

DESIGN OPTIMIZATION OF MICRO HYDRO TURBINE USING ARTIFICIAL PARTICLE SWARM OPTIMIZATION AND ARTIFICIAL NEURAL NETWORK

^a**Lie Jasa**, ^b**Ratna Ika Putri**, ^c**Ardyono Priyadi**, ^d**Mauridhi Hery Purnomo**

^{a,b,c,d}Instrumentation, Measurement, and Power Systems Identification Laboratory

Electrical Engineering Department, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia

^aElectrical Engineering Department, Udayana University, Bali, Indonesia

^bElectrical Engineering Department, Politeknik Negeri Malang, Malang, Indonesia.

Email: liejasa@unud.ac.id

Abstrak

Turbin digunakan mengkonversi energy potensial menjadi energy kinetik. Kapasitas Energy yang dihasilkan dipengaruhi oleh sudu-sudu turbin yang dipasang pada tepi. Sudu turbin dirancang seorang ahli dengan sudut kelengkungan tertentu. Efisiensi dari turbin dipengaruhi oleh besarnya sudut, jumlah dan bentuk sudu. Algoritma PSO dapat digunakan untuk komputasi dan optimasi dari design turbin mikro hidro. Penelitian ini dilakukan dengan; Pertama, Formula design turbin dioptimasi dengan PSO. Kedua, Data hasil optimasi PSO diinputkan kedalam jaringan ANN. Ketiga, training dan testing terhadap simulasi jaringan ANN. Dan yang terakhir, Analisa kesalahan dari jaringan ANN. Data PSO sebanyak 180 record, 144 digunakan untuk training dan sisanya 40 untuk testing. Hasil penelitian ini adalah MAE= 0.4237, MSE=0.3826, dan SSE=165.2654. Error training terendah didapatkan dengan algoritma pembelajaran trainlm. Kondisi ini membuktikan bahwa jaringan ANN mampu menghasilkan desain turbin yang optimal.

Kata kunci: Turbin, PSO, ANN, Energi

Abstract

Turbines are used to convert potential energy into kinetic energy. The blades installed on the turbine edge influence the amount of energy generated. Turbine blades are designed expertly with specific curvature angles. The number, shape, and angle of the blades influence the turbine efficiency. The particle swarm optimization (PSO) algorithm can be used to design and optimize micro-hydro turbines. In this study, we first optimized the formula for turbine using PSO. Second, we input the PSO optimization data into an artificial neural network (ANN). Third, we performed ANN network simulation testing and training. Finally, we conducted ANN network error analysis. From the 180 PSO data records, 144 were used for training, and the remaining 40 were used for testing. The results of this study are as follows: MAE = 0.4237, MSE = 0.3826, and SSE = 165.2654. The lowest training error was achieved when using the trainlm learning algorithm. The results prove that the ANN network can be used for optimizing turbine designs.

Keywords: Turbine, PSO, ANN, Energy

INTRODUCTION

Turbines are simple machines used to convert the flow of water into rotation. A turbine is commonly circular and made of wood or iron. Turbine blades are installed in line on the edge of the turbine wheel [1][2]. The blades are driven by water flowing along the wheel edge. The recorded wheel shaft torque, which is equal to the resulting kinetic energy [4], depends on the magnitude of water impulse acting on the turbine blades [3]. A nozzle is used to direct water onto the blades. The nozzle position is determined depending on the turbine installation location. Possible nozzle locations are top, middle, or bottom of the turbine. Turbine efficiency is determined by the angle of curvature, number of blades installed, and blade shape.

The angle of curvature of the blades is one of the factors that influence turbine performance. C.A. Mockmore and F. Merryfield built a model Banki turbine and performed a series of tests on it [5]; their results indicated that turbine performance depends on nozzle curvature angle 16° . In this study, we optimize turbine design formulas with particle swarm optimization (PSO) algorithm by using head input (H) and water discharge (Q) as parameters.

The PSO algorithm is used widely in optimization processes for transient modeling [6], power transformer protection schemes [7], and harmonics estimation [8]. Meanwhile, the artificial neural network (ANN) algorithm is used for position control [9]. Combinations of PSO and ANN have been applied for forecasting [10], determining cut-off grade [11], predicting temperature [12], and recognizing patterns [13]. The ANN algorithm is used widely for modeling. However, its performance depends on data generalization. Significant characteristics of data generalization pertain to data correlation. Data correlation reduces the characteristic of data representation, which lowers the ability of ANN during learning. To overcome this disadvantage, outputs of the principal component analysis (PCA) algorithm are used for ANN network

training and testing. [14]. Neural network PCA (NNPCA) is a combination of ANN and PCA. NNP PCA applies the Lavenberg-Marquadt learning method to speed up training [15]. It is used for power transformer protection [14] and forecasting greenhouse gas emissions [16].

In this article, the PSO algorithm was used to optimize the curvature of turbine blade angle α_1 in order to achieve maximum turbine efficiency. The output of PSO optimization was recorded in an Excel spreadsheet. Of the recorded PSO data, 80% was for training and the remaining 20% was for testing. PCA was used to pre-process the data before they were input into the ANN. These Data of PSO were used by NNP PCA to design a new Banki turbine model. NNP PCA consists of three layers: two hidden layer and one output layer. The learning algorithm used the tribas, logsig, and tansig activation functions. The performance of the Lavenberg–Marquadt algorithm was compared with that of gradient descent by using three combinations of activation functions. The learning process was used to update weights and bias values, which were selected randomly

RESEARCH METHODS

This method applied in this research was developed for designing PSO-optimized Banki turbines. Furthermore, PSO data outputs were used for NNP PCA training and testing. The network of NNP PCA trained using various learning methods and activation functions. The simulation results were analyzed to determine the best network performance.

PARTICLE SWARM OPTIMIZATION

birds in a swarm, Kennedy, an American psychologist, and Eberhart, an electrical engineer, developed the PSO algorithm [11]. The PSO algorithm is an optimization technique and a type of evolutionary computation technique. PSO is initialized to a random solution, and it uses an iterative search for arriving at the optimal value [12]. Each individual in the group is called a particle in a D-dimension solution space. The

position vector of the i th particle is represented as $X_i = (X_{i1}, X_{i2}, \dots, X_{in})$. The best position found by i th particle in the latest iteration is denoted by $P_i = (p_{i1}, P_{i2}, \dots, P_{in})$, known as pBest. Accordingly, the best position found in the entire swarm is denoted $P_g = (P_{g1}, P_{g2}, \dots, P_{gn})$, known as Gbest. The velocity vector of the i th particle is represented by $V_i = (V_{i1}, V_{i2}, \dots, V_{in})$. The velocity and position of the i th particle are defined as seen in Equation (1) and Equation (2).

$$V_{in} = wV_m + c_1 r_1 (P_{in} - X_i) + c_2 r_2 (P_{gn} - X_{in}) \quad (1)$$

$$X_{in} = X_{in} + V_{in} \quad (2)$$

where w is a constriction factor, c_1 and c_2 are learning factors, and r_1 and r_2 are random numbers generated consistently in the $0 - 1$ range. A linear inertia weight was introduced by Shi and Eberhart [11]. The weight inertia decreasing is modified as Equation (3).

$$W_{(iter)} = w_{max} \left(\frac{w_{max} - w_{min}}{iter_max} \right) iter \quad (3)$$

where w_{max} is the initial inertia weight, w_{min} is the final inertia weight, $iter_max$ is the maximum number of iterations in the evolution process, and $iter$ is the current number of iterations. Usually, w_{max} is set to 0.9 and w_{min} is set to 0.4.

OPTIMIZATION FORMULA WITH PSO

Figure 1 shows the Banki turbine design used in this study. The input and output power equations of the Banki turbine are influenced by the values of H , g , C , ω , ψ , α_1 , β_1 , and β_2 . The values of constant parameters such as H , C , and g did not change during optimization. Therefore, the values of α_1 , β_1 , and β_2 can be optimized by changing the blade angle to enhance turbine efficiency.

Figure 2 shows a schematic diagram of turbine design optimization using PSO. PSO inputs include water discharge (Q) and head (H). The optimization strategy used in this study is shown in Figure 3. The optimized efficiency equation is shown in Equation (4).

$$\eta = (2C^2 \frac{u_1}{v_1}) \left(\cos \alpha_1 - \frac{u_1}{v_1} \left(\frac{(1+\psi \cos \beta_2)}{\cos \beta_1} \right) \right) \quad (4)$$

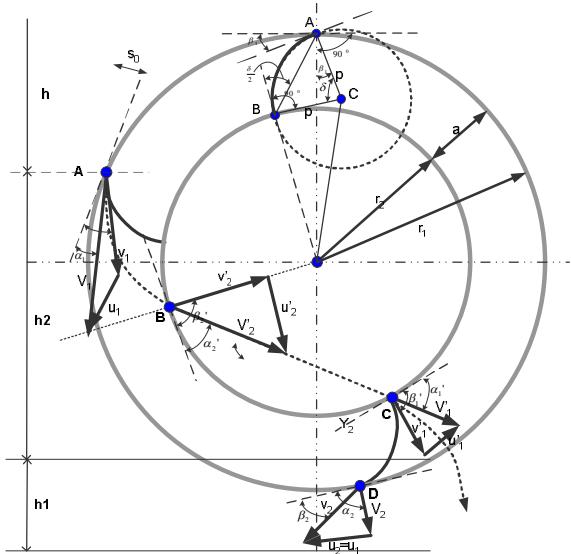


Figure 1. Banki turbine design [5]

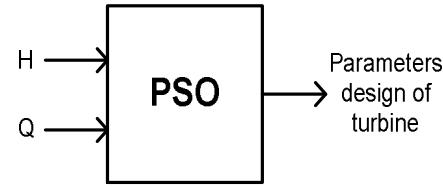


Figure 2. Turbine design using PSO Optimization

The main factors that influence the efficiency value obtained using Equation (4) are as follows:

$$V_1 = C \sqrt{2gH} \quad (5)$$

$$u_1 = \left[\frac{C}{(1+\psi)} \right] (V_1 \cos^2 \alpha_1) \quad (6)$$

$$HP_{in} = \frac{\omega Q V_1^2}{C^2 2g} \quad (7)$$

$$HP_{in} = \left(\frac{\omega Q u_1}{g} \right) \left((v_1 \cos \alpha_1 - u_1) \left(\frac{(1+\psi \cos \beta_2)}{\cos \beta_1} \right) \right) \quad (8)$$

Meanwhile, the inequality constraints are as follows:

$$\cos \alpha_1 \min \leq \cos \alpha_1 \leq \cos \alpha_1 \max \quad (9)$$

$$\cos \beta_1 \min \leq \cos \beta_1 \leq \cos \beta_1 \max \quad (10)$$

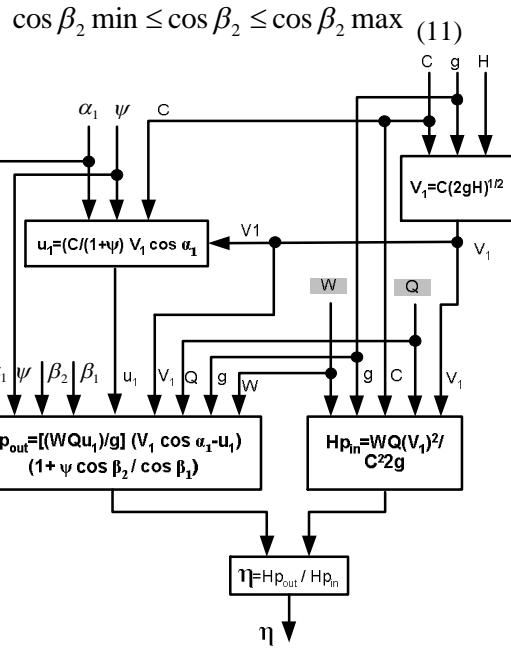


Figure 3. Proposed Optimization Strategy

According to the block diagram in Figure 3 above, V_1 is influenced by H , G , and C . In addition, V_1 acts as the input for U_1 , $H_{p_{in}}$, and $H_{p_{out}}$. U_1 is determined using the values of C , ψ , α_1 , and V_1 .

$H_{p_{in}}$ is determined using the values of Q , C , G , ω , and V_1 , while $H_{p_{out}}$ is determined using the values of Q , V_1 , g , ω , u_1 , ψ , α_1 , β_1 , and β_2 . The difference between $H_{p_{in}}$ and $H_{p_{out}}$ is the efficiency value. Matlab was used for simulation during optimization to obtain the maximum value of efficiency (η) using the optimized values of α_1 , β_1 , and β_2 angles.

ARTIFICIAL NEURAL NETWORK

ANN is a simple model of biological neurons that use the human brain to make decisions and arrive at conclusions. An ANN consists of interconnected processing elements working together to solve a particular problem. Neural networks learn from previous experiences. ANN is configured for applications such as pattern recognition or data classification through learning. Learning is conducted by adjusting neuronal weights. Each neuron model consists of processing elements with synaptic

connection inputs and one output. Neurons can be defined as

$$y_k = \varphi \left(\sum X_j * W_{kj} \right) \quad (12)$$

where X_1, X_2, \dots, X_j is the input signal, $W_{k1}, W_{k2}, \dots, W_{kj}$ is the weight of synaptic neuron k , $\varphi(.)$ is the activation function, and y_k is the output signal of the neuron.

The architecture of the layered neural network with feed-forward using PCA is shown in Figure 4. This neural network consists of an input layer, two hidden layers, and one output layer. All layers are fully connected and are of the feed-forward type. The output is a non-linear function of the input and is controlled by a weight, which was determined in the learning process. Back-propagation was used in the learning process for applying the supervised learning paradigm.

Differentiated activation function values should be limited during the back-propagation learning process. The sigmoid function was the most used activation function, and its value was limited between 0 (minimum) and 1 (maximum). Before passing the output signals were to the next neuron layers, the outputs were summed off according to each neuronal scale based on the sigmoid function.

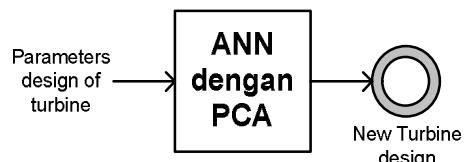


Figure 4. New turbine design using ANN

The key to error propagation learning lies in the ability to alter synaptic weights of error responses. Figure 5 shows a block diagram of the back-propagation algorithm.

Information provided by the back-propagation algorithm, in which the errors are re-filtered by the system, is used to adjust the relationships among the layers in order to improve system performance. The error back-propagation process consists of two layers network passes, namely, forward pass and backward pass.

Pass front, an activation pattern wherein the sensory network is applied to the node

whose effects are delivered through the network from layer to layer, yielded a set of outputs in the form of actual network responses.

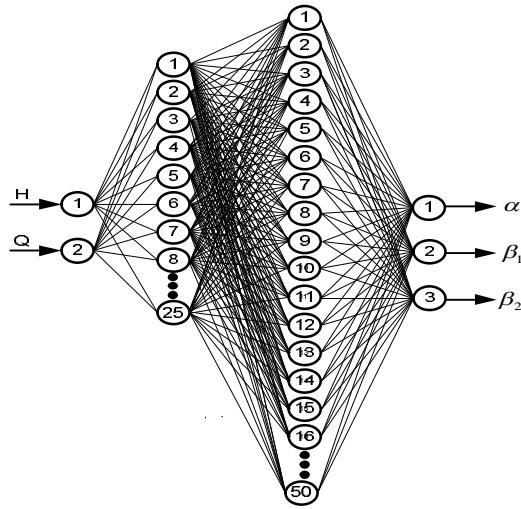


Figure 5. Node of ANN turbine model

The actual network response was subtracted from the desired response to generate an error signal. The error signal was propagated backward through the network in the direction of synaptic connections. Synaptic weights were adjusted to ensure that the actual network response was closer to the desired response. The error of the entire set was low enough to be acceptable for minimizing the sum of squares of errors, where most mean square methods were used.

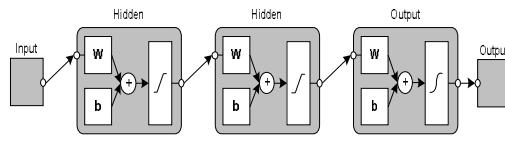


Figure 6. Block diagram of ANN model architecture

The developed artificial neural network consists of three layers (as shown in Figure 6). H and Q serve as inputs, while α_1 , β_1 and β_2 are the outputs. The Lavenberg–Marquadt algorithm was employed in the learning process.

The back-propagation method requires different activation functions. The sigmoid type activation function is the most widely used function for such training [14].

For input data vectors Z_1, Z_2, \dots, Z_d with m neural network outputs S_1, S_2, \dots, S_m ,

$$S_i = \varphi \sum_{i=1}^m W_i Z_i \quad (13)$$

where w = weight, $w_i = [w_{i1}, w_{i2}, \dots, w_{im}]$ T , and φ = non-linear sigmoid activation function

The adaptation weight of for neuron i is determined as follows:

$$\Delta W_{ij} = \eta \left[S_i Z_i - S_i \sum_{k=1}^i W_{kj} S_k \right] \quad (14)$$

Error

The training and error measurement testing were conducted using the mean absolute error (MAE), sum square error (SSE), and mean square error (MSE) methods. The MAE was measured based on the average error prediction accuracy.

$$errorMAE = \frac{\sum |e|}{n} \quad (15)$$

Where e = error, n = period of numbers.

$$SSE = \sum (e_i)^2 \quad (16)$$

where $e_i = X_t - F_t$, X_t = actual data period t , F_t = value forecast period t .

The MSE methods evaluate predictions by squaring, summing, and dividing error values by the number of observations. This approach yields large prediction errors because the error is squared.

$$MSE = \frac{\sum (e_i)^2}{n} \quad (17)$$

Where: $e_i = X_t - F_t$, X_t = actual data period t , F_t = Value forecast period t and n = number of periods.

RESULT AND DISCUSSION

The experiment was initiated by PSO data reading. The data consisted of 180 records, of which 80% were used as training data and the remaining 20% were used as testing data. The ANN network consisted of 2 inputs and 3 outputs. ANN inputs were water discharge

(Q) and height (H), while the ANN outputs in terms of turbine parameters were α_1 , β_1 and β_2 .

Before ANN training, the data were pre-processed with PCA. The goal was to limit the ANN-trained data.

The ANN network was created using 25 neurons in the first hidden layer, 50 in the second hidden layer, an activation function for each layer, and *trainlm* as the learning method. Furthermore, the training was conducted based on the following data parameters: epochs 20000 and goal 10e-5.

The ANN network training data are listed in Table 1. However, only 25 of the 144 actual data items are listed owing to page limitations. The time required for training depends on the amount of training data, expected goals, and momentum values. During training, regression, state of training, and network performance can be observed.

Table 1. Data training ANN¹⁾

Data	H	Q	α_1	β_1	β_2
1	28	30	15,00349	28,94485	29,6193
2	13	30	15,00153	30,15477	29,5736
3	1	40	15,00377	30,8157	31,28478
4	46	30	15,00104	30,09418	29,96393
5	38	35	15,0005	30,86848	29,11059
6	32	40	15,00415	28,61786	31,90379
7	50	30	15,00385	28,17254	29,84671
8	39	35	15,0004	29,00195	30,96754
9	2	35	15,00037	29,02552	30,81902
10	48	35	15,00283	29,711	30,00177
11	19	40	15,00205	29,17531	29,9392
12	4	40	15,00508	28,78239	30,85641
13	30	30	15,00045	29,69512	30,68776
14	4	30	15,00116	28,00599	31,01034
15	23	40	15,00101	28,26018	31,94735
16	21	30	15,00028	30,10534	29,62567
17	41	30	15,00212	30,09672	29,97349
18	42	30	15,00256	30,11445	29,16756
19	7	30	15,00279	30,16723	29,94206
20	37	40	15,00062	28,84708	31,07606
21	56	40	15,0006	28,53736	29,97849
22	51	40	15,00107	29,96171	31,58335
23	58	35	15,0018	30,53878	29,58849
24	20	35	15,00212	30,09672	29,97349
25	53	40	15,00115	28,35935	31,17255

¹⁾ Displaying 25 of 144

After ANN network training, we commenced testing. The results of ANN network data testing are summarized in Table 2. The test data was read by the ANN network with each node containing determined bias values. The training data input to the ANN network are listed in Table 2 below.

Table 2. Data testing of ANN²⁾

Data	H	Q	α_1	β_1	β_2
145	23	30	15,00284	29,99236	31,82703
146	49	30	15,00159	28,91937	30,35536
147	33	40	15,00006	30,76733	30,13301
148	25	35	15,00029	28,36294	31,65149
149	21	35	15,00094	30,19596	30,72177
150	47	30	15,00041	29,8677	31,8705
151	5	30	15,00338	30,03695	31,89771
152	27	40	15,00019	28,80556	29,2072
153	34	40	15,00176	28,38404	29,92039
154	2	30	15,00232	28,14753	29,49773
155	46	35	15,00509	28,38879	29,20653
156	47	35	15,00024	29,13715	30,0923
157	16	40	15,00286	29,8888	31,50794
158	52	35	15,00228	30,67071	30,52028
159	8	35	15,00072	30,94923	30,74546
160	35	30	15,00049	28,44285	31,80416
161	57	35	15,0003	30,78191	31,4074
162	19	30	15,0003	30,40495	31,5428
163	9	30	15,0008	28,90849	30,78821
164	28	35	15,00159	28,91937	30,35536
165	37	30	15,00067	28,1255	31,3103
166	9	40	15,00203	30,6778	30,58792
167	36	30	15,00095	30,23006	29,03487
168	59	40	15,00237	28,39553	31,53792
169	14	30	15,00006	30,76733	30,13301

²⁾ Displaying 25 of 40

In this study, we applied the Lavenberg–Marquadt learning algorithm compared with gradient descent. We applied the tribas, logsig, and tansig activation functions. The experiment was conducted on every layer variation of the model. In this study, we employed various combinations of the tribas, logsig, and tansig activation functions. In addition, we compared the learning algorithms *trainlm* and *traingd*, as summarized in Table 3.

Table 3. Activation function Model ANN

Model	Activation function			Learning Methods
	Hiden1	Hiden2	output	
M1	Tribas	Logsig	Tansig	traingd
M2	Tribas	Logsig	Tansig	trainlm
M3	Tribas	Tansig	Logsig	traingd
M4	Tribas	Tansig	Logsig	trainlm
M5	Tansig	Logsig	Tribas	traingd
M6	Tansig	Logsig	Tribas	trainlm
M7	Tansig	Tribas	Logsig	traingd
M8	Tansig	Tribas	Logsig	trainlm
M9	Logsig	Tansig	Tribas	traingd
M10	Logsig	Tansig	Tribas	trainlm
M11	Logsig	Tribas	Tansig	traingd
M12	Logsig	Tribas	Tansig	trainlm

We analyzed the ANN data outputs to find the smallest values of MSE, MAE and SSE. The Lavenberg-Marquadt algorithm was applied to the ANN to compute the exact weight of each node. After obtaining the smallest MSE value, we tested the value on existing data. The NNPCA output data were analyzed to obtain optimum turbine design parameters by using the ANN.

From on Figure 7, the lowest MSE training value was achieved using M2 (0.3352) and the highest using M8 (0.4482). The lowest MAE training value was achieved using M2 (0.3996) and the highest using M3 (0.4639). The lowest MSE testing value was achieved using M5 (0.5427), while the highest was achieved using M11 (0.6505). The lowest MAE was achieved using M5 (0.5294), while the highest was achieved using M9 (0.5601). These findings indicated that M2 was the best model. The conditions under M2 resulted in the lowest MSE value in training in comparison with those under other models. Thus, these conditions were regarded as optimal for running the ANN.

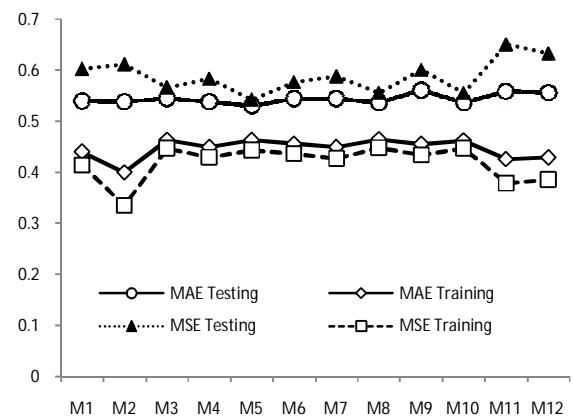


Figure 7. MSE and MAE: testing and training

According to Figure 8, the lowest SSE training value was achieved using M1 (144.8293) and the highest using M3 (193.946), while the lowest SSE testing value was achieved using M5 (58.6063) and highest using M11 (70.2545). These findings indicated that based on training values, M1 was the best model. However, based on the testing values, M2 was the best model. Considering the MAE, MSE and SSE values, M2 was regarded as the best ANN network model for turbine design.

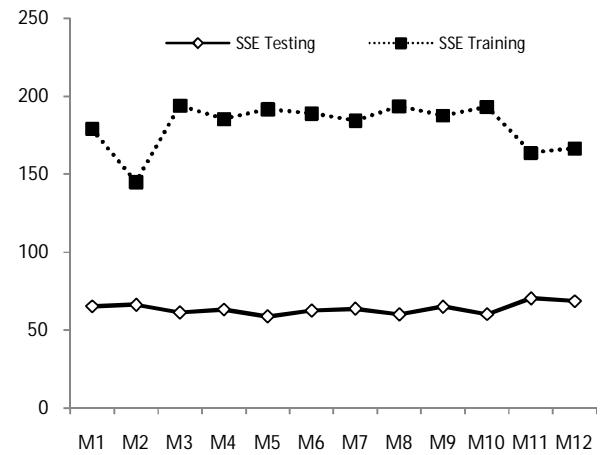


Figure 8. SSE testing and training

NNPCA training process regression when using M2 is shown in Figure 9. The figure indicates that the data gathered on the blue line run as expected. Figures 10 and 11 describe NNPCA state training and MSE at 383 epochs.

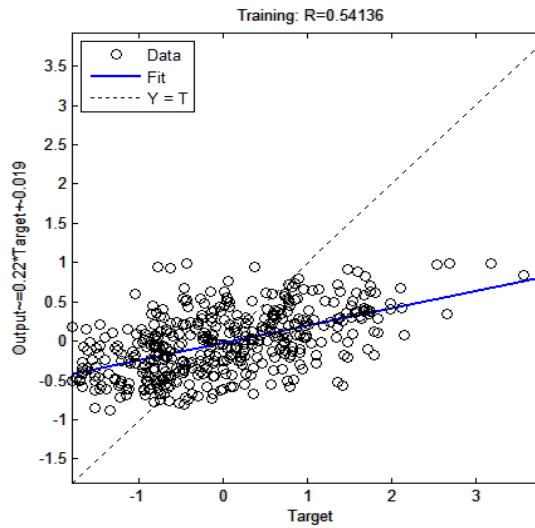


Figure 9. Regression of NNPCA

The ANN network used here was based on a three-layer specification. The first hidden layer was composed of 25 neurons, while the second hidden layer was composed of 50 neurons. The tribas, logsig, and tansig activation functions, as well as the trainlm learning method, were applied to the ANN.

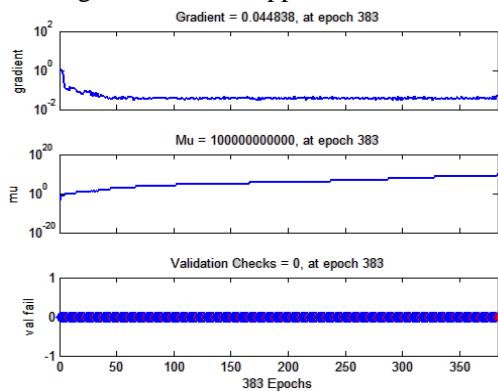


Figure 10. Training State of NNPCA

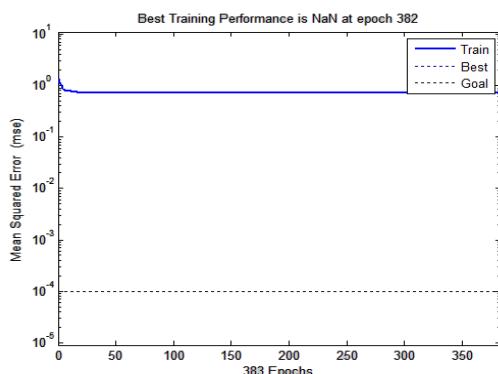


Figure 11. MSE of NNPCA

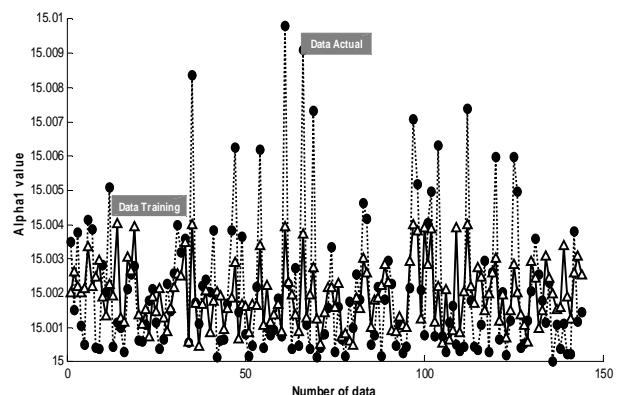


Figure 12 Training result with NNPCA

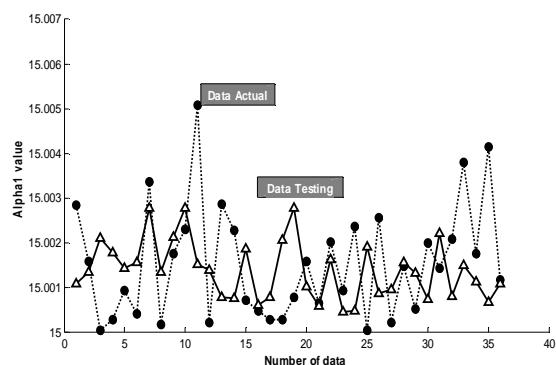


Figure 13. Testing result with NNPCA

The repetition of epochs was 20000 with a target of error 10⁻⁵. Figure 12 shows a comparison of actual data and α_1 training data. For validation, Figure 13 shows a comparison α_1 testing using NNPCA with actual data. After training and testing, the following results were obtained: training MAE: 0.4237, training MSE: 0.3826, training SSE: 165.2654; testing MAE: 0.5660, testing MSE: 0.6696, and testing SSE: 72.3167.

CONCLUSION

The PSO algorithm was used to optimize the Banki turbine design process. Using H and Q as input parameters, we obtained the values of α_1 , β_1 , and β_2 . The obtained parameter values were the most optimal for achieving the highest efficiency because the blade angle is the most prominent parameter governing the efficiency of Banki turbines.

NNPCA is an artificial neural network that applies PCA for pre-processing data. NNPCA was used to input the existing

knowledge in the PSO-optimized data into an ANN network. The process of learning and testing was performed using tribas, logsig, and tansig. Tansig proved to be the best activation function, while the Lavenberg–Marquadt learning algorithm could generate the lowest MAE and MSE values.

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