STOCK PRICE PREDICTION USING OLL NEURAL NETWORK COMPARED WITH MULTIPLE LINEAR REGRESSION

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Abstract

Predicting the direction of stock price movement has been one of the most widely investigated and challenges for both investors and scholars. A considerable body of research has been devoted to the analysis of stock markets, leveraging advanced methodologies hailing from mathematical, computational, economic, and diverse interdisciplinary domains. This study introduces the Optimization Layer by Layer Neural Network (OLLNN) as a modern approach aimed at refining the weight adjustment process within each layer through the resolution of linear problems, thereby enhancing modeling precision and expediting convergence. To empirically evaluate the OLLNN's efficacy, we conducted a case study of PTTXP firm, a globally significant oil and gas production company with a multi-billion-dollar valuation, employing it as a subject for predicting daily closing stock prices. The predictive variables encompass a group of energy commodity daily prices such as Brent oil, WTI oil, and LNG prices, in conjunction with PTTXP's own stock price, some stock index, and associated indicators. Furthermore, we employ Multiple Linear Regression (MLR) as a benchmark for prediction accuracy. A comparative analysis of the results indicates that both methods yield similar Mean Absolute Percentage Error (MAPE) values, approximating around 1.00%. Moreover in validation, the OLLNN performs prediction of new dataset with the highest accuracy of 0.87% error. These findings underscore the potential of OLLNN as a valuable tool for enhancing the accuracy of stock price movement predictions.

***Keywords*: Artificial Neural Network; Multiple Linear Regression; Stock price prediction.**

1. Introduction

The stock market constitutes a fundamental pillar of the contemporary economy. The endeavor to forecast various aspects of stock performance, encompassing opening prices, highest and lowest prices, closing prices, and trading volumes, is a persistent pursuit among individuals seeking to optimize their investments. Accurate stock price predictions offer investors an enhanced probability of realizing profits within the stock exchange. However, this task is intrinsically challenging due to a multitude of influential factors, including economic conditions, political policies, industrial developments, market news, and natural phenomena, all of which contribute to the dynamic and volatile nature of stocks. Consequently, the prediction of stock market behavior is characterized by high complexity stemming from its nonlinear and multidimensional attributes [1,2].

In recent years, numerous techniques and models have been explored and employed in the pursuit of stock market prediction. These methodologies encompass Artificial Neural Networks (ANNs) [3,4], Support Vector Machines (SVMs) [4-6], Autoregressive Integrated Moving Average (ARIMA) models [5], Adaptive Exponential Smoothing, Prospect Theory, and Multiple Regression [7].

Artificial Neural Networks (ANNs) represent a class of nonlinear networks that possess qualities such as self-organization, data-driven adaptability, self-learning capabilities, and memory associations, akin to human cognitive processes. ANNs have demonstrated their utility in classification, prediction, and pattern recognition tasks, particularly in the domain of financial time series prediction. Various types of ANNs, including Back Propagation Neural Networks (BPNNs), have been employed to predict stock trends and prices [3,4].

In this work, we introduce a fast-converging neural network model termed the Optimization Layer by Layer Neural Network (OLLNN) for stock price prediction. This model is designed to facilitate speculative investors by predicting the direction of stock price movements, specifically whether prices will remain unchanged, rise, or fall relative to the previous day's closing price. To evaluate the effectiveness of the OLLNN model, we conduct a case study of PTTXP, the largest oil and gas production company in Thailand, with an annual revenue of approximately 10 billion USD from both inshore and offshore operations. The primary input parameters for the OLLNN prediction model are daily energy commodity prices, including Brent oil, WTI oil, and LNG prices, as well as stock indices, forex data, and the previous day's stock price. Mean Absolute Percentage Error (MAPE) metric are employed to assess the predictive model's accuracy and assess the model's practicality by examining its ability to correctly predict stock price movements.

Furthermore, we implement Multiple Linear Regression (MLR) as a comparative benchmark to establish a baseline performance for stock price prediction. MLR employs the same set of seven predictor inputs to forecast the closing stock price of the case study company. Like OLLNN, a predictive model is constructed using MLR. The results of MLR are analyzed to assess practical utility and are compared with OLLNN to evaluate predictive capabilities.

Section 2 of this paper provides a brief algorithm of OLLNN and offers an overview of prior research on the application of ANNs to stock market prediction. Section 3 presents a detailed profile of the case study company and the predictor parameters utilized in the predictive model. Section 4 presents the methodology for determining the optimal architectural configuration for the OLLNN model and outlines the approach employed to create a reliable MLR model. The experimental results of OLLNN, based on knowledge investment data, are compared with the MLR models to demonstrate the advantages of the OLLNN approach. Section 5 summarizes the paper with highlighted findings and conclusions.

2. Literature Review

2.1. *A brief of OLL neural network*

It's important to emphasize that, although every neural network aims to create a predictive model for stock prices, the structure and algorithms employed by each network for this purpose vary substantially. The fundamental framework of OLL, depicted in Figure 1, includes an input layer, one or more hidden layers, and an output layer. Every input node is linked to all hidden neurons through weighted connections denoted as Wji, while all hidden neurons are interconnected with all output neurons through weighted connections labeled as Vkj.

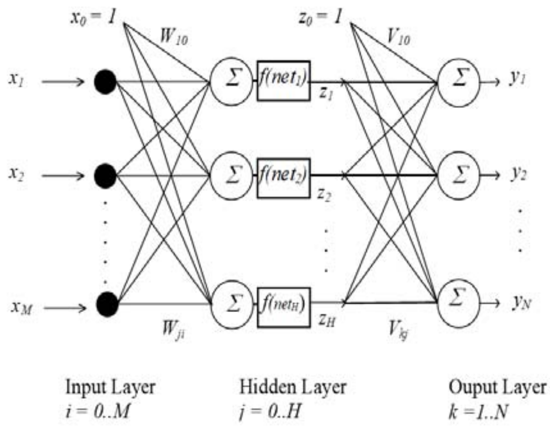

Fig. 1. Basic structure of OLLNN with one hidden layer

The core concepts of the OLL learning algorithm involve adjusting the weights within each layer based on their interdependencies, independent of other layers. Additionally, the optimization of the hidden layer is streamlined into a linear problem [8], as outlined in the algorithm for a single hidden layer, as follows:

Training Algorithm of OLL with one hidden layer (Fig. 1)

Step 1 Initialize weights
- Set all weights (W_{ji} ,V_{kj}) to small random values
- Set weight factor μ=0.0001,

Step 2 Optimization of output-hidden layer weights

- The gradient of cost function with respect to V is calculated to derive the optimal weight V for all training patterns. Thus,

$V_{jk} = A^{-1}.b$

where the A and b matrix are given by:

$A_{(j,j1)}$ = matrix $[a_{j,j1}]$; $a_{jj1} = \sum^{p}[o_j\, o_{j1}]$: j,j_1=0..H

$b_{(j,k)}$ = matrix $[b_{j,k}]$; $b_{jk} = \sum^{p}[t_k\, o_j]$: k = 1..N

p = number of training patterns

t_k = target output of output neuron k

Step 3 Optimization of the input-hidden layer weights

- Transform non-linear part into linear problem. Then the linearized weights in each output layer node can be calculated as follow:

$Vlin_{kj} = \sum^{j} [f'(net_j)\, V_{kj}]$

where f′(net) = derivative of the sigmoidal function

- Calculate weight correction term (ΔW_{opt}) for all training patterns.

$\Delta W_{opt} = Au^{-1}.bu$

where Au = matrix $[a_{(ij,hm)}]$;

bu = vector$[b_{(j,i)}]$

$a_{(ji,hm)}$: for $(j \neq h) = \sum^{p} \sum^{k}[(Vlin_{kj}x_i)(Vlin_{kh}x_m)]$

: for $(j = h) = \sum^{p} \sum^{k}(Vlin_{kj}x_i)(Vlin_{kh}x_m)$

$+ \mu/H^{*}\, abs(V_{kj}) f''(net_j)\, x_i\, x_m$

$b_{ji} = \sum^{p} \sum^{k}[(t_k - y_k)\, Vlin_{kj}\, x_i]$

H = number of neurons in hidden layer

- Calculate weight test (W_{test})

$W_{test} = W_{old} + \Delta W_{opt}$

Step 4 Update of the input-hidden layer weights

- Base on W_{test}, the new RMS error is calculated

If (New RMS > RMS) then go back to Step 3 and increase μ (μ = μ*1.2)

Else update weights

$W_{new} = W_{test}\ (= W_{old} + \Delta W_{opt})$

and decrease μ (μ= μ*0.9) for next iteration

Step 5 Do step 2 - 4 until test stop condition is true. (acceptable RMS or end of number of iterations)

2.2. *Artificial neural network for stock price prediction*

Artificial Neural Networks (ANNs) rank among the most extensively employed models in contemporary research. The landscape of ANN approaches has been comprehensively explored, as delineated by Vui et al. [9]. Furthermore, various scholars have probed these ANN methodologies, with Bing et al. employing BPNN to forecast the Shanghai Stock Exchange Composite Index [10], and Wensheng et al. conducting a comparative study of Nonlinear Independent Component Analysis (NLICA) and BPNN for the Asian stock market [11]. Chen et al. also contributed to this discourse by examining the utility of the LSTM model [12], while Nelson et al. carried out a comparative analysis between LSTM, Random Forest (RF), and Multilayer Perceptron (MLP) models [13].

Extensive research endeavors have been dedicated to refining and modifying ANN models. For instance, Vargas et al. introduced innovations by incorporating word-embedding and sentence-embedding techniques with the Recurrent Convolutional Neural Network (RCNN) [14]., while Ding et al. harnessed the Neural Tensor Network (NTN) and event-embedding CNN [15]. Furthermore, Qiu et al. advanced the field by developing a Genetic Algorithm-enhanced ANN (GA-ANN) model [16], and Ticknor introduced a modified Bayesian ANN variant [17]. Kang et al. further innovated by integrating a Generative Adversarial Network (GAN) model with MLP and LSTM components [18]. Akita et al. leveraged the LSTM approach in conjunction with paragraph vectors [19], and Olivera et al. adapted an ANN for the prediction of market behavior and stock market trends [20]. Notably, Li et al. conducted a comparative analysis, concluding that kernelized ELM and SVM exhibited higher precision compared to BPNN and standard ELM [21].

In addition to ANN, the Support Vector Machine (SVM) model has gained widespread adoption as a research tool. Some works applied SVM to predict stock market prices using large-scale public news data, and Hegazy et al. conducted a comparative study between the Least-Squares SVM algorithm and Particle Swarm Optimization (PSO) in the realm of the financial sector [22]. Beyond the two prominent models of ANN and SVM, several other modeling approaches, including regression techniques, have been explored for stock market prediction. Sharma et al. comprehensively reviewed the gamut of regression models in this context [23]. Additionally, support vector regression (SVR) has garnered attention and been optimized through the novel application of a chaos-based firefly algorithm, as elucidated by Kazem et al. [24]. Furthermore, Alkhatib et al. [25] ventured into the utilization of the K-Nearest Neighbors (KNN) model, integrating it with a non-linear regression approach for stock price prediction, with a specific focus on six major companies listed on the Jordanian stock exchange.

3. Development of knowledge base of a case study company

3.1. *A background of a case study company*

PTT Exploration and Production Public Company Limited (PTTXP) is a leading energy company based in Thailand with a global presence. Established in 1985, PTTXP is a subsidiary of PTT Group, one of Thailand's largest and most influential conglomerates. PTTXP is dedicated to the exploration, production, and development of oil and natural gas resources both domestically and internationally. With a strong commitment to sustainability and responsible resource management, the company operates with a focus on minimizing environmental impact and promoting social responsibility.

PTTXP's operations span across various regions, including Southeast Asia, the Middle East, Africa, Oceania, and the Americas. The company's expertise in upstream activities encompasses the exploration and production of oil and gas, including deep-water and unconventional resources. PTTXP leverages cutting-edge technology and industry expertise to extract valuable hydrocarbons efficiently and safely. Nowadays PTTXP’s Market capital is about 20 billion us dollars with revenue from selling oil and gas about 10 billion us dollars yearly.

3.2. *Predictor parameters of stock price prediction model*

For the purpose of forecasting the stock price of the case company, PTTXP, both neural network-based (OLLNN) prediction and multiple linear regression (MLR) models were employed, utilizing a total of seven selected input parameters. Among these parameters, four are related to energy commodity prices: Brent oil price in USD (BRENT), WTI price in USD (WTI), Liquid Natural Gas price in USD (LNG), and the USD to Thai Baht exchange rate (USD/Thai). The remaining three parameters pertain directly to the stock price itself, encompassing the previous day's closing stock price (PTTXPt-1), the Relative Strength Index of the stock price (RSI), and the SET100 Thai stock index (SET100). The predictive model's output is the closing stock price of PTTXP on the current day.

All data utilized in this analysis were sourced from daily price records retrieved from international investment data platforms, specifically investing.com and siamhchart.com [26,27]. The study employs the period spanning from January to August 2023, incorporating a dataset of 162 data pairs for the construction of the predictive model. Subsequently, data from the following month, September 2023, were reserved for the validation of the predictive model and for assessing the accuracy of its predictions. Figure 2 provides a visual representation of the parameters utilized in the stock price prediction model.

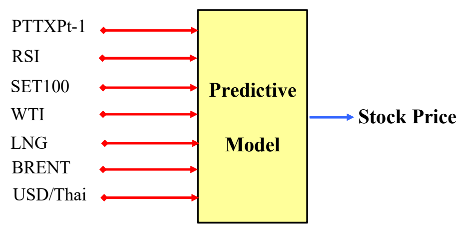

Fig. 2. Predictive model for stock price prediction

4. Results and Comparison

4.1. *Multiple linear regression for prediction model*

4.1.1. Development of MLG predictions model

A dataset comprising 162 paired data, encompassing both input and output variables, has been employed in the development of the Multiple Linear Regression (MLG) model. In this modeling process, seven predictor parameters are utilized as inputs, while the closing stock price represents the output variable. Given the potential issue of multicollinearity inherent in multiple regression analysis, a statistical approach is adopted. Specifically, the Best-subset method is employed to analyze the most pertinent input variables, thereby decreasing the influence of multicollinearity.

To identify these crucial input variables, a statistical software tool is applied, facilitating the computation of essential metrics which are Mallow's Cp and the associated coefficient of determination (R-sq) for the best subset regression. The result of analysis is shown in Figure 3.

Best Subsets Regression: Stock_Price versus PTTEPt-1, RSI, ...

Response is Stock_Price

Vars	R-Sq	R-Sq (adj)	R-Sq (pred)	Mallows Cp	S	PTTEPt-1	RSI	SET10	WTI	LNG	BRENT	USD/Thai
1	91.9	91.8	91.7	27.9	2.5130	X						
1	59.5	59.3	58.6	769.1	5.6123						X	
2	92.3	92.2	92.0	19.6	2.4502	X			X			
2	92.3	92.2	92.0	20.9	2.4591	X					X	
3	92.6	92.5	92.2	14.8	2.4096	X			X			X
3	92.6	92.5	92.2	14.9	2.4105	X			X	X		
4	93.0	92.8	92.5	8.2	2.3552	X			X	X		X
4	92.8	92.6	92.3	13.3	2.3924	X				X	X	X
5	93.3	93.0	92.7	4.4	2.3197	X	X			X	X	X
5	93.2	93.0	92.7	5.5	2.3280	X	X		X	X		X
6	93.3	93.0	92.6	6.2	2.3257	X	X	X		X	X	X
6	93.3	93.0	92.6	6.3	2.3265	X	X		X	X	X	X
7	93.3	93.0	92.5	8.0	2.3315	X	X	X	X	X	X	X

Fig. 3. Best subsets of multi regression model

Given the observation of a low Mallows Cp value and a correspondingly high adjusted R-squared (R-Sq(Adj.)), it is shown that the inclusion of five input variables in the Multiple Linear Regression (MLG) predictive model is suitable. Specifically, these five factors, denoted as PTTXTt-1, RSI, LNG, BRENT, and USD/Thai, have been selected based on a Mallows Cp value of 4.4, which aligns with an R-squared (adj.) of 93.0%. Subsequently, exclusively these five variables are utilized in the development of the MLP regression model, with the comprehensive analysis illustrated in Figure 4. The regression equation is expressed as Eq. (1). It is noted that all input variables of the resulting regression model demonstrate statistical significance at a confidence level of 95%.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	56.8	14.9	3.82	0.000	
PTTEPt-1	0.6672	0.0537	12.43	0.000	6.84
RSI	0.0707	0.0213	3.32	0.001	1.56
LNG	2.505	0.657	3.81	0.000	2.04
BRENT	0.3621	0.0731	4.95	0.000	3.15
USD/Thai	-1.281	0.361	-3.55	0.001	1.82

Fig. 4. Coefficient of multi regression model

$$\text{Predicted Price} = 56.8 + 0.6672\text{PTTXPt-1} + 0.0707\text{RSI} + 2.505\text{LNG} + 0.3621\text{Brent} - 1.281\text{USD/Thai} \quad (1)$$

4.1.2. *Validation of MLG prediction model*

Following the construction of the predictive model, a new dataset is introduced to the regression equation to compute the closing price of the stock. However, the focusing objective of this prediction task is to anticipate stock movements, which encompass price stability, upward price shifts, or downward price trends. This approach enhances the practicality and precision of stock price predictions. The results pertaining to the prediction of stock price movements spanning 21 days are presented in Figure 5.

The findings reveal that the MLG model successfully predicts the correct direction of stock movement with MAPE of 0.97%. Such a level of accuracy proves to be valuable for speculators engaged in stock trading activities.

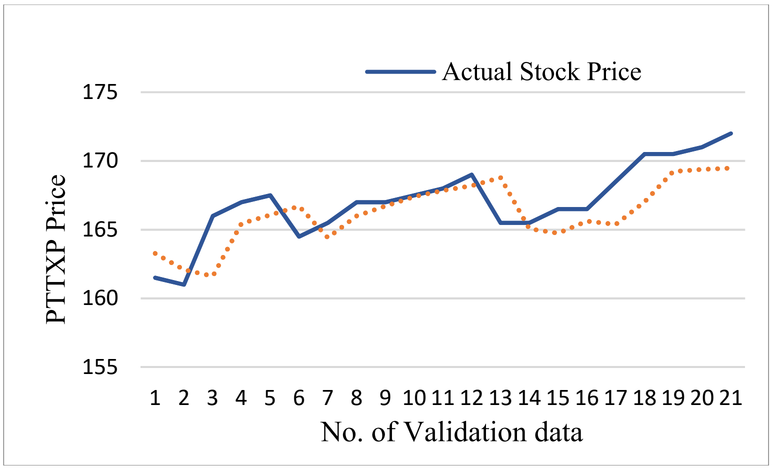

Fig. 5. Comparing prediction of validation dataset

4.2. ***OLL neural network for prediction model***

4.2.1. *Architecture of OLLNN model*

In the development of the predictive Optimization Layer by layer Neural Network (OLLNN) model, a dataset consisting of 162 paired data points, comprising both input and output variables, is employed. Notably, this dataset is separated into two distinct subsets: one serves as the training data for model construction, while the other functions as testing data, facilitating an assessment of the model's performance and the determination of an optimal architecture. The Root Mean Square (RMS) error, as delineated in Eq. (2), is adopted to measure the model's accuracy.

$$\text{RMS error} = \sqrt{\frac{\sum (\text{target} - \text{output})^2}{\text{no. of data}}} \tag{2}$$

Approximately 20% of the dataset, corresponding to 33 datasets, is designated as testing data, while the remaining 80% constitutes the training data, amounting to 129 data points. The input layer comprises seven nodes, aligning with the seven input parameters, while a single output node is designated to represent the outcome of stock price prediction. To ascertain the optimal configuration of hidden nodes within the hidden layer, an exploratory investigation is conducted, varying the number of hidden nodes from 2 to 15. The selection of the hidden node count corresponds to the configuration yielding the lowest RMS Error for the testing data, thus optimizing the predictive model. The outcomes of this investigation are depicted in Figure 6.

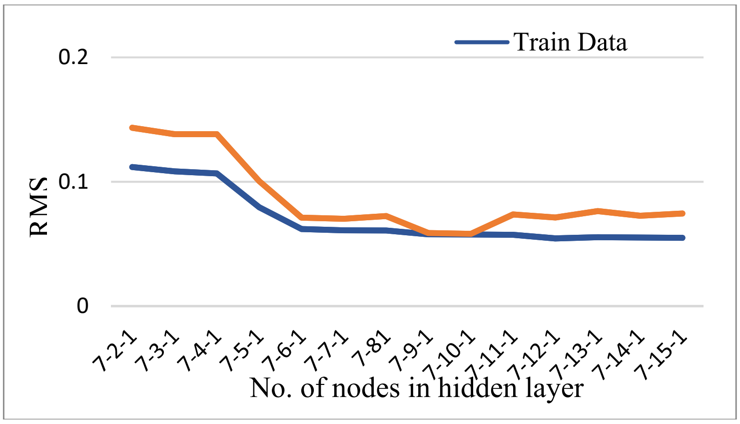

Fig. 6. RMS Error with number of hidden nodes

The analysis indicates that a configuration of ten hidden nodes yields the lowest RMS Error for the testing data, measuring at 0.0581, while the training data exhibits an RMS Error of 0.0576. Consequently, a 7-10-1 OLLNN architecture is adopted for this study, which achieves a Mean Absolute Percentage Error (MAPE) of 0.99 % for the test data, as depicted in Figure 7.

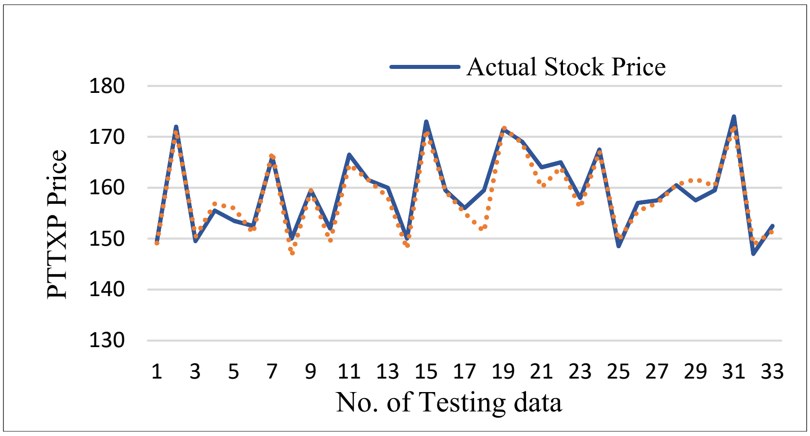

Fig. 7. Comparing prediction of testing dataset

4.2.2. Validation of OLLNN predictions model

Similar to the MLG model following the construction of the predictive model, the new dataset is introduced to the OLLNN predictive model to compute the closing stock price. However, the focusing objective remains the prediction of stock movement direction for future use. This approach augments the practicality and precision of stock price predictions. The outcomes pertaining to the prediction of stock price movements spanning 21 days with MAPE of 0.87 % and the compare actual stock prices with predicted prices are presented in Figure 8.

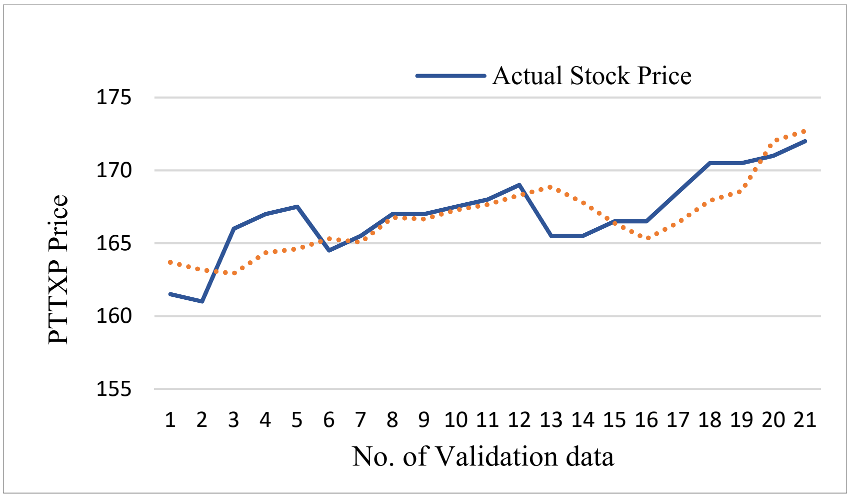

Fig. 8. Comparing prediction of validation dataset of OLLNN

4.3. *Comparison of MLG and OLLNN for prediction model*

In this section, we undertake a comparison between the outcomes obtained from OLLN and MLR, recognizing that MLR possesses inherent limitations when employed in the realm of stock price prediction. Among its notable drawbacks is its reliance on the assumption of linearity. In practice, stock price fluctuations are shaped by a myriad of non-linear factors, encompassing aspects such as investor sentiment, news events, and market psychology. We present the results in Table 1, which include the Mean Absolute Percentage Error (MAPE) for these two approaches.

Date	Actual Stock Price	Predicted Price by MLR	% Error	Predicted Price by OLLNN	% Error
Sep 1	161.50	163.28	-1.10	163.69	-1.35
Sep 4	161.00	162.08	-0.67	163.16	-1.34
Sep 5	166.00	161.62	2.64	162.93	1.85
Sep 6	167.00	165.45	0.93	164.35	1.58
Sep 7	167.50	166.07	0.85	164.61	1.73
Sep 8	164.50	166.71	-1.34	165.31	-0.49
Sep 11	165.50	164.42	0.65	165.07	0.26
Sep 12	167.00	165.99	0.60	166.77	0.14
Sep 13	167.00	166.72	0.17	166.66	0.20
Sep 14	167.50	167.40	0.06	167.27	0.14
Sep 15	168.00	167.85	0.09	167.66	0.20
Sep 18	169.00	168.20	0.47	168.30	0.41
Sep 19	165.50	168.79	-1.99	168.86	-2.03
Sep 20	165.50	165.07	0.26	167.79	-1.38
Sep 21	166.50	164.74	1.06	166.38	0.07
Sep 22	166.50	165.63	0.52	165.30	0.72
Sep 25	168.50	165.38	1.85	166.42	1.23
Sep 26	170.50	167.02	2.04	167.93	1.51
Sep 27	170.50	169.23	0.75	168.57	1.13
Sep 28	171.00	169.38	0.95	172.01	-0.59
Sep 29	172.00	169.48	1.47	172.70	-0.41
		MAPE	0.97%	MAPE	0.87%

Table 1. Comparison of MLR and OLLNN prediction of validation dataset

The results reveal that the Mean Absolute Percentage Error (MAPE) values for the datasets used in constructing the predictive models are quite comparable, standing at 0.87% for OLLN and 0.97% for MLG models. Furthermore, OLLNN exhibits a slightly superior level of accuracy in terms of percentage correctness when compared to MLG. In this particular work, OLLNN demonstrates its capability to yield favorable outcomes in predicting stock prices, as evidenced by an alternative case study.

5. Conclusion

Artificial Neural Networks (ANNs) have become a valuable tool for improving the accuracy of predicting stock market price indices, outperforming traditional methods. This transformation can be attributed to the increased computational power of modern computers, enabling swift and precise processing of extensive datasets. In this context, the Optimization Layer by Layer Neural Network (OLLNN) serves as a primary methodology for constructing predictive models.

This study centers on applying OLLNN to forecast the daily closing stock prices of PTTXP, an international oil and gas production company located in Thailand. Given PTTXP's operational context within the energy sector, the predictive model relies primarily on input parameters related to energy commodity prices. These inputs include variables such as Brent oil prices, WTI oil prices, LNG prices, and selected stock indicators, including foreign exchange rates of the Thai Baht. The necessary knowledge-based data for training and testing the OLLNN model is sourced from publicly accessible investment databases. Additionally, a Multiple Linear Regression (MLG) approach is employed as a baseline performance benchmark for predictive modeling. After determining the OLLNN architecture, we compute the Mean Absolute Percentage Error (MAPE) for both the predictive OLLNN model and the MLG model to assess their predictive accuracy. The obtained MAPE values are 1.00% and 1.13 %, respectively, indicating the significant predictive efficacy of both models.

This research specifically focuses on predicting the directional movements of PTTXP's stock prices, catering to speculators primarily interested in price trends, whether they are upward or downward. To evaluate the accuracy of these directional predictions, a validation dataset spanning approximately one month are used. The results demonstrate that the OLLNN model achieves a high accuracy of 0.87% error highlighting the effectiveness of the proposed predictive model in estimating stock price movement directions.

In future research endeavors, while the current model shows promise for prediction, it may be relevant to develop heuristics that can dynamically adapt to the changing stock market environment. Additionally, introducing a novel ANN model characterized by superior adaptive learning capabilities could further enhance predictive accuracy and responsiveness.

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Conflict of interest

All authors declare no conflicts of interest in this work.

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