Predict Foreign Exchange Revenue from CPO Commodity Exports Using Backpropagation Neural Network

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Abstract. Export of CPO and its derivative products is one of the biggest revenues for Indonesian foreign exchange. Through this research, predictions of foreign exchange earnings from CPO exports are made using backpropagation artificial neural networks. The data used in the form of export data for the period September 2013 to December 2016. The final results of this research using epoch 10000, learning rate 0.2, and hidden layer 10.

1. Introduction
Forecasting is a statistical method that plays an important role in making decisions. Forecasting method serves to estimate what will happen in the future based on past data. Forecasting can be done with many models, such as ARIMA, smoothing, decomposition, and so on. But with the development of technology, researchers have a desire to develop intelligent machines with a number of simple elements. In 1943 a new method was born based on the human neural network, Artificial Neural Network (ANN). ANN is defined as an information processing system that has characteristics resembling human biological neural networks. ANN is able to recognize activities based on past data, which data will be studied by ANN so that it has the ability to make decisions about data that has not been studied [1].

In international trade activities such as export and import activities, payment instruments are recognized by the world. Foreign exchange is a bank balance in foreign currency that has exchange rates from Bank Indonesia. Foreign exchange reserves are net assets of foreign assets, one of which is used to finance import activities, and managed by Bank Indonesia [2]. The main source of Indonesia's foreign exchange reserves is the result of government oil and gas exports. Foreign exchange generated from exports is useful to support the creation of a healthier financial market, maintain the stability of the rupiah value for national economic development. Indonesia is one of the developing countries and also a commodity producer that is still able to raise foreign exchange reserves. One of the biggest incomes from foreign exchange comes from export activities. The state needs foreign exchange so that export and import activities take place optimally.

Previous research discussed forecasting export and import activities in Indonesia. There are various methods available in terms of forecasting, including accuracy, scope, time horizon, and costs. Our research focuses on foreign exchange predictions. The ANN method that the writer will choose to predict foreign exchange earnings is the backpropagation method that is expected to be appropriate in solving the problem in this research. Research related to forecasting as well as implementing the
backpropagation method was carried out by previous researchers. Mislan, et al. in 2015 used backpropagation to predict rainfall in Tenggarong, East Kalimantan - Indonesia. Rainfall data totaling 276, taken from 1986 to 2008. A total of 216 data (75%) were used for training and 60 data (25%) for testing. The research produced good forecasting accuracy with an MSE value of 0.00096341 and a number of epoch 1000 [3]. In other research Muhammad in 2010 predicted the exchange rate of the rupiah against the US dollar for January - February 2010 using the backpropagation method and ARIMA (Box-Jenkins). The training data used is 80% and for testing is 20%. The MAPE value of the forecasting results with backpropagation is 0.925062% while the ARIMA (Box-Jenkins) value is 1.07946%. This shows that backpropagation proved to be more accurate than ARIMA (Box-Jenkins) because it has the smallest error value [4]. Muwakhidin in 2014 conducted research using the backpropagation and Radial Basis Function (RBF) methods to predict Indonesian sharia stock indexes. In backpropagation architecture, the researcher uses 4 input layers, 5 hidden layers, and 1 output layer. In the RBF architecture the researcher uses 4 input layers, 8 hidden layers, and 1 output layer. It is known that the backpropagation method is the best method compared to RBF because it produces MAPE of 0.023% and 0.53%, respectively [5]. Mahrina in 2014 compared the method of backpropagation and LVQ in predicting rainfall in the city of Medan. Backpropagation is considered able to provide accuracy in predicting rainfall in the last 30 years compared to LVQ. Both provide good results in the prediction of the dry season. The accuracy for backpropagation is between 75-99% and LVQ 60-82% [6].

2. Material and Method
The material and methods used in this research are explained as follows:

2.1. General Architecture
This research consists of several steps that begin with the retrieval and selection of data, where the data has been processed, such as deleting duplicate text, columns that are not relevant to research, and calculating the average value of each month, making it easier for researchers in subsequent analyses. These data are divided into two, namely training data and testing data. Then the data transformation is done to achieve the stability of the data scattering and adjust the data value with the range of activation functions. The training process with backpropagation begins with determining the weights with small numbers randomly. Backpropagation has two phases, namely feed forward and backward.

![General Architecture](image.png)

Figure 1. General Architecture.
The testing process is carried out after the training data ends. Then the weight used in the feed forward phase is the result of the training that was updated. After getting the forecasting result with backpropagation, calculate the estimated error value with MSE (Mean Square Error). The last stage is denormalization of data. Data normalization is used to convert data into the initial unit of historical data of exported goods. The output obtained from this process is the value of foreign exchange forecast for each item for the next period. Every step taken will be explained in the next section.

2.2. Input

The data used in this research is in the form of historical data of commodities exported from September 2013 to December 2016. The commodities in question are commodities of Crude Palm Oil (CPO) and its derivative products, namely oilcake, Palm Fatty Acid Distillate, RBD Palm Kernel Oil, RBD Palm Kernel Olein, RBD Palm Kernel Stearin, RBD Palm Oil, RBD Palm Olein, and RBD Palm Stearin. Examples of historical data on commodities exported along with the values of the parameters used in this research can be seen in Table 1.

| No. | Period | Foreign Exchange |
|-----|--------|------------------|
| 1   | Sep-13 | 254928           |
| 2   | Oct-13 | 305423           |
| 3   | Nov-13 | 259795           |
| 4   | Dec-13 | 252022           |
| 5   | Jan-14 | 273452           |
| ... | ...    | ...              |
| 394 | Oct-16 | 787030           |
| 395 | Nov-16 | 649144           |
| 396 | Dec-16 | 438250           |

Before carrying out the foreign exchange forecasting process using backpropagation, the data will be transformed or normalized, where the data is changed in the range of 0.1 to 0.9 using Equation 1.

\[ X_i = \frac{0.8(x_i - \text{min})}{\text{max} - \text{min}} + 0.1 \]  

(1)

2.3. Backpropagation Neural Network

Backpropagation method is an advanced learning method developed from the perceptron method. Backpropagation has a multilayer network architecture while the perceptron uses a single layer. Backpropagation method is a good method in solving complex problems. This is possible because this network of methods is trained with supervised learning. When a pair of input patterns and the desired pattern are given, the weights are changed to minimize the difference in the output pattern and the desired pattern. This exercise is done repeatedly so that all the patterns that are issued can meet the desired pattern. The following are the stages of the training algorithm for networks with one hidden layer:

- Stage 0: Initialize weights (set in small random values);
- Stage 1: As long as the stop condition is not met, do stages 2-8;
- Stage 2: Perform steps 3-8 for each pair of training data;
- Feed forward phase:
  - Stage 3: Each neuron in the input layer \((X_i, i = 1, 2, ..., n)\) receives the signal and passes it to the hidden layer;
- Stage 4: Add the weights to the hidden layer \( Z_j, (j = 1, 2, \ldots, p) \) with Equation 2. The \( Z_j \) output value is obtained by using the binary sigmoid activation function;

\[
\begin{align*}
    z_{\text{net}_j} &= v_{j0} + \sum_{i=1}^{n} x_i v_{ji} \\
    Z_j &= \frac{1}{1 + e^{-z_{\text{net}_j}}}
\end{align*}
\]  

Equation 2  
Equation 3

- Stage 5: For each neuron in the output layer \( Y_k, (k = 1, 2, \ldots, m) \), calculate all network outputs with Equation 4. The output value of \( Y_k \) is obtained by using the binary sigmoid activation function;

\[
\begin{align*}
    y_{\text{net}_k} &= w_{k0} + \sum_{j=1}^{p} Z_j v_{kj} \\
    Y_k &= \frac{1}{1 + e^{-y_{\text{net}_k}}}
\end{align*}
\]  

Equation 4  
Equation 5

Backward phase:
- Stage 6: Calculate the factors of \( \delta \) in the output unit \( Y_k, (k = 1, 2, \ldots, m) \) using Equation 6;

\[
\delta_k = (t_y - y_k) y_k (1 - y_k)
\]  

Equation 6

\( \delta_k \) is an error unit that is used to change the weight of the layer in the next stage, then calculate the change in weight (used later to change the new value of \( w_{jk} \)) with learning rate (\( \alpha \)) using Equation 7;

\[
\Delta w_{jk} = \alpha \delta_k Z_j
\]  

Equation 7

- Stage 7: Calculate the sum of \( \delta_{\text{net}_j} \) in the hidden layer \( Z_j, (j = 1, 2, \ldots, p) \) using Equation 9. Calculate the factor in the hidden unit using Equation 10. Then calculate the change rate of weight (which is used to obtain the new weight value) using Equation 11;

\[
\begin{align*}
    \delta_{\text{net}_j} &= \sum_{k=1}^{m} \delta_k w_{jk} \\
    \delta_j &= \delta_{\text{net}_j} Z_j (1 - Z_j) \\
    \Delta v_{ij} &= \alpha \delta_j x_i
\end{align*}
\]  

Equation 8  
Equation 9  
Equation 10

Weight and bias update phase:
- Stage 8: For each neuron in the output layer \( Y_k, (k = 1, 2, \ldots, m) \), change the weight and bias values;

\[
W_{jk}(\text{new}) = W_{jk}(\text{old}) + \Delta w_{jk}
\]  

Equation 11

Each neuron in the hidden layer \( Z_j, (j = 1, 2, \ldots, p) \), changes the weight and bias values.

\[
V_{ij}(\text{new}) = V_{ij}(\text{old}) + \Delta v_{ij}
\]  

Equation 12

After network training is complete, pattern recognition can be done. In backpropagation training, the network output value is only obtained in the feed forward phase. The activation function used is a binary sigmoid function.

2.4. Designing a Neural Network Architecture
The architecture for the Neural Network can be seen in Figure 2.
Figure 2. Architecture of Neural Network

with the following explanation:
- The input layer \((X_i)\) has 3 neurons plus 1 neuron bias, the hidden layer \((Z_j)\) has 3 neurons plus 1 neuron bias, while the output layer \((Y_k)\) has 1 neuron.
- \(X_1\) to \(X_3\) are neurons in the input layer, \(Z_1\) to \(Z_3\) are neurons in the hidden layer, and \(Y\) is the output layer neuron.
- \(b_1\) is the bias that leads to the hidden layer, while \(b_2\) is the bias that leads to the output layer.
- \(V_{ij}\) is the connection weight value from the input layer to the hidden layer, while \(W_{jk}\) is the connection weight value from the hidden layer to the output layer. \(V_{ij}\) is the connection weight between bias and neurons in the hidden layer, while \(W_{0k}\) is the connection weight between bias and neurons in the output layer.

3. Result and Discussion
The training is conducted five times for each commodity with a period of every eight months. Then look for the error value generated against the actual data with the prediction, resulting in an MSE value for each commodity. The epoch used is 10000, learning rate 0.2, error goal 0.0001, and hidden layer 10. Information about training data can be seen in Table 2.

Table 2. Training data description sample.

| Commodity | No. | Training Data       | Prediction | Actual  | Error  |
|-----------|-----|---------------------|------------|---------|--------|
| RBD Palm  | 1   | Sep 2013 - Apr 2014 | 902335     | 896951  | 0.0252 |
| Palm      | 2   | May 2014 - Dec 2014 | 1316037    | 1314265 | 0.0047 |
| Stearin   | 3   | Jan 2015 - Aug 2015 | 607623     | 697641  | 0.0240 |
|           | 4   | Sep 2015 - Apr 2016 | 663618     | 564741  | 0.0081 |
|           | 5   | May 2016 - Dec 2016 | Jan 2017: 592746 | 0.0141 |

Tests carried out using foreign exchange data one month from each training period. Table 2 showed that the RBD Palm Stearin foreign exchange training in the period September 2013 - April 2014 produced a predictive value of 902335, while the actual foreign exchange in May amounted to 896951. This can be influenced by the amount or amount of data and parameters, and the parameter value at the learning rate or epoch used in the training and testing process. The prediction results for January 2017 obtained for RBD Palm Stearin commodity are 592746 with MSE 0.0141.

The test serves to display information about the results of testing foreign exchange earnings predictions using backpropagation. The testing process can be carried out after the training process displays results. The results of the prediction of foreign exchange earnings are known and can be seen in Table 3.
Table 3. Foreign exchange projection results for January 2017 and MSE.

| No. | Commodity   | Prediction | MSE  |
|-----|-------------|------------|------|
| 1   | Oilcake     | 326729     | 0.015|
| 2   | CPO         | 2038196    | 0.017|
| 3   | PFAD        | 137890     | 0.014|
| 4   | PK Oil      | 556548     | 0.013|
| 5   | PK Olein    | 723703     | 0.015|
| 6   | PK Stearin  | 487002     | 0.02 |
| 7   | Palm Oil    | 205603     | 0.015|
| 8   | Palm Olein  | 926187     | 0.016|
| 9   | Palm Stearin| 592746     | 0.014|

4. Conclusion
Based on the testing of the foreign exchange earnings prediction system of the CPO commodity export sector using backpropagation, it can be concluded that backpropagation can be used to predict a data, but the large or small resulting error is influenced by several things, such as parameter values used for learning rates and epochs, many or the least amount of data and its variables.

The prediction system for foreign exchange earnings from the CPO commodity export sector using backpropagation still has weaknesses that need to be developed again. For research with the same case, it is recommended for future researchers to be able to add the number of data variables and add momentum values to get more accurate results, as well as add to the object to be studied, such as other export commodities.

References
[1] A. Hermawan, Jaringan Saraf Tiruan, Teori dan Aplikasi, Yogyakarta: Andi, 2006.
[2] J. Benny, "Ekspor dan impor pengaruhnya terhadap posisi cadangan devisa di Indonesia," EMBA, vol. 1, no. 4, pp. 1406-1415, 2013.
[3] Mislan, Haviluddin, S. Hardwinarto, Sumaryono and M. Aipassa, "Rainfall Monthly Prediction Based on Artificial Neural Network: A Case Study in Tenggarong Station, East Kalimantan - Indonesia," Procedia Computer Science, vol. 59, pp. 142-151, 2015.
[4] M. Muhammad, "Perbandingan Jaringan Syaraf Tiruan Backpropagation dan Metode ARIMA (Box-Jenkins) sebagai Metode Peramalan Kurs Rupiah terhadap Dollar Amerika Serikat," Universitas Sumatera Utara, Medan, 2010.
[5] I. Muwakhidin, "Peramalan Indek Saham Syariah Indonesia (ISSI) Menggunakan Model Backpropagation Neural Network dan Radial Basis Function Neural Network," Universitas Negeri Yogyakarta, Yogyakarta, 2014.
[6] T. Mahrina, "Analisis Perbandingan Backpropagation dengan Learning Vector Quantization (LVQ) untuk Memprediksi Curah Hujan di Kota Medan," Universitas Sumatera Utara, Medan, 2015.