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A novel leading moving average indicator using ANFIS-Wavelet hybrid method for financial market forecasting

Mohammad Kazemi[†*], **Hamed Mohammadi Peyhani**[‡], **Mohsen Akbari**[§]

[†] *Department of Statistics, Faculty of Mathematical Sciences, University of Guilan, Rasht, Iran*
[‡] *Department of Information Science, University of Ottago, Dunedin, New Zealand*
[§] *Department of Business Administration, Faculty of Management and Economics, University of Guilan, Rasht, Iran*
Email(s): m.kazemi@guilan.ac.ir, h.peyhani@gmail.com, m.akbari@guilan.ac.ir

Abstract. Technical analysis aims to identify market trends and forecast future direction to support profitable trading decisions. This paper introduces a novel leading moving average indicator based on a hybrid ANFIS-Wavelet approach. The proposed method consists of two main components. First, a hybrid model combining an Adaptive Network-based Fuzzy Inference System (ANFIS) and Wavelet Transform (WT) is employed to forecast future market prices, with the full wavelet decomposition of the price time series serving as input parameters for ANFIS. Second, a leading moving average is constructed using both historical and forecasted prices. Similar to the other leading indicators, the proposed indicator can serve as a market predictor due to its incorporation of forecasted values. Empirical evaluation on NASDAQ-listed stocks demonstrates that this indicator is effective as a trading decision-support tool in financial markets, such as stock exchanges.

Keywords: Artificial neural network (ANN), financial forecasting, moving average, time series, wavelet transform.
AMS Subject Classification 2010: 62M10, 91B84

1 Introduction

In financial markets, technical indicators can be divided into two main types: leading and lagging. Leading indicators change before the market starts to follow a particular direction and are typically used as short-term predictors. The Relative Strength Index (RSI) and Stochastic Oscillator are among the most well-known leading indicators. In contrast, lagging indicators follow market price movements and focus on identifying the market trend. However, they cannot predict market fluctuations; instead, they only

*Corresponding author

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confirm long-term trends since they are based solely on the past prices. The moving average (MA) is the most widely used lagging indicator. By filtering out short-term volatility, MAs help traders identify the underlying trend more clearly. In trending markets, key MAs (such as the 50-day or 200-day) often act as support (in uptrends) or resistance (in downtrends). MAs are simple and easy to use, requiring no complex calculations, which makes them beginner-friendly and widely understood. However, it's important to note that MAs do not predict future price movementsthey only confirm existing trends.

The key to success in financial market trading lies in the ability to accurately predict future market fluctuations. As the adage goes, traders aim to "buy low and sell high" to generate profits. Numerous studies have addressed financial market forecasting, though it is important to note that, given the current state of human knowledge, accurately predicting exact market prices over the long term remains impossible. Consequently, researchers have developed sophisticated methods to minimize forecasting errors.

Among forecasting systems, the Adaptive Network-based Fuzzy Inference System (ANFIS) has emerged as a popular tool, combining the strengths of Artificial Neural Networks (ANN) and fuzzy logic. Its effectiveness has made it a preferred choice among researchers and has been applied across various domains. In finance, it has been used to forecast stock market returns. For instance, Cheng et al. [8] used ANFIS to forecast stock prices in Taiwanese markets. Boyacioglu and Avci [7] used six macroeconomic variables along with three stock indices as ANFIS input variables to predict the Istanbul Stock Exchange index. Atsalakis and Valavanis [3] used fifteen different combinations of past stock prices as ANFIS inputs to forecast short-term trends in the stock market. Esfahanipour and Aghamiri [18] used technical indices as the ANFIS input variables for stock price prediction. Wei et al. [33] used multiple technical indicators as ANFIS input variables to predict stock price trends. Atsalakis et al. [2] used Elliot Wave Theory with an ANFIS system to predict stock prices. Melin [25] presented an ensemble of ANFIS models for the prediction of chaotic time series. Svalina [28] proposed an ANFIS model to forecast the next five days' closing price of the Zagreb Stock Exchange Crobex index.

Tan et al. [30] used an ANFIS model with reinforcement learning (RL) to create a decision-making model for identifying price trend movements in financial markets. Wei [31] proposed an ANFIS hybrid method based on an adaptive expectation genetic algorithm for forecasting stock market prices. Wei [32] proposed a novel GA-weighted ANFIS model to predict the Taiwan stock market index. Chang et al. [11] used autoregressive and volatility in an ANFIS hybrid model for TAIEX forecasting. Bagheri et al. [5] proposed a novel hybrid ANFIS-Wavelet-QPSO method for forecasting exchange rates in the FX market. Cheng et al. [9] used multi-stock volatility causality and a new fusion ANFIS model to predict Taiwan stock market prices. Ebrahimpour et al. [17] proposed a hybrid method based on ANFIS and three MLP neural networks to predict price trends in the Tehran Stock Exchange. Chen [12] proposed an ANFIS hybrid model based on particle swarm optimization for tuning subtractive clustering parameters to predict business failures. Ansari et al. [4] proposed an ANFIS model based on economic and statistical analysis as an uncertainty detection system during a recession period. Liu et al. [23], Chiang [13], and Lin et al. [22] used ANFIS with Quantum-behaved Particle Swarm Optimization (QPSO) for membership function tuning.

Furthermore, Barak et al. [6] have also developed a forecasting model based on the wrapper ANFIS. Two Raw-based and Signal-based approaches were devised to extract the models input variables with 15 and 24 features. Wei [34] suggested a hybrid ANFIS model that incorporated the empirical mode decomposition to predict the TAIEX index prices. Kristjanpoller and Michell [21] explored a stock market risk-forecasting model by incorporating ANFIS and GARCH techniques and used an ANN to increase the GARCH model's forecasting accuracy. Altan et al. [1] proposed a hybrid-forecasting model for digital currency time series, which was based on the long short-term memory (LSTM) neural network and empirical wavelet transform decomposition along with the Cuckoo Search (CS) algorithm. Do et al. [16] developed two proficiency-forecasting models used to forecast the daily Vietnamese stock index. The developed models are based on two artificial intelligence techniques, including ANFIS and LSTM. Orozco-Castaeda et al [26] developed an ARIMA-ANFIS model for BTCUSD price prediction and risk assessment. Zhang et al. [36] proposed a new hybrid model combining Wavelet Transform (WT), ARIMA and LSTM models to predict share price index futures.

The studies above mentioned show that ANFIS-based stock forecasting models have a solid historical foundation and are particularly popular among researchers due to their learning behavior and modeling nonlinear market data. However, the performance of ANFIS method is directly relevant to its input parameters.

This paper is motivated by the need for a forward-looking technical indicator that addresses the limitations of traditional MAs. Lagging MAs are best used in trend-following strategies rather the predicting reversals. They work well in strong trending markets but should be combined with other indicators for better accuracy. In this paper, we propose a new hybrid ANFIS-Wavelet approach to incorporate forecasted prices, transforming the MA into a leading indicator. Specifically, we first use wavelet decomposition to extract multi-scale features from price data, enhancing the quality of ANFIS inputs. Then, we develop a 5-day Leading MA (LMA5) that integrates historical, current, and forecasted prices, enabling earlier trend detection. The integration of wavelet-based ANFIS with MA indicators presents a promising approach for enhancing the accuracy of market trend forecasting and predicting future trajectories in related domains. We demonstrate the predictive superiority of the proposed method over traditional MAs through empirical testing on NASDAQ data.

The remainder of this paper is organized as follows: Section 2 and Section 3 review ANFIS and Wavelet Transform theory, Section 4 details our methodology, and Section 5 presents experimental results. Finally, we conclude the paper in Section 6.

2 Adaptive-network-based fuzzy inference system

Fuzzy logic was first introduced by Zadeh [35] in the 1960s as a framework for handling uncertainty and imprecision in data. A key characteristic of fuzzy logic is its ability to assign data to multiple overlapping sets, represented through linguistic variables. Models developed using fuzzy logic are typically expressed as a collection of if-then rules. A Fuzzy Inference System (FIS) consists of three fundamental components: (1) fuzzy rules, (2) membership functions, and (3) a reasoning mechanism. There are three primary types of fuzzy inference systems:

i. Mamdani system ([24]): produces a fuzzy output that requires defuzzification to obtain a crisp value,

ii. Takagi-Sugeno (TS) system ([29]: generates a real-valued output, typically as a linear combination of input variables,

iii. Tsukamoto system: utilizes monotonous membership functions to derive the output.

Each of these systems offers distinct advantages depending on the application, with Mamdani and Takagi-Sugeno being the most widely used in practice.

The ANFIS, introduced by Jang [20], is a neuro-fuzzy model based on a Sugeno-type fuzzy system that combines the learning capabilities of ANNs with the interpretability of fuzzy logic. The underlying framework employs a Takagi–Sugeno fuzzy inference system, as follows ([35]):

$$\begin{aligned}&\text{Rule 1: if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{then } f_1 = p_1x + q_1y + r_1,\\ &\text{Rule 2: if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2.\end{aligned}$$

The general architecture of ANFIS for a fuzzy inference system with two inputs (x and y) and one output (f) is illustrated in Figure 1. It consists of a five-layer feedforward neural network, where each layer performs a specific step in the fuzzy reasoning process. In each layer, $O_{k,i}$ denotes the node at the i-th position of the k-th layer. The operational details of each layer are described as follows:

- Layer 1 (Fuzzification Layer): This layer produces membership values for input variables using a membership function. For input x (or y), the output of the i-th node is:

$$O_{1,i} = \mu_{A_i}(x), \quad i = 1,2, \tag{1}$$

  where A_i is the linguistic label (*small , large, etc.*) associated with this node function. In other words, $O_{1,i}$ is the membership function of A_i, and it specifies the degree to which the given x satisfies the quantifier A_i. Usually we choose $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}},$$

  or

$$\mu_A(x) = \exp -(\frac{x-c_i}{a_i})^2,$$

  where $\{a_i, b_i, c_i\}$ are known as premise parameters. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label A_i.

- Layer 2 (Rule Layer): This layer computes the firing strength of each fuzzy rule via multiplication of the incoming signals and sends the results to the next layer:

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,2. \tag{2}$$

- Layer 3 (Normalization Layer): This layer normalizes firing strengths to ensure they sum to 1:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2. \tag{3}$$

- Layer 4 (Defuzzification Layer): This layer computes the weighted output of each rule using a linear function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_ix + q_iy + r_i), \quad i = 1,2, \tag{4}$$

  where $\bar{w}_i$ is the layer 3 output and the parameters p_i, q_i and r_i are referred to as subsequent parameters.

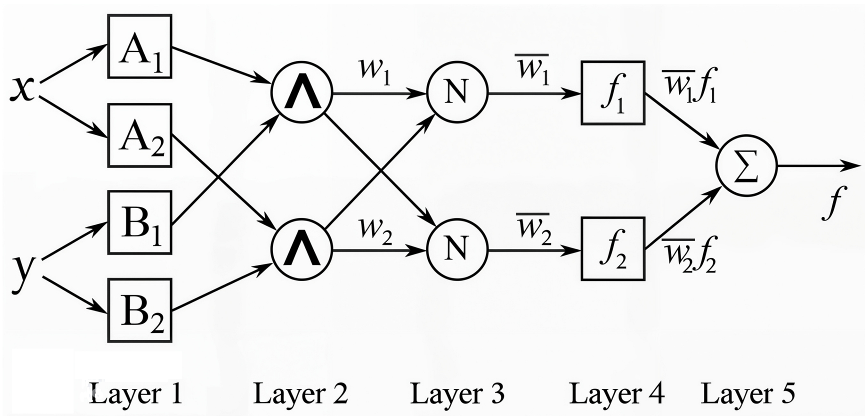

Figure 1: ANFIS general architecture.

- Layer 5 (Output Aggregation Layer): This layer contains only one node and sums all incoming signals to produce the final crisp output:

$$O_{5,1} = \text{overall output} = \sum_i \bar{w}_i f_i. \tag{5}$$

3 Wavelet transform

The WT is a widely used signal processing technique for extracting time-frequency information from signals ([10]). It decomposes a signal into components localized in both time and frequency by projecting it onto wavelet basis functions.

Given a signal $f(t)$, its wavelet decomposition up to level J can be expressed as a series of projections onto scaling (father) and wavelet (mother) functions, typically represented as:

$$f(t) = \underbrace{\sum_k a_{J,k}\phi_{J,k}(t)}_{\text{Coarsest approximation}} + \underbrace{\sum_{j=1}^{J}\sum_k d_{j,k}\psi_{j,k}(t)}_{\text{All details from levels 1 to } J}, \tag{6}$$

where

- $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are the scaling function (represents the "overall shape" of the signal) and wavelet functions (captures details), respectively, defined as:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t - k),$$
$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k).$$

  The mother scaling function $\phi(t)$ and mother wavelet function $\psi(t)$ are the foundational functions in wavelet theory, from which all scaled and translated versions $\big(\phi_{j,k}(t), \psi_{j,k}(t)\big)$ are derived. Their mathematical forms depend on the specific wavelet family (e.g., Haar, Daubechies, Symlets).

- $a_{j,k}$ and $d_{j,k}$ represent the approximation (smooth) and detail (high-frequency) coefficients, respectively, computed by projecting the signal onto the corresponding wavelet bases:

$$a_{j,k} = \int f(x)\varphi_{j,k}(x)dx,$$
$$d_{j,k} = \int f(x)\psi_{j,k}(x)dx.$$

Finally, the original signal $f(t)$ is reconstructed as the sum of its smoothed and detailed components:

$$f(t) = A_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t), \tag{7}$$

where

$$A_J(t) = \sum_k s_{J,k}(t)\phi_{J,k}(t),$$
$$D_j(t) = \sum_k d_{j,k}(t)\psi_{j,k}(t).$$

There are two main types of WT: the Continuous WT (CWT) and the Discrete WT (DWT). If $W(a,b)$ is the CWT of $f(x)$, then

$$W(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} f(x)\psi\left(\frac{x-b}{a}\right)dx.$$

If $w(p,q)$ is the DWT of $f(x)$, then

$$w(p,q) = 2^{-p/2}\sum_{t=0}^{T-1} f(t)\psi\left(\frac{t-q\cdot 2^p}{2^p}\right),$$

where T is the length of $f(x)$. For more details on wavelet analysis, refer to [14], [15], [27], and [10] for wavelets on the interval and the fast wavelet transform.

4 The proposed method

In this paper, we present a novel leading MA indicator, developed in two main stages. In the first stage, a hybrid ANFIS-Wavelet method is employed to forecast market prices for the next two days. In this stage, the wavelet decomposition of the price time series serves as the input parameters for ANFIS. In the second stage, the leading MA indicator is constructed using both historical and forecasted market prices. The details of the proposed methodology are described in the following subsections.

4.1 Stage 1: forecasting market price

ANFIS is a well-established method in financial forecasting. However, its performance heavily depends on the input parameters. Unlike previous studies that relied on technical indicators due to their simplicity, this work employs wavelet decomposition of the price time series as input to ANFIS, enhancing its predictive capability. The proposed forecasting model in this stage is shown in Figure 2. This stage is performed in three sequential steps:

First step (wavelet decomposition): The input price time series is decomposed using Daubechies 4 (db4) wavelet with three decomposition levels. This yields one approximation series (low-frequency trends, level 3) and three detail series (high-frequency fluctuations, levels 13). These components capture multi-scale market behaviors, making them ideal inputs for forecasting.

Second step (ANFIS structure): A Sugeno-type FIS is generated using fuzzy c-means (FCM) clustering. The four wavelet-derived series serve as inputs, with each input fuzzified via membership functions (e.g., bell-shaped).

Third step (training and prediction): The model is trained on historical data to learn the relationship between wavelet components and price movements. Once trained, it forecasts prices for the next two days, which are then used to compute the leading moving average.

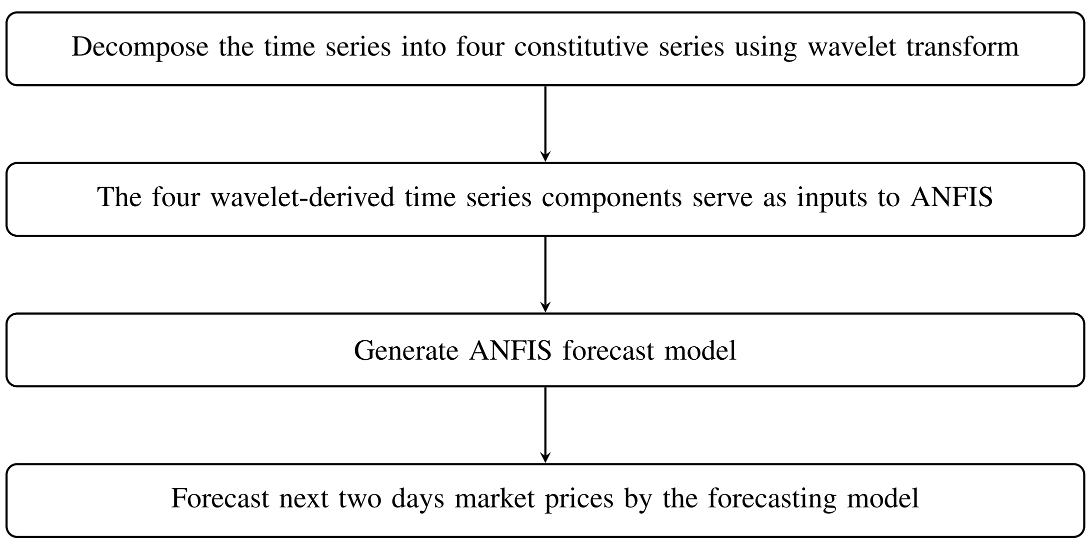

Figure 2: Flowchart of the forecasting model

4.2 Stage 2: creating leading moving average

Following the forecasting of next two days' market prices by our ANFIS-Wavelet model, we construct a LMA5 indicator that incorporates: historical prices (two preceding days), current market price and forecasted prices (two subsequent days). Specifically, the proposed leading moving average is computed using a symmetric 5-day window:

$$\mathrm{LMA}_t = \frac{P_{t-2} + P_{t-1} + P_t + \hat{P}_{t+1} + \hat{P}_{t+2}}{5},$$

where P_{t-k} represents the actual closing price at time $t-k$ (historical data), P_t is the current observed price and $\hat{P}_{t+k}$ denotes the forecasted prices for time $t+k$.

This novel moving average is unique in its integration of both backward-looking and forward-looking price data, fundamentally distinguishing it from traditional moving averages, which are lagging indicators due to their reliance solely on past prices. This innovative architecture allows the LMA5 to function as both of a trend-confirmation tool (through its historical price components), and a predictive indicator (via its forecasted price elements). Figure 3 illustrates the conceptual framework of the leading moving average.

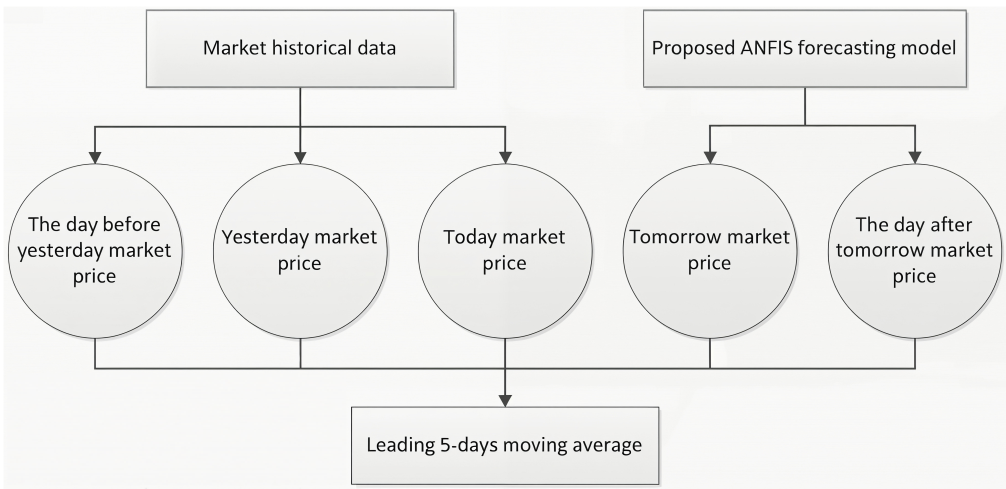

Figure 3: Schema of the proposed leading moving average.

5 Experiments and results

To evaluate the performance of the proposed method, we used daily closing prices of Apple Inc. covering 500 trading days, spanning from January 2023 to December 2024, as illustrated in Figure 4. The data was obtained from the official NASDAQ website. We divided the dataset into training and testing sets, using the first 410 days (approximately 80% of the data) for model development and the remaining 90 days (approximately 20%) for performance evaluation.

In the first stage, we performed wavelet decomposition on the training time series data using Daubechies 4 (db4) with three decomposition levels. This process generated one approximation component (A_3) and three detail components ($D_1 - D_3$). Figure 5 illustrates the complete decomposition of Apple Inc.'s daily closing prices.

Then the four decomposed time series components served as input parameters for the ANFIS model. We employed FCM clustering to generate FIS, which extracts a set of rules capable of modeling the input data behavior. The implementation was performed in `MATLAB` using the `genfis3` function with `sugeno` specified as the FIS type parameter, resulting in a Sugeno-type FIS structure. The trained ANFIS model was then evaluated using the final 90 days of data as the test set. Figure 6 compares the actual test data with the ANFIS-forecasted prices, while Figure 7 shows the curve fitting plot, illustrating the model's predictive accuracy for Apple Inc. stock prices. In this plot, the regression line helps visualize the linear relationship between actual prices and LMA5 predictions, while the $y = x$ line serves as a reference for perfect prediction scenarios.

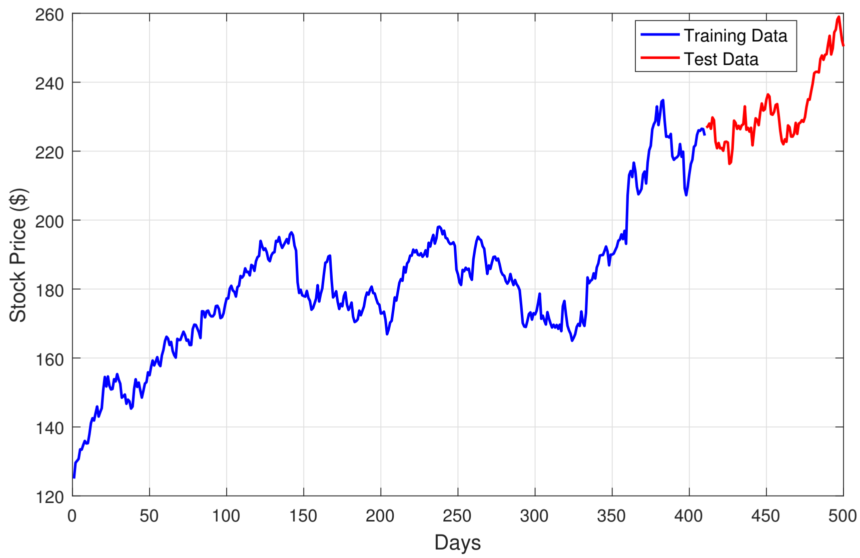

Figure 4: Apple Inc.'s daily closing prices between January 2023 and December 2024.

In the second stage, the leading MA indicator is constructed using historical and forecasted stock prices. The results depicted in Figure 8 demonstrate a comparative analysis between the Simple MA (SMA) and the proposed LMA5 for Apple's stock prices. While the SMA, relying solely on historical data, exhibits a lag in trend detection, the ANFIS-Wavelet enhanced LMA5 reacts faster to shifts in the market. A particularly illustrative case occurs at Day 426, where the LMA5 reverses its trajectory from upward to downward, signaling a price correction and suggesting its not a good time to buy more stocks. In contrast, the SMA maintains its previous trajectory because its based only on past data. This anticipatory behavior of the LMA5 stems from its incorporation of forecasted price data, enabling earlier detection of trend reversals. The results show that the LMA5 is an advanced technical indicator, reducing delays in signals and providing useful insights when markets are unstable.

6 Conclusion

This paper presents a novel methodology for developing a leading MA indicator through a two-stage approach. The first stage involves constructing a forecasting model using an ANFIS architecture, where WT decomposes the input time series into four constitutive time series that serve as ANFIS inputs. The second stage develops a 5-day leading MA that incorporates historical, current, and forecasted market prices. Experimental results demonstrate that the proposed method performs effectively in financial analysis, particularly in stock exchange markets.

According to the Efficient Market Hypothesis (EMH) ([19]), stock closing prices should reflect all available information, including economic and political factors. Consequently, market price forecasting remains challenging for both traders and computer-based expert systems. While soft computing techniques have shown promise in financial forecasting, EMH suggests that precisely predicting stock prices is inherently impossible - a potential limitation of our proposed method.

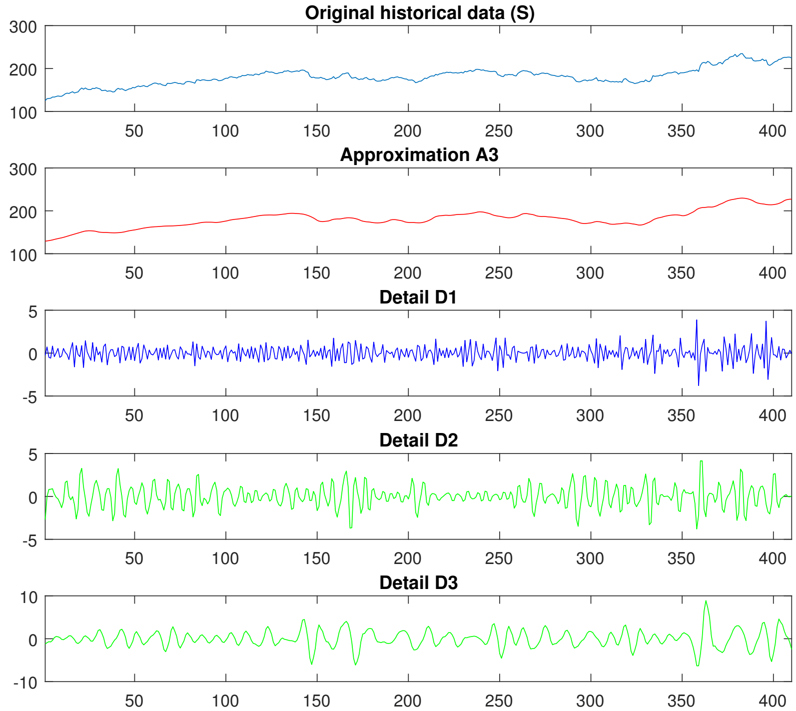

Figure 5: The wavelet decomposition of Apple Inc.'s daily closing prices.

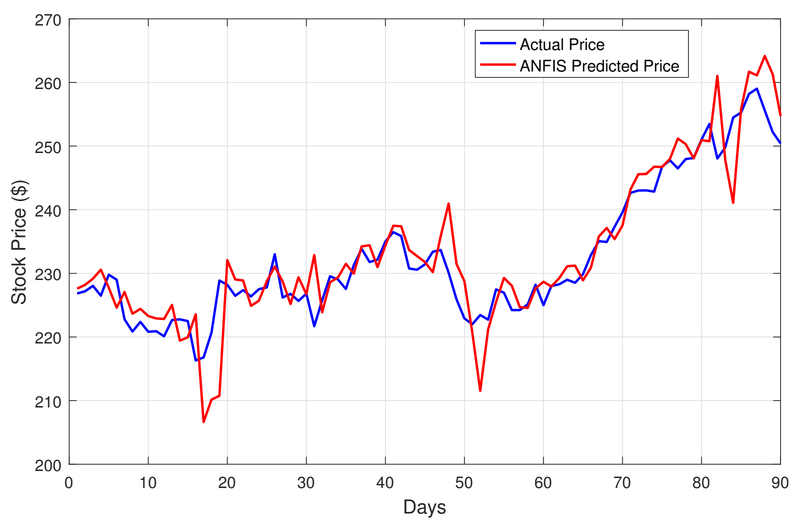

Figure 6: Actual daily closing prices of Apple Inc. (blue) compared with ANFIS-predicted prices (red).

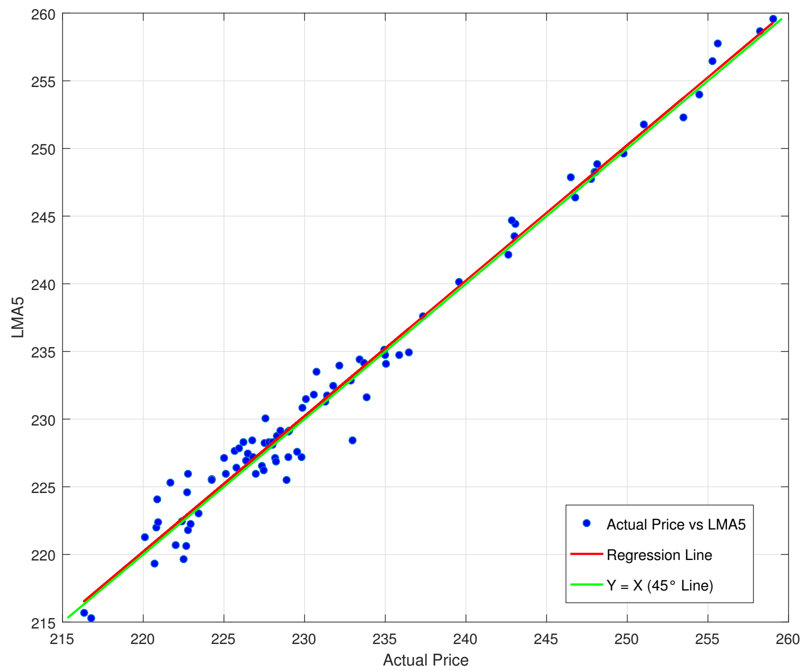

Figure 7: Curve fitting plot for actual and predicted Apple Inc. stock prices.

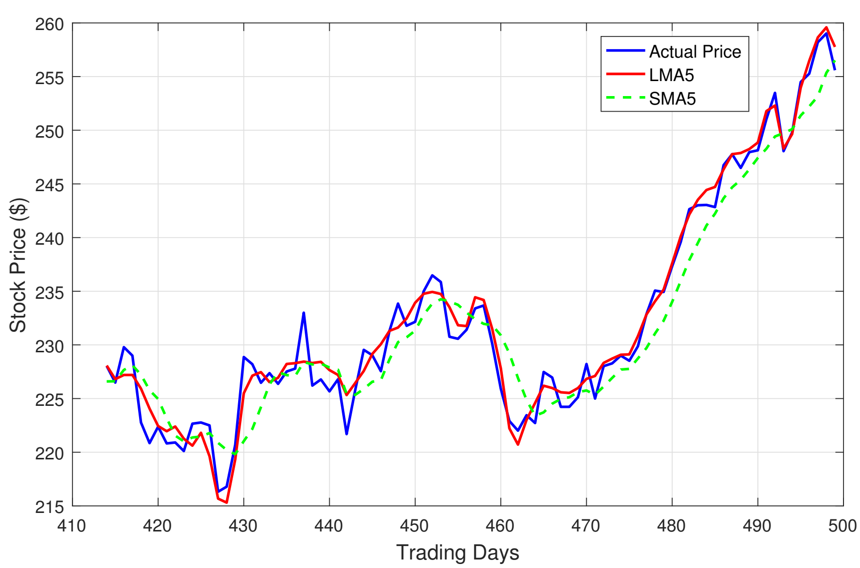

Figure 8: Proposed leading moving average (red) and simple moving average (green).

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