THE IMPLEMENTATION OF EVALUATION FOOD SECURITY INFORMATION SYSTEM BASED IN EXPERT SYSTEM TO SUPPORT REGIONAL POLICY REGULATION AND FORECASTING A FOOD PRICE USING NEURAL NETWORK

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ABSTRACT

One of the issues in government policy is a policy of stabilization of food prices. The characteristics of food products namely, fluctuating prices and production that is seasonal. Various regulatory appears that its essence is to keep the price increase can be controlled and stabilized and had minimal impact against inflation. A frequently encountered problem is related to the trend of the prices of foodstuffs and information about predictions of future food prices are very minimal, not using the information technology in the processing of the data. Food is one of the basic human needs that can't be delayed, substituted with other ingredients. Food is also a basic component for realizing quality human resources and as a key pillar of national development that plays a role in maintaining economic, social and political stability. The problem that often faced is related to the availability of food, the distribution of poor rice, food price trend and the information available today is very minimal, not yet using information technology equipment in data processing. In this research will be developed forecasting model that suitable or suitable for food price, that is by statistic forecasting method, such as trend analysis, decomposition, exponential smoothing, moving average and ARIMA and artificial intelligence forecasting model that is by Artificial Neural Network method. The results obtained for forecasting food prices using the Artificial Neural Network model are the most suitable models, since they have the smallest MSE values compared to other MSE models. The average MSE of the best model is 10816,767 for the in-sample model. While the forecasting results using the best model, obtained MSE value of 2422987.2 for out-sample model.

Keywords: trend, exponential smoothing, decomposition, neural network, forecasting

INTRODUCTION

One of the issues in government policy is a policy of stabilization of food prices. The characteristics of food products namely, fluctuating prices and production that is seasonal. Various regulatory appears that its essence is to keep the price increase can be controlled and stabilized and had minimal impact against inflation. A frequently encountered problem is related to the trend of the prices of foodstuffs and information about predictions of future food prices are very minimal, not using the information technology in the processing of the data. In addition to predict or forecast a situation in the future is very difficult because the uncertainty factor is very big influence. However, there must still be an accurate method or method for prediction or forecasting by relying on sufficient data for future decision-making and planning. One of the most developed forecasting methods today is the time method. Singgih Santoso said (2009), describing time series data is data displayed based on time, such as monthly data, daily data, weekly data, annual data or other time types. The characteristic of time series data is the existence of a specified time range rather than data at a given time. Time series analysis and forecasting are active areas of research. That is, until now still continued research on accuracy in the process of forecasting time series associated with the decision-making process. Some researches do research in time series using statistical methods, neural network (neural network), wavelet, and fuzzy system. Forecasting models based on statistical mathematical models such as moving average, exponential smoothing, regression (parametric and not parametric), and most frequently used are ARIMA (Box Jenkins). Forecasting model based on artificial intelligence such as neural network, genetic algorithm, simulated annealing, genetic programming, classification and hybrid. These methods have different flaws and advantages. Moreover, the problems in the real world are often complex problems and one model may not be able to cope with them well (DT Wiyanti and R Pulungan, 2012). For that has been done research to compare the accuracy of forecasting results with statistical methods and artificial neural network method. Among these are Z. Tang, et al (1991), performing time-series forecast analyzes using Neural Networks vs. Box-Jenkins. RM Atok and Suhartono (2000) compared Neural Networks, ARIMA Box-Jenkins and Exponential Smoothing Methods for time series forecasting. Furthermore, Suhartono et al. (2005) also conducted a comparative study (comparative study) on time series forecasting models with seasonal trends and patterns to find out if more complex models always yield better forecasts than statistical models. In the comparative study, the methods compared were Winter's, Decomposition, Time Series Regression, ARIMA and Neural Network. The result is concluded that complex models do not always produce better forecasts than simple statistical models. The data used in the study are international airplane passenger data from January 1949 to December. Ariyo Adebiyi, et al (2014), conducted a study to compare ARIMA and Artificial Neural Network models in predicting stock prices. Selection of these methods depends on various aspects that affect the aspects of time, data patterns, system model types observed, the level of forecast accuracy or desired forecast and so forth. That's why a problem arises if the observation or testing is done on a dynamic system that has a data pattern system with a formulation that is always changing or in other words a system that has a high difficulty level to make a model formulation at a certain time. In addition, to apply the statistical method, the data must meet certain assumptions according to the data pattern. By using technology in the field of Artificial neural network technology (Neural Network) hence identification of data pattern system be done by approach method of learning or training that is to determine the weight of link between optimum node. The main advantage of artificial neural networks is the ability of parallel computing by learning from the patterns taught. Based on their ability to learn, artificial neural networks can be trained to study and analyze patterns of past data and try to find a formula or function that will connect the pattern of past data with the desired output at this time or in the future. Based on that, in this study the authors are interested to conduct a comparative study, comparing whether a simple statistical forecasting model such as trend analysis, decomposition, and exponential smoothing and ARIMA can generate more accurate forecasts than complex models such as artificial neural networks. to predict or forecast the average food prices (people) in 2017. From the results of these comparisons will be selected the best forecasting models for the average food prices and this can be used as a reference for making policies corresponding food prices in the city of west java. The data used in this research is the average data of food price other than rice in weekly period in place from January 2014 until December 2016 (there are 53 data for each variable).

RESEARCH METHODOLOGY

Data collection method used in this study is non-participant observer, where researchers only observe the data that is available without participating to be part of a data system. The data needed is the average data of food prices in addition to rice taken from 7 market locations in the city of Place in the weekly period. Based on existing data, forecasting will be done with simple statistical methods such as trend analysis, exponential smoothing, decomposition and ARIMA as well as complex methods of ANN (Artificial Neural Network). Existing data is divided into two parts, namely the model period (in-sample) of 53 data and the prediction period (out-sample) of 20 data. Figure 1 shows the time series plots for each variable.

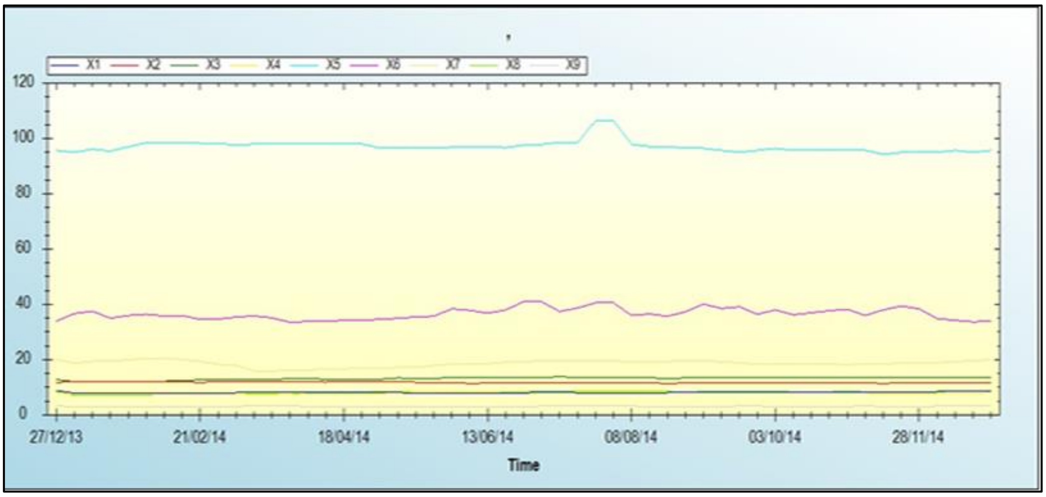

Figure 1. Time Variable Plot of Variables

Model formation is performed using data contained in the model period. Having obtained the best model of each method then do the forecasting with the model. To know the performance of each forecasting method, the comparison of forecasting results both in the data modeling period (In Sample), as well as testing period (out sample) by using the value of MSE (Mean Squared Error). The MSE value of the method used is compared to obtain a method that gives a smaller error rate than other methods. MSE values from methods used in comparison to get the method gives a smaller error rates compared to other methods. The framework of the above Thoughts are presented in the form of Figure 2 below:

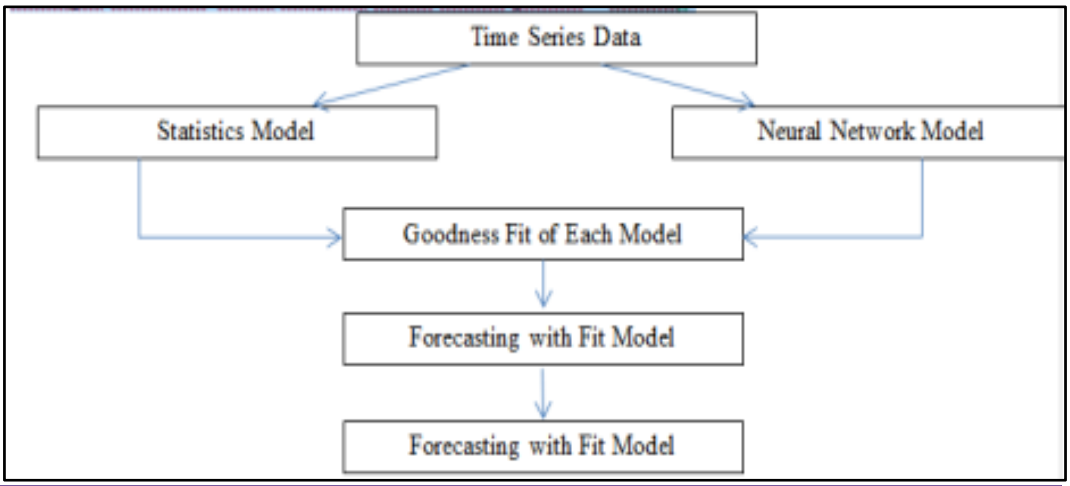

Figure 2

Based on the framework of thought in Figure 2, in the general outline of this study is to prepare time series data, analyze existing time series data using statistical methods and neural network backpropagation, determine the appropriate model for each variable and test the suitability of each model, forecasting by using a suitable model, performing a comparison of the accuracy of forecasting results with each model. For data processing and data analysis with statistical method will be used tools in the form of expert model existing in software or software statistics IBM SPSS version 21.0. As for artificial neural network method using software or software Zaitun Time Series version 0.2.1 which is a special software developed for time series analysis.

RESULTS AND DISCUSSION

Result of Analysis and Data Modeling with Statistical Method

The following will explain the results of data analysis and data modeling for statistical forecasting method using Expert Model on IBM Software SPSS version 21.0

Table 1. Description of the Best Model for Each Variable

Model Description

			Model Type
Model ID	Rice	Model_1	Simple
	Sugar	Model_2	Simple
	Cooking Oil	Model_3	Simple
	Wheat Flavour	Model_4	Simple
	Beef	Model_5	ARIMA(0,0,1)
	Chicken	Model_6	Simple
	Eggs	Model_7	ARIMA(0,1,2)
	Corn	Model_8	Simple
	Soy	Model_9	ARIMA(0,0,1)

Based on table 1, out of 9 variables analyzed there are 6 variables (X1, X2, X3, X4, X6 and X8) have the best model form of simple exponential smoothing da tone 3 variables (X5, X7 and X9) have the best model form ARIMA.

Table 2. Parameters for the Exponential Smoothing Model

Exponential Smoothing Model Parameters

Model			Estimate	SE	t	Sig.
Rice-Model_1	No Transformation	Alpha (Level)	1.000	.107	9.346	.000
Sugar-Model_2	No Transformation	Alpha (Level)	.361	.101	3.569	.001
Cooking Oil-Model_3	No Transformation	Alpha (Level)	.740	.120	6.174	.000
Wheat Flavour-Model_4	No Transformation	Alpha (Level)	.870	.120	7.237	.000
Chicken-Model_6	No Transformation	Alpha (Level)	.649	.127	5.103	.000
Corn-Model_8	No Transformation	Alpha (Level)	.670	.108	6.195	.000

Table 3. Parameters for ARIMA Model

Exponential Smoothing Model Parameters

Model			Estimate	SE	t	Sig.
Rice -Model_1	No Transformation	Alpha (Level)	1.000	.107	9.346	.000
Sugar r-Model_2	No Transformation	Alpha (Level)	.361	.101	3.569	.001
Oil Model_3	No Transformation	Alpha (Level)	.740	.120	6.174	.000
Butter -Model_4	No Transformation	Alpha (Level)	.870	.120	7.237	.000
Chicken -Model_6	No Transformation	Alpha (Level)	.649	.127	5.103	.000
Corn -Model_8	No Transformation	Alpha (Level)	.670	.108	6.195	.000

The data contained in tables 2 and 3 show the magnitude of the parameters of each best model and the standard error. Diagnostic tests were performed using t-statistics. Based on tables 2 and 3, the t-statistic score is compared with the t table value at 95% confidence level regardless of the sign. The value of t table at 95% confidence degree is 1,960. Therefore, all parameter values are statistically significant and can be used in forecasting models.

Table 4. Model Conformity Test (Goodness of Fit Model)

Model Statistics													
		Model Fit statistics								Ljung-Box Q(18)			
Model	Number of Predictors	Stationary R-squared	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.	Number of Outliers
Rice-Model_1	0	-1.196E-006	.426	157.417	.821	66.847	11.935	942.857	10.193	5.823	17	.994	0
Sugar-Model_2	0	.225	.551	159.165	.980	115.482	3.647	427.180	10.215	13.483	17	.703	0
Cooking Oil-Model_3	0	.053	.843	202.996	.996	129.841	5.508	664.860	10.701	12.774	17	.751	0
Wheat Flavour-Model_4	0	.019	.751	159.861	1.233	99.870	8.428	632.070	10.224	15.528	17	.557	0
Beef-Model_5	0	.536	.536	1519.110	.840	827.253	8.510	9057.044	14.802	13.965	17	.670	0
Chicken-Model_6	0	.045	.402	1579.348	3.202	1180.878	12.042	4335.063	14.804	17.105	17	.447	0
Eggs-Model_7	0	.127	.850	451.647	1.717	314.797	10.016	1602.518	12.302	8.636	17	.951	0
Corn-Model_8	0	.091	.572	342.683	2.683	213.631	21.832	1528.267	11.749	6.857	17	.985	0
Cassava-Model_9	0	.286	.286	136.546	3.381	104.990	14.052	401.476	9.983	10.724	17	.871	0

Based on the results of conformity test model as in table 4, it can be concluded that the forecasting model for each variable is appropriate and good because the values of the standard size of the model such as MSE, MAPE, MAE is quite small. Therefore, the model obtained can be used for data forecasting the next period, which is 52 weeks to come. The results of data forecasting week 54 to week 73, can be seen in table 5 below:

Table 5. Forecasting Results with the Best Statistics Model

		Forecasting week-																			
Model		54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73
Rice-Model_1	Forecast	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9	8842.9
	UCL	9158.7	9289.6	9390.0	9474.6	9549.2	9616.6	9678.6	9736.3	9790.5	9841.8	9890.5	9937.1	9981.8	10024.8	10066.2	10106.4	10145.3	10183.0	10219.7	10255.5
	LCL	8527.0	8396.1	8295.7	8211.1	8136.5	8069.1	8007.1	7949.4	7895.2	7844.0	7795.2	7748.6	7703.9	7660.9	7619.5	7579.3	7540.5	7502.7	7466.0	7430.2
Sugar-Model_2	Forecast	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7	11610.7
	UCL	11930.1	11950.4	11969.5	11987.6	12004.9	12021.4	12037.3	12052.7	12067.5	12081.9	12095.8	12109.4	12122.6	12135.4	12148.0	12160.3	12172.3	12184.0	12195.5	12206.8
	LCL	11291.4	11271.1	11252.0	11233.9	11216.6	11200.1	11184.2	11168.8	11154.0	11139.6	11125.7	11112.1	11098.9	11086.1	11073.5	11061.2	11049.2	11037.5	11026.0	11014.7
Cooking Oil-Model_3	Forecast	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0	13537.0
	UCL	13944.3	14043.7	14126.6	14199.1	14264.5	14324.5	14380.2	14432.4	14481.8	14528.7	14573.5	14616.5	14657.7	14697.6	14736.1	14773.4	14809.6	14844.8	14879.1	14912.5
	LCL	13129.6	13030.2	12947.4	12874.8	12809.4	12749.4	12693.7	12641.5	12592.1	12545.2	12500.4	12457.5	12416.2	12376.4	12337.9	12300.6	12264.3	12229.1	12194.9	12161.4
Wheat Flavour-Model_4	Forecast	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5	8133.5
	UCL	8454.3	8558.8	8642.2	8713.8	8777.5	8835.4	8888.9	8938.9	8985.9	9030.5	9072.9	9113.6	9152.6	9190.1	9226.4	9261.5	9295.5	9328.6	9360.8	9392.2
	LCL	7812.7	7708.2	7624.7	7553.1	7489.4	7431.5	7378.0	7328.1	7281.0	7236.5	7194.0	7153.4	7114.4	7076.8	7040.5	7005.4	6971.4	6938.3	6906.1	6874.8
Beef-Model_5	Forecast	96921.0	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1	97099.1
	UCL	99938.0	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2	101237.2
	LCL	93904.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0	92961.0
Chicken-Model_6	Forecast	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8	34050.8
	UCL	37220.0	37829.0	38352.5	38819.0	39243.6	39636.1	40002.8	40348.2	40675.5	40987.5	41286.0	41572.7	41848.8	42115.5	42373.6	42624.0	42867.3	43104.0	43334.7	43559.8
	LCL	30881.7	30272.7	29749.2	29282.7	28858.0	28465.5	28098.9	27753.5	27426.1	27114.2	26815.7	26529.0	26252.9	25986.2	25728.1	25477.7	25234.4	24997.7	24767.0	24541.9
Telur-Model_7	Forecast	20141.5	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2	20313.2
	UCL	21035.3	21577.2	22111.5	22520.1	22864.0	23166.8	23440.3	23691.9	23925.9	24145.7	24353.5	24551.2	24740.0	24921.1	25095.4	25263.5	25426.1	25583.7	25736.7	25885.5
	LCL	19247.7	19049.1	18514.8	18106.3	17762.4	17459.6	17186.0	16934.5	16700.5	16480.7	16272.8	16075.2	15886.3	15705.2	15531.0	15362.9	15200.3	15042.7	14889.7	14740.9
Corn-Model_8	Forecast	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1	8696.1
	UCL	9383.8	9523.9	9643.6	9749.7	9846.1	9935.0	10017.9	10096.0	10169.9	10240.3	10307.6	10372.2	10434.4	10494.4	10552.6	10608.9	10663.6	10716.9	10768.8	10819.4
	LCL	8008.5	7868.3	7748.7	7642.5	7546.1	7457.2	7374.3	7296.2	7222.3	7152.0	7084.7	7020.0	6957.8	6897.8	6839.7	6783.3	6728.6	6675.3	6623.4	6572.8
Cassava-Model_9	Forecast	3199.5	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9	3116.9
	UCL	3466.8	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6	3434.6
	LCL	2932.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2	2799.2
For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period,																					

Result
of Analysis and Data Modeling with Artificial Neural Network Method, The following will explain the results of data analysis and data modeling for the method of neural network forecasting version 0.1.2

Table 6. Artificial Neural Network Model with Sigmoid Bipolar Activation Function for each Variable

Network Architecture									
Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9
Input Layer Neurons	12	12	12	12	12	12	12	12	12
Hidden Layer Neurons	12	12	12	12	12	12	12	12	12
Output Layer Neurons	1	1	1	1	1	1	1	1	1
Activation Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function	Bipolar Sigmoid Function
Back Propagation Learning									
Learning Rate	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Momentum	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Criteria									
Error	0.090131	0.001476	0.10727	0.032478	0.070523	0.00279	0.03196	0.127651	0.000019
MSE	1142.767849	15.507689	5782.678117	605.384121	148881.731	2120.395281	9979.858935	5466.876572	0.093859
MAE	23.854393	2.127274	52.067825	17.370974	285.34208	26.940395	73.107961	41.944319	0.155316

Based on table 6 above, of the 9 variables analyzed by artificial neural network using Bipolar Sigmoid activation function, there is only 1 variable that is X2 whose MSE value is small (15,51), while 8 other variables have big MSE value MSE ≥ 100). This shows the model is less suitable. For that will be tried with other artificial neural network architecture that is with Hyperbolic Tangent activation function. The results of data analysis with the new architecture can be seen in table 7 below.

Table 7. Artificial Neural Network Model with Hyperbolic Typical Activation Function for each Variable

Network Architecture									
Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9
Input Layer Neurons	12	12	12	12	12	12	12	12	12
Hidden Layer Neurons	12	12	12	12	12	12	12	12	12
Output Layer Neurons	1	1	1	1	1	1	1	1	1
Activation Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function	Hyperbolic Tangent Function
Back Propagation Learning									
Learning Rate	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Momentum	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Criteria									
Error	0.028863	0.000007	0.148719	0.000817	0.044624	0.000032	0.008372	0.095835	0.000015
MSE	302.764942	0.081349	8935.835308	13.890066	85172.10265	23.91119	2049.1837	4006.223546	0.064746
MAE	12.434188	0.143615	65.807776	2.529535	198.579776	2.568358	32.524767	34.418216	0.170536

Based on table 7 above, from 9 variables analyzed by artificial neural network method using Hyperbolic Tangent activation function, there are 4 variables that MSE is small (MSE ≤ 100), that is variable X2, X4, X6, and X9, while 5 variables others, X1, X3, X5, X7 and X8 have large MSE values (MSE> 100). This shows that the model is suitable for 4 variables and less suitable for the other 5 variables. Therefore it is necessary to try again for other artificial neural network architecture. The results of data forecasting week 54 to week 73, can be seen in the table 8 and 9 below:

Table 8. Results of Forecasting with Sigmoid Bipolar Neural Network Method

Forecasting week- JST Bipolar Sigmoid																				
Model	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73
Rice-Model_1	8882.7	8889.5	8891.0	8889.4	8888.7	8837.9	8838.3	8850.7	8856.8	8855.8	8854.6	8854.2	8852.9	8849.6	8848.2	8850.3	8851.8	8851.9	8851.6	8851.4
Sugar-Model_2	11403.1	11403.9	11481.4	11484.4	11490.6	11548.1	11489.9	11371.9	11346.3	11360.5	11384.4	11410.4	11422.1	11395.5	11361.9	11348.5	11350.7	11359.5	11370.0	11373.8
Cooking Oil-Model_3	13522.1	13431.6	13467.6	13531.2	13532.0	13571.6	13520.7	13528.9	13498.2	13500.3	13505.4	13527.6	13557.0	13542.6	13546.9	13517.2	13523.6	13513.4	13514.4	13529.4
Wheat Flavour-Model_4	8096.5	8049.5	8267.2	8233.2	8234.2	8313.2	8262.0	8323.3	8272.0	8233.7	8321.8	8269.8	8220.3	8225.3	8224.7	8221.8	8237.6	8240.6	8250.7	8263.4
Beef-Model_5	95166.2	95076.8	94949.8	94688.3	94776.0	94901.9	94836.5	94983.1	94863.6	94884.6	94826.3	94696.9	94701.3	94662.1	94674.6	94714.0	94696.2	94706.7	94688.8	94664.1
Chicken-Model_6	37191.3	38273.1	34089.9	33224.4	33211.9	34339.5	34064.0	33579.6	35508.6	35132.7	34081.6	35722.6	40079.4	38256.0	33709.2	36232.7	38115.1	39938.6	33770.2	34220.2
Telur-Model_7	19856.6	19683.5	19337.7	19139.9	19272.5	19377.2	19604.0	19482.1	19339.9	18766.6	18464.4	18386.8	18264.1	18020.5	17644.9	17072.2	16581.9	16394.1	16510.9	16826.7
Corn-Model_8	8375.4	7775.7	7578.7	7913.6	8744.7	8751.1	8718.2	7798.0	7063.7	7087.3	8759.9	8770.2	8709.8	7689.7	7096.7	7903.8	8734.1	8749.1	8778.7	7607.0
Cassava-Model_9	3393.6	3435.5	3441.1	3388.4	3328.1	3135.7	3049.8	3086.6	3363.9	3451.5	3454.4	3304.9	3059.7	3104.7	3440.6	3370.0	3450.3	3457.3	3431.3	3444.0

Table 9. Results of Forecasting with Hyperbolic Tangent Neural Network Method

	Forecasting week- JST Hyperbolic Tangent																			
Model	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73
Rice-Model_1	8893.2	8895.2	8895.2	8895.2	8892.5	8865.6	8861.7	8860.8	8859.4	8859.1	8858.9	8858.8	8858.8	8858.8	8858.8	8858.8	8858.8	8858.8	8858.8	8858.8
Sugar-Model_2	11492.7	11542.8	11676.3	11627.9	11583.9	11598.4	11606.2	11504.6	11542.9	11626.2	11673.3	11597.3	11554.0	11575.7	11560.5	11539.6	11618.6	11638.1	11642.9	11516.9
Cooking Oil-Model_3	13548.0	13501.0	13508.3	13581.5	13570.6	13587.2	13549.8	13531.2	13512.0	13539.0	13537.5	13556.3	13579.9	13551.9	13562.6	13532.3	13536.2	13544.7	13548.2	13559.4
Wheat Flavour-Model_4	8149.9	8043.2	8307.2	8307.7	8162.0	8433.6	8219.6	8285.3	8466.0	8175.3	8276.8	8323.8	8069.3	8172.1	8230.3	8054.7	8127.9	8125.4	7909.5	8193.7
Beef-Model_5	95139.4	94916.3	94974.0	94412.0	94842.5	94776.3	94761.4	95117.7	94698.4	94936.1	94669.1	94511.1	94634.9	94427.9	94628.3	94599.2	94560.7	94689.5	94494.3	94550.8
Chicken-Model_6	34391.0	35550.6	33169.5	33178.7	33271.9	35212.0	33904.4	38227.3	34167.9	38393.3	34307.9	40215.6	39806.2	40180.9	36654.0	37731.5	38066.5	39365.9	37530.1	40829.6
Telur-Model_7	19917.9	19747.0	19067.5	18666.0	18685.0	18789.2	19122.0	19653.7	19949.4	19396.6	18620.3	18236.3	17900.3	17103.6	16451.8	16396.0	16509.0	16623.5	16875.6	17120.4
Corn-Model_8	8535.1	8071.7	8071.7	8356.5	8697.6	8700.5	8678.9	7992.6	7093.8	6915.5	7397.9	8743.8	8616.0	8705.3	8356.3	8528.7	8616.2	8696.0	8645.0	8521.8
Cassava-Model_9	3217.8	2848.6	2879.2	2943.2	3145.0	3451.1	3459.0	3344.7	2836.1	2857.7	3014.8	3142.8	3457.9	3458.2	3408.5	2842.1	2837.1	3106.8	3200.3	3452.6

COMPARISON OF THE RESULTS

After getting the most suitable model for each variable using the method of statistical or neural networks, then the next will be made based on the results of the comparison of the accuracy of his model values of MSE, i.e., the middle value (mean squared error squared error) by the following formula.

$$MSE = \frac{1}{n}\sum_{I=1}^{n} e_i^{2} \quad \ldots\ldots (1)$$

Comparison of Analysis and Data Modeling Results with Statistical Methods and Artificial Neural Network Methods. The comparison results for each model can be seen in table 10 below:

Table 10. Results of Forecasting with Hyperbolic Tangent Neural Network Method

NO.	VARIABLE	MSE FOR FIT MODEL						BEST MODEL
		TREND	DEKOMPOSISI	EXPONENTIAL SMOOTHING	MOVING AVERAGE	ARIMA	JST	
1	X1	27095.31855	25050.38885	20664.20017	15528.21	25266.101	302.76494	JST hyperbolic tangent
2	X2	22079.18417	20246.49176	22040.07636	25060.02	27260.037	0.081349	JST hyperbolic tangent
3	X3	41786.70405	38864.44024	42667.73325	37565.03	43625.240	5782.6781	JST bipolar sigmoid
4	X4	46884.96519	44074.66051	27670.89151	22183.87	26410.579	13.890066	JST hyperbolic tangent
5	X5	3848620.437	3620942.152	2934537.19	3828231	2307696.530	85172.103	JST hyperbolic tangent
6	X6	2434674.802	2243158.965	2466683.699	2876351	2339783.745	23.91119	JST hyperbolic tangent
7	X7	980145.0403	908196.1272	238561.9276	215146.7	203985.388	2049.1837	JST hyperbolic tangent
8	X8	106627.8357	98580.45189	97178.70703	80832.33	115666.433	4006.2235	JST hyperbolic tangent
9	X9	23448.83817	21679.11454	22537.89991	19657.86	18644.766	0.064746	JST hyperbolic tangent
Mean		836818.125	780088.088	652504.7027	791172.9	567593.202	10816.767	JST hyperbolic tangent

Based on the MSE value of the model suitable for each variable, it can be concluded that forecasting model with artificial neural network method using hyperbolic tangent activation function, is the best model because of 9 variables analyzed, 8 variables have MSE value for neural network model hyperbolic tangent and 1 variable has the smallest MSE value for the sigmoid bipolar artificial neural model. Forecasting results using the best model can be seen in table 11 below:

Table 11. Forecasting Results with Best Forecasting Model

Week-	Periode	X1 true	X1 fore	error	X2 true	X2 fore	error	X3 true	X3 fore	error	X4 true	X4 fore	error	X5 true	X5 fore	error
54	2/1/2015	7900.0	8893.2	993.2	12071.4	11492.7	578.7	12642.9	13522.1	879.3	8142.9	8149.9	7.0	96000.0	95139.4	860.6
55	9/1/2015	7900.0	8895.2	995.2	12214.3	11542.8	671.5	12071.4	13431.6	1360.1	7500.0	8043.2	543.2	95285.7	94916.3	369.4
56	16/01/15	7900.0	8895.2	995.2	12214.3	11676.3	538.0	12000.0	13467.6	1467.6	7500.0	8307.2	807.2	96428.6	94974.0	1454.6
57	23/01/15	7971.4	8895.2	923.7	12214.3	11627.9	586.3	12000.0	13531.2	1531.2	7500.0	8307.7	807.7	95714.3	94412.0	1302.3
58	30/01/15	8085.7	8892.5	806.8	12357.1	11583.9	773.3	12071.4	13532.0	1460.5	7500.0	8162.0	662.0	97285.7	94842.5	2443.2
59	6/2/2015	8085.7	8865.6	779.9	12357.1	11598.4	758.8	12214.3	13571.6	1357.3	7571.4	8433.6	862.2	98714.3	94776.3	3938.0
60	13/02/15	8014.3	8861.7	847.4	12357.1	11606.2	750.9	12214.3	13520.7	1306.4	7571.4	8219.6	648.1	98714.3	94761.4	3952.9
61	20/02/15	8014.3	8860.8	846.5	12357.1	11504.6	852.5	12571.4	13528.9	957.4	7571.4	8285.3	713.8	98714.3	95117.7	3596.6
62	27/02/15	8014.3	8859.4	845.2	12000.0	11542.9	457.1	12642.9	13498.2	855.4	7571.4	8466.0	894.6	98571.4	94698.4	3873.0
63	6/3/2015	8085.7	8859.1	773.4	12285.7	11626.2	659.5	12571.4	13500.3	928.9	7571.4	8175.3	603.9	98571.4	94936.1	3635.3
64	13/03/15	8300.0	8858.9	558.9	12285.7	11673.3	612.4	12571.4	13505.4	934.0	7642.9	8276.8	634.0	97857.1	94669.1	3188.0
65	20/03/15	8300.0	8858.8	558.8	12142.9	11597.3	545.6	12714.3	13527.6	813.3	7785.7	8323.8	538.1	98285.7	94511.1	3774.6
66	27/03/15	8371.4	8858.8	487.3	12142.9	11554.0	588.9	12714.3	13557.0	842.8	7785.7	8069.3	283.6	98285.7	94634.9	3650.8
67	3/4/2015	8257.1	8858.8	601.6	12071.4	11575.7	495.7	13142.9	13542.6	399.7	7642.9	8172.1	529.2	98285.7	94427.9	3857.8
68	10/4/2015	8185.7	8858.8	673.1	12071.4	11560.5	510.9	13142.9	13546.9	404.0	7928.6	8230.3	301.7	98285.7	94628.3	3657.4
69	17/04/15	8185.7	8858.8	673.1	12000.0	11539.6	460.4	12857.1	13517.2	660.0	8071.4	8054.7	16.7	98285.7	94599.2	3686.5
70	24/04/15	8114.3	8858.8	744.5	12071.4	11618.6	452.9	12857.1	13523.6	666.4	8214.3	8127.9	86.4	98285.7	94560.7	3725.0
71	1/5/2015	8185.7	8858.8	673.1	12071.4	11638.1	433.3	12857.1	13513.4	656.2	8214.3	8125.4	88.9	98285.7	94689.5	3596.2
72	8/5/2015	8185.7	8858.8	673.1	12071.4	11642.9	428.5	12928.6	13514.4	585.9	8357.1	7909.5	447.6	96857.1	94494.3	2362.9
73	15/05/15	7900.0	8858.8	958.8	12214.3	11516.9	697.4	12857.1	13529.4	672.3	8357.1	8193.7	163.5	96857.1	94550.8	2306.4
Mean		8097.9	8868.3	770.4	12178.6	11585.9	592.6	12582.1	13519.1	936.9	7800.0	8201.7	482.0	97678.6	94717.0	2961.6

Table 12. Error Calculation Results with Best Forecasting Model

Week-	Periode	X6 true	X6 fore	error	X7 true	X7 fore	error	X8 true	X8 fore	error	X9 true	X9 fore	error
54	2/1/2015	37142.9	34391.0	2751.9	20285.7	19917.9	367.8	9428.6	8535.1	893.5	3428.6	3217.8	210.8
55	9/1/2015	36714.3	35550.6	1163.7	18857.1	19747.0	889.9	8000.0	8071.7	71.7	2857.1	2848.6	8.6
56	16/01/15	37571.4	33169.5	4401.9	19428.6	19067.5	361.0	8000.0	8071.7	71.7	2857.1	2879.2	22.1
57	23/01/15	35000.0	33178.7	1821.3	19428.6	18666.0	762.6	7428.6	8356.5	927.9	2857.1	2943.2	86.1
58	30/01/15	36000.0	33271.9	2728.1	20071.4	18685.0	1386.4	7428.6	8697.6	1269.0	2857.1	3145.0	287.8
59	6/2/2015	36428.6	35212.0	1216.5	20285.7	18789.2	1496.5	7285.7	8700.5	1414.8	3000.0	3451.1	451.1
60	13/02/15	35857.1	33904.4	1952.7	20571.4	19122.0	1449.4	7857.1	8678.9	821.7	3000.0	3459.0	459.0
61	20/02/15	36000.0	38227.3	2227.3	20071.4	19653.7	417.8	7857.1	7992.6	135.5	3142.9	3344.7	201.8
62	27/02/15	34571.4	34167.9	403.5	19428.6	19949.4	520.8	8000.0	7093.8	906.2	3142.9	2836.1	306.8
63	6/3/2015	34714.3	38393.3	3679.0	18285.7	19396.6	1110.8	8000.0	6915.5	1084.5	3142.9	2857.7	285.1
64	13/03/15	35428.6	34307.9	1120.7	18000.0	18620.3	620.3	8142.9	7397.9	745.0	3142.9	3014.8	128.0
65	20/03/15	35857.1	40215.6	4358.5	16000.0	18236.3	2236.3	8142.9	8743.8	601.0	3285.7	3142.8	142.9
66	27/03/15	35142.9	39806.2	4663.4	15928.6	17900.3	1971.8	8142.9	8616.0	473.2	3285.7	3457.9	172.2
67	3/4/2015	33571.4	40180.9	6609.5	16285.7	17103.6	817.9	8000.0	8705.3	705.3	3285.7	3458.2	172.4
68	10/4/2015	33857.1	36654.0	2796.8	16285.7	16451.8	166.1	8571.4	8356.3	215.1	3142.9	3408.5	265.6
69	17/04/15	33857.1	37731.5	3874.4	16642.9	16396.0	246.8	8571.4	8528.7	42.8	3142.9	2842.1	300.8
70	24/04/15	34285.7	38066.5	3780.8	16714.3	16509.0	205.3	8571.4	8616.2	44.7	3142.9	2837.1	305.8
71	1/5/2015	34428.6	39365.9	4937.3	17071.4	16623.5	447.9	8571.4	8696.0	124.6	3142.9	3106.8	36.1
72	8/5/2015	34571.4	37530.1	2958.7	16857.1	16875.6	18.5	8571.4	8645.0	73.5	3142.9	3200.3	57.5
73	15/05/15	35000.0	40829.6	5829.6	17214.3	17120.4	93.9	9285.7	8521.8	763.9	3357.1	3452.6	95.4
Mean		35300.0	36707.7	3163.8	18185.7	18241.6	779.4	8192.9	8297.0	569.3	3117.9	3145.2	199.8

If the average value for the forecast result is compared with the average value of the actual data, then the results obtained as an error calculation in the table 13 below:

Table 13. The results of the Calculation Error with the best forecasting Model

No.	Variable	Mean of			
		X-True	X-Fore	Error (ei)	ei^2
1	X1	8097.9	8868.3	770.4	593577.6
2	X2	12178.6	11585.9	592.6	351213.7
3	X3	12582.1	13519.1	936.9	877855.7
4	X4	7800.0	8201.7	482.0	232298.1
5	X5	97678.6	94717.0	2961.6	8770904.7
6	X6	35300.0	36707.7	3163.8	10009586.2

7	X7	18185.7	18241.6	779.4	607448.7
8	X8	8192.9	8297.0	569.3	324084.8
9	X9	3117.9	3145.2	199.8	39915.7
MSE					**2422987.2**

Based on the results in table 13, it can be concluded that the value of MSE for the best forecasting model is still very large. This suggests that further analysis is needed to obtain a better forecasting model, which can reduce the value of MSE forecasting models. Large MSE values are likely to be caused by fluctuating, erratic data, so that data patterns are difficult to learn and hard to predict well. Therefore, new methods of forecasting are developed, which are collaboration (hybrid) of statistical methods and artificial neural networks that can minimize the value of MSE and get a more accurate model.

CONCLUSIONS AND RECOMMENDATIONS

Based on data analysis and data modeling using statistic method, it can be concluded that the best model is Simple Exponential Smoothing model (there are 5 variables) and ARIMA model (there are 3 variables). For forecasting model with artificial neural network, the best model is using hyperbolic tangent activation function (there are 8 variables) while 1 variable has the best model with bipolar sigmoid activation function. Overall, when comparing MSE values for each of the best models, the smallest MSE value is the neural network forecasting model using the hyperbolic tangent activation function (8 variables) and the artificial neural network forecasting model using the sigmoid bipolar activation function (1 variable). The average MSE of the best model is 10816,767 for the in-sample model. While the forecasting results using the best model, obtained MSE value of 2422987.2 for out-sample model. Based on these results it is necessary to conduct further research to analyze data using other forecasting methods, one of which is possible with the collaboration (hybrid) between statistical methods and neural networks to get smaller MSE results and forecasting model becomes more accurate.

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