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Resilient back-propagation algorithm, technical analysis and the predictability of time series in the financial industry

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A R T I C L E I N F O

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A B S T R A C T

In financial industry, the accurate forecasting of the stock market is a major challenge to optimize and update portfolios and also to evaluate several financial derivatives. Artificial neural networks and technical analysis are becoming widely used by industry experts to predict stock market moves. In this paper, different technical analysis measures and resilient back-propagation neural networks are used to predict the price level of five major developed international stock markets, namely the US S&P500, Japanese Nikkei, UK FTSE100, German DAX, and the French CAC40. Four categories of technical analysis measures are compared. They are indicators, oscillators, stochastics, and indexes. The out-of-sample simulation results show a strong evidence of the effectiveness of the indicators category over the oscillators, stochastics, and indexes. In addition, it is found that combining all these measures lead to an increase of the prediction error. In sum, technical analysis indicators provide valuable information to predict the S&P500, Nikkei, FTSE100, DAX, and the CAC40 price level.

1. Introduction

Stock market prediction is of great importance in financial industry for portfolio optimization and derivatives pricing. Modeling and forecasting of stock market using artificial neural networks (ANN) has received a growing interest since the 2000s (Atsalakis & Valavanis, 2009). The ANN are adaptive nonlinear soft computing systems that can learn from patterns and capture hidden functional relationships in a given data even if the functional relationships are not known or difficult to identify (Zhang et al., 1998). In particular, they are capable of parallel processing of the information with no prior assumption about the model form and the process that generates the data. In addition, ANN are robust to noisy data; hence the network is capable to model non-stationary and dynamic data (Rumelhart et al., 1986). Theoretically, a neural network can approximate a continuous function to an arbitrary accuracy on any compact set (Cybenko, 1989; Funahashi, 1989; Hornik, 1991). Based on

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the supporting statement that soft computing methods use quite simple input data to provide predictions (Atsalakis & Valavanis, 2009), the most commonly used inputs to ANN to predict stock markets are the technical analysis measures (Baek &Cho, 2002; Ajith et al., 2003; Jaruszewicz & Mandziuk, 2004; Chen et al., 2005; Chun & Park, 2005; Doesken et al., 2005). Depending on the learning algorithm, there are several ANN architectures including the well known multi-layer feed-forward network. The latter maps input real valued vectors to an output of real valued vectors. The multi-layer feed-forward network is composed of an input, output, and one or more hidden layer all containing neurons. The purpose of the hidden layer nodes is to capture nonlinear structures and dynamics from the input data. The connections among the neurons have weights that are adjusted during the learning process. The back-propagation (BP) algorithm that was introduced by Rumelhart et al. (1986) - which is widely recognized as a powerful algorithm for training feed-forward neural networks - was largely adopted for stock market prediction (Atsalakis & Valavanis, 2009). In the basic BP algorithm the weights are adjusted in the steepest descent direction (negative of the gradient). However, it suffers from a slow convergence rate and often yields suboptimal solutions because it applies the steepest descent method to update the weights (Brent, 1991; Riedmiller & Braun; 1993). The resilient BP is one of the related algorithms introduced to address this problem (Riedmiller & Braun; 1993). The resilient algorithm is a local adaptive learning technique that eliminates the harmful influence of the size of the partial derivative on the weight step. As a result, only the sign of the derivative is considered to indicate the direction of the weight update. For this reason, the resilient algorithm provides faster local adaptation (Riedmiller & Braun; 1993) of weights and biases without sacrificing the accuracy of the network (Dutta et al., 2006). Finally, the resilient algorithm was successfully applied in engineering and science problems (Baykal & Erkmen, 2000; Temurtas et al., 2004; Esugasini et al., 2005; Dutta, 2006; Boukadoum et al., 2009; Zaqoot et al., 2010).

The purpose of this paper is to use the resilient back-propagation neural networks to predict international stock markets using technical analysis measures as inputs. The contribution is twofold. First, unlike previous studies (Atsalakis & Valavanis, 2009) the resilient back-propagation algorithm is adopted for faster and accurate results. Second, the performance of the resilient back-propagation neural network is examined depending on the type of technical analysis measures. Indeed, they can be categorized into four groups (Achelis, 1995): oscillators, stochastics, indexes, and indicators. In addition, we investigate whether the combination of those measures helps improving the predictive accuracy of the resilient back-propagation algorithm.

The remainder of this paper is organized as follows. In Section 2, the resilient back-propagation neural network is introduced. Section 3 gives the simulation results. Finally, some conclusions are drawn in Section 4.

2. The resilient back-propagation neural network

Artificial neural networks (ANN) are computational intelligent systems developed to mathematically mimic the computational operations of the human brain. They are effective at approximating complex nonlinear functions (Zhang, 2001). The structure of a neural network is composed of one or more hidden layer that contains computational units called neurons. The strengths of the interconnections between neurons in layers are represented by weights. The relationship between the output y and the inputs ($x_1, x_2, \ldots, x_p$) can be mathematically represented as follows:

$$y_t = w_0 + \sum_{j=1}^{q} w_j \cdot g\left(w_{0,j} + \sum_{i=1}^{p} w_{i,j} \cdot x_{t,i} \right) \tag{1}$$

where g is a nonlinear function to be approximated, $w_{i,j}$ (i=0, 1, 2,…, p, j=1, 2, …, q) and w_j (j=0, 1, 2, …, q) are the weights, p is the number of input neurones in the input layer, and q is the number of neurones in the hidden layer. The information enters the network through the input layer, processed and transfered in the hidden layer, and exits through the output layer. The output transfer function to be considered in this work is the sigmoid function given by:

$$sig(x) = \frac{1}{1+\exp(-x)} \tag{2}$$

The weights are computed such that the cost function of the neural network is minimized. In particular, the cost function is an overall accuracy criterion such as the following mean squared error E is minimized:

$$E = \frac{1}{N}\sum_{t=1}^{N}(e_t)^2, e_t = y_t - \left(w_0 + \sum_{j=1}^{q} w_j \cdot g\left(w_{0,j} + \sum_{i=1}^{p} w_{i,j} \cdot x_{t,i} \right)\right) \tag{3}$$

where N is the number of error terms. The minimization of E is achieved by nonlinear optimization algorithms in which the weights $w_{i,j}$ of the neural network are changed. In the case of the resilient back-propagation algorithm, the weights are changed as follows:

$$\Delta w_{i,j}(n) = \begin{cases} \eta A_{i,j}(n) & if \quad \frac{\partial E}{\partial w_{i,j}(n-1)}\frac{\partial E}{\partial w_{i,j}(n)} > 0 \\ \mu A_{i,j}(n) & if \quad \frac{\partial E}{\partial w_{i,j}(n-1)}\frac{\partial E}{\partial w_{i,j}(n)} < 0 \\ 0 & if \quad \frac{\partial E}{\partial w_{i,j}(n-1)}\frac{\partial E}{\partial w_{i,j}(n)} = 0 \end{cases} \tag{4}$$

where $A_{i,j}(n)$ is an update value at iteration n, and η and μ are respectively the increase and decrease factor such that $0 < \mu < 1 < \eta$. Thus, the resilient back-propagation algorithm does not use the magnitude of the gradient. Instead, it is a direct adaptation of the weight step based on local gradient sign. Finally, a training sample is used to compute the weights, and a separate hold-out sample is used for the testing phase. The performance of the resilient back-propagation neural network is evaluated by means of three statistics: the root mean of squared errors (RMSE), mean absolute errors (MAE), and mean absolute deviation (MAD). They are defined as follows:

$$RMSE = \left(N^{-1} \sum_{t=1}^{N} (F_t - R_t)^2 \right)^{0.5} \tag{5}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |F_t - R_t| \tag{6}$$

$$MAD = \frac{1}{N}\sum_{t=1}^{N} |F_t - \overline{F}| \tag{7}$$

where R_t, F_t, and $\overline{F}$ are respectively the observed price, forecasted price and the average of forecasted price over the testing (out-of-sample) period; for example t =1 to N.

3. Data and simulation results

The data used in this paper are the daily closing prices of five international stock markets namely the S&P500 (USA), Nikkei (Japan), FTSE100 (UK), DAX (Germany), and the CAC40 (France). The data set covers 1316 daily observations from January 3rd 2007 to March 26th, 2012. The first 1184 observations are used for training the resilient back-propagation neural network, whilst the last 132 observations are used for out-of-sample forecasting. The daily closing prices of the five markets are shown in Fig. 1. As mentioned in introduction, four categories of technical analysis measures are used as inputs to the resilient back-propagation neural network. The first category is called oscillators. It includes accumulation oscillator, Chaikin oscillator, moving average, stochastic oscillator, acceleration, and momentum. The second category is called stochastic measures. It includes Chaikin volatility, fast stochastics, slow stochastics, and Williams R. The third measures are called indexes. They include negative volume index, positive volume index, and relative strength index. Finally, the indicators including distribution line, Bolling band, highest high, lowest low, median price, on balance volume, price change, price-volume trend, typical price, volume change, weighted close, and Williams accumulation/distribution. A detailed description of all these measures is given in Achelis (1995).

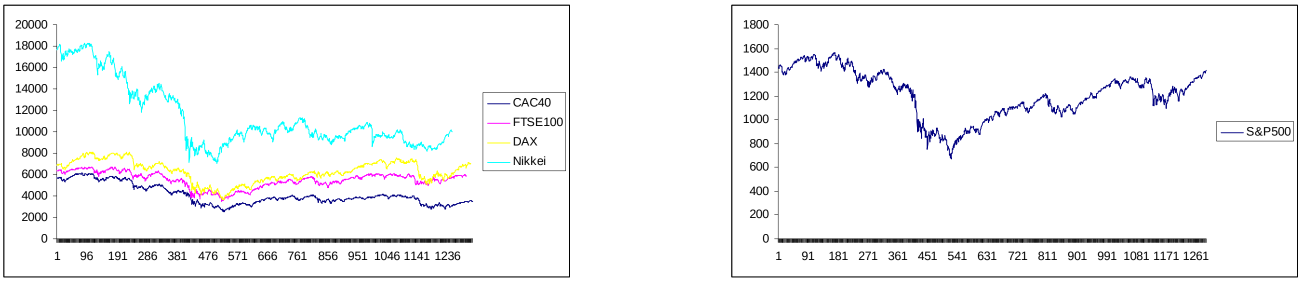

Fig. 1. Daily closing prices

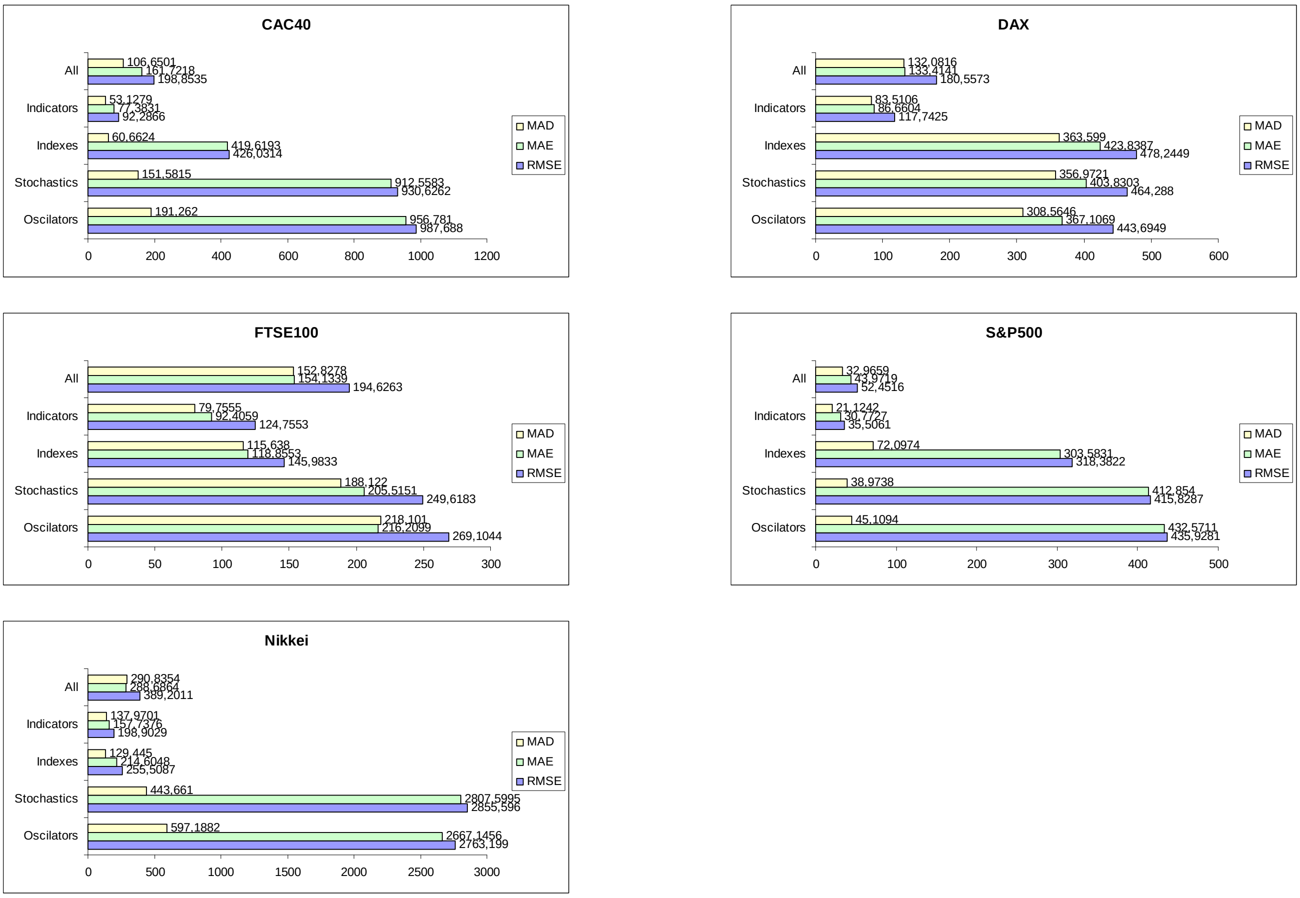

Fig. 2. Simulation results

The simulation results (out-of sample forecasting) shown in Figure 2 indicate four major findings. First, based on RMSE, MAE, and MAD statistic the indicators category provide the lowest error for all markets. This result suggest that technical analysis indicators contain valuable information to be used to predict the future value of the S&P500, Nikkei, FTSE100, DAX, and the CAC40. Second, the oscillators and stochastics are not suitable to predict the price level of those markets. Indeed, the RMSE, MAE, and MAD all achieve their highest values when oscillators and stochastics are used as inputs to the resilient back-propagation neural network. Third, technical analysis indexes perform better than oscillators and stochastics categories. Finally, combining the four categories of technical analysis measures in one set of information does not help improving the accuracy of the resilient back-propagation neural network. This result suggest that a high level of noise results from the overall set of technical analysis measures, and that noise affect negatively the accuracy of the neural network; especially the update of the network weights. In sum, this work shows a strong evidence of the effectiveness of technical analysis indicators to better forecast international stock markets than technical analysis oscillators, stochastics, and indexes.

4. Conclusion

This study compares four categories of technical analysis measures in the problem of the price level prediction in four major developed international stock markets using resilient back-propagation artificial neural networks. The four categories are the indicators, indexes, oscillators and stochastics. Based on root mean of squared errors, mean absolute errors, and mean absolute deviation statistic, the out-of-sample simulation results indicate that technical analysis indicators contain the most valuable information to be used to predict the price index future value of the S&P500, Nikkei, FTSE100, DAX, and the CAC40. In addition, the combination of all these categories in one information set leads to a considerable increase in the prediction error.

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