Application of Markov Model and Artificial Neural Network in Crude Oil Price Forecasting for PETRONAS Malaysia

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Abstract

Crude oil price forecasts are an important component of sustainable development of many countries as crude oil is an unavoidable product that exist on earth. In this paper, a model based on markov model and artificial neural network for crude oil price forecasting was developed and their relative performances were compared using SEM (AMOS). Four different error analysis techniques were employed to evaluate the most accurate model. Path analysis of structural equation modelling was used to buttress the findings of the error analysis, path analysis modeled the relationships of the forecasted prices and the actual crude oil price in order to get the most accurate forecast. The key variables used to develop the models were monthly crude oil prices from PETRONAS Malaysia. The markov model were found to provide more accurate crude oil price forecast than the artificial neural network. The results of this study indicate that markov models are a potentially promising method of crude oil price forecasting that merit further study.

Keywords
Markov model; Artificial neural network; Crude oil; Price; PETRONAS

1. Introduction
Large fluctuations in crude oil prices have caused great concern among both market participants and regulators. One of the reasons for this concern is that the oil price uncertainty has a substantial influence on the economy [1]. Theories of both investments under uncertainty and real options predict that an uncertainty about oil prices can reduce current investment. In addition, the volatility is a key input in pricing options and a major determinant of the value at risk. Therefore, the modelling and forecasting of crude oil prices are of considerable importance for economic development [1].

However, forecasting crude oil price has been one of the biggest challenges to the artificial intelligent (AI) community. The objective of forecasting research has been largely beyond the capability of traditional AI research which has mainly focused on developing intelligent systems that are supposed to emulate human intelligence. By its nature, crude oil price is mostly complex, non-linear and volatile. The rate of price fluctuations in such series depends on many factors, such as political, economic and social [2]. Therefore, developing AI systems for this kind of forecasting requires an iterative process of knowledge discovery and system improvement through data mining, knowledge engineering, theoretical and data-driven modelling, as well as trial and error experimentation. Crude oil has become an integral part of the global economy. Any fluctuation in crude oil prices influences our personal and corporate financial lives, and the economic health of a country. An 'intelligent' prediction model for crude oil price forecasting would be highly desirable and of wider interest [1][2].

Oil and gas play a momentous role in Malaysia, PETRONAS, the country's owned oil and gas company contributed RM73.4 billion in total to the Federal and State Governments of Malaysia in 2013 comprising RM27 billion in dividend, RM33.3 billion in taxes and RM12 billion in cash payments and RM1.1 billion of Export Duty. This is a significant sum and amounts to 30% of the government's expenditure in 2013.

However, the average selling price for crude oil between 2011 and 2014 was USD109 per barrel. The average price in the first 20 days of 2015 was USD49.66 per barrel. As such the recent fall in crude oil prices would have profound impact on Malaysia. This paper employed Markov Model and Artificial Neural Network to forecast the future price of crude oil price and provides a possible future price range for crude oil of PETRONAS Malaysia.

However, Andrey Andreyevich Markov (June 14, 1856 – July 20, 1922) was a Russian mathematician. He is best known for his work on the theory of stochastic Markov processes. His research area later became known as Markov process and Markov chains[3]. Andrey Andreyevich Markov introduced the Markov chains in 1906 when he produced the first theoretical results for stochastic processes by using the term "chain" for the first time. In 1913 he calculated letter sequences of the Russian language[4]. A generalization to countable infinite state spaces was given by Kolmogorov (1931). Markov chains are related to Brownian motion and the ergodic hypothesis, two topics in physics which were important in the early years of the twentieth century. But Markov appears to have pursued this out of a mathematical motivation, namely the extension of the law of large numbers to dependent events. Out of this approach grew a general statistical instrument, the so-called stochastic Markov process[5].

Similarly, in mathematics generally, probability theory and statistics particularly, a Markov process can be considered as a time-varying random phenomenon for which Markov properties are achieved. In a common description, a stochastic process with the Markov property, or memorylessness, is one for which conditions on the present state of the system, its future and past are independent [6]. Markov processes arise in probability and statistics in one of two ways. A stochastic process, defined via a separate argument, may be shown to have the Markov property and as a consequence to have the properties that can be deduced from this for all Markov processes. Of more practical importance is the use of the assumption that the Markov property holds for a certain random process in order to construct a stochastic model for that process[6]. In modeling terms, assuming that the Markov property holds is one of a limited number of simple ways of introducing statistical dependence into a model for a stochastic process in such a way that allows the strength of dependence at different lags to decline as the lag increases. Often, the term Markov chain is used to mean a Markov process which has a discrete (finite or countable) state-space[7]. Usually a Markov chain would be defined for a discrete set of times (i.e. a discrete-time Markov Chain) although some authors use the same terminology where "time" can take continuous values.

Moreover, one of the first successful applications of ANNs in forecasting is reported by Lapedes and Farber (1987), (1988). Using two deterministic chaotic time series generated by the logistic map and the Glass-Mackey equation, they designed the feed-forward neural networks that can accurately mimic and predict such dynamic nonlinear systems. Their results show that ANNs can be used for modeling and forecasting nonlinear time series with very high accuracy.

Following Lapedes and Farber, a number of papers were devoted to using ANNs to analyze and predict deterministic chaotic time series with and / or without noise. Chaotic time series occur mostly in engineering and physical science since most physical phenomena are generated by nonlinear chaotic systems. As a result, many authors in the chaotic time series modeling and forecasting are from the field of physics.

A typical feed forward with back propagation network should have at least three layers- an input layer, a hidden layer, and an output layer. Appropriate selection of number of hidden layers and the number of neurons in each of them needs experimentation[8]. We train the ANN using the Levenberg-Marquardt algorithm, a standard training algorithm from the literature. The training function produce forecast results on the basis of MSE (Mean square error) minimization criteria. In one complete cycle of the training process, a set of input data is presented to the input node. The corresponding target output is presented to the output node in order to show the network what type of behavior is expected. The output signal is compared with the desired response or target output[9]. In each step of iterative process, the error signal activates a control mechanism which applies a sequence of corrective adjustments of the weights and biases of the neuron. The corrective adjustments continue until the training data attains the desired mapping to obtain the target output as closely as possible. After a number of iterations the neural network is trained and the weights are saved. The test set of data is presented to the trained neural network to test the performance of the neural network.

A substantial amount of research has been published in recent times and is continuing to find optimal forecasting models for crude oil price [10]. Most of the forecasting research has employed the statistical time series analysis techniques like ARMA model, GARCH model as well as the multiple regression models [10]. In recent years, numerous crude oil price forecasting techniques based on AI, fuzzy logic, hybridization of fuzzy system, support vector machines have been proposed. Most of them have their own shortcomings [11]. For example, fuzzy is very much problem oriented because of its chosen structural design. Some researchers have used fuzzy systems to develop a model to forecast crude oil price behaviour. To build a fuzzy system one requires some background expert knowledge [11]. In this research, we make a comparison between markov model and artificial neural network for crude oil price forecasting for PETRONAS Malaysia. We locate pattern(s) from the past datasets that match with today's crude oil price behaviour, then interpolate these two datasets with appropriate neighbouring price elements and forecast tomorrow's crude oil price.

2. Methodology

In finding a markov model, assuming we have a state sequence $\{q_n, \cap \in \mathbb{N}^+\}$, we can find the transition frequency F_{ij} in the sequence by counting the number of transitions from state S_i to state S_j in one step. Then the one-step transition frequency matrix for the sequence $\{q_n\}$ can be constructed as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mm} \end{bmatrix} \qquad F = \begin{pmatrix} F_{11} & F_{12} & F_{13} & \cdots & F_{1m} \\ F_{21} & F_{22} & F_{23} & \cdots & F_{2m} \\ F_{31} & F_{32} & F_{33} & \cdots & F_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ F_{m1} & F_{m2} & F_{m3} & \cdots & F_{mm} \end{pmatrix}$$

Where $a_{ij} = \dfrac{F_{ij}}{\sum_{j=1}^{m} F_{ij}}$, If $\sum_{j=1}^{m} F_{ij} > 0$

0, If $\sum_{j=1}^{m} F_{ji} = 0$

Suppose there are three states: up, same and down, to simulate the movement of the crude oil price. Here is an explanation of up, same and down. We only compare two crude oil prices, v_{n-1} and v_n - v_n is the current price, v_{n-1} is the price of yesterday, if $v_n - v_{n-1} > 0$ is called up, $v_n - v_{n-1} < 0$ is called down and, $v_n - v_{n-1} = 0$ represents same. We use the information to calculate the transition probabilities. There are only three states. On the assumption that the state space is $S = S_1, S_2, S_3$. S1 = up, S_2 = same and S_3 = down.

Up, same and down are three states, which are decided by comparing the previous closing price and the current closing price. We calculate the number of days that both the first day and the second day are up by using the data. We also get the number of days that the first day is down and the second day is up.

However, the human brain contains billions of interconnected neurons. Due to the structure in which the neurons are arranged and operate, humans are able to quickly recognize patterns and process data. An ANN is a simplified mathematical representation of this biological neural network. It has the ability to learn from examples, recognize a pattern in the data, adapt solutions over time, and process information rapidly. The application of ANNs to crude oil price frecasting is rapidly gaining popularity due to their immense power and potential in the mapping of nonlinear system data. A crude oil price forecasting may be nonlinear and multivariate, and the variables involved may have complex interrelationships. Such problems can be efficiently solved using ANNs. The processes that involve several parameters are easily amenable to neurocomputing. Among the many ANN structures that have been studied, the most widely used network structure in the area of hydrology is the multilayer, feed-forward network. An ANN consists of a number of data processing elements called neurons or nodes, which are grouped in layers. The input layer neurons receive the input vector and transmit the values to the next layer of processing elements across connections. This process is continued until the output layer is reached. This type of network in which data flows in one direction (forward) is known as a feed-forward network [12]. The application of ANNs has been the subject of a large number of papers that have appeared in the recent literature. Therefore, this paper will be limited to main concepts. A 3-layer, feed-forward ANN is shown in Figure 1. It has input, output, and hidden middle layers. Each neuron in a layer is connected to all the neurons of the next layer, and the neurons in one layer are not connected among themselves. All the nodes within a layer act synchronously. The data passing through the connections from one neuron to another are multiplied by weights that control the strength of a passing signal. When these weights are modified, the data transferred through the network changes; consequently, the network output also changes. The signal emanating from the output node(s) is the network's solution to the input problem.

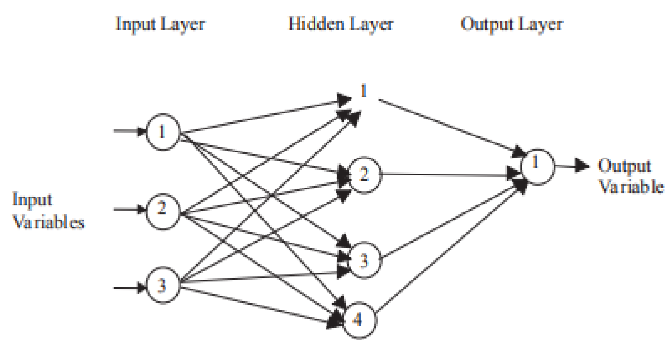

Figure 1. A 3-layer ANN architecture used for flow estimation.

Each neuron multiplies every input by its interconnection weight, sums the product, and then passes the sum through a transfer function to produce its result. This transfer function is usually a steadily increasing S-shaped curve, called a sigmoid function. The sigmoid function is continuous, differentiable everywhere, and monotonically increasing. The output y_j is always bounded between 0 and 1, and the input to the function can vary ±∞. Under this threshold function, the output y_j from the j_{th} neuron in a layer is

$$y_j = f\left(\sum w_{ji}x_i\right) = \frac{1}{1+e^{-\left(\sum w_{ji}x_i\right)}}$$

Where w_{ji} = weight of the connection joining the j_{th} neuron in a layer with the i_{th} neuron in the previous layer, and x_i = value of the i_{th} neuron in the previous layer.

Training of ANNs
The process of determining ANN weights is called learning or training and is similar to the calibration of a mathematical model. The ANNs are trained with a training set of input and known output data. At the beginning of training, the weights are initialized, either with a set of random values or based on some previous experience [13]. Next, the weights are systematically changed by the learning algorithm such that for a given input the difference between the ANN output and actual output is small. Many learning examples are repeatedly presented to the network, and the process is terminated when this difference is less than a specified value. At this stage, the ANN is considered trained. The backpropagation algorithm based upon the generalized delta rule proposed by Rumelhart was used to train the ANN in this paper. In the back-propagation algorithm, a set of inputs and outputs was selected from the training set and the network calculates the output based on the inputs. This output is subtracted from the actual output to find the output-layer error. The error is backpropagated through the network, and the weights are suitably adjusted. This process continues for the number of prescribed sweeps or until a prespecified error tolerance is reached [14].

However, the methods employed in this paper are effective compared to other methods used by different researchers because of the minimum error we got. The methods of both models were found effective in forecasting crude oil price in this paper.

3. Result of Markov Model

We chose the actual values of crude oil price from the PETRONAS dated from 1996 to 2015 yielding 20 years. However, in this model, there are three states, on the assumption that the state space is S = (S1, S2, S3), S1 = up, S2 = same and S3 = down. The definition of up is $u_n - u_{n-1} > 1$, where the u_n is the current closing index and the u_{n-1} is the previous closing index. The definition of same is $/u_n - u_{n-1}/ \leq 1$, the definition of down is $u_n - u_{n-1} < 1$. We train the real crude oil price and use the definition of the states to get our result.

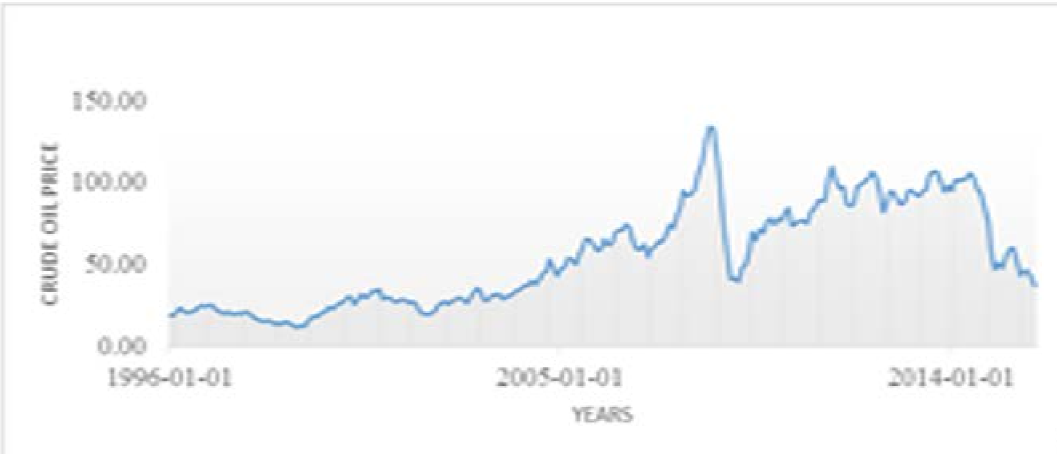

Figure 2: Actual Movement of Crude Oil Price from 1996 to 2015

In finding the trend of the crude oil price movement, we found the state transition probability. By calculating the number of days that both first day and second day are up, we could find the probability from up to up. Then we got the number of days that first day is up and the second day is down.

$S_1 \Longrightarrow S_1 \Longrightarrow 89$days $\quad S_1 \Longrightarrow S_2 \Longrightarrow 0$days $\quad S_1 \Longrightarrow S_3 \Longrightarrow 53$days

$S_2 \Longrightarrow S_1 \Longrightarrow 0$days $\quad S_2 \Longrightarrow S_2 \Longrightarrow 0$days $\quad S_2 \Longrightarrow S_3 \Longrightarrow 0$days

$S_3 \Longrightarrow S_1 \Longrightarrow 53$days $\quad S_3 \Longrightarrow S_2 \Longrightarrow 0$days $\quad S_3 \Longrightarrow S_3 \Longrightarrow 44$days

Where S_1 = up, S_2 = same and S_3 = down. Then we get the transition matrix as follows

$$A = \begin{bmatrix} 89/142 & 0 & 53/142 \\ 0 & 0 & 0 \\ 53/97 & 0 & 44/97 \end{bmatrix} \qquad \hat{A} = \begin{bmatrix} 0.6268 & 0 & 0.3732 \\ 0 & 0 & 0 \\ 0.5464 & 0 & 0.4536 \end{bmatrix}$$

$$A^2 = \begin{bmatrix} 0.5968 & 0 & 0.4032 \\ 0 & 0 & 0 \\ 0.5903 & 0 & 0.4097 \end{bmatrix} \qquad \lim_{n \to \alpha} \mathrm{A}^n = \begin{bmatrix} 0.5942 & 0 & 0.4058 \\ 0 & 0 & 0 \\ 0.5942 & 0 & 0.4058 \end{bmatrix}$$

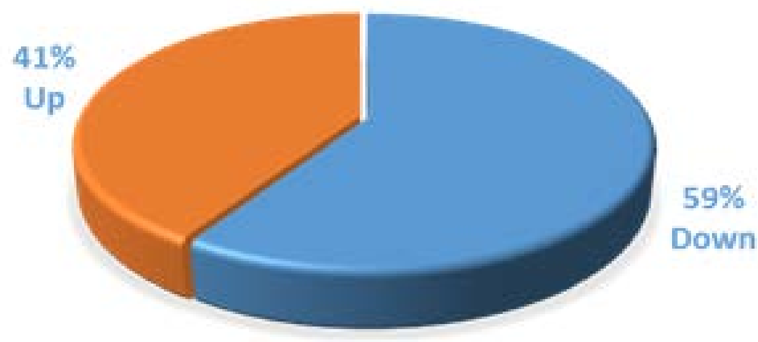

Figure 3: Trend of the Crude Oil Price Forecasting from January 1996 to December 2015

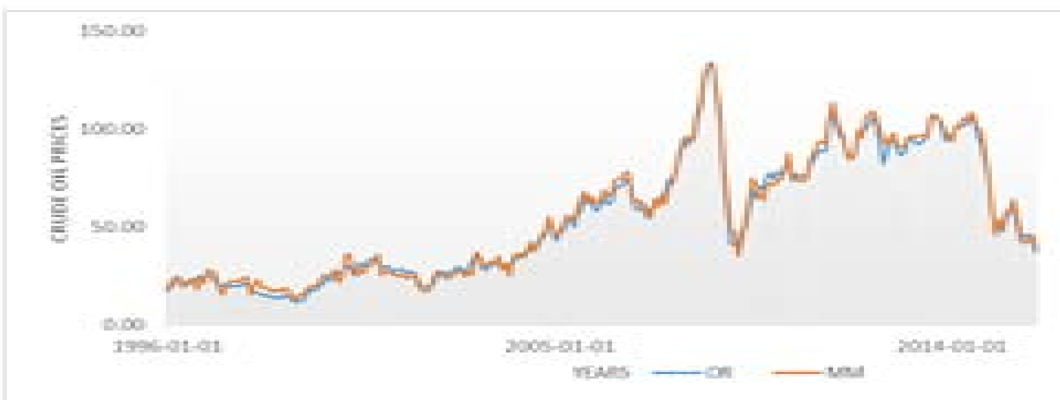

Figure 4: Actual and Forecasted Movement of Crude Oil Price from 1996 to 2015 Using MM

In the above model, we got information about three states which are up, same and down. According to the above result, the transition matrix is stable, and the most likely trend of crude oil price is down since the probability of down is biggest. The previous price dated December 2015 was $37.19 and the price of predicted day dated January 2016 was $31.68 respectively. This shows that the forecasting is tuned to be accurate and reliable.

The date is from 1996 to 2015 yielding 240 months. The blue line illustrates the movement of the true values of the crude oil price while the red line illustrates the movement of the forecasted crude oil price using MM.

4. Results of Artificial Neural Network

The neural network consists of an interconnected group of artificial neurons and computes the output by fitting a linear combination of a nonlinear transformation of the linear combination of the explanatory variables. It was originally inspired by the nervous system in animals [15]

We chose the same data of crude oil price from the PETRONAS dated 1996 to 2015 yielding 20 years (240 months). We used Artificial Neural Network to forecast the crude oil price as we did using the previous models.

Output layer of the Artificial Neural Network is a linear weighted sum. So it is much faster and easier than to run the network, and it has better result on nonlinear mapping. For comparing the difference easily, it is the same data which was used by us in the previous models [16][17]. The model below show the actual as well as the forecasted crude oil price using artificial neural network.

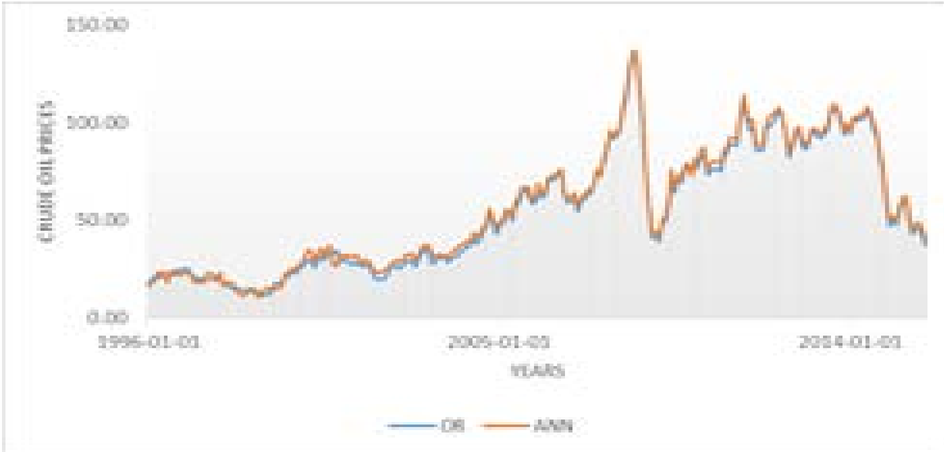

Figure 5: Actual and Forecasted Movement of Crude Oil Price from
1996 to 2015 Using Artificial Neural Network

In the above model, we used data of crude oil prices to forecast the future prices of the same crude oil. According to the above result, the test performance were 39.3 while the train performance were 8.8 respectively. The most likely trend of crude oil price is down since the probability of down is biggest. The previous price dated December 2015 was $37.19 and the price of forecasted day dated January 2016 was $40.3 respectively. This shows that the forecasting is tuned to be accurate and reliable. The date is from 1996 to 2015 yielding 240 months. The blue line illustrates the movement of the true values of the crude oil prices while the red line illustrates the movement of the forecasted values by the ANN.

5. Result of Error Analysis

After models' development, it is necessary to evaluate the models to find out the most accurate model. In this paper, the researcher employed four different evaluation techniques with the aim of evaluation the most accurate model. The evaluation technique employed are mean absolute percentage error (MAPE), absolute error (AE), mean absolute error (MAE) and root mean square error (RMSE) as shown in the table below.

Table 1: Result of Error Analysis

Models	MAPE %
MM	0.06923
ANN	0.12962
Models	**AE %**
MM	3.50825
ANN	5.29764
Models	**MAE %**
MM	4.25282
ANN	5.03083
Models	**RMSE %**
MM	4.77797
ANN	6.11609

The table above shows the result of the error analysis by employing four different errors, the results of MAPE shows MM as the most accurate with 0.06923% then ANN with 0.12962%. Base on the results of MAPE MM is the best model with minimum error. Similarly, when using AE, the results reads that MM has 3.50825%, then ANN has 5.29764%, the results clearly show that the MM has the minimum error compared with the other ANN.

Moreover, Results of MAE shows that MM is the best model with minimum error then ANN, the results of MAE is 4.25282 for MM, 5.03083 for ANN respectively. Once again, the result of RMSE shows that MM is also the best model in this research paper with the error 4.77797 then ANN with the error 5.43545.

However, the error analysis results of the four error analysis techniques employed in this paper (MAPE, AE, MAE and RMSE) clearly shows that MM has the minimum errors than ANN. This shows that, MM is the best forecasting model in this research paper.

6. Result of Path Analysis

Path analysis is type of causal modeling (or structural equation modeling) for investigating postulated relationships among variables. Path analysis is neither a statistical procedure nor an experimental design, and under no circumstances does it ever prove causality [18][19]. Unlike procedure such as correlation and multiple regressions, which examine only covariance between variables, path analysis assumes that several conditions for defining a causal relationship are met. Among the most important of these are the assumptions that the occurrence of one event is sufficient for the occurrence of later event.

The diagram below modeled the relationships between actual crude oil price and the forecasted crude oil price.

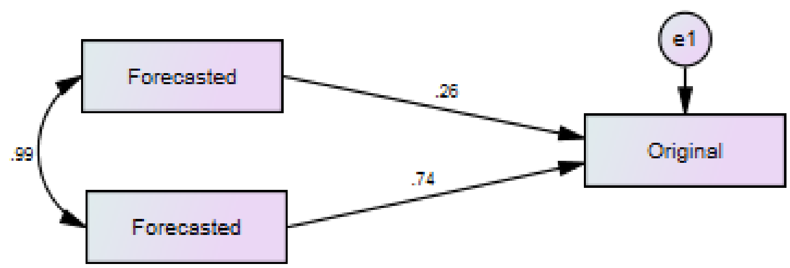

Figure 6: Actual and Forecasted Movement of Crude Oil Price from
1996 to 2015 Using Path Analysis

The above model shows the relationships between two forecasted models and actual crude oil price (MM and ANN). It shows that the price forecasted using MM is more accurate and is closely related to the actual crude oil price with the p value 0.74, while ANN is closely related to the actual price with the p value of 0.26.

However, the above model shows clearly that crude oil price forecasted using Markov Model (MM) is more closely related to the actual crude oil price with the p value of 0.74. This also underpinned or explained that, Markov Model has less error in crude oil price forecasting compared with the other models employed in this paper (i.e Artificial Neural Network).

Conclusion

This paper forecasts crude oil prices for PETRONAS Malaysia by employing two different models (i.e MM and ANN). We chose the real price of crude oil dated from 1996 to 2016 yielding 20 years. The crude oil price forecasting models developed were based on markov model and artificial neural network. The related data was collected from PETRONAS Malaysia. Four error analysis techniques (MAPE, AE, MAE and RMSE) were employed to validate the developed models. A path analysis of structural equation modelling (SEM) was developed to buttress the findings of the four error analysis techniques and determine the best model among the two models developed. Markov model was discovered as the best model with less error compared to artificial neural network in this paper.

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