical Engineering all from the University of Yıldız in 1991, 1993, 1997, respectively.  In 1992 he

joined the Department of Electrical Engineering at the same university, then he joined the Department of Electrical Engineering, Celal Bayar University in 1994 and became an assistant professor there in 2002. He is engaged in the research of power systems, renewable energy and artificial neural networks.

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