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A Research on Markov Model and Hidden Markov Model in Crude Oil Price Forecasting for PETRONAS Malaysia

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Abstract—Crude oil price forecasting is an essential component of sustainable development of many countries as crude oil is an unavoidable product that exists on earth. In this paper, a model based on a hidden Markov model and Markov model for crude oil price forecasting was developed, and their relative performance was compared. Path analysis of Structural Equation Modelling was employed to model the effects of forecasted prices and the actual crude oil price to get the most accurate forecast. The key variables used to develop the models were monthly crude oil prices s from PETRONAS Malaysia. It was found that the hidden Markov model was more accurate than the Markov model in forecasting the crude oil price. The findings of this study show that the hidden Markov model is a potentially promising method of crude oil price forecasting that merit further study.

Keywords: Hidden Markov Model, Markov Model, Forecasting Crude Oil, Price

I. INTRODUCTION

Crude oil price fluctuations have since become a major concern area by economists and financial analysts as well as the statistician that are interested in modelling. Among the main reason for this interest is the economy development of many countries is significantly affected by oil price volatility [12]. Many theories predict that crude oil price volatility can reduced investment because of the fear of incurring lost[2]. Similarly, the fluctuation is the main key in pricing crude oil and the major determinant of the value. Therefore, forecasting crude oil prices is of great importance for many economies.

Among the biggest challenge of AI is the crude oil price forecasting, the main aim of forecasting is mainly been above the ability of outdated AI research that had been used to develop an intelligent system that is supposed to imbibe human intelligent. Crude oil price is usually non-lineraity, complex in nature,and has a volatile nature. The rate of price volatility of crude oil is based on several factors, for instance, political, ecnomic and social [7]. However, to develop an AI system for crude oil price forecasting needs a deep knowledge and understanding of data mining as well as modelling.

It is well know that fluctuation in crude oil prices influences economic health of a country, corporate financial lives, and our personal. An 'intelligent' model for forecasting the crude oil price would be attracted a great of attention [2].

Oil and gas play a momentous role in Malaysia, PETRONAS is the country's owned oil and gas company that contributed immensely to the economic development of Malaysia. PETRONAS contributed in the education sector of Malaysia; it also helped to the annual budget of Malaysia almost every year[4].

However, the average crude oil price between 2011 and 2014 was USD109. However, the average price of crude oil per barrel in the first 20 days of 2015 was USD49.66. In this regard, the recent fall in crude oil prices will have a profound impact on Malaysia. This paper employed Markov Model and Hidden Markov Model to predict the future rate of crude oil dynamics and provides a possible future price range for crude oil of PETRONAS Malaysia.

Many research has been conducted to find out accurate forecasting for crude oil price[5]. Many of the forecasting models have used time series analyses such as ARMA model, GARCH model and also multiple regression models[1]. Of recent, many crude oil price forecasting methods such as AI, fuzzy logic, hybridisation of the fuzzy system, SVM have been developed[15]. They also have their limitations[12]. Fuzzy has a problem of structural design[6]. Previous studies employed fuzzy systems to forecast crude oil price volatility. It needs one to have the background knowledge to build a fuzzy system[8]. In this research, we make a comparison between MM and HMM o forecast crude oil price PETRONAS Malaysia. We find a pattern(s) from the historical data that is aligned with today's crude oil price settings, then interpret this data with appropriate neighbouring price elements and forecast tomorrow's crude oil price.

II. METHODOLOGY

In finding a Markov model, assuming we have a state sequence $\{q_n, \cap \in N^{+}\}$, we found the transition frequency F_{ij}in sequence by calculating how many numbers of transitions we have from state $S_i$to state $S_j$in the first step. Next, the one-step transition frequency matrix for the sequence $\{q_n\}$can be described as follows

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

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

Assumed we have three state transition matrices: Up, Same and Down to forecast the movement of crude oil price, below is the definition of the three state transition matrices used in this paper, $v_{n-1}$and v_n, whereby v_n describes current price, while

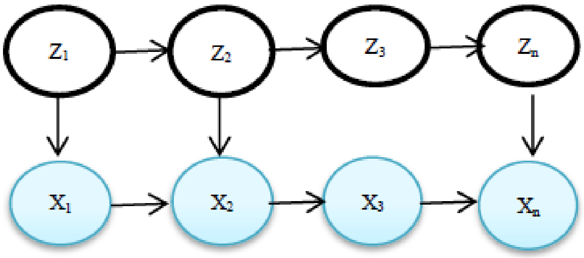
v_{n-1}describes the yesterday price, if v_n - v_{n-1} less than 0 is called down, $v_n - v_{n-1}$more than 0 is called up, while if $v_n - v_{n-1}$ equal 0 is called same

By using the above definition, the transition probabilities on the assumption is calculated, indicating the state space is S = S_1, S_2, S_3. S1 = up, S_2 = same and S_3 = down

Suppose we have random variables as (probabilistic model)

$Z_1,\ldots Z_n$

$X_1,\ldots X_n$ These random variables can be described by using following 'trellis' diagram



Graphical Model for HMM

The graphical model involves the following joint distribution

$$P(x_1,\ldots x_n, z_1,\ldots z_n) = P(z_1)P(x_1 I z_1)\prod_{k=2}^{n} P(z_k I z_{k-1})P(x_k I z_k)$$

Parameters:

1. Transition Probability: $T_{ij} = P(z_{k+1} = j I z_k = i)(ij \in \{1,\ldots m\})$
2. Emission Probability: $\in_i (x) = P(x I z_k = i)$ for $i \in \{1,\ldots m\}$
3. Initial Distribution: $\pi(i) = P(z_1 = i)$ i.e $\{1,\ldots m\}$

We used three (3) algorithms to adjust the hidden Markov model as follows:

1. Baum-welch algorithm
2. Viterbi algorithm
3. Forward-backwards algorithm

III. 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.

Figure 1: Actual Movement of Crude Oil Price from 1996 to 2015
Source: PETRONAS (2016)

The definition of up is $u_n - u_{n-1}>1$, then u_n represents the current price, and the u_{n-1} represents the previous price. Same is defined as $/u_n - u_{n-1}/ \leq 1$, the down can be defined as $u_n - u_{n-1}< 1$. We trained the real crude oil price and employed the definition of the three states transition matrices to get our result.

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

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

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

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

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

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

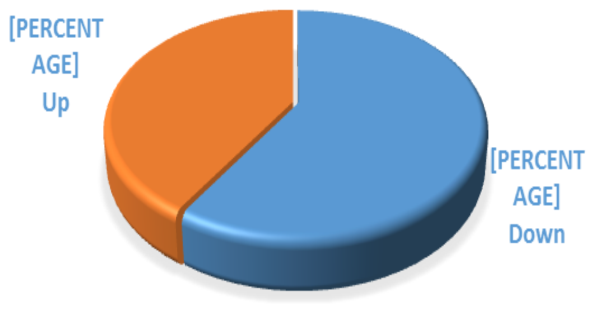


Figure 2: Trend of the Crude Oil Price Forecasting from January 1996 to December 2015
Source: Research Analysis (2017)

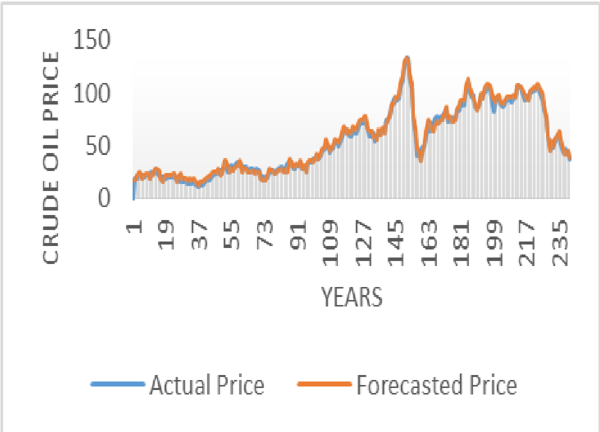


Figure 3: Actual and Forecasted Movement of Crude Oil Price from 1996 to 2015 Using Markov Model
Source: Research Analysis (2017)

The model above shows clearly the information of three states transition probabilities, which are U = up, S = same and D = down. The results showed that the transition matrix is normal, and the crude oil price of tomorrow is down as the biggest probability is down with 59%. The previous price dated December 2015 was $37.19 and the predicted price dated January 2016 was $31.68 respectively. The results indicated that the forecasting is tuned to be accurate and reliable.

IV. RESULT OF HIDDEN MARKOV MODEL

The same data with the previous model is used to develop HMM, HMM has three parameters (A, B, π). $\pi = (\pi_i)$ is the initial distribution, we assumed that π satisfy Gaussian distribution and is a random distribution as well. We then assume there are three states, i.e. Same, Up and Down which are the probabilities of the state transition matrices where $a_{ij} = P(qt+1 = S_j \mathrm{I} q_t = S_i)$. The confusion matrix is showed by $B = \{b_j(k)\}$, where $b_j(k) = P(O_t = U_k \mathrm{I} q_t = S_j)$ satisfy Gaussian distribution.

We employed Baum-Welch algorithms to adjust the parameters of HMM. Thus, a new model $\hat{\lambda} = (\hat{A}, \hat{B}, \hat{\pi})$ is developed which could make the maximization of $P(O \mathrm{I} \hat{\lambda})$. We employed a Viterbi Algorithm to calculate the most likely state sequence. By doing such, we will be able to know the probable state of today $\hat{S}_i$. The probable state of tomorrow is known by the state transition matrix, which is $A = \{\hat{a}_{ij}\}$. Because we assume $\hat{b}_j(k)$ satisfy Gaussian distribution, we could forecast the probable crude oil price of tomorrow when we know the most likely state of tomorrow. The result is shown below:

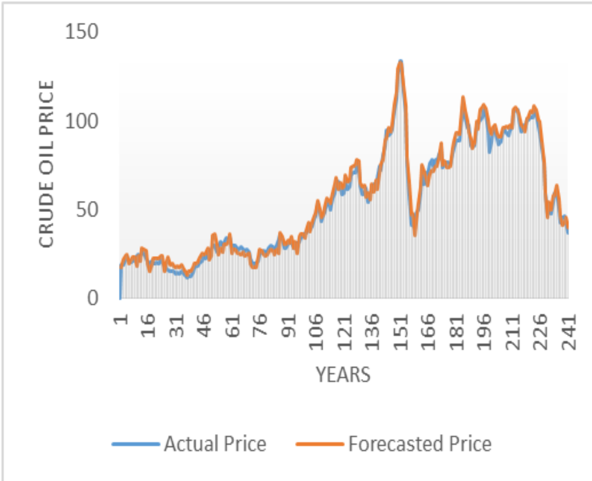


Figure 4: Actual and Forecasted Movement of Crude Oil Price from 1996 to 2015 Using Hidden Markov Model
Source: Research Analysis (2017)

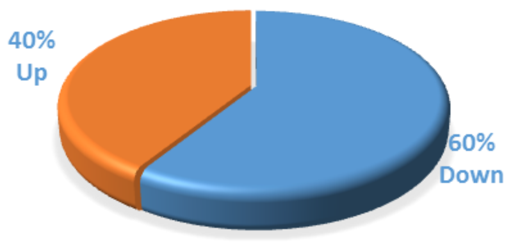


Figure 3: Trend of the Crude Oil Price Forecasting from January 1996 to December 2015
Source: Research Analysis (2017)

The model above shows the three states transition matrices are stable and the most probable trend is down since the probability of down is biggest with the 60%. The crude oil price of December 2015 was $37.19 and forecasted value/price of crude oil dated January 2016 was $31.68. This shows clearly that the forecast is accurate and reliable.

V. RESULT OF PATH ANALYSIS

We used path analysis of structural equation modelling in this paper to buttress the relationships and underpinned the accuracy of the forecasted model between Markov and hidden Markov models concerning their accuracy in forecasting crude oil prices if compared with the actual prices. The diagram below shows the most accurate forecasting model between the two we used above

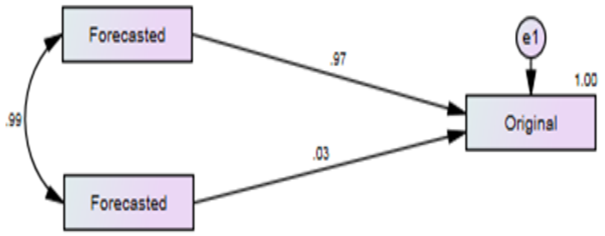


Figure 4: a Path analysis

Source: Research Analysis (2017)

The above diagram shows the relationships between crude oil price forecasting using a hidden Markov model and the Markov model. It shows that HMM is more accurate with .97 degree of accuracy than MM with .03 degree of accuracy. This explained that HMM has little error in forecasting crude oil prices if compared with MM.

VI. CONCLUSION

Crude oil is a natural resource that is found beneath the earth or in the sea; this natural resource plays a very vital role in the economic development of many countries. Any swinging of crude oil prices will undoubtedly affect the economic indices of many countries. In this paper, monthly crude oil prices data were employed to forecast future crude oil price. This paper explained the application and compared the accuracy of the Hidden Markov Model and Markov Model in crude oil price forecasting for PETRONAS Malaysia. The analyses were done using Matlab and SPSS/AMOS software. Path analysis of structural equation modelling was employed to model the relationships between forecasted and actual crude oil price. HMM is more accurate in forecasting crude oil price than MM as explained by path analysis technique of structural equation modelling. Based on the study, it can be concluded that the Hidden Markov Model could produce a more accurate result than that of the Markov Model in forecasting based on the description of history patterns in crude oil prices.

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