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PREDICTING STOCK MARKET BEHAVIOR BY COMBINING MULTILAYER PERCEPTRON NEURAL NETWORKS AND DYNAMIC MODE DECOMPOSITION

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Abstract. The stock market acts as an indicator of the overall health of the economy, and its proper performance indicates growth in businesses and the expansion of the economy. In this research, based on Dynamic Mode Decomposition (DMD) and Multilayer Perceptron (MLP) neural network, a new hybrid method is presented for stock market forecasting. This hybrid method (DMD-MLP) extracts dominant and consistent data and uses them to predict the upward or downward trend of stock prices. To prove the effectiveness of this method, examples of different groups of the stock market have been presented, where in them, there are bullish, bearish, or neutral behaviors. These examples include Iran Gelatin Capsule Production, Ofogh Kourosh, Day Bank, Mellat Bank, Dana Insurance, and Pasargad Bank. The results show that the proposed method performs better than the MLP neural network in predicting the movements of the stock market, and the use of the DMD algorithm in MLP has a significant effect on improving predictions.

1. Introduction

The stock market plays a crucial role in economic dynamism and business development. It provides an opportunity for companies to attract the financial resources they need from investors by issuing

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shares, and to utilize this capital for launching new projects, expanding operations, and creating employment opportunities. As a result, the performance of the stock market directly affects economic growth and wealth distribution in society.

The primary objective of stock price prediction algorithms is to provide accurate and optimized analyses to select a portfolio of stocks that yields the highest return for investors. These algorithms aim to forecast future price behaviors by analyzing historical data and employing mathematical models and machine learning techniques. Forecasting tools based on artificial intelligence and neural networks assist investors in choosing stocks that are likely to perform better in the future.

One of the most widely used machine learning techniques for analyzing and forecasting financial data is the Multilayer Perceptron (MLP) neural network. MLPs are highly capable of modeling complex and nonlinear patterns. The introduction of the single-layer perceptron by Rosenblatt in 1957 marked the beginning of artificial neural networks (ANNs) [21]. However, after Minsky and Papert's criticisms in 1969 concerning the limitations of the single-layer perceptron, attention shifted toward multilayer networks [15]. Due to their ability to understand and detect complex patterns, MLPs are considered one of the main tools for analyzing complex datasets, particularly in the financial domain.

Recent studies highlight the widespread use of neural networks for stock price prediction. For instance, Pakdaman Naeini et al. employed MLPs and Recurrent Neural Networks (RNNs) for stock price forecasting [18]. In 2018, Achkar et al. compared BPA-MLP and LSTM-RNN methods, evaluating their respective strengths and weaknesses [1]. In 2021, Doaei et al. proposed a model that combines MLP and metaheuristic algorithms to predict daily stock prices in the Tehran Stock Exchange [6]. Recently, a hybrid model based on MLP has been used for stock price prediction [27]. In another study, RNNs were utilized for this task [14]. In 2023, Kurani et al. reviewed neural networks used for stock price prediction [9], and [19] provided a review of neural networks applied in forecasting stock market movements.

On the other hand, the Dynamic Mode Decomposition (DMD) method has been developed since the 1930s as a tool for dynamic system analysis and data dimensionality reduction. It has recently emerged as a prominent method for analyzing financial data [12, 22, 26]. DMD identifies spatial and temporal patterns in data, enabling a more precise analysis of financial market fluctuations [16]. Kutz et al. extended the theoretical foundations of DMD, introducing novel algorithms that have expanded the applicability of this method [13]. In 2019, Brunton et al. published a comprehensive book on the applications of DMD in dynamical systems [20]. More recently, in 2023, Karimkhani et al. improved the performance of LSTM[1] networks by integrating them with DMD for forecasting financial market behavior [11].

[1]Long Short-Term Memory

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Given the complexity and volatility of financial markets, accurate stock price forecasting remains one of the key challenges in the fields of machine learning and data science. Although traditional models such as MLP are still widely used, modern hybrid approaches can significantly enhance the performance of these networks in practical applications. This paper introduces a hybrid DMD-MLP model based on MLP and DMD and employs it to forecast stock prices in the stock market. By analyzing historical data and existing patterns, this method enhances the prediction accuracy of MLP and supports investors in making more informed and precise decisions.

2. **Main Results**

Recent studies have shown that financial markets often lack correlation among their signal samples. This can affect the accuracy of neural network models such as MLP in forecasting market trends. To address this issue, a hybrid method called DMD-MLP is proposed, offering a more practical approach to predict the upward or downward movement of stock prices. Recently, a combination of the DMD method and LSTM networks has been introduced for financial market prediction [11]. This section describes the MLP, DMD method, the proposed DMD-MLP algorithm, and the experimental results.

2.1. **Multilayer Perceptron (MLP).** ANNs are a key and widely used subfield of artificial intelligence and machine learning. These networks consist of interconnected processing units called neurons, organized hierarchically in layers with weighted connections [8]. The main goal of ANNs is to learn complex patterns and relationships within data through a training process to create a mapping from inputs to outputs.

Neural networks are especially effective in nonlinear and complex problems where traditional modeling approaches are inadequate. They can extract hidden features from input data and establish appropriate mappings to outputs. This capability has made neural networks widely applicable in many areas [7].

In recent years, neural networks have attracted significant attention for time series forecasting due to their high capability in modeling nonlinear relationships and extracting complex patterns. Their flexible structure enables them to learn hidden dependencies between past and future observations without relying on rigid statistical assumptions.

The MLP neural network, as an advanced model in supervised machine learning, is widely used for classification and prediction problems. Due to its complex structure, this type of network has a high capability to learn nonlinear patterns and extract complex features from data.

The MLP network consists of at least three layers:

- Input Layer: This layer receives the input features.
- Hidden Layer(s): These typically include multiple layers with varying numbers of nodes.

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- Output Layer: This layer transforms the information extracted by the hidden layers into the final output.

Due to its high computational power and adaptability to complex data, the MLP network is commonly used in pattern recognition, prediction, imaging, and data analysis problems. It is known as a powerful tool in many scientific and industrial fields and plays a significant role in the advancement of modern technologies.

2.2. **Dynamic Mode Decomposition (DMD).** DMD method, introduced by Schmid [22], was initially developed in fluid dynamics. The DMD technique builds upon Proper Orthogonal Decomposition (POD), utilizing efficient computations similar to Singular Value Decomposition (SVD), and tries to provide effective dimensionality reduction.

DMD is a data analysis technique used to extract and identify coherent spatiotemporal patterns from time-dependent data. It is beneficial for analyzing systems with dynamic behavior, such as fluid flow, vibrations, or other physical processes. DMD operates on time-series data and aims to decompose the system into its underlying dynamic modes. These dynamic modes are characterized by their eigenvalues and eigenvectors, which describe the frequencies and spatial structures of the patterns. The DMD algorithm is inherently data-driven and begins by measuring the system's state variables at sequential time intervals. These instantaneous data are then used to construct a matrix, and SVD is applied. The SVD method provides a foundation for identifying dynamic modes and their associated amplitudes.

Once the dynamic modes are extracted, they can be used to reconstruct the original data or to forecast the system's future behavior. This algorithm is applied across various domains, such as fluid dynamics, neuroscience, structural dynamics, and video processing, enabling the extraction of meaningful information from complex high-dimensional datasets.

To explain the relations of the DMD algorithm, consider the following dynamical system:

$$\frac{dx}{dt} = f(x, t; \mu), \tag{2.1}$$

where $x(t) \in \mathbb{R}^n$ denotes the system states at time t, μ contains system parameters, and f denotes the system dynamics. The vector x is typically high-dimensional, with $n \gg 1$, often arising from the discretization of a partial differential equation. The continuous-time system in (2.1) induces a discrete-time representation by sampling the system at intervals of Δt, such that $x_k = x(k\Delta t)$. The resulting discrete-time system is:

$$x_{k+1} = F(x_k). \tag{2.2}$$

Analytical solutions for the nonlinear system in (2.1) are generally not available. Therefore, numerical approaches are used to predict future states. The DMD algorithm operates using observational

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data, even in cases where f is unknown, relying solely on data to approximate dynamics and forecast future states. DMD approximates the system by a linear dynamical system:

$$\frac{dx}{dt} = Ax, \tag{2.3}$$

with the initial condition $x(0) = x_0$. Accordingly, we have [13]:

$$x(t) = \sum_{k=1}^{n} \phi_k \exp(\omega_k t) b_k, \tag{2.4}$$

where ϕ_k and ω_k are the eigenvectors and eigenvalues of matrix A, respectively, and b_k are the coordinates of $x(0)$ in the eigenvector basis. Let

$$\Phi = [\phi_1, \phi_2, \dots, \phi_n], \quad \Omega = \mathrm{diag}(\omega_1, \dots, \omega_n), \quad b = [b_1, \dots, b_n]^T,$$

then we have:

$$x(t) = \Phi \exp(\Omega t) b. \tag{2.5}$$

Based on the continuous-time linear system (2.3), we define the discrete-time system as:

$$x_{k+1} = Ax_k. \tag{2.6}$$

This system can be represented as:

$$x_k = \sum_{j=1}^{r} \phi_j \lambda_j^k b_j, \tag{2.7}$$

where λ_j and ϕ_j are the eigenvalues and eigenvectors of matrix A, and b_j are the projections of initial state x_1 on the eigenvector basis. Let

$$\Phi = [\phi_1, \dots, \phi_r], \quad \Lambda = \mathrm{diag}(\lambda_1, \dots, \lambda_r), \quad b = [b_1, \dots, b_r]^T,$$

then

$$x_k = \Phi \Lambda^k b, \tag{2.8}$$

and consequently, $x_1 = \Phi b$.

The DMD algorithm yields a low-rank eigendecomposition of the matrix A that optimally fits the measurements x_k for $k = 1, 2, \dots, m$, by minimizing the least squares error:

$$\|x_{k+1} - Ax_k\|_2 \tag{2.9}$$

for all $k = 1, 2, \dots, m-1$. This approximation is optimal within the sampling window where A is constructed and can be used not only for forecasting but also for decomposing the system dynamics into different time scales.

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The main objective here is to obtain an optimal matrix A to approximate equations (2.6) and (2.7). To minimize the error in (2.9) for all measurements, the m data points are arranged into two matrices X and X'. We can partition the large data matrix as follows:

$$X = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \cdots & x_{m-1} \\ | & | & & | \end{bmatrix} \tag{2.10}$$

$$X' = \begin{bmatrix} | & | & & | \\ {x'}_1 & {x'}_2 & \cdots & {x'}_{m-1} \\ | & | & & | \end{bmatrix} \tag{2.11}$$

The data under consideration are likely generated by a nonlinear dynamical system. Our objective is to identify an optimal linear approximation of this system. This linear model, as expressed in equation (2.6), can be represented in terms of the data matrices as:

$$X' \approx AX. \tag{2.12}$$

Such linear approximations are employed through numerical decomposition methods to predict future system states and to analyze its underlying behavior. Based on equation (2.12), a practical estimate for the matrix A is given by:

$$A = X'X^{\dagger}, \tag{2.13}$$

where $X^{\dagger}$ is the Moore-Penrose pseudoinverse. This formulation minimizes the reconstruction error defined by:

$$\|X' - AX\|_F, \tag{2.14}$$

where the Frobenius norm $\|\cdot\|_F$ is defined by:

$$\|X\|_F = \sqrt{\sum_{j=1}^{n}\sum_{k=1}^{m} x_{jk}^2}. \tag{2.15}$$

Equations (2.13) and (2.14) essentially perform a linear regression of the data onto the dynamics governed by matrix A. However, there is a significant distinction between this approach and traditional regression-based model reduction techniques.

2.3. **DMD algorithm.** The steps of DMD algorithm are as follow:

1) Compute the reduced SVD of X:

$$X = \tilde{U}\tilde{\Sigma}\tilde{V}^*,$$

where $\tilde{U} \in \mathbb{C}^{n\times r}$, $\tilde{\Sigma} \in \mathbb{C}^{r\times r}$, $\tilde{V} \in \mathbb{C}^{m\times r}$, and $r \leq m$ is the rank of the reduced-order SVD.

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2) Compute the full-rank matrix A using the pseudoinverse of X:

$$A = X'\tilde{V}\tilde{\Sigma}^{-1}\tilde{U}^*. \tag{2.16}$$

To avoid high-dimensional computations, we compute a reduced matrix $\tilde{A}$ using POD as:

$$\begin{aligned}\tilde{A} &= \tilde{U}^* A \tilde{U}\\ &= \tilde{U}^* X'\tilde{V}\tilde{\Sigma}^{-1}.\end{aligned} \tag{2.17}$$

This reduced matrix $\tilde{A}$ shares the nonzero eigenvalues with the full matrix A, allowing us to work efficiently in a low-dimensional space.

3) Compute the eigendecomposition of $\tilde{A}$:

$$\tilde{A}W = W\Lambda, \tag{2.18}$$

where the diagonal entries of Λ are the DMD eigenvalues and the columns of W are the corresponding eigenvectors.

4) Reconstruct the high-dimensional DMD modes Φ using:

$$\Phi = X'\tilde{V}\tilde{\Sigma}^{-1}W. \tag{2.19}$$

These DMD modes Φ are the eigenvectors of the original high-dimensional matrix A associated with eigenvalues in Λ.

Finally, we can obtain the approximate future states using:

$$x(t) = \Phi \exp(\Omega t) b, \tag{2.20}$$

where b is the initial amplitude vector, Φ contains the DMD modes, and $\Omega = \mathrm{diag}(\omega)$ is a diagonal matrix of eigenvalues ω_j.

2.4. **The DMD-MLP Method.** In this hybrid method, stock market data are first collected. Then, the DMD algorithm is applied to extract dominant and coherent structures from the data. The output of this algorithm yields an estimated system response that captures the dominant and coherent structures within the data [11]. The extracted features are then fed into an MLP model to predict future stock market behavior.

Next, we present the main steps of the proposed DMD-MLP hybrid algorithm designed for stock price prediction:

2.5. DMD-MLP Algorithm.

1) Data Collection: First, the stock price data including date and closing price for each stock is collected.
2) Data Preprocessing: After collecting the data, preprocessing begins. This step involves aligning the data using the DMD-based dynamic analysis algorithm. In addition, normalization is performed to evaluate the statistical distribution of the data:

$$y_i = \frac{x_i - \overline{x}}{S} \tag{2.21}$$

   where y_i is the normalized data, $\overline{x}$ is the mean, and S is the standard deviation.
3) Data Partitioning: The data are divided into two main sets: Training Data and Testing Data. Typically, 80% of the data is used to train the model and 20% to evaluate its performance.
4) Model Training: Using the training data, the MLP model is trained. During this stage, weights and biases are adjusted to achieve optimal performance.
5) Model Evaluation: The testing data are used to evaluate the performance of the DMD-MLP model and its effectiveness in predicting stock prices.

2.6. **Experimental Results.** In this section, we compare the performance of the MLP and DMD-MLP methods using a robust evaluation metric known as Root Mean Square Error (RMSE). The findings suggest that DMD-MLP demonstrates a strong ability to predict upward or downward trends similar to the real market behavior. The performance of the hybrid DMD-MLP method will be evaluated using several different behavioral examples. We use the closing price data of 800 trading days for six Iranian stocks:

- Iran Gelatin Capsule Production (Dekapsoul)
- Ofogh Koorosh (Ofogh)
- Dey Bank (Day)
- Mellat Bank (Webmelat)
- Dana Insurance Company (Dana)
- Pasargad Bank (Vapas)

In the training phase, the first 650 days of data are used for model training. In the testing phase, the remaining 150 days are reserved for prediction and validation. The results demonstrate superior performance of our method DMD-MLP compared to standard MLP, and significantly lower RMSE values than the MLP approach. For instance, in Bank Pasargad, RMSE decreased from 0.203 (MLP) to 0.174 (DMD-MLP).

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3. Conclusions

To predict the upward or downward trends in the stock market, this study introduces a novel hybrid method called DMD-MLP, based on the MLP neural network and the DMD method. In essence, through the DMD algorithm, we extract the coherent and dominant components of the data, which capture the primary trend of the target time series. We demonstrate the effectiveness of this method through several examples and obtain valuable results compared to the standalone MLP approach. Given the high potential of the DMD algorithm, we can leverage it along with its derived variants, as an add-on for neural architectures and other data-driven methods. Moreover, this approach can be applied to time series prediction in various domains.

References

[1] R. Achkar, F. Elias-Sleiman, H. Ezzidine and N. Haidar, Comparison of BPA-MLP and LSTM-RNN for stocks prediction, *in 6th International symposium on computational and business intelligence (ISCBI)*, (2018) 48–51.

[2] G. Ahmadi and Z. Akbari, Investigating air pollutants in Lorestan province and predicting their concentration using multi-layer neural network with stable online training (case studies: Khorramabad and Poldakhter), *Nivar*, **48** no. 126-127 (2024) 109–126.

[3] G. Ahmadi and M. Dehghandar, Chaotic time series prediction using rough-neural networks, *Math. Interdisc. Res.*, **8** no. 2 (2023) 71–92.

[4] C. C. Aggarwal, *Neural networks and deep learning*, Springer, 2018.

[5] C. M. Bishop and N. M. Nasrabadi, *Pattern recognition and machine learning*, Springer, 2006.

[6] M. Doaei, S. A. Mirzaei and M. Rafigh, Hybrid multilayer perceptron neural network with grey wolf optimization for predicting stock market index, *Advances in mathematical finance and applications*, **6** no. 4 (2021) 883–894.

[7] I. Goodfellow, Y. Bengio and A. Courville, *Deep learning*, MIT Press, 2016.

[8] S. Haykin, *Neural networks and learning machines (3rd ed.)*, Pearson, 2009.

[9] A. Kurani, P. Doshi, A. Vakharia, et al. A Comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting, *Ann. Data. Sci.*, **10** (2023) 183–208.

[10] Y. C. Liang, H. P. Lee, S. P. Lim, W. Z. Lin, K. H. Lee and C. G. Wu, Proper orthogonal decomposition and its applications-part i: Theory, *Journal of Sound and Vibration*, **252** no. 3 (2002) 527–544.

[11] R. Karimkhani, Y. E. Tabriz and G. Ahmadi, A new hybrid method of dynamic mode decomposition and long short-term memory for financial market forecasting, *Journal of Mathematics and Modeling in Finance*, **3** no. 2 (2023) 1–16.

[12] B. O. Koopman, Hamiltonian systems and transformation in Hilbert space, *Proceedings of the National Academy of Sciences*, **17** no. 5 (1931) 315–318.

[13] J. N. Kutz, S. L. Brunton, B. W. Brunton and J. L. Proctor, *Dynamic mode decomposition: data-driven modeling of complex systems*, SIAM, 2016.

[14] M. Lu and X. Xu, TRNN: An efficient time-series recurrent neural network for stock price prediction, *Information Sciences*, **657** (2024) 119951.

[15] M. L. Minsky and S. A. Papert, *Perceptrons: an introduction to computational geometry*, MIT Press, Cambridge, 1968.

[16] J. Mann and J. N. Kutz, Dynamic mode decomposition for financial trading strategies, *Quantitative Finance*, **16** no. 11 (2016) 1643–1655.

[17] T. M. Mitchell, *Machine learning* (McGraw-Hill international editions computer science series), 1997.

[18] M. P. Naeini, H. Taremian and H. B. Hashemi, Stock market value prediction using neural networks, in *International conference on computer information systems and industrial management applications (CISIM)*, (2010) 132–136.

[19] A. T. Oyewole, O. B. Adeoye, W. Afua Addy, C. C. Okoye, O. C. Ofodile and C. E. Ugochukwu, Predicting stock market movements using neural networks: A review and application study, *Computer Science and IT Research Journal*, **5** no. 3 (2024) 651–670.

[20] T. Peters, *Data-driven science and engineering: machine learning, dynamical systems, and control*, Cambridge, Cambridge University Press, 2019.

[21] F. Rosenblatt, *The perceptron, a perceiving and recognizing automaton Project Para*, Cornell Aeronautical Laboratory, 1957-58.

[22] P. J. Schmid, Dynamic mode decomposition of numerical and experimental data, *Journal of fluid mechanics*, **656** (2010) 5–28.

[23] Y. G. Song, Y. L. Zhou and R. J. Han, Neural networks for stock price prediction, arXiv preprint arXiv:1805.11317, (2018) pp. 13.

[24] G. W. Stewart, On the early history of the singular value decomposition, *SIAM Review*, **35** no. 4 (1993) 551–566.

[25] R. S. Sutton and A. G. Barto, *Reinforcement learning: an introduction (2nd ed.)*, MIT Press, 2018.

[26] J. H. Tu, *Dynamic mode decomposition: Theory and applications*, Princeton University, 2013.

[27] D. Wu, X. Ma and D. L. Olson, Financial distress prediction using integrated Z-score and multilayer perceptron neural networks, *Decision Support Systems*, **159** (2022) 113814.

[28] P. Yu and X. Yan, Stock price prediction based on deep neural networks, *Neural Computing and Applications*, **32** no. 6 (2020) 1609–1628.

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