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Forecasting Oil Palm Production Based on a Nonlinear Autoregressive Exogenous (NARX) Neural Network Model

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A time series data analysis and prediction tool that is able to predict the yield of oil palm is needed to ensure an acceptable forecasting quality. An attempt was made in this study to develop a Nonlinear Autoregressive Exogenous (NARX) neural network model of oil palm production using MATLAB. This NARX model was used to predict the yield of oil palm in the states of Kelantan, Johor, Sabah and Sarawak in Malaysia. The performance of the NARX model was tested and validated using the Levenberg-Marquardt (LM) training algorithm and was compared with the Autoregressive Integrated Moving Average (ARIMA) model. The best performance of the NARX model was achieved at 70 per cent:15 per cent:15 per cent, with 10 neurons in the hidden layers and a delay value of four for Sarawak. For Kelantan and Johor, the NARX model produced the best result using the parameters of 70 per cent:10 per cent:20 per cent, with 13 neurons in the hidden layers and a delay value of four. The best result for Sabah was achieved using the parameters of 70 per cent:15 per cent:15 per cent, with 13 neurons in the hidden layers and a delay value of four. The results demonstrated that the proposed NARX model was more effective in modeling and forecasting time series data than the ARIMA model. The NARX model registered a minimum mean square error and mean absolute percentage error with a maximum average accuracy percentage and correlation coefficient.

Keywords: *Oil palm cultivation, yield predictions, nonlinear autoregressive exogenous neural network, autoregressive integrated moving average.*

Oil palm products are major agricultural commodities in Malaysia. The palm oil industry is expected to grow, given the annual increase in palm oil production. In addition to vegetable oil, palm oil products are also used as raw materials for chemical production (Barcelos *et al.*, 2015). The palm oil industry must prepare raw materials, both in terms of quantity and quality, according to market demand. Plantation companies aim to achieve timely and accurate production of palm oil (Otieno *et al.*, 2016). Thus, state and private plantation companies should design tools that can predict production costs and meet market demands. Production forecasts can be used as a reference target for oil palm production. One constraint of private-owned palm oil companies is their failure to reach high targets. Thus, methods should be developed to predict production accurately.

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Forecasts of crop yields can be used as a basis for decision-making with regard to the marketing of agricultural commodities. Yield prediction is crucial in agricultural production and administration, local food supply, trade and international food production and environmental sustainability (Frelat *et al.*, 2016). Forecasting in various aspects related to agriculture is important, given the dynamic conditions of oil palm production. Despite the strong need for accurate forecasts, the current status of these predictions is far from satisfactory. Weather variability within and between seasons is an uncontrollable factor that generates inconsistent yields. Weather, pollution and other variables affect crops differently during various stages of development. Thus, the extent of the effect of these variables on crop yield depends on the magnitude of these variables, as well as on the distribution pattern of the variables during the crop season (Rahman & Robson, 2016).

Regression models are commonly employed for forecasting. However, time series models are more advanced than regression models and are more suitable for predicting future values. Considerable research has been conducted to forecast future values using time series models (Bhardwaj *et al.*, 2015). Models of time series data are quantitative forecasting models. These models, often called intrinsic quantitative models, are aimed at identifying the patterns in a historical data series and extrapolating the patterns in a sequence of data based on the pattern of future data (Arbain & Wibowo, 2012). Various studies on time series models rely on statistical models. Numerous methods can be applied to describe temporal behaviour. These approaches include autoregressive processes (AR) and Autoregressive Integrated Moving Average (ARIMA) models. An effective time series analysis provides comprehensive statistical modeling and covers various styles ranging from pre-processing to the lack of pre-processing and seasonal time series (Diaconescu, 2008). According to Ferreira *et al.* (2015), one of the problems that hinder the development and use of these methods is the requirement for a probability distribution of the data. Existing methodologies are sometimes unsuitable for specific situations and fail to describe behaviours that dynamically change with time.

The use of ARIMA models for forecasting is a common approach that is addressed traditionally by regression models. Although the methods are widely understood and relatively easy to compute, they consider the addition or removal of one variable at a time, depending on the selected variables (Bhardwaj *et al.*, 2015). According to Ficken (2015), it is difficult to establish specific parameters that exert a considerable effect collectively because linear relationships or linear correlations consider only one parameter at a time. Therefore, models based on a sequential approach significantly limit the number of models being examined. This finding suggests that an exhaustive approach is not feasible compared to other approaches that show a few variables.

An accurate prediction of yields in plant production should be used with other processing units to minimise costs, achieve consistent product quality and manage different processes. This can be carried out using an Artificial Neural Network (ANN) system (Pantani *et al*., 2016; Nabavi-Pelesaraei *et al*., 2016). An ANN is an artificial intelligence tool for solving problems related to clustering and pattern recognition (Dayhoff & DeLeo, 2001). ANNs are suitable for prediction problems (Kose & Arslan, 2017). ANNs provide more features than the ARIMA time series modeling given that it deals with data that are not natural problems. The non-linear features of these networks have multiple uses and are not required by the standard specifications of models or the probability distributions on assumed data. These networks can identify chaotic components more effectively than most alternative methods; thus, an important susceptibility of the time series model is that it possesses chaotic components (Khandelwal *et al.*, 2015; Egrioglu *et al.*, 2015; Haviluddin & Jawahir, 2015).

According to Rad *et al.* (2015), a neural network model provides a good match for data. An out-of-sample analysis that provides speculations requires statistical modeling skills to choose a perfect neural network model. Hence, the relationship between neural network models and models of autoregressive and moving averages can be merged without competing models to match and good speculations (Taskaya-Temizel & Casey, 2005). The specific dynamic networks examined were either concentrated networks with the dynamics only at the input layer or feed-forward networks. The nonlinear autoregressive network with exogenous inputs (NARX) is a repeated dynamic network with feedback connections that include numerous layers of the network. The NARX model is based on the linear ARX model, which is usually used in time series modeling (Boussaada *et al.*, 2018). The major formula for the NARX model is as follows:

$$y(t) = f\,[y(t-1), y(t-2), \ldots, y(t-n_y),\; u(t-1), u(t-2), \ldots, u(t-n_u)]$$

where $u(t)$ and $y(t)$ represent the input and output of the model at time t, n_u and n_y are the lags of the input and output of the system and f a nonlinear function. The NARX model is implemented using a feed-forward neural network to approximate the function diagram of the resulting network, as shown in *Figure 1*. The NARX model has many applications. It can be used in predictions to indicate the next value of an input signal, and can also be used for nonlinear liquidation.

Mathematical forecasting minimises the mean square error of forecasting, assuming that *t* refers to the current time period when the required forecasts are calculated to predict the value of viewing that will occur after h at any of the time periods. This method is applied to predict the value of viewing (y_{t+h}) that did not occur, which is called h in this case, of the prediction horizon or lead time (Diaconescu,

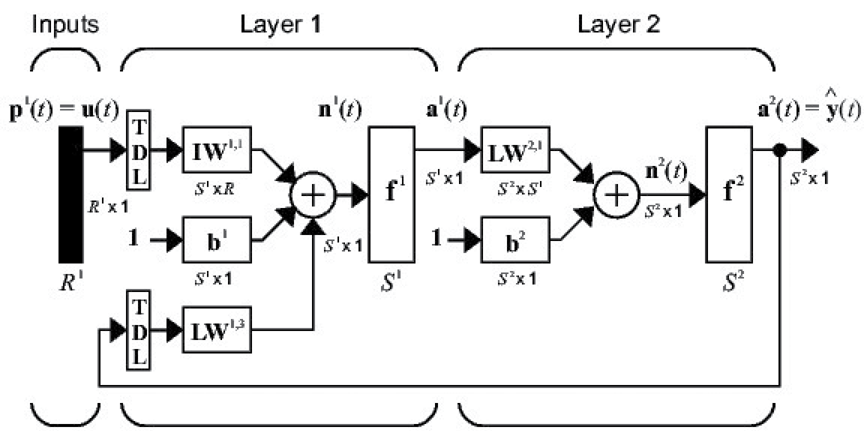


Figure 1 Block diagram of NARX

2008;Guzman *et al.*, 2017). Statistically, objective forecasts of oil palm production based on time series variables are necessary to obtain reliable forecasts. This information can be widely used if the oil palm yield and the quality response to different conditions can be predicted early and accurately. This information may be of particular importance to the purchasing decisions of farmers, who optimise late season agronomics, and the marketing decisions of millers. Various simplifications are embodied in the statistical modeling framework, which compromise feasibility and efficiency.

This study built a suitable and appropriate NARX model that can be used to forecast the yield of oil palm production in various areas in Malaysia. The NARX model, as well as different training architectures and the ARIMA model, were examined and compared using MATLAB software.

MATERIALS AND METHODS

The related works on oil palm production in multiple states in Malaysia including the time series analysis that was performed using the NARX and ARIMA models will be presented in this section.

Time series

A time series dataset is a dataset that consists of observations ordered in time. In principle, a time series model is used to predict the values of data (Yn+1, Yn+2,…..,Yn+n) based on the data (X n+1, X n+2,….X n+n) where Y is dependent variables and Xn is independent variables (Diaconescu, 2008). In the present study, a time series dataset was obtained from the Malaysian Palm Oil Board (MPOB), Meteorological Department and Department of Statistics Malaysian Prime Minister's Department, as shown in *Table 1*. The data on the fresh fruit bunch yield (tonnes per hectare) were used throughout an 11-year period of harvest in the states of Kelantan, Johor, Sabah and Sarawak. This period spanned from January 2005 to December

TABLE 1
INPUT AND OUTPUT VARIABLES

Input data		*Output*
Quality of land		
• Percentage of mature (%)		
• Percentage of immature (%)		
Climate		
• Rainfall (mm)	• Temperature (^{0}C)	*FFB Yield (tonnes/ha)
• Rain day	• Surface wind speed (m/sec)	
• Humidity (%)	• Evaporation (mm)	
• Radiation (Mjm-^{2})	• Cloud cover (oktas)	
Air pollution (ppm)		
• Ozone (O_3)		
• Carbon monoxide (CO)		
• Nitrogen dioxide (NO_2)		
• Sulfur dioxide (SO_2)		
• Particulate matter of less than10 microns in size (PM_{10})		

2015. The dataset and the plotted dataset is shown in *Figure 2*.

The data on the quarterly oil palm yield were analysed using MATLAB R2013b. The quarterly oil palm yield data had to be normalised in the interval of [0, 1] using statistical data normalisation, which is usually expressed as (Haviluddin & Tahyudin, 2015):

$$X_i = \frac{0.8(X - X_{MIN})}{(X_{MAX} - X_{MIN})} + 0.1 \qquad (1)$$

where: X_i is the actual value of the sample; X_{MAX} takes a large value, and X_{MIN} takes a sample of data that is less than the minimum value. Next, an inverse transform process was performed in order to get the actual value, and

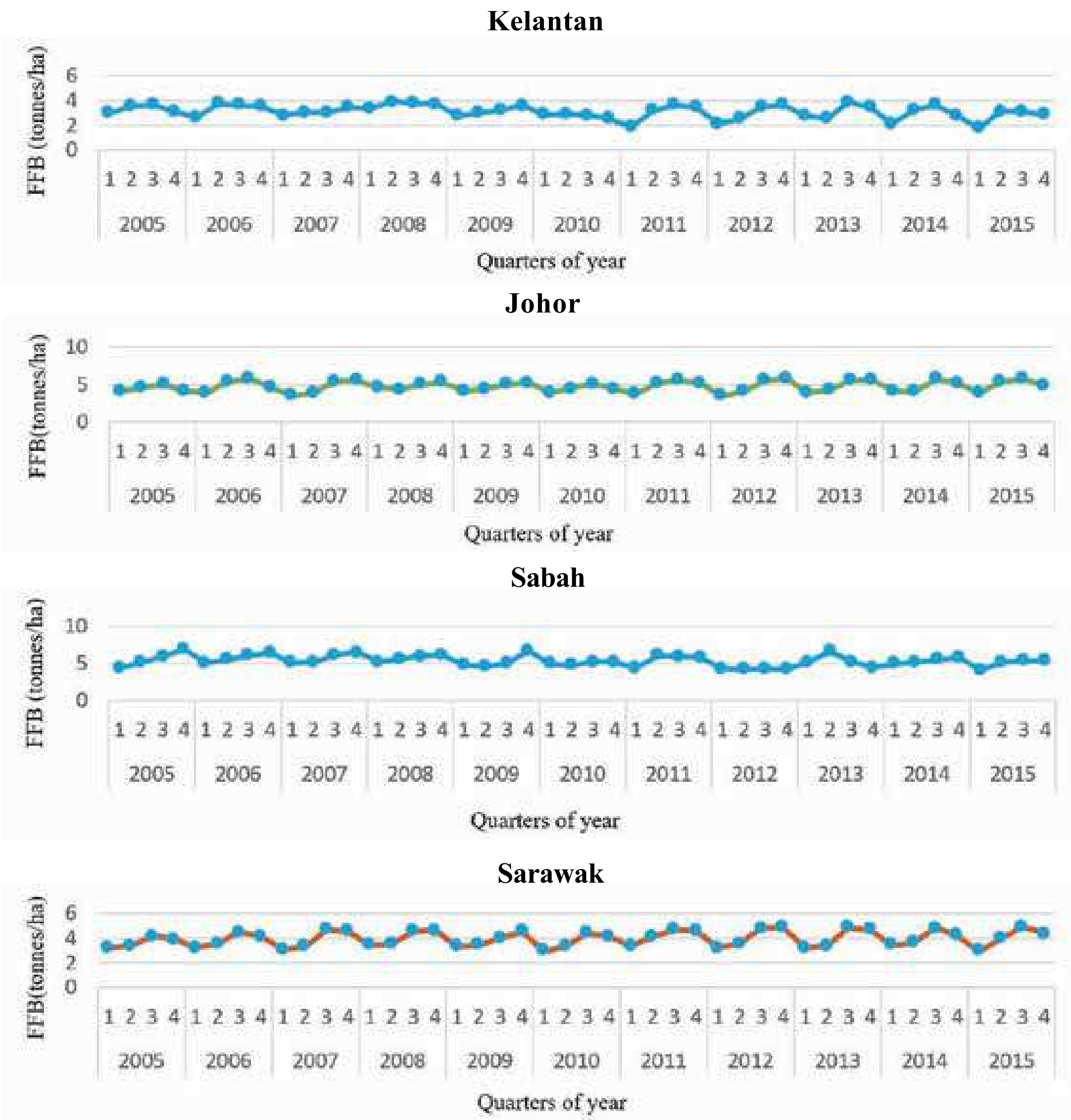


Figure 2 Time series plot of average FFB yield (data Jan. 2005 to Dec. 2015)

the final dataset was obtained after the normalisation process using machine learning.

NARX model

The NARX model is based on the linear ARX (autoregressive with exogenous terms) model, which is also called the NARX recurrent neural network. This model can be used in a time series dataset with feedback connections that include numerous layers of the network. In this study, the NARX model used feedback from a dynamic neural network with a structure as shown in *Figure 3*. The inputs of the NARX model consisted of two sets, namely, the external and previous outputs of the yield. The formula for the NARX model is given as:

$$Y_{n+1} = \mathcal{F}[y_n \ ; \ X_n] \qquad (2)$$

where y_n and X_n are the external (exogenous) output and input, respectively; and f is a nonlinear function that is generally used as a multilayer neural network. In this research, the NARX model was able to identify the exogenous y_n and X_n variables that affected the estimation of the time series. The input order offered the number of past external variables that were added to the network.

In this evaluation, the time series data had to be organised in the order of time in one retro. The organised datasets were composed of 132 samples for each state. The data will be divided into three partitions as training, validation, and testing partitions, two constructions of 70 per cent (training):15 per cent (validation):15 per cent (testing) and 70 per cent (training):10 per cent (validation):20 per cent (testing) were set up for implementation. The architecture of the NARX model was also designed with 5, 7, 10, and 13 neurons in the hidden layers. The delay values of two and four, for each NARX model architecture, were configured with the Levenberg-Marquardt (LM) (train lm) learning procedure. The training was mechanically stopped, as indicated by the MSE, to determine the best NARX model. In other words, the MSE performance value was used to identify the difference between the actual and predicted data. A comparison of all the NARX model architectures using the MSE and R-values was supported.

ARIMA model

One of the famous methods used for forecasting time series data is the ARIMA method. This method is used to analyse time series data by integrating the autoregressive (AR) and moving average (MA) methods. ARIMA (p, d, q) is a general method formulated with respect to a stationary data series, where

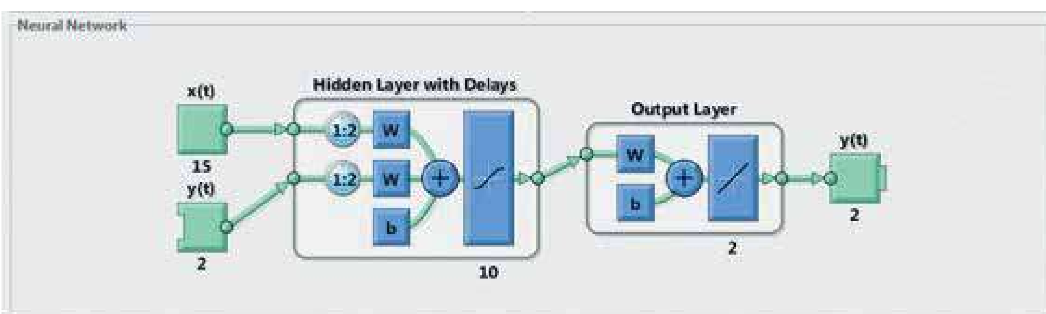


Figure 3 Snapshot of NARX model

p is the number of processes in AR, d is the number of differences for a time series of data to be stationary, and q is the number of processes in MA (Taskaya-Temizel & Casey, 2005). The four forecasting stages are as follows:

(i) Identification model: The data series will be carefully examined to determine whether the series contains trends, seasonality, cycles, or random phenomena, where processes are required.
(ii) Parameter estimation: A model validation is aimed at ensuring that the right model is used. In this study, the t-statistic and p-value were used.
(iii) Model checking: The proposed model should be hypothesised and a diagnostic test must be conducted before it can be used for forecasting. In this test, the p-value was checked to determine whether it was greater or less than 0.05.
(iv) Forecasting: The forecasted values in the confidence limit (upper and lower limits) should provide a 95 per cent confidence interval. In this study, the trial and error method was used to obtain a good model and prediction.

Forecast and forecasting evaluation

Two forecasting periods were used in the analysis, namely an in-sample and an out-of-sample period. The in-sample period, from January 2005 to December 2014, was implemented to generate the specifications for the NARX and ARIMA models. To evaluate the out-of-sample forecasting ability, some observations at the end of the sample period were not included when generating the models. The out-of-sample period covered from January to December 2015.

Forecasting: A satisfactory model can be used for prediction purposes. The performance of the network was evaluated, and suitable and acceptable results were obtained. The following performance measure functions were employed:

(i) Mean square error (MSE) for evaluating the accuracy of the proposed ANN model and ARIMA model. These functions are given in the following equations:

$$MSE = \frac{1}{N}\sum_{1}^{N}(XI - YI)^2 \qquad (3)$$

(ii) Mean absolute percentage error (MAPE).

$$MAPE = \frac{1}{N}\sum_{1}^{N}\frac{/(XI - YI)/}{XI} \times 100 \qquad (4)$$

(iii) Average accuracy percentage (AAP).

$$(AAP\%) = 100\% - MAPE \qquad (5)$$

where: XI is the actual yield, YI is the forecasted yield, N is the number of data points for I = 1, 2,….N.

RESULTS AND DISCUSSIONS

The forecast models that were tested on the data were the NARX model, that used the supervised LM training algorithm, and the ARIMA model.

Results of NARX

A model with an MSE can be used for learning the time series data. The training results of the architecture of the NARX model in each state was shown after the models had been successfully built and trained. As shown in *Tables 2, 3, 4* and *5*, almost all the values of R were above 0.90 during the training of the network. The overall performance of the NARX model was above 0.90 and between 0.88 and 1. The result showed that the output produced by the network was closely similar to the target and that the model was satisfactory. After performing several experiments using the two architectures, the results showed that the NARX model produced the best result in Sarawak when the parameters of 70 per cent:15 per cent:15 per cent were used. These parameters had 10 neurons in the hidden layers and a delay value of four. In Kelantan and Johor, the NARX model produced the best result when the parameters of 70 per cent:10 per cent:20 per cent were utilised, with 13 neurons in the hidden layers and a delay value of four. The results showed that the best result was obtained in Sabah when the parameters of 70 per cent:15 per cent:15 per cent were used, with 13 neurons in the hidden layers and a delay value of four. Arbain and Wibowo (2012) showed that the forecasting ability of NARX neural networks is sensitive to the number of hidden nodes. However, the forecasting ability of neural networks is sensitive to the number of input nodes, so various processes were used to achieve better performances (Taskaya-Temizel & Casey, 2005).

The predicted scatter plots of the NARX model *versus* the actual values using the LM algorithm for the training, validation, and testing of the datasets is shown in *Figure 4*. The results of the predicted model fully matched the actual values for the training, validation, and testing of all the datasets. The results showed the highest values of R in the training, validation, and testing. In other words, the NARX architecture can be used as a model to predict the yield of oil palm in each state. If this value is equal to 1, then there is a perfect correlation between the targets and outputs (Diaconescu, 2008).

TABLE 2
THE NARX TRAINING RESULTS FOR KELANTAN

States	*NARX architecture*	*No. of neurons hidden*	*No. of delays*	*Mean square error (MSE)*			*Correlation coefficient (R)*		
				Training	*Validation*	*Testing*	*Training*	*Validation*	*Testing*
Kelantan	70%:15%:15%	5	2	.00034	.00031	.00041	.9593	.9694	.9316
			4	.00009	.00021	.0009	.9887	.9819	.9919
		7	2	.00015	.00031	.00043	.9821	.9784	.9415
			4	.00008	.00015	.00015	.9991	.9844	.9811
		10	2	.00017	.00023	.00036	.9767	.9816	.9708
			4	.00001	.00008	.00007	.9997	.9991	.9992
		13	2	.00006	.00024	.00031	.9355	.9629	.9700
			4	.00000	.00007	.00008	.9999	.9993	.9917
	70%:10%:20%	5	2	.00038	.00061	.00058	.9529	.9505	.9358
			4	.00009	.00009	.00028	.9882	.9944	.9719
		7	2	.00029	.00029	.00040	.9647	.9601	.9588
			4	.00001	.00005	.00004	.9981	.9959	.9951
		10	2	.00021	.00024	.00032	.9764	.9803	.9615
			4	.00006	.00012	.00007	.9992	.9910	.9939
		13	2	.00030	.00030	.00059	.9618	.9798	.9420
			4	.00000	.00001	.00004	.9999	.9999	.9950

TABLE 3
THE NARX TRAINING RESULTS FOR JOHOR

States	*NARX architecture*	*No. of neurons hidden*	*No. of delays*	*Mean square error (MSE)*			*Correlation coefficient (R)*		
				Training	*Validation*	*Testing*	*Training*	*Validation*	*Testing*
Johor	70%:15%:15%	5	2	.00021	.00013	.00051	.9764	.9924	.9622
			4	.00002	.00005	.00010	.9997	.9999	.9904
		7	2	.00009	.00024	.00023	.9913	.9759	.9846
			4	.00000	.00000	.00000	.9999	.9999	.9999
		10	2	.00000	.00003	.00024	.9999	.9997	.9843
			4	.00000	.00001	.00009	.9999	.9987	.9992
		13	2	.00001	.00001	.00002	.9999	.9986	.9980
			4	.00000	.00001	.00009	.9999	.9988	.9999
	70%:10%:20%	5	2	.00045	.00054	.00048	.9575	.9496	.9581
			4	.00001	.00006	.00005	.9999	.9999	.9994
		7	2	.00009	.00010	.00015	.9905	.9909	.9880
			4	.00001	.00006	.00005	.9999	.9999	.9994
		10	2	.00001	.00002	.00004	.9980	.9999	.9899
			4	.00000	.00000	.00000	.9999	.9999	.9999
		13	2	.00004	.00001	.00014	.9980	.9999	.9899
			4	.00000	.00000	.00000	1.000	.9999	.9999

TABLE 4
THE NARX TRAINING RESULTS FOR SABAH

States	*NARX architecture*	*No. of neurons hidden*	*No. of delays*	*Mean square error (MSE)*			*Correlation coefficient (R)*		
				Training	*Validation*	*Testing*	*Training*	*Validation*	*Testing*
Sabah	70%:15%:15%	5	2	.00036	.00023	.00046	.9511	.9821	.9442
			4	.00005	.00015	.0017	.9938	.9819	.9783
		7	2	.00028	.00036	.00024	.9636	.9635	.9707
			4	.00001	.00009	.00001	.9983	.9881	.9807
		10	2	.00001	.00004	.00004	.9984	.9943	.9951
			4	.00002	.00009	.00001	.9996	.9993	.9998
		13	2	.00009	.00002	.00003	.9988	.9961	.9963
			4	.00004	.00003	.00002	.9999	.9995	.9997
	70%:10%:20%	5	2	.00040	.00113	.00064	.9436	.8857	.9422
			4	.00004	.00016	.00009	.9942	.9804	.9882
		7	2	.00007	.00011	.00041	.9919	.9778	.9331
			4	.00007	.00002	.00004	.9991	.9973	.9942
		10	2	.00001	.00004	.00007	.9980	.9962	.9910
			4	.00004	.00003	.00001	.9999	.9964	.9991
		13	2	.00003	.00007	.00002	.9959	.9926	.9965
			4	.00001	.00006	.00004	.9983	.9994	.9945

TABLE 5
THE NARX TRAINING RESULTS FOR SARAWAK

States	NARX architecture	No. of neurons hidden	No. of delays	Mean square error (MSE)			Correlation coefficient (R)		
				Training	Validation	Testing	Training	Validation	Testing
Kelantan	70%:15%:15%	5	2	.00037	.00039	.00081	.9716	.9563	.9302
			4	.00001	.00011	.00160	.9984	.9899	.9482
		7	2	.00031	.00016	.00045	.9745	.9851	.9712
			4	.00001	.00001	.00002	.9990	.9985	.9830
		10	2	.00016	.00037	.00047	.9864	.9721	.9596
			4	.00003	.00001	.00002	.9997	.9987	.9977
		13	2	.00010	.00032	.00057	.9914	.9720	.9583
			4	.00002	.00002	.00021	.9997	.9978	.9827
	70%:10%:20%	5	2	.00055	.00049	.00052	.9513	.9616	.9610
			4	.00010	.00027	.00050	.9905	.9780	.9731
		7	2	.00085	.00056	.00083	.9273	.9559	.9292
			4	.00003	.00003	.00012	.9997	.9971	.9900
		10	2	.00019	.00044	.00051	.9835	.9563	.9547
			4	.00001	.00004	.00004	.9989	.9964	.9967
		13	2	.00017	.00036	.00040	.9852	.9710	.9704
			4	.00004	.00004	.00005	.9996	.9958	.9954

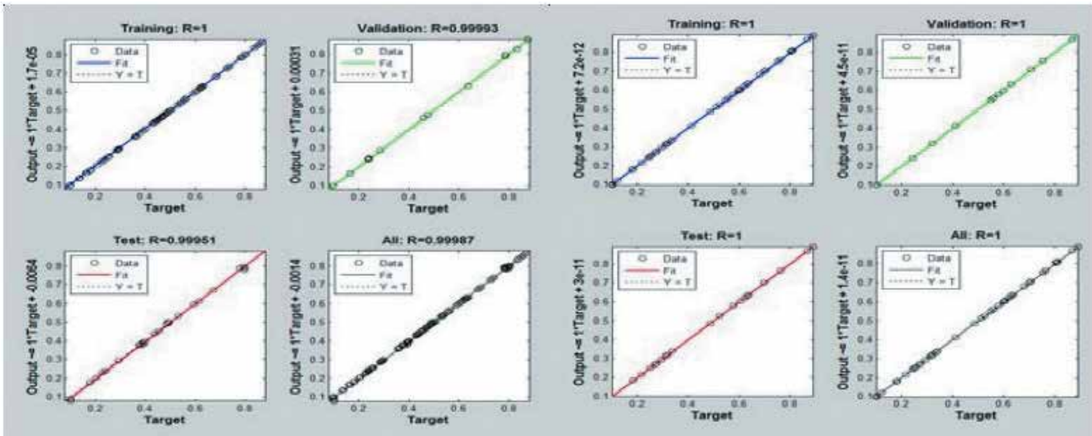
The scatter plots of the best validation performance of the NARX model at each epoch for the LM training algorithm is presented in *Figure 5*. The NARX network training converged quickly, where training stopped after 36, 12,169, and 13 epochs for Kelantan, Johor, Sabah and Sarawak, respectively.

Results of ARIMA

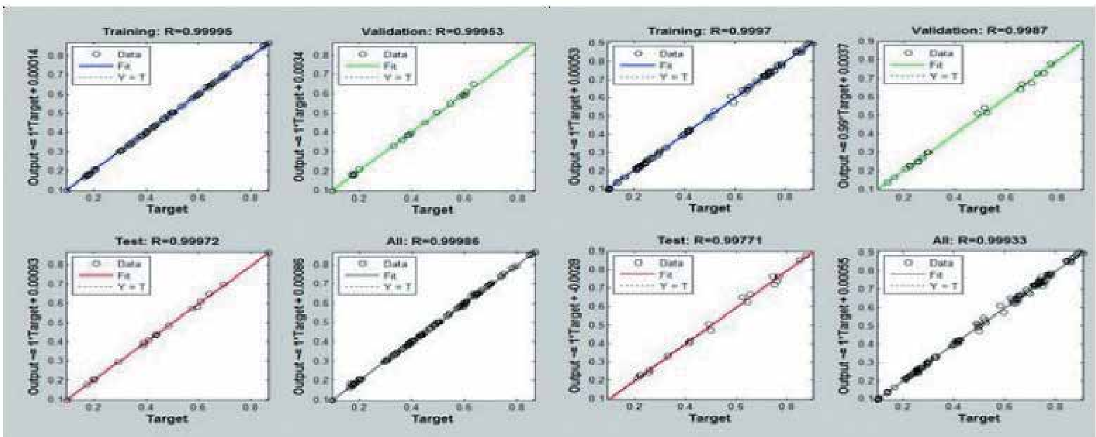
Seven characteristics of a good ARIMA model were considered in order to attain a forecast with minimal errors (Taskaya-Temizel & Casey, 2005):

(i) A parsimonious characteristic provides a strong practical orientation for developing a model. Parsimony means that only the smallest number of coefficients are included to explain the available data.
(ii) The AR model is stationary, which implies that the time series has a constant mean and variance through time.
(iii) The MA is invertible, where the requirements indicate the coefficient of MA.
(iv) The high-quality estimated coefficients at the estimation stage refer to the AR and MA coefficients. In theory, the coefficients must be statistically and significantly different from zero.
(v) The model has statistically independent residuals.
(vi) The residuals of the estimated model should be normally distributed.
(vii) The model has sufficiently small forecast errors, which satisfactorily forecast the future and normally fit the past data as well.

The best results obtained from the ARIMA model (*Table 6*) indicates the forecast statistics



A. Kelantan **B. Johor**



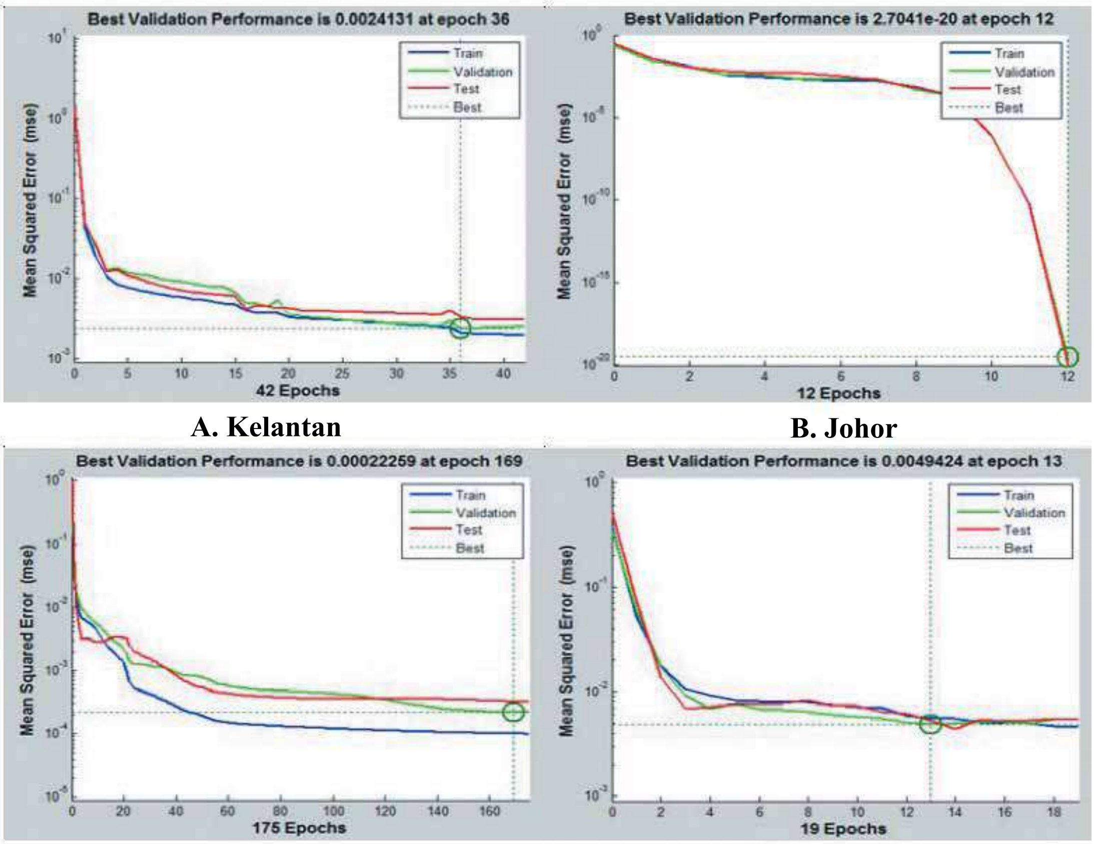
C. Sabah **D. Sarawak**

Figure 4 The scatter plots of NARX model predicted versus *actual values*

from the multivariate model in Kelantan, Johor, Sabah and Sarawak. The selection was based on the fact that the lower the MSE and R work out, the better is the model at learning the time series data. The training results of the ARIMA model in each state are shown. Some of the results were provided after successfully building and training the ARIMA models. Almost all the values of r were above 0.67 during training (*Table 6*). The overall performance of the ARIMA model was above 0.67 and between 0.67 and 0.8569. The result showed that the output produced by the ARIMA model was similar to the target and that the model was reasonable. The result for Sabah was very low, but the p-value and F-test of significance results exhibited significant differences in the model. These results are similar to previous work. The ARIMA model consistently did not do a good job, it showed low efficiency in modelling and in forecasting time series (Haviluddin & Jawahir, 2015).

Evaluations and forecast accuracy

The main objective of this research paper was



A. Kelantan **B. Johor**

C. Sabah **D. Sarawak**

Figure 5 Training performance of the NARX

TABLE 6
PERFORMANCE OF THE ARIMA MODEL

States	*Correlation coefficient*	*MSE*	*p-value*	*Significance F*	*Lower 95%*	*Upper 95%*
Kelantan	0.756	0.210	0.00579	0.00948	2.3823	4.7192
Johor	0.787	0.2072	1.08E-09	6.15E-09	4.54017	10.6850
Sabah	0.672	0.255	1.45E-05	0.013	2.4263	5.7897
Sarawak	0.8569	0.1163	0.02090	9.58E-11	2.09491	6.90374

to forecast the amount of oil palm production in Kelantan, Johor, Sabah, and Sarawak. The empirical results of the forecasting were presented. The forecasting performance of each model was analysed based on the statistical criteria. The time series response indicating the displays, inputs, and targets is shown in *Figure 6*. This study considered one-step forecasts of oil palm yields based on two fitted models, namely, the NARX neural network and ARIMA models. The forecast covered the period from January 2005 to December 2014. The data were divided into four quarters per year. Before computing the forecast of the oil palm yield, estimations were made of the models that were consistent with the actual yield. For the one-step-ahead forecasting, all the models effectively forecasted based on the results between the actual and forecast values. However, the percentage difference between the actual value and that of the multivariate model, namely, the NARX model, was smaller than that of the univariate model, ARIMA. All the models successfully predicted the sharp turns, which consisted of periods between 2005 and 2014 in Kelantan, Johor, Sabah and Sarawak.

The model verification focused on checking the residuals of the model to determine if any systematic pattern could be removed to improve

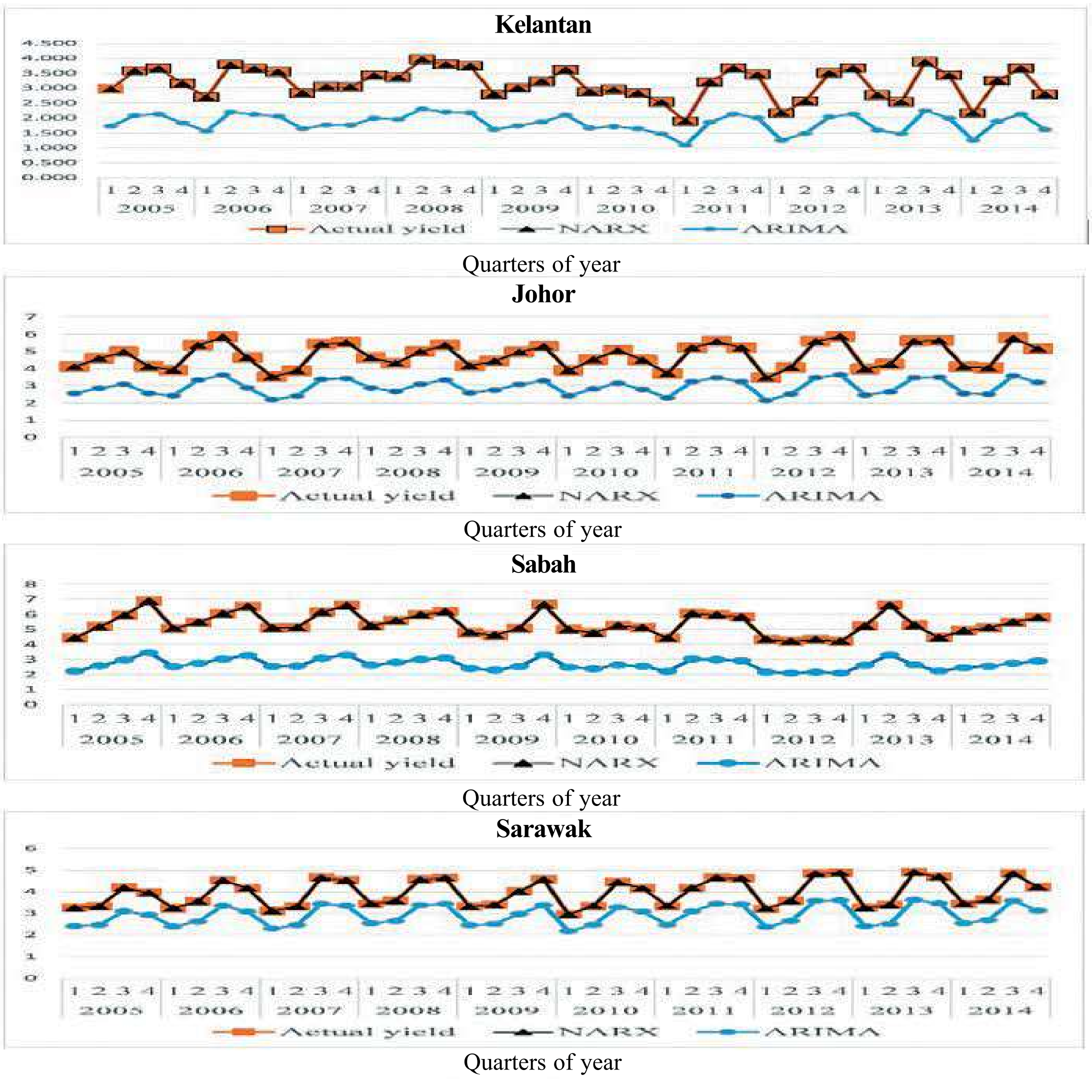


Figure 6 Actual yield compared with forecast yield using NARX and ARIMA models

the chosen model. A comparison between the NARX and ARIMA forecasts, with the actual values based on the MSE and MAPE, and the average accuracy percentage (AAP) within the studied states is provided in *Table 7*. The table shows that in the average accuracy percentage between the forecasts by the ARIMA models, the actual value was large and differed with the forecasted value. The finding indicated that 50 per cent to 74 per cent of the models did not perform well with time. Although the average accuracy percentage between the forecasts by the NARX models had a record-high value of between 99 per cent and 99.8 per cent, the values of the MSE and MAPE for the NARX models were lower than those of the ARIMA models. This finding indicated the good performance of the multivariate forecasting model based on the statistical results. The best models were used for forecasting the performance of the NARX methods using low MSE, MAPE and high AAP. The results showed that the best value of r for the NARX architecture models was 0.999, which indicated that the results fit the available data sufficiently to satisfy the forecasting. Therefore, the NARX model was proven to be an appropriate model for forecasting the data being studied. The NARX model can be used as an alternative model to predict the yield amount of oil palm as it produced good MSE, MAPE, AAP and R-values. In the same investigation with a different case, Haviluddin and Tahyudin (2015) proved the NARX model is more important than other models for nonlinear data behaviour system.

CONCLUSIONS

An approach was developed to devise an estimation model that can predict the yield of oil palm production under different conditions

TABLE 7
FORECAST AND MODELS EVALUATION

States	*Forecasting by*	*Date*				*Forecast performance*		
		Q1	*Q2*	*Q3*	*Q4*	*MSE*	*MAPE*	*AAP*
Kelantan	Target	1.78	3.16	3.13	2.86			
	NARX	1.7764	3.15368	3.12374	2.85428	6.2261E-05	0.2	99.8
	ARIMA	1.0324	1.8328	1.8154	1.6588	1.372855	42	58
Johor	Target	3.93	5.36	5.78	4.94			
	NARX	3.8907	5.3064	5.7222	4.8906	0.00255	1	99
	ARIMA	2.4366	3.3232	3.5836	3.0628	3.681713	38	62
Sabah	Target	4.07	5.21	5.43	5.34			
	NARX	4.0618	5.19958	5.41914	5.32932	0.000102	0.2	99.8
	ARIMA	2.035	2.605	2.715	2.67	6.356844	50	50
Sarawak	Target	2.95	3.97	4.96	4.39			
	NARX	2.9441	3.96206	4.95008	4.38122	6.83371E-05	0.2	99.8
	ARIMA	2.18	2.9378	3.6704	3.2486	1.15	26	74

Note: MSE = Mean square error
MAPE = Mean absolute percentage error
AAP = Average accuracy percentage

based on the NARX and the ARIMA models to address the issue of time series data with non-linear characteristics. The results showed that the NARX network can be successfully applied to time series modelling and prediction tasks. The accuracy of the model in predicting the yield amount for oil palm production was measured in terms of the MSE, MAPE, AAP and R-values. The NARX model can be considered as an alternative model for forecasting the yield amount for oil palm production in the states of Kelantan, Johor, Sabah and Sarawak.

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