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Time Series Based Crude Palm Oil Price Forecasting Model with Weather Elements using LSTM Network

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Abstract: ***In field of agro economic, Crude Palm Oil (CPO) price forecasting is still heavily relies on human expertise. This paper proposes a CPO price forecasting model to assist the palm oil plantation organization in anticipating more effectively monthly fluctuations and manage the supply and demand efficiently avoid problems of price going very low. The parameters used by the predictor consist of weather variables, namely, temperature, rain amount, pressure, humidity and radiation as well as past CPO price. CPO price for past 10 years collected from MPOC and the environmental parameters collected from meteorology department of Malaysia during the period 2005 to 2016, were used to model CPO price using a Long-Term Short Memory Network (LSTM). Our results showed that the LSTM model predicted monthly fluctuations of the price with an average accuracy of 90%. The contribution suggests that the LSTM based forecasting could assist worldwide palm planters in decision making on palm oil crop management and operation processes.***

Keywords: Artificial Neural Network, Forecasting; Machine Learning, Time series, Weather Elements

I. INTRODUCTION

Accurate forecasting for time series based crude palm oil (CPO) price is critical for CPO traders and farmers. Weather has always been an important factor for research scientist in predicting various commodity yields and diseases around the world. Most of the commodity price forecasting models use traditional methods such as statistical methods or by performing technical analysis. In this study, a time series-based CPO price forecasting using feed forward neural networks and long short-term memory were tested with selected weather elements as predictors. The result was compared to identify the best model for time series-based CPO price forecasting. This initial analysis has allowed us to carry out a comparison of forecasting quality for different neural network architecture using weather variables as predictors.

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II. RELATED WORKS

A. Weather Based Forecasting

Power, agriculture and healthcare are the main areas which use weather as an important predictive factor. The forecasting of electricity consumption and load of electricity is influenced by weather elements. Past research shows that the demand for electricity is affected by weather changes. Weather variables has been used in the prediction of demand for electricity. Reference [1] utilized moving window of current values of weather and history of electricity load for short term electricity load forecasting. Reference [2] used solar irradiance, relative humidity and temperature to forecast 24-hour solar power for a plant using Artificial Intelligence Network (ANN) to perform the prediction. Reference [3] utilized weather variables to produce one day ahead hourly forecasting of photovoltaic power output. Weather variables also used in biomedical field to predict certain diseases and illness such as malaria and dengue. Lagged weather data used in predicting malaria cases, performed well in identifying malaria cases. Malaria epidemic was identified with reasonable accuracy and better timelines with weather derived prediction model [4]. Dengue prediction with weather variables by [5] and [6] also assisted in the early detection of the epidemic.

B. Weather based forecasting in the Agriculture Sector

Several researchers have used weather-based forecasting techniques to predict the yield of various types of agricultural crops. [7] designed back-propagation ANN in approximating a nonlinear yield function in predicting corn yield using rainfall factor as a predictor. In a similar vein [8] and [9] have used three important climate factors (temperature, precipitation and solar radiation) as key predictors of crop yields. In another study by [11] who examined the effects of rainfall on crop output and crop prices, rainfall factor was found to show a positive and strong correlation with crop output but recorded a negative and weak correlation with prices of the crop. Cointegration analysis by [12] in 2013 found that futures and spot prices affected with changes in rainfall with different lags. The weather elements have been utilized in CPO production as stated by [13] and [10] used monthly temperature anomalies to predict the yields of palm oil. Another agro meteorological research shows weather shocks such as drought has caused higher prices for soybean, thus agrometeorological conditions can lead to uncertainty and price risk in local and global markets [22]. A detailed research on weather factors impact on commodity prices is also suggested by [14] on CPO price movement. Another study by [10] in Malaysia who predicted oil palm growth and oil palm yield revealed that climate change and its lagged effects as two important predictors. The study shows a high correlation between temperature and oil palm growth and also a high correlation between temperature and oil palm yield. A palm oil report by palm oil analyst showed that weather is a key factor to palm oil supply equation and behaves as a catalyst to CPO price movement [15]. These analyses become a motivation factor to include weather as a predicting factor in this study to forecast the CPO price.

C. Impact of Weather Elements On CPO Price

Weather elements are found to be vital factors which contribute to crops yield and it is important to understand the effects of weather changes to crops yield and prices. Thus, it is important that researchers dealing with CPO prices fully understand these issues.

Malaysia has a conducive humid weather that supports the growth of oil palm crops. Some of the important requirements to achieve highest oil palm bunch production are; i) a minimum rainfall of around 1,500mm/year, ii) absence of dry season, iii) evenly distributed sunshine (2000 h year-1) and iv) a temperature condition range between 29 to 33°C for maximum temperature and 22 to 24°C for minimum temperature. [17].

Past studies show various factors that serve as important predictors of CPO prices. Among the important weather element factors that have significant relationship with CPO price are as follows:

1) Amount of Rainfall

Past research shows that it is difficult to relate rainfall to yield level accurately [18]. Rainfall used as a factor to predict the corn yield as studied by [7] and [11]. The result of this studies revealed that rainfall is positively correlated with agricultural output and negatively correlated with agricultural price. A cointegration analysis by [12] found that both futures and spot prices affected with changes in rainfall with different lags. Research also shows high temperature and an increase in rainfall negatively impact palm oil production [19] thus effecting the price of CPO.

2) Temperature

As a tropical crop, palm oil trees require high temperature to achieve optimum growth. A temperature condition range between 29 to 33°C for maximum temperature and 22 to 24°C for minimum temperature is highly recommended to reap a optimum yield. However, it is quite difficult to segregate the effect of maximum and minimum temperature. The suggested best mean temperature range seems to be in the range of 24–28°C [8],[9],[17], [35],[36]. [9] used temperature, precipitation and solar radiation for predicting the effects of climate change on crop yields. [10] used monthly temperature anomalies to predict the yields of palm oil in Malaysia.

3) Radiation

A theoretical model by [20] suggested that a yield loss of 2.6 t FFB/ha per year may be caused by a decrement of solar radiation around 6.23 to 5.69GJ/m2 per year. Total sunshine hours per year also shown a correlation to yield [17], [21]. Formation of haze also significantly reduced radiation intensity in Malaysia and Indonesia which may cause effects on the CPO yield and prices. Smoke and dust from forest fires during droughts period in the El Niño years of 1997 and 1998, also caused low radiation which affected growth and production of palms [17].

III. METHOD AND DATA

A. Data

In this study the monthly Malaysian CPO price data, from 2006 to 2016 were used for prediction analysis using ANN. Each data set has total of 138 data of prices. Monthly crude palm oil prices of south for 10 years were collected from the Malaysian Board of Palm Oil portal. A set of weather variables such as monthly rain amount, temperature and humidity was retrieved from the Malaysian meteorological department. There is an extensive coverage by weather stations with data available from National Meteorology Department. Monthly weather report on rainfall amount, air pressure, max temperature, min temperature and air humidity and sun radiation were collected. This data also undergoes quality checks and identifies if there is missing data or outliers. Among the data, sun radiation data was missing for all the years except 2006. Thus, monthly radiation data of removed from the data set during the data cleansing process as the data has incomplete set. Thus, monthly CPO prices, rain amount, min temperature, max temperature and humidity were used as predicting factors in this study.

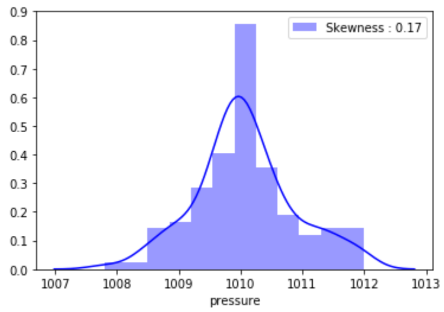

Fig. 1. Skewness of pressure

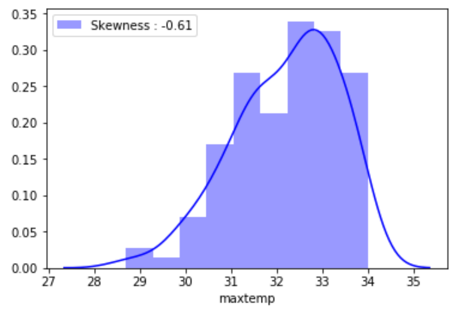

Fig. 2. Skewness of maximum temperature

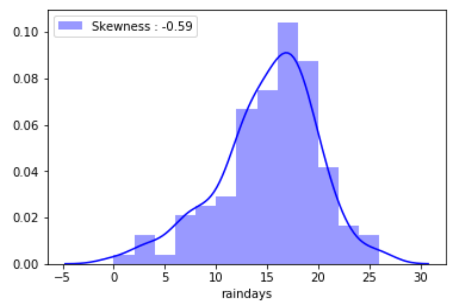

Fig. 3. Skewness of maximum temperature

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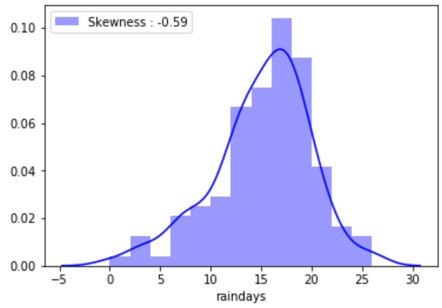

Fig. 4. Skewness of rainy days

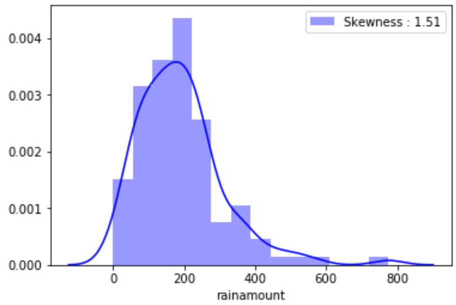

Fig. 5. Skewness of rain amount

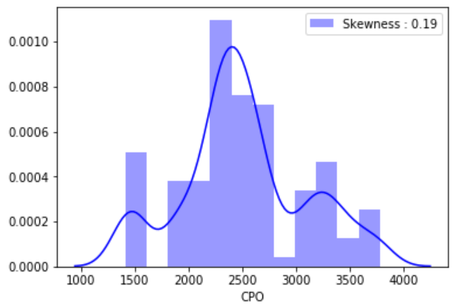

Fig. 6. Skewness of CPO Price

Fig. 1 to **6** demonstrated that the substantial positive skewness As CPO price is our target variable. The CPO Price feature also showed positive skewness (right skewed). Since linear models usually perform better on normally distributed data and these specifications render some difficulties in applying standard statistical analysis, such as linear regression which will lead to achieve unreliable results [29], thus a nonlinear approach using ANN and LSTM is used in this experiment [29].

B. Experiment

In this work, Firstly Feed Forward Neural Network with multi-layer perceptron (MLP) was utilized and later LSTM model were tested. Python used to develop the FFNN and LSTM model to train and test the forecasting model using combined weather predictors.

1) Artificial neural network (ANN)

The notion of artificial neuron as a mathematical function is inspired from biological neurons simulation as described by McCulloch and Pitts [23]. ANN consists of several layers, with each layer having several neurons. Generally, the ANN topology consists of minimum three layers, namely one input layer, one or more hidden layers and an output layer. The complexity of the problem will decide the number of hidden layers and the number of neurons in each layer. In order to receive the input data as a vector from external environment, input layers need to interact with the external environment. The desired output of the model will be in the output layer. The development process of ANN model is started with locating an appropriate input data set, and followed by determining the number of hidden layers and neurons in each layers. The last step would be to train and to test the entire network model. The desired output of the network depicted in **Fig.7** can be expressed in the following mathematical equation:

$$Y_t = f_2[\sum_{j=1}^{J} w_j f_1(\sum_{i=1}^{I} w_i x_i)]$$

Fig.7. Mathematical Equation

$\mathbf{Y_t}$ is representing the output of the model whereas Xi is representing the input variables and the weights between neurons of the input and hidden layer and between hidden layer and output are constituted by $\mathbf{w_i}$ and $\mathbf{w_j}$ respectively. f1 is the activation functions for the hidden layer and ***f2*** is the activation functions of the output layer.

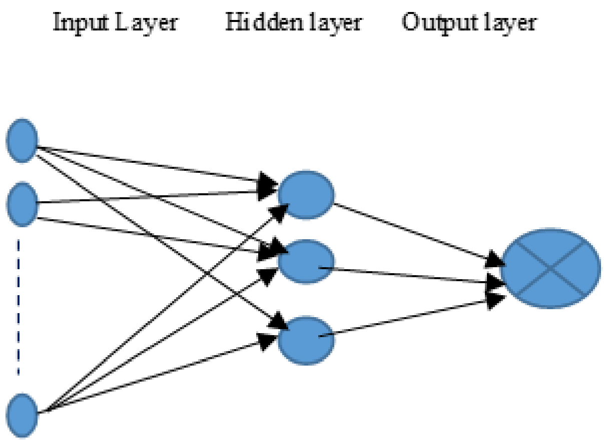

Fig. 8. Three layers

The network we built had combination of one to four inputs and one output. Monthly weather elements were fed as inputs and CPO price as output. In this architecture one hidden layer and two hidden neurons was chosen. The architecture tested with sigmoid in both hidden layer activation function and output layer activation function respectively [25]. There were various methods in splitting the data for training and testing process such as cross-validation, bootstrap and holdout [26]. Data was divided according to holdout method. As for training and test sets, the first 70% of data observations were used as training set and the remaining 30% of data observations were used as the test set.For the assessment of the model performance, Root Mean Squared Error (RMSE) has been used for model evolution. RMSE measures the square root of average of squares of the prediction errors.

RMSE = sqrt (sum ((predicted - actual)^2) / N)

2) Long Short-Term Memory (LSTM)

[30] introduced a special kind of Recurrent Neural Network known as Long Short Term Memory networks (LSTM) which has ability to learn long term dependencies in 1997, Only a few published papers apply LSTMs to time series forecasting tasks, all of which, to our knowledge, are outside of the crude palm oil price context. [31] for reading cursive writing and showed best

performance using RNN–LSTM. Most recently, [32] in 2018 uses RNN with Long Short-Term Memory to captures the spatio-temporal dependencies in local rainfall to assess the hydrological impacts of global climate change on regional scale. While we could not locate any published papers using LSTMs for multivariate time series price forecasting for palm oil domain, several papers use statistical method and feedforward neural nets for this task[33][34].Vanishing or exploding gradients problem in recurrent network is resolved using LSTM for long term learning process. Standard neural network layers replace by LSTM cell block in a recurrent network for LSTM networks. LSTM cells consisted of various components, such as the input gate, the forget gate and the output gate. The gates functions explained in detail in this section. Here is a graphical representation of the LSTM cell unrolled in time is shown in Fig 1.8. In Figure 1.8, *x(t)* is the cell's input at time *t*. And *h(t)* is the cell's output at time *t*. C (t −1) and C(t) are the LSTM Cell States at time (t−1) and t respectively, which are the key reason for LSTM to learn long term dependency without gradient vanishing risk. Specifically, designed structure called Gates control the cell states. There are three gates:

i) forget gate *f(t)* which conditionally decides what information to throw away from the block; A forget gate is responsible for removing information from the cell state. Performance optimization of LSTM is carried out as below. The information from cell state that no longer required for LSTM to comprehend certain phenomena or less important information is discarded by using multiplication filter.

This forget gate takes in two inputs; h_{t-1} and x_t.h_{t-1} is the hidden state from the previous cell or the output of the previous cell and x_t is the input at that time step. The provided inputs are then multiplied by weight matrices and consequently added with a bias. Then after, a sigmoid function is applied to above calculated value. The output of the sigmoid function is a vector, which has values ranging from 0 to 1 which correspond to the number attached to the cell state. Basically, the sigmoid function is imperative to make decision on which value to be retained and which value to be omitted. In the case when a "0" output for a output in the cell, it implies that the forget gate would command the cell state to forget to ignore the entire piece of information. On the other hand, a value of '1' implies that the forget gate wants to keep the piece of information completely. The sigmoid function's vector output is multiplied to the cell state.

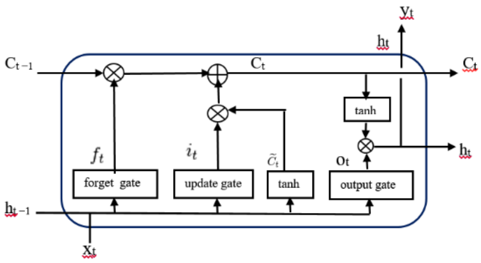

Fig. 9. Long Short-Term Memory (LSTM) [28]

The LSTM model was built with keras library using phyton and pandas.

IV. RESULT AND DISCUSSION

The result of the weather predictors combination that were used as input to predict the CPO price movement is shown in Table 1.

I_0 = CPO Price
I_1 = Rain Amount
I_2 = Min Temperature
I_3 = Max Temperature
I_4 = Humidity

Experiments conducted using FFNN and LSTM. A comparison test also was conducted with a widely used statistical model, holt-winter using all the combined weather predictors as shown in **Table 1**. The results showed that LSTM had significantly the least error with lower RMSE.

Table 1: Result Comparison Between Ann And Holt-Winter and LSTM

Combination Input	Method	RMSE
$I_{0+} I_{1+} I_{2+} I_{3+} I_4$	ANN	363.67
$I_{0+} I_{1+} I_{2+} I_{3+} I_4$	Holt-winter	603
$I_{0+} I_{1+} I_{2+} I_{3+} I_4$	LSTM	280.463

V. CONCLUSION

This study was attempted to predict CPO prices by considering combined weather indices as potential predictors. The result obtained showing the LSTM model with weather elements demonstrates significant improvement with the least RMSE. This model only considered weather factors as independent variables. More non-weather variables are proposed for future study. Other machine learning techniques is also proposed for future experiment as well as to validate the results of this findings.

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