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NEURAL PREDICTION OF POWER FACTOR IN WIND TURBINES

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ABSTRACT

The power generated by wind turbines depends on several factors. One of them is the power factor also known as blade efficiency. In this study, the power factor is predicted using Artificial Neural Networks (ANN) and comparisons made with conventional model approach for the selected turbine profiles mostly used in practice. The study has shown that the prediction of power factors from seven input parameters by ANN yields better results than those of the conventional model.

Keyword:: *wind turbine, power factor, artificial neural networks.*

1. INTRODUCTION

Sustainability of power supplies is one of the most challenging issues that the world faces today since the conventional sources of energy, mainly the fossil fuels, are coming to an end[1]. On the other hand, demand for energy increases not only in developing countries but all over the world. Energy wars may already be observed in many parts of the world. To this end, renewable energy sources such as sun, wind and wave are being discovered as life-saving jackets. Actually some renewable sources such as sun, wind and wave energy have already been in use.

Wind energy is the fastest developing renewable energy resource because of its several advantages such as ease of development, environmental friendliness, cost effectiveness and the existence of several feasible sites to establish wind farms. Therefore, design of wind power plants receives much more attention than ever before. The most important part of a wind power plant is the wind turbine which transforms the wind's kinetic energy into mechanical or electric energy. The system is basically comprised of a blade, a mechanical part and an electric engine connected to each other. The 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 wind power is proportional to the third power of wind speed, wind speed is the most important factor that affects wind energy. Hence the location of the wind farm is crucial in order to exploit winds of enough speed.

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 is predicted using artificial neural networks (ANN) from eight input variables. A Back Propagation Algorithm is used to train the network for NACA 4415 and LS-1 profile types with 3 and 4 blades. Characteristic values of the two profiles are given in Figures 1, 2 and 3 [2-4]. Appropriate momentum and training coefficients used during the training process are selected through several trials [4]. Comprehensive reviews of ANN applications in energy systems in general [5] and in renewable

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energy systems in particular [6] are available. Regarding the use of wind energy, there are several applications of ANN such as a classification mechanism for determining average wind speed and power [7].

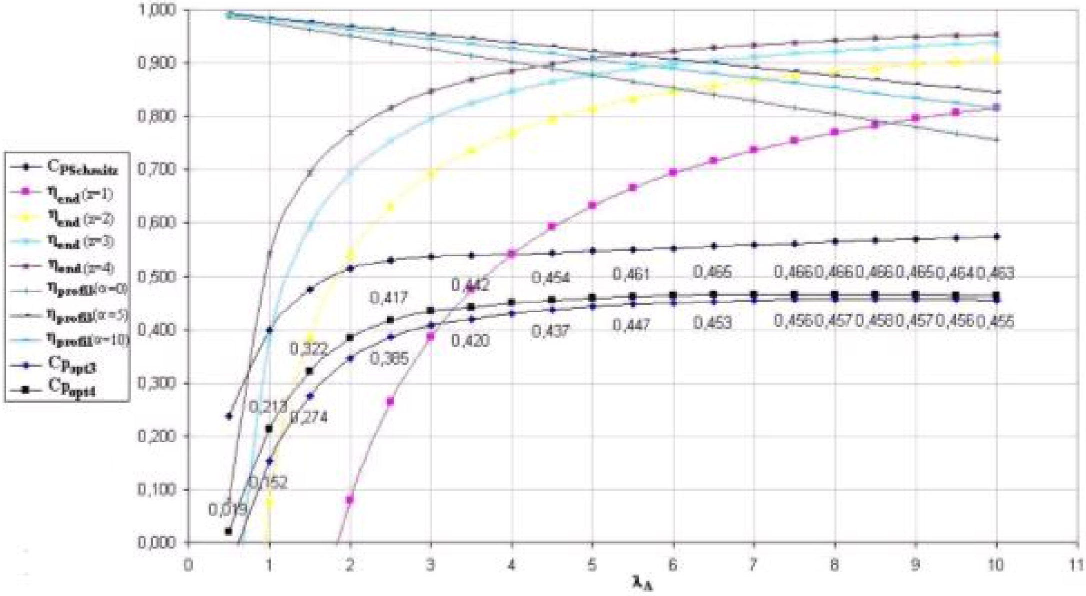

Figure 1. *Plot of the values of the profile type NACA 4415.*

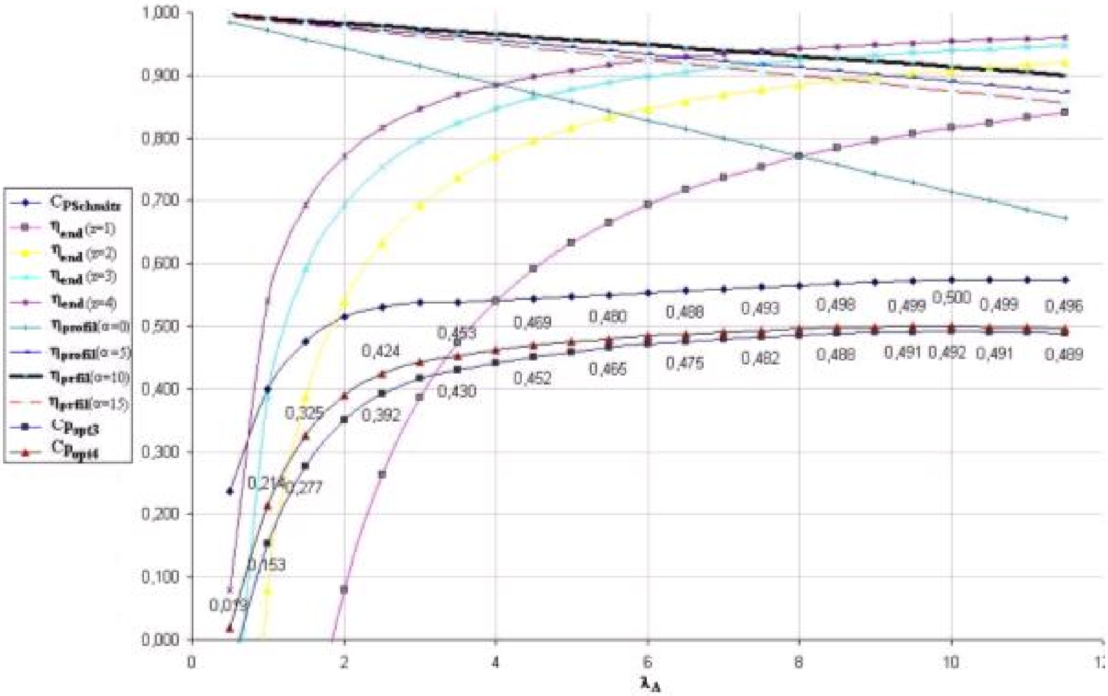

Figure 2. *Plot of the values of the profile type LS-1*

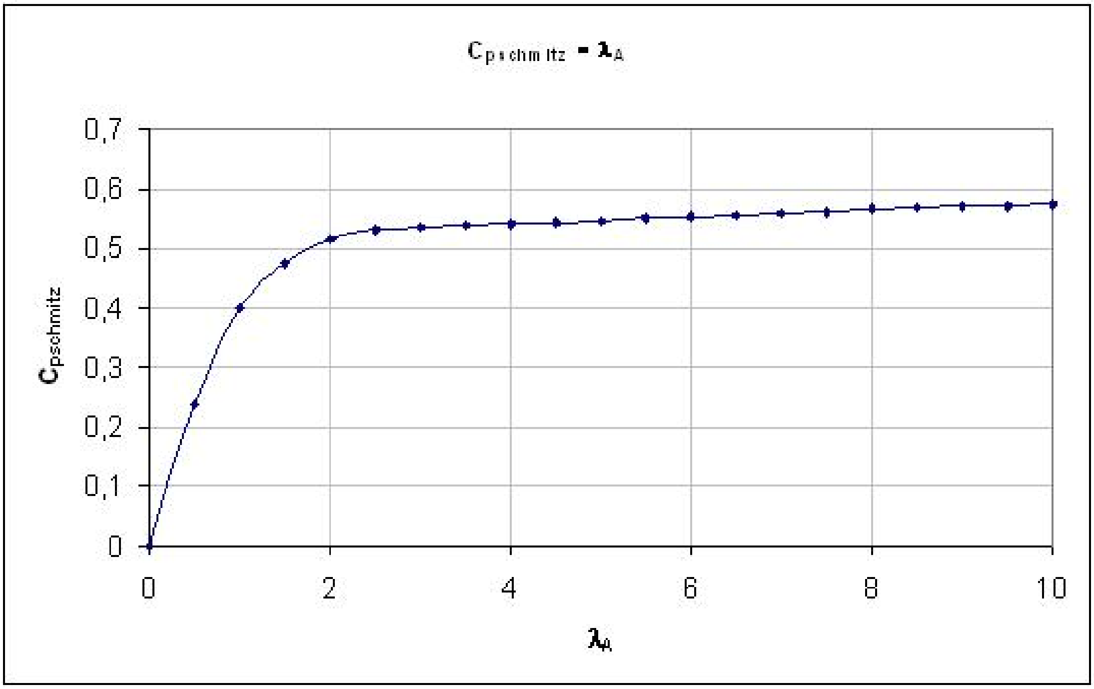

Figure 3. *$Cp_{schmitz}$ - λ_A curve*

2. ARTIFICIAL NEURAL NETWORKS

Suppose that a three-layer neural network as shown in Figure 4 as n_i input neurons, n_h hidden neurons and n_o output neurons. If o_j^m represents the output of the $j-th$ neuron in the $m-th$ layer and W_{ij}^m the weight on connection joining the $i-th$ neuron in the $(m-1)-th$ layer to the $j-th$ neuron in the $m-th$ layer, then

(1)

where the function f(.) can be any differentiable function. Usually the sigmoid function is used as follows:

$$f(x) = 1/\ 1+e^{-x} \qquad (2)$$

This function limits the outputs O_j^m among 0 and 1. It is possible to shift the function f(.) along x-axis by adding a threshold value to the summation term of (1) before the function f(.) is applied [8].

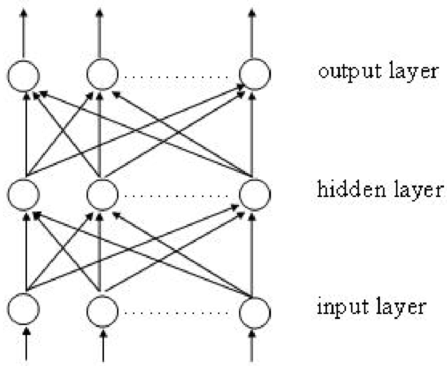

Figure 4. *A three layer feed forward ANN*

To achieve the required mapping capability, the neural network is trained by repeatedly presenting a representative set of input/output patterns with back propagation error and weight adjustment calculation in order to minimize the global error E_p of the network, i.e.;

$$E_p = \frac{1}{2}\sum_{j=1}^{n_0}(t_{pj} - o_{pj}^m)^2 \qquad (3)$$

where t_{pj} is the target output of neuron j and o_{pj}^m is the computed output from the neural network corresponding to that neuron. Subscript

p indicates that the error is considered for all input patterns.

The minimization of this average sum-squared error is carried out over the entire training patterns. As the outputs o_{pj}^{m} are functions of the connection weights w^{m} and the outputs o_{pj}^{m-1} of the neurons in layer $m-1$ which are functions of the connection weights w^{m-1}, the global error E_p is a function of w^{m} and w^{m-1}. Here w with superscript refers to the connection matrix. A backpropagation algorithm is used in the optimization [9].

3. FORMULATION OF THE PROBLEM

The power factor can be defined as the ratio between the power in turbine shaft (P_p) and the wind power (P_r) due to its kinetic energy right before the turbine plane, which yields

$$C_P = \frac{P_P}{P_r} \tag{4}$$

The wind power, P_r, in the air flow passing through the circle with a radius of R immediately before the turbine plane can be defined as;

$$P_r = \frac{1}{2}\rho\pi R^2 V_r^3 \tag{5}$$

where ρ is the density of the air and V_r is the wind speed. The maximum power factor is 59.26% which is called Betz limit and the real value obtained in practice can be 45 % at the maximum [4]. The reason why the real value is less than the theoretical one is that there are the losses not considered in theory. These losses are [1-3,9]:

profile losses
end losses
eddy losses
blade number losses

3.1. Profile losses

This can be considered using

$$\eta_{\text{profile}} = 1-(\lambda_A / \varepsilon), \tag{6}$$

where λ_A is tip speed ratio and ε is the number of slip(slide) and can be expressed as

$$\varepsilon = \frac{C_L}{C_D}, \tag{7}$$

where C_L is the coefficient of lift force of chosen profile and C_D is the coefficient of drag force[1-3].

3.2 End losses

In the end of a blade, airflow from the lower side of the profile to the upper side takes place. Coupling with the airflow coming towards the blade, this airflow widens gradually. In the calculations, this can be considered as

$$\eta_{end} = 1-(1{,}84/z.\lambda_A), \tag{8}$$

where z is the number of turbine blade[1-3,9].

3.3 Eddy losses

According to the Betz theory the wind does not change before and after the turbine plate. However the air mass encountering the blade changes its direction. The eddy losses can be calculated by $C_{pschmitz}$ -λ_A diagram (Figure 3) [3] if the same profile is used throughout the blade [1-3].

3.4. Blade number losses

In a turbine with more than four blades, the air movement through blades gets complicated and its theoretical analysis can not easily be made. Therefore, the theory of Glauert-Shmitz previously mentioned applies to the turbines with four our less wind turbine blade [1-3, 9]. Condisering the losses mentioned, the power factor can be re-expressed as

$$C_p = f(A, \lambda_A, C_{pschmitz}, \eta_{end}, \eta_{profile}, \eta_{eddy}, \eta_{blade\ number}), \tag{9}$$

where A represents the type of profile used, λ_A is the tip speed ratio, $C_{pshmitz}$ is Shmitz coefficient and the η values are the associate losses. As seen from Eqn. (9), assessment of the power factor is quite cumbersome, for which an effective procedure is needed. The procedure is designed to estimate optimum power factors for 3-blade and 4-blade turbines. The profile types considered are LS-1 and NACA 4415. The properties of these profiles are presented in Figs. 1, 2 and 3 [2]. The input parameters are taken as those included in Eq. (9) except for the eddy losses. 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. DESIGN OF THE ANN

The design process includes the following steps:

(i) Preparation of suitable training data
(ii) Selection of a suitable ANN structure
(iii) Training of the ANN
(iv) Evaluation of the trained network

It is important to appreciate that the design process is iterative. It is possible that a particular structure chosen in step (ii) may not train the neural network to a designer's satisfaction. In this situation, the structure has to change and the ANN should be retrained. Also the trained network may not perform satisfactorily on test data. In that situation the network structure should be changed and network is retrained and tested.

The training patterns should contain all the necessary information to generalize the problem. Having been collected the data values, they are normalized between [0, 1]. The test data is randomly selected from the training data set. The same normalization procedure should be applied to the test data.

The selection of neural network includes the selection of number of layers, choice of transfer function, number of inputs and number of neurons in each layer. Alternative architectures including different number of layers and the neurons should be tried to find the best performing structure. As already mentioned, a three-layer feed-forward network can model complex-mapping functions reasonably well and, therefore, is adopted for this application. A sigmoid non-linear mapping function helps in modeling functions of arbitrary shape and is employed in this application. The number of neurons in the input layer and hidden layers are decided by experimentation which involves training and testing different network configurations. The neural network literature [10-12] provides guidelines for selecting the number of neurons for a starting network.

Training of the selected network is done using the training patterns and back propagation algorithm. Training is stopped when the mean squared error between actual outputs and desired outputs stops improving. However, at that point, if the designer is not satisfied with the training and performance of the ANN, the training data and structure of the ANN are modified and the design process is repeated.

5. ESTIMATION OF THE OPTIMAL POWER FACTOR

The proposed approach is applied to profile types for LS-1 ve NACA4415. The number of input neurons was chosen as seven inputs. The input variables are given by

$$x(t)= [\ A,\ \lambda_A,\ C_{pschmitz}, \eta_{end3},\ \eta_{end4},\ \eta_{profile1},\ \eta_{profile2}], \quad (10)$$

where A is an integer number representing the type of profile, 1 for LS-1 and 2 for NACA4415; λ_A is the tip speed ratio, $C_{pschmitz}$ is the schmitz coefficient mentioned previously; η_{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. On the other hand, the output variables take the form:

$$y(t)= [C_{popt3}, C_{popt4}], \quad (11)$$

where C_{popt3}, C_{popt4} are the power factors for the wind turbines with 3 and 4 blades. Once the ANN structure is formed the next step is to train the network to check whether the structure is capable of producing the output variables from the inputs satisfactorily. To carry out this process, a set of data is normally needed. To this end, for all input and output variables 30 training samples were formed from the characteristic values given in Figures 1, 2 and 3 and given in Table 1 and 2 for the two profile types considered. The performance of training process is measured according to whether the training error is minimal. The structure of the network (number of layers and neurons) training and momentum coefficients were altered to minimize the error to find the best architecture.

The variation of training error with respect to the number of neurons in the hidden layer is presented in Figure 5. As seen from Figure 5, the training error is minimal when the number of neurons is 4. Therefore, the number of neurons in hidden layer is chosen as 4. Therefore, an artificial neural network comprising an input layer with seven neurons, a hidden layer with four neurons and an output layer with two neurons have been selected.

The three-layered network trained above was then tested. The testing process was carried out using nine different (from the training samples) samples and the outputs are presented in Table 3. As seen from Table 3, the performance of the network is satisfactory with small deviation from the values obtained from the curves given in Figs. 1, 2 and 3. The conventional values given in Table 3 are obtained from Figs. 1, 2 and 3 and included in Tables 1 and 2. Therefore, it can be stated that the proposed methodology provides more detailed values in an attempt to obtain the optimal power factor wind turbines rather than using the small number of data obtained from the curves whose derivations require rather complicated process.

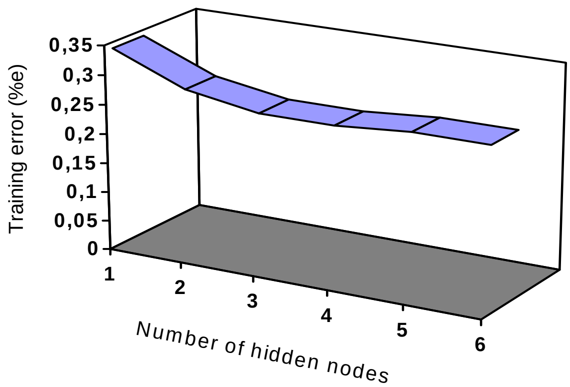

Figure 5. *The effect of number of nodes in hidden layer*

Table 1. *Calculated Values for the Profile Type NACA 4415*

λ_A	$C_{PSchmitz}$	η_{end} (z=1)	η_{end} (z=2)	η_{end} (z=3)	η_{end} (z=4)	$\eta_{profile}$ ($\alpha=0^0$)	$\eta_{profile}$ ($\alpha=5^0$)	$\eta_{profile}$ ($\alpha=10^0$)	$C_{P\ opt3}$	$C_{P\ opt4}$
0,5	0,238	-2,6800	-0,8400	-0,2267	0,0800	0,9878	0,9922	0,9908	-0,0534	0,0189
1.0	0,400	-0,8400	0,0800	0,3867	0,5400	0,9756	0,9845	0,9816	0,1523	0,2127
1,5	0,475	-0,2267	0,3867	0,5911	0,6933	0,9633	0,9767	0,9724	0,2742	0,3217
2.0	0,515	0,0800	0,5400	0,6933	0,7700	0,9511	0,9690	0,9632	0,3460	0,3843
2,5	0,531	0,2640	0,6320	0,7547	0,8160	0,9389	0,9612	0,9540	0,3852	0,4165
3.0	0,537	0,3867	0,6933	0,7956	0,8467	0,9267	0,9535	0,9448	0,4073	0,4335
3,5	0,538	0,4743	0,7371	0,8248	0,8686	0,9144	0,9457	0,9355	0,4196	0,4419
4.0	0,541	0,5400	0,7700	0,8467	0,8850	0,9022	0,9380	0,9263	0,4296	0,4491
4,5	0,544	0,5911	0,7956	0,8637	0,8978	0,8900	0,9302	0,9171	0,4371	0,4543
5.0	0,547	0,6320	0,8160	0,8773	0,9080	0,8778	0,9225	0,9079	0,4427	0,4582
5,5	0,550	0,6655	0,8327	0,8885	0,9164	0,8655	0,9147	0,8987	0,4470	0,4610
6.0	0,553	0,6933	0,8467	0,8978	0,9233	0,8533	0,9070	0,8895	0,4503	0,4631
6,5	0,556	0,7169	0,8585	0,9056	0,9292	0,8411	0,8992	0,8803	0,4528	0,4646
7.0	0,559	0,7371	0,8686	0,9124	0,9343	0,8289	0,8915	0,8711	0,4547	0,4656
7,5	0,562	0,7547	0,8773	0,9182	0,9387	0,8166	0,8837	0,8619	0,4560	0,4662
8.0	0,565	0,7700	0,8850	0,9233	0,9425	0,8044	0,8760	0,8527	0,4570	0,4665
8,5	0,568	0,7835	0,8918	0,9278	0,9459	0,7922	0,8682	0,8435	0,4576	0,4665
9.0	0,570	0,7956	0,8978	0,9319	0,9489	0,7800	0,8605	0,8343	0,4570	0,4654
9,5	0,572	0,8063	0,9032	0,9354	0,9516	0,7677	0,8527	0,8250	0,4563	0,4641
10.0	0,574	0,8160	0,9080	0,9387	0,9540	0,7555	0,8450	0,8158	0,4553	0,4627

Table 2. *Calculated Values for the Profile Type LS-1*

λ_A	$C_{PSchmitz}$	η_{end} (z=1)	η_{end} (z=2)	η_{end} (z=3)	η_{end} (z=4)	$\eta_{profile}$ ($\alpha=0^0$)	$\eta_{profile}$ ($\alpha=5^0$)	$\eta_{profile}$ ($\alpha=10^0$)	$\eta_{profile}$ ($\alpha=15^0$)	$C_{P\ opt3}$	$C_{P\ opt4}$
0,5	0,238	-2,680	-0,840	-0,227	0,080	0,986	0,994	0,996	0,994	-0,054	0,019
1,0	0,400	-0,840	0,080	0,387	0,540	0,971	0,989	0,991	0,988	0,153	0,214
1,5	0,475	-0,227	0,387	0,591	0,693	0,957	0,983	0,987	0,981	0,277	0,325
2,0	0,515	0,080	0,540	0,693	0,770	0,943	0,978	0,983	0,975	0,351	0,390
2,5	0,531	0,264	0,632	0,755	0,816	0,929	0,972	0,978	0,969	0,392	0,424
3,0	0,537	0,387	0,693	0,796	0,847	0,914	0,967	0,974	0,963	0,416	0,443
3,5	0,538	0,474	0,737	0,825	0,869	0,900	0,961	0,970	0,956	0,430	0,453
4,0	0,541	0,540	0,770	0,847	0,885	0,886	0,956	0,965	0,950	0,442	0,462
4,5	0,544	0,591	0,796	0,864	0,898	0,871	0,950	0,961	0,944	0,452	0,469
5,0	0,547	0,632	0,816	0,877	0,908	0,857	0,945	0,957	0,938	0,459	0,475
5,5	0,550	0,665	0,833	0,888	0,916	0,843	0,939	0,952	0,931	0,465	0,480
6,0	0,553	0,693	0,847	0,898	0,923	0,829	0,934	0,948	0,925	0,471	0,484
6,5	0,556	0,717	0,858	0,906	0,929	0,814	0,928	0,944	0,919	0,475	0,488
7,0	0,559	0,737	0,869	0,912	0,934	0,800	0,923	0,939	0,913	0,479	0,491
7,5	0,562	0,755	0,877	0,918	0,939	0,786	0,917	0,935	0,906	0,482	0,493
8,0	0,565	0,770	0,885	0,923	0,943	0,771	0,912	0,931	0,900	0,486	0,496
8,5	0,568	0,784	0,892	0,928	0,946	0,757	0,906	0,926	0,894	0,488	0,498
9,0	0,570	0,796	0,898	0,932	0,949	0,743	0,901	0,922	0,888	0,490	0,499
9,5	0,572	0,806	0,903	0,935	0,952	0,729	0,895	0,918	0,881	0,491	0,499
10,0	0,574	0,816	0,908	0,939	0,954	0,714	0,890	0,913	0,875	0,492	0,500
10,5	0,574	0,825	0,912	0,942	0,956	0,700	0,884	0,909	0,869	0,491	0,499
11,0	0,574	0,833	0,916	0,944	0,958	0,686	0,879	0,905	0,863	0,490	0,498
11,5	0,574	0,840	0,920	0,947	0,960	0,671	0,873	0,900	0,856	0,489	0,496

Table 3. *Comparison of Power Factor as Obtained by ANN and Conventional Method (CM).*

Test No	By ANN		By CM		Error (%)	
	Cp_{opt3}	Cp_{opt4}	Cp_{opt3}	Cp_{opt4}		
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
9	0.3298	0.3374	0.3320	0.3390	0.66	0.47

6. CONCLUSIONS

An ANN-based approach estimation of power factor in wind turbines is presented in this paper. Because of the capabilities of parallel information processing and generalization of the ANN, the proposed algorithm is found to be fast and accurate. The proposed algorithm can be used for computations of power factor with the use of state variables in wind turbines.

The proposed approach is illustrated in this paper by using selected wind turbine types (LS-1 and NACA4415). Test results have demonstrated that the trained ANN can accurately predict power factor for different profile types through its generalization and adaptability capabilities. The further applications to the other mostly used profile types such as Clark Y, NACA 2412, RAF-15, C-80, Göttingen 398, and M-6 can be achieved in the same manner as introduced in this paper.

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