



Available online at <http://scik.org>

J. Math. Comput. Sci. 2022, 12:141

<https://doi.org/10.28919/jmcs/6992>

ISSN: 1927-5307

CIRCULATION ANALYSIS AND FORECASTING OF FUEL SALES USING THE BACKPROPAGATION ARTIFICIAL NEURAL NETWORK METHOD

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Abstract: The availability of a general fuel supply for the community is an interesting matter to study. This is because fuel is a basic need for the community. This paper aims to model and predict the general fuel demand and circulation using the Backpropagation Artificial Neural Network (ANN) method. A neural network consists of a set of numbers in simple processing elements called neurons, units, cells, or nodes. Each neuron is connected to the other neurons in a manner directed by communication links and by interrelated weights. Weights are represented as information that will be used by the network to solve a problem. In this study, secondary data is used on the volume of fossil fuel sold daily at the Hasanuddin gas station in Makassar from January 1, 2018 – March 29, 2021, with a lot of data 1121 days. The types of fossil fuels studied are Premium and Peralite. The results obtained indicate that the best model obtained for the Peralite ANN architecture with 4 inputs and 5 neurons in the hidden layer has the best accuracy with a MAPE of 17.64% which is classified as good, while the Peralite ANN architecture with 7 inputs and 25 neurons in the hidden layer has accuracy. the best with a MAPE of 14.64% which is classified as good.

Keywords: Artificial Neural Network; back propagation; fuel supply.

2010 AMS Subject Classification: 68T07, 62P20.

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Received November 14, 2021

1. INTRODUCTION

The Indonesian population is a potential market for various kinds of products, including fuel oil, lubricants, and gas products. The level of the Indonesian economy is getting better, marked by positive economic growth; this has an impact on the increase in ownership of the number of motorized vehicles, both two-wheeled and four-wheeled. The number of Indonesians who own two-wheeled vehicles is recorded at 120,101,047 units, and four-wheeled vehicles are recorded at 16,440,987 units [1].

A large number of vehicles affects the national fuel oil consumption. This huge potential for fuel oil consumption attracts foreign parties to participate in marketing their fuel oil products in Indonesia. Until now, many foreign companies have participated in selling fuel in Indonesia. Public refueling stations are familiar places in daily life. According to Communication and Relations Pertamina Marketing Operation Region III, with the largest sales in the world is in Indonesia, specifically on the Cikampek Km 19 Toll Road [2].

Public refueling stations is also the spearhead of marketing the fuel distribution network for the community. The government, as the owner of the company, tries to fulfill the fuel needs of public society through Public refueling stations. Therefore, the government opens opportunities for Pertashop business partnership cooperation to Village Governments, Cooperatives, and entrepreneurs throughout Indonesia. By this collaboration, Pertamina is targeting out of 7,196 sub-districts in Indonesia; as many as 3827 sub-districts that do not yet have a distribution agency will be built one Pertashop outlet. This reality makes entrepreneurs interested in collaborating with Pertamina to build the Public refueling stations.

Sales data recorded from time to time can be used to see the projected development of a company, whether it is increasing or decreasing. Sales forecasts will provide an overview of the ability of sales in the future. Sales forecasts can also be used as a basis for production planning so that there will be no overproduction and underproduction [3]. Forecasting the level of fuel sales needs to be done because by predicting the number of fuel sales, gas stations can take whatever policies that they will do to satisfy customers, while related research on forecasting sales levels has previously

been done by several researchers, including analyzing of operation and assessment economy of hybrid fueling stations by considering traffic flow information [4]. In addition, Li, et al., (2018) analyzed the integrated optimization model for the location of hydrogen refueling stations [5].

Artificial Neural Network is one solution that can be used to establish the model in forecasting. ANN is an information processing system that has several performance characteristics that are generally found in biological neural networks. The result of this analysis is to build a model to predict the selling price of fuel oil in the future. Based on previous research, the researcher is interested in analyzing fuel sales forecasting using ANN at Hasanuddin Public Refueling Station.

2. LITERATURE REVIEW

2.1. Artificial Neural Network

An artificial Neural Network is an information processing system that has several performance characteristics that are generally found in biological neural networks [6]. A neural network consists of a set of numbers in simple processing elements called neurons, units, cells, or nodes. Each neuron is connected to the other neurons in a manner directed by communication links and by interrelated weights. Weights are represented as information that will be used by the network to solve a problem [6].

ANN is determined by three things [7]:

- a. The pattern of connections between neurons (called network architecture)
- b. Methods for determining link weights (called training/learning/algorithm methods)
- c. Activation function

Y receives input from neurons x_1 , x_2 , and x_3 with the respective weights of the relationship being w_1 , w_2 , and w_3 . The three neuronal impulses are added together.

$$net = x_1w_1 + x_2w_2 + x_3w_3 \quad (1)$$

The magnitude of the impulse received by Y follows the activation function $y = f(net)$. If the value of the activation function is strong enough, the signal will be forwarded. The value of the activation function (network model output) can also be used as the basis for changing the weights.

2.2 Backpropagation

This method trains the network to strike a balance between the ability of the network to recognize patterns during training and respond correctly to input patterns that are similar (but not identical) to the patterns used during training [6]. Backpropagation has several units of neurons that are in one or more hidden layers. Figure 1 is an illustration of backpropagation with n inputs (plus a bias), a hidden layer consisting of p units (plus a bias), and m output units. v_{ji} is the line weight from the input unit x_i to the hidden display unit z_j (v_{j0} is the line weight connecting the bias in the input unit to the hidden display unit z_j). w_{kj} is the weight from hidden screen unit z_j to output unit y_k (w_{k0} is weight from hidden screen bias to output unit z_k) [8].

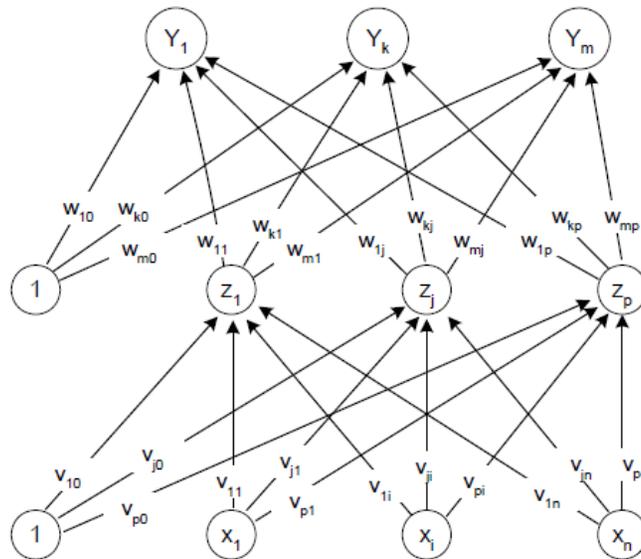


Figure 1. Ilustrasi backpropagation

Backpropagation training includes three phases [8]:

Phase I: Forward propagation

During forward propagation, the input signal ($= x_i$) propagated to the hidden layer using the specified activation function. The output of each hidden layer unit ($= z_j$) is then propagated forward again to the hidden layer on it using the specified activation function. And so on until it produces network ($= y_k$).

Next, the network output ($= y_k$) is compared with the target to be achieved ($= t_k$). The

difference between $t_k - y_k$ is the error that occurred. If this error is less than the specified tolerance limit, then the iteration is stopped. However, if the error is still greater than the tolerance limit, then the weight of each line in the network will be modified to reduce errors that occur.

Phase II: Backward propagation

Based on the error $t_k - y_k$, the factor δ_k ($k = 1, 2, \dots, m$) is calculated which is used to distribute the error in the unit y_k to all hidden units that are directly connected to y_k . δ_k is also used to change the line weights that are directly related to the output unit. In the same way, the factor δ_j in each unit in the hidden screen is calculated as the basis for the change in weight of all lines originating from the hidden unit in the screen below it. And so on until all the factors δ in the hidden unit that are directly related to the input unit are calculated.

Phase III: Changes in weight

After all the factors δ is calculated, the weight of all the lines simultaneously modified. The weight change of a line is based on the factor δ neuron factor on the screen above it. For example, the change in weight of the line leading to the output layer is based on δ_k in the output unit.

The three phases are repeated until the termination conditions are met. Generally, the termination condition that is often used is the number of iterations or errors. The iteration will be stopped if the number of iterations carried out has exceeded the maximum number of iterations specified, or if the error that occurs is less than the allowable tolerance limit.

2.3 Activation Function

In backpropagation, the activation function used must meet several conditions, namely: continuous, easily differentiable and a non-degrading function. One of the functions that meet these three conditions so that it is often used is the binary sigmoid function which has a range (0, 1), namely [9]:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

Another alternative is to use the sigmoid activation function only on screens that are not output

screens. In the identity function output screen: $f(x) = x$, activation function used [9].

2.4 Goodness of Fit Model

In the case of supervised learning, the measurement of model performance obtained from the training process can be compared directly with the output. The error value between the prediction and the output can be used as a reference. A small error value generally indicates a good model [10]. With the output value is Y , the value of the prediction is \hat{Y} , and the number of data is n , then used [11]:

$$MSE \text{ (Mean Square Error)} = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n} \quad (3)$$

2.5 Forecasting Performance

Mean Absolute Percentage Error (MAPE) is calculated using the absolute error in each period divided by the observed observed value for that period. Then, average those fixed percentages. This approach is useful when the size or size of the predictive variable is significant in evaluating prediction accuracy [12]. MAPE shows how much error the prediction is compared to the true value.

$$MAPE = \frac{\sum_{i=1}^n \frac{|Y_i - \hat{Y}_i|}{Y_i - \hat{Y}_i}}{n} \times 100\% \quad (4)$$

3. MATERIAL AND RESULTS

3.1 Data Source

The data used in this study is secondary data on the volume of fossil fuel sold daily at the Hasanuddin gas station in Makassar from January 1, 2018 – March 29, 2021, with a lot of data 1121 days, the types of fossil fuel studied are Premium and Peralite.

3.2 Analysis Method

The stages of data analysis carried out are as follows:

1. Preprocessing Data
 - a. Identify or eliminate data outliers

- b. Transforming data into smaller intervals, namely at intervals of 0.1 to 0.9 by using the following equation:

$$x' = \frac{0.8(x - a)}{b - a} + 0.1 \quad (5)$$

2. Determination of Network Inputs and Targets

- a. Seeing the significant lag in the PACF plot of sales data
- b. In the PACF plot if there is a line that passes through the confidence interval, meaning that a significant lag
- c. Determination of inputs and targets for training data and test data using the sliding window method

3. Preparation of Artificial Neural Network

- a. Initialize all weights with small random numbers
- b. Initialize all weights with small random numbers
- c. Counting all outputs in hidden units z_j ($j = 1, 2, \dots, p$)

$$z_{net_j} = v_{j0} + \sum_{i=1}^n x_i v_{ji} \quad (6)$$

$$z_j = f(z_{net_j}) = \frac{1}{1 + e^{-z_{net_j}}}$$

- d. Counts all network outputs in the unit y_k ($k = 1, 2, \dots, m$)

$$y_{net_k} = w_{k0} + \sum_{j=1}^p z_j w_{kj} \quad (7)$$

$$y_k = f(y_{net_k}) = \frac{1}{1 + e^{-y_{net_k}}}$$

- e. Calculating δ factor output unit based on the error in the output of each unit y_k ($k = 1, 2, \dots, m$)

$$\delta_k = (t_k - y_k) f'(y_{net_k}) = (t_k - y_k) y_k (1 - y_k) \quad (8)$$

- f. Calculating δ factor hidden units based on an error in each hidden unit z_j ($j = 1, 2, \dots, p$)

$$\delta_{net_j} = \sum_{k=1}^m \delta_k w_{kj} \quad (9)$$

Factor δ hidden units:

$$\delta_j = \delta_{net_j} f'(z_{net_j}) = \delta_{net_j} z_j(1 - z_j)$$

g. Calculating all weight changes

Change the weight of the line leading to the output unit:

$$w_{kj}(new) = w_{kj}(old) + \Delta w_{kj}; (k = 1, 2, \dots, m; i = 0, 1, \dots, p) \quad (10)$$

Change the weight of the line leading to the hidden unit:

$$v_{ji}(new) = v_{ji}(old) + \Delta v_{ji}; (j = 1, 2, \dots, p; i = 0, 1, \dots, n) \quad (11)$$

h. If the conditions are not met, then modify all the weights simultaneously and then initialize again

4. Determine the best model by looking at the smallest Mean Square Error

5. Predicting fossil fuel sales.

4. RESULTS AND DISCUSSION

4.1 Data Transformation

Data transformation is carried out to adjust the data value to the range of activation functions used in the network. The goal is to obtain data intervals that match the activation function used, namely the binary sigmoid activation function. The results of the sales data transformation can be seen in table 1.

Table 1: Transformation Results of Daily Sold Fossil Fuel Volume

Daily Fossil Fuel Volume Sold							
10499.60	17096.58	13445.73	15982.31	12144.26	15727.08	8348.45
Daily Fossil Fuel Volume Sold After Transformation							
0.4033	0.6208	0.5013	0.5843	0.4587	0.5760	0.3346

Table 1 shows that the use of the binary sigmoid activation function requires the data to be transformed first, because the output range of the binary sigmoid activation function is between 0 and 1 (0.1).

4.2 Determination of Network Inputs and Targets

Determination of the network input is done by looking at the significant lag-lag PACF plot of the data the closing price and the closing price after differencing the Minitab application; PACF value represents the correlation observation to t. In the PACF plot, if a line crosses the confidence interval, it means that the lag is significant. Based on the lag identification, the next step is to determine the input and target models. Determination of inputs and targets for training data and test data using the sliding window method.

4.3 Neural Network Architecture Forming

Neural network architecture forming with backpropagation algorithm using newff command on Matlab is:

```
Newff(minmax(data_latih, [20 1]), {'logsig', 'purelin'}, 'traingdx')
```

There are 20 neurons on the hidden layer and one neuron on the output layer on that command. The activation function used on hidden layers is logsig (biner sigmoid) dan on the output layer is purelin (identity). The learning algorithm that is used is traingdx.

a. Data distribution

ANN model form using backpropagation method on this research by dividing the data into two parts, namely training data and testing data. Then the results will be compared between 80% of the training data and 20% of the testing data.

b. Determine the number of neurons in the hidden layer

Backpropagation learning is performed by determining the number of neurons in the hidden layer by comparing the accuracy of some of these neurons, starting from 5 neurons, 10 neurons, 15 neurons, 20 neurons, to 25 neurons. The best model is selected based on the smallest MSE value in the testing process.

c. Determine initial weight and initialization of ANN parameters

In determining the initial weight, the weights will be generated from the input layer to the hidden layer, the weight from the input bias to the hidden layer, the weight from the hidden layer to the output layer, and the weight from the hidden layer bias to the output layer, the following command is used to store any weight changes at the training stage:

```
value_hidden = net_output.IW{1,1};  
value_output = net_output.LW{2,1};  
bias_hidden = net_output.b{1,1};  
bias_output = net_output.b{2,1};
```

where,

- a) `net_output.IW` is the weight on the input layer to the hidden layer
- b) `net_output.LW` is the weight on the hidden layer to the output layer
- c) `net_output.b` is bias value that used in the input and hidden layers.

The parameters given in this research are:

```
net.performFcn = 'mse';  
net.trainParam.goal = 0.0001;  
net.trainParam.show = 20;  
net.trainParam.epochs = 10000;  
net.trainParam.mc = 0.95;  
net.trainParam.lr = 0.1;
```

where,

- a) `net.trainParam.epochs` is the maximum number of epochs
- b) `net.trainParam.goal` is the target error value
- c) `net.trainParam.show` is an error calculation report
- d) `net.trainPerform.Fcn` is the error performance used
- e) `net.trainParam.Lr` is the learning rate
- f) `net.trainParam.mc` is the value of the momentum constant

The initialized parameters are processed with the following command:

```
[net_output, tr, Y, E] = train(net, data_training, target_training);
```

4.4 Neural Network Artificial Model Forming

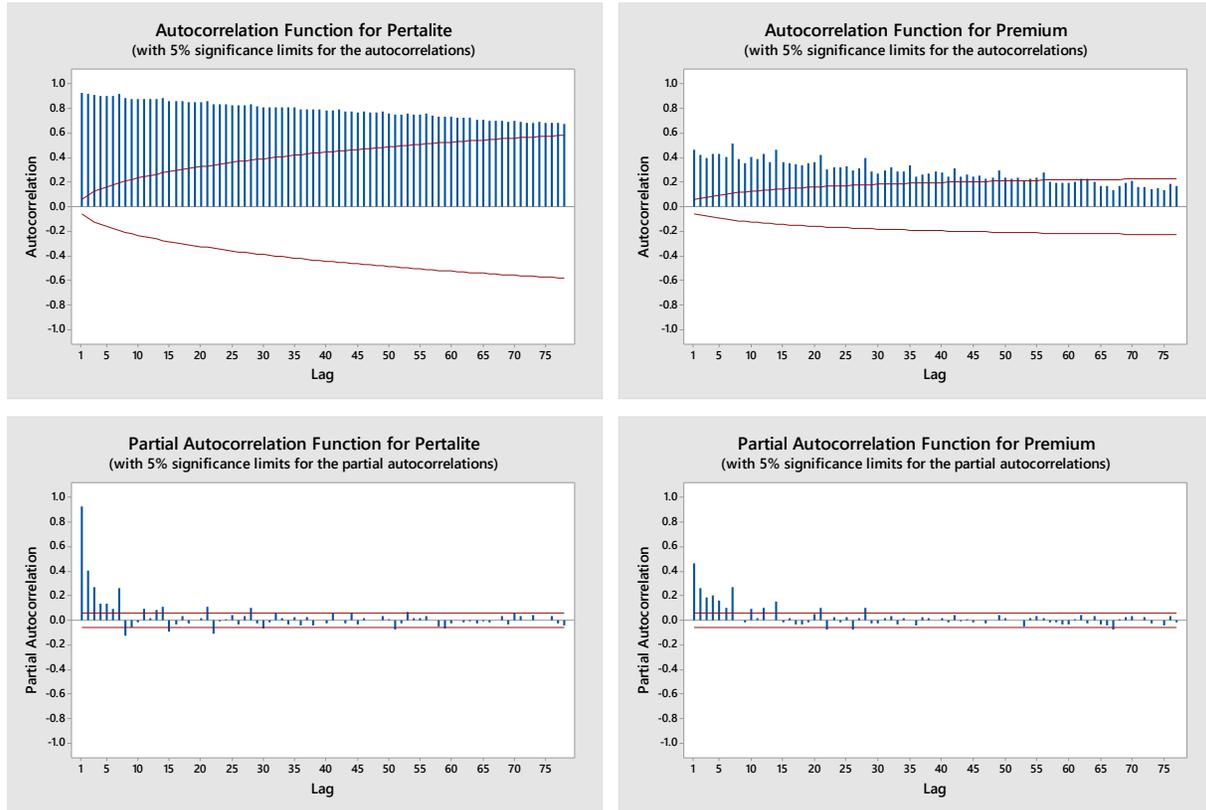


Figure 2: ACF and PCF of Fossil Fuel Sales Volume

On figure 2. ACF shape decreases exponentially and the PACF shape is truncated (significant line) at lags 1, 2, 3, 4, 5, 6, and 7. Then the dimensions of the input, output, and test data matrices using the sliding window method such as table 2.

Table 2: Matrix Dimensions of Fossil Fuel Sales Volume with a ratio (80:20)

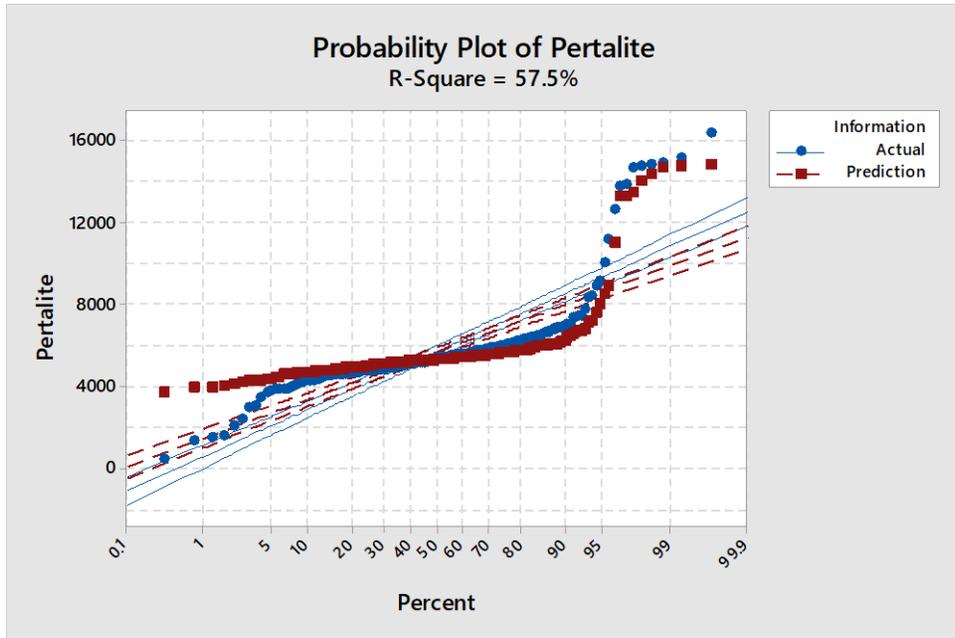
Input	Matrix Dimensions		
	Input Data	Output Data	Testing Data Input
H-1	1×897	1×897	1×224
H1 – H2	2×896	1×896	2×224
H1 – H3	3×895	1×895	3×224
H1 – H4	4×894	1×894	4×224
H1 – H5	5×893	1×893	5×224
H1 – H6	6×892	1×892	6×224
H1 – H7	7×891	1×891	7×224

At this stage, the training and testing process uses 5 variations in the number of neurons in the hidden layer, namely 5, 10, 15, 20, and 25 neurons. The training model on the variation in the number of hidden layers is used to test the test data. The test results are shown in table 3.

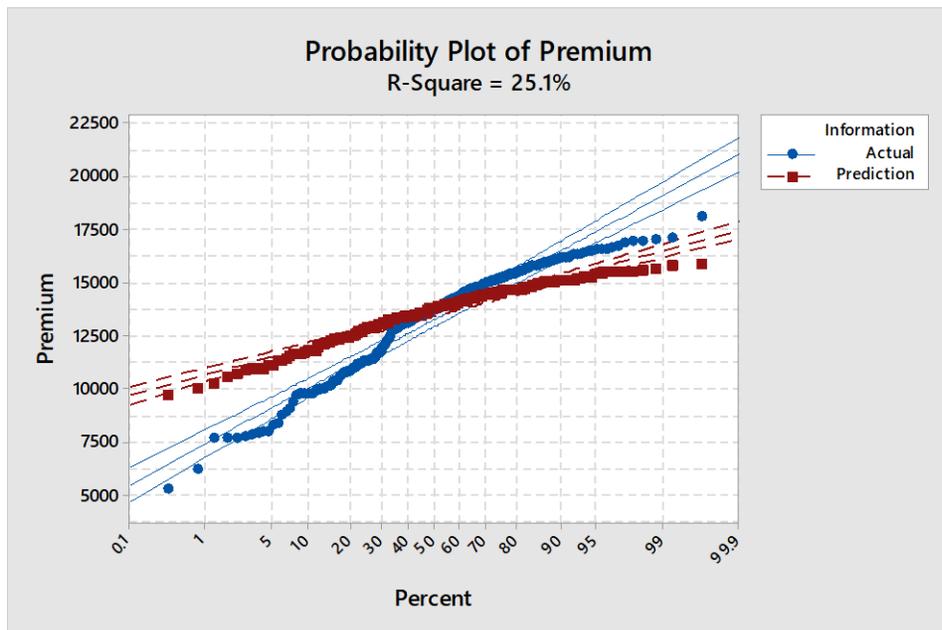
Table 3: Fossil Fuel Sales Volume Data Test Results

Fossil Fuel Types	Number of Days as Input	MSE Test Data (Hidden Layer Neurons)				
		5	10	15	20	25
Pertalite	Input 1	0.01242	0.00128	0.00118	0.00134	0.00136
	Input 2	0.00091	0.00107	0.00101	0.00095	0.00133
	Input 3	0.00103	0.00104	0.0009	0.00095	0.00095
	Input 4	0.00078	0.00101	0.00086	0.00101	0.00087
	Input 5	0.00079	0.00097	0.00096	0.00099	0.00093
	Input 6	0.0009	0.00113	0.00103	0.00088	0.00083
	Input 7	0.00102	0.00093	0.00087	0.00094	0.00095
	MSE Minimum	0.00078	0.00093	0.00086	0.00088	0.00083
Premium	Input 1	0.00761	0.00768	0.00778	0.00762	0.0077
	Input 2	0.00713	0.00726	0.00758	0.00739	0.00731
	Input 3	0.00679	0.00681	0.00696	0.00725	0.00729
	Input 4	0.00678	0.00653	0.00655	0.00589	0.00624
	Input 5	0.00642	0.00652	0.00661	0.00678	0.00697
	Input 6	0.00668	0.00645	0.00616	0.00627	0.00658
	Input 7	0.00536	0.00556	0.00548	0.0052	0.00515
	MSE Minimum	0.00536	0.00556	0.00548	0.0052	0.00515

On table 3 the smallest MSE value is in the Pertalite type with the number of inputs 4 days before the day of sale with 5 neurons in the hidden layer, which is 0.00078. For comparison, the Premium type with the number of inputs 7 days before the day of sale with 25 neurons in the hidden layer is 0.00515, the test results are shown in Figure 3.



(a) Prediction of 4 inputs with 5 neurons Peralite Sales Volume



(b) Predictions of 7 inputs with 25 neurons Premium Sales Volume

Figure 3: Comparison of prediction results with actual values

On Figure 3, it is shown that the distribution of the predicted data for Peralite forms the same pattern and coincides with the prediction results obtained by a coefficient of determination of 57.5%, which indicates that the prediction results for the type of peralite have a fairly high similarity. Meanwhile, the distribution of Premium predicted data forms a relatively different and slightly coincident pattern. The prediction results obtained a coefficient of determination of 25.1%, which indicates that the prediction results for the Peralite have a fairly low similarity, and are much smaller than the Peralite, this is due to the inventory of Premium goods often occurs under production at certain times, it is different from the case of Peralite goods that are almost every day.

4.5 Model Determination

The various models have been built with two types of fuel, namely Peralite sales volume and Premium sales volume. With the number of inputs and the number of hidden neurons that vary, the number of predictive models built in this research are 70 models. The best model obtained in this research is for the Peralite fuel with the number of inputs 4 days before the day of sale with 5 neurons in the hidden layer or can be written:

$$y_k = w_{k0} + \sum_{j=1}^5 w_{kj} \left(\frac{1}{1 + e^{-(v_{j0} + \sum_{i=1}^4 x_i v_{ji})}} \right)$$

meanwhile, the Premium fuel the number of inputs 7 days before the day of sale with 25 neurons in the hidden layer or can be written:

$$y_k = w_{k0} + \sum_{j=1}^{25} w_{kj} \left(\frac{1}{1 + e^{-(v_{j0} + \sum_{i=1}^7 x_i v_{ji})}} \right)$$

Where w_{k0} is the bias weight of the hidden layer to the output layer, w_{kj} is j-th hidden layer weight of output layer, v_{j0} is input layer bias weight to hidden layer, v_{ji} is input layer weight to hidden layer, and x_i is the i-th input variable.

4.6 Forecasting

By using 80% of the training data, the forecasting error is as follows:

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Table 4: Fossil Fuel Sales Volume Prediction Error

Pertalite				Premium			
Actual	Forecasting	Forecasting Error	Absolut Percentage Error	Actual	Forecasting	Forecasting Error	Absolut Percentage Error
5112.45	4719.38	-393.07	7.69%	11443.5	12426.4	982.98	8.59%
4659.37	4837.72	178.352	3.83%	11910.8	12083.7	172.886	1.45%
4614.95	4989.81	374.863	8.12%	10886.8	10932.9	46.1318	0.42%
4486.99	4867.28	380.294	8.48%	9101.1	10929	1827.9	20.08%
457.05	3713.21	3256.16	712.43%	15082.4	11794	-3288.4	21.80%
5090.83	4648.18	-442.65	8.70%	13190.5	12969.9	-220.6	1.67%
5011.99	4300.51	-711.48	14.20%	13552.2	12862.9	-689.34	5.09%
3876.23	4522.6	646.368	16.68%	15008.5	12346.5	-2662	17.74%
4291.36	4830.48	539.12	12.56%	14295.6	13376.5	-919.09	6.43%
5079.11	4784.35	-294.76	5.80%	9754.06	13409.2	3655.19	37.47%
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
10088.3	13083.8	2995.44	29.69%	11491.9	14081.6	2589.75	22.54%
13863.5	6813.08	-7050.4	50.86%	8348.45	15505.9	7157.46	85.73%
MAPE			17.64%	MAPE			14.64%

On table 4, the MAPE per day for Pertalite is 17.64% which is classified as good. While the MAPE per day for Premium is 14.64% which is classified as good (Widitriani, et al, 2020).

5. CONCLUSION

The best model obtained from daily fuel sales volume data at the Hasanuddin gas station in Makassar from January 1, 2018 – March 29, 2021 for the Pertalite ANN architecture with 4 inputs and 5 neurons in the hidden layer has the best accuracy with a MAPE of 17.64% which is classified as good, while for Pertalite ANN architecture with 7 inputs and 25 neurons in the hidden layer. Has the best accuracy with a MAPE of 14.64% which is classified as good.

ACKNOWLEDGEMENT

The authors thank Hasanuddin University for funding this research through an internal research grant No: 915/UN4.22/PT.01.03/2021

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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