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Modelling and Forecasting of Monthly Crude Palm Oil Price of Malaysia using Hybrid Wavelet-Modified GMDH Model

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This study comprises developing a more appropriate hybrid wavelet-modified GMDH model for forecasting the monthly crude palm oil (CPO) price of Malaysia. In the proposed hybrid model, the complex data of monthly CPO price is decomposed into different sub series using discrete wavelet transform (DWT) and then it has been linked with modified GMDH model. Sigmoid, radial basis, tangent and polynomial functions are selected as transfer functions in modified GMDH for the best fit and correct model compared to conventional GMDH. The monthly CPO data were taken from Malaysian Palm Oil Board (MPOB) spanning the period January 1983 to November 2019. The capabilities of modified GMDH and hybrid wavelet-modified GMDH in modelling and forecasting the monthly CPO price are determined by MAE, RMSE, MAPE, R and R^2. The MAPE of the proposed hybrid wavelet-modified GMDH model for the monthly CPO price of Malaysia is less than 4 % and coefficient of correlation (R) is 0.99, which show an excellent fit compared to the individual modified GMDH model. The proposed hybrid model provides the best alternative tools to help the Malaysian industry deal with price variations and assists Malaysia in playing a dominant role worldwide in the international market.

Keywords: Hybrid wavelet-modified GMDH Model; Discrete wavelet transform; CPO; Modelling and forecasting; Transfer functions

I. INTRODUCTION

Crude palm oil (CPO) has played a major role in the economic growth of Malaysia, which is ranked as the second-largest producer of crude palm oil in the world (Ahmad, Ping & Mahamed, 2014; Khalid, N *et. al.*, 2018; Khamis *et. al.*, 2018; Mohamad Hanapi *et. al.*, 2018; Ismail, Talib & Mokhtar, 2019). The appropriateness of the forecasting methods and the ability of these models to predict the crude palm oil price has become an important matter due to the price variation and an uncertain future, which affect international markets around the world. Accurate forecasting of CPO price is essential for enhancing the Malaysia socioeconomic level as palm oil has become a vital source of income (Khalid, N *et al.*, 2018).

The group method of data handling (GMDH) neural network has been successfully developed for modelling of linear and non-linear time series forecasting (Hwang, 2006; Kalantary, Ardalan & Nariman-Zadeh, 2009; Ebtehaj *et al.*, 2015). The distinguishing feature of group method of data handling is a heuristic self-organisation method which implements an automatic selection of necessary input variables without using any event in advance of any empirical evidence, often subjectively among the input and output variables (Ikeda, Ochiai & Sawaragi, 1976; Kondo, Pandya & Zurada, 1999; Kondo & Pandya, 2000; Rayegani & Onwubolu, 2014). The GMDH model can also find the number of layers and the number of neurons in hidden layers. However, the conventional GMDH model has some limitations. For example, it produces complex polynomial for simple experimental data and for highly nonlinear systems, it

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produces complex network model (Basheer & Khamis, 2016). The complex network of conventional GMDH model causes the consumption of more time devoted to analysis to predict the results, which makes it unsuitable for practical applications. Also, there may be a possibility of multico-colinearity, which occurs in the learning calculation of neurons, leading to instability in the prediction values of time series (Kondo, Ueno & Takao, 2013). Currently, there are several reviews about the hybrid modelling, which suggest that hybrid system obtained better performance and accuracy level as compared to the traditional or conventional system (Kim, Seo & Park, 2009; Samsudin, Saad & Shabri, 2011; Dhawan, Dongre & Tidke, 2013; Shabri & Samsudin, 2014a; Basheer & Khamis, 2017).

In this study, a new hybrid wavelet-modified GMDH model is proposed for the monthly crude palm oil (CPO) price forecasting of Malaysia. The complex data of monthly CPO price is effectively managed by the modification of conventional GMDH model, which is then hybridised with the discrete wavelet decomposition technique to enhance the forecasting accuracy. In the first part, modified GMDH neural network algorithm is introduced in which radial basis, sigmoid, polynomial and tangent functions are selected as transfer functions. These transfer functions are simultaneously integrated into GMDH for modified GMDH model. The advantages of these transfer functions are that the output can be easily determined for any given input(s), pick up the best and correct model to overcome the non-linearity of the data, which clarify the relationship between the given inputs and proper output. Furthermore, modified GMDH-neural network has used regularized least square estimation, which overcome the multi-collinearity problem and produced accurate and stable prediction compared with conventional GMDH model. In the second part, discrete wavelet transform (DWT) is selected as preprocessed clean and pure data by using discrete wavelet transform, in which the complex data of palm oil price is decomposed into different sub series in such a way that error criteria is minimised. The statistical performance measures such as RMSE, MAE, R, R^2 and MAPE are used to evaluate the performance of the hybrid wavelet modified GMDH neural network for comparison with individual modified GMDH model for the Malaysia monthly crude palm oil price forecasting.

II. METHODOLOGY

In the methodology section, first we discuss the individual forecasting model used in this study, followed by the experimental study framework. These models include GMDH, Modified GMDH, Wavelet analysis, hybrid wavelet modified GMDH. The models will be used for the forecasting of Malaysia monthly crude palm oil price.

A. Group Method of Data Handling (GMDH)

GMDH is a mathematical modelling method that presents a useful approach to the recognition of high order non-linear system. In 1971, A.G-Ivakhnenko first introduced this multilayered network to establish a rival technique to stochastic approximation (Abu-kheil, 2009). Initially, GMDH method was worked out to solve the problem of modelling and classification based on regression polynomials of complex order. The general connection of GMDH method between the input and output variables can be shown by a Volterra series, also known as Kolmogorov-Gabor polynomial (Ivakhnenko, 1971; Najafzadeh, Barani & Hessami Kermani, 2013).

$$y = b_0 + \sum_{i=1}^{P} b_i x_i + \sum_{i=1}^{P}\sum_{j=1}^{P} b_{ij} x_i x_j + \sum_{i=1}^{P}\sum_{j=1}^{P}\sum_{k=1}^{P} b_{ijk} x_i x_j x_k + \dots \quad (1)$$

where P represents input variables and 'b' represents the variable coefficients (weights). The response variable is shown by 'y' and the lagged time series data, which is to be regressed as represented by 'x_i' and 'x_j'.

Equation (1) is a complete picture of the complex and nonlinear system for the GMDH algorithm. However, in many applications, second-order polynomial known as partial descriptions are used (Mottaghitalb, 1996; Kondo, Ueno & Kondo, 2005; Ghazanfari *et al.*, 2017). The partial description consists of two variables, which are used for the prediction of output values is given in Equation (2).

$$y = b_0 + b_1 x_i + b_2 x_j + b_3 x_i x_j + b_4 x_i^2 + b_5 x_j^2 \quad (2)$$

For each P model, the value of the coefficient b is determined by solving Gauss normal equation. In each layer, the coefficients or weights in each neuron of the polynomials are estimated by least square fitting algorithm and calculated by equation,

$$X_k B_k^T = Y \tag{3}$$

In each layer, the coefficients are obtained as

$$B_k^T = (X_k^T X_k)^{-1} X_k^T Y \tag{4}$$

where

$$X_k = \begin{bmatrix} 1 & x_{1i} & x_{1j} & x_{1i}x_{1j} & x_{1i}^2 & x_{1j}^2 \\ 1 & x_{2i} & x_{2j} & x_{2i}x_{2j} & x_{2i}^2 & x_{2j}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{Pi} & x_{Pj} & x_{Pi}x_{Pj} & x_{Pi}^2 & x_{Pj}^2 \end{bmatrix}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ . \\ y_P \end{bmatrix} \quad \text{with} \quad B_k^T = \begin{bmatrix} b_0 \\ b_1 \\ . \\ . \\ . \\ b_5 \end{bmatrix}$$

and P is the training set number of observations.

GMDH main work is established on the forward propagation of signal data that passes through the nodes of the network. It works on same principal that is used in classical neural networks. Conventional GMDH basic steps are given as:

[Step 1]:

Consider the input data, divide it into training and testing data,

$$\mathbf{X} = \{ x_1, x_2, x_3 ..., x_P \}$$

In the first layer from the input vector $N_1 = P$ Neurons/nodes, where P is the number of inputs. Set k = 1 and the value of threshold.

[Step 2]:

In the training set data, formulate new variable and set up new polynomial, which is regressed for the first layer and make a quadratic expression like that shown in Equation (5).

$$P_k C_2 = \frac{P_k (P_k - 1)}{2} \tag{5}$$

where (k = 1, 2..., p)

[Step3]:

According to RMSE value at each hidden layer analyze the contributing of nodes. Eliminate or exclude the variables that are least effective in the previous column X and replace them with the new column. The simple architecture network of GMDH is shown Figure 1.

[Step 4]:

The algorithm of GMDH is executed by reproducing step 2 and step 3 until the errors of the data, which are found in each layer, start to decrease. The iteration is then terminated and the GMDH network has been completed. The flow chart of GMDH algorithm is shown in Figure 2.

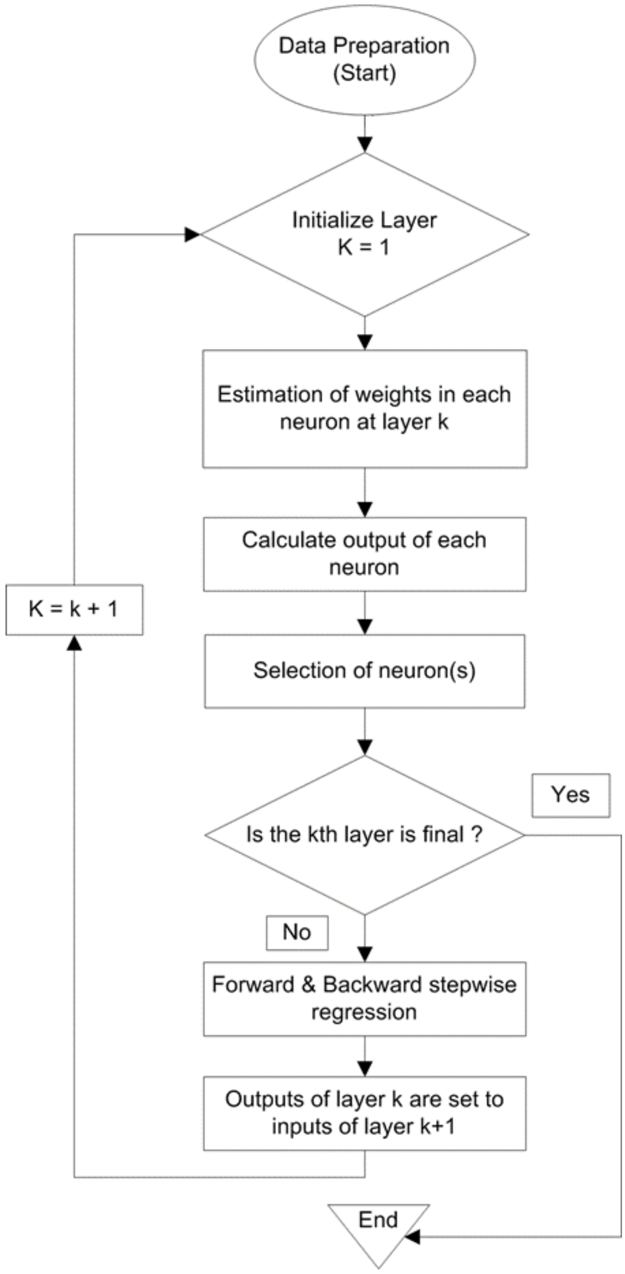


Figure 1. GMDH Algorithms Flow Chart

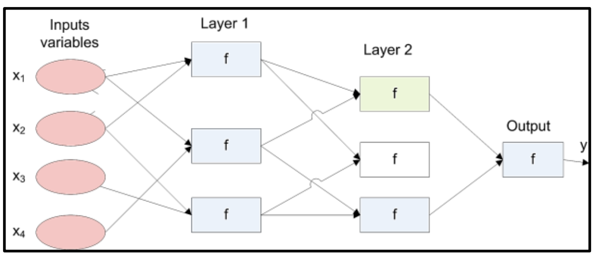


Figure 2. Architecture network of GMDH

B. Modified GMDH

Modified GMDH model is the enhancement of conventional GMDH, so that we can improve the prediction accuracy of conventional GMDH model. It is reported that many researchers consider and use only the transfer function of the quadratic polynomial in two variables, known as partial quadratic polynomials, in order to predict the output. However, to increase the accuracy of conventional GMDH and its enhancement, many transfer functions are available. Kondo *et al.* (2007) discussed that instead of using single transfer function in the conventional GMDH, it is much better to use heterogeneous transfer functions within a GMDH model, as it gives more accurate result than single transfer function. The hybridization of transfer functions enhance the accuracy measurement and give good result as compared to single transfer function (Taghizadeh-Mehrjardi, R *et al.*, 2021).

In this research, four types of transfer functions are proposed namely sigmoid, radial basis, polynomial and tangent, which are shown in Table 1. These transfer functions have enhanced the accuracy measurement of conventional GMDH. After using these transfer functions as input to the conventional GMDH, it is known as modified GMDH. The purpose of implementation of these transfer functions is not only to improve the accuracy of GMDH algorithm, but also to present how different transfer functions can be integrated into an improved network.

Table 1. The suggested transfer functions

Transfer Function	$z = f(y)$	Transformations
Sigmoid Function	$z = \dfrac{1}{1+e^{-y}}$	$y = \ln\left(\dfrac{z}{1-z}\right),\ z \neq 1$
Radial Basis Function	$z = e^{-y^2}$	$y = \sqrt{-\ln(z)}$
Tangent Function	$z = \tan(y)$	$y = \tan^{-1}(z)$
Polynomial	$z = y$	$y = z$

Here, y is presented below for GMDH and modified GMDH algorithm and is known as a response variable, whereas x_i and x_j are the pair of variables (covariate variables) as described in GMDH neuron/node and b_i = $\{b_o, b_1, b_2, b_3, b_4, b_5\}$ are the coefficients or weights.

$$y = b_0 + b_1 x_i + b_2 x_j + b_3 x_i x_j + b_4 x_i^2 + b_5 x_j^2$$

(Polynomial function)

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots + b_M x_M$$

(Linear function)

In modified GMDH algorithm, optimum neuron architecture can be selected from the four neuron architectures simultaneously such as sigmoid function neuron, radial basis function neuron, polynomial neuron and tangent function neuron. The interesting and important aspect of these transfer functions are that they can be used individually or simultaneously. For single or individual transfer function such as tangent, sigmoid, RBF or polynomial function are used in neurons, each neuron calculation is performed according to the selected single transfer function and no other transfer functions are used in the whole process. In the case of all transfer functions, which are used simultaneously in the prospective algorithm, each neuron consists of four transfer functions and selects only the transfer function that has the smallest external criteria due to the better fit of the neuron on the data. The selected transfer function is responsible for each neuron. The modified GMDH neural network uses principal component regression analysis, which overcome the multi-collinearity problem and produce accurate and stable prediction compared with conventional GMDH neural network (Dag & Yozgatligil, 2016).

C. Discrete Wavelet Transform (DWT)

The DWT is an application of the wavelet transform and it is used as a discrete set of the wavelet which consists of two parts, namely scales and translations (Swee & Elangovan, 1999; Okkan & Ali Serbes, 2013; Ramos *et al.*, 2017). A particular rule of scales and is that discrete wavelet transform disintegrates the signal into two sets of wavelets, which is mutually orthogonal. Choosing the scales and translations or positions, which are based on power of 2, is known as dyadic and translation scales. The original data is divided into two components after the decomposition process known as approximate (As) and detail coefficients (Ds). The decomposition tree of DWT is shown in Figure 3. The level of decomposition number in the DWT can be found by the following formula shown in Equation (6) (Nourani, Alami & Aminfar, 2009).

$$L = \text{int}[\log(N)] \tag{6}$$

where,

L = decomposition level,
N = number of data in time series
Int = integers

In this study, we use L = 3 (decomposition level), for N = 443 observations of monthly CPO price data in time series. Figure 3 shows the output of DWT decomposition tree. The main steps and study framework used in the discrete wavelet analysis are shown in Figure 4.

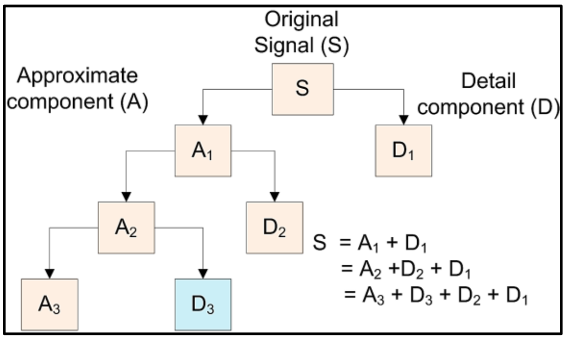


Figure 3. Decomposition tree of DWT

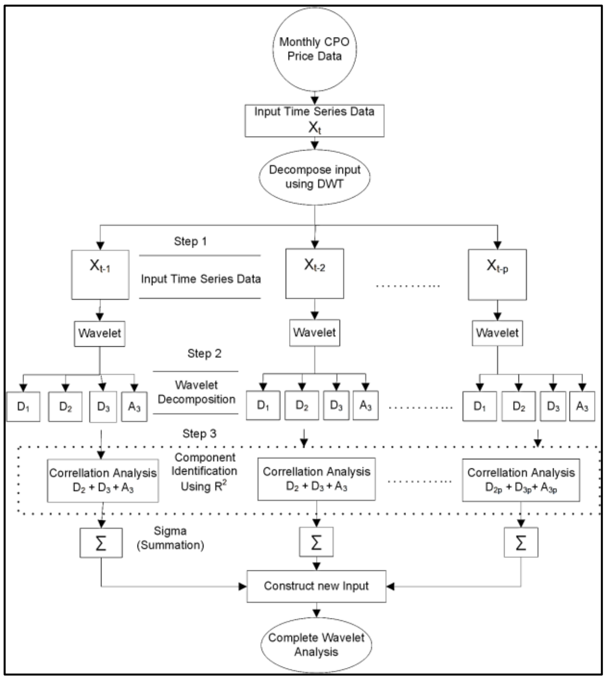


Figure 4. Study framework used in the discrete wavelet analysis

D. Hybrid Wavelet- Modified GMDH Model

Hybrid neural networks play an important role to improve the forecasting accuracy (Hernández, G *et al.*, 2020). The structure of hybrid wavelet-modified GMDH neural network is shown in Figure 5. The discrete wavelet analysis is linked as an input to the modified GMDH, know as hybrid wavelet modified GMDH. Figure 5 shows the flowchart of implementing the algorithm of hybrid wavelet modified GMDH model. The implementation of hybrid model algorithm consists of the following steps.

1. Select original time series data
2. Architecture of discrete wavelet transform algorithm
3. Effective wavelet component identification using r^2
4. Construct new inputs
5. Architecture of modified gmdh algorithm with four transfer functions
6. Hybrid wavelet modified gmdh (final output)
7. Forecast

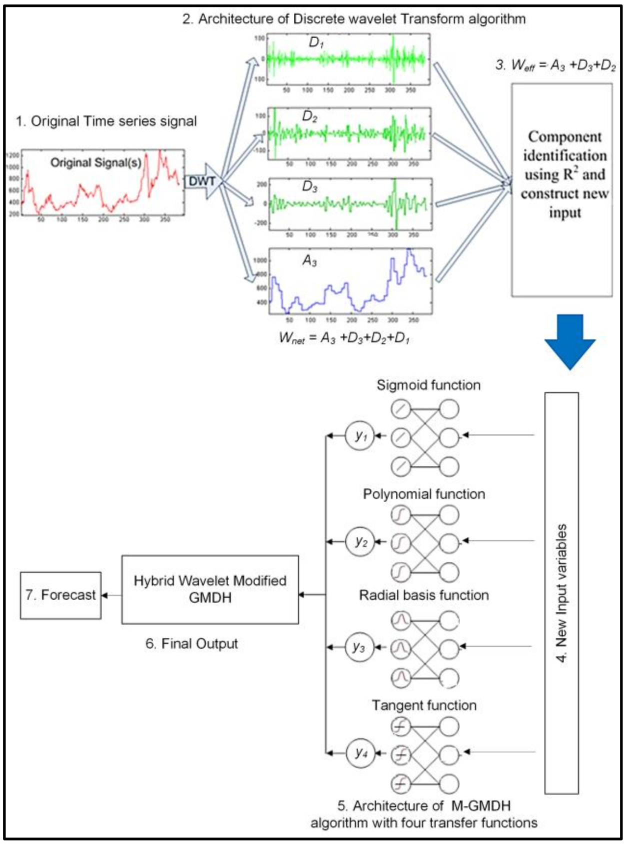


Figure 5. Flowchart of hybrid wavelet-modified GMDH algorithm

III. PERFORMANCE EVALUATION

To determine the performance of prediction of each model, the important statistical measures of errors are given by the following formulas.

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t| \tag{7}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \tag{8}$$

$$\text{MAPE} = \left(\frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right|\right)\times 100\% \tag{9}$$

Correlation coefficient (R),

$$R = \frac{\frac{1}{N}\left[\sum_{t=1}^{N}\left(y_t - \mu_{y_t}\right)\left(\hat{y}_t - \mu_{\hat{y}_t}\right)\right]}{\sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_t - \mu_{y_t}\right)^2}\sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\hat{y}_t - \mu_{\hat{y}_t}\right)^2}} \tag{10}$$

Coefficient of determination (R^2)

$$R^2 = \left[\frac{\frac{1}{N}\left[\sum_{t=1}^{N}\left(y_t - \mu_{y_t}\right)\left(\hat{y}_t - \mu_{\hat{y}_t}\right)\right]}{\sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_t - \mu_{y_t}\right)^2}\sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\hat{y}_t - \mu_{\hat{y}_t}\right)^2}}\right]^2 \tag{11}$$

where

N = Number of data points

y_t = Observed values at the time t

μ_{y_t} = mean of the observed values

$\hat{y}_t$ = Forecasted values at the time t

$\mu_{\hat{y}_t}$ = mean of forecasted value

IV. RESULTS AND DISCUSSION

In this study, the Malaysia monthly CPO price (USD/Metric-Ton) time series data are selected as an experimental sample. The time series uses data from January 1983 to Nov 2019, with a total of 443 observations, in which 354 observations are selected for the training set data (Jan 1983-June 2012) and 89 observation are selected as a testing set data (July 2012-Nov 2019). The data for the training set is used to check the understanding of methods on prediction and the rest of testing part is used to check the ability of methods on forecasting. Given a set of 443 observations made at uniformly spaced time intervals, the location of CPO is rescaled to the time axis to become the set of {1, 2...443}. For example, the first location in 1983 is written as time 1, the second location in 1983 to 2 and so on. The hybrid wavelet modified GMDH and modified GMDH modelling and its implementation are performed and fitted to the monthly CPO price for training set data (Jan 1983-June 2012) and testing set data (July 2012-Nov 2019). The forecasting accuracy (fit) and future values of forecast are measured for both the training and testing sets of the time series data.

A. Modified GMDH Modelling and Its Implementation

In modified GMDH, we used R package GMDH, suggested by Dag & Yozgatligil (2016), which integrates the transfer functions such as radial basis, sigmoid, polynomial and tangent functions, into GMDH. Transfer functions (sigmoid, radial basis, tangent and polynomial) are employed to enrich and improve the prediction accuracy of conventional GMDH model using R language. Figure 6(a) shows the predicted values after using transfer functions such as radial basis, sigmoid polynomial and tangent functions into GMDH model for the training data of monthly crude palm oil price and Figure 6(b) presents the scatter plot of the optimal model between observed values and predicted values, which explains the correlation coefficient (R) and coefficient of determination (R^2) for the predicted model. The forecasting accuracy measurements for training and testing data are given in Table 3.

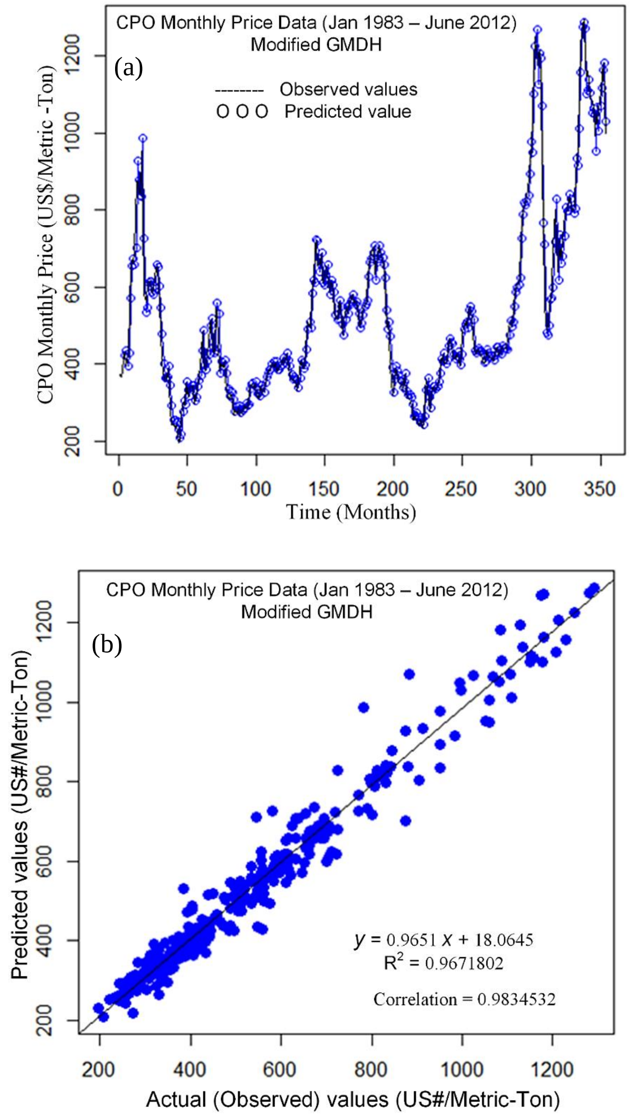


Figure 6. Modified GMDH (a) Crude palm oil price versus Time (b) Scatter plot

B. Discrete Wavelet Analysis

Figure 7 shows actual time series of monthly CPO price, which have approximate (A3) and detail (D1, D2 and D3) components of time series using daubechies wavelets of orders 3 (db3). The simulation tool of Mat-Lab (Mathworks, 2015a) has been used for the discrete wavelet decomposition of monthly CPO price. Figure 7(a) shows the actual time series plot for the training data of monthly CPO price. After using discrete wavelet analysis through mat-lab simulation, detail components (D1, D2, D3) have been shown in Figures 7(b)-7(d), respectively. Figures 7(e) and 7(f) represent approximate component (A3) and sum of the most effective wavelets components (D2+D3+A3), respectively.

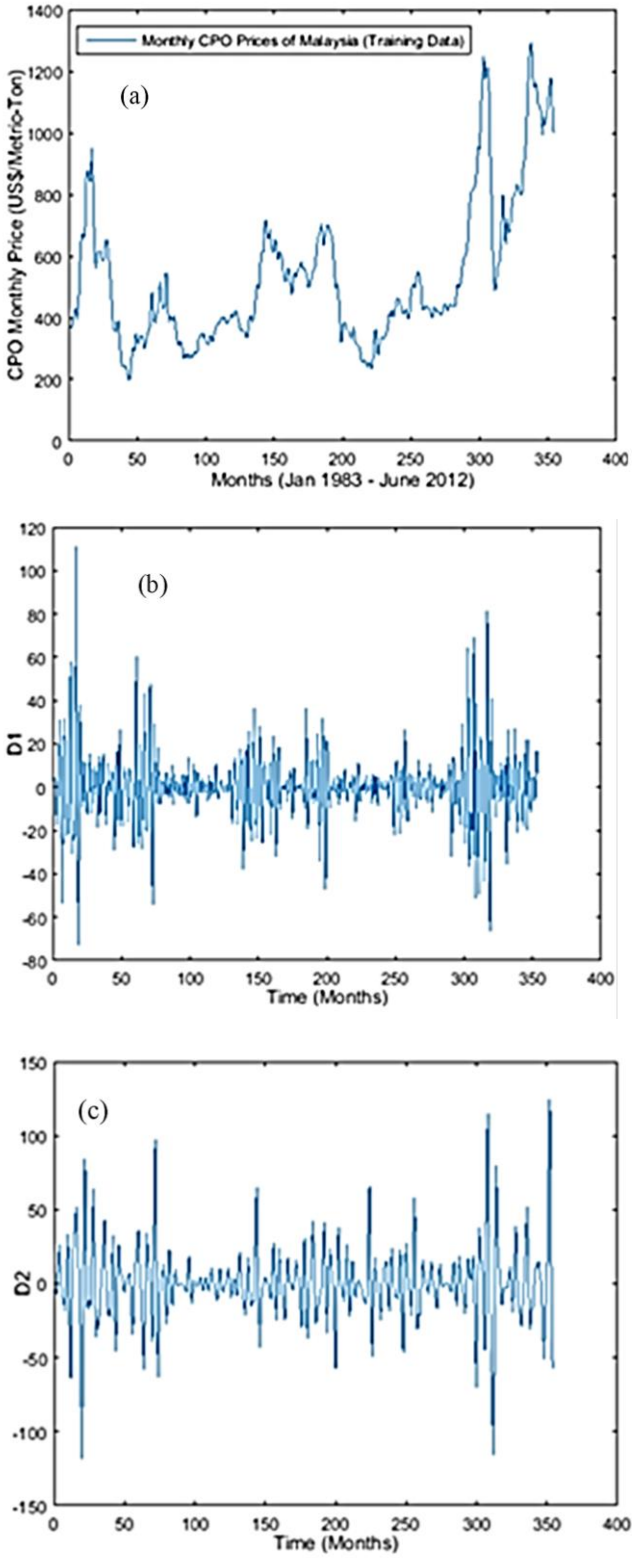
Now for the efficiency of the developed model, it is important to select the most effective wavelet components, which are determined by using the co-efficient of determination (R^2) (Pandhiani & Shabri, 2013; Shabri & Samsudin, 2014b; Seo *et al.*, 2015). The correlation coefficients (R) between discrete wavelet component and actual CPO price based on 3 level decomposition are given in Table 2. It can be seen from these combinations that 'D1' is dropped due to low coefficient of correlation. After summing the most effective wavelets components (A3, D3 and D2) as shown in Figure 7(f), we set up the new input, which is used for the hybridisation of discrete wavelet transform and modified GMDH model.

Table 2. The correlation Coefficient (R) between Discrete Wavelet Component and actual CPO Prices of Training data (Jan 1983- June 2012)

Wavelet Components	R	R^2	R^2 (%)
D1	0.0799	0.0064	0.64 %
D2	0.1074	0.0115	1.15 %
D3	0.1229	0.0151	1.51 %
A3	0.9841	0.9685	96.85 %

C. Wavelet-modified GMDH Modelling and Its Implementation

In this part of hybrid modeling, we link wavelet analysis as an input to the modified GMDH, known as hybrid wavelet modified GMDH. Figure 8(a) shows the predicted values after using hybrid wavelet modified GMDH model for the training data set of monthly crude palm oil price and Figure 8(b) presents the scatter plot of the optimal model between observed values and predicted values, which explains the correlation coefficient (R) and coefficient of determination (R^2) for the predicted model. The forecasting accuracy measurement for training and testing data values are given in Table 3. From the comparison of forecasting accuracy measurement of training and testing data shown in Table 3, it is found that hybrid wavelet modified GMDH displayed better results in comparison with modified GMDH neural network.



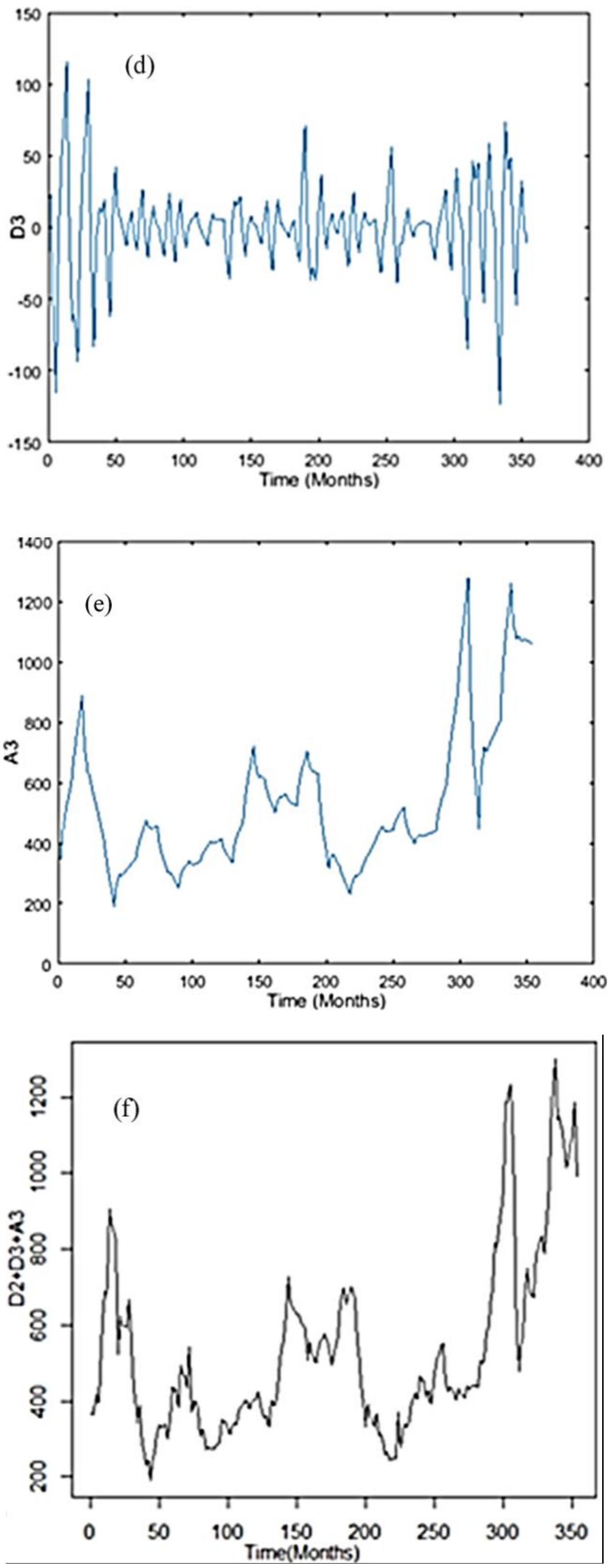


Figure 7. Discrete Wavelet analysis (details (Ds) and approximate (As)) components for training data set

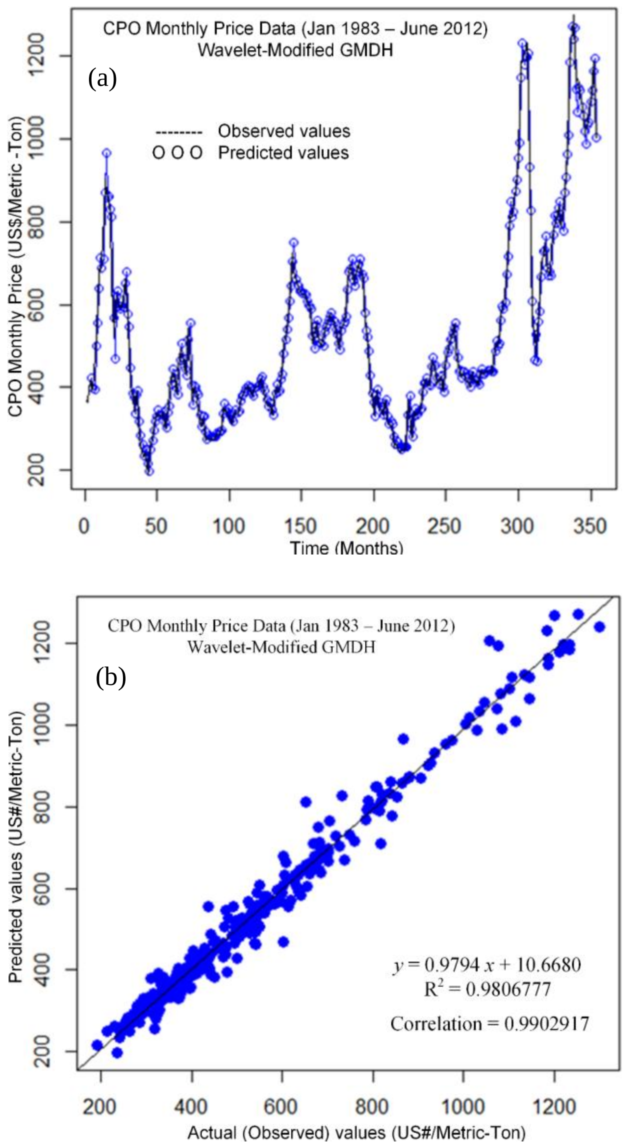


Figure 8. (a) Crude Palm Oil Price versus Time of hybrid wavelet-modified GMDH model, and (b) Scatter plot of hybrid wavelet-modified GMDH model

Table 3. Forecasting Accuracy (fit) of Monthly CPO price of Malaysia

Accuracy (fit) for Training data (Jan1983 - June 2012)					
Model	MAE	RMSE	MAPE	*R*	*R*²
Modified GMDH	29.3947	43.0464	5.7260	0.9834	0.9672
Hybrid wavelet modified GMDH	21.9328	32.9266	4.3934	0.9903	0.9807

Accuracy (fit) for Testing data (Jul 2012 – Nov 2019)					
Modified GMDH	24.9281	32.5712	3.2618	0.9504	0.9033
Hybrid wavelet modified GMDH	17.6272	23.8862	2.3891	0.9731	0.9469

V. CONCLUSION

This study has presented the modelling and forecasting of monthly Crude Palm Oil price of Malaysia using hybrid wavelet-modified GMDH model. The forecasts of monthly CPO price of Malaysia are studied by using the heuristic GMDH modelling, which has developed through its modification by transfer functions and hybridised with the discrete wavelet analysis techniques. The discrete wavelet transform (DWT) has used pre-processed clean and pure data in such a way that error criteria is minimised. The performance measurements of the hybrid wavelet modified GMDH and modified GMDH models are determined by statistical measures such as RMSE, MAE, R, R^2 and MAPE. The result of the hybrid wavelet modified GMDH model has shown to be more precise compared to the modified GMDH model. The MAPE of the proposed hybrid wavelet modified GMDH model for the monthly CPO price of Malaysia is less than 4 % and coefficient of correlation (R) is 0.99, which have shown an excellent fit compared to the individual modified GMDH model. The empirical findings of the proposed hybrid model provide the best alternative tools to help the Malaysian industry in dealing with the price variations and assist Malaysia in playing a dominant role worldwide in the international markets.

VI. ACKNOWLEDGEMENT

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