Neutrosophic MOOSRA with Whale Optimization Algorithm for Unraveling Financial Futures through Inverse Problem Solving

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Abstract

Resolving financial futures through inverse problem-solving delves into the complicated process of deciphering the difficulties subjective in the financial market to forecast behaviours and future trends. Inverse problem-solving involves working backwards from observed outcomes to uncover the underlying conditions or parameters, unlike prediction models, which often rely on past information to predict future outcomes. This method in the finance sector includes untangling the numberless factors influencing the market dynamics, like technological advancements, economic indicators, investor sentiment, and geopolitical events. Analysts can tease out hidden patterns and relationships within financial data using statistical techniques and complex mathematical algorithms, enabling them to generate accurate predictions of market volatility, asset prices, and other crucial metrics. The financial future becomes less opaque through the lens of inverse problem solving, providing policymakers and investors great foresight and insight into navigating the uncertainties of global markets. Hence, this study introduces a Neutrosophic MOOSRA with Whale Optimization Algorithm (NMOOSRA-WOA) for Unraveling Financial Futures through Inverse Problem Solving. The NMOOSRA-WOA incorporates linear scaling normalization, NMOOSRA-based prediction, and WOA-based parameter tuning to boost the robustness and accuracy of financial predictions. The NMOOSRA technique generates predictions based on past financial time series data. Moreover, the framework integrates the Whale Optimization Algorithm (WOA) for parameter tuning, leveraging whale pods' search abilities to optimize predictive performance and finetune model parameters. The NMOOSRA-WOA provides a comprehensive algorithm for financial prediction by synergistically combining these methodologies, which facilitates more accurate forecasts of market trends, asset prices, and other critical indicators. Experimental results on real-time financial datasets demonstrate the superiority and efficacy of the proposed framework over other classical prediction techniques, highlighting its potential for risk management within dynamic financial markets and real-time applications in investment decision-making.

Keywords: Financial Market; Inverse Problem Solving; Whale Optimization Algorithm; Machine Learning; Neutrosophic MOOSRA

1. Introduction

A financial market is a highly challenging adaptive model [1]. The complexity mainly originates from the contact between market participants and markets —the existing atmosphere of markets affects the tactics of market participants. In contrast, market participants' complete behaviour chooses the economic market's tendency [2]. According to the Adaptive Markets Hypothesis (AMH), market participants' behavioural preferences, such as overconfidence, loss aversion, and overreaction, constantly exist [3]. Presently, financial predicting is highly valued in academic groups, economic groups, and people's everyday life. News and data on financial predictions associated with futures, stocks, and exchange rates can originate all over the Television (TV) media, the Internet, and newspapers. However, financial actions are mainly complex and focus on numerous uncertainties, making it challenging to hold future tendencies [4]. With esteem to the present financial state and the vigorous growth of the market economy, the government should know the actual condition of national financial development and market changes and grip more precise financial data. Furthermore, once the market environment varies, the heuristics of the old environment may no longer function, thus corrupting social biases [5]. As an outcome, the financial market's trend, linked with market participants' inclined tactics, makes the financial market very challenging to

DOI: https://doi.org/10.54216/IJNS.240113
Received: August 18, 2023 Revised: December 19, 2023 Accepted: April 03, 2024

forecast. Numerous efforts have been made to predict the market movement using numerous methodologies [6]. Technical analysis has been usually employed, but these models are inclined to lose analytical power after they are issued.

Few studies use machine learning (ML) models such as feedforward neural networks, SVM, ensembles and economic market forecasts [7]. They attained good performance at the ML level but consumed no similar outcomes from a financial viewpoint. The development of numerous ML theories and methods has resulted in significant performance developments for various tasks in computer vision (CV), voice recognition, natural language processing (NLP), and game playing. Deep learning (DL) is one of the most common ML models, and it plays a significant part in attaining these activities [8]. Financial market interchange data is one of the most well-known time series, which has got more attention in the ML area since an exact type of deep recurrent neural networks (DRNN) and artificial neural networks (ANN) execute very well for time series forecasts [10].

This study introduces a Neutrosophic MOOSRA with Whale Optimization Algorithm (NMOOSRA-WOA) for Unraveling Financial Futures through Inverse Problem Solving. The NMOOSRA technique generates predictions based on past financial time series data. Moreover, the framework integrates the Whale Optimization Algorithm (WOA) for parameter tuning, leveraging whale pods' search abilities to optimize predictive performance and finetune model parameters. The NMOOSRA-WOA provides a comprehensive algorithm for financial prediction by synergistically combining these methodologies, which facilitates more accurate forecasts of market trends, asset prices, and other critical indicators. Experimental results on real-time financial datasets demonstrate the proposed framework's superiority and efficacy over other classical prediction techniques, highlighting its potential for risk management within dynamic financial markets and real-time applications in investment decision-making.

2. Related Works

Kim et al. [11] projected a novel structure dependent upon physics-informed NN and convolution transformers. The performance of the offered structure is directly equated to other recognized DL structures like normal physics-informed NN, ConvLSTM model, and self-attention ConvLSTM technique. Cao et al. [12] project a new method to relate accurate finance and ML methods. Likewise, the Quasi-Reversibility Method (QRM) system is employed. The model also utilized ML to train systems to create the finest forecast. The current research phase unites QRM with CNN, which simultaneously acquires data through a vast quantity of data points. Chen et al. [13] present the usage of analytical DNN to straight and quickly resolve an equivalent ERT inverse issue. Cross-entropy loss was mainly employed to improve systems and create non-linear mapping from ERT voltage dimensions to dual probabilistic spatial crack distributions. In this struggle, ANN and CNN are initially trained utilizing pretend electrical data.

In [14], the financial stress index extends general economic danger. This technique builds the stress index for five financial sub-markets and merges the stress index using the Markov regime-switching technique. On this foundation, the research employed interpretable ML approaches to estimate systemic financial danger and analyze and equate the outcomes of the basic interpretable ML methods and the post-hoc explainable models. Zhang et al. [15] offer a novel technique for variational mode decomposition, CNN, Bi-LSTM, and MLP (VMD–CNN–BILSTM-MLP) technique. GA defines the parameters of the VMD system. At first, using the method, carbon futures values are cracked down into subsequences of dissimilar frequencies. Then, an MLP approach has been used. Lastly, every subsequence's forecast value is linearly inserted to get the concluding outcome of the entire method.

Wang and Liu [16] develop a dual-phase deep combination paradigm reliant upon ideal multi-factor analysis and multi-scale decomposition. Optimum multi-scale decomposition models have been created. The VMD and singular spectrum analysis (SSA) techniques are also employed. The estimated entropy is utilized to scale the time-series difficulty. The multi-factor analysis model utilizes a joint feature selection model. A dual-stage deep combination has been executed by employing BIGRU to obtain the latest forecasts. Yang et al. [17] make a stock price forecast technique over NN. Furthermore, the adaptive alteration of inertial weight has been developed, and the system has been enhanced by linking with NN. Moreover, based on the improved model, this research builds a stock price forecast model reliant on NN. Lastly, this paper projects experimentation to verify the work of the model based on the arithmetical research outcomes.

DOI: https://doi.org/10.54216/IJNS.240113
Received: August 18, 2023 Revised: December 19, 2023 Accepted: April 03, 2024

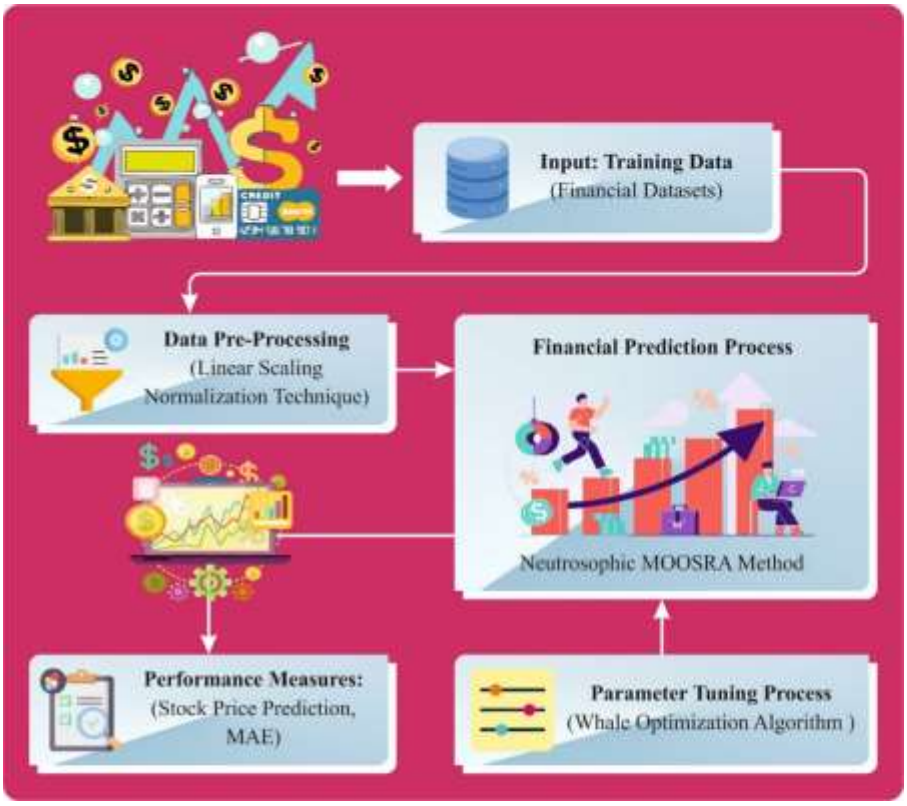

Figure 1: Workflow of the NMOOSRA-WOA method

3. The Proposed Method

In this study, we have introduced an NMOOSRA-WOA for unravelling financial futures through inverse problem-solving. The NMOOSRA-WOA incorporates linear scaling normalization, NMOOSRA-based prediction, and WOA-based parameter tuning to boost the robustness and accuracy of economic predictions. Fig. 1 defines the workflow of the NMOOSRA-WOA method.

A. Data Normalization

Linear scaling normalization is an elementary method in financial markets for normalizing data through varying scales, which enables meaningful analysis and fair comparisons. First, we determine the range of values within the dataset to implement data normalization. Then, the minimum and maximum values are evaluated within that range. Lastly, the linear scaling formula is applied for each data point,

$$Scaled\ Value = \frac{(X - Min\ Value)}{(Max\ Value - Min\ Value)} \times (New\ Max - New\ Min) + New\ Min \quad (1)$$

This equation scales the data point to fit within the desired range [0,1] or any specified interval. Linear scaling normalization ensures that data from different sources or with various units are effectively analyzed and combined in decision-making and financial modelling processes, promoting consistency and accuracy.

B. NMOOSRA-based Prediction

This section remembers a few vital fuzzy set models and neutrosophic notions [18].

Definition2.1. Assume that x is a precise element of the universe of discourse X next a fuzzy set A is definite by a fuzzy membership function (μ_A) that acquires the membership value in the unit closed range of 0 and 1. i.e. μ_A: $X \rightarrow [0, 1]$

Definition2.2. A fuzzy decision matrix of $m \times n$ was definite as $A = [\mu_{ij}]_{m\times n}$. In contrast, μ_{ij} denotes the fuzzy membership value of the element in A produced by decision-makers as per the substitutes on measures.

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Definition2.3. Assume that B refers to a neutrosophic set in the non-empty set X or universal discourse and object x in B contains the model $B = \{< x, \mu_B(x), \sigma_B(x), \gamma_B(x) >; x \in X\}$, whereas $\sigma_B(x)$, $\mu_B(x)$, and $\gamma_B(x)$ the degree of indeterminacy, degree of truth, and degree of falsity membership, correspondingly which consume their values in the unit closed range of 0 and 1, and fulfils the subsequent relation $0 \leq \mu_B(x) + \sigma_B(x) + \gamma_B(x) \leq 3$.

Definition2.4. A triangular single value of neutrosophic number $B = \{(l_1, m_1, u_1); \mu_B(x), \sigma_B(x), \gamma_B(x)\}$ is a unique kind of neutrosophic set on real number set R, whose degree of indeterminacy, falsity and truthness membership functions were determined below:

$$\mu_B(x) = \begin{cases} \frac{(x - l_1)T_B}{m_1 - l_1} & (l_1 \leq x \leq m_1), \\ T_B & (x = m_1), \\ \frac{(u_1 - x)T_B}{u_1 - m_1} & (m_1 \leq x \leq u_1), \\ 0 & otherwise. \end{cases}$$

$$\sigma_B(x) = \begin{cases} \frac{(m_1 - x + I_B(x - l_1))}{m_1 - l_1} & (l_1 \leq x \leq m_1), \\ I_B & (x = m_1), \\ \frac{(x - u_1 + I_B(u_1 - x))}{u_1 - m_1} & (m_1 \leq x \leq u_1), \\ 1 & otherwise. \end{cases}$$

$$\gamma_B(x) = \begin{cases} \frac{(m_1 - x + F_B(x - l_1))}{m_1 - l_1} & (l_1 \leq x \leq m_1), \\ I_B & (x = m_1), \\ \frac{(x - u_1 + F_B(u_1 - x))}{u_1 - m_1} & (m_1 \leq x \leq u_1), \\ 1 & otherwise. \end{cases}$$

whereas $T_B, I_B, F_B \in [0,1]$ and $l_1, m_1, u_1 \in R$.

At first, the MOOSRA method was proposed, and many researchers used it as a selection procedure. The initial step is the creation of a decision matrix that contains four parameters: substitutes accessible for range, measures upon the range that has to be prepared, weight endorsed to individual alternate and performance computation by substitutes through the secure set of standards. The parallel procedure was approved here for the neutrosophic MOOSRA model, where the complete process is defined as follows.

Step1: Create a neutrosophic triangular scale

Step2: Initialize the consistency for pair-wise comparison matrix

Step3: Form random reliability index for numerous standard

STAGE I: Obtain the specialist's data in a neutrosophic situation

Stage I begins with the idea of the neutrosophic matrix in which every substitute's output about every condition is assessed.

Step4: Form the pair-wise evaluation decision matrix of every norm by decision maker's verdicts as stated below

$$C^M = \begin{bmatrix} B_{11}^M & \cdots & B_{1z}^M \\ \vdots & \ddots & \vdots \\ B_{y1}^M & \cdots & B_{yz}^M \end{bmatrix}$$

Step5: Discover crisp values of combined pair-wise comparison matrix of criteria

The formulation for discovering the collective pair-wise decision matrix is

$$B_{uv} = \langle \left(\frac{1}{M} \sum_{i=1}^{M} l_{uv}^i, \frac{1}{M} \sum_{i=1}^{M} m_{uv}^i, \frac{1}{M} \sum_{i=1}^{M} u_{uv}^i \right); \frac{1}{M} \sum_{i=1}^{M} T_{uv}^i, \frac{1}{M} \sum_{i=1}^{M} I_{uv}^i, \frac{1}{M} \sum_{i=1}^{M} F_{uv}^i \rangle$$

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Here, M denotes the number of decision-makers, l_{uv}^{M}, m_{uv}^{M}, $and\ u_{uv}^{M}$ represent the lower, middle, and upper limit of neutrosophic numbers, and I_{uv}^{M}, F_{uv}^{M}, $and\ T_{uv}^{M}$ signifies the indeterminacy, falsity, and truth membership values correspondingly.

By utilizing the score function of B_{uv}, change neutrosophic measures to crisp value,

$$s(B_{uv}) = \left| \frac{(l_{uv} * m_{uv} * u_{uv})^{(\tau_{uv}+I_{uv}+F_{uv})}}{9} \right| \quad (2)$$

Whereas u, m, l represent the corresponding upper, middle, and lower measures of triangular neutrosophic values.

STAGE II

Step6: Compute the weight of criteria (w_u^y)

Calculate average row value by $w_u = \frac{\sum_{i=1}^{z} s(B_{uv})}{z}; u = 1,2,3, \dots, y; v = 1,2,3, \dots, z$

Step7: The assumed calculation measures the standardization of crisp values

$$w_u^y = \frac{w_u}{\sum_{u=1}^{y} w_u} \quad (3)$$

STAGE III Estimate expert judgement utilizing a rate of consistency

Step8: Compute the sum of weight columns, i.e. multiply the weight of measures with every value of the pair-wise comparison matrix

Step9: The weighted sum value was separated by the weight of every norm

Step10: Calculate $\lambda_{\max}$ value by discovering the means of the preceding step

Step11: Calculate the reliability index by the below-mentioned formulation

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

Here, n denotes the criteria number.

Step12: Calculate the rate of consistency by the below given calculation

$$CR = \frac{CI}{RI} \quad (4)$$

Whereas CI means consistency index, RI is a random index, $and\ CR$ stands for consistency rate

STAGE IV MOOSRA Model

Step13: Create decision verdict values of every substitute on criteria in terms of triangular neutrosophic pair-wise comparison decision matrix

Step14: Use the function of score to compute the crisp value of the combined contrast decision matrix

Step15: Discover the standardization of the decision matrix by

$$B_{uv}^{*} = \frac{B_{uv}}{\sqrt{\sum_{u=1}^{y} B_{uv}^{2}}}$$

Step16: Calculate the total number of practical and non-useful measures of the matrix's weighted standardized values, which correspondingly signify Y^{+} and Y^{-}.

$$Y^{+} = \sum_{j=1}^{g} w_v\, x_{ij}^{*}$$

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$$Y^{-} = \sum_{j=g+1}^{n} w_v \, x_{ij}^{*}$$

Step17: Complete performances of every substitute are attained by MOOSRA technique utilizing the below-given formula

$$y_i^{*} = \frac{\sum_{j=1}^{g} x_{ij}^{*}}{\sum_{j=g+1}^{n} x_{ij}^{*}}$$

Step18: The position of the substitutes is acquired as per the complete performance score of every alternative y_i^{*}

C. Hyperparameter Tuning

Finally, the WOA can be employed. In 2016, Mirjalili and Lewia presented a metaheuristic optimization technique for the WOA [19]. It will gain motivation from the hunting approach of humpback whales. The WOA mainly comprises three functions: encircling the prey, moving towards the prey, and searching for prey. Fig. 2 defines the steps involved in the WOA.

1. Encircling Prey

Humpback whales first identify the prey's position before neighbouring it. If the optimum solution has been recognized, the places of the alternative selections have been subsequently modified. The accurate formula for such modifications has been represented in Eqs. (5) and (6).

$$\vec{D} = \left|\vec{C}.\vec{X} * (t) - \vec{X}(t)\right| \tag{5}$$

$$\vec{X}(t+1) = \vec{X} * (t) - \vec{A} \cdot D \tag{6}$$

From these mathematical formulae, $X *$ defines the best solution vector, coefficient vectors are denoted as $\vec{A}$ and $\vec{C}$, and t characterizes the existing iteration.

The coefficient vectors $\vec{A}$ and $\vec{C}$, computation of the vectors will represented in Eq. (7) and Eq. (8)

$$\vec{A} = 2\vec{a}\,.\vec{r} - \vec{a} \tag{7}$$

$$\vec{C} = 2.\vec{r} \tag{8}$$

Now, $\vec{a}$ signifies the minimizing vector at 2 to 0 in the iteration, and $\vec{r}$ denotes the random vector with the specified formulae.

Figure 2: Steps involved in WOA

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2. Bubble Net Attacking Technique

While the prey is positioned, the whale tactics employ two movements: spiralling and tightening the circle. During the spiral movement, it becomes crucial to differentiate among the best search agents. Eqs. (9) and (10) create the spiral movement mathematical formulae.

$$X(t+1) = \vec{D}'.e(bl).\cos(2\pi l) + \vec{X}*(t) \quad (9)$$

$$\vec{D}' = \vec{X}*(t) - \vec{X}(t) \quad (10)$$

These statistical equations for l can comprise a random value at interval $[-1,1]$, and b denotes the logarithmic spiral constant. Applying the $\vec{A}$ and $\vec{C}$ vectors, it will be possible to determine the locations of points adjacent to the best search agent to be recognized.

Whales must be chosen if it is moving in a linear or spiral way while hunting. The expressions are presented in Eqs. (11) and (12),

$$\vec{X}(t+1) = \{\vec{X}(t) - \vec{A}.\vec{D}p < 0{,}5 \quad (11)$$

$$\vec{D}.ebl.\cos(2\mu l) + \vec{X}*\ (t)p => 0{,}5 \quad (12)$$

p, [0,1] means a randomly generated number.

3. Search for Prey

The value of vector $\vec{A}$ defines if the global or local searches have been executed. A general search should be performed if the condition is A>1 or A<-1. Due to such conditions, points that will be more away than the ultimate points to be elected. Eqs. (13) and (14) exhibit the statistical formulae for seeking prey.

$$\vec{D}' = \vec{C}.\vec{X}rand - \vec{X} \quad (13)$$

$$\vec{X}(t+1) = \vec{X}rand - \vec{A}\cdot\vec{D} \quad (14)$$

We know that $\vec{X}rand$ determines a randomly selected search agent.

4. Result Analysis

The performance evaluation of the NMOOSRA-WOA technique is provided under three datasets.

Table 1 and Fig. 3 represent brief predictive results of the NMOOSRA-WOA technique on the Axis Bank dataset. The results indicated that the NMOOSRA-WOA technique correctly predicted stock prices. With time 50 and an actual value of 53.93, the NMOOSRA-WOA technique predicted a stock price of 77.38. Next, with a time of 100 and an actual value of 68.60, the NMOOSRA-WOA method predicted a stock price of 86.23. Besides a time of 200 and an actual value of 100.91, the NMOOSRA-WOA system predicted a stock price of 115.61. Moreover, with time 300 and an actual value of 124.39, the NMOOSRA-WOA method predicted a stock price of 131.28, respectively.

Table 1: Predictive outcome of NMOOSRA-WOA technique under Axis Bank dataset

Stock Price Prediction - Axis Bank Dataset		
Time	Actual Stock Price	Predicted Stock Price
0	56.84	946.93
50	53.93	77.38
100	68.60	86.23
150	74.44	95.04
200	100.91	115.61

DOI: https://doi.org/10.54216/IJNS.240113
Received: August 18, 2023 Revised: December 19, 2023 Accepted: April 03, 2024

250	115.59	133.21
300	124.39	131.28

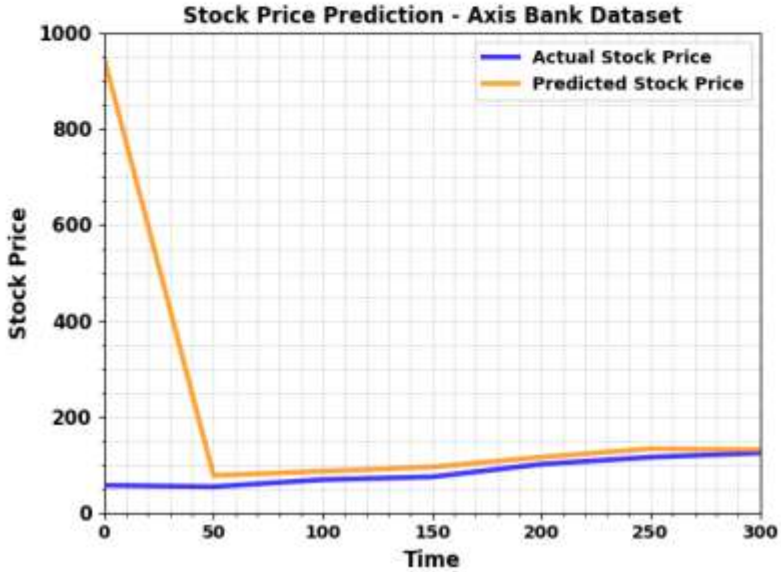

Figure 3: The predictive outcome of the NMOOSRA-WOA model at the Axis Bank dataset

Table 2 and Fig. 4 denote a detailed predictive outcome of the NMOOSRA-WOA technique on the BHEL dataset. These experimentation outcomes indicated that the NMOOSRA-WOA method appropriately predicted the stock prices.

Table 2: Predictive outcome of the NMOOSRA-WOA model at BHEL dataset

Stock Price Prediction - BHEL Dataset		
Time	Actual Stock Price	Predicted Stock Price
0	51.43	939.90
100	69.16	78.04
200	148.96	160.76
300	134.19	125.31
400	116.49	95.80
500	89.86	80.99
600	163.68	140.10
700	184.40	166.69
800	190.30	178.51

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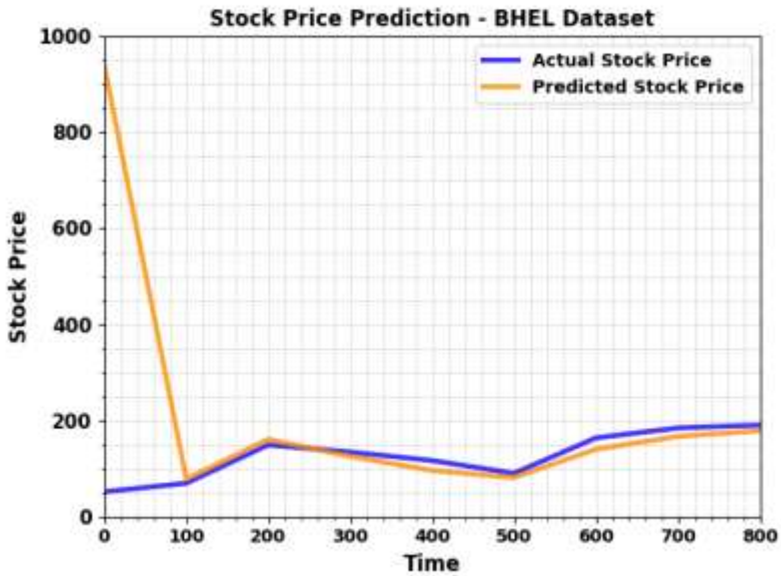

Figure 4: Predictive analysis of the NMOOSRA-WOA system at the BHEL dataset

Based on time 100 and an actual value of 69.16, the NMOOSRA-WOA algorithm predicted a stock price of 78.04. Meanwhile, with a time of 200 and an exact value of 148.96, the NMOOSRA-WOA system predicted a stock price of 160.76. Also, with a time of 400 and an actual value of 116.49, the NMOOSRA-WOA technique predicted a stock price 95.80. Finally, with a time of 800 and an actual value of 190.30, the NMOOSRA-WOA model predicted a stock price of 178.51 correspondingly.

Table 3 and Fig. 5 examine comprehensive predictive outcomes of the NMOOSRA-WOA method on the Maruti dataset. These experimental gained values pointed out that the NMOOSRA-WOA method appropriately predicted the stock prices.

Table 3: Predictive outcome of the NMOOSRA-WOA technique on the Maruti dataset

Stock Price Prediction-Maruti Dataset		
Time	Actual Stock Price	Predicted Stock Price
0	53.13	969.94
20	59.26	71.46
40	40.90	74.51
60	47.01	65.35
80	53.17	71.50
100	62.34	80.64
120	68.42	74.54

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Received: August 18, 2023 Revised: December 19, 2023 Accepted: April 03, 2024

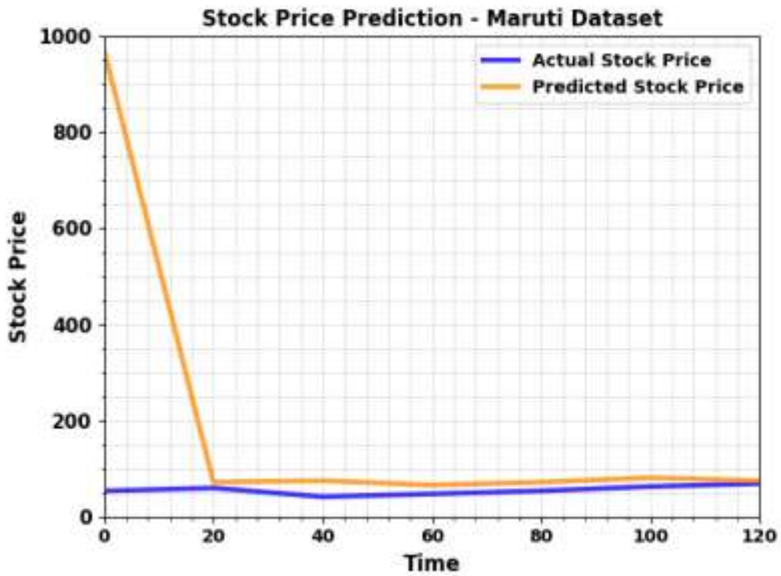

Figure 5: The predictive outcome of the NMOOSRA-WOA method on the Maruti dataset

According to time 20 and its actual value of 59.26, the NMOOSRA-WOA algorithm predicted the stock price of 71.46. Similarly, with time 60 and its actual value of 47.01, the NMOOSRA-WOA method predicted a stock price of 65.35. Next, time 80 and its actual value of 53.17, the NMOOSRA-WOA algorithm predicted the stock price of 71.50. In conclusion, with time 120 and its actual value of 68.42, the NMOOSRA-WOA technique predicted a stock price of 74.54.

Table 4 and Fig. 6 show comparative MAE results of the NMOOSRA-WOA technique on three datasets. On BHEL data, the NMOOSRA-WOA technique gains a reduced MAE of 0.0034, while the MM-HPA, GAN-HPA, MMGAN-HPA, and DBODL-SIPPFF models obtain increased MAEs of 0.0134, 0.0123, 0.0159, and 0.0080, respectively.

Table 4: Comparative MAE results of the NMOOSRA-WOA model at three datasets

MAE					
Stock Ticker	MM-HPA	GAN-HPA	MMGAN-HPA	DBODL-SIPPFF	NMOOSRA-WOA
BHEL	0.0134	0.0123	0.0159	0.0080	0.0034
AXISBANK	0.0157	0.0159	0.0155	0.0062	0.0051
MARUTI	0.0162	0.0164	0.0119	0.0065	0.0032

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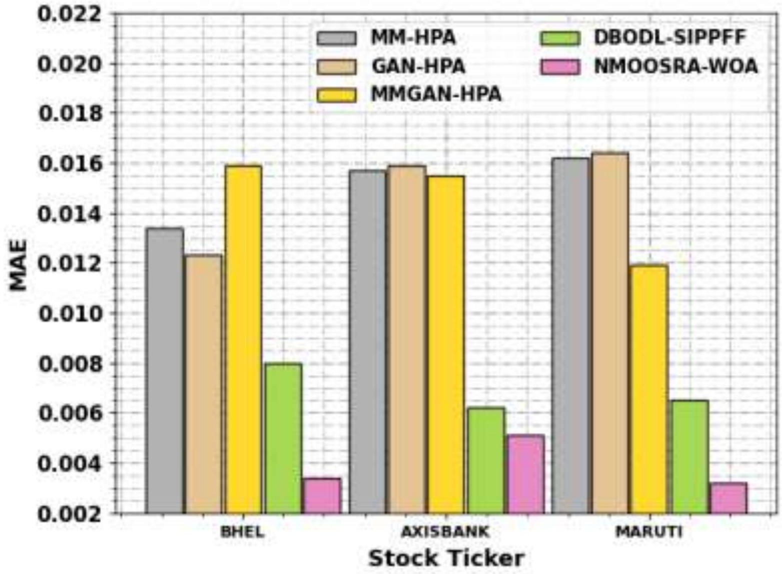

Figure 6: MAE results of the NMOOSRA-WOA method under three datasets

Also, in AXISBANK data, the NMOOSRA-WOA technique gets decreased MAE of 0.0051, whereas the MM-HPA, GAN-HPA, MMGAN-HPA, and DBODL-SIPPFF algorithms attain increased MAE of 0.0157, 0.0159, 0.0155, and 0.0062. Finally, MARUTI data, the NMOOSRA-WOA system obtains a diminished MAE of 0.0051; however, the MM-HPA, GAN-HPA, MMGAN-HPA, and DBODL-SIPPFF techniques achieve improved MAE of 0.0162, 0.0164, 0.0119, and 0.0065. Hence, the NMOOSRA-WOA technique reports better performance.

5. Conclusion

In this study, we have introduced an NMOOSRA-WOA for unravelling financial futures through inverse problem-solving. The NMOOSRA-WOA incorporates linear scaling normalization, NMOOSRA-based prediction, and WOA-based parameter tuning to boost the robustness and accuracy of economic predictions. The NMOOSRA technique generates predictions based on past financial time series data. Moreover, the framework integrates the WOA for parameter tuning, which leverages the search abilities of whale pods to optimize predictive performance and finetune model parameters. Experimental results on real-time financial datasets demonstrate the proposed framework's superiority and efficacy over other classical prediction techniques, highlighting its potential for risk management within dynamic financial markets and real-time applications in investment decision-making.

Funding: “The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through a large group Research Project under grant number RGP2/462/44”

Conflicts of Interest: “The authors declare no conflict of interest.”

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DOI: https://doi.org/10.54216/IJNS.240113
Received: August 18, 2023 Revised: December 19, 2023 Accepted: April 03, 2024