

Data-Driven Time Series Modeling with Hurst Exponent for Nonlinear Indexes' Forecasting by Artificial Neural Networks

Yeliz Karaca[1,2(✉)] and Osvaldo Gervasi[3]

[1] University of Massachusetts Chan Medical School (UMASS), Lake Avenue North, Worcester, MA 01655, USA
yeliz.karaca@ieee.org

[2] Massachusetts Institute of Technology (MIT), Massachusetts Avenue, Cambridge, MA 02139, USA

[3] University of Perugia, Department of Mathematics and Computer Science, Perugia, Italy
osvaldo.gervasi@unipg.it

Abstract. Neural networks reveal the benefit of requiring less formal statistical training owing to their capability of detecting complex nonlinear relationships between dependent and independent variables implicitly. Machine learning, artificial neural networks (ANN) and deep learning, on the other hand, show their upper hands in forecasting and prediction processes involved in various domains, including the analyses concerning financial indexes among other ones. Besides these advances and applications, time series models based on financial data expressed by financial theories may form as a basis for forecasting a series of data. When theories may not directly be applicable to predict the market values with external impacts, ANNs can be applied as a prediction tool for forecasting the market value series. Due to its robustness as a statistical means for examining sequential data over time, time series analyses examine financial stock market indices by identifying trends, predictive details and changing patterns toward accurate and efficient analyses in dynamic and nonlinear markets. Accordingly, the current study aims at forecasting based on the daily values of FCHI (France) and GSPC (India) indexes. Hurst exponent is applied to the dataset consisting of the Open, High, Low and Close values of the FCHI and GSPC indexes. Modeling for the purpose of the study is carried out by feed-forward backpropagation (FFBP) algorithm which is among the ANNs. The forecasting accuracy obtained from the modeling of the index values based on the past daily close attributes of 20 days is compared with respect to Mean Squared Error, and the results have validated the forecasting of indexes. As the steps, Hurst exponent is initially applied to the daily values (Open, High, Low, Close) of FCHI and GSPC indexes, leading to the generation of the dataset with more attributes. As the following step, the dataset with more attributes consisting of the FCHI and GSPC daily values are split into training dataset and test dataset for forecasting the indexes. Subsequently, the model constructed is used to compare the two datasets.

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2026
O. Gervasi et al. (Eds.): ICCSA 2025 Workshops, LNCS 15886, pp. 152–164, 2026.
https://doi.org/10.1007/978-3-031-97576-9_10

The forecasting accuracy of the index values' modeling based on the daily close values of 20 days is compared by Mean Squared Error. Lastly, modeling through the FFBP algorithm application to the new dataset generated and the FCHI and GSPC indexes enables the comparison and performing of forecasting with regard to these indexes. In addition, interpolation method is employed for managing missing data in the dataset. This approach is intended to a new mode of scheme and implementation tactics in an extended form to reveal the interaction between time series analysis, predictive modeling and indices. Thus, the models to be constructed can be evaluated regarding comprehensive outlooks that are concerned with decision-making, investment strategies' optimization and risk mitigation in various domains with accurate, reliable and data-driven aspects.

Keywords: Data-driven modeling · Nonlinear forecasting · Time series analysis · Hurst exponent · ANN · FFBP algorithm · Data interpolation method · Complexity modeling · Max-min normalization · Financial indexes

1 Introduction

Modeling based on predictive aspects builds on time series analysis by employing past data for the forecasting of future outcomes, and thus, correlations and causations concerning data enable to make informed decisions, strategic planning and management. Time series analysis in mathematical modeling addresses data points gathered sequentially over time, which allows for the capturing trends, fluctations and/or patterns that are critical for the interpreration of past behaviors as well as for the forecasting of future events. Producing a numeric score based on inputs including a variety of asset prices, a financial index can be used to follow up the performance of assets and securities in a standardized way. In that respect, indixes have key roles in the summarizing and normalizing of data, providing a consolidated metric to represent dynamic datasets. For instance, stock market indices track the performance of a group of securities. When time series and predictive models are integrated, indices will enhance the capabililty of interpretability and provide a clearer level of understanding by which trends as well as forecasts can effectively be monitored and communicated.

A statistical measure is used to classify time series and infer the level of difficulty in predicting and choosing an appropriate model for the series at hand [24]. Predicting changes of indexes long term trend is an important problem for validating strategies of investment to the financial instruments. Changes in this characteristic can enable one to predict the turning point of indexes value long term trend. In finance, stocks represent a certain portion of a company's capital [24]. They offer returns to their investors and stockholders while enabling companies to grow and gain recognition by providing them with resources [13,23,24]. While investigating the fractal nature of financial markets – specifically, the tendency of a time series to regress strongly to its mean or to cluster in a direction introduced

to fractal geometry, as Hurst's generation, the term Generalized Hurst Exponent [23]. The Hurst exponent is employed as a measure of the long-term memory of a time series, and long-term correlation memory refers to the interdependences existing among observation periods of the time series even if these periods are separated. In case of examination of long-term dependencies of the indexes, the investors could have better opportunities for informed decision-making processes related to daily data (open, low, high, close). The level of indexes' inefficiency and long-term correlation memory can be measured by applying several statistical and econometrical indicators, one of the most extensively-used measures being the Hurst exponent. These indicators are designed in a way that can measure the level of efficiency of the indexes' information without having knowledge concerning the underlying causal factors. To cite some work from literature, the following indicators have been used fort he analzing of the indexes. Kannan et al. [5], Roman et al. [18] and Ake et al. [1] performed financial index forecast applications with the data mining methods, while Inaoka [4], Evertsz [2], Moyano et al. [12] and Qian [16] conducted financial time series analysis with fractal and multifractal methods. In addition, Sakalauskas [19] applied index trading strategies with Shannon entropy and Hurst exponent indicators. Fuwape et al. [14], on the other hand, used fractal and entropy analysis for share indexes and domestic products, and Rejichi et al. [17] used test Hurst exponent behaviour for index efficiency purposes. Furthermore, machine learning, artificial neural networks (ANN) and deep learning have provided significant advances in forecasting and prediction in various domains, including the analyses concerning financial indexes. Machine learning addresses the development of algorithms enabling the systems to learn from data and thus to improve their performance by offering sound frameworks for identifying patterns and in big datasets. ANNs are adaptive to tasks that require nonlinear modeling and feature extraction which are assets that make ANNs effective for analyzing complex financial datasets. Deep learning algorithms are capable of recognizing patterns that are sequential and significant for purposes like predicting time series data such as economic indicators and stock market trends. The employment of machine learning and deep learning can allow researchers and practitioners to unravel nuanced insights and differences so that predictive models can be built toward anticipating future market behaviors [26]. The use of neural network models and hybrid models is proposed in a study which evaluates the effectiveness of neural network models that are acknowledged to be effective and dynamic in stock-market predictions. The models are analyzed by multi-layer perceptron, dynamic artificial neural network as well as hybrid neural networks using generalized autoregressive conditional heteroscedasticity for extracting new input variables with real exchange daily rate values belonging to the index of NASDAQ Stock Exchange [3]. The use of natural language processing (NLP) models in financial mathematics is also at stake in a work which used a mathematical-based sentiment analysis and deep learning models for forecasting the S&P 500 Index based on the summary text data to calculate sentiment scores [10]. Forecasting the shifts in stock indices plays a critical role for validating the potential strategies of monetary mechanisms, which is examined in a study characterizing complexity and self-similarity

based on fractal and entropy analyses for stock market forecast modeling. The authors applied these methods to demonstrate the critical significance of Hurst exponent (HE) computed by Rescaled Range (R/S) fractal analysis when used as indicator along with Shannon entropy (SE) and Renyi entropy (RE) concerning the stock indices' capability of future forecasting [9]. For the purposes of effective data selection and robust prediction, complexity and self-similarity characterization is addressed in another study which obtained analyses based on fractal analysis and wavelet entropy via the seven recognized indexes and formed the forecasting model by applying the ANN algorithms to the datasets [6]. The aim of forecasting stock indices by ANN algorithms is done through the comparison of two Hölder regularity functions forecasting accuracy by characterizing self-similar patterns in time series. The application of the ANN algorithms reveals how the most significant attributes are identified by Hölder functions in finance datasets [8].

Time series models based on financial data conveyed by financial theories may form as a basis for forecasting a series of data. At times such theories might not directly be applicable to predict the market values with external impacts. Notwithstanding, ANNs are preferred to be applied as a prediction tool for forecasting market value series. Time series analysis owing to its robustness as a statistical means for examining sequential data over time comes with its applications in the examination of financial stock market indices by identifying trends, predictive insights and seasonal patterns toward accurate and efficient analyses in dynamic markets. The current study aims to produce forecasting based on the daily values of FCHI (France) and GSPC (India) indexes between 2020 and 2024. Hurst exponent is applied to the dataset consisting of the Open, High, Low and Close values of the FCHI and GSPC indexes, which has made it possible to identify 16 new indicators. The modeling is performed by feed-forward backpropagation (FFBP) algorithm, which is as one of the ANNs proves to be among the widely implemented neural network topologies. The forecasting accuracy obtained from the modeling of the index values based on the past daily close attributes of 20 days is compared with respect to Mean Squared Error (MSE) whose result has validated the forecasting of indexes, showing the importance of Hurst exponent method.

The remainder of the paper is organized as follows: Sect. 2 presents the materials, methods and methodology with Hurst Exponent and FFBP, while Sect. 3 addresses experimental results. The last section is the conclusion, discussion and future directions.

2 Materials and Methods

2.1 Nonlinear Dynamic Time Series Data

Nonlinear dynamic time series data depict the sequences of observations in which the relationship between variables changes in a complex and nonlinear manner over time. When compared with linear time series, nonlinear dynamic time series data have the capability of capturing nuanced details and behaviors observed in

real-world phenomena, one of which is those in financial markets. The aim in the end is to reveal underlying patterns and predict future outcomes with higher accuracy levels. The dataset of the current study involves the daily values of FCHI and GSPC indexes based on the close levels at American dollar as the currency between April 2, 2020 and December 29, 2024. The dataset belonging to the stocks has been retrieved from the web address of the World Bank [25]. Table 1 provides information on the nonlinear dynamic time series data including the indexes, parameters and dataset size.

Table 1. Nonlinear Dynamic Time Series Data.

Indexes	Parameters	Dataset Size
FCHI	Open	1280×32
	High	
	Low	
	Close	
GSPC	Open	1280×32
	High	
	Low	
	Close	

Figure 1 depicts the flow chart concerning the application of Hurst exponent to the financial time series on the financial time series index dataset.

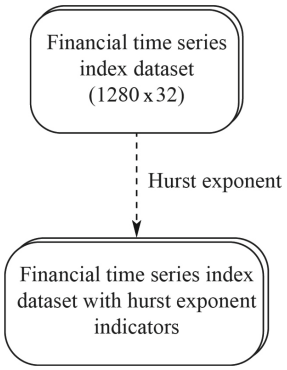

Fig. 1. Time Series Index Dataset with the application of Hurst Exponent.

The indexes belong to FCHI and GSBC stocks being traded for five weekdays within a week, and for the missing data in the dataset, interpolation method has been applied.

2.2 Methods and Methodology

Hurst Exponent. The Hurst exponent referring to the index of dependence or index of long-range dependence quantifies the relative tendency of a time series. The Hurst exponent, H, is defined with respect to the asymptotic behaviour of the rescaled range as a function of the time span of a time series [15].

For a time series $X = X_1, X_2, \ldots, X_n$, R/S analysis method steps are provided in the following mannner:

Step (1): The mean of the m value is calculated according to Eq. 1.

$$m = \frac{1}{n} \sum_{i=1}^{n} X_t \tag{1}$$

Step (2): The Z time series is calculated based on Eq. 2.

$$Y_t = X_t - m, \quad t = 1, 2, \ldots, n \tag{2}$$

Step (3): The cumulative deviation of the Z is calculated as per Eq. 3.

$$Z_t = \sum_{i=1}^{t} Y_i, \quad t = 1, 2, \ldots, n \tag{3}$$

Step (4): The range series is calculated in line with Eq. 4.

$$R_t = \max(Z_1, Z_2, \ldots, Z_t) - \min(Z_1, Z_2, \ldots, Z_t) \quad t = 1, 2, \ldots, n \tag{4}$$

Step (5): The calculation of the standard deviation of the S series is according to Eq. 5.

$$S_t = \sqrt{\frac{1}{t} \sum_{i=1}^{t} (X_i - u)^2} \quad t = 1, 2, \ldots, n \tag{5}$$

u value is the mean value from X_1 to X_t. Its mean is found in the regions of $[X_1, X_t], [X_{t+1}, X_{2t}]$ up to $[X_{(m-1)t+1}, X_{mt}]$. m = floor (n/t), and for the calculation in application, a t value that can be divided by n is chosen to use all the data [6]. Given these, Hurst exponent is employed for evaluating long-term correlation memory and classifying the time series. It equals to 0.5 if the analyzed time series is completely random. In this study, HE = 0.55 and its value approaches to 1, so it can be noted that the analyzed time series is persistent and has particular trend is not likely to show variations.

Artificial Neural Network (ANN). Neural networks have the ability to detect complex nonlinear relationships between dependent and independent variables implicitly. Since they require less formal statistical training, they are employed for detecting all the possible interactions between predictor variables. Furthermore, the significance of ANNs comes to the fore as they enable machines

to learn from data and to make intelligent decisions on real time basis. This capability of ANNs makes them applicable for the solution of problems with changing data while allowing for making the required adjustments as new variables and developments emerge. This adaptability is important in data-driven modeling strategies and methods, providing robustness in accuracy through a variety of nonlinear time series models [11].

Feed-Forward Back Propagation Algorithm (FFBP). Feed-forward back propagation has the aim of learning and mapping the relationships between inputs and outputs with the learning rule employed to adjust the system's weight values and threshold values to attain the minimum error [21]. It is also used to convey the complex relationship between the input and output values in a network set with each node or neuron having a value determined by the input received from the other units of the network system [20]. FFBP algorithm shows further benefits when compared with conventional methods considering the error percentage renders the program to extend on different types of field data [7]. Accordingly, each unit in the middle and output layers has a transfer function that transfers the signal it receives. The input layer units do not have a transfer function, but they are used to distribute input signals to the network. In addition to this, each connection has a numerical weight, which modifies the signals that pass through it. A three-layer feedforward network with a single output unit, k middle layer units and n input units is provided in Fig. 2.

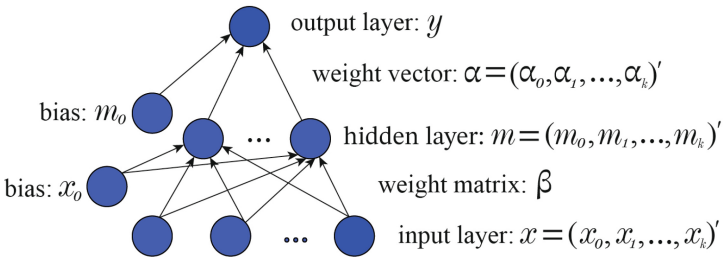

Fig. 2. The general structure of the FFBP algorithm.

The input layer can be represented by a vector. $X = (x_1, x_2, \ldots, x_n)'$ the hidden layer can be represented by a vector $M = (m_1, m_2, \ldots, m_n)'$, and y is the output. Any middle layer unit receives the weighted sum of all inputs and a bias term (denoted by x_0, x_0 always equals one) and produces an output signal.

$$m_j = F\left(\sum \beta_{ij} x_i\right) = F\left(X' B_j\right), j = 1, 2, \ldots, k, i = 0, 1, 2, \ldots, n \qquad (6)$$

In Eq. 6, F is the transfer function, x_i is the i_{th} input signal, and β_{ij} denotes the weight of the connection from the i_{th} input unit to thef h hidden layer unit.

In the same way, the output unit receives the weighted sum of the output signals of the middle layer units, and produces a signal.

As Eq. 7, shows:

$$y = G\left(\sum a_j m_j\right), j = 0, 1, 2, \ldots, k \tag{7}$$

G refers to the transfer function, e_j is the weight of the connection from the j_{th} middle layer unit to the output unit, and $j = 0$ indexes a bias unit m_0 which always equals to one.

$$y = G\left(a_0 + \sum_{j=1}^{k} a_j F\left(\sum \beta_{ij} x_i\right)\right) = f(X, \theta) \tag{8}$$

In line with Eq. 8, X is the vector of inputs, and

$$\theta = (a_0, a_1, \ldots, a_k, \beta_{01}, \beta_{02}, \ldots, \beta_{0k},\ \beta_{11}, \beta_{12}, \ldots, \beta_{1k}, \beta_{n1}, \beta_{n2}, \ldots, \beta_{nk})$$

is the vector of network weights. It is possible for F and G to take several functional forms, such as the threshold function which produces binary (0/1) output, the sigmoid (or logistic) function which produces output between 0 and 1. Equation (8) can be interpreted as a nonlinear function which represents the described three-layer feedforward neural network.

3 Experimental Results

Forecasting analysis of information efficiency and long-term correlation memory has been addressed in this study (see Table 1 for dataset details and parameters). The modeling has been done with the daily values (Open, High, Low, Close) of FCHI and GSPC indexes. Hurst exponent and FFBP algorithm have been used for the future forecasting of the indexes and comparison of the indexes. Linear interpolation method has been employed for the generation of the index values whose daily close values are missing. For these purposes of this study, the following steps (Fig. 3) have been implemented:

(i) The dataset made up of the Open, High, Low, and Close values of each of the FCHI and GSPC indexes included 32 attributes. Hurst exponent was applied to the daily values (Open, High, Low, Close) of FCHI and GSPC indexes, which led to the generation of the dataset with 48 attributes.
(ii) The dataset (with 48 attributes) consisting of the FCHI and GSPC daily values was split into training dataset and test dataset with 75% and 25%, respectively, for the indexes' forecasting purposes.
(iii) The model constructed was used to compare the dataset with 32 attributes and the one with 48 attributes (training and test dataset). The forecasting accuracy of the index values' modeling based on the daily close values of 20 days was compared by using Mean Squared Error (MSE), which shows the significance of the Hurst exponent in forecasting the indexes.

(iv) Modeling through the application of FFBP algorithm, one of the ANN algorithms, to the new dataset generated and to FCHI and GSPC indexes enabled the conducting and comparison of forecasting for these two indexes.

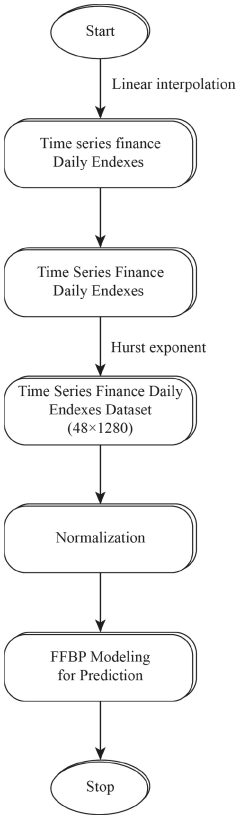

Fig. 3. Flowchart of the proposed time series financial dataset modeling.

All the computations, figures and related analyses were conducted by Matlab [22].

3.1 Data-Driven Time Series Modeling with FFBP Algorithm

Data-driven modeling approaches with the application of ANNs are beneficial for employment in various applications including those related to finance. ANNs, as being nonlinear nonparametric models, allow one to thoroughly utilize the data, through which the structure and parameters of a model are determined. Additionally, the dataset (1280×48) is normalized by max-min normalization method for this method based on the daily values of FCHI and GSPC indexes

in this study. The modeling in this study has been done by FFBP algorithm by taking the corresponding output values related to the close values of 20 days concerning FCHI and GSPC indexes. This is depicted in Fig. 4, accordingly.

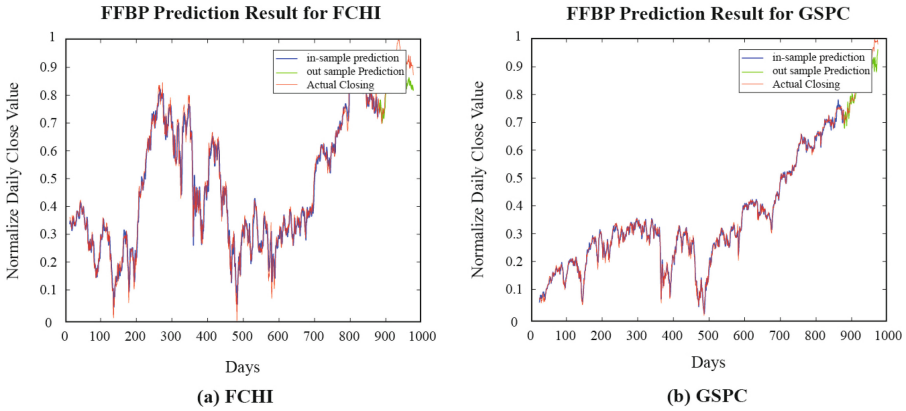

Fig. 4. Modeling of FCHI and GSPC indexes with FFBP algorithm.

Figure 4 provides the trends FCHI and GSPC indexes with the daily close values in the dataset (1280×48) based on past data. 75% and 25% make up the training dataset and test dataset, respectively. Modeling is achieved by FFBP algorithm and MSE results have been obtained, as presented in Table 2 and Fig. 4.

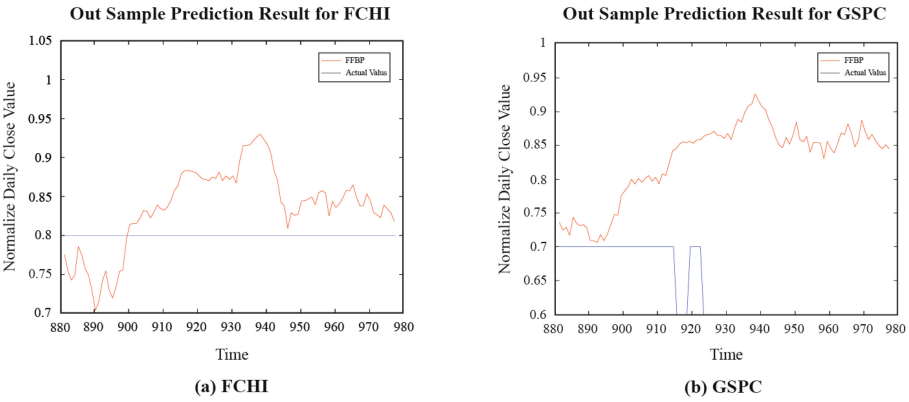

Fig. 5. Analysis results of the constructed model with FFBP and MSE.

Table 2. Numerical results of the time series indexes' modeling with FFBP and MSE.

Index	FFBP
FCHI	7.5155×10^{-4}
GSPC	6.4477×10^{-4}

The comparison of the FCHI and GSPC indexes as presented in Table 2 based on the forecasting processes of FFBP algorithm and MSE yield 7.5155×10^{-4} for FCHI index and 6.4477×10^{-4} for GSPC index (Fig. 5).

4 Conclusion, Discussion and Future Directions

Predictive modeling building upon time series analysis entails the employment of past data for the forecasting of future outcomes, which has the aim of making informed decisions with high levels of accuracy. Time series analysis in mathematical modeling deals with data points collected sequentially over time, and it enables one to capture patterns, varying trends and fluctuations that may prove to be critical to interprerat past behaviors and forecast future events. Along with these considerations, forecasting stock exchange rates is acknowledged to be an important financial problem, which marks the aim of the current paper whose aim is to generate forecasting based on the daily values of FCHI (France) and GSPC (India) indexes between 2013 and 2017 time periods. Hurst exponent has been applied to the dataset consisting of the Open, High, Low and Close values of the FCHI and GSPC indexes, which has made it possible to identify 16 new indicators. The modeling is performed by one of the ANN algorithms, namely feed-forward backpropagation (FFBP) algorithm. The forecasting accuracy obtained from the modeling of the index values based on the past daily close attributes of 20 days is compared with respect to Mean Squared Error (MSE) whose result has validated the forecasting of indexes and demonstrated the importance of Hurst exponent method. To these ends, the following steps have been implemented. Firstly, the dataset made up of the Open, High, Low and Close values of each of the FCHI and GSPC indexes includes 32 attributes, and Hurst exponent has been applied to the daily values (Open, High, Low, Close) of FCHI and GSPC indexes, which has led to the generation of the dataset with 48 attributes. Secondly, the dataset with 48 attributes consisting of the FCHI and GSPC daily values have been split into training dataset and test dataset with 75% and 25% portions, respectively for the forecasting purposes of the indexes. Subsequently, the model constructed has been used to compare the dataset with 32 attributes and the dataset having 48 attributes (training and test dataset). The forecasting accuracy of the index values' modeling based on the daily close values of 20 days has been compared by Mean Squared Error (MSE) which has shown the importance of Hurst exponent in forecasting of the indexes. Finally, modeling has been achieved through the FFBP algorithm application to the new dataset generated and to the FCHI and GSPC indexes, which have enabled the

comparison and performing of forecasting regarding these indexes. Furthermore, the interpolation method has been used to manage missing data in the dataset. The use of sample data can provide a new mode of approach and implementation strategies for future studies in an extended form to illustrate the interaction between time series analysis, predictive modeling and indices. The models to be constructed can be evaluated based on comprehensive outlooks regarding decision-making, investment strategies' optimization and risk mitigation in various domains with orientations and transition from reactive to proactive schemes with the support of accurate, reliable, robust as well as data-driven approaches and practices.

References

1. Ake, B., Ognaligui, R.: Financial stock market and economic growth in developing countries: the case of Douala stock exchange in Cameroon. Int. J. Bus. Manag. **5**(5) (2010)
2. Evertsz, C.J.: Fractal geometry of financial time series. Fractals **3**(03), 609–616 (1995)
3. Guresen, E., Kayakutlu, G., Daim, T.U.: Using artificial neural network models in stock market index prediction. Expert Syst. Appl. **38**(8), 10389–10397 (2011)
4. Inaoka, H., Ninomiya, T., Taniguchi, K., Shimizu, T., Takayasu, H., et al.: Fractal network derived from banking transaction-an analysis of network structures formed by financial institutions. Bank Jpn. Work Pap. **4**, 1–32 (2004)
5. Kannan, K.S., Sekar, P.S., Sathik, M.M., Arumugam, P.: Financial stock market forecast using data mining techniques. In: Proceedings of the International Multiconference of Engineers and computer scientists. vol. 1, pp. 1–5 (2010)
6. Karaca, Y., Baleanu, D.: A novel R/S fractal analysis and wavelet entropy characterization approach for robust forecasting based on self-similar time series modeling. Fractals **28**(08), 2040032 (2020)
7. Karaca, Y., Cattani, C.: Computational methods for data analysis. Walter de Gruyter GmbH & Co KG (2018)
8. Karaca, Y., Cattani, C.: A comparison of two hölder regularity functions to forecast stock indices by ANN algorithms. In: International Conference on Computational Science and Its Applications, pp. 270–284. Springer (2019)
9. Karaca, Y., Zhang, Y.D., Muhammad, K.: Characterizing complexity and self-similarity based on fractal and entropy analyses for stock market forecast modelling. Expert Syst. Appl. **144**, 113098 (2020)
10. Kim, J., Kim, H.S., Choi, S.Y.: Forecasting the S&P 500 index using mathematical-based sentiment analysis and deep learning models: a FinBERT transformer model and LSTM. Axioms **12**(9), 835 (2023)
11. Lee, J.: A neural network method for nonlinear time series analysis. J. Time Series Econ. **11**(1), 20160011 (2019)
12. Moyano, L., De Souza, J., Queirós, S.D.: Multi-fractal structure of traded volume in financial markets. Phys. A **371**(1), 118–121 (2006)
13. Nystrup, P., Madsen, H., Lindström, E.: Long memory of financial time series and hidden markov models with time-varying parameters. J. Forecast. **36**(8), 989–1002 (2017)

14. Ogunjo, S., Fuwape, I., Temiye, M.: Impact of global financial crisis on the complexity of emerging markets: case study of the Nigerian stock exchange. Pramana **95**(4), 206 (2021)
15. Qian, B., Rasheed, K.: Hurst exponent and financial market predictability. In: IASTED conference on Financial Engineering and Applications, pp. 203–209. Proceedings of the IASTED International Conference. Chicago Cambridge, MA (2004)
16. Qian, X.Y., Liu, Y.M., Jiang, Z.Q., Podobnik, B., Zhou, W.X., Stanley, H.E.: Detrended partial cross-correlation analysis of two nonstationary time series influenced by common external forces. Phys. Rev. E **91**(6), 062816 (2015)
17. Rejichi, I.Z., Aloui, C.: Hurst exponent behavior and assessment of the MENA stock markets efficiency. Res. Int. Bus. Financ. **26**(3), 353–370 (2012)
18. Roman, J., Jameel, A.: Backpropagation and recurrent neural networks in financial analysis of multiple stock market returns. In: Proceedings of HICSS-29: 29th Hawaii International Conference on System Sciences. vol. 2, pp. 454–460. IEEE (1996)
19. Sakalauskas, V., Kriksciuniene, D.: Tracing of stock market long term trend by information efficiency measures. Neurocomputing **109**, 105–113 (2013)
20. Shaik, N.B., Pedapati, S.R., Taqvi, S., Othman, A., Dzubir, F.: A feed-forward back propagation neural network approach to predict the life condition of crude oil pipeline. Processes **8**(6), 661 (2020)
21. Tan, Z.X., Thambiratnam, D.P., Chan, T.H., Gordan, M., Abdul Razak, H.: Damage detection in steel-concrete composite bridge using vibration characteristics and artificial neural network. Struct. Infrastruct. Eng. **16**(9), 1247–1261 (2020)
22. The MathWorks, Inc.: MATLAB 2023 version 9.12.0 (R2023a), Software, Natick, MA, (2023)
23. Titman, S., Keown, A.J., Martin, J.D.: Financial management: Principles and applications. Pearson (2018)
24. Tsay, R.S.: Analysis of Financial Time Series. John Wiley & Sons (2005)
25. World Bank: World bank (2025). https://www.worldbank.org. Accessed 03 Apr 2025
26. Zhang, G.P.: Time series forecasting using a hybrid Arima and neural network model. Neurocomputing **50**, 159–175 (2003)