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The Cost Realization on Time Frame Shift of Securities

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Abstract
Investors use a variety of investing methods depending on the time scales () of their short-term and long-term investment time horizons (ITH). The nature of the market varies greatly depending on the type of investment. Hurst exponents (H) and normalised variance (NV) techniques based on empirical mode decomposition (EMD) have been used to identify key features of the market over various time horizons. For the stock price's decomposed intrinsic mode functions (IMF), the values of H and NV have been estimated. We found H1 0.5 0.04 and H1 0.75 for the IMFs with time periods ranging from a few days to 3 months and 5 months, respectively. Two time series from the IMFs have been reconstructed based on the value of H1: a) Short-term time series [XST (t)] with H1 = 0.5.b) long-term time series [XLT (t)] with H1 0.75 and a time span of 5 months. The XST (t) and XLT (t) indicators reveal that market dynamics in short-term ITH are random and connected in long-term ITH. We also discovered that the NV is very low in short-term ITH and gradually increases in long-term ITH. The results also reveal that in the long run, stock prices are connected with the company's fundamental factors. The discovery may aid investors in developing investment and trading strategies for both short-term and long-term investment goals.

Keywords: Hurst exponent, Hurst mode decomposition, short-term investment time horizon, long-term investment time horizon, time scale, normalized variance.

1. INTRODUCTION

The stock market is a complex dynamical system whose evolution is determined by the activity of many sorts of investors or traders [1-5]. Investors/traders profit from the stock market by employing various investment and trading techniques based on investment time horizons (ITH) [6, 7,8,9,10]. The engagement of diverse investors, reaction to information, and short-term and long-term investment strategies all play important roles in stock price fluctuation [11,12,13]. There are two sorts of investors in the stock market: short-term investors who invest for short-term gain and long-term investors who invest for long-term benefit [14, 15,16,17]. According to studies, the ITH for short-term investors can range from a single day to a few months, whereas it can range from a few months to several years for long-term investors [18, 19,20,21,22]. Technical analysis is used by fund managers and foreign currency dealers in various nations for short-term ITH and fundamental analysis is used for long-term ITH [24,25,26,27,28]. The time scales ( ) of short-term and long-term ITH are often chosen arbitrarily by investors based on investment experience [29, 30]. As a result, identifying from stock price time series using a well-defined technique may be beneficial to both short-term and long-term investors. Because the market is typically reverting in short-term ITH [31-37], traders using technical analysis fail to create significant returns [38]. Long-term ITH, on the other hand, can yield big returns or assist in deciding whether to leave a particular stock to minimise loss by analysing a company's financial health using basic characteristics [39-42]. Fundamental analysis is an important method for determining the relationship between a stock's price and fundamental characteristics such as book to market (B/M), sales to price, debt to equity, earnings to price, and cash flow [43-46]. The stock price is found to be favourably related to the fundamental variables [47-52]. A thorough examination of the association between short-term and long-term ITH is required in order to make sound investment decisions. In the near term, the market is seen to be governed by investors' psychological behaviour. Yet, the fundamental elements are the most important deciding factors in long-term ITH. Typically, investors arbitrarily pick between short-term and long-term investing horizons [53-59]. We recently employed structural break analysis to demonstrate that the for the short term is frequently less than a few months [60]. The distinction between short- and long-term dynamics in terms of is critical in predicting future prices. In this study, we used empirical mode decomposition (EMD)-based Hurst exponent (H) analysis to estimate the of the stock price in the short-term and long-term ITH for twelve key global stock indices and the stock price of specific companies. Based on the H, we recreated short-term and long-term time series[61-65]. Lastly, the correlation coefficient between long-term time series and fundamental variables was calculated. We establish here that short-term ITH is typically less than 3 months and long-term ITH is greater than 5 months. According to correlation analysis, the long-term stock price is favourably connected with the basic variables. The remainder of this work is structured as follows: Part 2 introduces the method of analysis, while Sections 3 and 4 outline the results, discussion, and conclusion, respectively.

2. Methodology:

The empirical mode decomposition, which can break complicated signals into a finite number of IMFs, is the key to this strategy. Local distinctive signals of different time scales of the original signal are contained in the decomposed IMF components (Nan et al., 2018). The EMD approach may smooth non-stationary data before performing the Hilbert transform to generate the time spectrum map, which can then be used to calculate the frequency with physical significance (Fu, 2018). This method is straightforward, direct, posteriori, and adaptable when compared to short-time Fourier transform, wavelet decomposition, and other methods because the basic function is decomposed by the data itself. The decomposition is called adaptive because it is based on the local properties of the signal sequence time scale.

Multilayer perceptrons (MLPs) were used in this study, along with the feedforward and BP methods. The feedforward and BP methods were employed to improve the accuracy of the MLPs, which is critical for financial market forecasting. Because this sort of NN is classified as supervised, it requires precise output for learning. The architecture is divided into three layers: input, concealed, and output. In this investigation, a conventional hidden layer of 64 neurons is used. In practise, this design demonstrates the excellent approximate performance of optimum statistical classifiers in difficult tasks. For the purpose of this experiment, MLPs architecture was chosen because it is the most commonly utilised network architecture for financial market forecasting.

Figure 1 depicts the proposed method for forecasting financial markets. It extracts features from massive volumes of transactional data. The market forecasts were then done using feature extraction in the prediction model. Each IMF projections are based on actual input data and are prepared on a single day within the sliding timeframe. The hyperparameters for the proposed model's BPNN are chosen back-to-back based on the accompanying reduction in out-of-sample loss. A BPNN is used to forecast each intrinsic function. The projected constituent components are then merged to get the overall predicted signal.

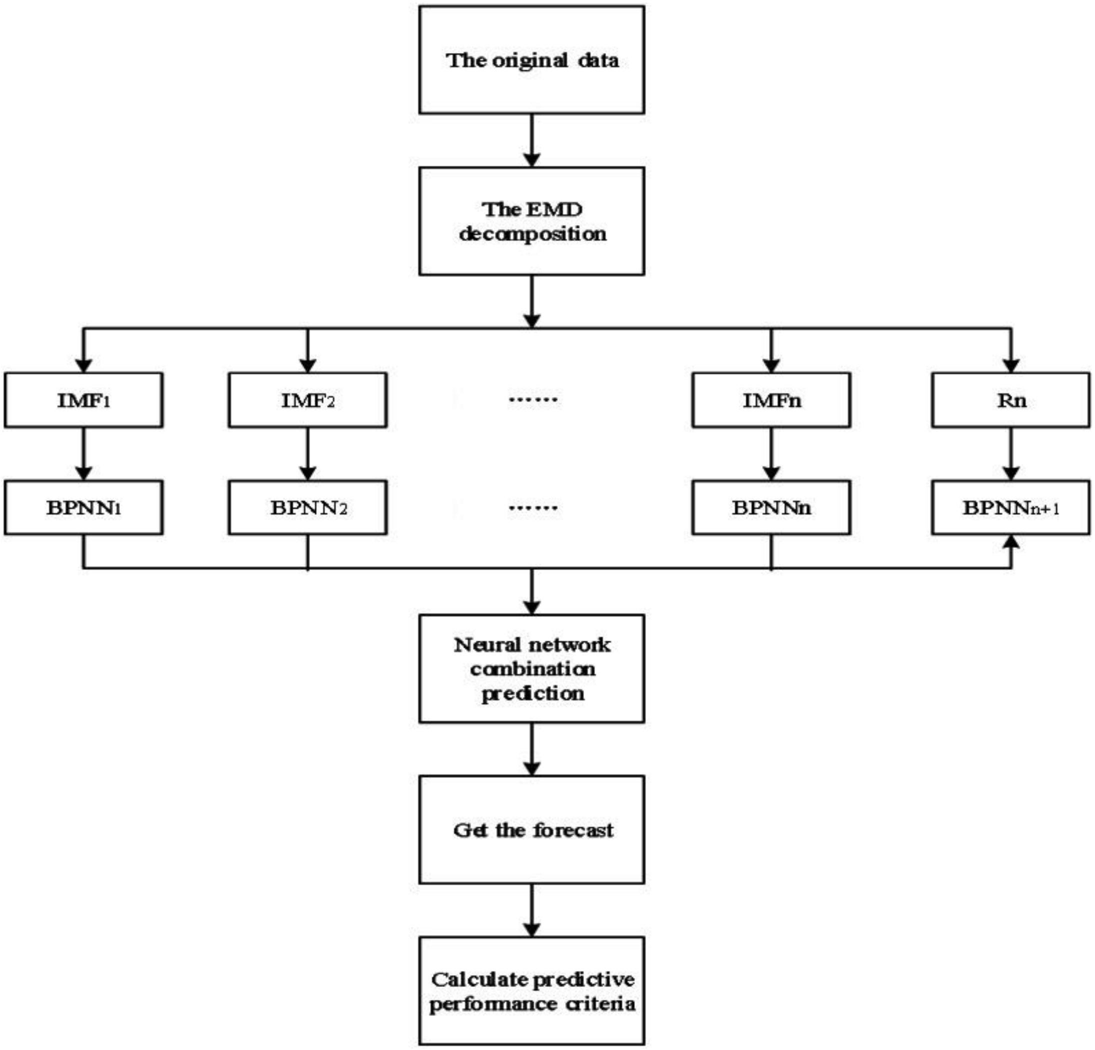

Figure1. Flowchart of the suggested (EMD + BPNN) technique for forecasting financial markets..

EMD is a nonlinear and non-stationary data series analysis method proposed by NASA's signal processing specialist (Huang et al., 1998). The Hilbert-Huang Transform is another name for EMD (HHT). It consists of two processes: EMD and HHT. With EMD, any complicated signal can be decomposed into many IMFs, and the number of IMFs is frequently limited. With well-performed HHT, these IMF series can accurately reflect each local oscillation of the original data series. As a result, the resultant Hilbert spectrum exhibits outstanding energy time-frequency characteristics (Fu, 2018; Nan et al., 2018).

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Algorithm 1: EMD

Input: A signal $S(t)$

i). Set $r(t) := S(t)$ and $k = 0$

While $r(t)$ is not distinct **do**

ii). Set $m(t) = r(t)$

While $m(t) != 0$ **do**

iii). Interpolate between min (respective max), ending up with some 'envelope' $e_{\min}(t)$ (respective $e_{\max}(t)$).

iv) Calculate the average $m(t) = \frac{e_{\min(t)} + e_{\max(t)}}{2}$

v) Extract $c(t) = r(t) - m(t)$, and symbolized $c(t)$ as $r(t)$

end while

vi). Set $k = k + 1$

vii). Set $\mathrm{IMF}_k(t) = c(t)$

viii). Set $r(t) = S(t) - \sum_{k=1}^{K} \mathrm{IMF}_k(t)$

end while

3. Results and Discussion

(a) Empirical analysis of the prediction effect of interval EMD model

EMD decomposes IMFs sequentially through various screening procedures, calculating the local average of signals from their upper and lower envelopes. The upper and lower envelopes represent the signal's local maxima and minima as determined by the spline interpolation process. Because the signal cannot be at the highest and minimum levels at the same time, the upper and lower envelopes will always appear divergently at both ends of the data series. In the screening process, errors are introduced (Cai et al., 2017). As the screening process progresses, such divergence will eventually "contaminate" the entire data set, generating serious distortions in the results. For extended data series, data at both ends can be deleted based on the extreme point, reducing the ensuing envelope distortion. Nevertheless, deleting data at both ends becomes utterly impractical for small data series.

In general, swings in financial market data series of trade prices are random, nonlinear, and non-stationary. The existing prediction model makes it difficult to properly understand the characteristics of various types of data and obtain accurate predictions. The value of a model that has good prediction ability for trading prices in the financial market is self-evident.

EMD time-frequency analysis is a new method for processing nonlinear and nonstationary signals that is fundamentally different from classic signal time-frequency analysis methods and has achieved great results in real applications.

By layer-by-layer screening, the EMD decomposition algorithm extracts the IMF components of the signal feature scales at distinct time points (Nait Aicha et al., 2018). The basic purpose of EMD decomposition is to smooth the signal, then perform HHT on the IMF component to produce the instantaneous frequency component that corresponds to the IMF component. The obtained instantaneous frequency has a physical meaning. The resultant Hilbert spectrogram is a two-variable function of time and frequency, from which frequency information can be derived at any time (Zhang & Zeng, 2017). For example, the magnitude and amplitude of the frequency, as well as the associated moments arising, can be retrieved, allowing detailed description of the time-frequency properties of the non-stationary and nonlinear signal.

Table 1. Evaluating The Forecost of Stock Model

Model	Accuracy factor	USD/CNY	EURO/CNY	JPY/CNY	CHF/CNY
Proposed Forecast	RMSE	0.011061	0.018999	0.000206	0.019752
	MAPE	0.001423	0.002051	0.002450	0.002249
	MAE	0.009247	0.016009	0.000149	0.016032
	TS	10.36	−18.44	−0.32	−18.09
RW Benchmark	RMSE	0.037337	0.039198	0.004327	0.165387
	MAPE	0.004162	0.004184	0.049092	0.0139802
	MAE	0.027068	0.032679	0.002951	0.100183
	TS	−66.88	−47.80	−72.49	−50.31

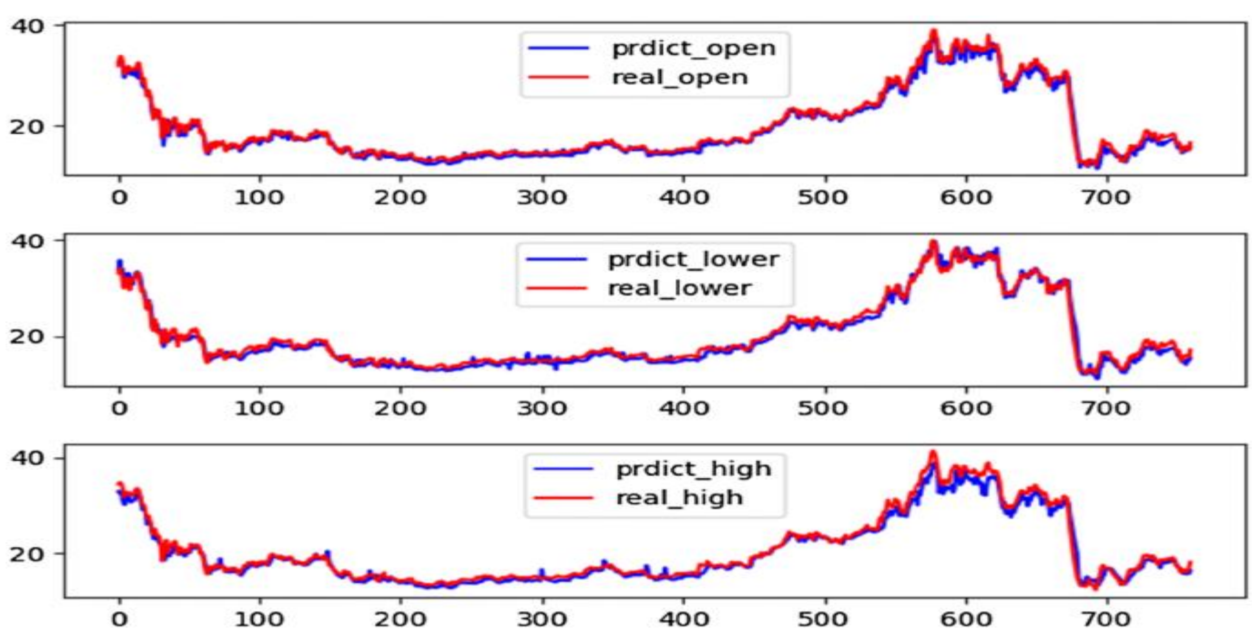

Figure 2: Study on the prediction of stock price based on the associated network model of LSTM

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We investigated the stock market utilising the empirical mode decomposition (EMD)-based Hurst exponent (H) analysis and the normalised variance (NV) technique in this paper. EMD Stock Exchange
The stock market is a venue where publicly traded corporations' shares are bought and sold.
Stock excahne acts as a go-between for the buyer and seller.

Figure 3: TSLA stock exchange using Yahoo Finance

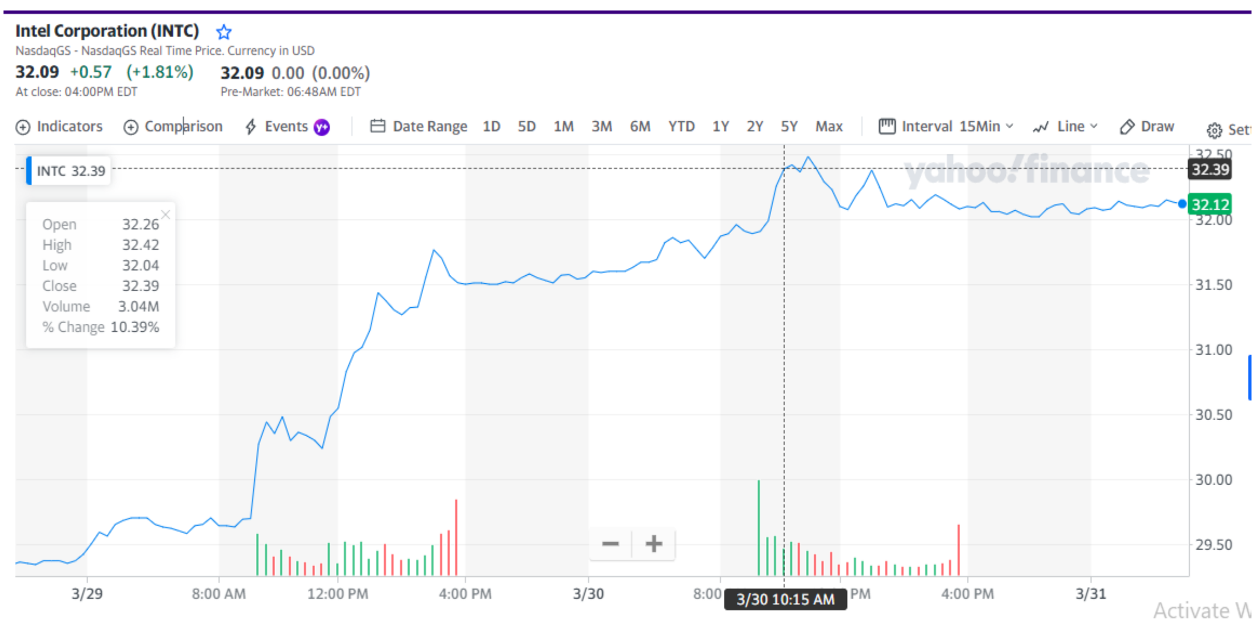

Figure 4: INTC stock exchange using Yahoo Finance

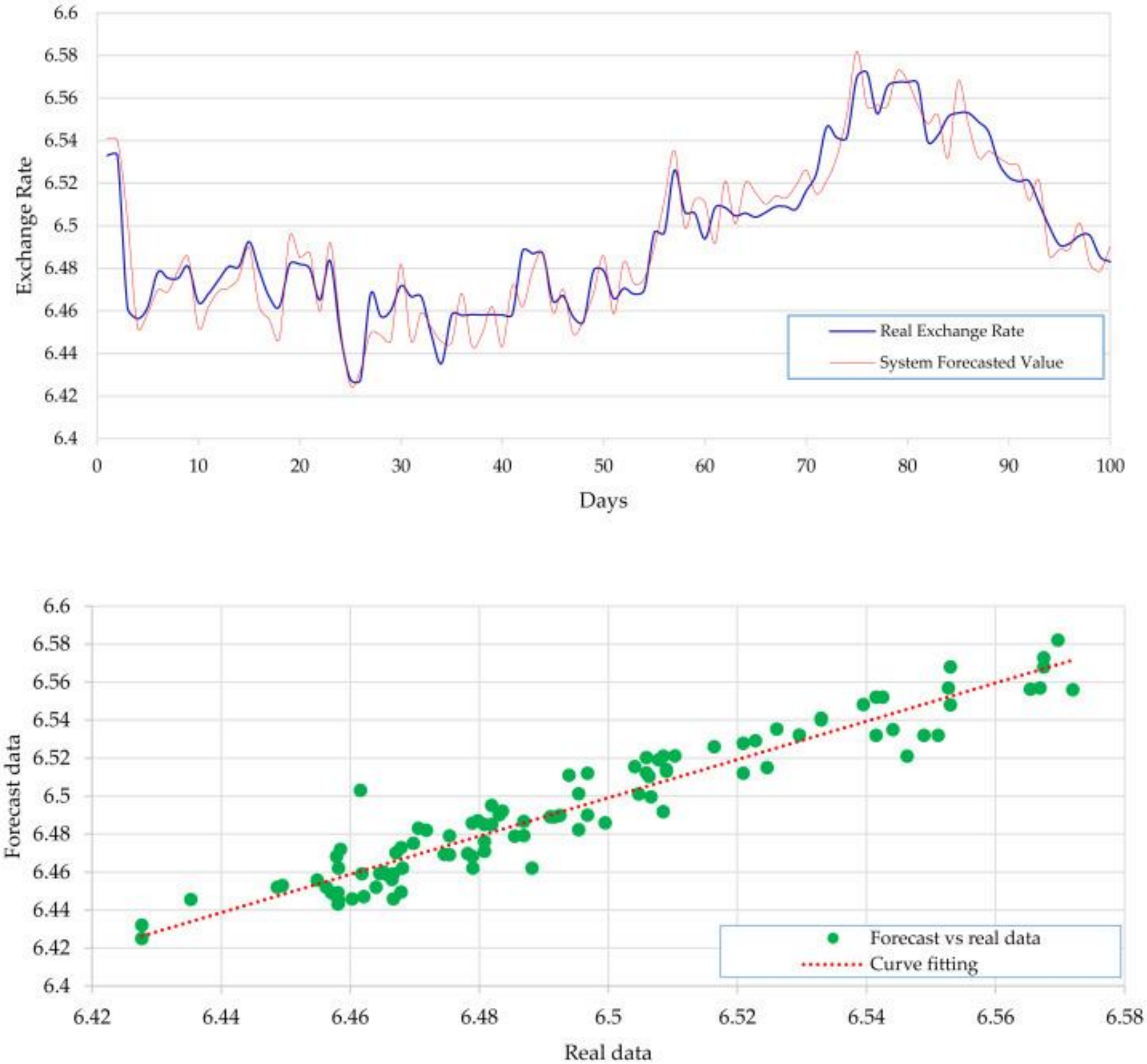

Figure 5: USD to CNY exchange rate forecast and actual graph (for interpretation of the references to colour in this figure legend).

The EMD-BPNN model outperforms other single reference models in terms of hit rate and prediction error. This demonstrates that the EMD decomposition approach can increase the neural network's prediction accuracy. This suggests that principal component analysis can reduce dimensionality and compress redundant data, enhance prediction accuracy to a degree, and lessen the time required to train neural networks. Particularly, while predicting, one or more of the highest frequency components may be ignored. As a result, the impact of high-frequency noise on prediction can be reduced. To erase the trend, all of the retrieved IMFs are included as decomposition results, except for the last component or components. This procedure is simply integrated with the smoothing of the data acquired if the highest frequency components are eliminated during the component addition process.

(b) Combination of deep learning and financial transaction

Deep learning may be used to a wide range of trading frequencies, from low-frequency stock-picking models to high-frequency algorithmic trading algorithms. Deep learning has thrived as an industry case at both the investment decision-making and transaction execution levels. For example, the hedge fund Cerebellum, founded in 2009, manages $90 billion in assets, use AI for adjunct forecasts, and has been profitable every year since 2009. Man Group, one of the world's largest hedge funds, began using AI to deploy passive investment five years ago. Currently, the assets managed by AI are profitable. Wall Street investment institutions like Goldman Sachs and JPMorgan Chase have also invested in artificial intelligence stock-picking tools. Machine learning is said to be capable of accurately predicting results and lowering costs.

Deep learning is a way of discovering laws from huge amounts of data using DNN models. Deep learning ANNs are made up of several neurons that are interconnected in a way similar to biological neural networks (brains). It is a self-confirming algorithm paradigm with nonlinear distributed parallel processing. Neurons are the basic building blocks of a neural network. A neuron receives and produces input signals given by other neurons. A neuron is mathematically equivalent to a nonlinear transformation (excitation function). A neural network model is produced when a group of neurons with a hierarchical structure is combined. Deep learning has enabled AI to achieve technical breakthroughs in a variety of domains, including image, speech, and natural speech processing. Nowadays, there are numerous practical applications of AI.

(c) Empirical results and discussion

Based on the FEPA model, an interval EMD algorithm is proposed here. The return rate of each index serves as the research sample, and the interval EMD model's forecast performance is empirically assessed. Among the significant conclusions are:

(1) The interval EMD model increases the FEPA model's prediction performance. The interval EMD model has a lower prediction error than the FEPA model. The interval EMD model has a substantially lower prediction error when compared to other reference models. The interval EMD model's hit rate in predicting the closing market price increases by only 2% when compared to the FEPA model. Nonetheless, the interval EMD model outperforms the FEPA model in predicting the highest and lowest prices by roughly 6% to 8%. Those gains demonstrate that the interval EMD model is effective at predicting FTS, particularly the short-term fluctuation tendencies of the highest and lowest prices.

(2) The comprehensive and efficient use of transaction price information aids in forecast accuracy. In actual transactions, analysts will use detailed price information to forecast future market price patterns. According to the empirical results, practically all data series are quite similar to random walks when only the closing market price is included. However, the interval EMD model, which uses full transaction price information, can increase the prediction power of stock index fluctuation tendencies.

4. Conclusion:

In this study, a prediction model for financial market forecasting is demonstrated. Using FTS data, the FTSEMD may build multi-layer IMF time series. The IMF series set is then transformed by PCA and its dimensionality is lowered to create an ANN for prediction. The PSO algorithm is used to increase the neural network model's prediction accuracy through parameter optimisation. By constantly looking for current optimality, the algorithm approaches the global optimal. Furthermore, the suggested model has the characteristics of being simple to implement, precise, and fast to convergence. The parameters are effectively optimised, and the model's priority among other machine learning models is revealed.

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