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PSO optimization on backpropagation for fish catch production prediction

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ABSTRACT

Global climate change is an issue that is enough to grab the attention of the world community. This is mainly because of the impact it has on human life. The impact that is felt also occurs in waters on the South Kalimantan region. This is of course can disrupt the productivity of fish in the marine waters of South Kalimantan. This study aims to make fish catch production prediction models based on climate change in the South Kalimantan Province because the amount of productivity of marine fish has fluctuated. This study uses climate data as input and fish production as output which is divided into two, namely training and testing data. Then the prediction is conducted using Backpropagation method combined with Particle Swarm Optimization method. The results of the study produced a prediction model with RMSE of 0.0909 with a combination of parameters used, namely, C1: 2, C2: 2, w: 0.7, learning rate: 0.5, Momentum: 0.1, Particles: 5, and epoch: 500. While the model used when predicting testing data produces RMSE of 0.1448.

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1. INTRODUCTION

Fish production in South Kalimantan are produces from various activities such as in the form of cultivation and catch. The amount of fish from marine catch in 2016 divided into quarter year. It reached 34,161 tons in the first quarter, 47,260 tons in the second quarter, 36,785 tons in the third quarter, and 58,299 tons in the fourth quarter [1–3]. There is a significant decrease and increase in the amount of fish production. Thus, it is difficult to provide policies related to fisheries production with such behavior. There are also problems related to the marketing of fish itself in order to increase regional income from the province itself.

There are a number of problems related to fish production in South Kalimantan which have resulted in a decline in local fish production as stated by the secretary of the South Kalimantan Marine and Fisheries Agency (DKP) that sea fisheries production in South Kalimantan has fluctuated from year to year due to fishermen from other regions illegal fishing including overfishing or not having a permit in the waters of South Kalimantan. There is also another issue related to climate, namely global warming. This of course also affects the condition of marine fisheries that occur in South Kalimantan.

In a study conducted by Muhammad Azhar Razak and Edwin Riksakomara, about forecasting the amount of fish production in Banjarmasin using the backprogation method. The results given in using the method succeeded in producing around 20% errors in the testing process with the supporting variables namely air temperature [4]. Other studies by Putri and Agus [5] in the prediction of catfish production in

Sleman District with the neuro fuzzy model can conclude that the results obtained by measuring MAPE are quite good at 20% in training data and data testing. Model obtained is the second model with input models based on catfish production data four months earlier. Other research also mentions that the backpropagation method along with optimization with PSO in the study of vegetable price predictions conducted by YE Lu, et al. obtained a good result. It can be seen the results of this study stating that the accuracy in the form of MSE given through research between predictions using only backpropagation and backpropagation along with PSO resulted in a value of 0.0029 and 0.0010. It can be seen from the research that PSO can be quite good at reducing the existing MSE so that better prediction results are obtained [6].

Based on what has been described above, the research conducted in this paper is aiming to predict fish catch production against climate change using the Backpropagation method in South Kalimantan province, but by having supporting variables or more inputs such as rainfall and wind speed coupled with Particle Swarm optimization. It is because the method applied using backpropagation and optimized with PSO can provide the best predictive results based on the existing research.

2. LITERATURE REVIEW

2.1. Fish production

As climate conditions change in the world, the resulting fish production experiences a rise and fall due to this phenomenon. In South Kalimantan itself, climate change affects the condition of existing fish production. Many studies have suggested the effect of fish production on climate , namely the direct interaction of climate for fish production that occurs [7–12]. Marine fish production is influenced by climate elements in the form of rainfall, wind speed, and air temperature.

2.2. Climate change

With the impact of climate change, the levels of CO2 in the air layer can also experience an increase which directly increases the temperature of the earth including aquatic components, such as rivers, lakes and the sea. Climate change is characterized by several phenomena, such as changes in average or median values and variations in climate elements [13–15]. Temperature increases in the long run and tends to increase over time. In addition, changes in rainfall patterns that are marked by the late start of the wet season and the end of the rainy season are faster. Where the rainy season is shorter but with a high intensity of rainfall, climate change can be said [16–18]. The occurrence of the phenomenon of climate change in Indonesia, especially in South Kalimantan can be observed from the changes in the average long-term rainfall in the region as shown in Figure 1.

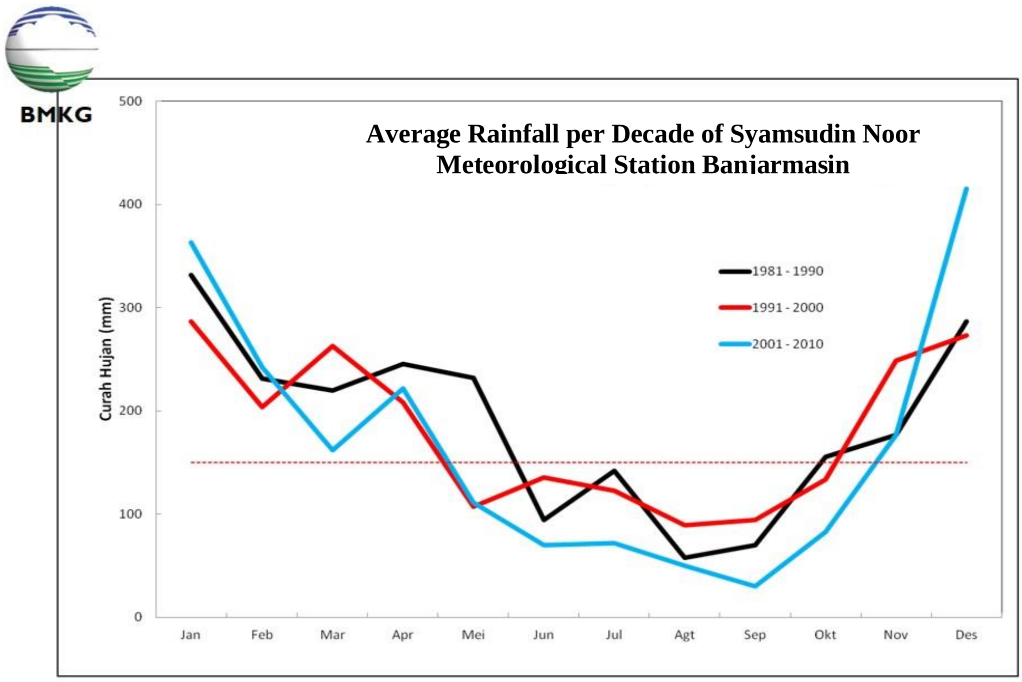

Figure 1. Graph of normal rainfall changes

2.3. Normalization

Data attribute values that vary in range often need to be normalized or standardized so that the data mining process is not biased. Normally data normalization is carried out in small ranges, such as 0-1 or 1 - (-1), so that all attributes will have the same weight. Normalization techniques are very important in data mining, especially classification and clustering [19, 20]. Of the many strategies used in normalization, this study used the normalization method called min-max. As the name implies, this method uses minimum and maximum values to convert data linearly. It can be seen through calculations or the following formula. After that there is a formula for normalizing normalized data [21–23]:

$$X' = \frac{(X - X_{min})}{(X_{max} - X_{min})} X'_{max} - X'_{min} + X'_{min} \tag{1}$$

where,
X' = normalization result
X = data that will be normalized
X_{max} = máximum value of overall data
X_{min} = minimum value of overall data
X'_{max} = new maximum value
X'_{min} = new minimum value

$$x = (x' \times (x_{max} - x_{min})) + x_{min} \tag{2}$$

where,
X = denormalization result
X' = data that will be denormalized
X_{max} = maximum value of overall data
X_{min} = minimum value of overall data

2.4. Root mean square error (RSME)

Root Mean Square Error (RMSE) is a measure to calculate the magnitude of errors in predictions, RMSE has been used as a standard statistical metric for measuring model performance in meteorology, air quality, and climate research studies [24, 25]:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (Yi - \hat{Y}i)^2}{n}} \tag{3}$$

where,
Yi = actual data
$\hat{Y}i$ = final data (estimated data)
N = amount of data

2.5. Backpropagation

Backpropagation is an algorithm on artificial neural networks that is often used in searching for optimal weights. In the backpropagation network there are the desired input patterns and output patterns. When a network is given a pattern, the values of weights are changed in order to minimize the difference between the output pattern of the network and the desired output pattern. Network training is carried out repeatedly until all output patterns from the network can recognize the desired output pattern [6, 21, 26].

The termination condition used in this algorithm is the maximum number of iterations and error targets. Training will be stopped if the number of training iterations exceeds the maximum number of iterations or if the error obtained in the training is smaller than the target error.

2.6. Particle swarn optimization

PSO is a population-based optimization technique developed by Eberhart and Kennedy in 1995, which was inspired by the social behavior of birds or fish flocks [22, 23]. PSO can be assumed as a group of birds looking for food in an area. Birds that are looking for food do not know exactly where the food is located, so what the bird does is look for the best strategy to find these foods by following the closest birds to these foods [6]. Following are the equations in the PSO formula:

$$vi,d = w * vi,d + c1 * R * (pbesti,d - xi,d) + c2 * R * (gbestd - xi,d) \quad (4)$$

$$xid = xi,d + vi,d \quad (5)$$

W = Inertial weighting factor
c1, c2 = learning rate constant
R = random number (0-1)
Xi, d = Current position of the i-th particle in the i-th iteration
Pbesti = Previous best position of i-th particle
Gbesti = The best particle among all parts in a group or population
n = Number of particles in a group
d = Dimension

3. RESEARCH METHODOLOGY

The design of the existing model is an illustration of the model that will be made according to the initial needs based on data analysis that has been done before. Data to be used are climate data and production data every 3 months. The data collected will be divided into two namely training data to get the model and testing data to evaluate the results of the model. The training data will be normalized and then trained using backpropagation and PSO, after getting the best model then we apply the model to the normalized testing data to get results. The description of the model design that will be made can be seen through the following Figure 2.

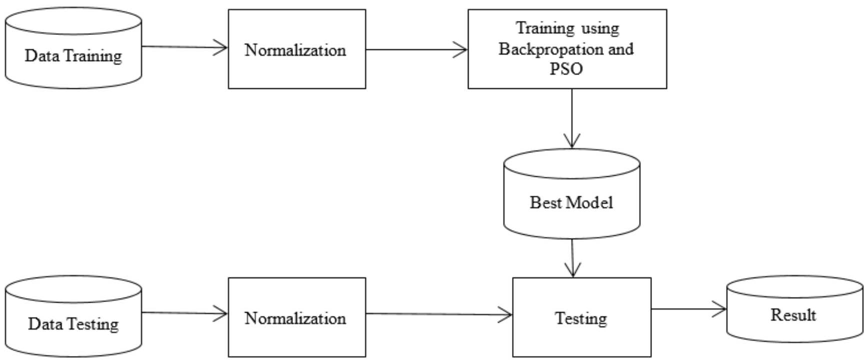

Figure 2. Model designing

4. RESULT AND ANALYSIS

4.1. Data processing

The data that will be used in this study is in the form of monthly climate data which includes related indicators that are needed. Climate data was obtained from the Class I Banjarbaru Meteorology and Geophysics Agency, where the climate data obtained from Syamsudin Noor station and technical implementing units in areas close to the sea. The climate data is from 2008-2016 and the climate data obtained is 102 data. The next data related to fish production was obtained through the South Kalimantan Province's Office of Marine and Fisheries where data obtained is fish production data in the form of production quarter totaling 36 data. The following input data is shown in Table 1 and the target data is shown in Table 2.

Table 1. Input data used

No	Year	Month	Rainfall	Wind Velocity	Temperature
1	2008	January	465	4	26
2	2008	February	81	3	27
…	..	..	..	..	..
107	2016	November	231	3	28
108	2016	December	723	3	27

Table 2. Target data to be used

No	Year	Fish Production (Quarterly)	Production in Ton
1	2008	January - March	35211
2	2008	April-June	30431
…	..	..	..
35	2016	July-September	36785
36	2016	October-December	58299

4.2. Discussion

4.2.1 Experiment to obtain best model

In the Backpropagation and PSO methods, there are parameters that will be used and the purpose of this step is to find the right combination of parameters that we can also see the results before. The parameters contained in the PSO method c1, c2, and w have been determined in advance or default because the results in the weight searching are found to be very good. The values given are c1 = 2, c2 = 2, w = 0.7, learning rate = 1-5, momentum = 0.1-0.5, number of particles = 5-7 and epoch = 500. Based on research conducted by Harry Ganda Nugraha and Azhari in the research title "Training of Artificial Neural Network Weight Using Particle Swarm Optimization for Forecasting Inflation Levels" it is said that hidden layers can affect the value of the obtained RMSE. The following is an attempt to get the result from different architecture that has the number of neurons 3 to 7 in the hidden layer and the results of the research can be seen below with the experimental data training ratio and the test is 80:20. With the given learning rate, the number of particles and fixed momentum, the experiment is conducted to see the effect given by the number of different neurons in the hidden layer.

As seen in Table 3, the value generated on the architecture with the number of nerves in the hidden layer is 3 has the smallest RMSE value than the others. This proves that the number of nerves or nodes in the hidden layer has an effect in minimizing the errors that occur, only the value given does not have a significant effect. Then the experiment will be carried out again by looking at the effect of the given learning rate on the value of the predictions. The result of prediction with different learning rate can be seen below.

As seen in Table 4 the smallest error value is generated by a learning rate with a value of 4. The results obtained through this value are 0.1075 on the data training list. In this case the learning rate itself is the value of the rate of learning to control changes in weight obtained through calculations in each iteration. Thus, the learning rate value of 4 can control the rate of learning in well-obtained weights not like the other values given. Next, the experiment is done again by making changes to the momentum value, this also aims at whether the value given can affect the value of the errors that occur. The following results from this experiment can be seen through the following Table 5.

Table 3. Experiment result of different hidden layer

Architecture	α	Momentum	Momentum	RMSE of Data Training	RMSE of Data Testing
9-3-1	**1**	**0.1**	**5**	**0.1469**	**0.2001**
9-4-1	1	0.1	5	0.1471	0.2014
9-5-1	1	0.1	5	0.1444	0.2226
9-6-1	1	0.1	5	0.1481	0.2270
9-7-1	1	0.1	5	0.1495	0.2287

Table 4. Experiment result of different learning rate

Architecture	*Learning Rate*	Momentum	Particle	RMSE of Data Training	RMSE of Data Testing
9-3-1	1	0.1	5	0.1469	0.2001
9-3-1	2	0.1	5	0.1346	0.2129
9-3-1	3	0.1	5	0.1304	0.2174
9-3-1	**4**	**0.1**	**5**	**0.1075**	**0.1797**
9-3-1	5	0.1	5	0.1156	0.2098

Table 5. Experiment result of different momentum

Architecture	α	Momentum	Particle	RMSE Data Training	RMSE Data Testing
9-3-1	4	0.1	5	0.1075	0.1797
9-3-1	4	0.2	5	0.0911	0.1598
9-3-1	4	0.3	5	0.0923	0.1532
9-3-1	4	0.4	5	0.0961	0.1646
9-3-1	**4**	**0.5**	**5**	**0.0901**	**0.1511**

As seen in Table 5, the results of experiment by making changes to the momentum value do not increase the RMSE value obtained. The best result is obtained when the momentum value given is 0.5. This proves that the momentum value does not significantly affect the RMSE value obtained. It also proves that if the given momentum value approaches the value of 1, where 1 is the maximum value of momentum, overshoot will occur. This is an error in forecasting where the value given exceeds the value that should be and this causes the change in weight obtained to be not varied. This process of giving different momentum values determines how fast the process is needed [21].

The next experiment is to find the smallest RMSE value obtained by changing the value of the existing particles. The following comparison can be seen in Table 6. Table 6 shows the results obtained after changing the number of particles. It is found that the addition of particles can actually make the RMSE value larger, ineffective and also in the process carried out the time needed is longer. This is because the number of particles given is greater so that the search for the best value takes longer.

Table 6. Experiment result of different amount of particles

Architecture	α	Momentum	Particle	RMSE Data Training	RMSE Data Testing
9-3-1	**4**	**0.5**	**5**	**0.0901**	**0.1511**
9-3-1	4	0.5	6	0.0972	0.1523
9-3-1	4	0.5	7	0.0909	0.1544

4.2.2 Method comparison

The comparison results of the two methods namely Backpropagation using PSO and Backpropagation without using PSO can be seen through the following Table 7. The results of these comparisons prove that the results given by the Backpropagation method using PSO get better RMSE results than methods that only use Backpropagation. This also proves that in the training process the PSO method is more effective than the Backpropagation method. the results of the comparison between the predictive value and the actual value of fish catch production in ton given by the two methods can be seen through the following Table 8.

Table 7. RMSE comparison of two method

Method	RMSE Training	RMSE Testing
Backpropagation+PSO	0.0909	0.1448
Backpropagation	0.1483	0.2121

Table 8. Comparison of Actual Data and Prediction Data from Two Methods

Actual Data (Ton)	Prediction Result	
	Backpropagation+PSO (Ton)	Backpropagation (Ton)
34161	40531	40204
47259	41250	40142
36785	41704	42312
58299	58257	58021
Difference Averages	4.257,75	4.741,25

Table 8 shows that the Backpropagation only method gives the most difference result between the actual value and the predictive value. This can be seen from the results of the average difference given by the two methods to the actual value. Backpropagation + PSO method has an average difference of 4,257.75 while the average difference results given by the Backpropagation only method are 4.741.25. Thus, the results of predicted value that are closer to the actual value are obtained by the Backpropagation + PSO method, because the difference between predicted and actual value is smaller.

5. CONCLUSION

Based on the results of the analysis and discussion of the experiments that have been carried out, it can be concluded that the results of predictions obtained are quite good. It is seen in the average difference between the predicted and the actual value of 4,257.75. As of predictions of fish production on climate change can be implemented using the Backpropagation method combined with PSO. Prediction models using monthly climate data from the Meteorological Station Syamsudin Noor produce RMSE of 0.1448 with a combination of parameters used, namely, C1: 2, C2: 2, w: 0.7, learning rate: 4, Momentum: 0.5, Particles: 5, and epoch: 500.

From these results it can also be concluded that to obtain the appropriate prediction model, the optimal combination of parameters and the suitability of the data with the parameters are needed to get the best predictive model results. In addition, the amount of data used also has influence, because the more data used in the training process and the more data variations can be learned by the model the accuracy results obtained will be higher. By applying the Backpropagation and PSO method, the RMSE accuracy value obtained from the prediction is 0.1448. This means that the method applied in this study is good enough to predict fish production against climate change (rainfall, wind speed, and temperature)

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