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Enhancing Stock Price Forecasting: Optimizing Neural Networks with Moving Average Data

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Abstract References

1 This research focuses on optimizing a neural network model for stock price prediction using Particle Swarm Optimization (PSO), considering the inherent risks and potential high returns associated with stock investment. Given the challenges posed by stock price volatility, this study combines Moving Average (MA) a fundamental statistical technique in stock market analysis with advanced data mining approaches, specifically neural networks and PSO, to enhance prediction accuracy. 1 The primary objective is to improve the efficiency of neural networks by minimizing error rates and equipping investors with more reliable tools for financial decision-making. The proposed methodology involves converting historical stock price data into a Simple Moving Average (SMA) over a 5-day period, followed by optimizing a neural network model using PSO. This optimization process fine-tunes key parameters, particularly the weight distributions of 7 various stock market indicators, including Open SMA, High SMA, Low SMA, and Close SMA. 36 Model performance is evaluated using Root Mean Square Error (RMSE) as a validation metric. 4 The findings indicate a significant enhancement in the predictive accuracy of the neural network model after PSO optimization. The optimal configuration is identified in a two-layer neural network with a specific node arrangement. This optimized model not only improves stock price forecasting precision but also has practical implications for investors and financial analysts in risk management and profit maximization.

KEYWORDS: Forecasting, Neural Network, Particle Swarm Optimization, Simple Moving Average, Stock Market

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Enhancing Stock Price Forecasting: Optimizing Neural Networks with Moving Average Data

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Abstract

This research focuses on optimizing a neural network model for stock price prediction using Particle Swarm Optimization (PSO), considering the inherent risks and potential high returns associated with stock investment. Given the challenges posed by stock price volatility, this study combines Moving Average (MA) a fundamental statistical technique in stock market analysis with advanced data mining approaches, specifically neural networks and PSO, to enhance prediction accuracy. The primary objective is to improve the efficiency of neural networks by minimizing error rates and equipping investors with more reliable tools for financial decision-making. The proposed methodology involves converting historical stock price data into a Simple Moving Average (SMA) over a 5-day period, followed by optimizing a neural network model using PSO. This optimization process fine-tunes key parameters, particularly the weight distributions of various stock market indicators, including Open SMA, High SMA, Low SMA, and Close SMA. Model performance is evaluated using Root Mean Square Error (RMSE) as a validation metric. The findings indicate a significant enhancement in the predictive accuracy of the neural network model after PSO optimization. The optimal configuration is identified in a two-layer neural network with a specific node arrangement. This optimized model not only improves stock price forecasting precision but also has practical implications for investors and financial analysts in risk management and profit maximization.

I. INTRODUCTION

Stock investment is a popular financial instrument among investors. Stocks are defined as financial instruments representing a proportion of ownership in a company [1]. This type of investment is categorized as high-risk but has the potential for high returns, meaning the possibility of greater profits in stocks is also accompanied by increased risks that investors must consider. To avoid the risks associated with stock investment, investors strive to predict stock price movements to make accurate investment decisions and maximize profits [2]. Stock price movements are influenced by several factors, including the flow of demand and supply [3]. The fluctuating nature of stock prices makes it challenging for investors to predict their movement. One technique used is observing the historical average stock price over a certain period, known as the Moving Average [4].

The Moving Average is a statistical method commonly used in stock price analysis, where the average price is calculated over a specific time period. This method helps reduce the impact of random short-term price fluctuations, providing a smoother overview of price movements. Additionally, the Moving Average is useful in identifying ongoing trends in stock prices, making it easier for investors to make decisions based on observed trend directions [5]. The use of Moving Average data can be combined with data mining algorithms for prediction. One algorithm that performs well in stock price prediction is the Neural Network. Neural Networks learn patterns in data to generate future stock price predictions. The combination of Neural Networks and Moving Average

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allows for the integration of information about stock price trends over a certain period. By considering patterns revealed by the Moving Average, Neural Networks can be optimized to provide more accurate predictions of future stock price movements.

This research holds significant scientific urgency as it contributes to the fields of finance, investment, and data analysis. The predictive methods developed in this study, such as Moving Average, Neural Network, and Particle Swarm Optimization (PSO), offer a deeper understanding of how to develop complex predictive techniques and improve accuracy in forecasting stock prices. This is crucial in the context of technical analysis and financial investment, as it can help investors in reducing their investment risks, thus making more informed investment decisions. Additionally, the use of PSO in optimizing Neural Network parameters has a significant impact in computer science and artificial intelligence, offering valuable contributions to the development of technology applicable in various aspects of daily life.

The central problem this research addresses is the challenge in predicting stock prices, which are often fluctuating and difficult to estimate. The study tests the hypothesis that optimizing Neural Networks with PSO and using Moving Average data can improve the accuracy of stock price predictions. This enhancement is expected to assist investors in maximizing their capital gains.

In tackling these challenges, a comprehensive understanding of the issue is crucial. The integration of Neural Network algorithms with Moving Average data is key, allowing for analysis of historical stock price data and identification of patterns for future predictions. Following this, Particle Swarm Optimization (PSO) is implemented to determine optimal Neural Network parameters, thereby optimizing prediction accuracy. This approach involves a thorough data mining analysis to explore hidden patterns and factors influencing stock prices, broadening the understanding of the variables affecting stock prices [6], [7].

Continuous evaluation of this model is vital, using metrics such as Root Mean Square Error (RMSE) to gauge its effectiveness in anticipating stock prices and contributing to investors' capital gains. Through these integrated steps, the solution developed is expected to be robust and effective in facing the complexities of stock price prediction.

II. LITERATURE REVIEW

In the domain of stock market forecasting, the study conducted by Farnaz Ghashami et al., titled "Prediction of Stock Market Index Using a Hybrid Technique of Artificial Neural Networks and Particle Swarm Optimization," represents a noteworthy advancement. This research investigates the application of Artificial Neural Networks (ANNs) in forecasting the NASDAQ stock market index. Initially, the study applies ANN for predictive analysis before integrating Particle Swarm Optimization (PSO) to enhance accuracy. By utilizing NASDAQ index data, the findings reveal that PSO-optimized biases and weights significantly improve the predictive precision of the ANN model. This study contributes to the growing body of literature on stock market forecasting by combining ANN and PSO, effectively overcoming inherent limitations of conventional ANN models, such as their tendency to converge to local minima. The empirical results validate the enhanced accuracy of this hybrid approach, highlighting its potential for delivering more reliable stock market predictions [8].

Similarly, the research conducted by F. Yang and associates, entitled 'Improved and Optimized Recurrent Neural Network Based on PSO and Its Application in Stock Price Prediction', concentrates on refining stock price prediction models via an optimized recurrent neural network (RNN) coupled with Particle Swarm Optimization (PSO). This study highlights the integration of PSO in fine-tuning the predictive efficiency of RNNs, which are conventionally employed in financial forecasting. The authors meticulously investigate the nuances of neural networks, particularly the merits and drawbacks of the backpropagation neural network. They propose enhancements through PSO, such as the adjustment of learning factors and inertia weight to elevate performance. An exhaustive evaluation of this improved model, juxtaposed against traditional methods, reveals that the modified model significantly excels in stock price forecasting, achieving a peak accuracy rate of 83.0%. This research underlines the synergy of merging machine learning techniques with optimization algorithms for financial applications, introducing a groundbreaking approach to ameliorate stock price prediction models [9].

The research paper "Prediction on the Highest Price of the Stock Based on PSO-LSTM Neural Network" by Yushan Zhang and Sitong Yang represents a notable advancement in stock price prediction. The authors explore the integration of Particle Swarm Optimization (PSO) with the Long Short-Term Memory (LSTM) neural network to overcome the limitations of traditional LSTM models in stock market forecasting. This study specifically utilizes historical data from American stocks, focusing on the NASDAQ index. It demonstrates that the LSTM model, optimized using the PSO algorithm, markedly enhances the accuracy in predicting stock prices. The performance of the PSO-LSTM model is rigorously evaluated through empirical research. The findings suggest that the PSO algorithm effectively facilitates rapid adaptation of the neural network to the stock market data, thereby yielding more precise predictions. This paper makes a substantial contribution to the field of financial forecasting, introducing an innovative approach that synergistically combines machine learning techniques with optimization algorithms. This novel method significantly advances the accuracy of predicting stock market trends, as evidenced in the study [10].

Previous research, including studies on integrating Particle Swarm Optimization (PSO) with various neural network models such as ANN, SVR, and LSTM, has shown significant improvements in stock market forecasting [6], [7], [10]. This parallels our research approach, which specifically aims to optimize neural networks using moving average data for stock price prediction. The inclusion of moving average data in our study serves as a key differentiator, enhancing the model's ability to capture and reflect more accurate market trends over time. The success of PSO in refining neural network predictions, as evidenced in prior studies, validates our methodology and bolsters the potential of our approach in achieving even greater accuracy and reliability in stock market forecasting. These previous studies underscore the importance of advanced computational techniques in financial forecasting and provide a solid foundation for our research. By combining machine learning techniques with optimization algorithms and incorporating moving average data, our study brings an innovative perspective to the financial domain, aiming to bridge the gap between traditional forecasting methods and contemporary computational advancements.

III. Methods

A. Data Collection

In this research, data collection is a crucial phase focused on gathering stock price data of the top companies based on market capitalization in the Composite Stock Price Index (IHSG). This data is sourced from Excel using the stockhistory function and includes stock prices of the top 10 companies from June 25, 2013, to June 25, 2023. The companies involved include Astra International Tbk. (ASII), Bank Central Asia Tbk. (BBCA), Bank Negara Indonesia (Persero) Tbk. (BBNI), Bank Rakyat Indonesia (Persero) Tbk. (BBRI), Bank Mandiri (Persero) Tbk. (BMRI), PT. Chandra Asri Petrochemical Tbk. (TPIA), H.M. Sampoerna Tbk. (HMSP), Indofood CBP Sukses Makmur Tbk. (ICBP), Telkom Indonesia (Persero) Tbk. (TLKM), Unilever Indonesia Tbk. (UNVR), with each time series providing data such as date, opening price, highest, lowest, closing, volume, and percentage change.

Transitioning from data collection to preparation, the research incorporates several key processes. These processes include moving average data selection, integration, cleaning, and normalization. The required columns for subsequent processes are Open SMA(5), High SMA(5), Low SMA(5), Close SMA(5), Closing, and Change %. Other columns are removed as they are not relevant. Integrating data from 10 Excel files into one results in a dataset comprising 23,887 rows of data.

Finally, acknowledging the importance of data quality, extensive data cleaning is not conducted as the data quality already meets the necessary criteria. This leads us to the critical step of data normalization, especially relevant in the context of stock price prediction using neural network models. This process adjusts the data value scale to a specific range, often between 0 and 1 [11], to ensure uniform scaling and prevent any single variable from dominating the learning process. This allows the model to focus more on relevant patterns in the data, setting the stage for accurate and efficient predictive analysis.

B. Moving Average Calculation

In this section, we delve into the procedure of transforming the data from the 'Open', 'High', 'Low', and 'Close' columns into a Simple Moving Average (SMA) over a 5-day period, a technique rooted in the widely used Moving Average (MA) indicator in financial analysis. This method assists investors in understanding the stock market's dynamics and aids in making informed decisions about when to buy or sell stocks [12]. Additionally, we have introduced a new column, 'Closing', to represent the stock's closing price on the subsequent day. As demonstrated in Fig. 1, the calculation involves generating a 5-day rolling average for each column, providing insights into both short-term market fluctuations and long-term stock trends.
The equation for the SMA is as follows:

$$MA_t(n) = \frac{d_{t-(n-1)} + \cdots + d_{t-1} + d_t}{n} \qquad (1)$$

Where $MA_t(n)$ represents the moving average calculated over n days and dt is the daily data averaged over the n-day period.

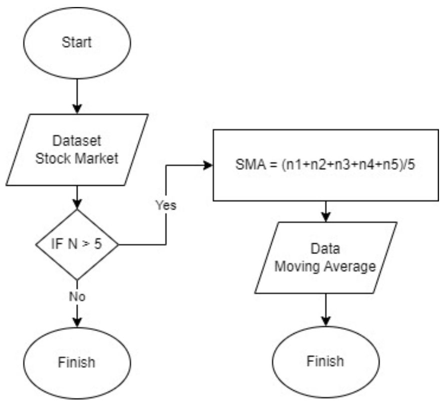

Fig. 1. Moving Average Process

The following Table 1 provides an overview of the Simple Moving Average (SMA) calculation process. This table includes columns for the date, open price, high price, low price, closing price, volume, percentage change, as well as the calculated SMAs for the open, high, low, and closing prices. The 'Closing' column represents the closing price of the stock on the following day.

TABLE 1
SIMPLE MOVING AVERAGE (5) CALCULATION PROCESS

Date	Open	High	Low	Price (close)	Vol	Change	Open SMA(5)	High SMA(5)	Low SMA(5)	Close SMA(5)
June 25 2013	7850	7900	7800	7850	29.89M	0.64%				
June 26 2013	7850	7900	7750	7800	29.71M	-0.64%				
June 27 2013	7900	7950	7850	7900	44.22M	1.28%				
June 28 2013	7950	8000	7850	7950	35.57M	0.63%				
June 30 2013	8000	8150	7950	8100	58.37M	1.89%	7910	7980	7840	7920
July 01 2013	8100	8150	7950	8050	32.81M	-0.62%	7960	8030	7870	7960
July 02 2013	8050	8150	8000	8100	36.08M	0.62%	8000	8080	7920	8020

C. Neural Network

Neural networks are sophisticated systems composed of interconnected adaptive units, replicating the interactions found in biological nervous systems when dealing with real-world objects [13]. Just as neurons in biological neural networks are linked and respond to stimulation by influencing other neurons, the abstracted model of a neuron in an M-P network functions similarly. Here, a neuron receives input 'x', processes it through connections weighted by 'w', and activates based on an activation function and threshold, as illustrated in Fig. 2 with a neuron and three input nodes.

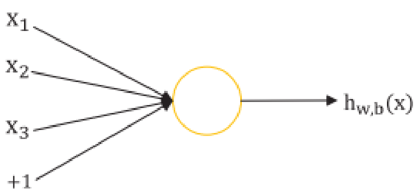

Fig. 2. Neural network with one neuron and three input nodes

Building on the concept of single neurons, the Multilayer Perceptron (MLP) represents an advanced form of artificial neural networks. An MLP typically consists of at least three layers: the input layer, one or more hidden layers, and the output layer. These layers, fully interconnected, work together to map input vectors to output vectors. The MLP, depicted in Fig. 3 with four hidden layers, extends the capabilities of a simple perceptron, overcoming its limitations in handling linearly inseparable data.

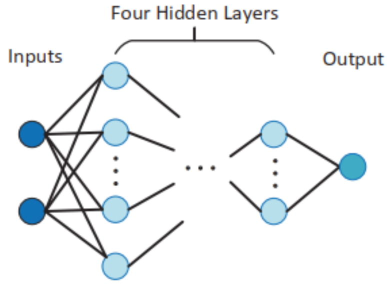

Fig. 3. Multilayer Perceptron (MLP) with four hidden layers

Delving deeper into the neural network's architecture, the input layer (X) connects to the first hidden layer (H1) with the relationship defined as H1 = f(W1X + B1), where W1 and B1 denote the weight and bias parameters, respectively, and f represents a non-linear activation function. This pattern repeats across multiple hidden layers, each with its unique weights and biases. The final output (Y) is calculated as Y = G(WLHL + BL), connecting the last hidden layer (HL) to the output. The function G, often the Softmax function, plays a crucial role in determining the final output. Importantly, slight adjustments in the weights (w) or biases (b) of neurons can significantly impact the network's output. Therefore, the Backpropagation (BP) algorithm and optimization techniques are crucial for iteratively refining these parameters to achieve accurate outputs.

D. Particle Swarm Optimization (PSO) Integration

PSO (Particle Swarm Optimization) is an evolutionary computation technique inspired by the social behavior of birds and fish, especially their coordinated and fluid movements. Known for its efficiency in searching and optimizing complex functions, PSO is highly valued for fine-tuning parameters in diverse computational models. As a swarm intelligence-based optimization method, PSO adheres to five primary principles applicable to creating artificial swarms: proximity, quality, diverse response, stability, and adaptability [14].

Our approach involves applying PSO to optimize the neural network's hyperparameters, which include learning rates, the number of hidden layers, and neurons in each layer. By treating these hyperparameters as particles within the PSO framework, each particle represents a potential solution, characterized by a specific set of hyperparameters. The PSO algorithm iteratively updates the position of each particle based on its own experience and the collective experience of the swarm, effectively searching for the optimal configuration that yields the best performance of the neural network.The integration process begins with the initialization of the swarm, where a predefined number of particles are randomly generated. Each particle's position corresponds to a unique set of hyperparameters for the neural network. The fitness of each particle is evaluated based on the performance of the neural network with its respective hyperparameters. This performance is typically measured in terms of prediction accuracy or error rates. The flow chart of PSO is shown in as Fig. 4.

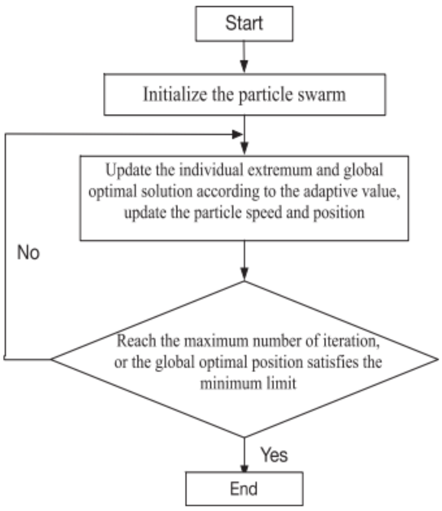

Fig. 4. Flowchart of PSO

E. Model Training and Validation

This section describes a holistic approach to model training and validation as depicted in Fig. 5**Error! Reference source not found.** which is a model of the framework. Model training is a critical stage where a neural network is exposed to a very large data set and at the same time it refines its parameters by recognizing patterns and relationships in the data, a process that is enhanced by data preprocessing steps such as cleaning, integration and transformation (for example, moving averages). Performance metrics, especially accuracy, are carefully tracked to ensure effective learning. At the same time, validation is an important process that uses a different test data set—previously unseen by the model during training—to measure its predictive performance. The models are assessed using standard strategic indicators, as exemplified in the evaluation stage by the use of Root Mean Square Error (RMSE) [15], RMSE is used as benchmarks for the accuracy of the model and its ability to generalize beyond the training data, thereby reducing the risk of overfitting.

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$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_l)^2} \quad (2)$$

The training phases do not stand alone; this is followed by a normalization process to standardize the input data, ensuring consistent scaling across inputs. Additionally, the integration of Particle Swarm Optimization (PSO) along with neural network rules serves to further optimize the model. The validation phase is concerned with applying cross-validation strategies and hyperparameter tuning, which improves the adaptability and performance of the model across various data segments. The culmination of this complex process results in a well-vetted and reliable model, ready to deploy, and capable of providing precise predictions and insights from new data input.

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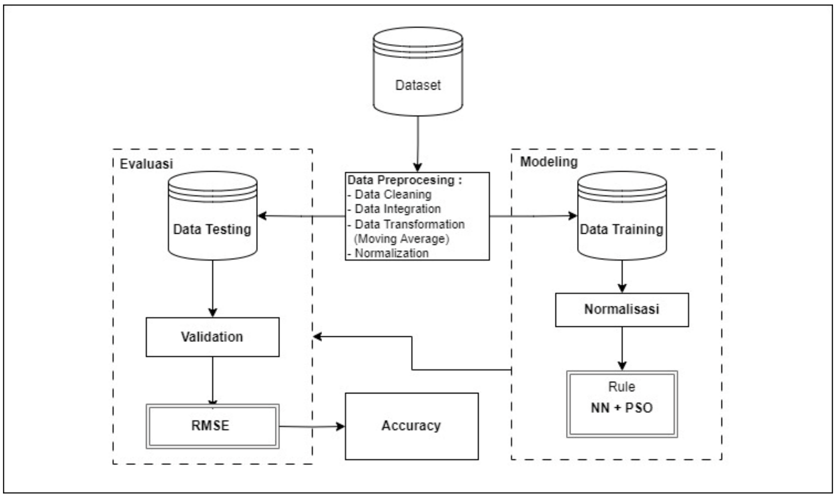

Fig. 5. Modeling

IV. RESULTS

A. Modelling

The modeling process is carried out using Google Colab. In Google Colab, we start by using the "Read Excel" module from Pandas to retrieve the dataset that has been prepared in the preprocessing stage. Next, our Neural Network model was built using “MLPRegressor” module from Scikit-learn with several parameters as shown in Table 2.

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TABLE 2
MODEL PARAMETERS

Parameter	Value
max_iter	5000
early_stopping	True
activation	logistic
random_state	42

The results of the Neural Network model begin with an initial configuration of 2 layers, each containing 3 nodes, as depicted in Fig. 6**Error! Reference source not found.**. Subsequently, we will measure the generated error values. Then, we gradually add layers and nodes to find the best values for Root Mean Square Error (RMSE). These values will serve as a reference for determining the maximum number of layers.

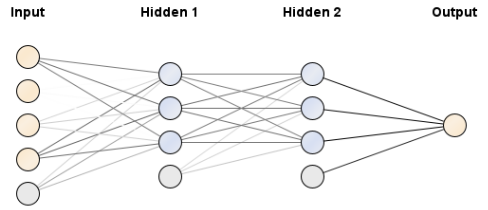

Fig. 6. Model Neural Network 2 Layer

In this phase, we leverage the power of Google Colab as an invaluable tool to carry out the modeling phase effectively. Initially the Neural Network configuration consisted of 2 layers, each containing 3 nodes. The main goal is to improve this configuration by iteratively modifying the number of layers and nodes, aiming to achieve the lowest possible Root Mean Square Error (RMSE). Evaluation uses X-Fold Cross Validation of 10 for training data and testing data. This optimization process plays an important role in the development of appropriate predictive models. Furthermore, the evaluation results including several trials involving the addition of layers are presented in Table 3.

TABLE 3
LAYER TEST RESULT

Test	Layer	RMSE
1	2	0.011258
2	3	0.014014
3	4	0.013274
4	5	0.011865
5	6	0.152110
6	7	0.212064
7	8	0.212022
8	9	0.212011
9	10	0.212007

From the experiments carried out by increasing the number of layers, it can be seen in **Error! Reference source not found.** that the RMSE value increases significantly starting from the 6th layer. This shows that adding more layers does not always result in a better model, and that the optimal layers for the model are found in layers 2 until 5.

Next, trials were carried out by increasing the number of nodes in each layer. This is done to assess how increasing the number of nodes affects model performance. The results of this experiment will help us determine the final configuration of the Neural Network model to achieve optimal accuracy in predicting data.

TABLE 4
NODE TEST RESULT

Test	Layer	RMSE
2	3	0.011258
2	4	0.014711
2	5	0.014325
2	6	0.013477
2	7	0.014512
2	8	0.014770
2	9	0.012587
2	10	0.012697
3	3	0.014014
3	4	0.011770
3	5	0.011381
3	6	0.011283
3	7	0.011913
3	8	0.012834
3	9	0.012924
3	10	0.011197
4	3	0.013274
4	4	0.012288
4	5	0.011629
4	6	0.012400
4	7	0.011628

4	8	0.011181
4	9	0.012303
4	10	0.011212
5	3	0.011865
5	4	0.011382
5	5	0.012142
5	6	0.011147
5	7	0.011607
5	8	0.011941
5	9	0.011144
5	10	0.011196

From the results depicted in Table 4 it is evident that the addition of nodes significantly impacts the reduction of the Root Mean Square Error (RMSE). In the configuration with two layers and four nodes, there is a reduction in RMSE marginally less than 0.001 compared to the three-node setup. A similar phenomenon is observed in the three-layer configuration, where an increased number of nodes contributes to the decrease in RMSE. However, a significant reduction in RMSE in the three-layer configuration is only achieved with a substantial increase in the number of nodes. Based on these two experiments, the optimal neural network model for stock price forecasting, aligned with Moving Average data, is identified in the two-layer configuration with four nodes. This model will be further optimized using Particle Swarm Optimization (PSO) to enhance performance and reduce error values.

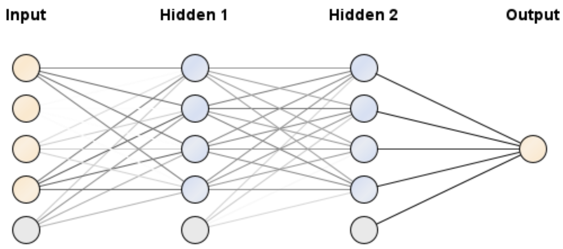

Fig. 7. Proposed Neural Network Model

Table 5 presents the test results of nodes in a neural network, detailing the weights for each node across two hidden layers and the output layer. For Hidden Layer 1, it shows weights for different Simple Moving Averages (SMA) and bias values for each of the four nodes. In Hidden Layer 2, weights are assigned to connections from each of the four nodes of the first layer, along with their respective bias values. The Output layer lists weights for each of the four nodes from Hidden Layer 2 and includes a threshold value.

TABLE 5
NODE TEST RESULT

Layer	Node	Weight
Hidden Layer 1	1	Open SMA(5): -0.482
		High SMA(5): -0.258
		Low SMA(5): -0.512
		Close SMA(5): -0.475
		Bias: 0.790
	2	Open SMA(5): 0.007
		High SMA(5): -0.726
		Low SMA(5): -0.571
		Close SMA(5): -0.368
		Bias: 0.578
	3	Open SMA(5): 0.595
		High SMA(5): 0.684
		Low SMA(5): 0.616
		Close SMA(5): 0.226
		Bias: -0.514
	4	Open SMA(5): 0.432
		High SMA(5): 0.634
		Low SMA(5): 0.155
		Close SMA(5): 0.542
		Bias: -0.709
	5	Open SMA(5): -0.420
		High SMA(5): -0.410
		Low SMA(5): -0.398
		Close SMA(5): -0.510
		Bias: 0.883

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6	Open SMA(5): -0.407 High SMA(5): -0.429 Low SMA(5): -0.401 Close SMA(5): -0.534 Bias: 0.974
7	Open SMA(5): 0.013 High SMA(5): 0.269 Low SMA(5): 0.518 Close SMA(5): 0.889 Bias: -0.783
8	Open SMA(5): 1.538 High SMA(5): 1.421 Low SMA(5): 1.587 Close SMA(5): 1.628 Bias: 0.053
9	Open SMA(5): 0.439 High SMA(5): 0.416 Low SMA(5): 0.209 Close SMA(5): 0.681 Bias: -0.837
Output	Node 1: 0.526 Node 2: -0.140 Node 3: -0.505 Node 4: 0.437 Node 5: -0.517 Node 6: -0.221 Node 7: 0.515 Node 8: 0.450 Node 9: 0.195

B. PSO Modelling

After securing the optimal neural network model, we then focus on optimizing each attribute, particularly through the application of Particle Swarm Optimization (PSO) to enhance performance. The primary goal is to perform a detailed evaluation of how PSO contributes to increasing the efficiency of neural network models, with an emphasis on error reduction. This section will cover the optimization process, highlighting the selection and fine-tuning of PSO parameters, and will elaborate on each step of the implementation. This approach will demonstrate the significant role of PSO in elevating the model's effectiveness. Our analysis aims to provide essential insights into the application of PSO optimization for boosting the efficacy of predictive models, particularly in the context of stock price forecasting. Fig. 8**Error! Reference source not found.** below illustrates the model developed in Rapid Miner for the optimization of the Neural Network using PSO.

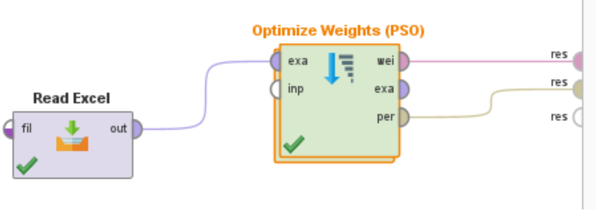

Fig. 8. Optimization with PSO

The RMSE results from applying PSO to optimize the neural network model for stock price prediction using moving average data indicate a reduction in error values, although not markedly significant. This can be attributed to the data normalization within a 0-1 range, resulting in proportionately smaller error values. The calculated RMSE stands at 0.010834. The weighting process using PSO is detailed in **Error! Reference source not found.**, w hich displays the weight distribution for various attributes optimized through Particle Swarm Optimization (PSO) in our neural network model. This table enumerates four primary attributes: Open SMA (5), High SMA (5), Low SMA (5), and Close SMA (5). Each attribute is allocated a distinct weight, highlighting its importance in the model. Notably, Open SMA (5) and Close SMA (5) are each given the highest weight of 1, underscoring their pivotal role in the model's predictive precision. On the other hand, High SMA (5) and Low SMA (5) receive weights of 0.416 and 0.787, respectively, indicating their less critical yet still meaningful influence on the model's overall performance.

TABLE 6
WEIGHT ATTRIBUTE PSO

Attribute	Weight
Open SMA (5)	-0.349
High SMA(5)	0.035

Low SMA (5)	0.095
Close SMA (5)	0.400

V. Discussion

The discussion section of the research on optimizing neural network models using Particle Swarm Optimization (PSO) for stock price prediction plays a crucial role in interpreting the results and drawing major conclusions. Here, we engage in a comprehensive analysis of our findings, integrating both empirical data and theoretical insights to build a strong argument. Firstly, we compare the performance of the optimized neural network model against unoptimized models. The weights assigned to attributes such as Open SMA (5), High SMA (5), Low SMA (5), and Close SMA (5) demonstrate the effectiveness of PSO in fine-tuning the model for enhanced accuracy in stock price predictions. The higher weights for Open and Close SMAs suggest their significant influence on the model's predictive power, a finding that aligns with established financial theories.

Moreover, this research contrasts the PSO-optimized neural network with other modeling methods, highlighting the advantages and potential limitations of our approach. This comparison not only validates the superiority of our model in certain aspects but also opens up avenues for further research and development.The results obtained from this study address a specific problem in financial engineering: improving the accuracy of stock price predictions. The application of PSO in adjusting weights of different attributes has shown a tangible improvement in the model's performance, a significant advancement in the field of financial predictive modeling.

Furthermore, our discussion delves into the new and significant findings that emerged from the study. This includes insights into how the model responds to different market conditions and the potential of PSO in other areas of financial modeling. The discussion also reflects on the practical implications of these findings, suggesting how investors and financial analysts can leverage this model for better decision-making in the stock market. Finally, the discussion acknowledges the limitations of the current study and proposes directions for future research. This may involve exploring other optimization techniques, testing the model across different financial markets, or integrating additional variables for a more comprehensive analysis. By doing so, we not only conclude our current research but also pave the way for future explorations in the field.

VI. Conclusions

This research on optimizing artificial neural network models using Particle Swarm Optimization (PSO) for stock price prediction provides significant contributions to the field of financial forecasting. The findings demonstrate that PSO effectively enhances the accuracy and efficiency of neural network models, particularly in handling the complexities of stock price prediction. By integrating Moving Average (MA) data with a neural network and refining its parameters through PSO optimization, this study achieves a substantial improvement in prediction precision. These results hold practical significance for investors and financial analysts by offering a more robust and reliable decision-making tool in volatile stock markets. This research not only underscores the technical efficacy of the hybrid approach but also highlights its practical value in mitigating investment risks and optimizing returns.

Looking forward, this study lays a strong foundation for further research and development in financial modeling. While the focus here is on stock price prediction, the broader applicability of PSO optimization extends to other domains within financial analytics and beyond. Future research could explore the application of PSO-enhanced neural networks across different financial markets, incorporate additional economic and market variables for a more comprehensive analytical framework, and investigate alternative optimization algorithms to compare and refine predictive performance. By continuously improving and testing these models, this research contributes to narrowing the gap between traditional forecasting techniques and modern computational advancements, thereby expanding the arsenal of tools available for financial forecasting and strategic decision-making in an increasingly dynamic economic landscape.

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