Forecasting smoked rubber sheets price based on a deep learning model with long short-term memory

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ABSTRACT

This research aimed to create suitable forecasting models with long-short term memory (LSTM) from time series data, the price of rubber smoked sheets (RSS3) using 2,631 data from the Rubber Authority of Thailand for the past 10 years. The data was divided into two sets: first series 2,105 data points were used to create the LSTM prediction model; second series 526 data points were used to estimate forecasting performance using the root mean square error (RMSE), the mean absolute percentage error (MAPE), and accuracy rate of the model. The results showed that the most suitable forecasting model for time series data, with a total of 9 LSTM layers comprised of 3 primary LSTMs. Each LSTM layer has the number of neurons 100, 150, and 200 to obtain an optimal neural network of the LSTM technique. The number of epochs and iteration was 30, 40, and 50. Dropout layers between each LSTM layer have a probability of 30%. The results of the test to measure the performance of the time series forecasting data showed that the 9-layer model with the LSTM model architecture of LSTM 3 layers gave the best forecast, with RMSE of 2.4121, MAPE of 0.0413 and 95.88% accuracy rate.

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1. INTRODUCTION

Thailand is the world's largest producer of natural rubber and has the potential to produce good quality rubber. Countries that produce natural rubber next to Thailand are Indonesia, Vietnam, and Malaysia. Para rubber is an important raw material to produce various products such as tires, rubber gloves, and rubber tubes. As a result, the rise and fall of para rubber prices had a significant impact on related industries [1]. Ribbed smoked sheet (RSS) is basically processed from latex. It is used as a raw material in industrial sectors such as the tire industry which is the biggest consumer. The next biggest uses are rubber elastics, rubber erasers, rubber tubes and rubber soles of shoes. Thailand had exported up to 63%, with the main consumer countries being China, Japan, and America respectively. From domestic price data for the past 10 years, it was found that rubber prices in the world market continued to decline from 2014 to 2018. The world economy was affected by the economic crisis of the European Union, the United States and spread throughout the world including China which is the world's largest consumer of rubber. It slowed purchasing and investment and began to rise in November 2016 and returned to a low in July 2017. Then, it continued to decline until the end of 2018 [2]. However, analysis of the situation of rubber prices in the international futures market in all three technical markets are Tokyo futures market, Shanghai, and Singapore suggest rubber prices are likely to rise in 2021. The short-term trend will shrink after a sell-profit occurs [3]. Therefore, the movement of rubber prices is very important to Thailand. The price of rubber will change according to supply and demand. In the world market and outstanding stocks, rubber prices have been highly volatile in the past, with the highest ever being around 190 baht per kilogram in 2011 [4]. Producers and exporters are at risk from the volatility of rubber prices.

Forecasting rubber prices is important and useful in both public and private export planning. The government can use it in strategic planning for trade and exports. This forecast also provides information to futures market investors, as well as farmers in assessing the situation of rubber prices in advance to prepare for risk management planning at the household level as well. However, forecasting the price of rubber smoked sheet grade 3 (RSS3) in Thailand found that the forecast was made using the exponential smoothing method (multiplicative seasonal variation) technique [5]. The slippage in 2015 was 7.72%, while the time series split-influence technique forecasted the price slippage in 2015 at 35.08%, Rattanavongsri *et al*. [6] presents forecasts using the relative strength index (RSI) method, the best result was 89.83% and the moving average convergence/divergence method was 86.29%, which had a high discrepancy. Nowadays, deep learning (DL) is an automated method of learning by mimicking the function of the human neural network by using the neural network system to overlap multiple layers (layers) and learn sample data. Data is used to detect patterns or classify the data, for example for predicting time series data: financial prediction by attention long short-term memory (LSTM) [7]; using DL with LSTM to predict currency exchange rates [8]; stock market prediction [9] or even predict the trend of earthquakes [10]. It can be seen that LSTM, a type of DL model, is very popular because it provides powerful prediction results.

Therefore, this research aimed to generate the forecasting model by using DL with LSTM for predicting the rubber smoked sheet price. We have used the prices for 10 years in the past from the Rubber Authority of Thailand website. This article will present related work in the next section. Then section 3 describes the methodology. Section 4 presents the results, and the conclusion will be the last section of this article.

2. RELATED WORK

A traditional research topic in econometrics and statistics has been time series forecasting [11], from simple methods such as winters' multiplicative exponential smoothing method or seasonal naïve, simple exponential smoothing [12]. When there is minimal data volume traditional univariate methods work well [13]. Compared to other machine learning techniques that are complex there is a quite low number of parameters to be. An ANN models a greater range of functions than statistical techniques and it is a good choice in the current situation [14].

Artificial neural network (ANN) is a mathematical model capable of calculating connections to mimic the functions and perceptions of the human brain. The beginning of this technique is from studying the bioelectric network in the brain, which consists of neurons and synapses. ANN a well-known AI method based on the concept of the nervous system of the brain [15]. The core concept of ANN consists of three main layers: the input layer, hidden layer, and output layer. ANN is at the center of DL which simulates the human brain functions in analyzing and data processing to make a decision [16], [17]. DL uses ANN hierarchical levels for deep analysis for rigorous learning of a dataset. They are scalable, powerful, and versatile, ideal to address highly complex large machine learning tasks, such as video recommending, speech recognition services, and classifying images [18]. An interesting algorithm with an ANN component, such as the convolution neural network (CNN), focuses on image recognition, and recurrent neural network (RNN) [19].

RNN is a type of ANN designed to solve tasks with sequence-based data such as video, or language (sequence of words) by using the feed principle where the internal state of the model returns to input data at that time, along with input. Previously called hidden state, it allows the model to recognize. In other words, there is more memory for the pattern of the input sequence. As shown in Figure 1, for example, if input the sentence "I love Thailand". From the left picture, when the picture unfolds loudly, the righthand side of the picture shows each step of the neural network. This sentence is read word by word. You will get X_1="I", X_2="love" and X_3="Thailand".

RNN model building is by respective data training. updating and rebuilding with each data pass through the chain [20]. RNNs have been developed into several variants such as LSTM to address the problem of RNNs dealing with long sequences of data. The long-short-term-memory (LSTM) network offered by Hochreiter and Schmidhuber [21] is a neural network designed for sequential data processing. This reuses the previous output for the next layer. The principle of this model is to keep the 'status' of each node, so that when going back, you will know what it really was before. What makes LSTM stand out is that the model can choose which information should be remembered and which data should be disposed of through the 'Forgot' states in that node. Figure 2 shows the underlying architecture of the LSTM [8].

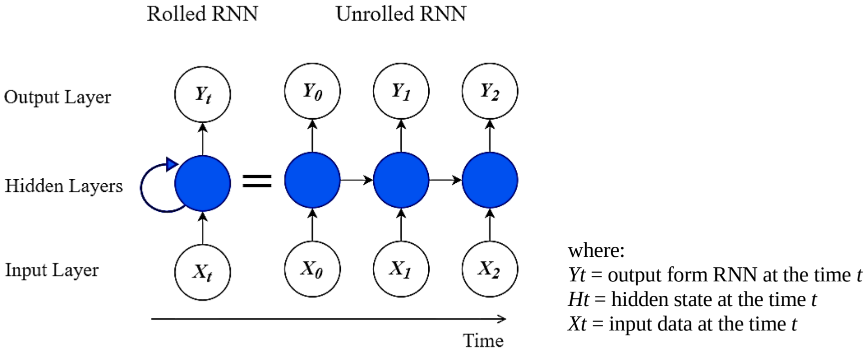

Figure 1. Recurrent neural network [22]

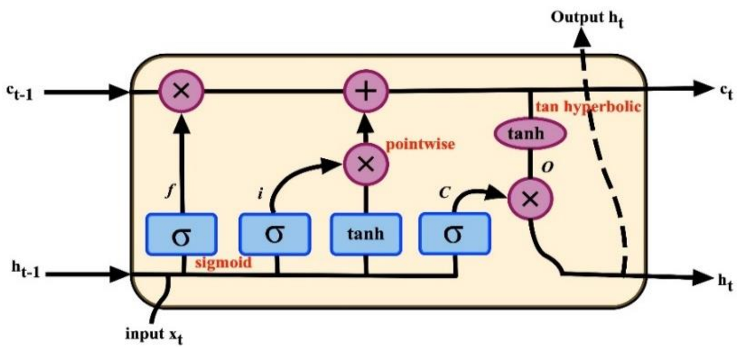

Figure 2. Architecture of LSTM cell (applied from [23])

In Figure 2, the inside of the LSTM cell contains functions that are used to create a special function: reading data, writing data, updating information, and forgetting information. This makes it more fluid to memorize the data in each of its nodes. Let i be the input gate, f is the forget gate, o is the output gate, c is cell state, h is hidden state, σ is the activation function, and W, U are the weight matrix and t is the time. The LSTM model helps to avoid vanishing gradient problems at each time step from RNNs method according to (1) to (6).

An input gate is a gate used to receive new incoming data to be recorded in each node, known as 'write' data with (1).

$$i = \sigma(x_t W_i + h_{t-1} U_i) \tag{1}$$

Forget gate is the gate to use to determine whether the incoming data deserves to be expelled at all or not to have escaped. The information needed to decide whether to keep this information or not comes from the incoming data at that node. This is combined with results calculated from the previous node through the sigmoid function and multiplied by the previous node's state using the pointwise multiplication formula with (2) for calculation.

$$f = \sigma(x_t W_f + h_{t-1} U_f) \tag{2}$$

The input gate receives information and memorizes it in the node itself. There is another node that will be pushed into the conversion process by the tan hyperbolic function. To get one more similar data to the output from the node, use (3).

$$c_t = (c_{t-1} \times f) + (i \times \sigma(x_t W_c + h_{t-1} U_c)) \tag{3}$$

After calculating, the resulting data will be the output. It will be taken pointwise to the information obtained from the input. This final result will be combined with the first data obtained from the forget gate (which was pointwise in the state from the previous node) again.

The output gate is the gate to tell if this information is ready to be the output. There are 3 outgoing data for each node in the LSTM. However, there are only two values: i) the calculated value with the status update (which is calculated from the update cell state procedure). This value will be passed immediately without passing any more functions to the next node. ii) The value of the input that is modified through calculations in the output gate. This value will be forwarded to the input of the next node. It is also sent as a result of that node through the same sigmoid function as other gates using (4).

$$o = \sigma(x_t W_o + h_{t-1} U_o) \tag{4}$$

The difference is that after it has passed the sigmoid calculation it will be taken pointwise to the current state of the node that has already been computed by another gate. The status value will be put into the tan hyperbolic or tanh function first. Then the result after entering the function is pointwise and the values obtained from the sigmoid function. The results obtained from this action will be split into two data, the results of that node and the data to be forwarded as incoming data on the next node using the (5).

$$h_t = \sigma(c_t) \times o \tag{5}$$

The steps for implementing an LSTM model can be summarized in five stages.

- Collection of historical information which is then used for making future predictions.
- Data processing stage which entails data transformation including normalization and standardizing data which is then divided into sets of training and testing for evaluation (80:20).
- Choose the features.
- Training neural network model, this is where information is fed into the neural network and trained to predict by random biases and weights. This model uses sequential input layer with 3 LSTM layers, dense activation layer and a dense output layer comprised of a linear activation function. *Optimizer:* ADAM optimizer by setting a different rate of learning for every time step and parameters. *Dropouts:* set the number of dropouts to 30%.
- Generate the output.

Let N be the set of the rubber smoked sheet price. This model used five steps ahead forecasts. The rubber price predicted by the variable Y_t is given by (6).

$$Y_t = \{y_{(t)}, y_{(t-1)}, \dots, y_{(t-(N+5))}\} \tag{6}$$

where N is the set of the rubber smoked sheet prices, $y_{(t)}$ is the ribbed smoked sheet price at the time day t, and $y_{(t-1)}$ is the rubber price on the previous trading day.

3. RESEARCH METHOD

Explaining research chronological, in order to design an experiment to create an appropriate time series forecasting model for RSS3 by LSTM technique, the data mining process includes standardized data mining operations based on the Cross-Industry Standard Process of Data Mining (CRISP-DM). There are six steps [24] as follows.

a. *Business understanding* phase is the process of understanding a business and which consists of selecting objectives, understanding business goals, assessing learning situations and making project plans.
b. *Data understanding* phase is a data understanding period that includes reviewing data requirements and preliminary data collection, surveys and quality assessments.
c. *Data preparation* phase is selecting the required data, data integration and formatting, data transformation and data cleaning.
d. *Modelling* phase is selection of suitable modeling techniques, development and validation of alternative modeling algorithms, parameter setting, and search tuning of model setup based on preliminary assessment of model performance.
e. *Evaluation* phase is simulation experiment evaluation process.
f. *Deployment* phase shows the process of implementing the model.

3.1. Data for testing suitable forecasting models of time series data for RSS3

To create a forecasting model using the LSTM technique of time series data for RSS3 uses data from the Rubber Authority of Thailand website for the past 10 years from January 2009 to December 2019, 2,631 values [4]. The movement of the time series as shown in Figure 3 creates a forecast model using the LSTM technique. The data was split into two sets, 2,105 (80%) of the first series used to construct the LSTM prediction model. A second set of 526 values (20%) were used to assess forecasting efficacy. The details of the data proportions are as shown in Table 1.

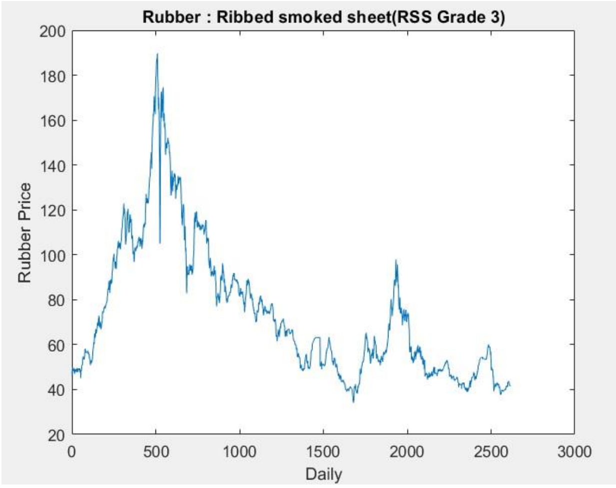

Figure 3. Movement characteristics of RSS 3 Prices from January 2009 to December 2019

Table 1. The segmentation of data, time-series data of RSS 3 for forecasting modeling with LSTM models

Dataset	Training dataset (80%)	Testing dataset (20%)	Total
Ribbed Smoked Sheet (RSS 3) Prices	2,105 (January 2009 to May 2017)	526 (June 2017 to December 2010	2,631

3.2. Forecasting measures

The tools used to evaluate the LSTM model were root mean square error (RMSE), mean absolute percentage error (MAPE) and accuracy [25]. The defined variables have the following significance: y_t is the actual value, f_t is the forecasted value, $e_t = y_t - f_t$ is the forecast error, and n is the size of the test set. Root-mean-square-error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} {e_t}^2} \tag{7}$$

Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100 \tag{8}$$

Accuracy:

$$Accuracy = \left(1 - \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100\right) \times 100 \tag{9}$$

3.3. Our proposed model

The researcher created a forecasting model for time series, rubber price, smoked sheet (RSS3), using the LSTM technique, where the architecture of the LSTM network consists of 9 layers:

a. An input layer is an import of 1-dimensional array of time series data, price of rubber smoked sheets (RSS3).
b. Three LSTM layers, with each LSTM layer assigned a number of neurons of 100, 150 and 200. The epochs and iteration of the neuralgia was assigned to 30, 40, and 50.
c. Three dropout layers between each LSTM layer define dropout layers with 30% probability.
d. A fully connected (fc) layer is a fully connected layer in a neural network, acting as a layer where all inputs from one layer connect to the next layer's activation function.
e. A regression output layer is the result of testing performance, forecasting, time series data, rubber price of smoked sheets (RSS 3).

Architectural structure of forecasting model, time series data, rubber price, and smoked sheet (RSS3) used the LSTM technique. As shown in Figure 4, the analysis results of suitable forecasting models with LSTM model are detailed. The optimal parameterization of the forecasting model with the LSTM model are shown in Tables 2 and 3.

Table 3 shows the construction of a set of training models using the ADAM optimizer. This model has a dimension array for the input and output neuron. The number of iterations and the number of epochs in the set of {30, 40, and 50} by setting the number of the time step is 5. The number of neurons for LSTM cell of each layer is the set of {100, 150, and 200}. We assign the learning rate of 0.005 and piecewise for the learning rate schedule.

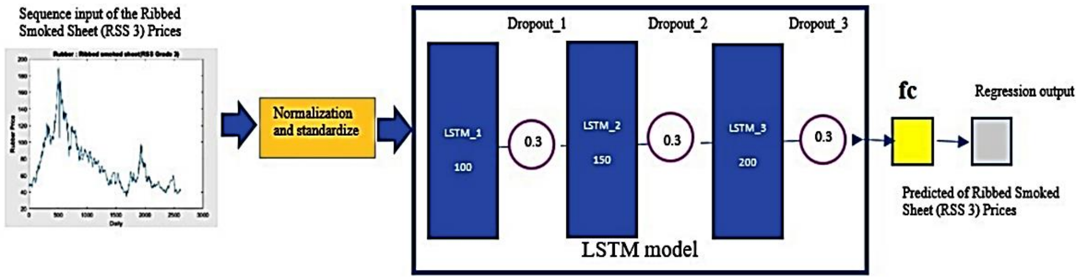

Figure 4. Our proposed LSTM model

Table 2. Analysis result of LSTM model

Layer	Name	Type	Activations	Learnable	
1	Sequence input Sequence input with 1 dimension	Sequence Input	1	-	
2	LSTM_1 LSTM with 100 hidden units	LSTM	100	Input Weights Recurrent Weights Bias	400x1 400x100 400x1
3	Dropout_1, 30% dropout	Dropout	100	-	
4	LSTM_2 LSTM with 150 hidden units	LSTM	150	Input Weights Recurrent Weights Bias	600x100 600x150 600x1
5	Dropout_2 30% dropout	Dropout	150	-	
6	LSTM_3 LSTM with 200 hidden units	LSTM	200	Input Weights Recurrent Weights Bias	400x1 400x100 400x1
7	Dropout_3, 30% dropout	Dropout	200	-	
8	Fc 1 fully connected layer	Fully Connected	1	Weights Bias	1x200 1x1
9	Regression output Mean-squared-error with response “Response”	Regression Output	-	-	

Table 3. The best parameters of the LSTM model

Parameters	Values
Optimizer	ADAM
Number of input neuron	1 (1D-array) {rubber price}
Number of output neuron	1 (1D-array) {rubber price predicted}
Number of iterations	Set (30, 40, 50)
The number of epochs	Set (30, 40, 50)
Number of the time step	5
Number of neurons for LSTM cell of each layer	100, 150, 200
Learning rate	0.005
Learning rate schedule	Piecewise

4. RESULTS AND DISCUSSION

The time-series forecasting model for rubber smoked sheet price (RSS 3) was also provided by LSTM. Two main series of tests were designed to compare and find the most suitable model of forecasting latex price information. Set 1 consists of 2 LSTM layers, with each LSTM layer assigned a number of neurons to 100 and 150, with epochs and iteration being 30, 40, and 50. Set 2 consists of 3 LSTM layers, each LSTM layer designated 100, 150 and 200 the number of neurons. The epochs and iteration (the number of epochs and the number of iteration) values were assigned to 30, 40, 50. The results of measuring the performance of the time series forecasting model and the price of rubber smoked sheets with LSTM model are shown in Table 4.

From the test results to measure the performance of a time series forecasting model, the price of RSS 3 with the LSTM model, in Table 4, the best results of the RMSE, MAPE and accuracy of our LSTM 2.4121, 0.0413 and 95.88% are found. Figure 5 the graph shows the best experimental results of the time series forecasting model, the price of RSS 3 with the LSTM model by displaying real time-series data, actual RSS3 price compared to time-series data, forecastable RSS 3 prices.

Table 4. Experimental results (ratio 80 of training data and 20% of testing data)

Data	LSTM units	Iterations/epochs	Performance Measure		
			RMSE	MAPE	Accuracy
Ribbed smoked sheet (RSS 3) Price	100, 150	30	3.4464	0.0586	94.14
		40	3.8448	0.0707	92.93
		50	2.5034	0.0420	95.80
	100, 150, 200	**30**	**2.4121**	**0.0413**	**95.88**
		40	3.6027	0.0641	93.59
		50	3.3124	0.0608	93.92

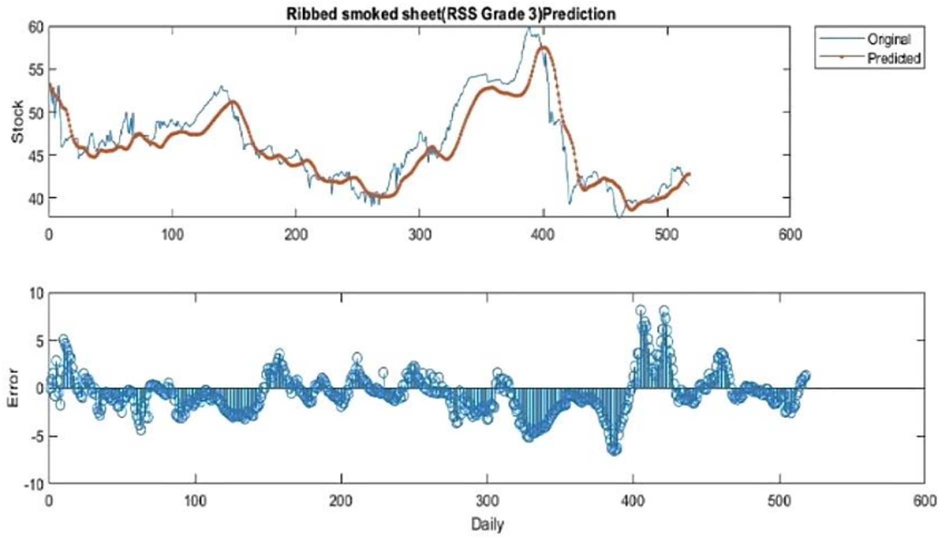

Figure 5. The best experimental results prediction of ribbed smoked sheet (RSS3)

5. CONCLUSION

This research proposes a method for constructing and selecting the most appropriate forecasting model for the time series, price of RSS3 using data from the website of the Rubber Authority of Thailand for a period of 10 years from January 2009 to December 2019, the designed LSTM has the input as RSS3 tire data by dividing the information into 2 parts: 80% of training data and 20% of testing data, using the information to do normalization and standardization before testing. All LSTM designs are 9 layers as shown in Table 2 with detailed parameters and the values used to run the model according to Table 3. To test the LSTM model with the most accurate forecasting results, two LSTM models were tested. The first set was tested using the number of neurons for LSTM cells of each layer of 100 and 150. The number of iterations in training data (number of iterations/the number of epochs) is set to 30, 40, and 50, respectively. The second set was tested using the number of neurons for LSTM cells of each layer of 100, 150, and 200. The number of iterations in training data (number of iterations/the number of epochs) is set to 30, 40, and 50, respectively. When comparing the test results using RMES, MAPE, accuracy, it was found that the second set had the highest percentage of forecast accuracy (accuracy: 95.88%), RMSE=2.4121, and MAPE=0.0413) respectively. For the next study, the investigator should also consider other factors in establishing the predictive modelling because of the price of fresh latex may not depend on a single factor such as manufacturer's rubber requirements, products of rubbers, automotive industry, oil price, exchange rate, international trade policy, stock market conditions, Singapore futures market price, and climatic conditions.

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