Application of Artificial Neural Networks to forecast *Litopenaeus vannamei* and *Penaeus monodon* harvests in Indramayu Regency, Indonesia

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Abstract. Besides minimizing environmental impact, one of the goals of ecological intensification for aquaculture is production. Production forecasting is needed to make policies in planning, especially in terms of meeting consumer demand. This paper introduces a method to forecast the total shrimp production for *Litopenaeus vannamei* and *Penaeus Monodon* in Indramayu Regency using artificial neural networks. In this case, we used backpropagation neural networks (BPNN). BPNN is a supervised learning algorithm and usually used by perceptron with many layers to change the weights associated with the neurons in the hidden layers. During the training process, the network calculated the output that will be generated based on the given input patterns. The network assigned and adjusted the weights of the input and also the hidden layer to obtain a network with good performance. Networks with small error values close to zero indicate good performance. The criteria used to test the performance of the artificial neural networks method are the root mean squared error (RMSE), the mean absolute percentage error (MAPE), and the correlation coefficient (r). Production data obtained from the relevant government agencies were used to train the algorithms as a part of an artificial intelligence process. This artificial intelligence forecasted the shrimp's harvest. Forecasting performance is indicated by the accuracy of the prediction process data compared to the real data. The best result for *L. vannamei* forecasting was obtained in the trainGD with MSE 0.0174 and MAPE 19.28%. The best results for *P. monodon* forecasting were obtained in the TrainRP with MSE 0.0200 and MAPE 22.99%.

Keywords: *Litopenaeus vannamei*, *Penaeus monodon*, Artificial Neural Networks, forecasting

1. Introduction

Ecological intensification as a new concept not only applied in agriculture but also in aquaculture. Besides minimizing environmental impacts, one of the goals of ecological intensification for aquaculture is increasing production [1, 2]. Production forecasting is needed in policy making as well.
as in strategic planning of aquaculture development as part of the effort to meeting consumer demands. Forecasting is a method for estimating or predicting events that will likely occur in the future using the combination of time series data and mathematical models. The current development of science and technology have made it possible that mathematical equation models can be worked out by computer systems in the form of an artificial neural network algorithm. Artificial Neural Network (ANN) is a computer program serving as an artificial representation of the human brain that can carry out the learning and training process and be able to make conclusions from the pieces of information it received [3].

Technically, the ANN components consist of neurons and the connections that connect these neurons called weights [3]. Neurons are typically organized into multiple layers called neuron layers. The input layer will first receive information given to ANN. This information will be passed to hidden layers. This hidden layer is the main function of ANN. In this hidden layer, the data received from the input layer will be processed and sent to the output layer. In this output layer, the learning process algorithm takes place [4]. Artificial neurons work in the same way as biological neurons. Input information will be sent to neurons with a certain weight. This input will be processed by a function that will add up the values of all incoming weights. This sum is compared with a certain threshold value through the activation function of each neuron. If the input passes a certain threshold value, the neuron will be activated, if it does not pass the threshold value, then the neuron will not be activated. If the neuron is activated, the neuron will send output through the output weights to all neurons associated with it [5].

Run Yu, et al., researched L. vannamei shrimp growth by using ANN and compared with nonlinear regression models [6]. Drews-Jr, et al., forecasted the harvest of Pink Shrimp in Patos Lagon Estuary using the approach of machine learning algorithms which included support vector machines, decision trees and rules learning and combined with meta-learning techniques [7]. ANN has also been used in several studies in the field of fisheries such as fish species identification, fish classification, and forecasting the life cycle of fish ranging from eggs, fish growth to fish age [8]. ANN has been used to predict yields of agricultural products such as rice in Nepal [9] and in the Phimai district, Thailand [10], both using the backpropagation algorithm.

Such a wide application of ANN might provide important insight into shrimp aquaculture in which is one of the main commodities of Indonesian fisheries. In 2017, the value of shrimp production reached Rp. 58,135,245,835,000 and occupied the top rank of the Indonesian fisheries commodity production [11]. Production forecasting is needed to make decisions or policies in the planning of aquaculture development especially to meet consumer demands. This paper used the method of artificial neural networks to provide a forecast regarding the total production of shrimp (L. vannamei shrimp and P. monodon) based on time series data.

2. Materials and methods

2.1. Backpropagation neural networks
The forecasting method in this research used backpropagation neural networks (BPNN). BPNN is a supervised learning algorithm and usually used by perceptron with many layers to change the weights associated with the neurons in the hidden layers. During the training process, the network calculated the output that will be generated based on the given input patterns. The network assigned and adjusted the weights of the input and also the hidden layer to obtain a network with good performance. Networks with small error values close to zero indicate good performance [12].

Neural network design is aimed to obtain high performance and good recognition networks with shorter time processing and a small number of iterations, low error rates, and accurate output. The first step in designing a network model is to determine the activation function. An activation function is a function that changes the input network or translates a previous activation into a new activation with a predetermined threshold value [13]. Activation functions are usually included between layers in the network to improve the ability of the multi-layer neural network [14]. The activation function often
used is the binary sigmoid function which has a range value between 0 and 1. Another function used is the bipolar sigmoid function which has a range value of -1 and 1.

The sigmoid function has a maximum value = 1. Therefore, if the target pattern is >1, the input and output patterns must be transformed first so that all the patterns have the same range as the sigmoid function used. Another alternative is to use the sigmoid activation function only on screens that are not output screens. On the output screen, the activation function used is the identity function: \( f(x) = x \) [15].

The proposed method BPNN algorithm in this study was implemented in Matlab and performed on notebook Intel® Core™ i7-7500U CPU @2.70 GHz with 8.0 GB installed memory under Microsoft Windows 10 Home Single Language edition.

2.2. Normalizing data
Production data of *L. vannamei* shrimp and *P. monodon* obtained from the relevant government agencies were used to train the algorithms as a part of an artificial intelligence process. Those datasets consisted of 60 production values every month for the past five years, from 2014 to 2018. Data normalization aimed to adjust the value of the input to the activation function used. Shrimp production has either 0 or positive values meaning that the normalization interval was between 0 and 1. The activation function used in this study was the binary sigmoid, so the normalization equation used was as follows:

\[
x' = \frac{b(x-a)}{b-a} + 0.1
\]

Where \( a \) is the minimum data, \( b \) is the maximum data, \( x \) is the original data, and \( x' \) is the normalized data.

2.3. Performance evaluation
The criteria used to test the performance of the artificial neural networks method are the root mean squared error (RMSE), the mean absolute percentage error (MAPE), and the correlation coefficient (r) [12, 16]. The expression of RMSE, MAPE, and correlation coefficients are as follows:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y_i')^2}
\]

\[
MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - y_i'}{y_i} \right| \times 100\%
\]

\[
r = \frac{\sum_{i=1}^{n} (y_i - \bar{y})(y_i' - \bar{y}')}{\sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2 \sum_{i=1}^{n} (y_i' - \bar{y}')^2}}
\]

Where \( n \) is the actual number of data, while \( y_i \) and \( y_i' \) represent the original data and the forecasted data. Whereas \( \bar{y}_i \) and \( \bar{y}'_i \) are the average value of original and predicted data.

3. Results and discussion

3.1. *L. vannamei* and *P. monodon* production data sets
The datasets of *L. vannamei* shrimp and *P. monodon* production are presented in Fig. 1. It appeared that the data had seasonal and cycle patterns every year. During January and February, the shrimp production tended to decrease, and then increased in March and followed by constant production values until the third quarter. Then, the shrimp production increased again in the fourth quarter. The shrimp production data also showed an increase in total production from year to year.
3.2. Networks Architecture

The first procedure of BPNN forecasting is to develop a network architecture and train it using training datasets. When the network performance shows a good result, the networks are stored and then reused to forecast the next data. In this study, the shrimp production data from 2014 to 2018 were divided into two sets, training data, and test data. Shrimps production data for 2014-2016 were used as the training data, and 2017 data were used as the target data. After obtaining a good network architecture, the simulation/testing was carried out using the production data of 2015 – 2017 to forecast the production values for 2018. The relative performance of the forecasting model can be determined by comparing the real production and forecasted data of 2018.

The network architecture design consisted of an input layer containing 3 years of production data; one output layer and three hidden layers containing 24 neurons in the first layer, 12 neurons in the second layer, and 1 neuron in the third layer. The activation function used was the binary sigmoid function. The training parameters used included the learning rate of 0.01, the maximum epoch of 1000, the MSE of equal to or less than $10^{-6}$ as a criterion for terminating the training process. In this study, there will be several training functions such as trainLM, trainGDX, trainGD, trainRP, and trainGDA. The architecture of backpropagation neural networks is shown in Fig. 2.
3.3. Forecasting of *L. vannamei* production

Fig. 3. shows the results of a comparison of the training functions of forecasting *L. vannamei* production using BPNN. The training functions used were trainLM, trainGDX, trainGD, trainRP, and trainGDA. The training process used 2014 – 2016 production data to forecast the shrimp production for 2017. Then, the developed network was simulated for 2018 production forecasting using the 2015-2017 shrimp production datasets. In the training stage, 2017 forecasting results produced similar values to the 2017 real production data on almost all training functions. Table 1. shows the performance of each training function. The lowest MSE, RMSE, and MAPE values were obtained by the trainGDA function followed by the trainLM and trainGD functions. These values indicate that the performance of *L. vannamei* shrimp forecasting training network in 2017 is quite good. The best ‘r’ value was also obtained by the trainGDA function followed by trainLM and trainGD, but the ‘r’ value in the trainRP and trainGDX functions were also considered good. This means that the forecasting network models successfully interpreted the tendency and variation of the 2014-2016 training data.

![Figure 3. Comparison between forecasting results with the real *L. vannamei* Shrimp production data](image)

Table 1. Training results comparison (*L. vannamei*)

| Year | trainLM | trainGDX | trainGD | trainRP | trainGDA |
|------|---------|----------|---------|---------|----------|
| 2017 | 0.0010  | 0.0016   | 0.0015  | 0.0011  | 0.0011   |
| MSE  | 0.0312  | 0.0404   | 0.0387  | 0.0336  | 0.0328   |
| RMSE | 3.28%   | 4.85%    | 4.28%   | 5.18%   | 2.67%    |
| MAPE | 0.9789  | 0.9626   | 0.9648  | 0.9739  | 0.9796   |
| R    |         |          |         |         |          |

Table 2. Prediction results comparison

| Year | trainLM | trainGDX | trainGD | trainRP | trainGDA |
|------|---------|----------|---------|---------|----------|
| 2018 | 0.0219  | 0.0211   | 0.0174  | 0.0341  | 0.0183   |
| MSE  | 0.1481  | 0.1453   | 0.1321  | 0.1847  | 0.1352   |
| RMSE | 20.86%  | 24.96%   | 19.28%  | 29.24%  | 21.59%   |
| MAPE |         |          |         |         |          |

However, the results of forecasting *L. vannamei* production for 2018 were different from the training results. Table 2 showed that MSE, RMSE, MAPE values are greater than that of the training data.
stage. This indicates that the results of forecasting are still not close to the actual data. This could be attributed to the relatively small amount of data used. Such limited information has caused the network models not able to generalize the input data. Another possible reason was that the *L. vannamei* production data in 2018 have fluctuation patterns different from the previous years.

### 3.4. Forecasting of *P. monodon* production

Similar results were obtained in the process of forecasting *P. monodon* production as shown in Fig. 4. The network's training performance indicates good and consistent results where ‘r’ correlation value was close to 1. This means that there was a strong correlation between the real data and production forecasting data for 2017. Table 3. shows the performance of each training function. MAPE, MSE, and RMSE values which indicate the deviation of the forecasted data from the real one are also quite low. Fig. 4 depicts that the forecasting values of *P. monodon* prawns during network training were close to the actual values.

![Figure 4. Comparison of forecasting results with the real *P. monodon* Shrimp Production data](image)

**Table 3.** Training results comparison (*P. monodon*)

| Year | trainLM | trainGDX | trainGD | trainRP | trainGDA |
|------|---------|----------|---------|---------|----------|
| 2017 | MSE 0.0020 | 0.0051 | 0.0027 | 0.0002 | 0.0007 |
|      | RMSE 0.0446 | 0.0716 | 0.0519 | 0.0154 | 0.0265 |
|      | MAPE 2.28% | 4.51% | 6.77% | 1.37% | 3.18% |
|      | R 0.9719 | 0.8816 | 0.9458 | 0.9962 | 0.9857 |

| Year | trainLM | trainGDX | trainGD | trainRP | trainGDA |
|------|---------|----------|---------|---------|----------|
| 2018 | MSE 0.0349 | 0.0427 | 0.0366 | 0.0200 | 0.0546 |
|      | RMSE 0.1868 | 0.2066 | 0.1913 | 0.1414 | 0.2337 |
|      | MAPE 26.60% | 32.06% | 29.89% | 22.99% | 37.99% |

However, the results of the network simulation where the network was used to forecast *P. monodon* production in 2018 showed a significant deviation. Table 4. shows that MSE, RMSE, MAPE values are greater than that of the training stage. The greatest RMSE value was in the training stage using the trainGDA function and the least was in the training process using the trainRP function. Similar to the results of forecasting *L. vannamei* production, forecasting of *P. monodon* shrimp production was also
not optimal arguably due to the limited input data causing ineffective ANN data generalization. The fluctuations of the total shrimp production within 2018 that is different from the previous years might also be responsible for the poor network performance results.

The best network for _L. vannamei_ forecasting was obtained in the trainGD with MSE 0.0174 and MAPE 19.28%. The best results _P. monodon_ forecasting were obtained in the TrainRP with MSE 0.0200 and MAPE 22.99%. Unlike conventional forecasting the accuracy of forecasting results using BPNN forecasting methods depend on network architecture, activation functions, and training parameters used such as learning rate and iteration. The BPNN network training process was under the procedure. However, when it applied to the test/simulation, the results obtained had MSE and MAPE values that were different from the time of the training. Possibly, the pattern of shrimp production data in 2018 has different characteristics with the data patterns of previous years.

4. Conclusion
Forecasting the shrimp production is required to properly plan the supply of shrimp production based on the market demands. It is also needed in the efforts to increase shrimp production. The BPNN method proposed in this study to predict _L. vannamei_ and _P. monodon_ productions has good performance during the training. However, the non-optimal result occurred during the production forecasting simulation. The lack of data from previous years and differences in patterns of fluctuation with the previous years are suspected as the causes of the difference between forecasting and actual shrimp production data.

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