JMPM: Jurnal Matematika dan Pendidikan Matematika
10 (1), 73-82
https://www.journal.unipdu.ac.id/index.php/jmpm

Print-ISSN : 2502-986X
Online-ISSN : 2502-9878
JMPM
Jurnal Matematika dan Pendidikan Matematika
Journals of Mathematics and Mathematics Education

Comparison Between Neural Network and Grey System Models for Cooking Oil Price

Fastha Aulia Pradhani[1*], Muktar Redy Susila[2], Ingka Rizkyani Akolo[3]
[1] Akuntansi, Sekolah Tinggi Ilmu Ekonomi Indonesia: Surabaya, Jawa Timur, Indonesia, 60118
[2] Manajemen, Sekolah Tinggi Ilmu Ekonomi Indonesia: Surabaya, Jawa Timur, Indonesia, 60118
[3] PGMI, IAIN Sultan Amai Gorontalo: Gorontalo, Gorontalo, Indonesia, 96112
*Corresponding author's email: fasthaaulia@stiesia.ac.id

Received: 12 April 2025 | Revised: 15 May 2025
Accepted: 21 June 2025 | Published: 3 July 2025

Abstract

Cooking oil is one of the primary raw materials used in Indonesia. In this study, a comparison of the two forecasting models from the two methods, namely Neural Network and Grey System, was carried out. Forecasting is carried out on cooking oil raw materials, namely CPO production volume and demand for related products, namely biodiesel, to analyze changes in cooking oil prices. The appropriate forecasting model is expected to be able to describe the pattern of cooking oil price fluctuations for the following few periods. The criteria for selecting the best model use the minimum MAPE testing value. The results show that the Grey System method produces the best forecasting model for biodiesel demand data with a small amount of data, while for the CPO variable, which has a larger amount of data, the best model is obtained using the Neural Network model, with the MLP (3-3-1) architecture.

Keywords: *cooking oil; neural network; grey system*

How to cite: Pradhani, F. A., Susila, M. R., & Akolo, I. R. (2025). Comparison between neural network and grey system models for cooking oil price. *JMPM: Jurnal Matematika dan Pendidikan Matematika*, *10*(1), 73-82. https://dx.doi.org/10.26594/jmpm.v10i1.3394.

INTRODUCTION

Cooking oil is one of the ingredients used in processing most foods consumed by the public, especially in Indonesia. Based on data from Ahdiat (2024), per capita cooking oil consumption has continuously increased throughout 2019-2023, but from 2021 to 2022, there was a decrease in cooking oil consumption due to the increase in cooking oil prices. In fact, according to a report from the Institute for Demographic and Poverty Studies, economic losses due to the increase in cooking oil prices are estimated to reach IDR 3.38 trillion (Yakti, 2022). The increase in cooking oil prices was triggered by several factors, including the scarcity of Crude Palm Oil (CPO) (Amanta & Nafisah, 2022).

CPO is oil obtained from the processing of oil palm fruit, which is processed into derivative products, such as cooking oil. This is by the theory stated Stevenson & Chuong (2014) that the condition of raw material scarcity can be one of the triggers for price increases in the market. The increase in CPO prices in the international market indirectly impacts the increase in derivative products due to the expensive and complex downstream costs (Mustafa, 2022).

Biodiesel is one of the derivative products derived from crude palm oil (CPO). The implementation of the B30 program has contributed to an increase in CPO demand by raising the biodiesel blending mandate from 20% to 30% in the production process (Khatiwada et al., 2021). This policy shift indicates that both CPO and biodiesel play a significant role in influencing fluctuations in cooking oil prices. Given the economic and policy implications, it is important to develop a forecasting model that captures the relationship between cooking oil prices and the production levels of CPO and biodiesel. Such a model is expected to provide a more accurate representation of price trends in the upcoming periods and serve as a valuable tool for policymakers, industry stakeholders, and consumers in anticipating and responding to market dynamics.

Forecasting is one of the decision-making and planning activities that involves predicting uncertainty in the future (Petropoulos et al., 2022). Companies forecast raw materials and demand for a product as a form of planning so that no shortage of raw materials can hamper the production process, resulting in the inability to meet consumer demand. Today, the development of forecasting methods is very rapid. In addition to qualitative forecasting, there is also quantitative forecasting. Qualitative forecasting is more subjective, while quantitative forecasting focuses more on past patterns to make predictions in the future. Forecasting is done by involving historical data. Quantitative forecasting methods are very diverse, starting from smoothing, decomposition, and causal methods. Even a forecasting method has been developed that has a way of working that imitates human neural networks. This method is known as the Neural Network (NN) method. Data processing is done through sensory input, which is processed on several neuron connections and ends at the output (Fausett, 2006).

One of the advantages of this method is that it does not require special assumptions like other forecasting methods (Dumitru & Maria, 2013). NN is also more efficient and straightforward, potentially capturing even complex relationships or non-linear relationships (Baboo & Shereef, 2010). Overfitting is one of the problems in using neural networks; the trained network produces accurate predictions only for training data, but the same results do not occur when testing new data. One solution to overcome this problem is to select the right number of hidden layers (Weigend, 2014). Research conducted by Panchal et al. (2011) also shows that modifying the number of nodes in the hidden layer can overcome cases of overfitting. The Grey System method is a forecasting method suitable for small amounts of data. The minimum data used in this method is four historical data points with the same interval (Julong, 1989). The characteristics of this method lie in calculating the AGO (Accumulated Generation Operation) value.

Previous research with a similar topic was conducted by Putra et al. (2019), the method used was the Cobb-Douglas equation, using several independent variables such as the price of bulk cooking oil, the price of packaged cooking oil, the price of chicken meat, the number of household members, and household income. The results showed that only the chicken meat variable did not affect Denpasar's demand for bulk cooking oil. Research using the forecasting method on world palm oil (CPO) prices in 2020 was also conducted by Arifin (2021) using six time series methods, namely moving average, double moving average, exponential moving average, double exponential smoothing, winter, and ARIMA-SARIMA. Of the six methods, the ARIMA (1,0,1) method has the best forecasting model. Research with the same discussion, regarding forecasting biodiesel raw material inventory, has also been conducted by Pradana (2019) using the double exponential smoothing method. This study took a case study of PT. Wilmar Nabati Gresik. The forecasting results show that the biodiesel raw material inventory for the next period is 705171.21, using alpha 0.1. Research on the comparison of the Neural Network method, Poisson regression, and negative binomial has also been conducted by Pradhani (2016) to predict dengue fever cases in Surabaya. The results show that the Neural Network method has the smallest error value, compared to the other two methods. Research using the Grey System method has also been conducted to predict olefins products (Fitri et al., 2018). The results show that the Grey System method can produce errors of up to 0.76% and accuracy of up to 99.24%, on data with a total of 6 periods.

This study used both variables to create forecasting models using Neural Network and Grey System. The biodiesel demand variable has less data compared to the CPO production data. The type of Neural Network used for this study is Feed Forward Neural Network (FFNN), which is a form of modeling in Neural Networks with non-linear functions that have very flexible characteristics to be used for various applications (Rashid, 2016). Furthermore, the best model is selected from the two models for each variable. The criteria for the best model are selected using the MAPE value. The method that produces a model with the minimum MAPE means that it has the minimum error, so it is the best model with the most accurate prediction. Previous studies have rarely used the Neural Network method for data with a small number of characteristics. This study aims to compare Neural Network and Grey System models in forecasting two variables with different data characteristics—CPO production volume and biodiesel demand—in order to determine the most appropriate method based on the amount of available data.

RESEARCH METHODOLOGY

The data used in this study comes from the Plantation Statistics Book published by the Directorate General of Plantations, Ministry of Agriculture of the Republic of Indonesia, for the CPO production volume variable. Forecasting the volume of CPO production is only done for data from the production results of Private Large Plantations, which have the most significant number of plantations in Indonesia, compared to 2 other two plantations. The total data used for forecasting the volume of CPO production is 42 data points (1980 - 2023). Meanwhile, the data on the volume of biodiesel demand is taken from the data of the Indonesian Biofuel Producers Association, with a total of 15 years of data (2009-2023).

Data analysis techniques are divided into two main parts, including the formation of a forecasting model using the Neural Network method and modeling using the Grey System. Previously, the description of both variables was carried out by creating a time series plot and calculating the mean, median, mode, and variance values. In the first step, data is divided into training and testing data on each research variable. Testing data is the last five years, while the rest is training data. Training data is used to estimate the forecasting model, while testing data is used to test and validate the resulting model estimates. The division of training and testing data is explained in Table 1.

Table 1. Training and Testing Data Allocation

Data Allocation	Years / Variables	
	CPO	Biodiesel
Training	1980	2009
Training	1981	2010
.	.	.
.	.	.
.	.	.
Training	2018	2018
Testing	2019	2019
Testing	2020	2020
Testing	2021	2021
Testing	2022	2022
Testing	2023	2023

Next step is conduct Feed Forward Neural Network modeling on CPO and biodiesel production variables. The architectural model used is a Multi Layer Feed Forward Neural Network or Multi Layer Perceptron (MLP). This architectural model adds one or more hidden unit layers between the input and output units. The form of the MLP architecture is shown in Figure 1.

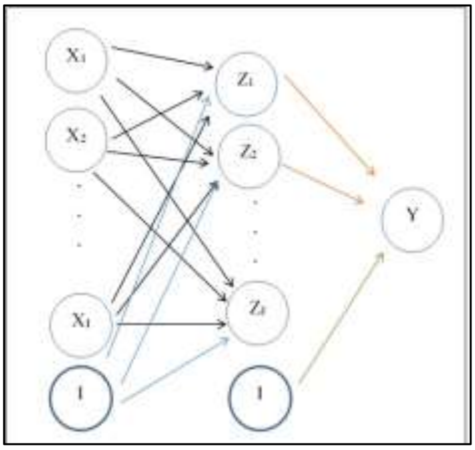

Figure 1. Architecture MLP FFNN

The stages for modeling with the FFNN method, firstly, determining the number of input units through significant lags on the autocorrelation plot (ACF). Then, normalizing the training data through the matlab function prestd. Next stages is determining the training setting consisting of maximum iteration (1000 iterations), initial weight initialization (selected through an iteration process of 100 times, then the selection of weights is seen based on the smallest MSE criteria), determining the learning rate, activation function (sigmoid for the hidden layer and purelin for the output layer), and determining the MSE criteria for stopping the learning process (MSE <0.05). Perform the learning process using the backpropagation training method and Levenberg Marquardt (LM) optimization to calculate new weights and biases. Backpropagation was chosen because of its ability to obtain a logical solution, even when the data used in the modeling has never gone through Sthe training process or the data is incomplete (Kong & Martin, 1995). The LM algorithm is also a very popular and robust method and is efficient for training on networks that are not too complex, as in this study (Bilski et al., 2020). After the learning process, the output unit is calculated using the following formula:

$$y_k = \varphi_k(b_k + \sum_{j \to k} w_{kj} \varphi_j (b_j + \sum_{i \to j} v_{ji} x_i)) \tag{1}$$

Next stages, calculating the MAPE testing value, then the change in value of each MAPE testing is done by making a line chart and selecting the number of hidden layers based on the minimum MAPE testing. Then, making the NN model obtained based on the number of layers in the input-hidden-output and creating a network architecture according to the best NN model.

The first step for Grey System modeling on CPO and biodiesel production variables is generating the first Accumulating Generation Operation (1-AGP) with the following notation:$x^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\right)$. Then , $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$, k = 1, 2, …, n. Next, generate for parameter definition a and b with the formula as follows.

$$\frac{dx_1^{(1)}}{dt} + ax_1^{(1)} = b \tag{2}$$

Description:
t = independent variable in the system;
a = development coefficient;
b = grey action quantity.
Furthermore, perform the estimated values of parameters a and b, such as:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_n \tag{3}$$

The following is the accumulation of matrix B:

$$B = \begin{bmatrix} -0.5(x_1(1) + x_1(2)) & 1 \\ -0.5(x_1(2) + x_1(3)) & 1 \\ \cdots & \cdots \\ -0.5(x_1(n-1) + x_1(n)) & 1 \end{bmatrix} \tag{4}$$

The constant vector Y_n is= $[x_0(2), x_0(3), \cdots, x_0(n)\ ]^T$
(5)

Next, defining a prediction model as follows:

$$\hat{x}^{(1)}(k) = \left(x^{(0)} - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a} \tag{6}$$

Next step is calculating Inverse Accumulative Generation Operation (IAGO) to get the forecast value: If $\hat{x}^{(1)}(1) = \hat{x}^{(0)}(1)$, orders *Inverse Accumulative Generation Operation* (IAGO) obtained from subtraction: $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(0)}(k)$. Given k = 1,2, …, n so that the subtraction sequence becomes $\hat{x}^{(0)} = \left[\hat{x}^{(0)}(2), \hat{x}^{(0)}(3), \ldots, \hat{x}^{(0)}(n+1)\right]$.

The last stage is calculating MAPE testing values to get the best model. MAPE is calculated using the following formula:

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \tag{7}$$

Then create a line chart from actual data, forecast data using both methods on each variable, and on the testing results. Analyze the line chart that has been created to find out the model that is closest to the actual data.

RESULTS AND DISCUSSION

This section presents and discusses the results of the analysis conducted in the study. Figure 2 illustrates the time series of CPO production volume and biodiesel demand volume, which serve as key variables in modeling the dynamics of cooking oil prices.

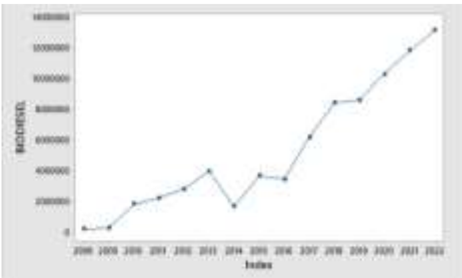
Figure 2(a). ***Time series*** **Plot CPO**

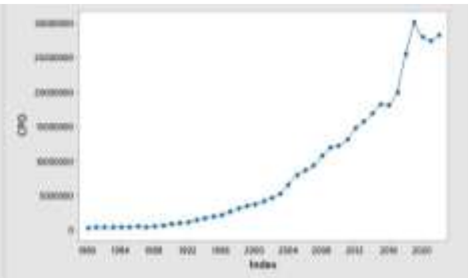
Figure 2(b). ***Time series*** **Plot Biodiesel**

In Figure 2, it can be seen that both plots have an upward trend. In the CPO variable, a sharp increase occurred in 2017, although there was a slight decrease in production in the previous year. Figure 2(a) shows that over the past 5 years, there has always been an increase in CPO production volume. Meanwhile, in the biodiesel variable, a sharp demand occurred in 2015, and the highest increase occurred in 2019. After 2016, there has also been a continuous increase in demand for biodiesel. The next stage before modeling is to describe the characteristics of the data based on the values of the centralization and dispersion measures of the data summarized in Table 2.

Table 2 shows that the diversity of data on the CPO variable tends to be higher than that on the biodiesel variable, meaning that the volume of CPO production each year tends to be more diverse than that of the biodiesel demand variable.

Table 2. Descriptive Statistics of CPO and Biodiesel

Variable	Minimum	Maximum	Mean	Std. Deviation
CPO	221544	30060003	8416989.698	9235598.982
BIO	190000	13151000	5222736.482	4231521.407

The following analysis stage is modeling the two variables using the Neural Network and Grey System methods, which begins with the division of training and testing data, per the provisions in the previous discussion. Modeling for both datasets begins with the Neural Network method. The initial stage of this modeling is to estimate model parameters by identifying the number of input-hidden-output units. The number of input units is identified based on the autocorrelation plot. The figure below shows the consecutive autocorrelation plots for CPO and biodiesel data.

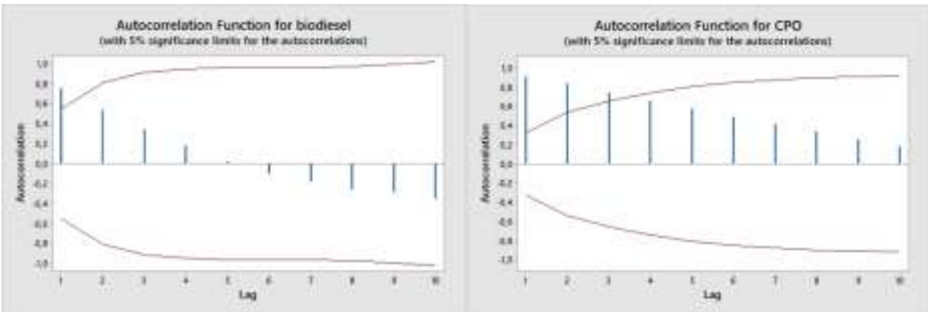

Figure 3(a). CPO Autocorrelation Plot **Figure 3(b) Biodiesel Autocorrelation Plot**

Based on the Figure 3, it can be seen that the significant lags are lags 1, 2, and 3 for the CPO variable, while for the biodiesel variable, it is only significant at lag 1. So the number of input units for the CPO production variable is 3 and 1 for the biodiesel variable. The next stage is to determine the number of hidden layers by trial and error. The criteria for selecting the number of hidden layers are based on the lowest MAPE value. The following is a presentation of the changes in MAPE values for the testing data on both variables.

In the Figure 4, it can be seen that the change in MAPE CPO begins with a low value up to the first three hidden layers, then experiences a relatively high increase in the number of hidden layers 4, and decreases again in the sixth hidden layer, then a similar pattern occurs again in the number of hidden layers 7 to 10. A similar pattern also occurs in biodiesel demand, the number of the first two hidden layers has a minimum MAPE value. There is a significant increase in the number of hidden layers 3, a decrease in hidden layer 4, and an increase again in the hidden layer, totaling six.

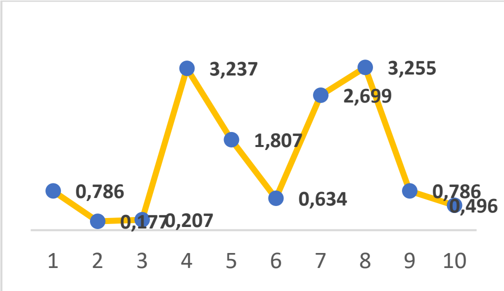

Figure 4(a). CPO MAPE Changes

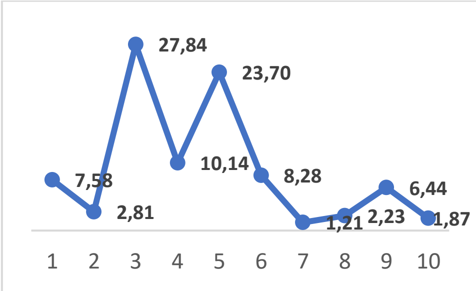

Figure 4(b) Biodiesel MAPE Changes

There is a decrease and a slight increase in the hidden layer, totaling 9. In the CPO variable, the minimum MAPE testing is located in the hidden layer totaling 3, while for the biodiesel variable, the number of hidden layers is 7, producing the minimum MAPE value. The number of output units in both variables is 1, because forecasting is only done for one variable each, namely CPO and biodiesel. The model formed using the neural network method has an MLP architecture (3-3-1) for the CPO variable and an MLP (1-7-1) for the biodiesel variable. The form of each network architecture in both models is presented in Figure 5.

The next stage is to estimate the model parameters using the Grey System method. The model parameters are estimated by calculating the least squares estimation method using equation (2). From this calculation, the parameters a and b are obtained respectively for the CPO variable, namely 1.1296 and 0.1587, and for the biodiesel variable, respectively, a = -0.0705 and b = -1.1305.

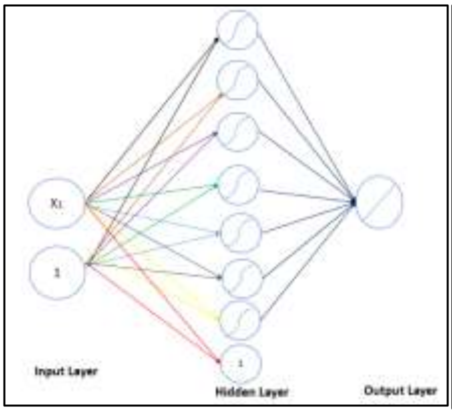

Figure 5(a). MLP (3-3-1)

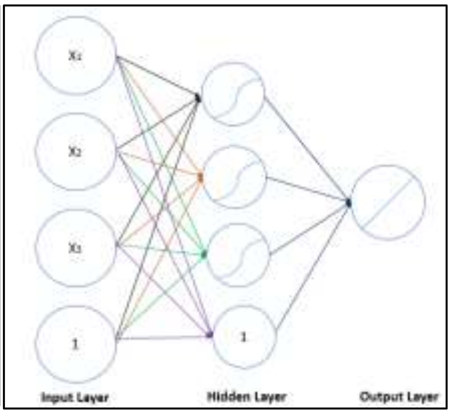

Figure 5(b) MLP (1-7-1)

The next stage is selecting the best model for CPO and biodiesel variables based on the lowest MAPE testing criteria. Both MAPE testing values for each variable with both methods are summarized in the Table below.

Table 3. MAPE for Both of Models

Variables	Neural Network	Grey System
CPO	0,207	7,710
Biodiesel	1,210	1,000

Based on Table 2, it can be shown that in the CPO variable, the minimum MAPE value is found in the modeling results using the Neural Network method. In contrast, the best model for the biodiesel variable is found in the Grey System modeling. In addition to using the MAPE criteria, the best model is also indicated by comparing the estimated values of the testing data with the actual data. The comparison results are presented through a line chart in Figure 6.

Figure 6 shows that for the CPO production variable, the plot of the estimated test data results using the Neural Network method is closer to the actual data plot than the Grey System method. In contrast, for the biodiesel demand variable, the plot of the estimated results using the Grey System method is closer to the actual data than the Neural Network method. This shows the same results with the lowest MAPE value, namely the CPO production variable forecasting model obtained from the Neural Network method; conversely, the best forecasting model for the biodiesel demand variable is obtained from the Grey System method.

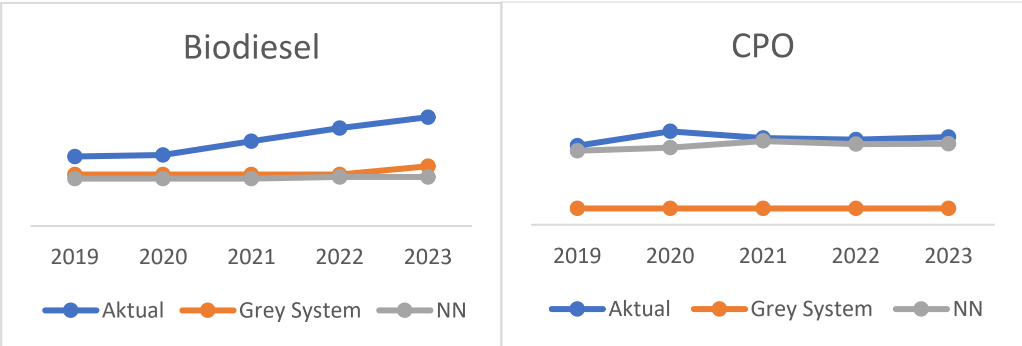

Figure 6. Line Charts of Actual and Forecast Result

After analyzing the data on both variables using the Neural Network and Grey System methods, the results showed that both variables used different methods to obtain the best model. In the CPO production volume variable, the best model was produced by the Neural Network method, while the Grey System method produced the biodiesel demand variable. This is in accordance with the characteristics of the Grey System method, which is a method that is suitable for data with small amounts. Research to predict the need for environmentally friendly alternative fuels using the Grey System method also produced the lowest MSE value compared to the Moving Average and Weighted Moving Average methods (Nariswari & Rosyidi, 2015).

The comparison of forecasting performance between the Neural Network and Grey System methods shows varying levels of accuracy depending on the volume of data used. For the CPO production variable, which consists of a larger dataset, the Neural Network method achieves a significantly lower average error of 3.24, compared to 51.62 using the Grey System method. This substantial difference indicates that the Grey System is less suitable for modeling large datasets.

On the other hand, for the biodiesel demand variable, which has smaller data volume, the performance gap between the two methods is narrower. The Neural Network yields an average error of 4.41, while the Grey System outperforms it with a smaller average error of 0.77. This suggests that the Grey System is more effective for modeling variables with limited data.

These findings are supported by previous research. Harlianto et al. (2021) found that the Grey System model provided more accurate predictions than the Neural Network model in forecasting tuberculosis morbidity rates in Indonesia, which also involved small datasets. Similarly, Wahyuningsih (2019) reported that Grey System achieved an error rate of 3% in natural gas forecasting, compared to 12% using Neural Network with backpropagation. However, Hsiao et al. (2009) presented contrasting results, showing that

Neural Networks were more accurate than Grey Systems in forecasting linear motion guidance data. In conclusion, the effectiveness of a forecasting method depends on the volume and characteristics of the data.

CONCLUSION AND SUGGESTIONS

The best CPO production forecasting modeling is produced using Neural Networks, with the MLP (3-3-1) architecture. Biodiesel demand, which has less data than CPO production, has the best model produced by the Grey System method. Further research suggests adding comparison methods to identify the most accurate forecasting method. It also recommends using the Neural Network method with Recurrent Neural Network learning to compare the two learning methods.

REFERENCES

Ahdiat, A. (2024, April 22). *Konsumsi minyak goreng per kapita indonesia naik pada 2023*. Katadata.Https://Databoks.Katadata.Co.Id/Demografi/Statistik/8bcbef964f3570c/Konsumsi-Minyak-Goreng-per-Kapita-Indonesia-Naik-Pada-2023.

Amanta, F & Nafisah, N. (2022). *Produktivitas kelapa sawit tetap terbatas seiring melonjaknya harga minyak goreng di Indonesia (Ringkasan Kebijakan No.12)*. Center for Indonesian Policy Studies. https://doi.org/10.35497/355798.

Arifin, B., Tanaya, I. G. L. P., & Usman, A. (2021). Peramalan harga kelapa sawit dunia pada tahun 2020-2024. *Prosiding SAINTEK*, *3*, 349 – 368. Universitas Mataram.

Baboo, S. S., & Shereef, I. K. (2010). An efficient weather forecasting system using artificial neural network. *International Journal of Environmental Science and Development*, *1*(4), 321-326. https://doi.org/10.7763/IJESD.2010.V1.63.

Bilski, Jarosław, Bartosz Kowalczyk, Alina Marchlewska, and Jacek M. Zurada. (2020). "Local Levenberg-Marquardt Algorithm for Learning Feedforwad Neural Networks." *Journal of Artificial Intelligence and Soft Computing Research* 10(4):299–316.

Dumitru, C., & Maria, V. (2013). Advantages and disadvantages of using neural networks for predictions. *Ovidius University Annals, Series Economic Sciences*, *13*(1), 444-449.

Fausett, L. V. (2006). *Fundamentals of neural networks: architectures, algorithms and applications*. Pearson Education.

Fitri, G. F., Agustina, F., & Marwati, R. Penerapan metode grey system pada peramalan produk olefin. (2018). *Jurnal EurekaMatika*, *6*(2), 52–63. https://doi.org/10.17509/jem.v6i2.14850.

Harlianto, D., Mardiyati, S., & Lestari, D. (2021). The comparison between recurrent neural network and grey model to predict Indonesia tuberculosis morbidity rate. *Journal of Physics: Conference Series*, *1722*(012093), 1–12. https://doi.org/10.1088/1742-6596/1722/1/012093.

Hsiao, Y. F., Tarng, Y. S., & Kung, K. Y. (2009). Comparison of the grey theory with neural network in the rigidity prediction of linear motion guide. *Wseas Transactions on Applied and Theoretical Mechanics*, *1*(4), 32–41.

Julong, D. (1989). Introduction to grey system theory. *The Journal of Grey System*, *1*(1), 1–24.

Khatiwada, D., Palmén, C., & Silveira, S. (2018). Evaluating the palm oil demand in Indonesia: production trends, yields, and emerging issues. *Biofuels*, *12*(2), 135–147. https://doi.org/10.1080/17597269.2018.1461520.

Kong, J. H. L., & Martin, G. (1995). A backpropagation neural network for sales forecasting. *Proceedings of ICNN'95-International Conference on Neural Networks*, *2*, 1007–1011. https://doi.org/10.1109/ICNN.1995.487558.

Mustafa, R. (2022). Pengaruh harga cpo (crude palm oil) di global market terhadap harga minyak goreng di pasar domestik. *Sibatik Journal: Jurnal Ilmiah Bidang Sosial, Ekonomi, Budaya, Teknologi, Dan Pendidikan*, *1*(8), 1565–1574. https://doi.org/10.54443/sibatik.v1i8.209.

Nariswari, N. L., & Rosyidi, C. N. (2015). Aplikasi metode grey forecasting pada peramalan kebutuhan bahan bakar alternatif ramah lingkungan di pt. indocement tunggal prakarsa tbk. *Performa: Media Ilmiah Teknik Industri*, *14*(2), 99-106. https://doi.org/10.20961/performa.14.2.10986.

Panchal, G., Ganatra, A., Shah, P., & Panchal, D. (2011). Determination of over-learning and over-fitting problem in back propagation neural network. *International Journal on Soft Computing (IJSC)*, *2*(2), 40–51. https://doi.org/10.5121/ijsc.2011.2204.

Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Ben Taieb, S., Bergmeir, C., Bessa, R. J., Bijak, J., Boylan, J. E., Browell, J., Carnevale, C., Castle, J. L., Cirillo, P., Clements, M. P., Cordeiro, C., Oliveira, F. L. C., De Baets, S., Dokumentov, A., … Ziel, F. (2022). Forecasting: theory and practice. *International Journal of Forecasting*, *38*(3), 705-871. https://doi.org/10.1016/j.ijforecast.2021.11.001.

Pradana, Yoga Bayu Aprilia. (2019). *Peramalan persediaan jumlah bahan baku biodiesel menggunakan metode double exponential smoothing (studi kasus pt. wilmar nabati gresik)* (Undergraduate thesis, Universitas Muhammadiyah Gresik).

Pradhani, F. A. (2016). *Perbandingan model neural networks dengan poisson regression dan negative binomial regression pada kasus demam berdarah dengue (dbd) in Surabaya* (Doctoral dissertation, Institut Teknologi Sepuluh Nopember).

Putra, I. M. A. D., Susrusa, K. B., & Artini, N. W. P. (2019). Analisis permintaan konsumen rumah tangga terhadap minyak goreng curah di kota denpasar. *Jurnal Agribisnis dan Agrowisata*, *8*(2), 195–204. https://doi.org/10.24843/JAA.2019.v08.i02.p08.

Rashid, T. (2016). *Make your own neural network*. CreateSpace Independent Publishing Platform.

Stevenson, W. J., & Chuong, S. C. (2014). *Manajemen operasi perspektif asia*. Salemba Empat.

Wahyuningsih, M. (2019). *Aplikasi perbandingan metode grey system theory gm 1.1 dan artificial neural network untuk prediksi produksi gas bumi* (Undergraduate thesis, Universitas Pembangunan Nasional Veteran Yogyakarta).

Weigend, A. S. (2014). On overfitting and the effective number of hidden units. *Proceedings of the 1993 Connectionist Models Summer School*, 335–342. Psychology Press.

Yakti, A. (2022, March 13). Akibat krisis minyak goreng, masyarakat diperkirakan rugi hingga rp 3,38 triliun. https://bisnis.tempo.co/read/1570294/akibat-krisis-minyak-goreng-masyarakat-diperkirakan-rugi-hingga-rp-338-triliun.