Identifying and Forecasting the Factors that Derive CPO Prices in Malaysia Using NARX Model

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Abstract: ***Determining the movement of the crude palm oil prices (CPO) is a crucial issue, whereby it always associated with the decision-making by businessman, investors, speculators and policymaker. Besides the CPO prices indicate that it is fluctuating all over a time and need to be forecast as to make it visible for the businessman, investors and policymaker in decision-making. The issues arises when most of the literature (1) relying too much on the historical data, whereby its predict series of CPO prices*** y_{t+1} ***given*** d ***past values of*** $y(t)$, ***(2) disregarded the important factors that also derives the CPO prices, and (3) depending too much on univariate time series forecasting. Therefore, this study considered soybean price, export of palm oil, rainfall, and palm oil stock level as the factors or inputs that derive the CPO prices in Malaysia. We applied the Autoregressive Distributed Lag (ARDL) as an effort to check the long run relationship with the listed factors. In predicting the CPO prices, we employ the Nonlinear Autoregressive with External (NARX) with three different training algorithms that are Levenberg-Marquardt, Bayesian Regulation and Scaled Conjugate Gradient. The general findings demonstrated that three of the algorithms using the listed inputs show decent results for CPO prices prediction. Therefore, the listed inputs should not be disregarded as this study confirmed that its influence the CPO prices in Malaysia***

Keywords: Crude Palm Oil Prices, Artificial Neural Network, Nonlinear Autoregressive with External, Forecast.

1. Introduction

The World has witnessed the palm oil businesses can be considered as one of the important economic resources for top producing countries such as Indonesia, Malaysia, Thailand and Nigeria in generating of capital investment, employments, export revenue, technology and management knowledge (Basiron & Weng, 2004; Ezealaji, 2011; Faruk, Belabut, Ahmad, Knell, & Garner, 2013; Olagunju, 2008; Pang & Lee, 2013; Rifin, 2011; Sharma, 2013; Thongrak, Kiatpathomchai, & Kaewrak, 2011). However, the price of palm oil keep fluctuates all over a time. According to Karia, Bujang and Ahmad (2013), the accuracy of crude palm oil (CPO) prices is important insight for the investors in dealing with the associated risks and uncertainties. Therefore, this study suggests that the need for CPO prices prediction that will significantly facilitate efficient decision in the fact of ever-increasing risks and uncertainties.

The most popular approach to predict CPO prices are univariate forecasting models (Karia *et al*. 2013). However this model is relying too much on the previous data of CPO prices, since its predict series y_{t+1} given d past values of $y(t)$. According to Duy, Sato and Inoguchi (2009) confirmed that the Artificial Neural Network (ANN) is a powerful model for prediction of time series data. The study of Sallehuddin, Shamsuddin, Hashim and Abraham (2009) confirms that the ANN model is supreme in forecasting the non-linear time series data. The study of Maier and Dandy (1996) suggest that the ANN model is fits model for the long term prediction. With the superiority of the ANN model, Karia *et al*. (2013) applied Nonlinear autoregressive (NAR) to predict the CPO prices in Malaysia. However, the implementation of the NAR model adding the same roots with the univariate models, whereby its predict series y_{t+1} given d past values of $y(t)$. The NAR model also disregarded the important factors of soybean price, export of palm oil, rainfall, and palm oil stock level which this study considers as important factors that also influence the CPO prices in Malaysia. As a result, this study considered the Nonlinear Autoregressive with External (NARX) model since it predict series y_{t+1} given d past values of $y(t)$ and another series of $x(t)$. Where, the another series of $x(t)$ will be presented by the listed important factors of soybean price, export of palm oil, rainfall, and palm oil stock level.

Therefore this study will conduct the CPO prices predictions using NARX model with three different training algorithms in regard the ANN training algorithm that adjust it weights as means to improve its training error. Therefore different training algorithm will produce different errors minimization (Abusnaina, Abdullah, & Kattan, 2014). But, first we will examine the relationship of another series of $x(t)$ and $y(t)$ using Granger causality test. The theory that lead to the consideration of $x(t)$ and $y(t)$ is autoregressive distributed lags (ARDL) model as a tool to identify the long-run relationship between the variables. In demonstrating that another series of $x(t)$ also derived the CPO prices $y(t)$. We conduct the in-sample and out-of-sample forecast from NARX model. Besides, we will evaluate the best fit model from three of the training algorithms using the Mean Squared Errors (MSE) and Root Mean Squared Errors (RMSE).

2. Material and Methods

This study employed five monthly data that are CPO price (y) as a target, while soybean oil (x_1), exported of palm oil (x_2), rainfall (x_3) and palm oil stock level (x_4) as an inputs that starching from January 2008 to December 2014 that consisting 84 observations. This study extract all of the data from World Bank, Department of Statistics Malaysia and Malaysia Palm Oil Board (MPOB).

Where y_{t+1} express as an output. Meanwhile target denotes as y. The inputs presented as x_1, x_2, x_3 and x_4. The ANN which gathers a set of organized neurons that mimic the human brain consisting three layers, and data is always hand on between these layers.

2.1 Artificial Neural Network (ANN)

As the presented by Figure 1 above, the NARX architecture in this study consists one target $y(t)$ and four inputs $x(t)$ variables. Any layers between the inputs and output are called as hidden layers where all the learning on the training and validation are carry out by the weight. In the diagram, the circles represent neurons and the lines represent synapse. The synapses are important where they take all the value of input and multiply with specific weight and then produce an output as the result. Nevertheless, the roles of neurons are adding together all the output and applying the activation functions that are complex. Certain activation function allows neurons network to model a complex non-linear pattern.

[As indicated in Figure 1]

2.1 Nonlinear Autoregressive with External (NARX)

The NARX model is normally used in the method of recognition area (Xie *et al*., 2009). All the particular vibrant networks examined so far have either been persistent networks, with the dynamics only at the input level, or feed forward networks. The nonlinear autoregressive network with exogenous inputs (NARX) is a frequent dynamic network; with response relations surrounded numerous level of the network. The NARX algorithm is based on the linear ARX model, which is normally used in time-series modelling. Figure 1 demonstrated the paradigm NARX network. The criterion NARX network used here is a two-layer feed forward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This network also uses tapped delay lines (d) to accumulate preceding standards of the input, $x(t)$, target $y(t)$ and output (y_{t+1}).

We start the preparation statistics with two delays for both the input and the output. So preparation commence with the third statistics aim there are two inputs to the series-parallel network, the $x(t)$ series and the y_{t+1} series. Detecting that the y_{t+1} series is regard as a response gesture, which is an input that is also an output (objective). The equation can be revealed as in equation (1) as follow:

$$y_{t+1} = f\left[y(t-1),...,y(t-d),x(t-1),...,(t-d)\right] \quad (1)$$

Where, y_{t+1} is the output of the NARX network and also response to the input of the network and tapped delay lines (d) that accumulate the earlier standards of $x(t)$ and y order. It also has been accounted that gradient descent learning can be more successful in NARX networks than in other regular structural design (Horne and Giles, 1995).

3. Results and Discussion

The analysis of this study starts with the Granger causality test. The use of Granger causality test is use to identify whether the time series data has causal relationship between all the variables. Therefore this study employed the approach conducted by the previous study of Anastassiou and Dritsaki (2005) using the F statistic. Table 1 demonstrated that there are three relationships, that are bilateral, unidirectional and no Granger relationships. Whereby, bilateral relationship shows two ways relationship between independent and dependent variables. Meanwhile unidirectional relationship is a single direction relationship either independent to dependent or dependent to independent variables. Lastly, no Granger relationships mean there is no relationship between independent and dependent variables.

Table 1 demonstrated variety of results. However this study highlights the important points on dependent variable of lnCPO. The evidence from this table suggests that there are bilateral relationship between the lnEXP and lnCPO. The EXP and CPO are significantly influenced to each other. Since there is no significant between lnRAIN and lnCPO, this study do not reject the H_0 of lnRAIN does not Granger cause to lnCPO. This table also revealed that there are unidirectional relationship between lnSOY and lnCPO, and lnSTCK with lnCPO. Both of the tests shows rejection of H_0 between the independent variable does not Granger cause to dependent variable. Therefore the Granger causality test confirm that lnEXP, lnSOY and lnSTCK have a Granger cause to lnCPO. Therefore this study extend the investigation on relationship between the series of $x(t)$ and $y(t)$ using ARDL model.

[As indicated in Table 1]

This study utilizes the ARDL models which is some of the variable are $i(0)$ and $i(1)$ but none is $i(2)$. The ARDL model above using different number of lags which are 2, 4 and 6 lags. After checking all this three models, the lag 6 has the lowest value of AIC. It is indicated that the model having lag 6 is the best model out of the three models. To proceed farther, we will concentrated on the lag 6 model to test on the serial correlation and the model stability in order to know the long run relationship between all the variables.

[As indicated in Table 2]
[As indicated in Table 3]

When we look at the F-stats and the probability value, it shows that we do not reject the H_0 since there is no significant either at 1%, 5% and 10% level. Therefore, Wald test fails to reject H_0 of there is no serial correlation.

[As indicated in Table 4]
[As indicated in Table 5]
[As indicated in Table 6]

The above estimation of Error Correction Term (ECT) model proved that we do not reject the H_0 since there is no evidence of serial correlation among the variables. Therefore, this study confirms that all of the tests that use to detect serial correlation proves that there is no autocorrelations among the series of $x(t)$.

3.1 Nonlinear Autoregressive with External (NARX) Results

In this learning, we randomly break up the 100% of the $x(t)$ and t time steps into 70% for training, 15% for validation and 15% for testing. As bring up earlier, we implement the feed-forward neural network based for NARX model. The training algorithm in this paper employed all the three algorithms which are Lavenberg-Marquardt, Beyesian Regularization and Scaled Conjugate Gradient.

Table 7 shows the evidence from target timesteps statistics of the NARX models for monthly CPO prices in Malaysia. This table also reveals two network structures for three training algorithms. The best network structure and training algorithm will be selected best from the information from MSE and R^2. This table demonstrates that there is not much difference among the ANN network structure and training algorithm.

[As indicated in Table 7]

Figure 2 present the NARX network architecture that utilized in projecting the CPO prices by using the Lavenberg-Marquardt algorithm. The best fits of the number of hidden layer size and the feedback delays are 10 and 5:5 respectively. In the meantime, the NARX model training was stopped up at the epoch point of 7 iterations. Table 7 present the end result achieve from the investigation of the NARX model. The analysis of the outcome for instant the value of R^2, MSE and RMSE are also accessible in the Table 7. The plots of the training, validation and test errors of the NARX model are revealed in Figure 3. This figure is fairly informative in numerous manners. Therefore, there is no evidence of overfitting by considering the following conditions. First of all, the plots of the test and validation errors are very similar. The plots of the test errors are not increase extensively prior than the validation errors increase. Second, there is no evidence of overfitting at the point of the best validation performance which occurred at 7 iterations. Next, the MSE are small in which present the evidence that the performance of the validation errors recover with the training errors.

[As indicated in Figure 2]
[As indicated in Figure 3]

Figure 4 present the NARX network architecture that develop in diagnostic the CPO prices by using the second algorithm of Bayesian Regularization. This algorithm generally requires additional time to analyze the result, but it can provide a best outcome in generalization of difficult, small and noisy datasets. The training in this algorithm will stop the analysis according to adaptive weight minimization. The best fits of the number of hidden layer size and the feedback delays are 10 and 5:6 respectively. In the meantime, the NARX model training was stopped up at the epoch point of 98 iterations. The plots of the test errors are not rising extensively prior than the train errors increase. There is no significant of over fitting at the point of the best test performance which occurred at 100 iterations. Next, the MSE are small in which provide the proof that the performance of the validation errors recover with the training errors.

[As indicated in Figure 4]
[As indicated in Figure 5]

Figure 6 present the NARX network architecture that employ in analytical the CPO prices by using the third algorithm of Scaled Conjugate Gradient. This algorithm mainly acquires less memory to analyze the outcome. The training in this algorithm will automatically stop when the generalization of analysis is not improving as indicated by a rising in the mean square error of the validation sample. The optimum fits of the number of hidden layer size and the feedback delays are 12 and 5:6 respectively. In the meantime, the ANN model training was stopped up at the epoch point of 39 iterations. The plots of the validation and test errors are having minor fluctuating process between each other. There is no evidence of overfitting at the point of the best test performance which occurred at 39 iterations. The performance stops at the best MSE calculation of 1.51757e-5.

[As indicated in Figure 6]
[As indicated in Figure 7]

Table 8 shows the In-sample of NARX forecasting using different types of architecture. All of the reported RMSE outcomes are statically significant by considering Diebold and Mariano (1995) perspectives. Considering three of the training algorithm, we found out that the Scaled Conjugate Gradient (5-12-1) provide the best result followed by Lavenberg-Marquardt (5-10-1) and Bayesian Regulation (5-10-1).

[As indicated in Table 8]
[As indicated in Figure 8]
[As indicated in Figure 9]

We use NARX with Scaled Conjugate (5-12-1) training algorithm to perform the out-of-sample forecast. The NARX validation present a superior forecast $\left(R^2 = 0.89\right)$ because the networks have trained the input-output outline well in the in-sample data set, therefore they utilized what they have be taught to enhanced forecast on the upcoming progress of the CPO prices. Reflecting to the out-of-sample forecasts, although the in-sample present a superior R^2 and slightly lower RMSE, the NARX model by considering inclusion series of $x(t)$ has capability to forecast the CPO prices. On the whole, NARX present good fit forecast of CPO prices in three-month ahead as demonstrated in Figure 11.

[As indicated in Figure 10]
[As indicated in Figure 11]

4. Conclusion

This study reveals that the CPO prices in Malaysia can be predicted using the another series of $x(t)$. The $x(t)$ are soybean oil (x_1), exported of palm oil (x_2), rainfall (x_3) and palm oil stock level (x_4). These factors should not be disregarded since it proves to be useful in providing important information of $t-1$ towards NARX model in CPO prices forecasting, y_{t+1}. Besides, the evidence from the Granger causality test also proved that there is a relationship between the $x(t)$ and the target (t). Moreover the ARDL model also demonstrated that there is a long-run relationship between $x(t)$ and the target (t).

In relation with the previous scholarly activity, Such as the study of Karia *et al.* (2013) applied the NAR model to predict the CPO prices, Ahmad and Latif (2011) predict the CPO prices using SARIMA model, all of them predict CPO prices y_{t+1} given d past values of $y(t)$. Whereby, this study highlights its important contribution by identifying the important factors of $x(t)$ that also derived the y_{t+1}. In this case the CPO prices y_{t+1} given d past values of $y(t)$ and another series of $x(t)$. General finding also shows that the NARX model, using three training algorithms that are Levenberg-Marquardt, Bayesian Regulation and Scaled Conjugate Gradient provides good fit forecast as not only in-sample forecasting, but also for the out-of-sample forecasting (three-month ahead).

The CPO prices prediction is important since its help the investors, speculators and policymaker to deal with the associated risks and uncertainties in the business. With proper prices forecasting will eventually provide useful insight for them to make a good decision or at least there is significantly time lag between decision making and actual time taking place.

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Figures legend

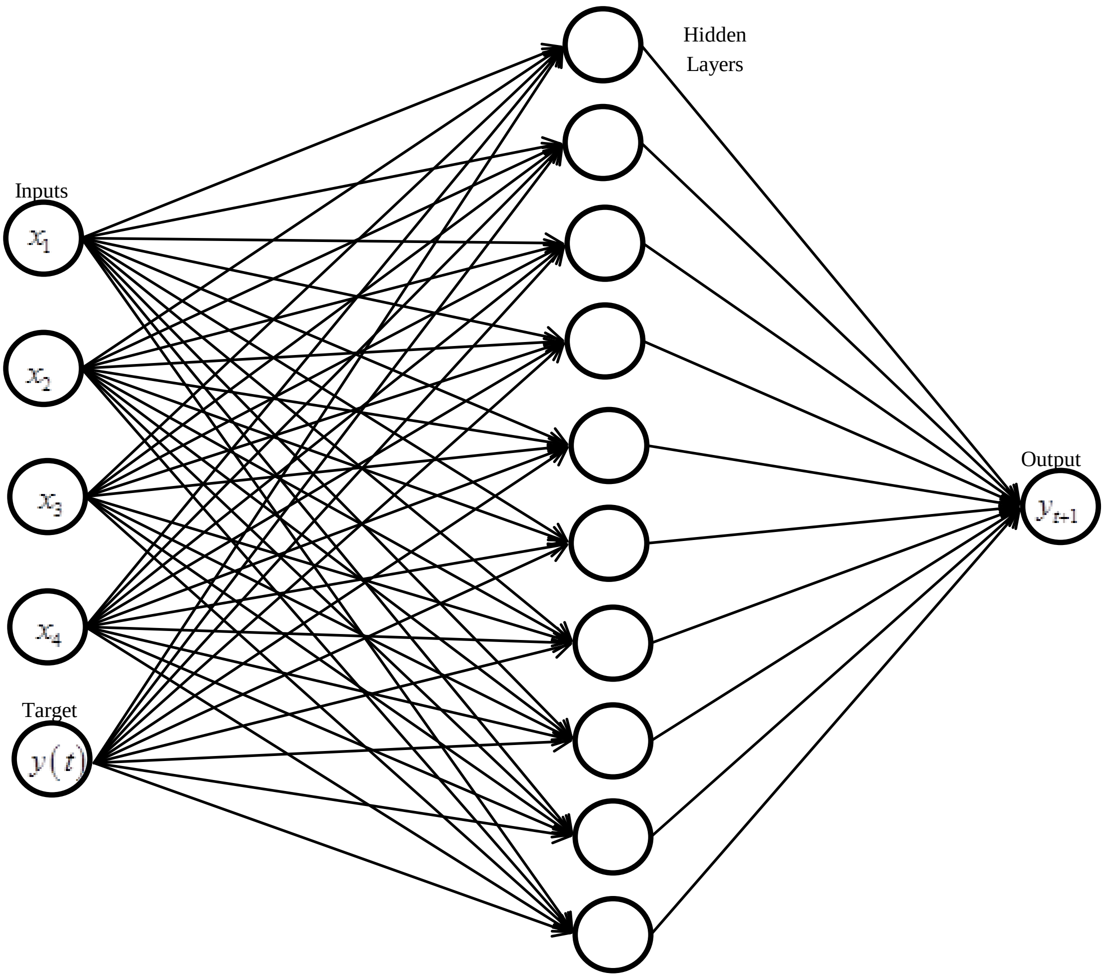

Figure 1: Graphical Artificial Neural Network Data Architecture Structure

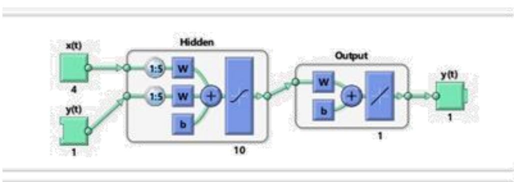

Figure 2: The NARX Network Architecture for the Levenberg Marquardt Algorithm

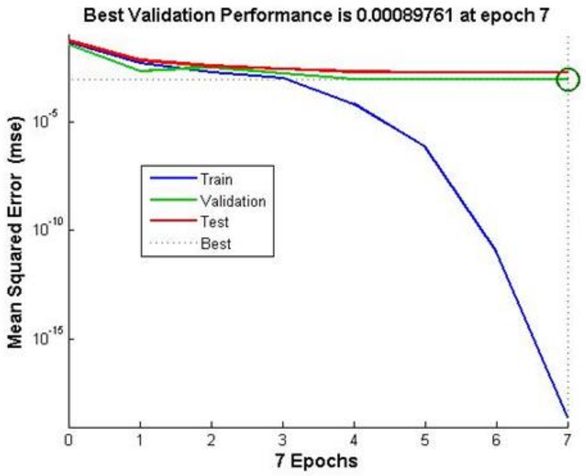

Figure 3: The Training, Validation and Test Errors of the NARX Model of the Levenverg- Marquardt Algorithm

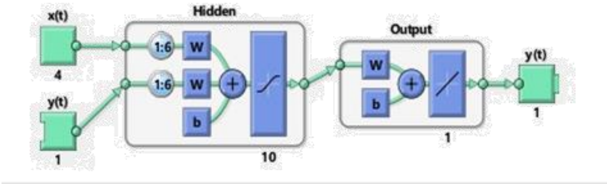

Figure 4: The NARX Network Architecture for the Bayesian Regulation Algorithm

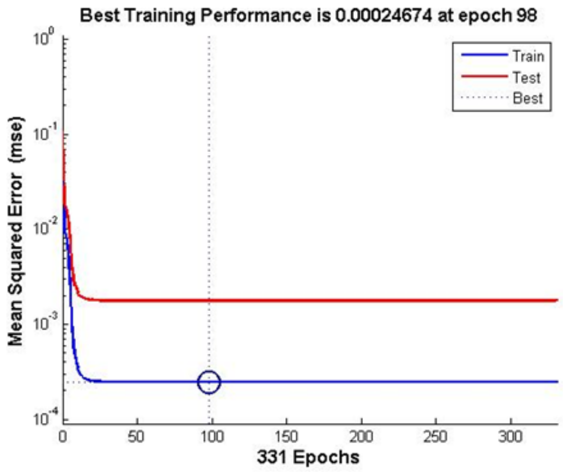

Figure 5: The Training, Validation and Test Errors of the NARX Model of the Bayesian Regulation Algorithm

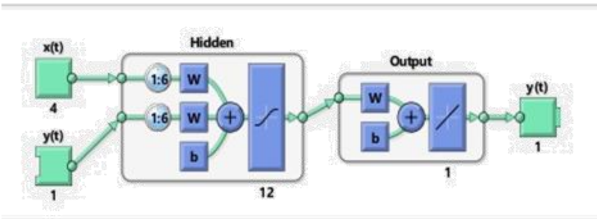

Figure 6: The NARX Network Architecture for the Scaled Conjugate Gradient

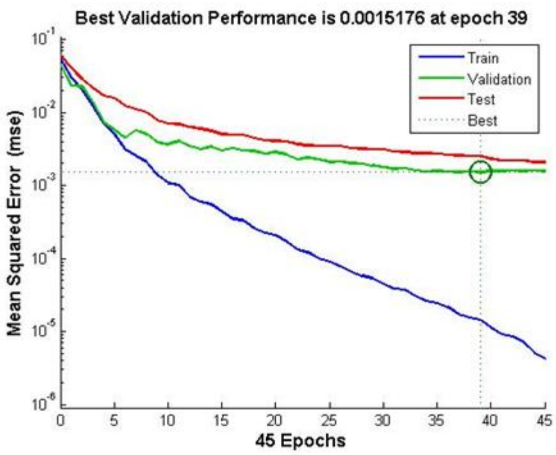

Figure 7: The Training, Validation and Test Errors of the NARX Model of the Scaled Conjugate Gradient

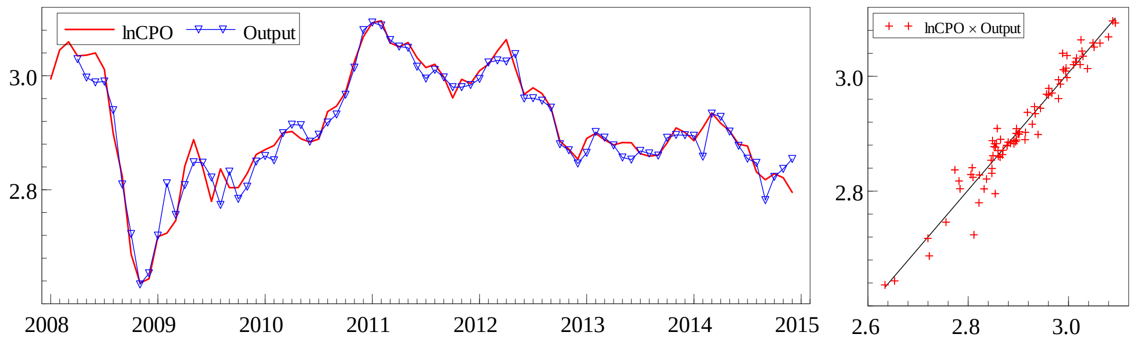

Figure 8: Line Graph and Scatter Plots for the CPO and NARX Prediction Using Levenberg-Marquardt Training Algorithm (5-10-1)

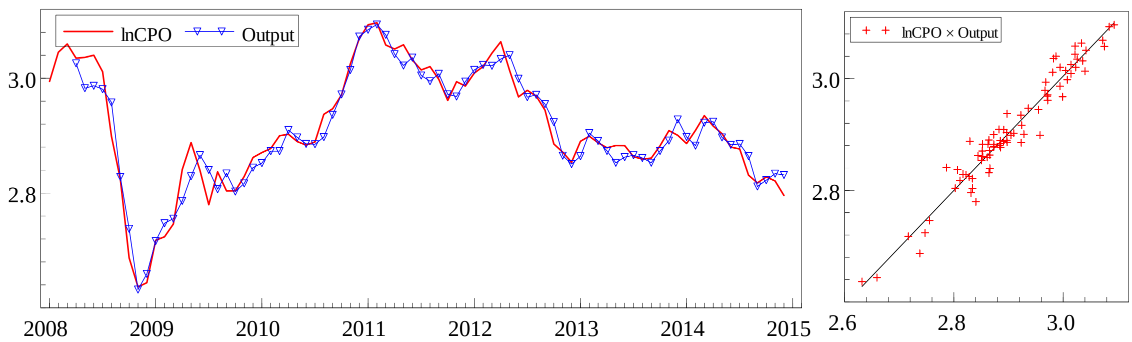

Figure 9: Line Graph and Scatter Plots for the CPO and NARX Prediction Using Bayesian Regulation Training Algorithm (5-12-1)

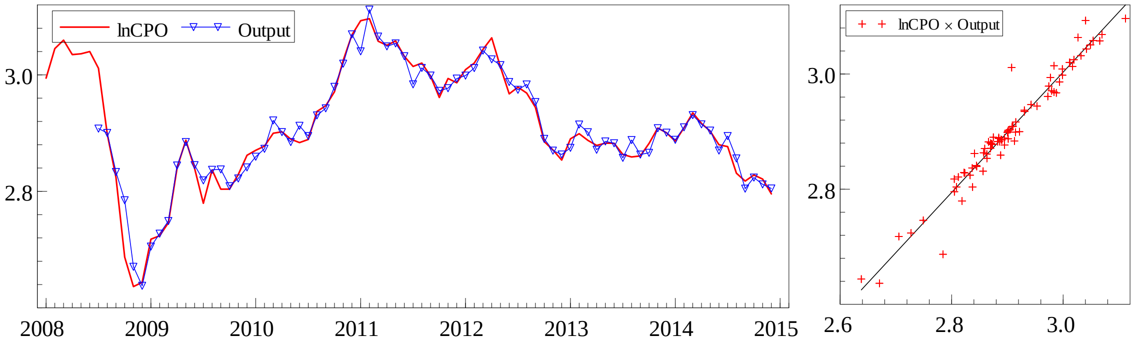

Figure 10: Line Graph and Scatter Plots for the CPO and NARX Prediction Using Scaled Conjugate Training Algorithm (5-12-1)

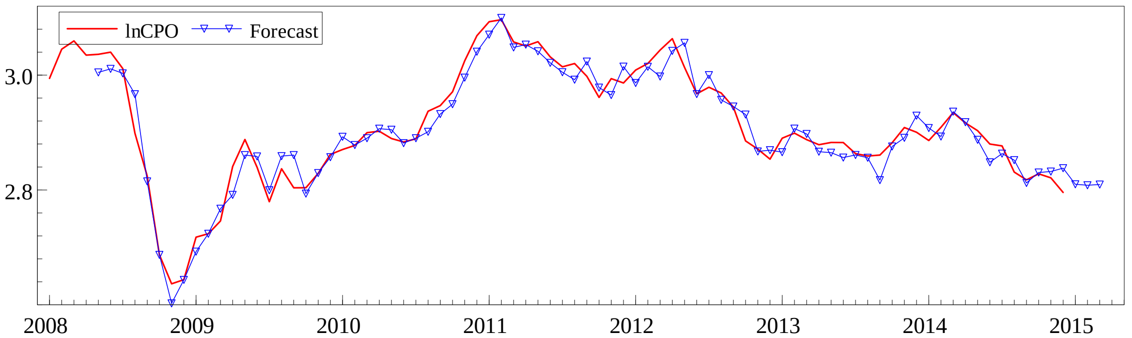

Figure 11: Out-Of-Sample Forecast of NARX Model Using Scaled Conjugate Training Algorithm (5-12-1)

Tables Legend

Table 1: The Pairwise Granger Causality Test

Dependent Variable	Hypothesis Tested	$F1$	$F2$	Decision $F1$	Decision $F2$
lnCPO	There is a bilateral relationship between lnEXP and lnCPO (lnCPO $\leftrightarrow$ lnEXP)	2.68630**	4.28588***	Reject H_0	Reject H_0
	There is no Granger cause between lnRAIN and lnCPO (lnCPO $\neq$ lnRAIN)	0.52338	0.34344	Do not reject H_0	Do not reject H_0
	There is a unidirectional relationship between lnSOY and lnCPO (lnCPO $\leftarrow$ lnSOY)	2.38143**	1.04521	Reject H_0	Do not reject H_0
	There is a unidirectional relationship between lnSTCK and lnCPO (lnCPO $\leftarrow$ lnSTCK)	263.067**	1.25779	Reject H_0	Do not reject H_0
lnEXP	There is no Granger cause between lnRAIN and lnEXP (lnEXP $\neq$ lnRAIN)	1.01317	1.78439	Do not reject H_0	Do not reject H_0
	There is a bilateral relationship between lnSOY and lnEXP (lnEXP $\leftrightarrow$ lnSOY)	2.87172***	2.81896**	Reject H_0	Reject H_0
	There is a unidirectional relationship between lnSTCK and lnEXP (lnEXP $\leftarrow$ lnSTCK)	2.79706**	1.35341	Reject H_0	Do not reject H_0
lnSOY	There is no Granger cause between lnRAIN and lnSOY (lnSOY $\neq$ lnRAIN)	0.27152	0.55497	Do not reject H_0	Do not reject H_0
	There is a unidirectional relationship between lnSTCK and lnSOY (lnSOY $\leftarrow$ lnSTCK)	0.77926***	1.57226	Reject H_0	Do not reject H_0
lnSTCK	There is a bilateral relationship between lnRAIN and lnSTCK (lnSTCK $\leftrightarrow$ lnRAIN)	2.67552**	2.44755**	Reject H_0	Reject H_0

Notes: The symbols ***, ** and * denotes 1%, 5% and 10% level of significance respectively

Table 2: The Autoregressive Distribute Lag (ARDL) Models

Lag Number	R^2	AIC	SIC	HOC	DWS
2	0.225133	-3.851432	-3.368005	-3.657907	2.046314
4	0.503192	-3.751498	-2.941961	-3.428564	1.991003
6	0.732405	-4.036017	-2.879648	-3.576693	2.206092

Table 3: Wald Test to Check the Long Run Relationship between $x(t)$ and $y(t)$

H_0	Lag Number	F -test	P -value	R^2	Decision
No Serial Correlation	6	0.970132	0.1352	4.001692	Do not reject H_0

Note: The symbol ***, ** and * denotes 1%, 5% and 10% level of significance respectively.

Table 4: Breusch-Godfrey Serial Correlation LM Test for ARDL Model

Test Statistic	Value	df	P -value	Decision
F -stat	4.791744	(5,34)	0.0020***	Reject H_0
χ^2	23.95872	5	0.0002***	Reject H_0

Note: The null hypothesis c(22)=c(23)=c(24)=c(25)=c(26)=0. The number of 22,23,24,25, and 26 are denotes as lncpo, lnexp, lnrain, lnsoy and lnstck respectively.

Table 5: Estimation of Error Correction Model (ECM)

R^2	F -stats	AIC	SIC	HQC	DWS
0.623260	1.974550	-3.916140	-2.880033	-3.505082	1.996087

Table 6: Breusch-Godfrey Serial Correlation LM Test for ARDL Model

H_0	R^2	F -stats	P -value	Decision
No Serial Correlation	0.000212	0.000537	0.999999	Do not reject H_0

Note: The symbol ***, ** and * denotes 1%, 5% and 10% level of significance respectively.

Table 7: Target Timesteps Statistics of the NARX Models for Monthly CPO Prices

Algorithm	NARX Structure	Target Time Steps	Target Values	MSE	R^2
Levenberg-Marquardt	5-10-1	Training	58	2.55118e-19	9.99999e-1
		Validation	13	8.97610e4	7.82208e-1
		Test	13	1.90716e-3	9.03198e-1
	5-12-1	Training	58	2.31037e-4	9.89112e-1
		Validation	13	1.57671e-3	9.17498e-1
		Test	13	1.01226e-3	9.68183e-1
Bayesian Regulation	5-10-1	Training	58	2.46740e-4	9.85570e-1
		Validation	13	0.00000e-0	0.00000e-0
		Test	13	1.76331e-3	9.78323e-1
	5-12-1	Training	58	5.15215e-4	9.72684e-1
		Validation	13	0.00000e-0	0.00000e-0
		Test	13	8.07004e-4	9.78823e-1
Scaled Conjugate Gradient	5-6-1	Training	58	1.01483e-4	9.94515e-1
		Validation	13	1.07555e-3	9.50694e-1
		Test	13	2.96861e-3	9.05283e-1
	5-12-1	Training	58	1.43683e-5	9.99050e-1
		Validation	13	1.51757e-3	8.67330e-1
		Test	13	2.50940e-3	9.00090e-1

Table 8: The In-Sample of NARX Forecasting Using Different Types of Architecture

Architecture	NARX	R^2	MSE	RMSE
Levenberg-Marquardt	5-10-1	0.9550	0.000426	0.033657
	5-12-1	0.9423	0.000546	0.044237
Bayesian Regulation	5-10-1	1.0000	0.000480	0.037445
	5-12-1	0.9991	0.000558	0.045234
Scaled Conjugate Gradient	5-6-1	0.9299	0.000692	0.263140
	5-12-1	0.9204	0.000625	0.025004