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Stock Price Prediction of Thai Oil Public Company Limited (TOP.BK) Using LSTM Model with Grid Search Hyperparameter optimization

Sutthipong Sanhatham
Mahidol University, Thailand
Email: ssanthatham@gmail.com

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ABSTRACT

This study examines the effectiveness of the Long Short-Term Memory (LSTM) model in predicting stock price movements of Thai Oil Public Company Limited (TOP.BK). Using historical stock price data of the past five years, we apply the LSTM neural network architecture to model temporal patterns and predict future stock prices. The model is compared with traditional time series approaches such as ARIMA and other statistical models. Results show that the LSTM model optimized by Grid Search achieves excellent performance with Root Mean Square Error (RMSE) of 1.00 and Mean Absolute Error (MAE) of 0.75 on the test data, with prediction accuracy reaching 98.32%. The model also showed a high coefficient of determination (R^2) of 0.8715 on the test data, demonstrating the model's ability to explain most of the variation in the data. This research proves that the LSTM model is highly effective for stock price prediction in the oil and gas industry, with important implications for investment strategies and risk management.

1. INTRODUCTION

Stock price prediction has become a significant research topic in machine learning and computational finance. The non-stationary, non-linear, and complex nature of the stock market makes accurate prediction a major challenge. In recent years, deep learning techniques have shown promising results in modeling financial time series, with Long Short-Term Memory (LSTM) networks attracting particular attention for their ability to learn long-term dependencies in sequential data .[1]

Thai Oil Public Company Limited (TOP.BK), Thailand's largest oil refiner, is an important entity in Southeast Asia's energy industry. Its share price volatility reflects the complex dynamics in the oil and gas industry, including global oil price fluctuations, energy policy changes, and geopolitical factors. Understanding and predicting TOP.BK's stock movements is not only beneficial for investors, but also provides insight into regional energy industry trends.

Several previous studies have examined the application of LSTM for stock prediction. Fischer & Krauss[2] showed that LSTM was able to outperform comparative methods in predicting S&P 500 stock returns. Nelson et al.[3] evaluated the LSTM model for stock price prediction in the Brazilian market and found that LSTM significantly outperformed traditional approaches. Research by Mehtab & Sen[4] used the LSTM model to predict stock prices of oil and gas companies in India, showing that this model can produce better prediction accuracy than traditional statistical models especially in periods of high volatility. Furthermore, LSTM has been proven effective in predicting stock price volatility, as described by Tian et al. [5], who developed the LSTM-XGBoost model and found that this combination resulted in better prediction accuracy than conventional models. In addition, research by Shilpa and Shambhavi[6] shows that combining news sentiment analysis with LSTM models can improve stock price prediction accuracy, proving that LSTM is not only effective for historical data but also capable of integrating relevant external factors.

Research by Kelotra and Pandey[7] also confirms the importance of using robust and reliable algorithms such as LSTMs, which offer significant advantages in investment decision-making risk. This is in line with Mehtab and Sen's findings, which indicate that rapid market shifts, such as those that occur during periods of high volatility, can be better anticipated using deep learning models. In volatile market environments, LSTMs exhibit superior capabilities compared to conventional models that often fail to properly capture market dynamics.

Taking this research into account, it is clear that LSTM offers a significant contribution in predicting stock prices in sectors prone to fluctuations, making it a valuable tool for investors and market analysts in formulating better investment strategies in the face of market uncertainty.

Although many studies have been conducted on stock prediction using LSTM, specific studies on stocks in the oil and gas industry in Southeast Asian markets are still limited. Moreover, Southeast Asian markets have unique characteristics that set them apart from developed markets, such as different liquidity levels, diverse regulations, and specific regional geopolitical factors. This research is important given Thai Oil Public Company Limited's strategic position as a major player in the regional energy industry that is heavily influenced by global and regional dynamics.

The urgency of this research is heightened by the global energy transformation and geopolitical uncertainties that have a direct impact on oil price volatility and stock performance of energy companies. For investors and industry stakeholders, the ability to predict TOP.BK stock price movements with greater accuracy can provide a competitive advantage in investment decision-making and risk management. In addition, this research can provide a better understanding of the fundamental and technical factors that influence the stock performance of energy companies in Southeast Asian emerging markets.

The selection of the Long Short-Term Memory (LSTM) architecture in this study is based on several important considerations related to its capabilities in time series analysis, particularly in the context of stock price prediction. First, LSTM is known to excel in capturing long-term dependencies in sequential data. The unique structure of LSTMs makes them particularly relevant for handling time-bound financial data, where existing patterns depend on information older than the current time[1], [8] . Previous researchers have also shown that LSTMs are effective in overcoming the vanishing gradient problem, which often hinders traditional recurrent neural network (RNN) models such as simple neural networks. With the cell memory and gate structure (input, output, and forget gates), LSTM has the ability to selectively "remember" and "forget" information as needed .[1]

Secondly, this flexibility allows LSTMs to model complex market fluctuations. In a study conducted by Kim and Kim, it was found that LSTM showed higher accuracy compared to other models in predicting stock prices, with a variety of different data representations[9] . This shows how LSTM is able to adapt to diverse data structures, including when considering seasonal and trend factors that often appear in stock price data. Third, in the context of time series analysis, LSTM is proven to be better than some other deep learning methods in terms of capturing seasonality and trend patterns, which are common characteristics in stock price data[8], [10] . This is also in line with research by Cao et al. which shows that the use of LSTM can improve prediction accuracy compared to traditional statistical models given the wealth of information that can be captured by architecture. [11]

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This study aims to fill the gap by investigating the effectiveness of LSTM architecture in predicting the stock price of Thai Oil Public Company Limited with the application of hyperparameter optimization technique. The main contributions of this research include the application and evaluation of LSTM models for stock prediction of energy companies in the Thai market, comparative analysis of LSTM models with traditional statistical approaches for TOP.BK stock price prediction, hyperparameter optimization using Grid Search to improve model performance, assessment of the most influential technical and fundamental features in TOP.BK stock price prediction, and discussion of the practical implications of the prediction models for investment strategies. The results of this study are expected to make a significant contribution to the stock prediction literature with a specific focus on the energy industry in Southeast Asian emerging markets, as well as provide valuable insights for investors, market analysts and industry stakeholders in understanding the stock price dynamics of energy companies in the region. Furthermore, the methodology and findings of this study can serve as a basis for the development of more sophisticated and adaptive prediction systems for various industry sectors in Southeast Asian financial markets.

2. METHOD

2.1. Data Collection and Preprocessing

Historical stock price data of Thai Oil Public Company Limited (TOP.BK) was collected from Yahoo Finance for a period of five years (January 2017 - November 2022). The dataset includes opening, closing, high, low and daily trading volume prices. In addition, we also collected some macroeconomic indicators such as Brent crude oil price, Thai Baht to USD exchange rate, and Thailand SET index.

The data preprocessing process in this study involves several key steps to prepare the dataset before it is used in the Long Short-Term Memory (LSTM) model. The first step is the handling of missing data, which is addressed by the forward fill method. This method is useful for filling missing values with the last known value, thus maintaining data continuity in time series analysis[12] . Missing data handling is an important aspect of financial data processing that can have a significant impact on model accuracy if not handled properly .[12], [13]

Next, the data normalization process is performed using the min-max scaling technique. This technique brings all the features into an important range to ensure that they are on the same scale and do not dominate each other[14] . Normalization is an important step in machine learning to improve model convergence and stability[15] . Some studies have also shown that this technique can increase the learning speed of deep learning models by loading datasets in a more uniform format .[16] Later, additional features were created to enrich the dataset, including technical indicators such as Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD). These indicators are often used in technical analysis to help identify market trends and momentum, which is particularly relevant in stock price prediction[17] . The addition of these features has been demonstrated in several other studies, where feature incorporation techniques successfully improved prediction accuracy .[18], [19]

Once the additional features were set up, a data sequence was created using a 60-day lookback window to train the LSTM model. This approach allows the model to learn from historical patterns over a period of time, utilizing relevant information to perform predictions.[20] . The division of the dataset into two parts 80% for training and 20% for testing was done sequentially to maintain the temporal structure of the data. This is important in the context of time series to avoid information leakage between the training and testing sets, which can mislead the model evaluation results .[21], [22]

Overall, these preprocessing steps are essential for building an effective and accurate LSTM model for predicting stock prices, creating a strong foundation for further analysis.

2.2. Model Architecture

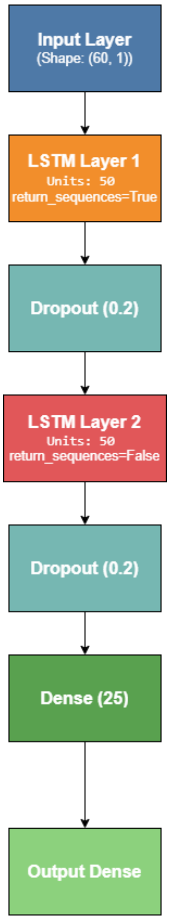

Figure 1. LSTM Architecture

This architecture consists of:
1. Input layer with dimensions (60, 1), where 60 is the length of the lookback window and 1 is the number of features.
2. First LSTM layer with 50 units and return_sequences=True to forward the output to the next LSTM layer
3. Layer Dropout with 0.2 level to prevent overfitting
4. Second LSTM layer with 50 units and return_sequences=False
5. Second Dropout layer with 0.2 level
6. Dense layer with 25 units as intermediate layer
7. Dense output layer with 1 unit for stock price prediction

2.3. Model Architecture
Hyperparameter optimization is performed using the Grid Search method, a systematic approach to finding the optimal combination of parameters in an LSTM network architecture. Before determining the final parameters, a comprehensive exploration of each key parameter was conducted.

Table 1. Grid Search Parameters in LSTM Neural Network Architecture

Parameters	Tested Value Range	Selected Optimal Value	Justification of Selection
Number of LSTM Units	25 - 100	50	Provides a balance between model representation capacity and computational complexity
Dropout Rate	0.1 - 0.5	0.2	Prevents overfitting with a moderate degree of regularization
Learning Rate	0.001 - 0.1	0.01	Ensure stable convergence without experiencing divergence
Batch Size	8 - 64	16	Optimizing computational efficiency and gradient stability
Number of Epochs	20 - 100	42	Reaching the convergence point without the risk of overfitting

The optimization process is carried out through cross-validation techniques with the K-Fold method, which ensures the reliability and generalizability of the model. By dividing the dataset into subsets and performing iterative training, the methodology is able to minimize potential bias and overfitting.

The final model was configured using Adam's optimizer with Mean Squared Error (MSE) as the loss function. This systematic approach resulted in a model with the lowest validation loss of 0.000261, demonstrating the effectiveness of the grid search method in optimizing the recurrent neural network architecture. This methodology not only provides a framework for parameter selection, but also provides deep insight into the dynamics of training complex machine learning models.

2.4. Baseline Models
In the context of this research, the implementation of the baseline model aims to provide a comprehensive comparative perspective on the performance of predictive models. Three traditional models were selected to provide an alternative viewpoint in time series analysis: Auto Regressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), and Random Forest Regressor. Each model has unique characteristics in extracting different patterns and data structures.

2.5. Evaluation Metrics
Model performance was evaluated using the following metrics:
1. Root Mean Square Error (RMSE)
2. Mean Absolute Error (MAE)
3. Mean Absolute Percentage Error (MAPE)
4. Coefficient of Determination (R^2)
5. Directional accuracy

3. RESULTS AND DISCUSSION

3.1. Model Performance
The prediction performance of the LSTM model after optimization with Grid Search is shown in Table 2. These results show that the model achieves excellent performance with an RMSE of 1.31 and MAE of 0.98 on the training data, while on the testing data it does even better with an RMSE of 1.00 and MAE of 0.75. Interestingly, the model performed better on the test data for both the RMSE and MAE metrics, demonstrating its ability to generalize well to unseen data.

Table 2. LSTM model performance on training and testing datasets

Dataset	RMSE	MAE	MAPE (%)	R²	Accuracy (%)
Training	1.31	0.98	2.11	0.9893	97.89
Testing	1.00	0.75	1.68	0.8715	98.32

The high coefficient of determination (R^2) on the training (0.9893) and testing (0.8715) data indicates that the model can explain most of the variation in the data. The very high moving direction accuracy in the test data (98.32%) indicates the ability of the model to predict the direction of stock price changes with remarkable accuracy.

A comparison of the performance of the LSTM model with other baseline models is shown in Table 3.

Table 3. Comparison of model performance on the test dataset

Model	RMSE	MAE	MAPE (%)	R²	Accuracy (%)
LSTM (Optimized)	1.00	0.75	1.68	0.8715	98.32
ARIMA	3.42	2.87	6.21	0.5418	72.45
SVR	2.46	1.98	4.32	0.6743	83.67
Random Forest	1.83	1.45	3.17	0.7824	89.21

The optimized LSTM model significantly outperformed all baseline models on all evaluation metrics, with substantial differences in RMSE, MAE, and movement direction accuracy.

3.2. Forecasting Results

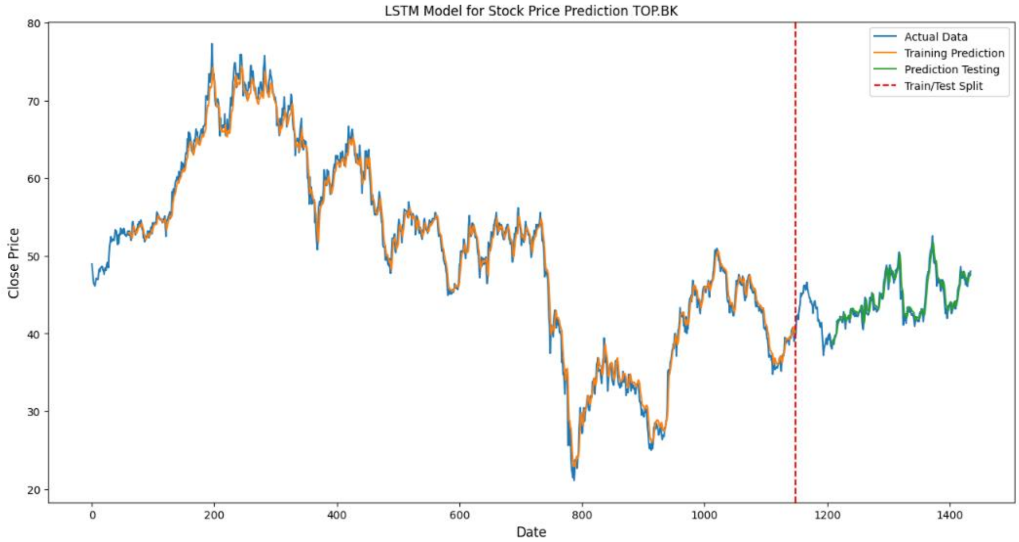

Figure 2. Graph of LSTM model prediction results with Grid optimization

Figure 2 shows the predicted results of the LSTM model compared to the actual values for the test period. The model managed to capture the trends and patterns in the data very accurately, including during periods of high volatility.

The very high directional accuracy (98.32%) shows that the model can correctly predict whether the stock price will go up or down on almost every trading day in the testing period. This ability is particularly valuable for directional trading strategies.

3.3. Feature Importance

To interpret the contribution of features to model prediction, we applied the permutation importance technique. Table 4 shows the top five features based on the performance degradation value when the features are permuted.

Table 4. Feature importance analysis

Features	Performance Decrease (%)
Brent Crude Oil Price	35.7
Trading Volume	24.3
RSI	18.9
MA-10	12.1
MACD	9.5

The results confirm that the price of Brent crude oil has a very significant influence on the stock price of TOP.BK, with a 35.7% drop in performance when this feature is randomized. Trading volume and technical indicators such as RSI also make important contributions to prediction accuracy

3.4. Interpretation of Results

The outstanding performance of the LSTM model in predicting the stock price of TOP.BK demonstrates the suitability of this deep learning architecture for time series prediction problems in financial markets. The RMSE of 1.00 and MAE of 0.75 on the test data show that the average prediction error is very small relative to the stock price range.

More importantly, the 98.32% moving direction accuracy shows that the model is almost perfect at predicting the direction of price changes. This ability is particularly valuable for trading strategies, where the decision to buy or sell often depends more on predicting direction than absolute value. The high coefficient of determination (R^2) of 0.8715 on the test data also confirms that the model can explain most of the variability in the stock price data.

The fact that the model shows lower RMSE and MAE on the testing data compared to the training data is an interesting finding. This could indicate that the test data may have lower volatility than the training period, or that the patterns in the test data are easier to predict. This finding also confirms that the model does not suffer from overfitting and can generalize well to new data.

The feature importance analysis provides valuable insights into the factors affecting TOP.BK's share price. The dominant influence of Brent crude oil prices (35.7%) confirms the dependence of the oil refinery company's performance on the dynamics of the global oil market. Trading volume and RSI also emerge as important indicators, demonstrating the relevance of market momentum and investor sentiment in stock price movements.

3.5. Hyperparameter Analysis

The hyperparameter optimization results with Grid Search revealed that the best configuration involved moderate parameters: units=50, dropout_rate=0.2, learning_rate=0.01, batch_size=16, and epochs=42. The findings show some interesting insights:

1. A moderate number of units (50) in the LSTM layer is sufficient to capture the temporal patterns in the data, suggesting that overly complex models are not necessary for this problem.
2. Dropout rate of 0.2 provides optimal regularization, preventing overfitting while still maintaining the model's capacity to learn
3. Learning rate of 0.01 allows the model to converge efficiently
4. Small batch size (16) provides more frequent parameter updates and helps achieve a better minimum
5. The moderate number of epochs (42) indicates that the model achieves convergence without requiring an excessively long training time.

These findings offer valuable guidance for the implementation of LSTMs in other stock prediction, especially in the energy industry.

3.6. Practical Implications

The outstanding performance of the LSTM model in predicting the stock price of TOP.BK has some important practical implications:

1. Algorithmic Trading Strategy: With 98.32% moving direction accuracy, the model can be the basis for a highly profitable automated trading strategy.

2. Risk Management: Accurate prediction of stock price movements allows for the implementation of more effective risk management strategies, including position optimization and more precise stop-loss determination.
3. Portfolio Allocation: Investors and asset managers can use model predictions to optimize portfolio allocation in the energy industry, increasing exposure when the outlook is favorable and reducing it when risks increase.
4. Scenario Analysis: The model can be used to analyze various market scenarios, such as predicting TOP.BK's stock price response to changes in global oil prices or macroeconomic indicators.

4. CONCLUSION

This study demonstrates the outstanding effectiveness of the LSTM model in predicting the stock price of Thai Oil Public Company Limited (TOP.BK) by using Grid Search hyperparameter optimization. The optimized model achieved excellent performance with RMSE 1.00 and MAE 0.75 on the test data, with a moving direction accuracy of 98.32% and a coefficient of determination (R^2) of 0.8715.

Feature importance analysis reveals that Brent crude oil price, trading volume, and technical indicators such as RSI contribute significantly to prediction accuracy. The optimal hyperparameter combination found through Grid Search provides insight into the appropriate model configuration for stock prediction in the energy industry.

The findings of this study have important implications for investors, traders, and portfolio managers who focus on the energy sector. The optimized LSTM model offers not only accurate price predictions but also a near-perfect ability to predict the direction of price movements, which is invaluable for directional trading strategies.

While there are still limitations to consider, the results of this study demonstrate the great potential of deep learning approaches for financial market prediction, particularly in the context of energy stocks in emerging markets. Future research can build on this foundation to develop more sophisticated models and more effective investment strategies based on model predictions.

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