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Prediction of Water Use Using Backpropagation Neural Network Method and Particle Swarm Optimization

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Abstract

Clean water production has not been well considered between the balance of water use by the community and the production of clean water that is in accordance with the needs of the community. Prediction of water use in meeting the daily needs of the community is very necessary in order to be able to produce efficient water. This research can help PDAM Kota in Kalimantan to be able to produce clean water in accordance with the use of clean water by the community. The Backpropagation Neural Network method focuses on the recapitulation of water use by the community. For better prediction results, optimization is done with Particle Swarm Optimization (PSO). It is expected that the results in this study can predict community water use in daily activities. The test results showed that the Prediction results had RMSE of 0.040 with parameters for training cycle 600 values, learning rate 0.1 and momentum 0.2, and neuron size was 3 and in particle swarm optimization population size 8, max.of gene 100, inertia weight value 0.3, the value of local best weight 1.0 and global value of best weight 1.0.

I. Introduction

Water is a very important resource in human life. Approximately 71% [1] of the earth's surface is a source of water. Although water sources are abundant, this is not an obstacle to the emergence of problems faced by urban communities, namely the difficulty of meeting clean water needs properly. This is the impact of the population growth rate, development development and increasing living standards. Different levels of population use become a problem in the provision of clean water availability.

Based on BPS data for 2017, the coverage of access to decent drinking water services in Indonesia has reached 72 percent and access to safe drinking water in urban areas has reached 80.8 percent. Meanwhile, the national target in the RPJMN (Rencana Pembangunan Jangka Menengah Nasional) for safe drinking water in 2019 has been set at 100 percent according to the mandate of Law No. 23/2014 on Regional Government which has a very important role in the development of the drinking water supply system in their respective territories [2].

PDAM is a Regional Drinking Water Company that provides clean water for the community in their daily activities. PDAMs are scattered in every Province, Regency and Municipality in Indonesia with a total of more than 374 companies [3].

Municipal PDAMs in Kalimantan, have varying water usage needs for each user. The population that continues to increase will also cause high water consumption. High water use has resulted in the need for clean water supplies to continue to increase while the supply of clean water continues to decrease every year [4].

From several factors, there are challenges for all PDAMs, especially Municipal PDAMs in Kalimantan, to optimize their clean water production. The trick is to make predictions of sufficient water usage in order to meet community needs. This prediction can later be used by the company to distribute water to customers so that there is no shortage or waste.

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To be able to predict water usage, several methods can be used, one of which is the backpropagation neural network method. This method is able to formulate experience and knowledge of forecasters, and is very flexible in changing the rule of forecasting [5].

The combination of the backpropagation neural network method and particle swarm optimization is expected to improve the accuracy of the prediction of clean water use. This is based on analysis of Muzakkir [6], the solution chosen for this problem is the application of the backpropagation method and particle swarm optimization as a method that predicts water consumption in PDAM Kota in Kalimantan. With the application of this method in the prediction case of PDAM Kota water usage in Kalimantan, it is hoped that it can produce more accurate predictions.

The clean water produced must be in accordance with the usage needs of each customer. Each customer has a different usage level. This is a consideration for how to make clean water production efficient. So that the water produced is not excessive or deficient according to the needs of each population

II. Literature Review

2.1 Neural Network

Neural network or neural network is an information processing system with characteristics and performance close to biological nerves. In addition to processing, artificial neural networks also have the ability to store information as defined by Simon Haykin [7], that artificial neural networks are simple processors that are numerous and work in parallel and distributed, which have the ability to store knowledge and provide when needed which consists of knowledge. possessed as a result of the learning process and the connections between neurons that function to store that knowledge.

Artificial neural networks are a generalized model of mathematical models of biological neural networks, assuming that:

1. Information processing occurs in many simple elements (neurons)
2. Signals are sent between neurons by means of links
3. The links between neurons have a weight that will amplify or weaken the signal
4. To determine the output, each neuron uses an activation function (usually not a linear function) which is assigned to the sum of the received inputs. The magnitude of this output is then compared with a threshold line [8].

Biological neuros are a "fault tolerant" system in two ways. First, humans can recognize an input signal that is somewhat different from what we have received before. For example, humans can often recognize someone whose face has been seen from a photo or can recognize someone whose face is slightly different from seeing them in a long time. Second, still be able to work well. If a neuron is damaged, other neurons can be trained to replace the function of the damaged neuron [9].

Artificial Neural Networks can exhibit a number of characteristics possessed by the human brain, including:

1. Ability to learn from experience
2. The ability to generalize to new inputs from the knowledge they have.
3. Ability to abstract the important characteristics of the input contain unnecessary data.

Basically, artificial neural networks have many types, but all types of neural networks have the same components.

Neural network models are demonstrated by their capabilities in emulation, analysis, prediction and association. The capabilities possessed by artificial neural networks can be used to learn and generate rules or operations from several samples or input that are entered and make predictions about the possible outputs that will appear or store the input characteristics given to the artificial neural network.

2.1.1 Neuron Model

One nerve cell can consist of 3 parts, namely: *summing function*, *activation function*, and *output*.

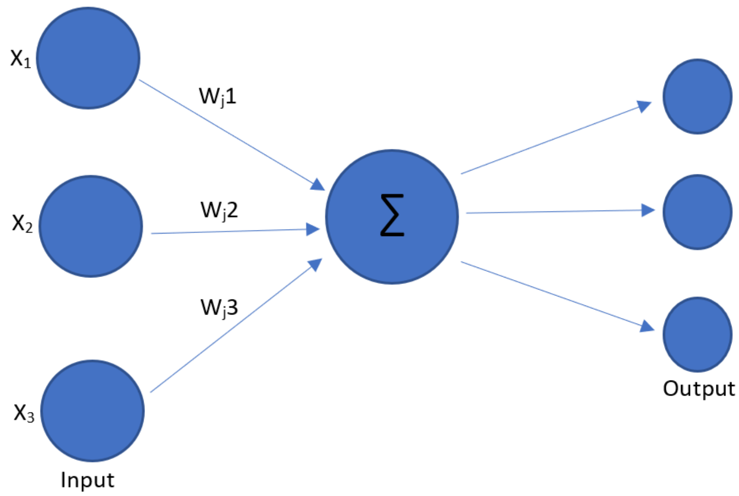

Figure 1 Neuron Model

In the neuron model image (Figure 1) we can see that artificial neuron cells are similar to biological neuron cells. Information (input) with a certain weight will be sent to the neuron. This input will be processed by a function by adding the existing weight values. The sum result will then be compared with a certain threshold value through the activation function of each neuron. If the input exceeds a certain threshold value, the neuron will be activated, otherwise the neuron will send output through weights to all its outputs to all neurons associated with it.

So it can be concluded that neurons consist of 3 constituent elements, namely [9]:

1. The set of units connected by a connection line. These paths have different weights / strengths. Robots that are positive will strengthen the signal and those that are negative will weaken the signal it carries. The number of structures and relationship patterns between these units will determine the network architecture (as well as the network model that is formed).
2. A unit of addition which adds up the signal inputs which have been multiplied by their weight.
3. The activation function will determine whether the signal from the neuron input will be forwarded to other neurons or not.

2.1.2 Backpropagation Neural Network

Backpropagation is a learning algorithm that is inherited and usually used by perceptrons with multiple layers to change the weights associated with neurons in the hidden layer. The Backpropagation Algorithm uses an output error to change its weight values in the backward direction. The forward propagation stage must be done first to get the error value. The Backpropagation algorithm was first formulated by Werbos and popularized by Rumelhart and Mccelland for use in artificial neural networks, and later this algorithm was named Backpropagation. This algorithm is a supervised method and is designed for operation on multi-layer feed forward networks. Backpropagation using its performance index is Mean Squared Error.

Backpropagation training includes three phases, namely the forward phase, the reverse phase, and the weight change phase. The forward phase is the first phase, where the input pattern is calculated forward from the input layer to the output layer using the specified activation function. The second phase is the reverse phase. Where in this phase the difference between the network output and the desired target is an error that occurs. The error is propagated backwards, and starts from the line that corresponds directly to the units in the output layer. The last phase or the third phase is the change in weight. In this phase, modify the weights to reduce the errors that occur. Here's a full explanation:

Phase I of Forward Propagation

During this phase, the input signal $(= x_i)$ is propagated to the hidden layer using the predefined activation function. The output from each hidden unit layer $(= z_j)$ will then be propagated forward again to the hidden layer above it using the specified activation function. This is done continuously until it can produce network output $(= y_k)$.

Then the network output (= y_k) is compared with the target to be achieved (= tk). Difference $t_k - y_k$ is an error that occurs. If the error is smaller than the tolerant limit, the weight on each line in the network will be modified to reduce the error that occurs.

Phase II of Backward Propagation

Based on the erorr $t_k - y_k$ calculated factor δ_k (k=1,2,...,m) which is used to distribute the error in the units to all hidden units which are directly connected to y_k is also used to change the line weights that are directly related to the unit of output.

Then it is done using the same method, calculating the δ_j factor in each unit in the hidden layer as the basis for changing the weight of all lines originating from hidden units in the lower layer. This is done until all δ factors in the hidden unit that are directly related to the input unit can be calculated.

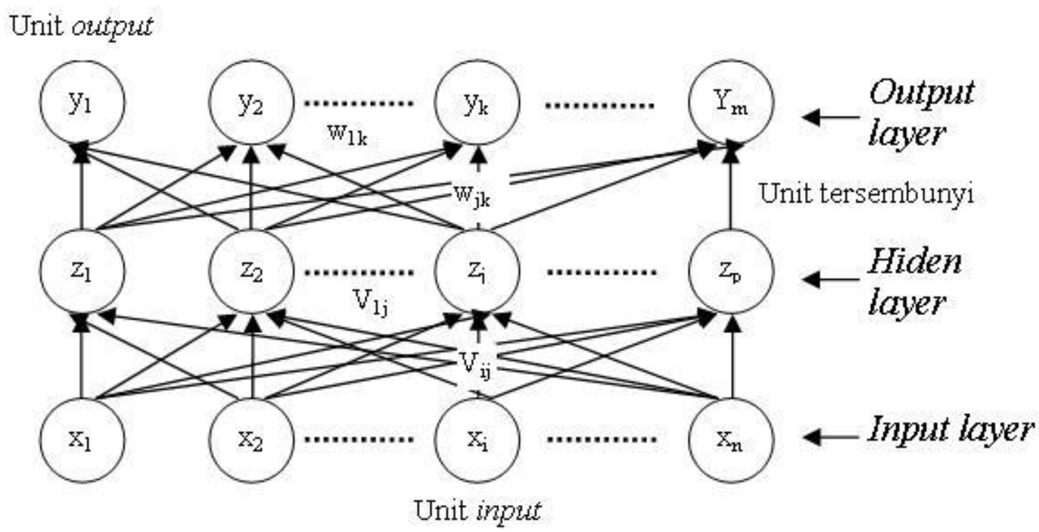

Figure 2 Backpropagation Architecture

2.2 Particle Swarm Optimization

Particle Swarm Optimization is an optimization method inspired by the movement behavior of herds of animals such as fish (*school of fish*), herbivores (*herd*), and birds (*flock*), which then simplifies each animal object into a particle. A particle in space has a position encoded as a coordinate vector. This position vector is considered to be the state that a particle is currently occupying in the search space. Each position in the search space is an alternative solution that can be evaluated using an objective function. Each particle moves with the speed V [10].

Particle Swarm Optimization, or what we know as PSO, applies the characteristics of each individual in one large group. Then combine these characteristics to solve the problem. Particle Swarm Optimization was first introduced in 1995, since then many researchers have derived and developed the PSO method [11].

The characteristic of PSO is the heuristic and probabilistic particle velocity regulation. If a particle has a constant velocity, visualizing the position of a particle will form a straight line. With the presence of external factors that deflect the line which then moves the particles in the search space, it is hoped that the particles can lead, approach, and ultimately reach the optimal point. The external factors referred to include the best position ever visited by a particle, the best position of all particles (it is assumed that each particle knows the best position of every other particle), and the creativity factor for exploration.

Particle Swarm Optimization has similar properties with computational techniques such as *Genetic Algorithms*. The PSO system is initialized by a random population of solutions and then looks for the optimum point by updating each generation result. This optimization method based on swarm intelligence is called a behaviorally inspired algorithm as an alternative to genetic algorithms, which are often called evolution-based procedures. In the context of multivariable optimization, the swarm is assumed to have a certain or fixed size with each particle whose initial position is located at a random location in a multidimensional space. Each particle is assumed to have two characteristics: position and velocity. Each particle moves in a certain space and remembers the best position ever traveled or found against a food source or objective function value. Each particle conveys information or its good position to other particles and adjusts the position and speed of each based on the information received about the good position.

According to Kennedy [10], for example, the behavior of birds in flocks of birds. Even though every bird has limitations in terms of intelligence, usually it will follow habits (rules) as follows:

1. A bird is not too close to another bird
2. The bird will direct its flight in the direction of the overall bird rate.
3. Will position himself with the average position of the other birds by keeping the distance between the birds in the flock not too far away.

So PSO is developed based on the following model:

1. When a bird approaches a target or food (or could be a minimum or maximum of a destination function) it quickly sends information to other birds in a particular flock.
2. Other birds will follow the direction to the food but not directly.
3. There is a component that depends on the mind of each bird, namely his memory of what has been passed in the past.

This model will be simulated in a space with certain dimensions with a number of iterations so that in each iteration, the position of the particles will increasingly point to the target target (minimization or maximization of the function). This process is carried out until the maximum iteration is reached or another termination criterion can be used.

In PSO, the swarm is assumed to be of a certain size with each particle of its initial position located at a random location in a multidimensional space. Each particle is assumed to have two characteristics: position and velocity. Each particle moves in a certain space and remembers the best known or found position against the food source or objective function value. Each particle conveys the information or its best position to other particles and adjusts the position and speed of each based on the information received about the position [12].

Even though each bird has limitations in terms of intelligence, it will usually follow the following rules: one bird will not get too close to another bird, the bird will direct its flight in the direction of the overall bird's average, will position itself roughly position the other birds so that the birds in the flock are not too far apart. The following is a mathematical formulation that describes the position and velocity of particles in a certain dimension of space [12].

$$X_i(t) \; = \; X_{i1}(t),\, X_{i2}(t), \dots, X_{iN}(t), \dots \; (2.2)$$
$$V_i(t) \; = \; V_{i1}(t),\, V_{i2}(t), \dots, V_{iN}(t), \dots \; (2.3)$$

Where:
X: particle position
V: particle velocity
N: the size of the dimensions of space
i: particle index
t: iteration t

The following is a mathematical model that describes the particle status updating mechanism [12]:

$$V_i(t) = v_i(t-1) + c_1 r_1 (X_i^L - X_i(t-1) + c_2 r_2 \big(X^G - X_i(t-1)\big) \dots (2.4)$$
$$X_i = V_i(t) + X_i(t-1) \dots (2.5)$$

Where :

$X_i^L = x_{i1}^L, x_{i2}^L, \dots, x_{iN}^L$ represents the *local best* of the i-th particle. Whereas $X^G = x_{i1}^G, x_{i2}^G, \dots, x_{iN}^G$ represents the *global best* of the whole herd. Whereas c1 and c2 are positive constants which are usually called *learning factor*. Then r1 and r2 are random numbers whose values are between 0 to 1. Equation (2.4) is used to calculate the speed of the particles that must be based on the previous velocity, the distance between the current position and the best position of the particle (*local best*), and the distance between the current position. with the best herd position (*global best*). Then the particles fly to a new position according to equation (2.5). After the PSO algorithm is executed with a certain number of iterations until it reaches the termination criteria, a solution will be found which lies in the *glohal best*.

III. METHODS

This research method explains the research design modeling procedure and implements the Backpropagation Neural Network method to predict the output in the form of clean water consumption and then optimizes it with the Particle Swarm Optimization method to get more accurate prediction results.

This research uses literature study as an initial stage by studying the theoretical basis of Backpropagation Neural Network and Particle Swarm Optimization (PSO), literature and references including journals, e-books, the internet and books related to this research.

This research has an important input, namely training data from the use of clean water in PDAM Kota in Kalimantan from 2015 to 2016 or data on customer water usage for 24 months. The training data will be processed using the Backpropagation Neural Network method. Then performed optimization with the Particle Swarm Optimization (PSO) method to produce a more accurate prediction.

The result of this research is to build a model that can predict water consumption by using the Backpropagation Neural Network method with the optimization of the results with Particle Swarm Optimization.

3.1 Model Design

The resulting design is an application model that has input in the form of training data from water usage which will later be processed using the Backpropagation Neural Network method with Particle Swarm Optimization (PSO). Output is a prediction of water consumption.

This stage is carried out to compile a conceptual framework of thought patterns, formulate hypotheses and analyze the object of research, and analyze system requirements that have been determined by the object as the object under study which is then made into a model design for predicting water use.

The design of the model in solving problems in this study uses the backpropagation neural network and the particle swarm optimization algorithm. The identification model design is as follows:

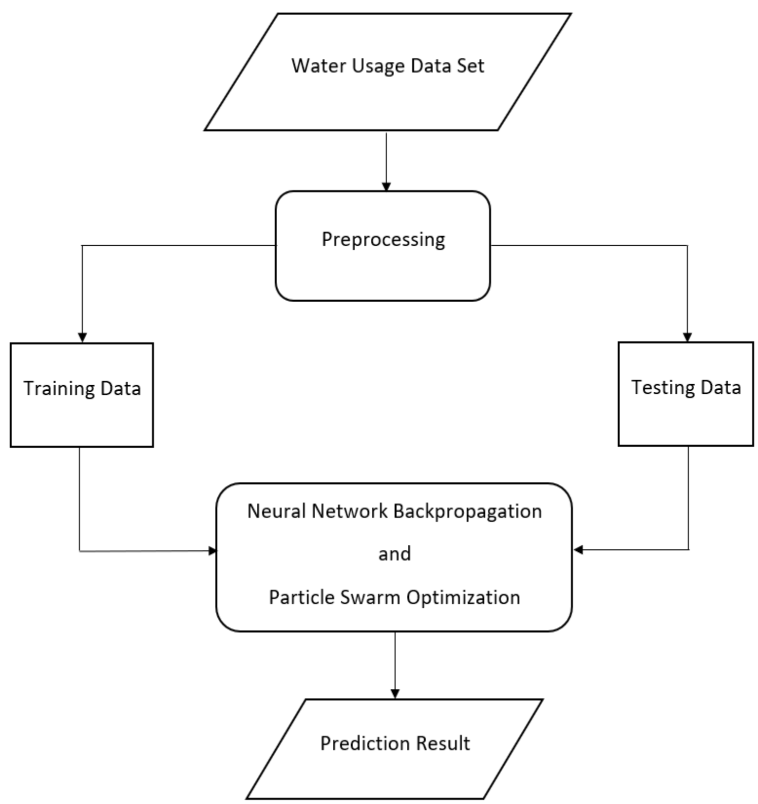

Figure 3 Model Design

IV. Results

4.1 Evaluation of Results with BPNN on Rapid Miner

To determine the best model between 1 period variable to 5 period variables in PDAM data using a validation number of 10 and a kernel numeric type, where the experimental model results from the neural network method using Rapidminer are measured using RMSE. Determination of parameters in the neural network is used to find the best model for making predictions, namely by finding the best value for each existing parameter.

After obtaining the best model from BPNN, the selected model in the next experiment was to determine its parameters, including the training cycle, learning speed and momentum as well as hidden layers. With the results obtained RMSE at least 0.043 with two layers obtained RMSE value, namely hidden layer 1 with size 5 and hidden layer 2 with size 2, training cycle 600, learning rate 0.1 and momentum 0.2. The best BPNN architecture obtained based on experiments that can be carried out can be seen in Figure 4.

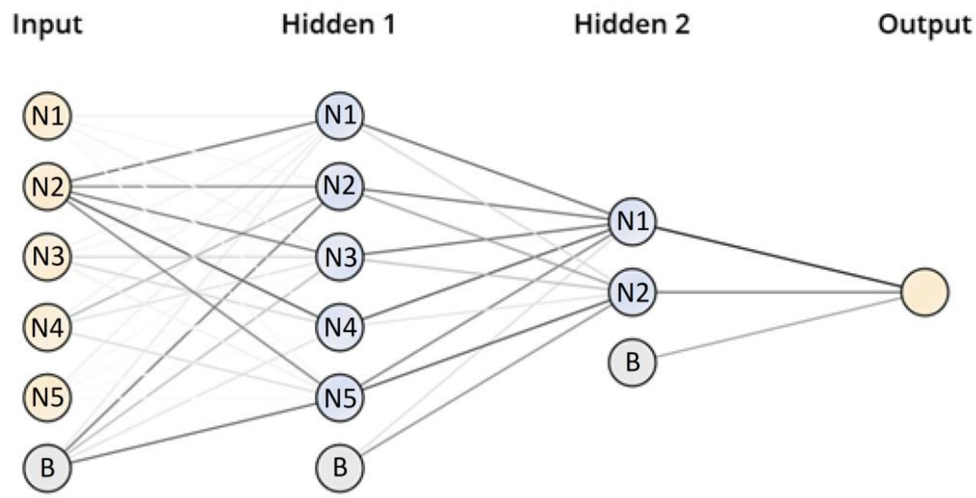

Figure 4 Architecture of Water Use Backpropagation Neural Network

The best architecture that shows three layers namely input layer, hidden layer, and output layer. Where the input layer has 5 neuron inputs plus bias; while the hidden layer has 6 neurons plus a bias in hidden layer 1 and 2 hidden neurons plus a bias in hidden layer 2; and the output layer has 1 output neuron.

```
Hidden 1:

Node 1 (Sigmoid)
----------------
blth: -0.224
normalized water price: 2,130
total normalization: -0.198
contract_no: 0.191
id: 0.226
Bias: -0.307


Node 2 (Sigmoid)
----------------
blth: 0.121
normalized water price: 1,764
total normalization: 0.122
contract_no: 1,057
id: -0.093
Bias: -1,942
```

```
Node 3 (Sigmoid)
----------------
blth: 0.176
normalized water price: 1,980
total normalization: -0,594
contract_no: -0.411
id: -0.083
Bias: -0.907

Node 4 (Sigmoid)
----------------
blth: 0.040
normalized water price: 2,445
total normalization: -0.574
contract_no: 0.041
id: -0.057
Bias: 0.402

Node 5 (Sigmoid)
----------------
blth: -0.109
normalized water price: 1,812
total normalization: 0.213
contract_no: -0.491
id: 0.064
Bias: -2,254
```

Hidden 2:

```
Node 1 (Sigmoid)
----------------
Node 1: -2.257
Node 2: -2,119
Node 3: -2.223
Node 4: -2,463
Node 5: -1,870
Bias: -0.448

Node 2 (Sigmoid)
----------------
Node 1: -0.534
Node 2: -1,381
Node 3: -0.906
Node 4: -0.384
Node 5: -2,517
Bias: 1,601
```

Output:

```
Regression (Linear)
-------------------
Node 1: -3,530
Node 2: -2.105
```

Information:
The weight values at node 1 to node 5 in the hidden layer 1 and node 1 to node 2 in hidden layer 2 are the weight values and the connecting bias on the input to get the value of each neuron in the hidden layer, while the weight value at node 1 until node 2 in the output is a link from the hidden layer to get the value on the output.

4.2 Evaluation of Results with BPNN and PSO on Rapid Miner

In testing using backpropagation neural network and particle swarm optimization, the backpropagation neural network model used is a model that has been tested before with the best parameters. To initialize the components in particle swarm optimization, the number of particles in the neural network is a representation of the particles in particle swarm optimization.

In the previous stage, the best model was produced using BPNN for 1 period variable up to 5 period variables where the values of training cycle, learning rate, momentum, and neuron size were 600, 0.1, 0.2, and 3 respectively with 2 period variables and obtained the RMSE result is 0.043. This stage is the result of an experimental model of the backpropagation neural network method based on particle swarm optimization using Rapidminer which is measured using RMSE. Experiments were carried out trial and error with a number of existing parameters both for BPNN and for PSO. The results obtained from this experiment state that the RMSE value obtained is lower. The following are the results of an experiment to determine the best model of backpropagation neural network based on particle swarm optimization.

Table 1 PSO Test Results

Population	***Max of generation***	**Inertia Weight**	***Local Best***	***Global Best***	**RMSE**
8	100	0.3	1	0,1	0,42
8	100	0.3	1	0,2	0,41
8	100	0.3	1	0,3	0,41
8	100	0.3	1	0,4	0,42
8	100	0.3	1	0,5	0,42
8	100	0.3	1	0,6	0,41
8	100	0.3	1	0,7	0,41
8	100	0.3	1	0,8	0,42
8	100	0.3	1	0,9	0,41
8	100	0.3	1	1,0	0,40

It can be seen from the experimental results in table 1 that testing using PSO-based BPNN with the existing parameters produces a low RMSE value. Where for the PSO parameter for the max.of generation 100 value and inertia weight 0.3 with the local best weight value 1.0 and the global best weight 1.0 value, the smallest RMSE value is 0.040. Based on the results of experiments that have been carried out with PSO-based BPNN using the best parameters and get the smallest RMSE results, namely 0.040 in the variable period 2.

4.3 Evaluation of Model Comparison Results

The following is the comparison of the RMSE values resulting from the experiments that have been carried out, namely experiments using backpropagation neural networks and backpropagation neural networks based on particle swarm optimization.

Table 2 Comparison of RMSE

Method	**RMSE**
Backpropagation Neural Network	0.043 +/- 0.026 (mikro: 0.051 +/- 0.000)
Backpropagation Neural Network Based on Particle Swarm Optimization	0.040 +/- 0.029 (mikro: 0.049 +/- 0.000)

Table 2 shows that the RMSE value obtained from the experiment using backpropagation neural network based on particle swarm optimization is better than the RMSE results obtained from experiments using backpropagation neural networks only.

V. CONCLUSIONS

5.1 Conclusion

The prediction of the amount of water usage using the PSO-based Neural Network Backpropagtaion algorithm was successfully carried out. Based on the research results, the lowest RMSE value is obtained in the backpropagation neural network based on particle swarm optimization with parameters for training cycle values of 600, learning rate 0.1 and momentum 0.2, and neuron size is 3 and in particle swarm optimization the value of population size 8, max.of value. geneation 100, inertia weight 0.3, local best weight 1.0 and global best weight 1.0 resulted in a better RMSE value. Testing using backpropagation neural network alone produces an RMSE value of 0.043, while using a backpropagation neural network model optimized with particle swarm optimization results in a smaller RMSE value of 0.040. The RMSE results obtained prove that the Particle Swarm Optimization method of optimizing the weight of the backpropagation neural network is proven to improve the performance of the algorithm and produce a better RMSE value than without the optimization method.

Based on the analysis and description above, it can be concluded that the prediction of water use uses the Backpropagation Neural Network and PSO. provide better and more accurate prediction results in predicting water use.

5.2 Suggestions

Based on the background, the researcher provides several suggestions that can be considered, namely:

1. Using all of the more customer data is not only limited to 2 years (2015-2016) in developing data processing patterns
2. Comparing the algorithms used, so not only Neural Network algorithms, can also make comparisons such as KNN and other Neural Networks
3. Implementing the program or application for PDAMs as big data which will be useful for other data mining processes.

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