Designing a Novel Model for Stock Price Prediction Using an Integrated Multi-Stage Structure: The Case of the Bombay Stock Exchange

Mojtaba Sedighi[1] and Fereydoon Rahnamay Roodposhti[2]

Abstract

Stock price prediction is considered a strategic and challenging issue in the stock markets. Considering the complexity of stock market data and price fluctuations, the improvement of effective approaches for stock price prediction is a crucial and essential task. Therefore, in this study, a new model based on "Adaptive Neuro-Fuzzy Inference System (ANFIS), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA)" is employed to predict stock price accurately. ANFIS has been utilized to predict stock price trends more precisely. PSO executes towards developing the vector, and GA has been utilized to adjust the decision vectors employing genetic operators. The stock price data of top companies of the Bombay Stock Exchange (BSE) from 2010 to 2020 are employed to analyze the model functionality. Experimental outcomes demonstrated that the average functionality of our model (77.62%) was achieved noticeably better than other methods. The findings verified that the ANFIS-PSO-GA model is an efficient tool in stock price prediction which can be applied in the different financial markets, especially the stock market.[3]

JEL: F30; F37; G10; G11; O16

Keywords: Stock Price Prediction, Technical Analysis, ANFIS, PSO, GA

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1. Introduction

Stock price prediction is a strategic and challenging activity in the modern financial world. Considering the importance and effects of precise stock market predictions, many researchers are trying to provide an efficient way to predict stock prices. Precise prediction techniques are so important in portfolio management which is crucial for various sectors, including stock markets, banks, investment companies, and insurance companies. Based on broad studies in academic investigations, many methods and models have been presented with different levels of success.

Stock market forecasters concentrate on improving techniques to predict stock prices correctly and trying to get higher returns by employing distinct investing procedures. One of these distinct strategies is technical analysis which has been applied to analyze investments and determine trading prospects by assessing statistical trends collected from trading activities, for instance, stock price fluctuations and volume of deals. Technical analysis focuses on historical price patterns of stock trends.

In contrast, fundamental analysis is an approach of examining securities by trying to determine the intrinsic value of a stock (Lev and Thiagarajan 1993). Technical analysis is one major school of thought that helps investors and traders when making investment decisions and forecasting stock prices (Murphy 1999). Technical analysts believe that past trading activities and stock price fluctuations could be helpful indicators to predict the future price of securities. Technical indicators are mathematical computations utilized by traders to predict stock price trends. These indicators merely work with historical data, including price and volume, to identify the probable direction of the stock price. They are employed as instruments to help investors in making buy/sell decisions (Brown and Jennings 1989).

In this investigation, a new method by integrating ANFIS, PSO, and GA has been designed for stock price prediction in the Bombay Stock Exchange. The model consists of three stages: The first stage is ANFIS, the second stage is PSO, and finally, the third stage is GA. The ANFIS method learns the principles and membership functions from data. ANFIS is adaptive network nodes and directional links with connected learning principles. ANFIS is the adaptive network of selection to be examined systematically and employed for high-frequency predictions (Jang and Sun 1995).

PSO is a metaheuristic worldwide optimization paradigm that utilizes the notion of public interplay to deal with issues. It has been utilized effectively for many different search and optimization troubles. PSO is a simple but strong search approach. PSO executes towards developing the vector, and GA has been utilized to adjust the decision vectors employing genetic operators. The goal of combining PSO-GA is to incorporate the benefit of the GA and PSO simultaneously (Davis 1991, Shi and Eberhart 1999).

In this study, a model named ANFIS-PSO-GA has been suggested to deal with stock price prediction challenge employing PSO to provide a high-quality solution. All methods have been implemented in “Mathworks MATLAB R2019”.

According to the above-noted items, stock price prediction is extremely important for financial specialists and stock traders. For this reason, we decided to design a powerful and successful method to predict the stock price precisely.

The rest of this paper is structured as follows: Section 2 reviews prior studies. The methodology and modeling are explained in section 3, and Section 4 proposes the results of this paper. In Section 5 discussion and conclusions of this investigation are presented.

2. Literature Review

Stock price prediction is an important financial issue that has attracted the attention of many researchers and traders. In previous years, many methods and models have been recommended for getting precise forecasts.

In one of the earliest investigations, Kimoto, Asakawa et al. (1990) introduced a method based on modular neural networks for stock price forecasting on the TOPIX. They improved several learning algorithms for the TOPIX, and their method attained precise forecasts and the simulation on stock trading revealed a great profit.

Donaldson and Kamstra (1999) utilized multiplayer feedforward networks with nonlinear combinations to forecast the S&P 500 stock index. Their method can account for the impacts of relations between time-series predictions. The results suggested that their technique functions better than other conventional predicting approaches.

(Kim and Han 2000) have offered the GA method for the determination of link weights for ANNs to forecast the stock price index. Their outcomes demonstrated that the GA method works better than the other two conventional methods

Leigh, Paz et al. (2002) integrated pattern recognition with NNs to forecast the New York Stock Exchange Composite Index. The outcomes showed the abilities of the offered hybrid method.

Diler (2003) trained neural networks depending on different technical indicators to approximate the trends of the ISE 100 Index. The results of their study displayed that the direction of the ISE 100 Index could be forecasted at a rate of 60.81%.

Cao, Leggio et al. (2005) intended to illustrate the precision of ANN in stock price forecasting for companies exchanged on the Shanghai Stock Exchange (SHSE). Their outcomes demonstrated that neural networks work better than linear methods. De Menezes and Nikolaev (2006) utilized a new NN structure which employed polynomials to create an ANN. They utilized the genetic algorithm to calculate ANN parameters. Their research provided better outcomes for some troubles however it requires progression.

Ince and Trafalis (2008) proposed a new approach for stock price forecasting by utilizing kPCA and SVR, based on the presumption that the upcoming price of a stock will depend on its technical indicators. In addition, they employed factor analysis to find out the most key input technical indicators for a prediction approach and applied MLP neural networks to construct the predicting approach. This research was conducted on the daily stock prices of the ten companies which traded on the NASDAQ. The results revealed that the suggested approaches generate more appropriate findings as compared to the kPCA-SVR. Moreover, there is not any significant difference in predicting capabilities between the MLP neural model and SVR concerning the MSE.

Zhang and Wu (2009) suggested a method named IBCO that was combined into BPN to develop a method for forecasting various stock indices. The results demonstrated that their method provides less computational intricacy, more desirable forecasting accuracy, and less training time.

Majhi, Panda et al. (2009) suggested a method named FLANN for stock price forecasting of leading stock exchange indices, including DJIA and S&P 500. They confirmed that the suggested method is an efficient method computationally.

Majhi, Panda et al. (2009) suggested a method named FLANN for short and long run forecasts of stock price for leading stock exchange indices: DJIA and S&P 500. Their suggested method is an efficient technique to stock price prediction.

Zhang and Wu (2009) offered a combination method that connected two ANFIS controllers to predict stock price fluctuations for the next day in the Athens and the NYSE. The offered technique worked effectively in trading simulation, and the results revealed that their approach works better than other approaches in terms of percentage of prediction accuracy.

Cheng, Chen et al. (2010) utilized the fuzzy time series model by combining RS and GA to predict Taiwanese stock prices. The outcomes indicated that their model performs better than other methods regarding precision.

Chang, Wei et al. (2011) offered a hybrid ANFIS model based on AR and volatility to predict the stock price of the TAIEX. To examine the functionality of prediction, their model is compared with other methods. The outcomes revealed that the model works better than other methods in terms of RMSE.

Hsieh, Hsiao et al. (2011) incorporated wavelet transformations and RNN to predict international stock market fluctuations. Additionally, they utilized the ABC algorithm to set the parameters of the RNN weights. This investigation represented the simulation outcomes of four international stock exchanges, which include DJIA, FTSE-100 Index, Nikkei-225 Index, and TAIEX. The outcomes indicated that their model significantly works better than other approaches.

Chen and Kao (2013) joined PSO and SVM in their fuzzy time series method. They indicated that the model performs better than other conventional methods for stock market predictions.

Wei (2013) has offered a method that employs an adaptive expectation genetic algorithm to optimize ANFIS for stock price prediction. In their method, there were four techniques that have used from important technical indicators. After RMSE examination, their outcomes showed that their method works better than the other three predicting methods for the six-year period of TAIEX.

Reddy and Clinton (2016) utilized the GBM approach to simulate stock price direction on the large listed Australian companies listed on the S&P/ASX 50 Index from 2013 to 2014. They employed three methods to examine the validity of the model, including correlation coefficient, MAPE, and direction prediction accuracy. The outcomes indicated that the chances that the stock price simulated with GBM move in the same direction as real stock prices were a little greater than 50%. Nevertheless, after the formation of the portfolio, the outcomes had better performance.

Sedighi, Jahangirnia et al. (2019) proposed a new stock price forecasting method, which employs ABC, ANFIS, and SVM, and provides a more accurate picture of future stock prices. Their method was based on twenty technical indicators on stock price data of the U.S. Stock market from 2008 to 2018. Eventually, it became clear that their model was more accurate and reliable than the other methods.

3. Methodology

In this section, a new hybrid model for stock price prediction is designed by applying PSO, GA and ANFIS to generate a more accurate approach in contrast to related methods. In the next subsections, the details of the three sections of our model have been explained.

3.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a type of adaptive networks containing both neural networks and fuzzy logic rules. Neural networks are monitored by learning algorithms that use a range of historical data to predict future values (Jang 1993).

The utilization of ANFIS causes it to be easier to reconcile the rule base choice to the status. Within this approach, the control base is chosen using neural network approaches using the reverse propagation algorithm. To improve the capabilities and functionality, the fuzzy logic characteristics, ex, the approximation of a nonlinear system by adapting the IF-THEN regulations, are adopted in such a modeling approach (Jang, Sun et al. 1997).

Two equations were utilized in the If-Then technique for the Takagi-Sugeno strategy, are cited below:

$$E1 = \text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ Then } f1 = p_1x + q_1x + r_1$$

$$E2 = \text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ Then } f2 = p_2y + q_2y + r_2$$

Wherein:
A_1, B_1, A_2, B_2 : Membership functions of each input x and y
$p_1, p_2, q_1, q_2, r_1, r_2$: Linear parameters in part-Then (consequent part)

According to Figure 1, the ANFIS structure has five layers.

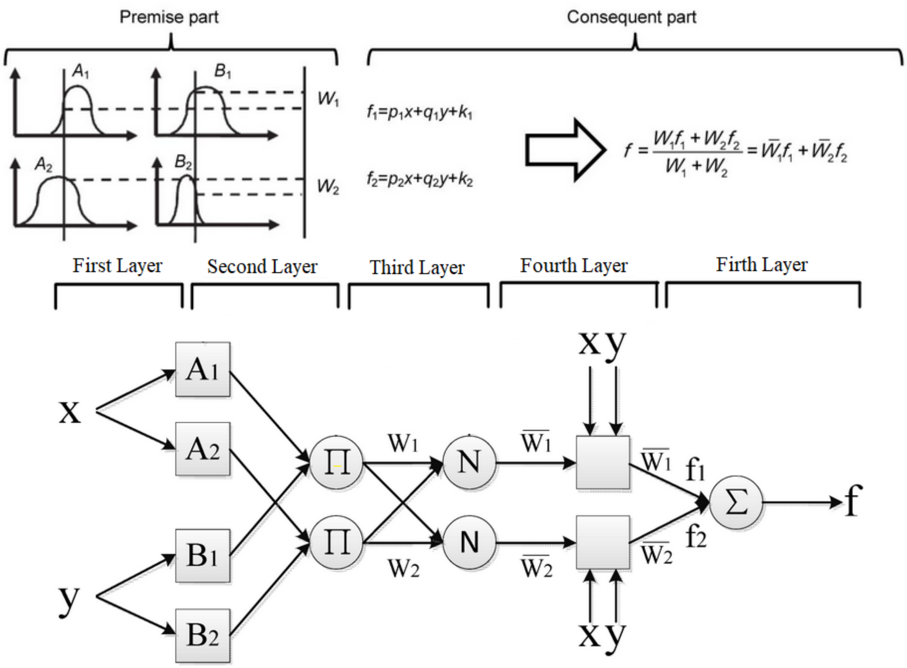

Figure 1. ANFIS Structure

Layer 1:

$$\mu_{Ai}(x) = \exp\left[-\left(\frac{x-c_i}{2a_i}\right)^2\right] \tag{1}$$

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b}} \tag{2}$$

$$O_{1,i} = \mu_{Ai}(x), \qquad i = 1,2 \tag{3}$$

$$O_{1,i} = \mu_{Bi-2}(y), \qquad i = 3,4 \tag{4}$$

Layer 2:

$$O_{2,i} = \mu_{Ai}(x) * \mu_{Bi}(y) \qquad i = 1,2 \tag{5}$$

Layer 3:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_i w_i}V \tag{6}$$

Layer 4:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{7}$$

$\bar{w}_i$: The normalized firing power from the previous layer
$(p_i x + q_i y + r_i)$: A parameter in the node.

Layer 5:

(8)

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

3.2 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) was developed by Kennedy and Eberhart (1995) which is a population-based search method. This algorithm starts by producing the initial particles and allocating them initial velocities. It measures the objective function at each particle place and specifies the best function value and the best place. It selects new velocities, depending on the present velocity, the particles' individual best places, and the best places of their neighbours (Eberhart and Kennedy 1995). Every particle realizes its best value so far (P_{best}) and the best among the group (G_{best}). Every particle changes its state utilizing its present velocity and its interval from P_{best} and G_{best}.

The velocity of every particle is calculated as follows:

$$V_i^{k+1} = W^k V_i^k + C_1 rand\left(P_{best} - X_i^k\right) + C_2 rand\left(G_{best} - X_i^k\right) \tag{9}$$

Wherein:

V_i^k: Velocity of i^{th} particle in k^{th} iteration.

$\boldsymbol{X_i^k}$: Position of the particle in k^{th} iteration.

W^k: Inertia Weight.

$$W^k = W_{max} - \left(\frac{W_{max} - W_{min}}{itermax}\right)\text{iter} \tag{10}$$

The position of the particle is adjusted by $X_i^{k+1} = X_i^k + V_i^{k+1}$

In the present PSO approach, the lower than inequality limitation is supplemented to the objective function to create a new objective function as:

$$F = \sum_{i=1}^{NG} a_i P_i^2 + b_i P_i + c_i + \left|\left(\sum_{i=1}^{NG} d_i P_i^2 + e_i P_i + f_i\right) - E_{limit}\right| \tag{11}$$

Equality limitation of true strength is operated in the following procedure.

The loading on the last generator (NG^{th} generator) is chosen as dependent and the level of NG^{th} generator is as follows:

$$P_{NG} = P_D - P_L - \sum_{i=1}^{NG-1} P_i \tag{12}$$

P_L: A function of all the generators comprising the dependent generator. It is calculated as follows:

$$\boldsymbol{P_L = \sum_{i=1}^{NG-1} \sum_{j=1}^{NG-1} P_i B_{ij} P_j + 2P_{NG} \sum_{i=1}^{NG-1} \left[B_{NG,i} P_i\right] + B_{NG,NG} P_{NG}^2} \tag{13}$$

After replacement the Equation 13 in Equation 12, we achieve Equation 14:

(14)

$$\boldsymbol{B_{NG,NG}P_{NG}^{2}} + \left[\boldsymbol{2\sum_{i=1}^{NG-1} B_{NG,i}P_i - 1}\right]\boldsymbol{P_{NG}} + \left[\boldsymbol{P_D} + \boldsymbol{\sum\nolimits_{i=1}^{NG-1}\sum_{j=1}^{NG-1} P_iB_{ij}P_j} - \boldsymbol{\sum_{i=1}^{NG-1} P_i}\right] = \boldsymbol{0}$$

Equation 14 is a quadratic in P_{NG} that can be solved, to achieve P_{NG}.

3.3 Genetic Algorithm (GA)

GA is an algorithm for dealing with both constrained and unconstrained optimization troubles. It was first released by Holland (1992), and its improvement was made by Goldberg (1989). GA is certainly one of the most-widely applied algorithms utilized by investigators in various areas for the optimization of complex issues. The GA framework, similar to the other evolution algorithms, is comprised of a population, wherein every individual in it is regarded as an answer to the trouble (Goldberg and Holland 1988).

An individual is named chromosome and it consists of various trouble variables which functions like genes in the algorithm. The search process is produced by improving a random population of chromosomes and generating the next generation of the population is performed via three operators, which are shown in Figure 2.

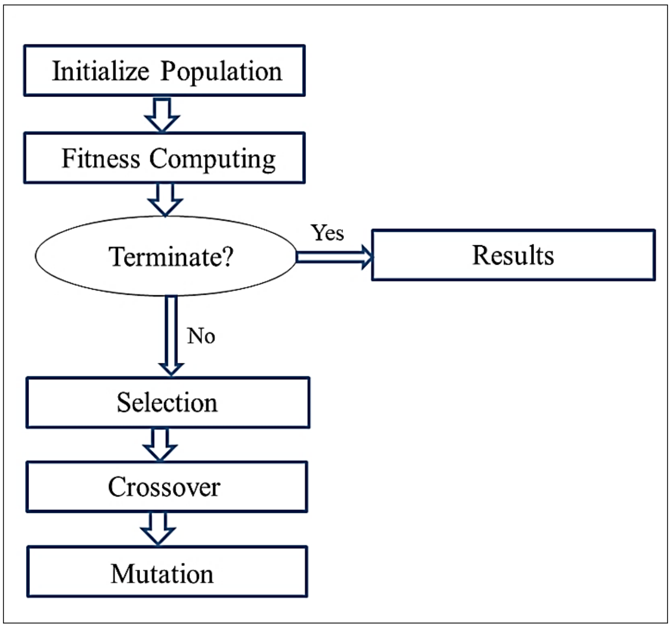

Figure 2. Genetic Algorithm Structure

3.4 Technical Indicators

In this paper, for all the companies, four parameters including "Open, High, Low, Close" were utilized to produce the following technical indicators:

- Absolute Price Oscillator
- Accumulation Distribution
- Average Directional Movement
- Average True Range
- Bollinger Bands
- Chande Momentum Oscillator
- Commodity Channel Index
- Directional Movement Index

- Moving Average Convergence Divergence
- On Balance Volume
- Parabolic Stop and Reverse
- Rate of Change
- Relative Strength Index
- Volume Oscillator
- Williams %R

3.5 Proposed Model

As shown in Figure 3, the structure of the offered model for the stock price prediction has been demonstrated.

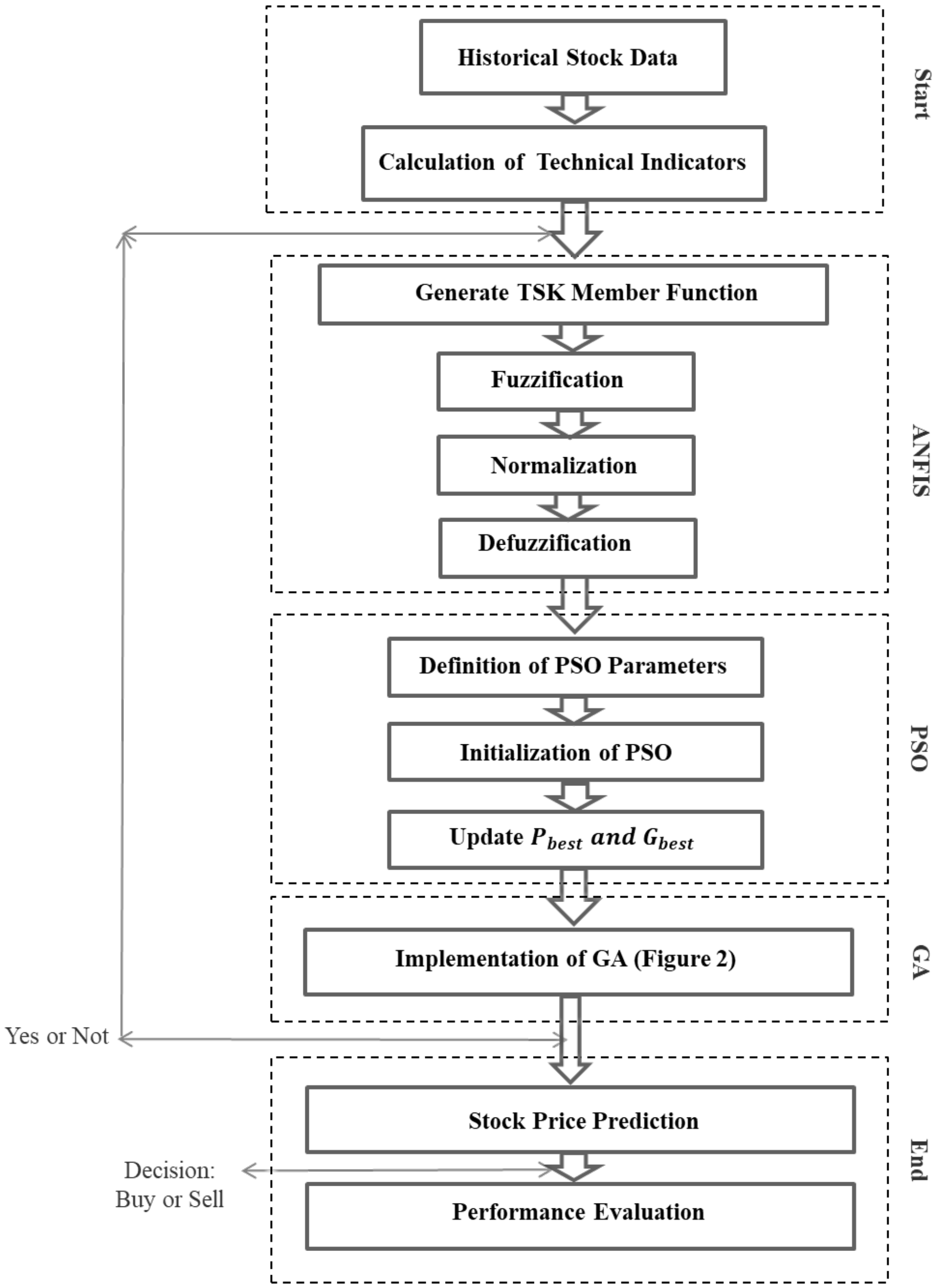

Figure 3. Presented Model

After the computations of technical indicators, they have been employed in the model as input variables. At first, we employed the ANFIS to predict stock price trends more precisely, and then the stock data were normalized. At the second stage, the PSO is utilized to enhance the functionality of ANFIS by setting the membership functions and minimizing errors. At the third stage, the GA is implemented to adjust the decision vectors employing genetic operators.

4. Results

4.1 Data and Parameter Setting

We implement the model utilizing the daily stock price of top companies of BSE. All data was gathered from "www.bseindia.com" and "www.indiainfoline.com".
The research period of our study is satisfactory for the examination of the model since the major economic and political events, such as different Business cycles including periods of expansions and contractions have occurred in this period. To improve the model efficiency, the period of investigation was divided into several years.

Table 1. Training | Testing Data

Training Data		Observations	Testing Data		Observations
From	**To**		**From**	**To**	
04/11/2010	03/18/2012	1303	04/11/2012	03/18/2014	1101
04/11/2014	03/18/2016	1378	04/11/2016	03/18/2018	1126
04/11/2018	03/18/2019	1435	04/11/2019	03/18/2020	1145

The information about the training and testing data indicated in Table 2. Around 75% of the data allocated for training, and 25% for testing.
In the execution of ANFIS-PSO-GA, it is necessary to consider the limitations of the BSE such as limitations of price variations and volume of the trades in the daily transactions. The instructions of deals of Bombay Stock Exchange have been considered in our model. The Bombay Stock Exchange is Asia's first exchange and the largest securities market in India. India has emerged as one of the world's fastest-growing economies, and it is projected to be one of the top three economies worldwide in the next ten years (Misra 2018).

4.2 Forecasting Performance Evaluation

The experimental data were utilized for analyzing the functionality of the model. The five measures were employed to make comparison between the actual and predicted prices. These criteria consist of RMSE, MAE, MAPE and Theil's U_1 and U_2. The equations of these criteria are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - P_t)^2} \tag{15}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|A_t - P_t| \tag{16}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - P_t}{A_t}\right|$$

$$Theil's\ U_1 = \frac{[\sum_{t=1}^{N}(A_t - P_t)^2]^{\frac{1}{2}}}{[\sum_{t=1}^{N} {P_t}^2]^{\frac{1}{2}}} \tag{18}$$

$$Theil's\ U_2 = \frac{\left[\frac{1}{N}\ \sum_{t=1}^{N}(A_t - P_t)^2\right]^{\frac{1}{2}}}{\left[\frac{1}{N}\sum_{t=1}^{N} {A_t}^2\right]^{\frac{1}{2}} + \left[\frac{1}{N}\sum_{t=1}^{N} {P_t}^2\right]^{\frac{1}{2}}} \quad ((19$$

Wherein:
A_t: Actual price at time t
P_t: Predicted price at time t

The comparison results of seven key indexes in the Bombay Stock Exchange (BSE) are presented in Tables 2-6 that confirmed the functionality of the model.

Table 2. The obtained outcomes of seven key indexes (BSE) based on RMSE

RMSE											
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
S&P BSE SENSEX	0.0088	0.0079	0.0065	0.0072	0.0086	0.0101	0.0094	0.0083	0.0078	0.0099	0.0114
S&P BSE SENSEX 50	0.0110	0.0059	0.0063	0.0141	0.0076	0.0125	0.0136	0.0079	0.0108	0.0087	0.0069
S&P BSE Bharat 22	0.0097	0.0073	0.0153	0.0058	0.0132	0.0079	0.0047	0.0105	0.0175	0.0078	0.0066
S&P BSE 500	0.0118	0.0068	0.0079	0.0055	0.0201	0.0178	0.0068	0.0114	0.0201	0.0093	0.0127
S&P BSE SmallCap	0.0065	0.0136	0.0120	0.0083	0.0058	0.0137	0.0211	0.0193	0.0064	0.0076	0.0113
S&P BSE MidCap	0.0076	0.0207	0.0143	0.0067	0.0094	0.0118	0.0099	0.0063	0.0126	0.0045	0.0086
S&P BSE LargeCap	0.0211	0.0145	0.0096	0.0119	0.0231	0.0072	0.0094	0.0122	0.0140	0.0203	0.0091

Table 3. The obtained outcomes of seven key indexes (BSE) based on MAE

MAE											
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
S&P BSE SENSEX	0.0196	0.0137	0.0046	0.0108	0.0211	0.0193	0.0064	0.0090	0.0114	0.0138	0.0212
S&P BSE SENSEX 50	0.0111	0.0085	0.0057	0.0135	0.0079	0.0100	0.0115	0.0078	0.0221	0.0048	0.0103
S&P BSE Bharat 22	0.0125	0.0136	0.0079	0.0108	0.0087	0.0069	0.0047	0.0103	0.0175	0.0001	0.0067
S&P BSE 500	0.0065	0.1022	0.0120	0.0083	0.0058	0.0059	0.0063	0.0141	0.0077	0.0060	0.0074
S&P BSE SmallCap	0.1076	0.0207	0.0143	0.0067	0.0094	0.0119	0.0099	0.0063	0.0126	0.0047	0.0087
S&P BSE MidCap	0.0214	0.0142	0.0096	0.0117	0.0231	0.0072	0.0094	0.0122	0.0140	0.0204	0.0092
S&P BSE LargeCap	0.1194	0.0039	0.0158	0.0049	0.0076	0.0212	0.0088	0.0079	0.0065	0.0138	0.0089

Table 4. The obtained outcomes of seven key indexes (BSE) based on MAPE

MAPE											
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
S&P BSE SENSEX	0.0082	0.0063	0.0071	0.0073	0.0045	0.0033	0.0049	0.0098	0.0058	0.0011	0.0074
S&P BSE SENSEX 50	0.0036	0.0072	0.0035	0.0012	0.0145	0.0236	0.0072	0.0023	0.0101	0.0062	0.0055
S&P BSE Bharat 22	0.0088	0.0064	0.0071	0.0020	0.0037	0.0044	0.0057	0.0011	0.0069	0.0179	0.0037
S&P BSE 500	0.0135	0.0127	0.0046	0.0032	0.0072	0.0086	0.0092	0.0027	0.0010	0.0076	0.0041
S&P BSE SmallCap	0.0069	0.0056	0.0087	0.0074	0.0047	0.0035	0.0075	0.0084	0.0095	0.0018	0.0023
S&P BSE MidCap	0.0028	0.0014	0.0065	0.0036	0.0022	0.0043	0.0068	0.0050	0.0064	0.0059	0.0047
S&P BSE LargeCap	0.0049	0.0092	0.0032	0.0005	0.0019	0.0033	0.0065	0.0024	0.0082	0.009	0.0085

Table 5. The obtained outcomes of seven key indexes (BSE) based on U_1

U_1											
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
S&P BSE SENSEX	0.0082	0.0063	0.0071	0.0073	0.0045	0.0033	0.0049	0.0098	0.0058	0.0011	0.0074
S&P BSE SENSEX 50	0.0036	0.0072	0.0035	0.0012	0.0145	0.0236	0.0072	0.0023	0.0101	0.0062	0.0055
S&P BSE Bharat 22	0.0088	0.0064	0.0071	0.0020	0.0037	0.0044	0.0057	0.0011	0.0069	0.0179	0.0037
S&P BSE 500	0.0135	0.0127	0.0046	0.0032	0.0072	0.0086	0.0092	0.0027	0.0010	0.0076	0.0041
S&P BSE SmallCap	0.0069	0.0056	0.0087	0.0074	0.0047	0.0035	0.0075	0.0084	0.0095	0.0018	0.0023
S&P BSE MidCap	0.0028	0.0014	0.0065	0.0036	0.0022	0.0043	0.0068	0.0050	0.0064	0.0059	0.0047
S&P BSE LargeCap	0.0049	0.0092	0.0032	0.0005	0.0019	0.0033	0.0065	0.0024	0.0082	0.009	0.0085

Table 6. The obtained outcomes of seven key indexes (BSE) based on U_2

U_2											
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
S&P BSE SENSEX	0.0103	0.0124	0.0119	0.0042	0.0082	0.0095	0.0082	0.0047	0.0023	0.0086	0.0051
S&P BSE SENSEX 50	0.0112	0.0099	0.0106	0.0005	0.0019	0.0021	0.0075	0.0034	0.0049	0.0019	0.0095
S&P BSE Bharat 22	0.0136	0.0167	0.0145	0.0020	0.0054	0.0034	0.0067	0.0021	0.0079	0.0056	0.0047
S&P BSE 500	0.0147	0.0162	0.0137	0.0036	0.0041	0.0043	0.0058	0.0060	0.0054	0.0069	0.0055
S&P BSE SmallCap	0.0181	0.0144	0.0162	0.0073	0.0045	0.0033	0.0039	0.0088	0.0068	0.0031	0.0084
S&P BSE MidCap	0.0107	0.0173	0.0190	0.0012	0.0056	0.0127	0.0062	0.0013	0.0124	0.0073	0.0064
S&P BSE LargeCap	0.0125	0.0151	0.0107	0.0138	0.0045	0.0032	0.0074	0.0091	0.0054	0.0022	0.0025

Table 7. The comparison results of methods

Method	RMSE	MAE	MAPE	U_1	U_2	Overall Performance
ANFIS-PSO-GA	1.1e-4	0.0009	0.0031	0.0012	0.0009	77.62%
ANFIS-PSO	6.4e-4	0.0142	0.0044	0.0489	0.0324	70.26%
PSO-GA	3.5e-4	0.0098	0.0065	0.0272	0.0256	68.45%
ANFIS	2.7e-4	0.0065	0.0072	0.0195	0.0143	61.23%
PSO	1.9e-4	0.0018	0.0086	0.0121	0.0088	59.74%
GA	9.5e-4	0.0182	0.0095	0.1025	0.0963	55.42%

Table 7 illustrates that the three criteria (RMSE, MAE, MAPE) for ANFIS-PSO-GA model are lower than the other models. Furthermore, Theil's U criteria of the model are more than other techniques (Theil 1958, Theil 1971). We utilized the procedure of (Sedighi, Jahangirnia et al. 2019) for executing ANFIS outlined in table 7. Based on the results in Tables 10 and 11, it could be realized that the ANFIS-PSO-GA could present the lowest error and the best precision. The ANFIS-PSO-GA is compared to other techniques that are verified by seven BSE indexes.

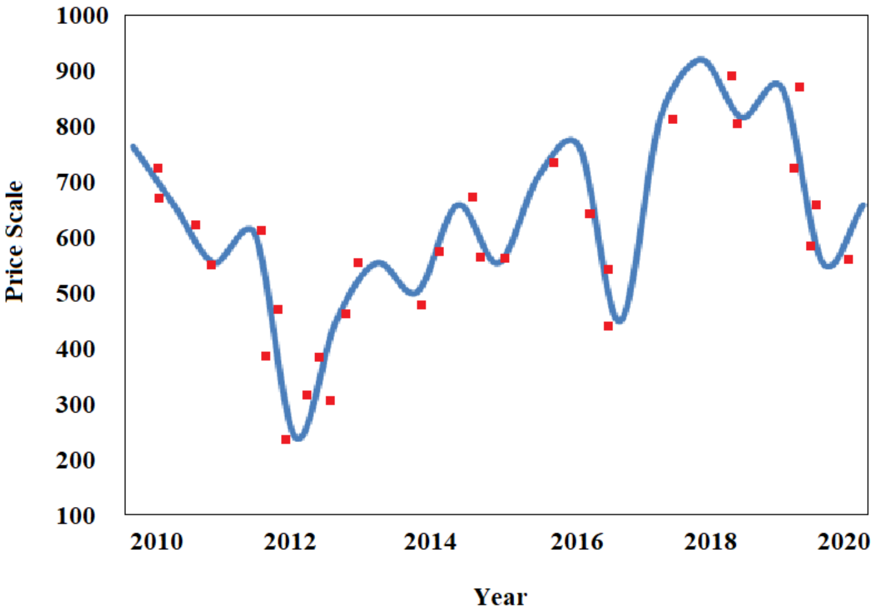

Figure 4. Performance Evaluation of ANFIS-PSO-GA

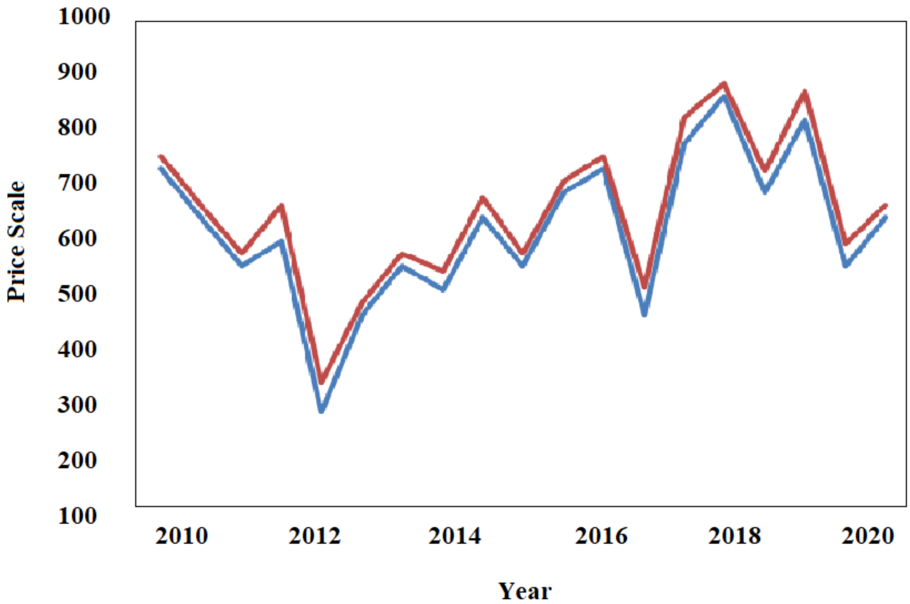

Figure 5. Model Fit

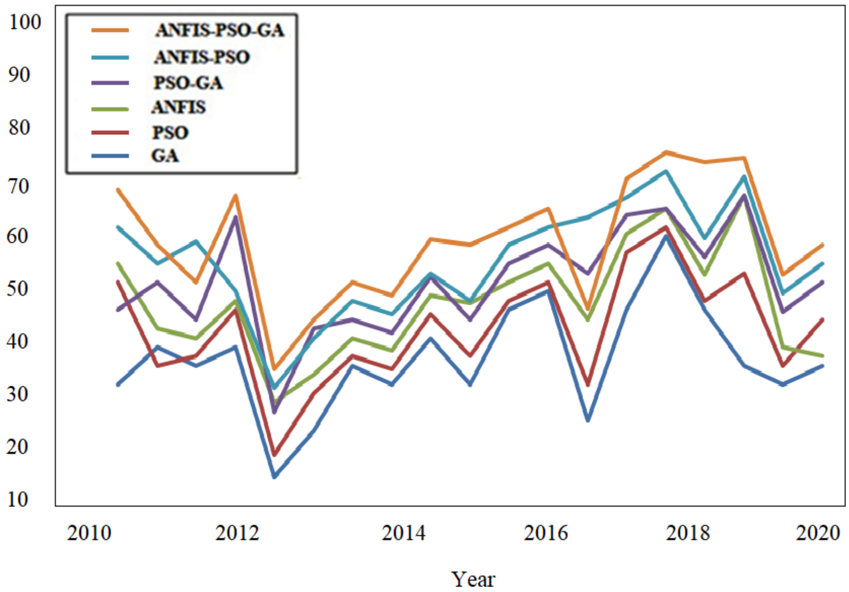

Figure 6. The Comparison Results of Models

The actual prices and predicted prices for ANFIS-PSO-GA model are shown in Figures 4 and 5. Comparison results of models are viewable in Figure 6 that is acceptable and sufficient. It demonstrates that the ANFIS-PSO-GA confirms the best performance.

5. Conclusion

Stock price prediction is necessary for the development of investment strategies in financial markets. This research revealed that the performance of stock price prediction could be considerably improved by utilizing ANFIS-PSO-GA model compared to other related methods.

In an effort to investigate the model, we applied it to stock price data of the Bombay Stock Exchange from 2010 to 2020. To show the overall performance, the model's five criteria were checked.

The experimental results revealed the effectiveness and robustness of the offered model compared to other related methods. Furthermore, the model is confirmed by predicting the daily stock price of companies which are admitted in the BSE. The technical indicators used in this study confirmed that they are helpful in forecasting the direction of stock price changes.

To our knowledge, our method is the first combination method that integrates three stages, including ANFIS, PSO and GA, for stock price prediction in the BSE.

The most important restrictions of this study are as follows: The lack of control of many of the conditions affecting the outcomes of the study, comprising the effect of parameters, for example, economic variables, political conditions, the situation of the global economy, laws and rules, etc., are beyond the reach of the researcher and can impact the offered model.

In future studies, the offered model can be further examined by utilizing other techniques.

Abbreviations

BSE	Bombay Stock Exchange
ANFIS	Adaptive Neuro-Fuzzy Inference System
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
TOPIX	Tokyo Stock Price Index
SHSE	Shanghai Stock Exchange

IBCO	Improved Bacterial Chemotaxis Optimization
NN	Neural Network
ANN	Artificial Neural Networks
SVR	Support Vector Regression
ABC	Artificial Bee Colony
FLANN	Functional Link Artificial Neural Network
ABC	Artificial Bee Colony
TAIEX	Taiwan Stock Exchange Capitalization Weighted Stock Index
SVM	Support Vector Machine
FTSE	Financial Times Stock Exchange
NYSE	New York Stock Exchange
DJIA	Dow Jones Industrial Average
GBM	Geometric Brownian Motion
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
NMSE	Normalized Mean Squared Error

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