PREDICTION OF STOCK PRICE USING HYBRID NEURAL NETWORK: A CASE OF COAL PRODUCTION COMPANY

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ABSTRACT

Stock market prediction is a critical issue in the field of economics. As machine learning technologies advance, an increasing number of algorithms are being utilized to forecast stock price movements. Nonetheless, predicting stock market trends remains a challenging task due to the inherent noise and volatility in stock market data. This paper addresses this challenge by proposing a novel hybrid neural network model designed to predict stock market prices using parameters related to commodity prices and stock indices. A case study company is mainly in coal production business in Thailand, which produce coal, sale, distribute and operate coal-fired power plants as well. The Multiple Linear Regression (MLR) and Back propagation neural network (BPNN) as traditional prediction technique are employed to comparatively investigate the accuracy and performance of the proposed HNN. Experiment results show that the prediction accuracy of HNN is superior to MLR but similar to that of the BPNN model. However, HNN has a good performance both in accuracy, speed and practice. It can help investing analysts and investors make their wise decisions.

Keywords: *Artificial Neural Network, Stock Price Prediction, Coal production, Hybrid Neural Network.*

1. INTRODUCTION

The stock market operates as a highly intricate and ever-changing system, which makes forecasting future price movements a considerable challenge [1]. The Efficient Market Hypothesis [2] and the Random Walk Hypothesis [3] suggest that predicting stock market trends may be inherently uncertain. Nevertheless, accurate stock market predictions are vital for making informed investment choices, managing risks, and maximizing returns.

Traditional forecasting methods in finance have predominantly relied on fundamental and technical analyses. Fundamental analysis focuses on investigative financial statements, market trends and macroeconomic views, while technical analysis uses price in historical data to picture future target prices. Beyond conventional approaches, statistical and econometric frameworks like the Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Vector Autoregression (VAR) are often utilized in the analysis of stock market time series. Nevertheless, these linear models frequently fall short in representing the intricate and nonlinear interactions among variables.

To overcome these limitations, there has been a growing trend among asset management firms and investment banks to adopt artificial intelligence, particularly deep learning [4]. Deep learning models have shown superior performance in stock market predictions compared to traditional linear and machine learning approaches. This is primarily due to their ability to process large datasets and uncover intricate, non-linear correlation between input parameters and predicted outcomes. The rise of deep learning has had a significant impact on the financial sector, especially in the domain of stock price forecasting. A major benefit of deep learning lies in its capability to automatically derive features from raw data [5-6], thereby reducing the need for manual operational modelling and increasing prediction precision. These models comprise multiple layers of interconnected neurons, where each layer is designed to extract progressively abstract features from the input data. Various deep learning architectures have been developed to tackle specific challenges and adapt to the unique characteristics of different datasets [7]. In this paper, Hybrid Neural network (HNN), is proposed for stock market prediction that leverages the parameters of commodity prices related to the main business of a case study company. A Company, namely BPPU, is a multi-billion firm that manufacture and distributes coal in Thailand and internationally. It operates through many segments: Domestic Coal, Overseas Coal, Energy, and Coal-fired Power Plant. The closing price of BPPU is the output of construction of these studying ANN predictive models. In addition, Multiple Linear Regression (MLR) and Back Propagation Neural Network (BPNN) are utilized as comparative benchmarks to establish a reference point for predicting stock prices. Both MLR and BPNN apply an identical set of six predictive variables to estimate the daily closing stock price of the company used in the case study. The outcomes from MLR and BPNN are examined to assess their effectiveness, and these results are contrasted with those obtained from the Hybrid Neural Network (HNN) to gauge predictive performance.

A concise algorithm for the HNN with details in references is given in Section 2, along with reviews of previous research related to the application of ANNs to stock price and indexes prediction. A brief analysis of the case study company, a coal production and coal fired power plant, including investigating the potential predictor variables incorporated into the predictive model are offered in Section 3. The next section discusses the approach used to determine the suitable architecture for the HNN model and details the method taken to develop a reliable MLR model. After establishing the predictive model, a new dataset is employed as validation data to evaluate the model's performance in forecasting stock prices. In Section 5, the experimental results of the HNN, informed by online investing data, are benchmarked with those obtained from the MLR and BPNN models to underscore the benefits of the HNN methodology. The work concludes with a summary of the principal findings and conclusions in the final section.

2. LITERATURE REVIEWS

2.1 Hybrid Neural Network Learning

A hybrid neural network combines different types of neural network architectures or integrates neural networks with other computational models to leverage their respective strengths. This approach can enhance performance in various tasks by addressing the limitations of individual models [8-9]. Here are some key concepts of a proposed hybrid neural network.

The fundamental structure of a Hybrid Neural Network, illustrated in Figure 1, comprises an input layer, hidden layer, and an output layer. Each input node is linked to every hidden node via weighted connections, and similarly, all hidden nodes are interconnected with every output node via weights connected between each layer.

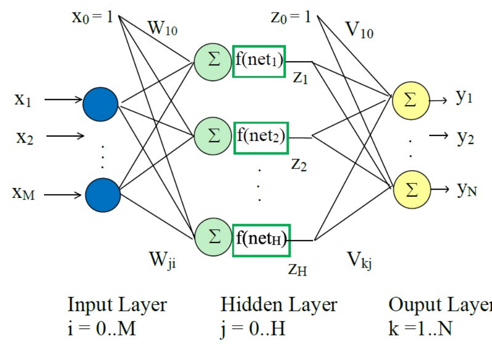

Figure 1: Structure of Multilayer Perceptron

The fundamental principle of the HNN learning algorithm involves the integration of both iterative and direct weight optimization techniques. This approach enhances training efficiency and helps to circumvent local minima. The network undergoes training by initializing with small random weights, followed by iterative adjustments of these weights through the Backpropagation algorithm, which includes an initial iteration aimed at improving training performance.

Subsequently, the direct weight optimization technique utilizing the Optimization Layer by Layer algorithm [10] is employed to finalize the weights, achieving a rapid convergence rate. This swift convergence is attributed to the fact that the weight optimization for each layer is simplified to a linear issue, with the values of weights in each layer being adjusted in relation to one another, while remaining independent of the other layers. The prime weight adjustment algorithm is presented as follows.

The weights in V matrix are adjusted for all training data iteratively in Eq. (1).

$$V_{jk} = A^{-1}.b \qquad (1)$$

where the matrix A and b are set by:

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

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

p = number of training dataset

t_k = target value of output node k

The optimal weight W for all training dataset. Thus,

$$\Delta W_{opt} = Au^{-1}.bu \qquad (2)$$

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where $Au = \text{matrix } [a_{(ij,hm)}]$;
$bu = \text{vector}[b_{(j,i)}]$
$a_{(ji,hm)}$: for $(j \neq h) = \sum^p \sum^k [(Vlin_{kj}x_i)(Vlin_{kh}x_m)]$
: for $(j = h) = \sum^p \sum^k (Vlin_{kj}x_i)(Vlin_{kh}x_m) + \mu/H^* \text{abs}(V_{kj}) f''(net_j)\, x_i\, x_m$
$b_{ji} = \sum^p \sum^k [(t_k - y_k)\, Vlin_{kj}\, x_i]$
H = number of neurons in hidden layer
$Vlin_{kj} = \sum^j [f'(net_j)\, V_{kj}]$
$f'(net)$ = derivative of the sigmoidal function

Therefore, the training algorithm for a neural network featuring a single hidden layer is outlined below to minimize complexity and enhance computational speed.

The training algorithm for a HNN that consists of a single hidden layer.

Step 1 Generate weights with a small random number (W_{ji}, V_{kj}) between -1 to 1

Set weight learning factor to 0.0001

Step 2 Use Backpropagation algorithm to train neural network in a small number of iterations (10-50 iterations). The random weights are adjusted toward the target output.

Step 3 Apply Linear operation to optimize the weight (V_{kj}) between output and hidden layers. The optimal values of weight V for all training dataset in Eq. (1) are calculated based on the gradient of cost function with respect to V matrix.

Step 4 Transform non-linear calculation into linear case for weight (V_{kj}) between hidden and output Layers. Subsequently, the linearized weights for each node in the output layer can be determined.

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

Step 5 Update of the input-hidden layer weights

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

Step 6 run repeatedly step 3 - 5 until the end of the specific number of iterations.

2.2 Utilization of Artificial Neural Networks for Forecasting Stock Market Trends

Artificial Neural Networks (ANNs) are widely used in contemporary research and have been extensively explored by various scholars. Vui et al. [11] delineated the landscape of ANN approaches, while Bing et al. utilized a Backpropagation Neural Network (BPNN) to predict the Shanghai Stock Exchange Composite Index [12], while Shahvaroughi Farahani and Razavi Hajiagha [13] evaluated the performance of an Artificial Neural Network (ANN) on India's National Stock Exchange (NSE). The work of Wensheng carried out a comparative study between Nonlinear Independent Component Analysis (NLICA) and Back Propagation Neural Network (BPNN) within the framework of the Asian stock market [14]. Selvamuthu et al. [15] undertook a study aimed at overcoming the challenges associated with time series data through the application of the Artificial Neural Network (ANN) algorithm. This algorithm is designed to analyze and forecast price fluctuations in stock exchanges. Meanwhile, Zahid Iqbal et al. [16] gathered data from various sources and employed three distinct methodologies: the de-noising technique utilizing a Feed-forward Neural Network (FFNN), the wmspca-Feed-forward Neural Network, and the Layered Recurrent Neural Network (LRNN). Additionally, Sutheebanjard and Premchaiswadi [17] proposed a novel approach for predicting the future SET index, which involved the use of a function whose coefficients were determined through evolutionary strategies. Moghaddam et al. [18] conducted a study on the predictive capabilities of artificial neural networks (ANN) in forecasting the NASDAQ. They created and tested two separate neural networks specifically designed for predicting the NASDAQ index. Ding et al. employed the Neural Tensor Network (NTN) along with an event-embedding Convolutional Neural Network (CNN) [19], while Ticknor introduced a variant of Artificial Neural Network (ANN) based on a modified Bayesian approach [20]. In 2016, following the demonetization in India, Chopra et al. [21] conducted an experiment. They created a Neural Network capable of forecasting the Indian stock market's performance despite the effects of demonetization. Typically, the stock market experiences volatility after a major alteration, as short-term investors are inclined to retract their investments. Kang et al. advanced the field by combining a Generative Adversarial Network (GAN) model with Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) components [22]. Jamous et al. [23] previously discussed the use of artificial neural networks (ANNs) for predicting stock market closing prices. Despite their potential, standalone ANNs have limitations that can lead to decreased prediction accuracy. To address this, hybrid models have been employed to overcome these constraints.

In addition to Artificial Neural Networks, the Support Vector Machine (SVM) model has been widely employed as an intelligent algorithm. DiPersio and Honchar [24] utilized SVM along

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with CNN (Convolutional Neural Network), MLP, and RNN (Recurrent Neural Network) to predict stock prices for the S&P 500 Index. Numerous research efforts have utilized Support Vector Machine (SVM) models to forecast stock market prices by analyzing vast amounts of public news data. Hegazy and his team performed a comparative study between the Least-Squares SVM (LS-SVM) algorithm and Particle Swarm Optimization (PSO) in the financial domain [25]. Besides the commonly applied ANN and SVM models, other methodologies, including regression techniques, have also been investigated for predicting stock market trends. Sharma and collaborators offered an extensive review of various regression models used in this field [26]. Phichhang Ou and Hengshan Wang [27] introduced ten distinct data mining methodologies, which include both Linear and Quadratic discriminant analysis, neural networks, tree-based classification, support vector machines, Bayesian classification utilizing Gaussian processes, logic models, and LS-SVM. These techniques were employed to predict the price movements of the Hang Seng index. Notably, LS-SVM and SVM demonstrated superior predictive performance. Support vector regression (SVR) has also garnered interest, particularly through its enhancement via a chaos-based firefly algorithm, as detailed by Kazem and his colleagues [28]. Inthachot et al. [29] applied artificial neural networks (ANN) in conjunction with genetic algorithms (G.A.) to analyze the trend of Thailand's SET50 index. The dataset comprised four input variables derived from different time frames: 3, 5, 10, and 15 days prior to the prediction. Qiu et al. made significant progress in the field by developing an ANN model enhanced with a Genetic Algorithm (GA) [30].

3. DEVELOPING DATABASE FOR A CASE STUDY COMPANY

3.1 A Company Profile of the Case Study

Since its establishment in 1983, when Banpu Public Company Limited (BPPU) commenced coal production for power generation, our organization has been guided by a comprehensive vision and an unwavering commitment to pursue high-quality energy resources across borders. Currently, BPPU stands as a prominent entity in the Asia-Pacific region, enhancing the quality of life for individuals by providing energy that serves as a fundamental pillar for economic and industrial advancement in numerous countries globally. In addition to amassing substantial experience and proficiency in effective business management, BPPU is dedicated to generating value for all stakeholders by adhering to sustainable business practices. These practices encompass a commitment to environmental stewardship, social responsibility, and sound corporate governance, aimed at fostering long-term value for communities, society, and shareholders alike. BPPU is recognized as a leading producer and distributor of premium thermal coal, collaborating with partners across various sectors worldwide, including independent power producers, cement, paper, petrochemical, textile, and food industries.

Presently, BPPU boasts robust coal mining operations in Indonesia, China, Australia, and Mongolia, contributing significantly to global energy security. For the fiscal year concluding on December 31, 2023, BPPU reported total assets amounting to USD 13 billion, revenue of USD 5.2 billion, and a market capital value of USD 6 billion.

3.2 Construction of Database for Predictive Models

To predict the stock price of BPPU, two different forecasting models were used: a neural network approach incorporating BPNN and HNN, and a multiple linear regression (MLR) model. The models utilized six input variables: five related to energy commodity prices (Natural Gas, WTI oil price, USD/Thai exchange rate, BRENT oil price, and Coal Price) and one related to the Thai stock index (SET100). The goal of these models was to estimate BPPU's closing stock price for the current day.

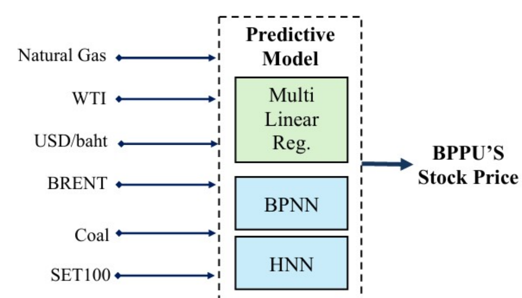

Figure 2: Input – Outputs of Predictive Models

The analysis was conducted using daily price data sourced from international investment platforms like investing.com [31]. The study covers the period between January and June 2024, employing a dataset comprising 122 data pairs to

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build the predictive model. Data from July 2024 was set aside for the purposes of validating the model and evaluating its accuracy. Figure 2 illustrates the input variables incorporated in the predictive model for BPPN's stock price.

4. PREDICTIVE MODELS AND RESULTS

4.1 Multiple Linear Regression for Predictive Modeling

4.1.1 Construct of the MLR Predictive Model

A dataset containing 122 paired observations of both input and output variables was employed to construct a Multiple Linear Regression (MLR) model aimed at predicting the closing stock price. Within this model, six predictor variables were selected as inputs, each potentially influencing the closing stock price. The primary objective of the model is to quantify the relationship between these predictor variables and the closing stock price, thus facilitating accurate predictions.

However, the inclusion of multiple predictor variables in a regression model often raises concerns about multicollinearity, which occurs when two or more predictor variables are highly correlated. Multicollinearity can inflate the variance of the coefficient estimates, leading to unreliable statistical inferences and reducing the model's predictive accuracy. To address this issue, a statistical approach was adopted to minimize the impact of multicollinearity.

In particular, the Best-subset selection method was employed to identify the most significant predictor variables for inclusion in the final model. This method involves evaluating all possible combinations of predictor variables and selecting the subset that optimizes a specific criterion, such as Mallows' Cp or the coefficient of determination (R-squared). By carefully choosing the best subset of variables, the model can achieve a balance between complexity and predictive power, while mitigating the adverse effects of multicollinearity.

The process of determining the key predictive variables was facilitated by statistical software, which calculated critical metrics, including Mallows' Cp and the coefficient of determination (R-squared) for each subset of variables. These metrics provide valuable insights into the model's performance, helping to identify the subset of variables that offers the best trade-off between accuracy and simplicity. The results of this analysis are visually depicted in Figure 3, highlighting the optimal subset of variables for the MLR model.

Best Subsets Regression: BPPU versus Natural Gas, WTI,

Response is BPPU

Vars	R-Sq	R-Sq (adj)	R-Sq (pred)	Mallows Cp	S	Natural Gas	WTI	USD/Thai	BRENT	COAL	SET100
1	61.7	61.3	60.2	122.5	0.30067			X			
1	54.5	54.1	53.2	166.5	0.32771						X
2	74.4	73.9	73.1	46.8	0.24700			X			X
2	69.4	68.9	67.9	77.2	0.26987		X				X
3	76.6	76.0	75.1	35.0	0.23687		X	X			X
3	76.1	75.4	74.4	38.4	0.23975	X		X			X
4	80.3	79.6	78.6	14.4	0.21837		X	X	X		X
4	79.1	78.4	77.2	21.7	0.22484	X		X		X	X
5	81.3	80.5	79.2	10.3	0.21372	X	X	X	X		X
5	80.5	79.6	78.5	15.4	0.21844		X	X	X	X	X
6	82.2	81.2	79.8	7.0	0.20966	X	X	X	X	X	X

Figure 3: Best Subset Result

The lowest Mallows' Cp value of 7.0 is selected, resulting in an adjusted R-squared value of 81.2%, indicating a strong relationship. Consequently, all six input variables are included in the model. The statistical significance of these variables has been tested, as illustrated in Figure 4. The regression equation is presented in Eq. (3) below, with all coefficients being statistically significant at 95% confidence.

$$
\begin{aligned}
\text{Predict} = {} & 7.92 + 0.2045\ \text{Natural Gas} - 0.1370\ \text{WTI} \\
& - 0.3456\ \text{USD/Thai} + 0.1385\ \text{BRENT} \\
& - 0.00858\text{COAL} + 0.005492\ \text{SET100}
\end{aligned} \tag{3}
$$

Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	7.92	2.84	2.79	0.006
Natural Gas	0.2045	0.0634	3.23	0.002
WTI	-0.1370	0.0321	-4.26	0.000
USD/Thai	-0.3456	0.0625	-5.53	0.000
BRENT	0.1385	0.0351	3.95	0.000
COAL	-0.00858	0.00373	-2.30	0.023
SET100	0.005492	0.000769	7.14	0.000

Figure 4: Coefficient of Multi Regression Model

4.1.2 Validation of the MLR Predictive Model

Following the development of the predictive model, a separate dataset was utilized to apply the regression equation for estimating the stock's closing price. The primary objective of this predictive analysis is to forecast stock price trends, including whether prices will stabilize, increase, or decrease. This approach improves the model's effectiveness and accuracy in predicting stock prices. The short-term prediction results, which span five days, are depicted in Figure 5. The results

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demonstrate that the MLR model accurately estimates the track of stock price change, with a Mean Absolute Percentage Error (MAPE) of 2.76%.

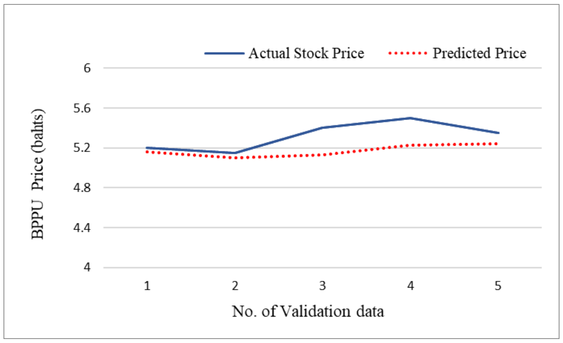

Figure 5: MLR Prediction of Validated data

4.2 Artificial Neural Network for Predictive Modeling

4.2.1 Architecture of ANN Models

To develop the Artificial Neural Network (ANN) predictive model, a dataset comprising 122 paired data points, representing both input and output variables, was employed. This dataset was split into two distinct subsets: one designated for training the model and the other for testing its performance. This division allows for the assessment of the model's accuracy and aids in determining the optimal architecture. The model's accuracy is measured using the Root Mean Square (RMS) error, as specified in Eq. (4).

$$\text{RMS error} = \sqrt{\frac{\sum (\text{target} - \text{output})^2}{\text{no. of data}}} \qquad (4)$$

Around 20% of the dataset, amounting to 20 data points, is reserved for testing, while the remaining 80%, or 102 data points, is utilized for training. The model's input layer comprises six nodes, each corresponding to one of the six input parameters, with a single output node dedicated to predicting the stock price. An exploratory analysis is performed to identify the optimal number of hidden nodes in the hidden layer, varying the number from 9 to 16. The configuration yielding the lowest RMS Error on the testing data is selected to maximize the model's predictive accuracy. Figure 6 displays the outcomes of this analysis.

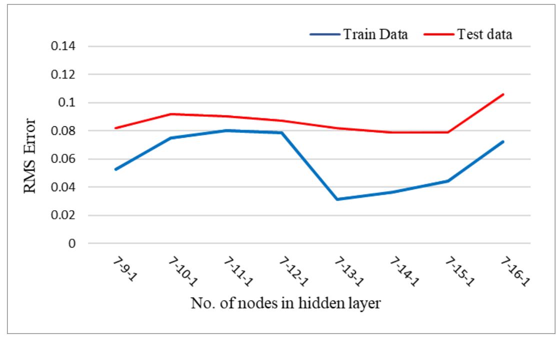

Figure 6: Selection of HNN Architecture

The analysis reveals that using a configuration with fourteen hidden nodes results in the lowest RMS Error for the testing data, recorded at 0.0786, which is higher than the RMS Error of 0.0364 observed for the training data. Consequently, a 6-14-1 HNN architecture is selected for this study, achieving a MAPE of 2.48% for the test data. In a similar manner to the HNN, the architecture of the BPNN is determined based on the minimum RMS Error of the testing data. A configuration with nine hidden nodes is selected, resulting in a 6-9-1 architecture that also yields a MAPE of 2.40% for the testing dataset.

4.2.2 Validation of ANN Predictive Models

In a manner akin to the MLR model utilized in the development of the predictive framework, the newly assembled dataset is subsequently applied to the BPNN and HNN predictive models to ascertain the closing stock price. Nevertheless, the primary aim continues to be the forecasting of stock movement direction for prospective applications. This methodology enhances both the practicality and accuracy of stock price forecasts. The results related to the prediction of stock price movements over the next five days indicate a MAPE of 1.73% by using the BPNN model and 2.19% by using the HNN model. A comparison of the actual stock prices against the predicted values is illustrated in Figure 7.

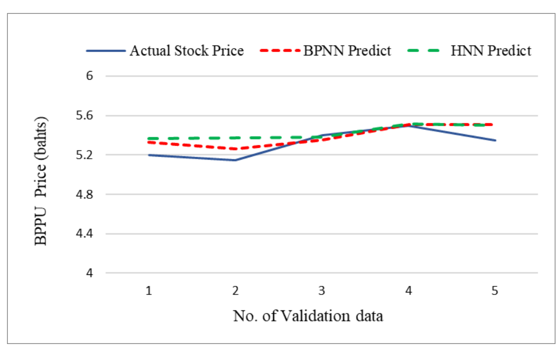

Figure 7: BPNN and HNN for Validation Data

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5. A COMPARATIVE STUDY OF MLR, BPNN AND HNN MODELS

This section involves a comparison of the results achieved through BPNN, HNN and MLR, acknowledging that MLR has inherent limitations when used for stock price prediction. One significant limitation of this method is its dependence on the assumption that variables' correlations is linearity. In practical, stock price movements are influenced by a range of non-linear factors, including investor sentiment, news developments, and market psychology. The results, including the Mean Absolute Percentage Error (MAPE) for these methods, are presented in Table 1.

Table 1: % Error of Models for Predicted Prices

Date	Stock Price	Forecast Price by MLR	% Error
1	5.20	5.16	0.81%
2	5.15	5.10	0.98%
3	5.40	5.13	5.01%
4	5.50	5.23	4.92%
5	5.35	5.24	2.07%
		MAPE	2.76%
Date	Stock Price	Forecast Price by BPNN	% Error
1	5.20	5.33	-2.50%
2	5.15	5.27	-2.24%
3	5.40	5.35	0.88%
4	5.50	5.51	-0.09%
5	5.35	5.51	-2.91%
		MAPE	1.73%
Date	Stock Price	Forecast Price by HNN	% Error
1	5.20	5.37	-3.23%
2	5.15	5.37	-4.28%
3	5.40	5.38	0.32%
4	5.50	5.52	-0.29%
5	5.35	5.50	-2.84%
		MAPE	2.19%

In Table 2 of Comparative of % MAPE, the findings indicate that the MAPE values for the datasets utilized in developing the ANN predictive models are relatively similar, with BPNN at 2.40% and HNN at 2.48%. Additionally, HNN shows a slightly higher level of precision in percentage accuracy compared to MLR. In this specific study, HNN proves its effectiveness in forecasting stock prices, as shown in an alternative case study.

Table 2: Comparison of % MAPE

Predicted Model	MAPE (%)	
	Testing Data	Validated Data
MLR	2.98 %	2.76 %
BPNN	2.40 %	1.73 %
HNN	2.48 %	2.19 %

ANOVA is also employed to assess the differences in accuracy among the three predictive models, as depicted in Figure 8. The results indicate that the accuracy measured by MAPE for BPNN and HNN models are not statistically different. However, the accuracy of the HNN model is significantly superior to that of the MLR model at a 95% confidence level.

```
Analysis of Variance

Source  DF   Adj SS    Adj MS   F-Value  P-Value
Factor   2  0.19076  0.095378    14.26    0.001
Error   12  0.08026  0.006689
Total   14  0.27102
```

Fisher Pairwise Comparisons

```
Grouping Information Using the Fisher LSD Method

Factor  N   Mean   Grouping
HNN     5  5.4279  A
BPNN    5  5.3919  A
MLR     5  5.1727     B
```

Figure 8: ANOVA Results of Three Predictive Models

6. CONCUSIONS

Artificial Neural Networks (ANNs) have emerged as a significant asset in enhancing the precision of stock market price index predictions, surpassing conventional forecasting techniques. This advancement is largely due to the enhanced computational capabilities of contemporary computers, which facilitate rapid and accurate analysis of large datasets. Within this framework, the Hybrid Neural Network (HNN) is identified as a key approach for developing predictive models.

This research focuses on utilizing the HNN model to predict the daily closing prices of BPPU, a major international coal producer and coal-fired power plant based in Thailand. Since the company operates within the energy sector, the model's predictive capabilities are primarily influenced by variables related to energy commodity prices, such as the prices of natural gas, WTI oil, Brent oil, and coal, along with relevant stock indicators and the Thai Baht exchange rates. The data required to train and validate the BPPU model is obtained from publicly available investment databases. To benchmark the accuracy of ANN predictive models, a Multiple Linear Regression (MLR) approach is used as a baseline methodology. After establishing the HNN structure, the MAPE is calculated for both the HNN and MLR models to gauge their predictive accuracy, yielding MAPE values of 2.48% and 2.98%, respectively, which underscores the substantial predictive capabilities of both methodologies.

This research is particularly aimed at forecasting the directional shifts in BPPU's stock prices, targeting speculators who are primarily concerned with price trends, whether they are ascending or descending. To assess the precision of these directional forecasts in speculative period, a validation dataset covering approximately five next days is employed. The findings reveal that the HNN model achieves a commendable accuracy rate with an error margin of 2.19%, thereby demonstrating the efficacy of the proposed predictive model in approximating the direction of stock price movements. Future work initiatives will continue to explore and refine these predictive methodologies. The adaptive learning algorithm of HNN can be developed to update the predictive model to perform simultaneously according to the new daily dataset.

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