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# Stock Return Forecasting Using Dynamic Nonlinear Methods: Parametric and Nonparametric Modeling

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## Abstract

Accurate stock market forecasting is a challenging and complex problem for the market analysts and decision makers. During the past decade's accuracy of different methods are examined yet there is no consensus on optimum forecasting method. In this regard, the main objective of present study is to investigate eligibility of nonlinear time series, such as exponential smoothing and regime-switching models beside Box-Jenkins scheme in forecasting of stock return time series. Data set consist of daily observations of Apple and Microsoft corporations as of 2024 to 2025. The Terasvirta-Lin-Granger procedure chaotic behavior of data generating process of the selected samples being examined. The Self-Exciting Threshold Autoregressive procedure combined with GARCH component (SETARMA-GARCH) and ARMA model combined with EGARCH component (ARMA-EGARCH) in order to capture the heterogeneous variance of financial time series, which yield dynamic hybrid models. Moreover, due to the overwhelming application of Artificial Intelligence methods in computation, besides the Exponential Smoothing (ES) approach as a non-parametric method, a recently developed Multilayer Perceptron Network (MLP) based on Feed-Forward-Back Propagation (FF-BP) algorithm being developed either. Both of the in-sample and out-sample forecasting are carried out and performance of models is evaluated using standard error criteria. Finally, the Diebold-Mariano test is employed in order to determine the significance of forecasting differences among the models. Findings indicated that the behavior of the return series for the both of the corporations are chaotic and nonlinear methods are appropriate in modeling. The exponential smoothing method outperformed the developed SETARMA-GARCH and ARMA-EGARCH procedures in terms of the majority of error criteria in the both of in-sample and out-sample forecasting. However, the MLP has outweighed the ES model based on every calculated error criteria. The estimated S-statistic of Diebold-Mariano test confirmed results of the forecasting in favor of the MLP method. This finding suggests application of the dynamic nonparametric methods in modeling and forecasting of the selected time series. Implication of such finding recommends use of dynamic nonlinear and nonparametric methods in financial series prediction.

**Keywords:** Stock Return Forecasting, Chaos Testing, Parametric and Nonparametric Methods, Dynamic Nonlinear Modeling, AI Approach.

**JEL Classification:** G11, G14, G17, G32.

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## 1. Introduction

Last decades were witness of an increasing attention to nonlinear methods of econometrics and particularly in the field of time series modeling. Nonlinear forecasting is crucial because many real-world systems, like financial markets, exhibit complex, non-proportional relationships between variables that linear models cannot accurately capture. By employing nonlinear forecasting techniques, the more accurate predictions, better understand underlying dynamics, and more informed decisions in various fields we can be achieved. Regarding to the framework of financial time series modeling, there is large number of models, which are designed base on linear autoregressive procedure; or moving average approach or in more complete form of autoregressive-moving average (ARMA) model that initially has introduced by Box & Jenkins (1970). Box-Jenkins method suggests that the current value of dependent variable can be linearly expressed as a function of its previous values and residuals; hence called a linear procedure. Simple linear structure of such models caused their enormous application in the literature of empirical studies. However, there exist series that cannot be simply modeled by such linear process and exhibit, in some extend, nonlinear behavior as cannot be well-fitted by the general ARMA model. Such phenomenon suggests application of more complex structures like nonlinear methods. In the econometrics literature, wide range of nonlinear models there exists and selection of the optimum method or an appropriate form is an important issue. As it is argued by Bradfield (2007), Brooks (2008) and Wang (2009), selection of each model should not be only based on time series characteristics under consideration, but also self-characteristics of the model are required to be noted as well. In this way, model selection will be relevant to the model's degree of fitness with the features of time series is being analyzed. One of the popular nonlinear methods is procedure of regime switching.

Regime switching models are designed to capture discrete changes in the data generating process (DGP) of data under consideration. Threshold Autoregressive models (TAR) are generally referring to the piecewise-linear models or regime switching models. They addressed to $z$ number of autoregressive components which one process switches to another one due to a specific amount (named the threshold value) of an independent variable. In TAR procedure, regime switching of dependent variable is due to the threshold value of an explanatory variable. As when as series cross over the threshold value, the process will shift to another regression line. Two different scenarios there exist in this sense, namely univariate and multivariate modeling, concerning to the number of included variables in the process of modeling. Hence, TAR model is considered as a multivariable model that is variation of dependent variable relying on the changes of independent variables. SETAR model is a special case of TAR schemes where regime switching is based on self-dynamics of the dependent variable; thus, SETAR model is considered as a univariate procedure. In the other words, unlike the TAR model that threshold value depends on an exogenous variable, in SETAR model threshold value is related to the endogenous variable. SETAR model initially is introduced by Tong (1978) and developed by Tong and Lim (1980) and Tong (1983). Motivated by study on complex nonlinear discrete systems, Tong developed a special type of time series models that would be able to regenerate properties of the original data generating process (DGP) of a sample series. This model hypothesized different AR process based on different threshold values. Advantages of using SETAR model are reflected in its abilities of producing several commonly observed phenomena, such as irreversibility, jumps, and limit cycles, which cannot be captured by the naive linear models such as ARMA model. In addition, regarding to the stylized facts of financial time series, volatility clustering is one of the indispensable features of such series that reveals in existence of a heterogeneous variance. In order to capture such phenomenon, Engle (1982) introduced Autoregressive Conditional Heteroscedasticity (ARCH) model by contriving an autoregressive (AR) form for variance equation. Following to Engle’s innovation, Bollerslev (1986) introduced Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model through introducing additional moving average component in the conditional variance equation and therefore variance equation resembling an ARMA structure. Capability of GARCH procedure in capturing the conditional variance of financial series is proved in the literature of financial time series and largely has utilized in the empirical studies. Therefore, although SETARMA models excel at capturing how time series evolve over time, including changes in regimes and behaviors, but merging of this model with a GARCH component can capture the nonlinear of regime changing and shifts from periods of low volatility to high volatility, which linear models struggle to represent. Hence, the enhanced SETARMA-GARCH model can provide better estimates of uncertainty and risk management for different scenarios. Likewise, Simple linear models such as AR, MA and ARMA assume a fixed and direct impact from exo-variables to endo-variables, but many systems involve complex interactions where the impact of one variable changes depending on the state of others or the level of volatility. For example, the financial markets and stock prices in particular have periods of high and low volatility behavior; in which, enhancing the mentioned models by volatility models (such as ARCH and GARCH family models) seems necessary. Therefore, such combination is implemented in the present study and EGARCH component is merged to ARMA model to improve the accuracy of forecasting. The reason of selection of EGARCH model reflected in the advantage of this method in asymmetric behavior capturing. Meaning that, good news and bad news with the same magnitude in the financial markets do not have the same effect on the market. Usually, bad news more amplified the volatility of the stock markets than the good ones of the dame weight. In comparison with the previous studies, such hybrid modeling brought relative novelty to the current study.

Artificial Neural Network (ANN) is a computer simulation model of the human brain. Neural networks are considered similar as the fundamental functional source of intelligence that includes perception, cognition, and learning for humans. Similar to human brain that is a collection of millions natural neurons, an ANN is also made of a collection of neurons. A combination of neurons that are related and connected to each other, construct a network that is known as a neural network. Results of many studies are in favor of the accuracy of ANN methods in financial markets forecasting (e.g Khadiri *et al.*, (2025), Gajdosikova & Michulek (2025), Zheng *et al.*, (2024), Pattanayak & Swetapadma (2024), Audrey *et al.*, (2023), Kurani *et al.*, (2023), Hosseinidoust *et al.*, (2016)). However, outcomes of some other studies have shown the precision of the econometrics models rather than the ANN methods (i.e Tripathi *et al.*, (2025), Jin & Xu (2025), Zakhidov (2024), Song *et al.*, (2024)).

Thus, the present study aims to shed more light on this conflict and reexamining and comparing the accuracy of the mentioned methods rather than each other.

Therefore, in the current study with regard to the importance of stock return forecasting, especially in the internationally integrated stock market and due to the inexistence of a global consensus about the eligibility of nonlinear models' simulation and prediction, a Self-Exciting Threshold Autoregressive Moving-Average (SETARMA) model is combined with a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) component to obtain the SETARMA-GARCH model. In addition, pay attention to the privilege of Exponential Smoothing (ES) method that is unlike the simple moving average that weights the past observations equally; exponential smoothing assigns exponentially decreasing weights over time and the ES method included in the present study as well. In order to have a comparison benchmark, developed hybrid SETAR-GARCH model and ES procedure are compared to another hybrid system that is linear ARMA combined with EGARCH process, which is ARMA-EGARCH model. As mentioned earlier, these models are compared to ANN method. All of these methods are employed for Apple and Microsoft corporations' stock return time series modeling and prediction in the form of in-sample and out-sample forecasting. Precision of each model is measured in terms of error criteria such as Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Bias Proportion (BP) and Variance Proportion (VP).

The structure of this study is as; first, some of the previous researches are mentioned in brief. Then, implemented methods and data sets will be introduced. At the end, conclusion of this research will be represented after detailed discussion about the empirical findings of the study.

## 2. Literature Review

Utilization of the nonlinear methods in time series forecasting goes back to the seminal works in 1980's that the nonlinear dynamic models became one of the most popular methodologies in the study of time series. Recently, the comparison between basic-statistical models and AI models has attracted the attention of researchers; for instance, Jin & Xu (2025) have investigated the real state sector of

China stock market using the quarterly national residential property price indices from 2005 to 2024 by using Gaussian process regressions with a variety of kernels and basic functions. For the purpose of model training and conducting forecasting exercises using the estimated models, cross-validation and Bayesian optimizations based upon the expected improvement per second plus algorithm are implemented. Findings showed that the constructed Gaussian process regression model outperformed several alternative machine learning models and econometric models. Their forecast performance is robust to different out-of-sample evaluation periods as well. Likewise, the comparison between sentiment models and short- and long-term memory AI models has also been investigated in some studies; for example, Tripathi *et al.*, (2025) addressed the challenges of econometric model and AI methods by proposing a hybrid model that integrates a Convolutional Long Short-Term Memory (LSTM) network. Using a two-year dataset of historical stock prices from HDFC Bank and incorporating sentiment analysis to capture the impact of market sentiment on price trends. Sentiment Analysis are carried out using major parameters in a Random Forest model to provide an additional sentiment-based input to the LSTM model. Results indicate that the LSTM model achieves a lower RMSE, MAE and MAPE showcasing strong alignment between predicted and actual prices. Findings representing underscoring the potential of hybrid machine learning architectures for financial time series forecasting.

Moreover, Zakhidov (2024) explored the pivotal role of economic indicators as indispensable tools for comprehending market trends and forecasting future performance. The research elucidated the significance of economic indicators in guiding strategic decision-making for businesses, investors, and governments alike. Through empirical analysis and theoretical frameworks, it demonstrated how these indicators serve as barometers of economic stability, aiding in risk assessment, trend identification, and the formulation of proactive strategies.

In addition, the comparison of forecasting accuracy between AI models and Markov switching models has been investigated in various studies. In this regard, Song & Song (2024) introduced a hybrid AI architecture for simultaneous risk quantification and return prediction across global equity markets. Analyzing stocks 2018-2023 with 128 financial data in a framework innovatively combined Risk

Encoding, Attention-based sector risk spillover networks and Temporal Modeling and Regime-switching detection via hidden Markov models. Outcomes implies that the hybrid AI model has a significant efficiency in stock market forecasting based on the low levels of error generated.

Besides, Hosseinidoust *et al.*, (2016) concentrated on the application of dynamic parametric and non-parametric systems in stock market forecasting of Tehran stock exchange market. The study focuses on two different methods namely dynamic-parametric method of ARMA-PGARCH and dynamic-nonparametric procedure of NARX artificial neural network. Predictions are exerted in the form of in-sample and out-sample using daily observations of TEPIX from 1997 to 2015. Forecasting horizon of next five working days has adopted for the out-sample prediction and eight error criteria are picked out in order to assess accuracy of each approach. Outcomes of implied higher precision of the dynamic neural network performance in comparison with the parametric method of ARMA-PGARCH. In addition, the results are in favor of inexistence of weak-form of informational efficiency in Tehran stock market.

Calin *et al.*, (2014) discussed a wide range of nonlinear methods of time series such as multivariate and univariate Threshold models (e.g. TAR, SETAR and SETARMA) and volatility models (e.g. ARCH, GARCH, GJR-GARCH, EGARCH etc.) and concluded that the nonlinear models have remarkable performance in forecasting of the financial time series. The out-sample predictability of different GARCH models for various horizons is investigated by Awartani & Corradi (2005) employing daily observations of S&P500 index by means of different GARCH-family models. Outcomes imply higher accuracy of the asymmetric GARCH models in comparison against the first generation of ARCH-family models. Leung *et al.*, (2000) developed various level estimation methods (i.e. adaptive exponential smoothing, VAR and multivariate neural network) and classification models (Logit, Probit and Probabilistic neural networks) for prediction of return and for direction of return of S & P500, FTSE100 and Nikkei for various periods. Results are generally in favor of the classification models and lower performance of the level estimation methods. The principal index of Brazilian stock market is studied by Faria *et al.*, (2004) based on adaptive exponential smoothing method and artificial neural network. Findings represented higher precision of neural network than the adaptive exponential smoothing method.

A glance on the application of regime switching models shows large number of empirical researches using these models in the exchange markets and macroeconomic variables. For instance, Engle (1994), Bergman & Hansson (2005), Ismail & Isa (2006) developed regime switching models for exchange rate and their findings exhibit higher precision of these models in the both in-sample and out-sample forecasting. Likewise, De Gooijer & Komar (1992), Potter (1995) and Peel &ss Speight (1998) developed SETAR models for modeling the GDP of different countries such as UK and US and their results indicate that switching models outperformed linear approaches. Moreover, Clements & Smith (1999) investigated the multi-period forecast performance of a number of empirical SETAR models for modeling the exchange rates and GNP either and results are in favor of higher performance of SETAR model than the linear models such as AR and MA.

In the field of stock market forecasting, Chang and Lam (2010) attempted to capture stock market return asymmetry and investigate the predictability of trading strategies based on SETAR model for Hong Kong and Singapore stock markets. Their findings imply efficiency of SETAR model in stock market forecasting. Furthermore, Terence *et al.,* (2009) compared performance of SETAR procedure with other models such as autoregressive model and moving average model using four major indices of China stock markets namely Shanghai and Shenzhen *A* and *B* share indices. Findings of this study indicate that the SETAR model has outperformed AR and MA models based on employed forecasting error criteria.

As can be seen from the research background, despite the existence of numerous studies in the field of forecasting and nonlinear modeling, very few studies have resorted to the use of hybrid models and combination of Mean-Equation modeling with Variance-Equation or volatility models. Thus, in the previous studies, comparisons between parametric (such as regime switching models) and nonparametric (such as exponential smoothing models) models have rarely been paid attention. In addition, comparisons of AI models with hybrid regime switching models have been very few. Therefore, it seems the present study can be innovative in these respects.

## 3. Methodology and Data

Data set of current study involves daily observations of Apple and Microsoft stock prices as two famous high-tech companies. Based on monthly "Market Watch"[1] reports in Jun 2015, these companies stand among the top active corporations in the international stock market. Data spans from 7th Aug 2024 to 7th Aug 2025 that covers daily observations within a year.

To check the level of integration of time series, two different types of unit root tests are employed namely Augmented Dickey-Fuller (1979) or ADF in short, and Zivot-Andrews (1992) unit root test, or ZA. The ADF unit root test is one of the most popular procedures utilized for finding stationarity of a time series. Results of this test might be misleading if there exist structural break or level shift at the series in hand. Therefore, due to the capability of Zivot-Andrews test in capturing stationarity by taking structural break or level shift into account, this test besides ADF test is employed in the current study. Afterwards, based on suggested procedure by Terasvirta *et al*., (1993) linearity or nonlinearity of time series will be examined to shed more light on existence of chaos in the selected time series. This method is neural-network based test and the null hypothesis consists of linearity in the mean equation. Using Taylor series expansion, this method estimate a test-statistic based on Chi squared-statistic and F-statistic. Moreover, Recursive Least Square (RLS) estimation is implemented to achieve threshold value of SETAR-GARCH model. All the developed models are examined using the popular diagnostic procedures such as ARCH-heteroscedasticity and Ljung-Box serial correlation tests. Results of the diagnostic tests are helpful to confirm validation of developed models. Eventually, the models are employed for the in-sample and out-sample forecasting. Forecasting horizon of the out-sample forecasting is next five working days. Accuracy of the developed model is computed based on error criteria, such as Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Bias Proportion (BP) and Variance Proportion (VP). Significance of the obtained differences is examined using the proposed procedure by Diebold-Mariano (1995). The focus of the current study is on Apple and Microsoft companies' stock returns, that are calculated based on the following formula:

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[1] https://www.marketwatch.com

$$R_t = \ln\left(P_t / P_{t-1}\right)$$

ARMA model originally is setup by Box & Jenkins (1976) and consists of two components as autoregressive and moving average and it general structure is shown in equation (1).

$$Y_t = \theta + \sum_{i=1}^{p} \beta_j u_{t-j} + \sum_{i=1}^{q} \alpha_i Y_{t-i} \tag{1}$$

Where $Y_{t-i}$ indicates autoregressive component with order ($q$) and $u_{t-j}$ suggests moving average part of order ($p$). ARMA model is capable in capturing mean equation behavior and in present study it will be combined by Exponential-GARCH method model of volatility. This combination causes that the mean and variance of financial series being involved in the modeling at the same time. The EGARCH model developed by Nelson (1991) in which the natural logarithm of the conditional variance is allowed to vary over times as a function of the lagged error terms rather than lagged squared one. General form of EGARCH model is presented by equation (2).

$$\log\left(\sigma_t^2\right) = +\sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \left(\frac{\varepsilon_{t-k}}{\sigma_{t-k}}\right) \tag{2}$$

The exponential nature of the EGARCH ensures that the conditional variance can never be negative. Likewise, presence of the leverage effects can be stated by the hypothesis of $\gamma_k \prec 0$ whereas the impact is asymmetric if $\gamma_k \neq 0$. Combination of ARMA and EGARCH models results in geniture a powerful hybrid model that is qualified to model mean and variance equation simultaneously and potentially reduce the level of forecasting errors.

SETAR model first proposed by Tong (1987) and its basic idea is to introduce *l-1* thresholds *rj(j=1,2,…l-1)* in the range of a time series and dividing time axis into *l* ranges. It distributes observation sequence $\{x(t)\}$ into different threshold ranges according to the value of $\{x(t-d)\}$ by delay steps ($d$)and then adopts different autoregressive models to clarify time series under consideration as a whole. General structure of SETAR model is represented by equation (3).

$$Y_t = I_t\left[\alpha_{10} + \sum_{i=1}^{p}\alpha_{1i}Y_{t-i}\right] + (1 - I_t)\left[\alpha_{20} + \sum_{i=1}^{r}\alpha_{2i}Y_{t-i}\right] + \varepsilon_t \tag{3}$$

Where the error term is a white noise process and $I_t$ is an indicator function such as:

$I_t = 1$ if $Y_{t-1} > \tau I_t = 0$ if $Y_{t-1} \leq \tau (d \leq p)$

Where $\tau$ is the threshold value, which separates regimes. A more general format of SETAR model can represent by a piecewise equation like equation (4).

$$Y_t = \begin{cases} \mu_{10} + \phi_{11}Y_{t-1} + \ldots + \phi_{1p}Y_{t-p} + u_{1t} & if\ Y_{t-k} \prec \tau \\ \mu_{20} + \phi_{21}Y_{t-1} + \ldots + \phi_{2r}Y_{t-r} + u_{2t} & if\ Y_{t-k} \geq \tau \end{cases} \tag{4}$$

SETAR model is empowered through combining with Generalized ARCH (GARCH) model. This model initiated by Bollerslev (1986) proposing joint estimation of both conditional mean and a conditional variance equation as shown in equations (5) and (6).

$$y_t = c + \beta y_{t-1} + \varepsilon_t \tag{5}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\beta_i u_{t-i}^2 + \sum_{j=1}^{p}\gamma_j \sigma_{t-j}^2 \tag{6}$$

$y_t$ indicates the mean equation with autoregressive form of order one and $\sigma_t^2$ representing the conditional variance equation. This function states that the variance ($\sigma_t^2$) of $\underline{u}$ at time $\underline{t}$ depends not only on the squared error term in the periods before, but also depends on its conditional variance at the previous periods.

In addition, in order to introduce the threshold value to the SETR-GARCH model, residuals of the recursive least square (RLS) estimation is adopted, in which the equation is estimated repeatedly using ever larger subsets of the sample data. Readily, if there are $k$ coefficients to be estimated in the $b$ vector, then the first $k$ observations are used to form the first estimate of $b$. Residuals of RLS method are extracted from equation (7):

$$w_t = \frac{(y_t - x'_{t-1}b)}{\left(1 + x'_t\left(X'_{t-1}X_{t-1}\right)^{-1}x_t\right)^{1/2}} \tag{7}$$

Where, $X_t$ is matrix of repressors at time $t$, $y_{t-1}$ represents vector of observations on the dependent variable, $b_{t-1}$ stands for estimated coefficient vector and $x'_{t-1}b$ shows vector of forecasted values. Exponential smoothing (ES) is a simple method of adaptive forecasting discussed by Bowerman & O'Connell (1979). Its advantage compared to regression models is that ES method does not utilize fixed coefficients and forecasts from this procedure adjust based upon past forecast errors. Two general form of this approach is introduced as simple ES and Error-Trend-Seasonal ES or ETS-ES. The single form of ES computes smoothed series $\hat{x}_t$ of $x_t$ recursively by evaluation of equation (8).

$$\hat{x}_t = \alpha x_t + (1-\alpha)\hat{x}_{t-1} \Rightarrow \hat{x}_t = \alpha \sum_{s=0}^{t-1} (1-\alpha)^s x_{t-s} \tag{8}$$

Where, $0 < \alpha \leq 1$ is the smoothing or damping factor. ETS-ES method originated by Hyndman *et al.*, (2002) and decomposed time series into three components of trend (T), seasonal (S), and error (E), where the trend term characterizes the long-term movement of time series, the seasonal term corresponds to a pattern with known periodicity and the error term is the irregular and unpredictable component of series. The simplest specification of ETS-ES with exclusion of trend and seasonal innovations is as follow:

$$\begin{cases} x_t = l_{t-1} + \varepsilon_t \\ l_t = l_{t-1} + \alpha\varepsilon_t \end{cases}$$

Where $x_t$ represents prediction error equation and $l_t$ exhibits the weighted average of the current value of the variable and its forecasted value. As mentioned by Hyndman *et al.*, (2008), Holt's approach of ETS-ES considers a linear trend method with multiplicative errors. Halt's approach of ETS-ES can be summarized as below:

$$\begin{cases} y_t = (l_{t-1} + b_{t-1})(1 + e_t) \\ l_t = (l_{t-1} + b_{t-1})(1 + \alpha e_t) \\ b_t = b_{t-1} + \beta(l_{t-1} + b_{t-1})e_t \end{cases}$$

Where $b_t$ shows the growth components of trend, $l_t$ is the level component of time trend and $Y_t$ implying the current value of the variable and its forecasted value.

Moreover, present study utilizes the suggested procedure by Diebold & Mariano (1995) in order to determine whether the computed forecasting errors of the distinctive models are significantly different. Given two forecasting error time series $e_1$ and $e_2$, a loss function such as $d_t$ is defined such that:

$$d = f(e_1) - f(e_2)$$

Where, the ( $f$ ) function can adopt two forms of squaring or absolution function. The developed loss function will be employed in the computation of S-statistic. Thus, the Diebold-Mariano test statistic can be defined by equation (9).

$$S = \left[\hat{V}\left(\bar{d}\right)\right]^{-1/2}\left(\bar{d}\right) \tag{9}$$

Where, $\hat{V}\left(\bar{d}\right)$ is the asymptotic variance of the mean of the difference between the forecasting errors as $\hat{V}\left(\bar{d}\right) \approx n^{-1}\left[\gamma_0 + 2\sum \gamma_k\right]$ and $\gamma_k$ is the k$^{th}$ auto covariance of loss function. The hypothesis testing of this procedure is defined as follow:

$$\begin{cases} H_0 : E\left[f\left(e_1\right)\right] = E\left[f\left(e_2\right)\right] \\ H_1 : E\left[f\left(e_1\right)\right] \neq E\left[f\left(e_2\right)\right] \end{cases}$$

If the computed S-statistic is negative and significant, the conclusion is that the first model is significantly dominant and more accurate than the second model. Diebold and Mariano test follows an asymptotic standard normal distribution.

In the present study a Multilayer Perceptron Network (MLP), which is a subset of Feed-Forward Networks, with Back-Propagation error correction algorithm (BP) is employed. This network includes three major layers as the first layer (or input layer) gathering and transmit them in to the next layer by multiplying them in random weights. The second layer (or hidden layer) processes the data in the core of neurons and multiplies them with random weighs before transmitting them to the last layer (output layer). The third layer is the output layer, which generates the output of the system. At this point, the feed-forward algorithm has completed its duty. The Back-Propagation (BP) algorithm compares results of the feed-forward process with the actual data to compute error of procedure and spreads this error through the network in the opposite direction that feed-forward does. All the weights that were randomly assigned at the beginning are refined and revised in such a way that the network produces the ideal output. The process has repeated several times until the network reaches the determined level of error criterion. The process is depicted in figure (1).

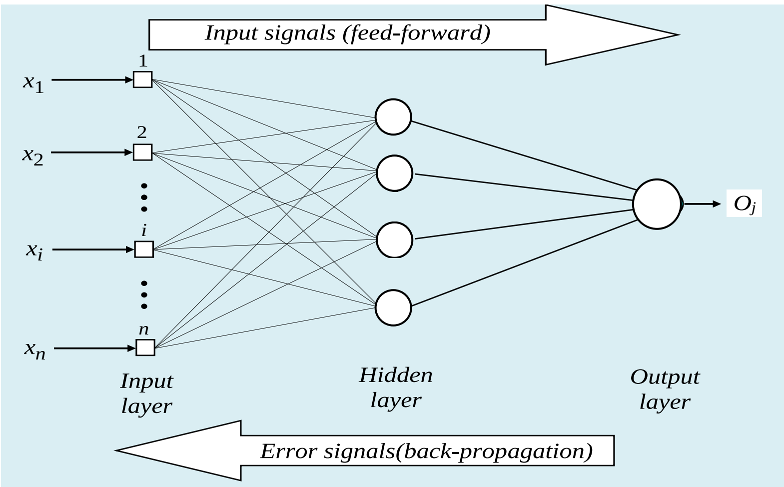


**Fig. 1: Directions of data spread and error propagation (Munakat, 2008).**

## 4. Empirical Findings

**Table 1. Descriptive Statistics**

| Series Name | Mean | Max | Min | Std.dev | Skewness | Kurtosis | Jarque-Bera (Prob) |
|---|---|---|---|---|---|---|---|
| Apple Stock Price | *222.14* | *250.05* | *172.42* | *15.98* | *-0.08* | *2.59* | *1.98 (0.36)* |
| Apple Stock Return | *-7.79E-05* | *0.14* | *-0.09* | *0.02* | *0.57* | *15.92* | *1745 (0.00)* |
| Microsoft Stock Price | *428.22* | *513.71* | *354.56* | *34.43* | *0.65* | *3.16* | *18.20 (0.00)* |
| Microsoft Stock Return | *0.0001* | *0.09* | *-0.06* | *0.01* | *0.64* | *11.71* | *803 (0.00)* |

(Research Findings).

Before interpretation of results of unit root tests, plots of Apple and Microsoft stock prices and returns are depicted in figure (2) and summary of descriptive statistics are reported in table (1).

Referring to table (1), Apple stock price is lower than the Microsoft in terms of Min-Max and on average. However, the risk of Apple stock price that is computing based on the Std. dev is much lower than the opponent company. The distribution of Apple stock price is normal basing the Jarque-Bera test but for the Microsoft it is not. Having a glance to the return series, the average of return on investment on the Apple stocks is higher than the Microsoft and it has higher risk as well. The both of the return series are not normally distributed within the selected period.

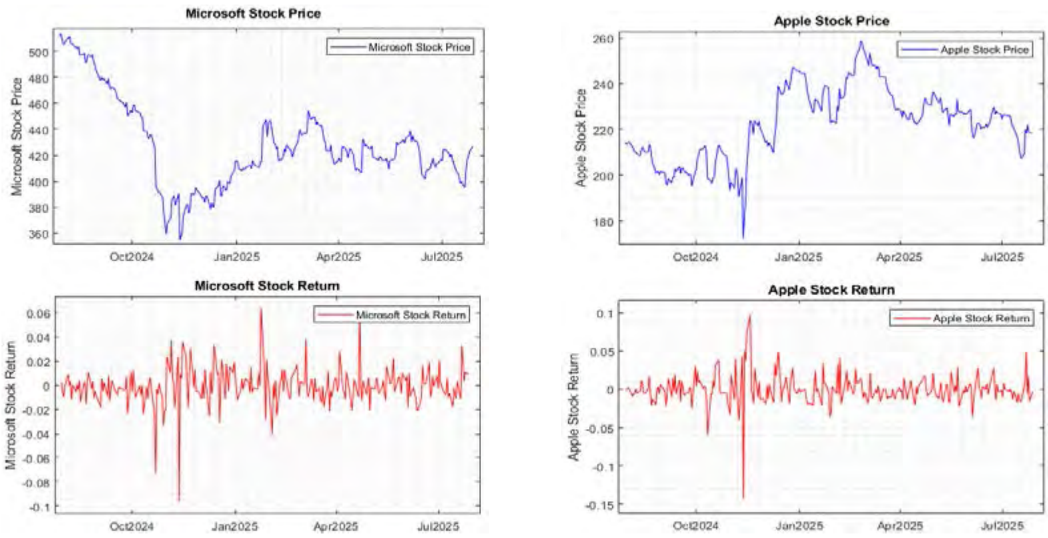


**Fig. 2: Daily Stock Prices and Returns of Apple & Microsoft Corporations (Research Findings).**

Graphically and with regard to the plotted figures of stock price of the both mentioned corporations, several upward and downward trends are apparent. Therefore, it implies inexistence of stationary in the stock price time series. However, return time series fluctuations are around the origin line implying stationarity of these series. Graphical interpretations are not sufficient and statistical tests are required to check the stationary issue. Therefore, stationary tests of Augmented Dickey-Fuller (ADF) and Zivot-Andrews (ZA) are carried out and their results are summarized in table (2).

Note that the both tests are executed in two forms, first only by inclusion of intercept and secondly by inclusion of trend and intercept. Results of ADF test clearly suggest that price indices are nonstationary. Due to the insignificant obtained t-statistics, the null hypothesis testing that claims existence of unit root procedure cannot be rejected; hence, there is unit root problem in the price series and they are nonstationary. Implementing ADF test on the computed return series suggests that the return series are stationary referring to the significant obtained t-statistics. This finding indicates rejection of null hypothesis of this test in favor of inexistence of unit root phenomenon; therefore, the computed return series are stationary.

**Table 2: Results of Unit Root Test**

| Type of Test | Test on the Apple Stock Price | | Test on the Apple Stock Return | |
|---|---|---|---|---|
| | Including Intercept | Including Trend & Intercept | Including Intercept | Including Trend & Intercept |
| *ADF* | -2.1713 | -2.6781 | -15.4452** | -15.4441** |
| *ZA* | -2.8791 | -2.9941 | -42.5965*** | -42.5853*** |
| | **Test on the Microsoft Stock Price** | | **Test on the Microsoft Stock Return** | |
| | Including Intercept | Including Trend & Intercept | Including Intercept | Including Trend & Intercept |
| *ADF* | -3.2351 | -3.3269 | -51.8143*** | -51.8250*** |
| *ZA* | -2.9328 | -2.0398 | -51.8571*** | -51.8695*** |

**Notice:** *,**,*** denote significant at the 10%, 5% and 1% level respectively
(Research Findings).

Although ADF results offering that the return series is stationary but due to the sample range and concerning to the recessions and market crash events during selected sample range, it is not convenience to merely relay on the ADF results and advanced type of unit root testing is required to carry out. As it mentioned earlier, Zivot-Andrews unit root test is employed and its results are reported in table (2). Interestingly, ZA results support findings of ADF test in favor of stationarity of the return series and non-stationarity of the price indices even at the presence of break in these time series (break point is highlighted by dash line). Therefore, as the result of unit root tests, in order to prevent having a spurious regression, the return time series should be used in the modeling procedure. In the next step, in order to shed more light on the matter of nonlinearity and existence of chaos in the return of the Apple and Microsoft stock return time series, test of Terasvirta *et al.*, (1993) is carried out and its outcomes are tabulated in table (3).

**Table 3. Results of Terasvirta-Lin-Granger Chaos Test**

| Name of Time Series | Estimated F-statistic | Estimated Chi$^2$-statistic |
|---|---|---|
| Apple Stock Price | 0.7517 *(0.63429)* | 5.4881 *(0.7348)* |
| Apple Stock Return | 0.7018 *(0.6704)* | 5.1313 *(0.6439)* |
| Microsoft Stock Price | 0.6433 *(0.8461)* | 4.7255 *(0.8859)* |
| Microsoft Stock Return | 0.5926 *(0.8963)* | 4.6703 *(0.8878)* |

**Note:** Reported Values in Parentheses are Estimated Probabilities
(Research Findings).

Remind that the null hypothesis indicates that the time series is linear and there is not enough evidence for the presence of chaos. With regard to the estimated “F” and “Chi-sqr” coefficients and especially referring to the estimated P-values, which are insignificant at 95% level of significant, the null hypothesis cannot be accepted and it can be concluded that stock price and their associated return time series have represented evidence on the existence of nonlinearity or chaos in their data generating process. This finding advises application of nonlinear models. Therefore, the return series should be used in the modeling as the results of the unit root tests and nonlinear types of models should be chosen for the modeling purposes. Selection of AR and MA orders also ARCH and GARCH components of ARMA-EGARCH model are based on the parsimony principle, which suggesting inclusion of lower orders of components that satisfying conventional diagnostic tests of modeling, such as heteroscedasticity, serial-correlation, normality and etc. In this regard, suggested ARMA-EGARCH model for Apple corporation is ARMA (1,1)-EGARCH (1,1,1) and for Microsoft company is ARMA(1,1)-EGARCH(1,1,1). Furthermore, outcomes of executed RLS method for threshold value detection in the both time series is plotted in figure (3).


**Fig. 3: Results of Recursive Least Square Method (Research Findings).**

In developing the SETAR model and in order to reduce the degree of model complexity, similar to other studies (i.e. Ismail & Isa (2006)) an equal number of lag and delay parameter is adopted for every regime. The controversial problem dealing with SETAR models is determination of threshold value. In present study, RLS method is employed to deal with such problem. Based on RLS out comes, suggested threshold value for Microsoft and Apple stock return is 0.15 and 0.09

respectively, which results are depicted in figure (3). The established SETAR-TGARCH model upon the extracted threshold values are SETARMA (1,2)-GARCH(1,1) and SETARMA(2,2)-GARCH(1,1) for Apple and Microsoft stock return relatively. In order to check whether the developed ARMA-EGARCH and SETAR-GARCH models are statistically significant, diagnostic tests such as Ljung-Box serial-correlation and the ARCH-heteroscedasticity test are implemented and their results are summarized in table (4). Referring to the estimated Q-statistic of Ljung-Box test that is insignificant, it can be concluded that there is no serial-correlation problem in the developed models. The conclusion is same for the ARCH-heteroscedasticity test and estimated coefficients for F-statistic and Chi$^2$-statistic are insignificant, implying that there is no heteroscedasticity problem in the constructed models. Therefore, results of the diagnostic tests confirm that the developed ARMA-EGARCH and SETARMA-GARCH models are statistically valid and can be employed for forecasting purposes. Regarding to the speed of transactions in the stock market, short horizon forecasting is more interesting than long horizon especially for private investors. Therefore, selected forecasting horizon at current study is next five working days or next week.

**Table 4. Results of Diagnostic Tests**

| | **Ljung-Box Serial-Correlation Q-statistic** | | | | | |
|---|---|---|---|---|---|---|
| Period | 1 | 4 | 8 | 12 | 16 | 20 |
| ARMA-EGARCH of Apple Co. | 0.4802<br>*(0.8412)* | 7.7983<br>*(0.0993)* | 9.2436<br>*(0.3228)* | 15.4101<br>*(0.2204)* | 15.6940<br>*(0.7472)* | 16.3742<br>*(0.6935)* |
| SETARMA-GARCH of Apple Co. | 0.2598<br>*(0.6103)* | 7.0192<br>*(0.1357)* | 9.8292<br>*(0.2771)* | 14.7282<br>*(0.2572)* | 16.3041<br>*(0.4325)* | 24.6610<br>*(0.2158)* |
| ARMA-EGARCH of Microsoft Co. | 0.3459<br>*(0.0865)* | 2.8755<br>*(0.1647)* | 5.8679<br>*(0.4384)* | 12.7249<br>*(0.3872)* | 18.2217<br>*(0.6764)* | 24.9422<br>*(0.7461)* |
| SETARMA-GARCH of Microsoft Co. | 0.9457<br>*(0.0824)* | 7.5344<br>*(0.1664)* | 17.1920<br>*(0.2487)* | 25.5269<br>*(0.3116)* | 38.6218<br>*(0.4233)* | 53.7225<br>*(0.5128)* |

| | **ARCH-Heteroscedasticity Test** | |
|---|---|---|
| | **F-statistic** | **Chi$^2$-statistic** |
| ARMA-EGARCH of Apple Co. | 0.0029<br>*(0.9565)* | 0.0029<br>*(0.9565)* |
| SETARMA-GARCH of Apple Co. | 0.0001<br>*(0.9957)* | 0.0001<br>*(0.9957)* |
| ARMA-EGARCH of Microsoft Co. | 0.058<br>*(0.5682)* | 0.057<br>*(0.5682)* |
| SETARMA-GARCH of Microsoft Co. | 0.0062<br>*(0.7451)* | 0.0062<br>*(0.7451)* |

**Note:** Reported Values in Parentheses Are Estimated Probabilities
(Research Findings).

The specification of the developed ANN has reported in table (5). Five layer has considered for this network and MSE error criterion has employed in order to set the neurons weights. The gradient of error function will be reduced using Levenberg-Marquardt algorithm and the nonlinear activation function of Tangent-Sigmoid has assigned to the core of hidden layers every cell cores. Outcomes of simulations are depicted in figure (4).

**Table 5: The FF-BP network specifications**

| Layers | Error Function | Activation Functions | Epochs | Topology | Applied Algorithm | Training Goal |
|---|---|---|---|---|---|---|
| 5 | MSE | Tangent-Sigmoid | 100 | [1-15-30-15-1] | LM | 1e-10 |

(Research Findings).

The first row of figure (4) consist of the network behavior before train, in which the neurons weights are randomly selected by the algorithm. The second row represents the behavior of the ANN after training and updating the stochastic initial weights. It can be observed that the network simulation process successfully captured the Data Generation Process (DGP) of the return series of the both companies. Networks error are figured in the third row, which due to the low values of the calculated errors, the accuracy of the developed networks in the simulation process can be comprehended. Results of in-sample prediction are tabulated at the following table. Comparison in-sample prediction of the developed models for Apple Corporation stock return time series based on MAPE criterion shows that the Exponential Smoothing (ES) method provided lower value than ARMA-EGARCH model and the regime-switching procedure. This finding implies higher accuracy of ES scheme than the other parametric methods of study.

Similarly, such outcome is again repeated based on bias proportion measurement and ES system exhibiting higher level of accuracy. In addition, the variance proportion criterion also indicates that the variation of simulated series by ES model is closer to the variation of the real return time series and the ARMA-EGARCH either SETAR-GARCH method generated higher levels of variation. Therefore, regardless of the RMSE criterion that endorsed the SETAR-GARCH model, the majority of error criteria explicitly recommended the exponential smoothing model as the successful method of capturing the data generating process of the stock return series of Apple Corporation. Moreover, comparison between ARMA-EGARCH and SETAR-GARCH model representing higher level of precision of the regime switching model that it can caused by nonlinear structure of the men equation of SETAR approach.

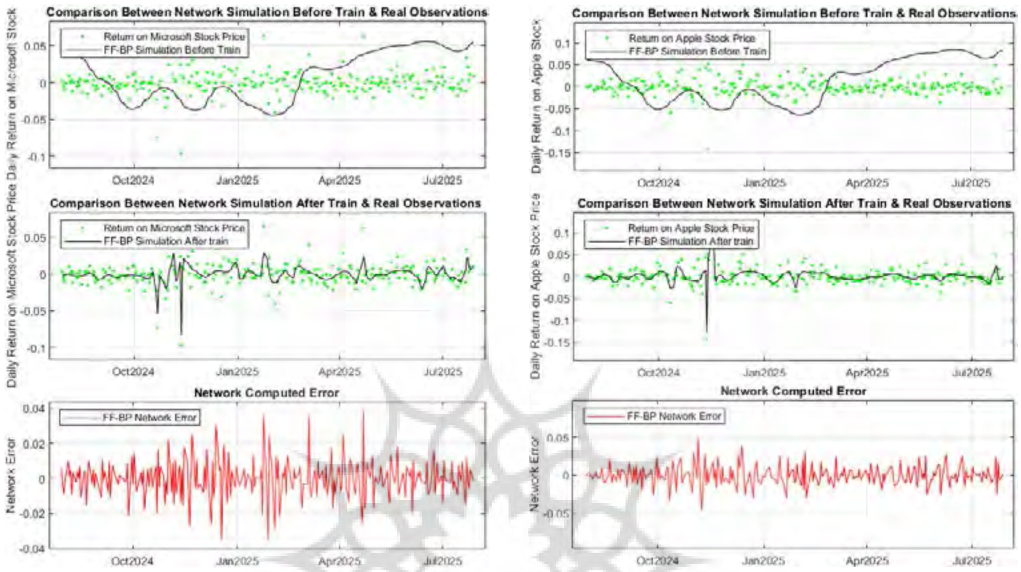


**Fig. 4: Results of Artificial Neural Network Simulation (Research Findings).**

Findings about the Apple Corporation are repeated once more based on stock return of Microsoft Corporation, which in terms of all the prediction error criteria, the method of exponential smoothing exhibited higher level of accuracy compared to the other procedures. Nevertheless, comparison between the ES procedure and ANN approach reveals the outstanding performance of AI method. The developed FF-BF model represented the lower level of error in term of the all calculated criteria. Therefore, for the in-sample prediction, ANN model has outperformed the other methods of the current study. For the out of sample forecasting, the selected forecasting horizon is the next five working days. The reason for this short forecasting-horizon selection is reflected in the nature of the stock market, which is associated with the high speed of transactions and participants in this market are more concern about the short-horizon price and return fluctuations. Results of the out-sample forecasting are depicted in figure (5). Usually models that are successful in capturing the DGP of a time series are expected to provide more accurate out-sample forecasting too.

**Table 6: Results of In-Sample Prediction**

| Model | RMSE | MAPE | BP | VP |
|---|---|---|---|---|
| ARMA-EGARCH of Apple Co. | 0.0395 | 103.6648 | 0.0006 | 0.7319 |
| SETARMA-GARCH of Apple Co. | 0.0366 | 99.8985 | 0.0001 | 0.7586 |
| ETS-ES of Apple Co. | 0.0376 | 64.8313 | 4.6E-07 | 6.5E-06 |
| MLP | **0.0001** | **13.629** | **1.02E-11** | **1.05E-13** |
| ARMA-EGARCH of Microsoft Co. | 0.0311 | 98.0141 | 0.0002 | 0.9165 |
| SETARMA-GARCH of Microsoft Co. | 0.0281 | 97.4215 | 0.0008 | 0.8813 |
| ETS-ES of Microsoft Co. | 0.0385 | 74.8522 | 2.5E-06 | 4.4E-05 |
| MLP | **0.0018** | **14.259** | **1.34E-11** | **1.11E-13** |

**Note:** σE-α is Equal to $\sigma \times 10^{-\alpha}$
**(**Research Findings).

As it is apparent from figure (5), the AI method has generated more close values to the real stock return time series of the both samples and vacillations are in line with the fluctuations of the real return series even compared to the exponential smoothing method. In contrast, the ARMA-EGARCH and SETAR-GARCH model have presented a linear out-sample forecasted values. Graphical comparison gives some insight about the accuracy of each model but is not sufficient, therefore error criteria were again computed and results are tabulated in table (7). The computed value of RMSE criterion of Apple Company for the ES model is lower than the regime switching and ARMA-EGARCH model, which implies that the accuracy of the exponential smoothing method compared to other two parametric methods are higher. Likewise, the calculated mean absolute percentage error criterion (MAPE) for the ES procedure is lower than the other two parametric models, which supports the result of the RMSE criterion about the precision of ES procedure. Likewise, the estimated bias proportion of the ES model is higher that is consist with the findings of the two previous criteria. Similarly, the results of variance proportion represent lower values for the exponential smoothing system in comparison with the ARMA-EGARCH and SETAR-GARCH model and implies that the mean and variance of forecasted values by the ES system are closer to the mean and variance of the real stock return series. Yet again, when the results of the MLP is included in comparisons, the results are in favor of this procedure and accuracy of MLP once more is proved than the ES procedure so the other rival methods.

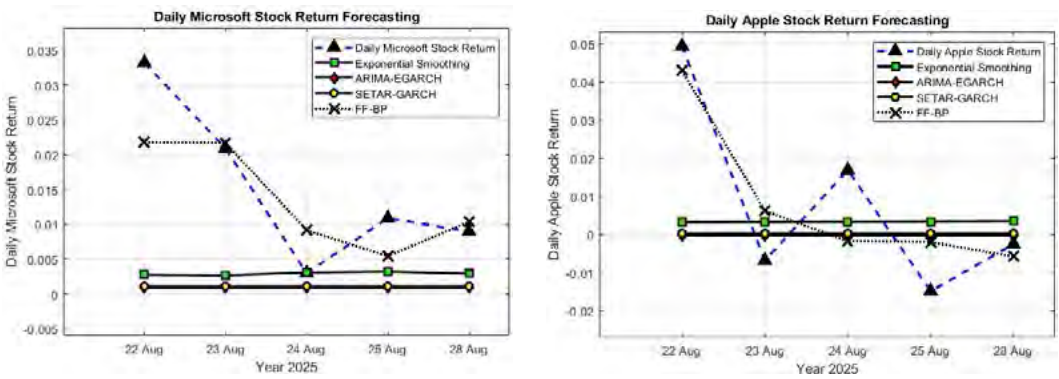


**Fig. 5: Out-Sample Forecasting of Research Models (Research Findings).**

Therefore, in the out-sample forecasting and based on all the computed error criteria, the MLP method has outperformed the Exponential Smoothing, ARMA-EGARCH and SETARMA-GARCH models in forecasting the Apple stock return series. This conclusion has reiterated by taking the Microsoft stock return forecasting into account. Meaning that, the MLP method has represented higher precision than the other methods of the present study. Furthermore, due to the nonlinear structure of SETAR-GARCH model, this method has outperformed the ARMA-EGARCH model based on the majority of error measurements in the both of selected time series. Findings of the current study are in line with outcomes of other researches such as Khadiri *et al.*, (2025), Gajdosikova & Michulek (2025), Zheng *et al.*, (2024), Pattanayak & Swetapadma (2024), Audrey *et al.*, (2023), Kurani *et al.*, (2023), Hosseinidoust *et al.*, (2016).

A breakdown of why ANNs can be more accurate than the econometric models based on the previous studies are as follow. First, the econometric models often assume linear relationships between variables. However, real-world data, particularly financial data, frequently exhibits complex, non-linear patterns that ANNs are designed to model effectively, Sameti *et al.*, (2011). Second, ANNs can learn and adapt to relationships in data without explicit assumptions about the functional form or the underlying data-generating process. This contrasts with traditional econometric methods, which rely on specific theoretical or functional forms that might not accurately represent complex real-world phenomena, Norouzian *et al.*, (2021). Third, trained neural networks act as experts in the data they have processed, enabling them to generalize information and learn complex mappings between inputs and outputs from examples, leading to improved predictive power, Madanchi Zaj *et al.*, (2023). Fourth, in time-series data, such as stock market indices, ANNs can better approximate long-range dependencies, which are crucial for accurate forecasting but often difficult for traditional models to capture, Xang *et al.*, (2018). Fifth, ANNs offer greater flexibility in modeling complex phenomena, such as volatility and asymmetry, which are common in financial markets and can lead to improved accuracy in volatility forecasts and risk management, Sahiner *et al.*, (2023). Sixth, ANNs learn directly from data, adjusting their internal parameters through a process of training to minimize errors and optimize their ability to predict future outcomes based on observed patterns, Ghiasi *et al.*, (2005).

**Table 7. Results of Out-Sample Forecasting**

| Model | RMSE | MAPE | BP | VP |
|---|---|---|---|---|
| ARMA-EGARCH of Apple Co. | 0.0063 | 87.3674 | 0.4244 | 0.5672 |
| SETARMA-GARCH of Apple Co. | 0.0057 | 85.3088 | 0.2855 | 0.6789 |
| ETS-ES of Apple Co. | 0.0020 | 71.6879 | 0.0303 | 0.0096 |
| MLP | 0.0001 | 24.5891 | 0.0015 | 0.0004 |
| ARMA-EGARCH of Microsoft Co. | 0.0076 | 110.8361 | 0.2364 | 0.7608 |
| SETARMA-GARCH of Microsoft Co. | 0.0069 | 92.2591 | 0.1578 | 0.7898 |
| ETS-ES of Microsoft Co. | 0.0013 | 70.2996 | 0.0551 | 0.0053 |
| MLP | 0.0002 | 29.5721 | 0.0019 | 0.0008 |

(Research Findings).

Lastly, in order to confirm that the suggested MLP method is truly more accurate than the ES model and the computed difference between the MLP procedure and the ES scheme are statistically significant, the Diebold and Mariano S-statistic is estimated. This test is based on the Squared Error (SE) loss function and for both of the in-sample and out-samples forecasting is computed. Results of this test are reported in table (8). Recall that a negative and significant value of the S-statistic implying that the first model is dominant and more accurate than the second model. Paying attention to the calculated forecasting error criteria and higher performance of MLP method compared to the ES procedure and higher performance of MLP than the ES, Diebold-Mariano test is established based on MLP and ES procedure as the first and second model.

**Table 8: Results Diebold-Mariano Test**

| First Model | Second Model<br>Exponential Smoothing |
|---|---|
| MLP | S-statistic for In-Sample Prediction |
| | -3.2381<br>*(0.0287)* |
| MLP | S-statistic for Out-Sample Prediction |
| | -2.0929<br>*(0.04601)* |

**Note:** Reported Values in Parentheses are Estimated Probabilities
(Research Findings).

The computed S-statistic that is estimated based on errors of MLP procedure and ES model is negative and significant in the both in-sample and out-sample forecasting indicating that the developed Artificial Intelligence methods of MLP in the current study is significantly more accurate than the Exponential Smoothing model. In other words, the ability of MLP in determining and capturing the data generating process of the both return series is significantly higher than the other models.

## 5. Conclusion

Accurate stock market forecasting still has remained as a challenging and complex problem for the market analysts as well as the authorities and decision makers. Main objective of present research is to investigate the eligibility of nonlinear parametric and nonparametric models such as ARMA-EGARCH, SETARMA-GARCH, Exponential Smoothing and Multi-Layer Perceptron neural network as an Artificial Intelligence (AI) method. Data set consist of Apple and Microsoft daily stock return observations spanning from Aug 2024 to Auf 2025. Augmented Dickey-Fuller

(ADF) and Zivot-Andrews (ZA) stationary tests are employed to find the level of integration in the time series. Moreover, through the method of Terasvirta-Lin-Granger the nonlinearity of the data generating process is investigated to shed more light on chaotic behavior of the selected stock return series. The Self-Exciting Threshold Autoregressive Moving-Average (SETARMA) model is combined with GARCH-component that yields SETAR-GARCH and ARMA model combined with Exponential-GARCH model (ARMA-EGARCH) in order to capture the heterogeneous variance, which is a typical characteristic of the financial time series. All methods are checked using the relevant diagnostic tests such as normality, serial correlation and heteroscedasticity. Furthermore, both of in-sample and out-sample forecasting are carried out and the models performance is evaluated using the popular forecasting error criteria such as RMSE, MAPE, Bias Proportion and Variance Proportion. In addition, to determine significance of the observed difference between models the Diebold and Mariano test is employed to confirm selection of the best method. Findings indicate that the developed neural network (MLP) is outperformed the other methods for both of in-sample and out-sample forecasting in terms of majority of the calculated error criteria. Moreover, outstanding performance of the SETARMA-GARCH model has observed in comparison with the ARMA-EGARCH model. The computed S-statistic of Diebold-Mariano test confirmed results of the forecasting in favor of significant accurate performance of MLP method than the ES method. Findings of current study suggest application of dynamic nonlinear-nonparametric methods in modeling of stock return time series. The primary policy implication of Artificial Neural Network (ANN) models outperforming econometric models in forecasting is the potential for more informed and proactive policy-making by governments and businesses. This improved accuracy can lead to better decision-making, such as implementing timely economic interventions, managing resource allocation more effectively, and developing more robust risk management strategies in both public and private sectors. ANNs' ability to capture non-linear relationships in data, which econometric models often struggle with, allows for a deeper understanding of complex economic systems, supporting more effective responses to economic challenges.

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**Observation Contribution**

The corresponding author got the main observation contribution in present study.

**Conflict of Interest**

All authors have participated in conception and design, or analysis and interpretation of the data; drafting the article or revising it critically for important intellectual content, and approval of the final version. The authors approved that there is no conflict of interest in publishing of the current study.

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# پیش‌بینی بازده سهام با استفاده از روش‌های غیرخطی پویا: مدل‌سازی پارامتریک و ناپارامتریک

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## چکیده

پیش‌بینی دقیق بازار سهام یک مسئله چالش‌برانگیز و پیچیده برای تحلیلگران و تصمیم‌گیرندگان بازار است. در اغلب مطالعات گذشته، دقت روش‌های مختلف مورد بررسی قرار گرفته است، اما هنوز در مورد روش پیش‌بینی بهینه اتفاق‌نظر وجود ندارد. هدف اصلی مطالعهٔ حاضر بررسی قابلیت مدل‌های سری‌های زمانی غیرخطی، مانند مدل‌های هموارسازی نمایی و رویکرد تغییر رژیم، در کنار روش باکس-جنکینز در پیش‌بینی بازده سهام است. داده‌ها شامل مشاهدات روزانهٔ شرکت‌های اپل و مایکروسافت از سال ۲۰۲۴ تا ۲۰۲۵م. است. آزمون تراسوریتا-لین-گرنجر رفتار آشوبناک فرآیند تولید داده‌ها را به اثبات رسانده است. رویکرد SETAR با مؤلفه GARCH و مدل ARMA با مؤلفه EGARCH برای کنترل اثر واریانس ناهمسان شرطی در سری‌های زمانی استفاده شده است که منجر به مدل‌های ترکیبی پویا می‌شود. علاوه‌بر این، با توجه به کاربرد گستردهٔ روش‌های هوش مصنوعی، علاوه‌بر رویکرد هموارسازی نمایی (ES) به‌عنوان یک روش ناپارامتریک، یک شبکهٔ پرسپترون چندلایه (MLP) نیز مورداستفاده قرار گرفته است که مبتنی‌بر الگوریتم پس‌انتشار خطا (FF-BP) است. پیش‌بینی‌ها در دو فرم درون نمونه‌ای و برون نمونه‌ای انجام شده و عملکرد مدل‌ها با استفاده از معیارهای خطای استاندارد ارزیابی می‌شود. درنهایت، از آزمون دایبولد-ماریانو برای تعیین معناداری تفاوت‌های پیش‌بینی بین مدل‌ها استفاده شده است. یافته‌ها نشان می‌دهند که سری‌های زمانی بازده سهام هر دو شرکت رفتاری آشوبناک داشته‌اند و روش‌های غیرخطی در مدل‌سازی آن‌ها مناسب‌تر هستند. روش هموارسازی نمایی از نظر اکثر معیارهای خطا در هر دو پیش‌بینی درون‌نمونه‌ای و برون‌نمونه‌ای، از مدل‌های SETARMA-GARCH و ARMA-EGARCH بهتر عمل کرده است. با این‌حال، روش MLP براساس تمامی معیارهای خطا، بر مدل ES برتری داشته است. آمارهٔ S تخمینی آزمون دایبولد-ماریانو، معناداری برتری رویکرد MLP را تأیید می‌نماید. این یافته‌ها، استفاده از روش‌های ناپارامتریک پویا را در مدل‌سازی و پیش‌بینی سری‌های زمانی منتخب پیشنهاد می‌کند؛ به‌عبارت دیگر، استفاده از روش‌های غیرخطی ناپارامتریک پویا در پیش‌بینی سری‌های مالی توصیه می‌شود.

**کلیدواژگان:** پیش‌بینی بازده سهام، آزمون آشوب، روش‌های پارامتریک و ناپارامتریک، مدل‌سازی غیرخطی پویا، مدل هوش مصنوعی.

**طبقه‌بندی JEL:** G11, G14, G17, G32.

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