Combination of Backpropagation Neural Network and Particle Swarm Optimization for Prediction of Water Production in Municipal Waterworks

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Abstract.

Purpose: As the population grows, the need for clean water also increases. Municipal Waterworks (PDAM) is an institution that regulates and manages the procurement of clean water for the community. So, the amount of water produced and distributed should be adjusted to the demand for water. Predictions on PDAM water production need to be done as planning and better preparation and facilitating and assisting in decision-making.

Methods: The study used the Neural Network backpropagation algorithm combined with Particle Swarm Optimization (PSO) to predict the amount of water PDAM should produce. Backpropagation has a good ability to make predictions. But backpropagation has a weakness that causes it to get stuck at a local minimum. This is influenced by the determination of weights that are not optimal. In this study, PSO had a role in optimizing error values on the network to gain optimal weight.

Result: This study obtained MSE values in the training and testing process of 0.00179 and 0.00081 from the combination model of backpropagation ANN and PSO. It is smaller than the ANN model without using an optimization algorithm.

Novelty: The combination of JST backpropagation and PSO can improve predictions' accuracy and produce optimum weights.

Keywords: PDAM Water Production, Backpropagation, ANN, PSO, Prediction
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INTRODUCTION

Water is a necessity in everyday life [1]. All life in the world needs water [2]. Water is also a basic need for humans [3]. The existence of water on earth is limited. An accurate prediction is needed to anticipate water shortages in the future [2]. Municipal waterworks is a company that carries out service functions to produce drinking water and clean water for the community [1]. One of the problems in municipal waterworks is related to the availability of clean water production to meet customer needs precisely. Therefore, a study is required in order to provide a solution regarding the prediction of clean water that must be produced [4].

One of the prediction methods applied is Artificial Neural Network (ANN) [5]. Backpropagation architecture is one of several ANN architectures that can be used to study and analyze past data patterns more precisely to obtain a more accurate output [5]. In previous research conducted by Sihotang, dkk [6], the backpropagation ANN algorithm can predict the number of non-star hotel visitors with an accuracy of 88. Another study conducted by Hasan, dkk [7] was carried out forecasting the sales of Bottled Drinking Water (AMDK) for the 2019 period using backpropagation ANN obtained an MSE value of 0.00043743 and a MAPE value of 6.88%. In another study conducted Sutawinaya, dkk [8], the study was conducted to predict rainfall by comparing two ANN architectures, namely backpropagation ANN and Adaline ANN. The results showed that the RMSE value of backpropagation ANN testing was 0.0435, and Adaline ANN was 0.067. Another study was conducted by Nurkholiq, dkk [10] to predict the long-term demand for electrical energy. Two methods were compared, namely backpropagation ANN and fuzzy logic. This study

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resulted in the error value between the expected results of fuzzy logic and backpropagation ANN, respectively 8.2413% and 2.8027%.

However, this backpropagation method has several drawbacks, including a slow convergence rate and being stuck in a local minimum [10][11]. This weakness is influenced by the initial weight, which is randomly selected, also in calculating the weight change of the backpropagation algorithm [12]. This weakness can be overcome using optimization algorithms such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), and PSO [13]. In previous research conducted by Maori [13], a study was conducted to predict Antam's gold price using the ANN method combined with two optimization methods, namely PSO and GA. The study results showed that ANN combined with PSO produced a better RMSE value, namely 0.026. Meanwhile, ANN combined with GA produces an RMSE value of 0.029 [14]. Compared to the ACO algorithm and Evolutionary Algorithm, PSO requires only old math operators, fewer computations, and generally has fewer lines of code. Thus, computationally simpler both in terms of memory and requirements. PSOs are popular for their simplicity of implementation and their ability to converge quickly and provide an acceptable solution [15]. This problem can be solved by using the PSO algorithm to obtain the ideal weight and minimum error value [10].

METHODS
Data Preparation
The data preparation step includes all activities to build a dataset used to train and test the model. This step consists of data selection, data normalization, and defining training data and test data.

Data Selection
In this step, the selection of data attributes from the PDAM Tirta Satria Banyumas water balance data 2018-2019 is carried out to be used as attributes in the application of the method. Two attributes will be used as input and one attribute as output. The attributes used are:
1. Production Capacity (m^3) is the capacity that produces water production through transmission pipes.
2. The number of customers is the number of people who subscribe to PDAM Tirta Satria Banyumas.
3. Production (m^3) is the production of air that is distributed after the chlorination/reservoir process.

Data Normalization
In this step, data normalization is carried out; normalization is carried out to transform the data to be measured on a broad scale. Equation 1 is used for normalization.

$$x' = \frac{x}{Max} \tag{1}$$

Description:
x' = normalized data
x = data to be normalized
Max = Maximum value of data

Defining Training Data and Test Data
After the data transformation is carried out, the data is obtained with a scale of 0.1 to 0.9. From the transformed data, then the data is divided into two parts, namely training data and test data. It will be separated by a ratio of 80% for training data and 20% for test data.

Data Analysis
Regression analysis is used to predict how far the value of the dependent variable will change if the value of the independent variable is manipulated or changed. The regression analysis conducted is a multiple linear regression analysis which is helpful in analyzing the relationship between many independent variables on one dependent variable. The production attribute is the dependent variable, while the production capacity and a number of customers are independent variables. The results of the regression analysis can be seen in Table 2.

Table 2. Multiple linear regression results

Dependent Variable	R	R2
Production	0.982	0.965

The R-value in Table 2 shows the multiple correlation coefficient between the independent and dependent variables. If the value of R approaches 1, the higher the relationship. With an R-value of 0.982, it can be concluded that all independent variables have a close relationship with the dependent variable production. The value of R^2 shows the coefficient of determination. Converting it to a percent shows the percentage of the influence of the independent variable on the dependent variable. With an R^2 value of 0.965, the percentage of influence of all independent variables on production is 96.5%, while the remaining 3.5% is influenced by other variables that are not included.

Backpropagation ANN Model Design
An artificial Neural Network (ANN) is a computational model based on the Biological Neural Network. The term artificial here is used because this neural network simulates the workings of biological neural networks that exist in humans and is applied by using a computer program in the decision-making process [16] - [17]. ANN can learn from experience, generalize the examples obtained, and abstract the essential characteristics of input even for irrelevant data [28]. With the excellent ability of ANN, some ANN applications are very suitable for classification, association, prediction, optimization, and self-organizing cases [7][18]. The network model is built using MATLAB. The flow of the ANN algorithm when applied to MATLAB can be seen in Figure 1.
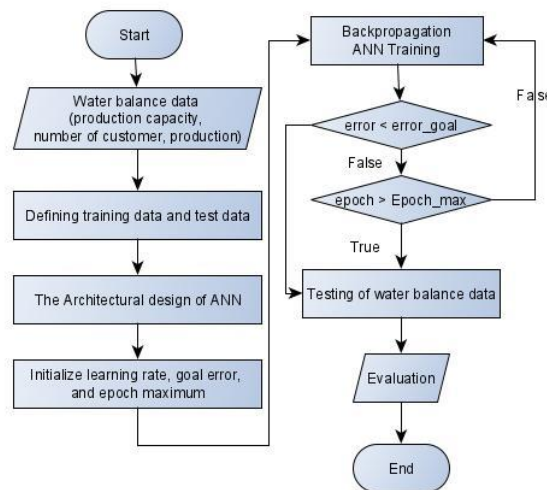
Figure 1. Flowchart of the backpropagation ANN algorithm

Backpropagation
Backpropagation is a learning algorithm in artificial neural networks [16]. Rumelhart, Hinton, and William introduced backpropagation in 1986, then Rumelhart and Mc Clelland developed it in 1988. This algorithm is included in supervised learning, where the sign of this method is to minimize errors in the output generated by the network. The backpropagation algorithm for neural networks is usually applied to multilayer networks. This algorithm has at least an input section, an output section, and several layers between input and output. The layer in the middle is called the hidden layer. Hidden layers can be one, two, three, and so on. The output of the last layer from the hidden layer is directly used as the neural network's output [17].

Hidden Layer Nodes
Network architecture is defined by the number of hidden layers, nodes in each hidden layer, and the learning rate. One hidden layer can solve some complex problems on a network. Therefore, one hidden layer was chosen to build the backpropagation ANN model in this study. Also, determining the number of neurons in the hidden layer is important for the ANN architecture.

Based on the previous step, namely data selection that has been tested using regression analysis, there are two neurons in the input layer (Ni) and one in the output layer (No). The number of neurons that must be used in the hidden layer is in the range of one to five. It should be noted that (2 Ni + 1) is the maximum limit of the number of neurons in the hidden layer.

With the divided dataset into training data and test data of 80% : 20%, it is 96: 24, and the optimal number of neurons is determined in the hidden layer. The training and testing results using a sample dataset carried out with an epoch range of one to five are shown in Table 3. The average R^2 value from the training and testing dataset for the five models is shown in Table 4 and Figure 2.

Table 3. The R^2 of ANN models to predict water production

M o d e l	N o d e s	Result									
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5	
		R^2		R^2		R^2		R^2		R^2	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	1	0.953	0.959	0.892	0.892	0.949	0.955	0.882	0.889	0.925	0.927
2	2	0.866	0.868	0.182	0.868	0.182	0.261	0.346	0.346	0.788	0.792
3	3	0.451	0.443	0.893	0.897	0.951	0.957	0.526	0.957	0.105	0.526
4	4	0.715	0.725	0.076	0.073	0.769	0.774	0.922	0.928	0.413	0.424
5	5	0.563	0.554	0.963	0.963	0.653	0.66	0.89	0.895	0.748	0.762

Table 4. The average R^2 value of ANN models to predict water production

Model	Nodes	Result	
		Average of R^2	
		Train	Test
1	1	0.92	0.924
2	2	0.473	0.627
3	3	0.586	0.756
4	4	0.579	0.584
5	5	0.763	0.767

Based on Figure 2, model number one with a node in the hidden layer has a higher performance than other models. Therefore, one was chosen as the number of nodes in the hidden layer in building the backpropagation ANN model. It should be noted that only the results from R^2 are used as criteria for selecting the best model.
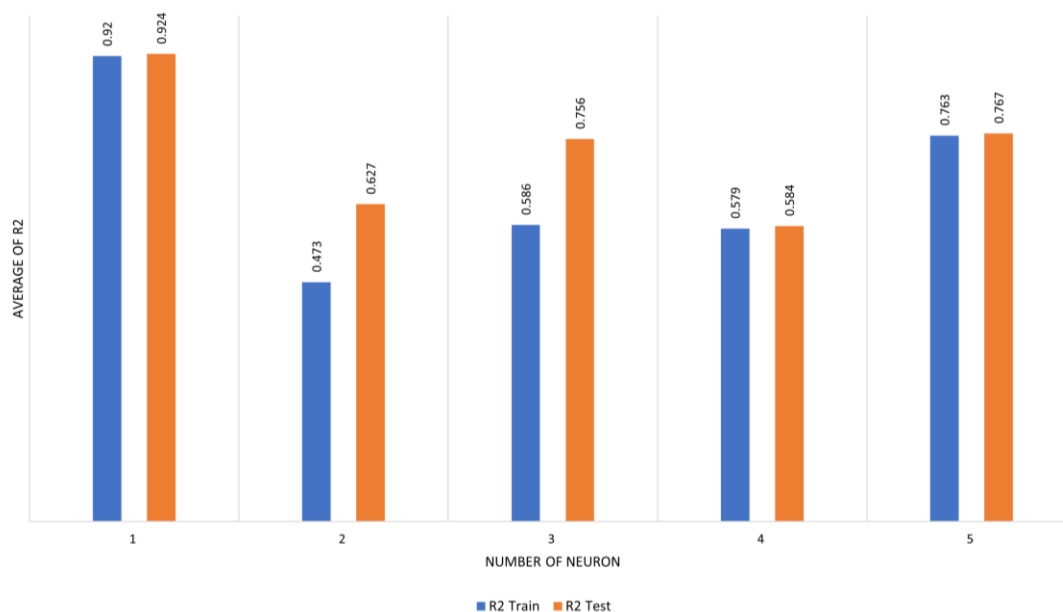

Figure 2. R2 values of both training and testing datasets for all five models

Learning Rate
After determining the number of nodes in the hidden layer, the next step is to determine the learning rate. A learning rate that is too small will cause the training rate to be slow due to small changes in the weights that occur. Meanwhile, fluctuations may occur if the learning rate is too large. Experiments were carried out using multiple learning rates with one epoch.

Based on the results of the variation experiment on the learning rate shown in Table 5, a model with a learning rate of 0.6 has the highest R^2 value of the four learning rates tested, both in the training and testing process. Therefore 0.6 is determined as the learning rate in building the backpropagation ANN model.

Table 5. The effect of the number of learning rate on the network performance

| Model | Learning Rate | Result R^2 | |
		Train	Test
1	0.01	0.927	0.934
2	0.25	0.923	0.93
3	0.4	0.487	0.48
4	0.6	0.935	0.942

ANN Backpropagation and PSO Combination Model Design
The flow chart of the combined model of Backpropagation ANN and PSO using MATLAB is shown in the Figure 3.
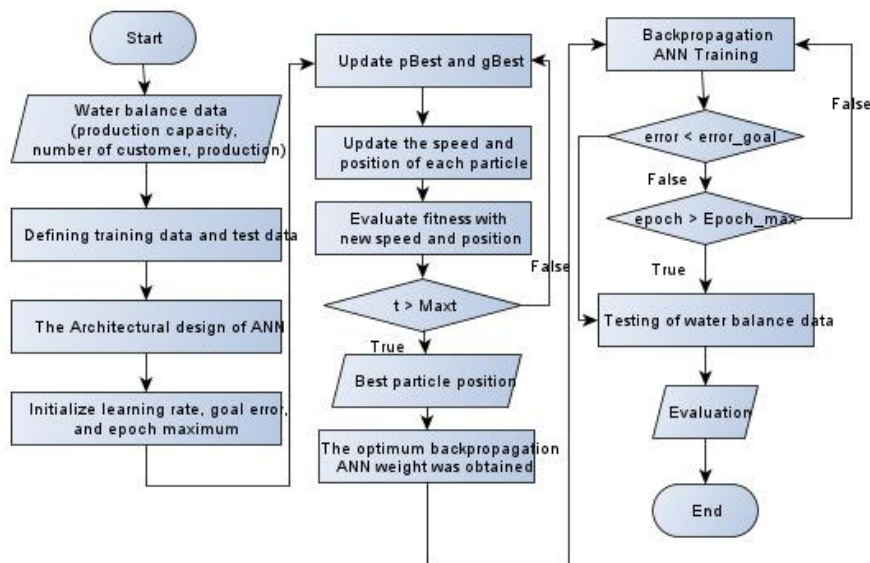

Figure 3. Flowchart of the combined model of backpropagation ANN and PSO

Swarm Intelligent
Swarm Intelligence (SI) is a scientific discipline involving natural and artificial systems. It consists of many individuals who use decentralized control to coordinate and self-organize [21,22]. This discipline focuses on collective behavior generated by local interactions between one individual and another and between individuals and the environment. Then, the logic of SI inspired most researchers to develop algorithms based on animal intelligence for solving optimization problems. Various algorithms on collective behavior are proposed to solve the optimization problem. The optimization problem causes the need for research to determine the minimum or maximum value of a function. This value is referred to as the optimal value [18].

Particle Swarm Optimization
One of the SI algorithms is Particle Swarm Optimization (PSO). PSO is a population optimization technique developed by James Kennedy and Russ Eberhart in 1995 [19]. This technique is inspired based on the social behavior of a flock of birds or a school of fish [20].
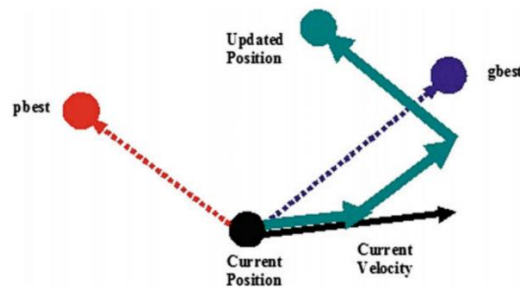
Figure 4. Illustration of particle movement in the PSO process [21]

Each bird is considered a particle representing the solution to a problem with a position (x) and velocity (v). PSO has two main functions, namely, speed update and position update. Which are used to update the speed and position of the particles so that they will continue to be accelerated until they are close to the best particle position of the particle (local best) and the best particle of the whole swarm (global best) to the minimum error condition reached. PSO starts with a random set of particles (solutions) generated [18].

Swarm Size

To determine the optimal number of particles in a swarm (swarm/population), a sensitivity analysis was performed on the number of PSO particles. A small number of particles may fail to achieve a convergent global solution, whereas many particles can cause a slow convergence process and reduce efficiency. This analysis was performed using 200 iterations for each swarm size with a predetermined value of acceleration constants, namely $C1 = C2 = 2$. The target of the sensitivity analysis is to find the minimum RMSE value and the maximum R^2 value on the network.

Table 6. Effects of different numbers of swarm sizes in predicting water production

Model	Swarm	Result				Rank				Total
		Train		Test		Train		Test		
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	25	0.978	0.034	0.982	0.03	4	3	4	4	15
2	50	0.977	0.034	0.982	0.031	3	3	4	3	13
3	75	0.978	0.033	0.982	0.03	4	4	4	4	16
4	100	0.977	0.034	0.982	0.031	3	3	4	3	13

Table 6 shows the sensitivity analysis results of training and testing using swarm sizes of 25 to 100. The model is perfect if R^2 is one and RMSE is zero. A simple ranking method is applied to select the best model to obtain the optimal swarm size. The results of the ranking scores on the training and testing of each model and the total ranking of each model are calculated. The total ranking with a score of 16 is the highest ranking compared to other models. Therefore, swarm size 75 was chosen in this study.

Termination Criteria

The second step of the sensitivity analysis is to determine the termination criteria. Termination criteria can be called a condition for ending the repeated procedure. In this case, the maximum number of iterations can be used as a termination criterion. In other words, the iterative process will stop if the maximum number of iterations is reached. There is no standard method that can be used to determine the maximum number of iterations. Therefore, a sensitivity analysis was carried out to find the correct maximum iteration. This analysis was carried out by adjusting the iterations with a range of 50 to 400 with a value of $C1 = C2 = 2$. The target of the sensitivity analysis is to monitor the RMSE value in each maximum iteration.

Table 7. Effect of the number of maximum iterations on the network performance

Model	Iteration	Train RMSE	Test RMSE
1	50	0.038	0.035
2	100	0.033	0.03
3	150	0.034	0.03
4	200	0.034	0.03
5	250	0.033	0.03
6	300	0.033	0.03
7	350	0.033	0.03
8	400	0.033	0.03

Table 7 shows the sensitivity analysis results with a swarm size of 75. Based on Table 7, a significant change occurred from the maximum iteration of 50 to a maximum of 100 iterations. Meanwhile, at the maximum iteration of 150 and 200, the RMSE value was more significant than the smaller maximum iteration. For a maximum iteration of 250 to 400, the RMSE value is equal to the RMSE value of a maximum iteration of 100. Therefore, the smallest maximum iteration value with the smallest RMSE is chosen as the termination criteria used in the model.

Acceleration Constants
The next step of the sensitivity analysis is to determine the optimal value of acceleration constants (C_1 and C_2). This value is suggested to be 2 for both constants C_1 and C_2. This original value ($C_1 = C_2 = 2$) was applied in several studies, but different values also solved various problems.

Table 8. Effects of different combinations of C_1 and C_2 in predicting water production

No	C1	C2	Result Train R^2	Result Train RMSE	Result Test R^2	Result Test RMSE	Rank Train R^2	Rank Train RMSE	Rank Test R^2	Rank Test RMSE	Total
1	0.8	3.2	0.976	0.035	0.98	0.032	9	10	9	10	38
2	1.333	2.667	0.979	0.033	0.982	0.03	12	12	11	12	47
3	1.714	2.286	0.977	0.034	0.981	0.031	10	11	10	11	42
4	3.2	0.8	0.976	0.035	0.98	0.032	9	10	9	10	38
5	2.667	1.333	0.977	0.034	0.981	0.031	10	11	10	11	42
6	2.286	1.714	0.977	0.034	0.981	0.031	10	11	10	11	42
7	2.5	2.5	0.976	0.035	0.981	0.032	9	10	10	10	39
8	2	2	0.979	0.033	0.983	0.03	12	12	12	12	48
9	1.75	1.75	0.978	0.033	0.982	0.03	11	12	11	12	46
10	1.5	1.5	0.976	0.035	0.98	0.032	9	10	9	10	38
11	1.25	1.25	0.975	0.035	0.98	0.032	8	10	9	10	37
12	1	1	0.977	0.034	0.981	0.031	10	11	10	11	42

Different combinations of C_1 and C_2 are applied using the PSO parameter obtained in the previous step (swarm size 75 and maximum iteration of 100). The results of the sensitivity analysis are shown in Table 8. As seen in Table 8, 12 models were constructed, and the results were presented for training and testing by taking R^2 and RMSE values. As with the previous stage, a simple ranking method is used to select the best combination. Based on the total rating score, model number nine ($C_1 = C_2 = 2$) has a higher performance than other models. Therefore, this value was chosen as the acceleration constant in this study.

Network Architecture
In the last step of BP-PSO modeling, the network architecture must be determined to train the system, just like the backpropagation ANN prediction model. This study uses the same backpropagation ANN model architecture to get the best comparison. Therefore, the architecture chosen in the backpropagation ANN model (2 x 1 x 1) is used in the BP-PSO model to predict PDAM water production.

RESULT AND DISCUSSION
Backpropagation ANN Model Training and Testing
Training and testing of PDAM water production predictions using backpropagation ANN are carried out using the architecture that has been determined in the previous stage. From the experiments on some backpropagation ANN parameters, the best architectural model is obtained with a structure (2x1x1) with a learning rate of 0.6 and a goal error of 1E-6. The attributes used as membership variables in the input layer based on the results of data analysis are production capacity and the number of customers with an output in

the form of water production. The training was conducted using 96 sets of data totaling 1000 epochs. At the same time, the testing process uses 24 sets of data.

The training process results using the backpropagation ANN model compared to the target values are shown in Figure 5.
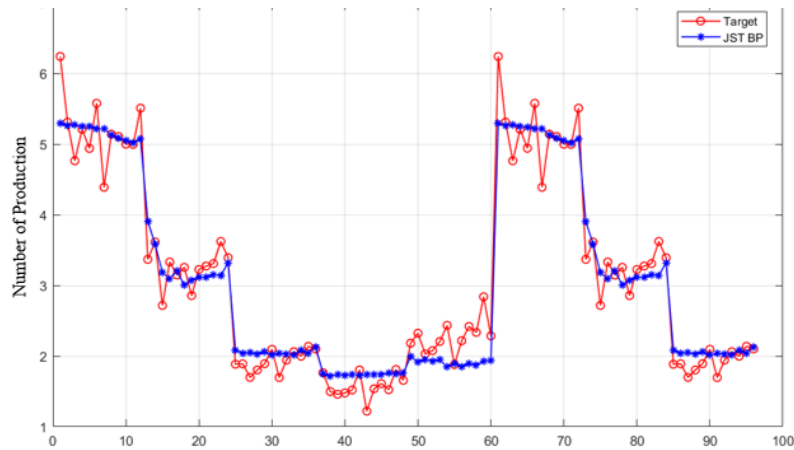

Figure 5. Graph of backpropagation ANN training results

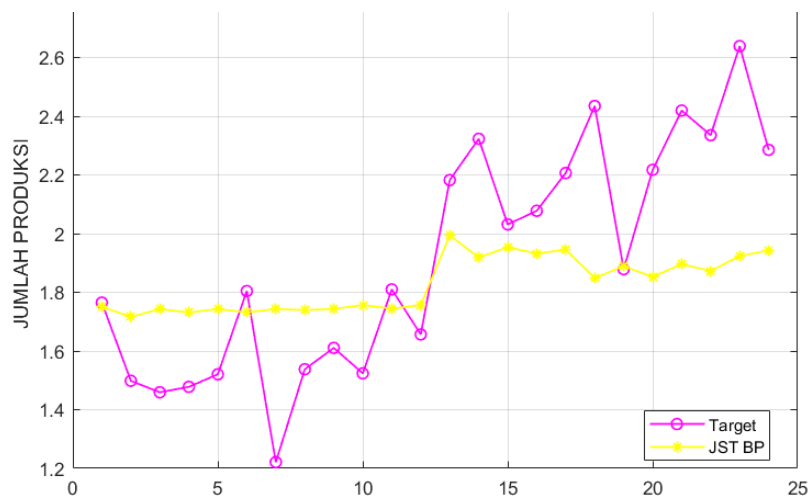Figure 6 shows a prediction result in the testing process compared to the target value.

Figure 6. Graph of backpropagation ANN test results

Combination Model of ANN Backpropagation and PSO Training and Testing
Training and testing of water production predictions using backpropagation ANN are carried out using the architecture that has been determined in the previous stage. The best model architecture is obtained with a structure (2 x 1 x1). With a learning rate of 0.6 and an error goal, 1E-6 combined with PSO with the model determined in the previous step, namely, swarm size 75 with a maximum of 100 iterations and acceleration constants C1 = C2 = 2. The training used 96 data sets, and the testing process used 24 data sets.

The training process results using a combination model of backpropagation ANN and PSO compared to the target values are shown in Figure 7.
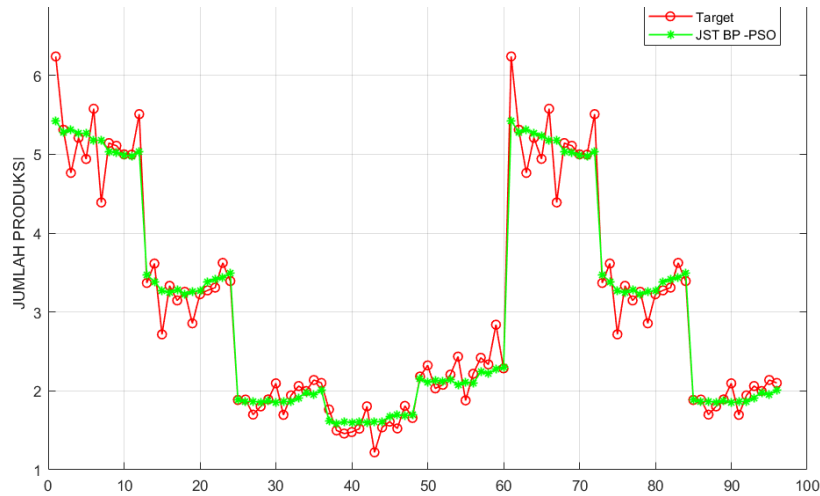

Figure 7. Graph of the train results of the combination of backpropagation ANN and PSO

Figure 8 shows the result of the prediction of water production in the testing process using a combination model of backpropagation ANN and PSO.
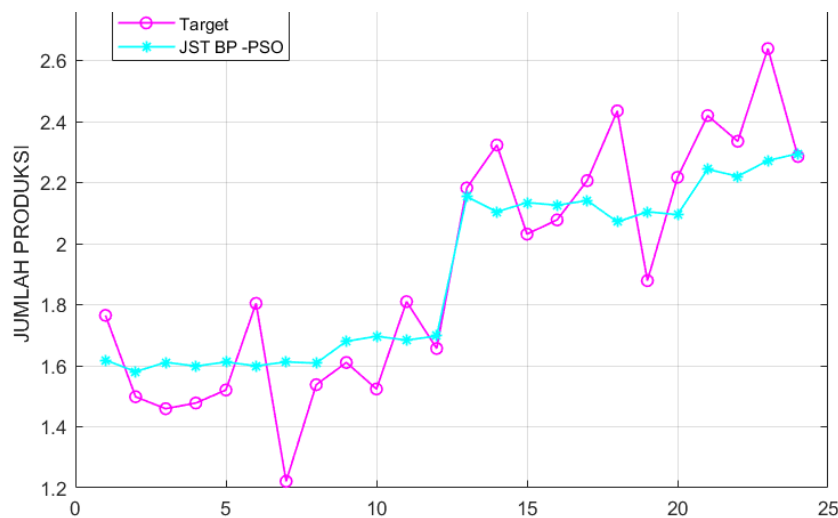

Figure 8. Graph of the test results of the combination of backpropagation ANN and PSO

Comparison of The Two Models
The algorithm has been implemented using two models. From the training and testing process of the two models, the MSE values were obtained, as shown in Table 9.

Table 9. Comparison of MSE values

Process	MSE	
	BP	**BP-PSO**
Train	0.00269	0.00179
Test	0.00268	0.00081

Based on Table 9, it is shown that the resulting MSE value in both processes, training and testing, the combination model of backpropagation ANN and PSO is smaller than the ANN model without using an optimization algorithm. The MSE value that is getting closer to zero shows that the error value of the prediction results is getting better. Based on the graphic image of the prediction results, it can also be seen

that the predicted value using the combination model of backpropagation ANN and PSO is closer to the target value than the backpropagation ANN model without utilizing an optimization algorithm. So, it can be said that the backpropagation ANN model can achieve the optimal weight obtained from the PSO algorithm.

CONCLUSION

Overcome the weaknesses in backpropagation ANN (BP) for the prediction of water production can be done through the application of the PSO algorithm in determining the weight to be used in backpropagation ANN. This is evidenced by the smaller MSE value of the training process of the combination testing model of backpropagation ANN and PSO, which is 0.00179 in the training process and 0.00081 in the testing process. Meanwhile, the MSE value in the training and testing process of the backpropagation ANN method was 0.00269 and 0.00268, respectively. The value measured using MSE from the combination model of backpropagation ANN and PSO is 0.00179 in the training process, and the testing process is 0.00081 using the best architectural model that has been determined by backpropagation ANN experimental parameters and sensitivity analysis on PSO parameters.

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