An Intelligent Model for Stock Market Prediction

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Abstract—**This paper presents an intelligent model for stock market signal prediction using Multi Layer Perceptron (MLP) Artificial Neural Networks (ANN). Blind source separation technique, from signal processing, is integrated with the learning phase of the constructed baseline MLP ANN to overcome the problems of prediction accuracy and lack of generalization. Kullback Leibler Divergence (KLD) is used, as a learning algorithm, because it converges fast and provides generalization in the learning mechanism. Both accuracy and efficiency of the proposed model were confirmed through the Microsoft stock, from wall-street market, and various data sets, from different sectors of the Egyptian stock market. In addition, sensitivity analysis was conducted on the various parameters of the model to ensure the coverage of the generalization issue.**

Keywords- stock market prediction; artificial neural networks; blind source separation.

I. INTRODUCTION

Financial market prediction has been one of the most challenging goals of the Artificial Intelligence (AI) research community. This research is meant to go far beyond the capabilities of traditional AI research, which primarily focuses on developing systems that are supposed to emulate human intelligence [1], because stock market is generally non-linear and volatile. The fluctuation rate may depend on many factors: equity, interest rate, securities, options, warrants merger and ownership of large financial corporations or companies. Still, no one can consistently predict the stock market movement. That is why this kind of AI prediction requires an iterative process of knowledge discovery and system improvement through knowledge engineering, data mining, theoretical and data-driven modeling, as well as trial and error [2].

The stock market has always been one of the most popular investments due to its high returns [3]. In this market, predictions are based on either fundamental analysis[1] ([4], [5]) or technical analysis[2] ([6], [7]). Fundamental analysis is related to analyzing the assets and the economic values of a security[3]. Recently, technological analysis[4] has been used in the prediction, as it aims at more accurate results, higher performance and broad calculations. It was motivated by the fact that one cannot perform any of technical or fundamental analysis manually on more than 2-3 securities at a time or even per trading session [8].

It is an interesting topic to predict the trend of a security price in the stock market. The prediction process is complicated due to its nonlinearity and uncertainty. In developing a stock prediction system, one of the most important tasks is to select the input variables. For example, only one-day return of the closing price of a stock was used in [9] while the difference between the price and the moving average, highest and lowest prices were used in [10] this is in addition to price series, volume of transactions, macro economic data and market indicators that were considered as input variables in [11].

However, there is no one technique or combination of techniques, which has been successful enough to consistently "beat the market" [12]. What works for a stock will not fit the other. With the development of the ANN, researchers and investors are hoping that the market mysteries can be revealed.

In this paper, a proposed model is presented to overcome the existing problems of accuracy and generalization in the stock market prediction. The proposed model uses MLP ANN, which is selected based on the literature survey of the previous models that use neural networks with one hidden layer [13]. This ANN is augmented through using the blind source separation technique in the learning phase. KLD [14] is used as the learning algorithm for the selected ANN.

The proposed model is based on technical analysis. It uses a set of technical indicators for the prediction, Simple Moving Averages (SMA), Exponential Moving Average (EMA) and Average Directional Index (ADX) for trend detection. A simple rule based system is added to classify the signals for “Buy”, “Sell” or “Hold”.

The rest of the paper is organized as follows: in section 2, an overview of the previous work is given. In section 3, a detailed description of the proposed prediction model is explained. In section 4, one provides one’s experimental results and analysis. Finally, conclusions are given in section 5.

II. STOCK MARKET PREDICTION MODELS

The area of stock market prediction has been pursued by many research groups [15]. Two main approaches were used by early researchers to tackle this problem, which are based on either ANNs or Fuzzy Logic [13], [15], [16]. Many applications were created based on

[1] Fundamental analysis of a business involves analyzing its financial statements and health, its management and competitive advantages, and its competitors and markets.
[2] Technical analysis is a security analysis discipline for forecasting the direction of prices through the study of past market data, primarily price and volume
[3] Security is a financial asset such as a share or bond. In stock market it’s referred to as a stock symbol.
[4] Technological analysis is based on using new technology and computation power to substitute old hand operated process. It can be an alternate for technical analysis, fundamental analysis or a hybrid of both.

these two approaches. Examples of early work were carried out using the first method, including the work of White [9], who applied ANN based models to detect nonlinear patterns in the price movement of IBM assets and Kimoto et al. [17], who used modular ANN on the Tokyo Stock Exchange Prices Indexes (TOPIX). All of these methods and models achieved accurate predictions, but yet this was performed on the market index not on certain stock with actual "Buy" and "Sell" signals.

XIAO et al. [18] applied four Radial Basis Function ANN (RBFNNs) trained by Localized Generalization Error Model (L-GEM) method, each of which corresponds to a particular candlestick pattern. This simple strategy was found to be effective, but they recommended using a better investment strategy. Liao et al. [19] utilized the stochastic time effective series ANN model on the Chinese stock index (HIS) and some of the US Stock Market indices. This model was found to be effective against the data of HSI, Dow Jones (DJI), NASDAQ Composite (IXIC) and S&P500.

Wang et al. [20] used Time Delay Neural Networks (TDNN) with the intention of investigating the influences of the trading volume on the short term predictions. Their study emphasized whether trading volume can improve the forecasting performance of ANN or whether ANN can take advantage of such nonlinearity to get more accurate results. The results showed that the trading volume cannot significantly improve the forecasting performance, when applied to S&P500 and DJI Market indices, from 1990 to 2002 [20].

There have been fewer studies on the second method. First, Sugeno et al. [21] proposed a general qualitative model based on fuzzy logic and applied it to stock market. Next, Hiemstra [22] introduced architecture for fuzzy logic forecasting support system for stock market prediction. Application of this architecture facilitated the process of knowledge base update and simulation. Finally, Wang [16] constructed a data mart to minimize the size of the stock market data, incorporated fuzzification techniques with the grey theory and applied the fuzzy grey prediction to the Taiwan stock market, from September 2000 to April 2001.

Combination between the aforementioned methodologies has been considered in the context of stock market predictions [13], [23]. Fuzzy systems and neural networks were combined by developing neural network architecture capable of simulating the behavior of fuzzy systems. Each layer in the neural network acts as a stage in the fuzzy system. For example, the first layer will be responsible for mapping the input to its membership function while the last layer performs the defuzzification stage. Not much work was invested in this direction, but some relevant examples are mentioned below.

Quah [13] proposed an Adaptive Neuro Fuzzy Inference System (ANFIS) for stock market prediction. ANFIS, which is an instance of the more generic form of Takagi-Sugeno-Kang (TSK) model [24], replaces the fuzzy sets in the implication with a first order polynomial equation of the input variables. Esfahanipour et al. [23] applied a model that contains TSK fuzzy rule based system [24] that is based on selected technical indicators as input variables from the Tehran stock market. Their contribution focused on the variables selection method using ANFIS. This approach is better than others, such as Back Propagation Neural Network (BPNN) or Multiple Regression Analysis (MRA). Yet, this was a basic step in the prediction process that missed adding various factors, such as fundamental analysis and macroeconomic change to be able to predict the price trend movement.

Novel paradigms, such as Genetic Programming (GP) and Markov Model, have been investigated in the stock market prediction. For example, El-telbany [25] proposed a Genetic Programming based approach for stock market prediction. The population consists of individuals represented by a specific data structure. On the other hand, Zhang et al. [26] applied Markov chain model. It was found that, using empirical results, this model was able to express the probability of a certain state of stock prices in the future. Yet, this model was not verified against real data to figure out the actual performance of the system and its behavior for generalization.

Comparative studies on various techniques discussed in this section have been presented in [13], [15], [25]. The purpose of these studies was to define the best technique to be used, since a vast number of techniques and methods were proposed in this context. For example, Egeli et al. [15] compared the MLP ANN and the Generalized Feed-Forward (GFF) ANN, for stock market prediction. This study was performed with the data of the Central Bank of the Republic of Turkey, for the period between 2001 and 2003. In addition, simple sensitivity analysis was provided to select the best parameters for the ANN architecture. The MLP provided acceptable results and was found to outperform the GFF. El-telbany [25] successfully compared his proposed GP results with a three layered GFF ANN. The input data was the Egyptian stock market index CASE30, from 2001 to 2003.

Finally, Quah [13] compared three techniques: optimized MLP ANN, ANFIS and General Growing and Pruning Radial Basis Function (GGAP-RBF). He applied these techniques to data from the DJIA symbol, Singaporean stock market, in the period from 2003 to 2004. This comparison revealed that the optimized MLP ANN was better than both ANFSI and GGAP-RBF.

The aforesaid techniques were quite promising when applied to real life historical data. The major problems encountered in these techniques were related to both accuracy and generalization of the model.

The goal of this research is not only to improve the prediction accuracy, but also to build a general model that can realize securities from different sectors and stock markets. The model should adapt to nonlinearity in the stock market and un-correlated data of different securities in stock markets. The proposed technique adopts the ANN architecture (MLP), based on the literature survey. The KLD learning algorithm is used to enhance the performance of the proposed ANN. KLD, being a blind source separation technique, helps in solving the generalization issue of the prediction problem. The proposed approach was found to provide more accurate results, converges faster and generalizes to different stocks.

III. Proposed Prediction Model

The proposed model comprises several stages as shown in Fig. 1. The first stage is concerned with the input selection. Next, the appropriate preprocessing is performed on the selected input data. Such preprocessing may be indicators calculation, fundamental assets evaluation or even data classification for the supervised learning of the ANN. The data is then passed to the ANN to be trained for the classification purposes. The main objective of the learning algorithm is to update the weights between the neural network neurons in order to minimize the error of the prediction results. The proposed technique uses a blind source separation technique; KLD [27], [28], as a learning algorithm for the MLP ANN.

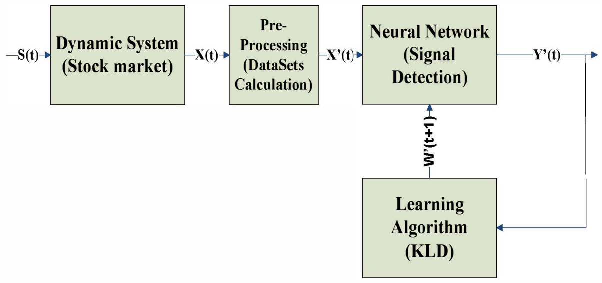


Figure 1. Block diagram illustrating the proposed model

A. Data Selection

The selected data is the stock market's daily data. Daily data is the data used in the stock market daily transactions, and it may be called market summary. The daily data is composed of (a) open price, which is the first trading price of a security on a given trading session, (b) close price, which is the final trading price of a security on a given trading session, (c) high price, which is the highest trading price of a security during a given trading session, (d) low price, which is the lowest trading price of a security during a given trading session, (e) volume, which is the amount of trades transacted for a security on a given trading session.

B. Data Preprocessing

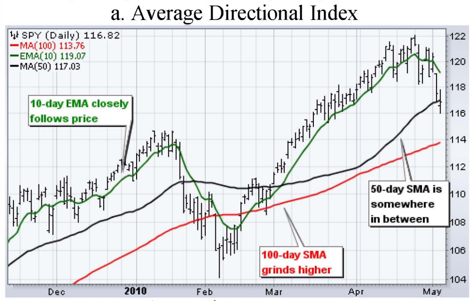
The input to this stage is the stock market daily data for a chosen security, as described in the previous subsection. The preprocessing step is concerned with computing the indicators shown in Table 1, with given window and filter sizes. The selection of the appropriate window size and filter size will be described in section 4.

TABLE 1. The used data set

Label	Indicator 1		Indicator 2		Trend Detection			Signal Filter
	Type	Window Size	Type	Window Size	Indicator	Window Size	Filter	
D1	SMA	20	EMA	35	ADX	35	2	3

The ADX was developed by Wilder [29] to indicate the strength of the trend as shown in Fig. 2.a. Knowing the trend of the security is a crucial issue since it affects the buy/sell decisions based on whether it is trending up/down or moving sideways. The ADX is an oscillator that ranges from 0 to 100. Readings above 60 are relatively rare. Readings below 20 indicate a weak trend, and Readings above 40 denote a strong trend. This indicator does not grade the trend as bullish or bearish, but it shows the strength of the current trend.

a. Average Directional Index



b. Moving averages

Figure 2. Technical indicators used in the proposed technique

The SMA is the average price of a given security over a certain period (window size) as shown in Fig. 2.b. It is common to be calculated based on the closing price of the security. A 14-day simple moving average is the 14 days sum of closing prices divided by 14.

Although moving averages are lagging indicators, since they are computed from the previous data, EMA reduces that lag by applying more weight to the recent prices. The weighting applied to the most recent prices depends on the window size of the moving average. This makes EMA follows the short term price movement while SMA follows long term price movement, as shown in Fig. 2.b.

After the indicators are being calculated, they are processed through a rule based system. This rule based system classifies the input signals into "Sell", "Hold" or "Buy". These classifications are used later in the supervised learning stage.

C. Neural Network

The used MLP ANN architecture has one hidden layer. Sigmoid function with range [-1, +1] was used as the activation function of each neuron as shown in Fig. 3. The number of input neurons is equal to the number of variables in the data set while the number of hidden neurons equals to twice the input neurons. The signal is being classified into three classes "Buy", "Sell" or "Hold". So, three output neurons are being used in the output layer. Each neuron should have the value [0 – 1] indicating the class it belongs to. For a given run, the output (0.8 0.12 0.08) means it is a "Buy" signal, since it is closer to the buy class, while (0.05 0.85 0.1) is a "Sell" signal. For any output to be valid, it should belong only to one class.

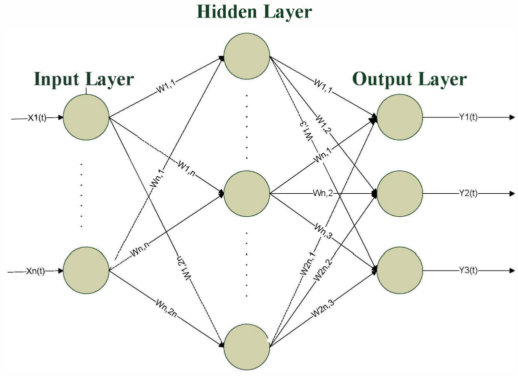


Figure 3 The implemented Neural Network Architecture

D. Learning Algorithm

During the iterative supervised learning of the ANN, the data is processed through an intermediate stage to normalize the output of the current stage, before entering the next iteration. Due to the nature of the KLD, the input to this function must be in the form of a probability distribution function, i.e. the magnitude of the output vector must be one. So, the output vector is normalized to match this criterion. Then, it is passed to the KLD to compute the divergence between the output signal and the desired signal. The weights are updated according to (1).

$$W' = W + \gamma * KLD(Y_{desired}, Y_{actual}) \tag{1}$$

where γ is the learning rate, which was set to 0.1 and KLD is the Kullback Leibler Divergence.

KLD is also known as information divergence [14], is an asymmetric difference measure between two probability distribution functions P and Q. It measures the expected number of extra bits needed to encode samples from P while using a code based on Q. It is illustrated in (2).

$$KLD(P, Q) = \sum_{i} P(i) * \log \frac{P(i)}{Q(i)} \tag{2}$$

IV. RESULTS AND DISCUSSION

Early researches focusing on ANN and expert systems faced a lot of challenges in the growing markets, such as the Egyptian market. Lack of historical data and mistakes found in the stock system represent the major weak points when training the neural network. For example, the opening price has never been saved since 1999. Now, the availability of such data and the updates in the stock system opened the space for soft computing to produce useful information for the traders. In this research work, the proposed model was tested using the daily data for EFG Hermes Holding (HRHO), El Nasr Clothing - Textiles Co. (KABO), Egyptian Electrical Cables (ELEC) and Microsoft (MS) from March 1999 to August 2008 with a total of 1900 records, except MS was 2600 records [8]. A random 15% of this data was used for testing.

The selected data was meant to cover a large margin of the stock market in terms of sectors, currency, trading volume and session type. First, HRHO was selected as a very active security with a large trading volume, in the investments sector and traded with the local currency. KABO was selected from the industrial sector, which has large trading volumes and is traded in USD. ELEC was selected from the Off-Trading Session (OTS), which is a 30 min session by the end of the trading day for corporates, which have some financial or legal violations and have a small trading volume. MS was chosen as a test case from an international mature stock market.

Most of the previous work concerning stock market predictions, emphasizes the movement in the market index itself [13], [15] - [17], [19], [23], [25], [30]. This gives a more insight into the market status, but such insight is not enough for an investor to make successful trading decisions. Even though the market may be trending upwards, investors can still lose money due to mistaken analysis of the security's current situation. As such, choosing security data from within the market, rather than the market index, increases the chances that resultant "Buy", "Sell" or "Hold" signal are more lucrative to the investor.

The appropriate window size, for the selected indicators in the data set, was selected based on the conducted sensitivity analysis. Beside the window size for the indicators, there are two other filters. The first is for the ADX signal. The purpose of this filter is to ensure the strength of the trend, i.e. to remove noise and false sudden moves in the price. The second one is for the "Buy", "Sell" or "Hold" signal. The purpose of this filter is to validate the signal and remove noise due to spikes in the price movement. Since rumors can tamper with a security price movement, especially in growing markets like Egypt, this generates noise that lasts over a relatively short period: one to two trading sessions. After that, the signal is corrected again to match the actual value of the assets represented by the security.

Sensitivity analysis was conducted on four variables: SMA window size, EMA window size, ADX filter and signal filter. For the window size, one tried the size range [2-72] while one tried the range [1-10] for the filters. For each variable, one tried each value from its given range with all possible combination of the other 3 variables. Variable ranges could not be larger, as this makes short term and medium term signals, trends and movements disappear. So, the neural network will capture only long term trades and will fail to detect short term and medium term trades. Therefore, the prediction model accuracy will decrease. Results of the proposed model were compared to that of the efficient ANN architecture from the previous work of early researchers [13], [15], [30] and [31].

According to this experiment, the best value for the ADX filter was 2 bars as shown in Fig. 4.a and Fig. 5.a. A bar represents the basic unit of the data aggregation. Since the data set used was aggregated on a daily level, a bar in this case means one trading day. The best value for the signal filter was 3 bars as shown in Fig. 4.b and Fig. 5.b. After 3 bars the signals detected are still of high accuracy. But, due to large filter size, some true, short term, signals were ignored because they were passed by such a long filter over the signal validity. The best values for SMA and EMA are shown in Fig. 4 and Fig. 5 (c & d) respectively. As shown, the prediction accuracy increases with increasing the parameters value until a certain threshold, at which some classifications are missed.

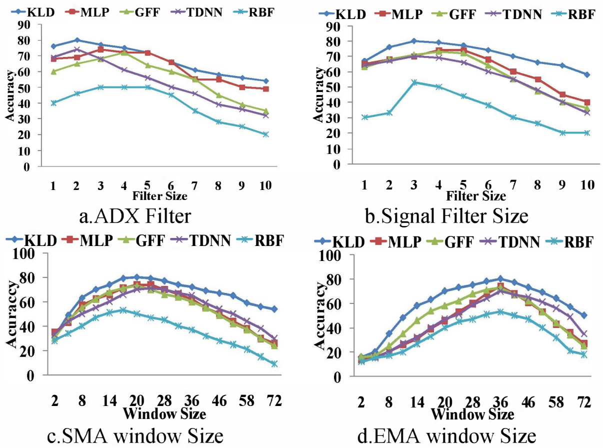


Figure 4 Sensitivity Analysis for HRHO data set parameters

This sensitivity analysis was performed also for the other 2 securities mentioned at the beginning of this section, KABO and ELEC. The results of these other 2 data sets were nearly the same for the proposed solution. But the other techniques behavior was inconsistent. For example, the MLP was being outperformed by the TDNN for the data of ELEC while they were nearly equivalent for the data of KABO. Besides, the RBF results were much closer to the MLP for the data of KABO and it dropped way far for the data of ELEC. It is interesting to point out that the behavior of the selected ANN architectures is strongly coupled with the data and the parameter values, as mentioned in section 2.

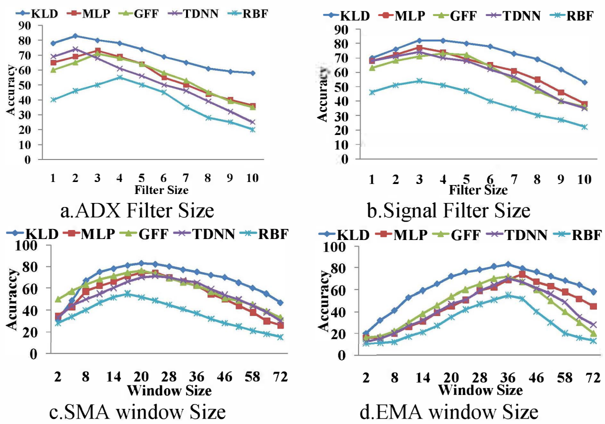


Figure 5 Sensitivity Results for MS data set parameters

In addition, the RBF ANN proposed by Quah [13] gave the worst accuracy, with the selected data set. On the other hand, the proposed model maintains the same behavior for different data. As shown in the figures above, the KLD graph pattern is approximately the same for all the selected securities (HRHO and MS). Moreover, the same pattern was maintained during the test for the other two securities (KABO and ELEC), with slight changes in some values. This shows a great progress in the generalization problem for the existing prediction models.

The maximum accuracy for most of the selected techniques was reached, using the parameters, as shown in Table 1. This was reached because such parameters realize as much as possible for short term, moderate term and long term moves, accompanied by their signal corrections. On the graphs, when one moves right, the parameter values and the accuracy increase. Then, the accuracy curve begins to drop again, as in this stage the selected parameters are more than enough to be affected by short term moves and some of the moderate term moves. So, most of the captured signals are long term signals. Therefore, the model fails to capture a major section of the market signals.

TABLE 2. Accuracy results of the experiment

Security	Technique				
	KLD	*MLP*	*GFF*	*TDNN*	*RBF*
HRHO	81	74	72	74	53
KABO	83	76	76	74	56
ELEC	80	74	73	71	53
MS	83	77	76	74	55

After using the best parameter values from the previous analysis, the results were compared to the previous work of Quah[13], Egeli et al. [15], Grosan et al. [30] and Jang [31] to ensure the accuracy of the proposed technique. The results were computed as the average of 20 separate cycles of training and testing. The maximum accuracy of the proposed technique is 83% as shown in Table 2. This adds 5% to 7% on the accuracy of the same neural network without the proposed technique.

The proposed technique converges faster than the other techniques. The previous techniques always reach the maximum epochs and do not stop at the minimum error criteria. The maximum limit of epochs is set so that the neural network does not fall in the over fitting problem. On the other hand, the proposed technique converges faster, on average 3000 epochs, when using the Mean Squared Error as the error measurement function.

Finally, ANOVA test [32] was performed on the results to ensure the statistical significance, i.e. the classifications accuracy was not a result of random act. ANOVA test resulted that the F was 9.6 while the critical F was 2.7. Therefore, the means are significantly different and the generalization effect is real.

V. CONCLUSION

This paper presented a new model based on blind source separation for stock market signal prediction, using Neural Networks. KLD was integrated with the neural network as the learning algorithm. This technique was tested with three securities from local Egyptian stock market covering wide sectors; MS security was also included as a test case from a mature global stock market. The accuracy of the proposed technique was confirmed in comparison with the results of the other most accurate previous techniques with average difference of about 5-7%. The proposed technique outperforms the other techniques in the training with an average of 3000 epochs to reach the minimum error while the other techniques stop at the maximum epochs limit to avoid over fitting. The proposed technique covers the generalization problem as mentioned in the sensitivity analysis. For future work, there are three issues that can be covered: improving accuracy, increasing the confidence degree of the prediction signal and optimizing the performance to reach real time prediction results. For the first problem, the proposed technique can be tested with a number of blind source separation techniques as a learning algorithm. Merging technical analysis and fundamental analysis or adding candle sticks patterns to some technical indicators with different weighting can help resolve the second problem. Finally, concurrent solutions will serve in the real time issue.

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