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Forecasting stock market short-term trends using a neuro-fuzzy based methodology

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ABSTRACT

A neuro-fuzzy system composed of an Adaptive Neuro Fuzzy Inference System (ANFIS) controller used to control the stock market process model, also identified using an adaptive neuro-fuzzy technique, is derived and evaluated for a variety of stocks. Obtained results challenge the weak form of the Efficient Market Hypothesis (EMH) by demonstrating much improved and better predictions, compared to other approaches, of short-term stock market trends, and in particular the next day's trend of chosen stocks. The ANFIS controller and the stock market process model inputs are chosen based on a comparative study of fifteen different combinations of past stock prices performed to determine the stock market process model inputs that return the best stock trend prediction for the next day in terms of the minimum Root Mean Square Error (RMSE). Gaussian-2 shaped membership functions are chosen over bell shaped Gaussian and triangular ones to fuzzify the system inputs due to the lowest RMSE. Real case studies using data from emerging and well developed stock markets – the Athens and the New York Stock Exchange (NYSE) – to train and evaluate the proposed system illustrate that compared to the "buy and hold" strategy and several other reported methods, the proposed approach and the forecasting trade accuracy are by far superior.

1. Introduction

The nature of the stock market prediction problem requires combining several computing techniques synergistically rather than exclusively, resulting in the derivation of complementary hybrid intelligent system models, including neuro-fuzzy ones. Neural networks recognize patterns and adapt themselves to cope with changing environments, while fuzzy inference systems incorporate human knowledge and expertise for inferencing and decision making. Integration of the two complementary approaches, together with certain derivative-free optimization techniques, results in neuro-fuzzy system models (Jang, Sun, & Mizutani, 1997).

This paper has been motivated by the challenge to predict as accurately as possible the *next day's stock market trend* using historical data of share prices. The underlying methodology is based on an overall neuro-fuzzy system composed of an ANFIS controller and the stock market process model (the plant model) also identified using a neuro-fuzzy technique.

Prior to the emergence of neuro-fuzzy techniques, most design methods used only linguistic information to build fuzzy logic controllers. Pure fuzzy logic based systems are not easily formalized and it is more of a trial and error effort than an engineering practice to define and fine-tune parameters of membership functions. When using learning algorithms, membership functions may be refined in a systematic way based on numerical information input–output data pairs provide. Linguistic information can be used to identify the structure of a fuzzy controller, and then numerical information can be used to identify parameters such that the fuzzy controller can reproduce desired actions more accurately (Jang, 1992, 1993; Jang & Gulley, 1995; Jang & Sun, 1995; Jang et al., 1997).

Before proceeding, it is essential to clarify why predicting the 'stock market trend', in reality predicting stock price changes or rate, is preferred over prediction of the 'stock market absolute values': it is impossible to predict future absolute values of stocks on a daily basis, particularly since the stock market is a memory less system; however, it is postulated, based on obtained results from real case studies, that with appropriate training over any (up-trend, down-trend, flat) horizon one has enough indicators to forecast trend with significant accuracy.

Stated differently, since the stock market process model is 'memory less', future trends may be predicted to some extend based on some key indicators and past behavior. Forecasting requires understanding of which market variables 'explain' stock market behavior, particularly in dynamic environments and volatile markets. Ideally, if the real underlying stock market model that generates the share values were available (known), then accurate prediction and forecasting would be possible; but this is not the case! Every stock market model is an approximate one due to

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inherent, unmodeled uncertainties and other unknown factors. Thus, once model uncertainty is acknowledged, soft computing techniques emerge as the best candidates chosen over standard benchmark linear models to deal with and solve such problems. Therefore, a neuro-fuzzy methodology is well justified.

To derive the proposed neuro-fuzzy system, historical data are collected and analyzed in order to determine (in engineering terms) the 'laws of stock market motion' as a function of chosen key variables that will help predict short-term future trends (stock price trend). Observing how the change of specific variables affect stock prices, dictates defining an appropriate 'reaction function' that best indicates to financial decision makers whether to buy or shift assets to cash, or to other risk-free assets.

It has been stated that prediction of stock market prices is futile and that the correlation of financial time series is economically and statistically insignificant because stock market prices follow a random walk (Hawawini & Keim, 1995). Most existing studies associated with stock market prediction support the well known efficient market hypothesis (EMH) according to which the current price of a stock fully reflects, at any time, available information assimilated by traders. As new information becomes available, any imbalance is immediately detected and accounted for by a counteracting change in stock market price (Fama, 1965). Based on the degree of stock market efficiency there are three forms of EMH:

- The strong form of the EMH states that all public information is immediately factored into the price of a stock, even in cases where there may be access to private/ internal information.
- The semi-strong form of the EMH states that all public information is considered to have been reflected in stock market prices immediately as it becomes known; however if such information is, somehow, a priori known, it may be used for extra profit.
- The weak form of the EMH states that any information resulting from examining the stock's past trading history is reflected in its price (Fama, 1991; Haugen, 1997). Since the past trading history is public information, the weak form is a specialization of the semi-strong form, which itself is a specialization of the strong form of the EMH.

According to the weak form of the EMH, the stock prices cannot be forecasted/ predicted based only on past values due to the random walk behavior of the stock market. However, the methodology presented in this paper and the reported results challenge the weak form of the EMH, since the proposed novel neuro-fuzzy system may predict with significant accuracy stock price trends using historical stock market prices.

Using data from the Athens Stock Exchange (ASE) and the NYSE the proposed methodology gives very encouraging results, by far better than the buy and hold (B&H) strategy and 13 other forecasting trend models. The trend of the National Bank of Greece (ETE) stock and the General Electric (GE) stock was predicted with an accuracy of 68.33%. This percentage of accuracy corresponds to a 2.15 ratio (68.33/31.77) of making a profitable stock transaction rather than a non profitable one. Other case studies of stocks from both markets return results with accuracy ranging between 58.33 and 68.33%, with an average forecasting accuracy of 63.21%. Even when considering the obtained mean forecasting accuracy, an investor is 1.72 times more likely to make a profitable transaction than a non profitable one.

The rest of the paper is organized as follows: Section 2 reviews related research, while Section 3 discusses the proposed methodology. Case studies are reported in Section 4, while conclusions are the topic of Section 5.

2. Literature review and related work

Many stockbrokers, financial analysts, individual investors and other stock market investors seem convinced that they can predict statistically stock market trends and make profits. Thus, many models have been derived to forecast stock market trends. In general existing approaches to predict stock market prices may be broadly classified in two types, fundamental analysis and technical analysis types (Black, 1982).

Fundamental analysis is based on macroeconomic data, such as exports and imports, money supply, interest rates, inflation rates, foreign exchange rates, unemployment figures, and specific company financial profile (dividend yields, earnings yield, cash flow yield, book to market ratio, price-earnings ratio, lagged returns, size, etc) (Basu, 1977; Campbell, 1987; Dourra & Siy, 2002; Fama, 1991; Fama & French, 1998a, 1998b; Fama & Schwert, 1977; Lakonishok, Shleifer, & Viahmy, 1994). Technical analysis (that ignores completely the EMH) is based on the rationale that history will repeat itself and that the correlation between price and volume reveals market behavior. Prediction takes place by exploiting implications hidden in past trading activities, and by analyzing patterns and trends shown in price and volume charts (Edwards & Magee, 1997; Epps & Epps, 1976; Martinelli & Hyman, 1998; Plummer, 1990; Smirlock & Starks, 1990; Treynor & Ferguson, 1985). Technical analysis based approaches to improve investment returns are reported Azoff (1994), Benachenhou (1996), Dourra and Siy (2002), Gately (1996), Marshall and Cahan (2005), Refenes, Burgess, and Bentz (1997), Schoneburg (1990), Trippi and Turban (1993), Ucenic and Atsalakis (2005b).

The fundamental and technical analysis to stock market price forecasting has different importance when examined under the view point of the forecasting horizon. If the forecasting time horizon covers one year or more, fundamental analysis is preferred; otherwise, if the horizon is shorter than one year, technical analysis is preferred. *In this paper, since the time horizon refers to predicting the next day's trend, the proposed methodology falls under the technical analysis approach.*

Further, researchers have also used artificial neural networks and other soft computing techniques to predict stock market prices or stock market trend. Representative work includes (Armano, Marchesi, & Murru, 2004a, 2004b; Baba & Kozaki, 1992; Baba & Suto, 2000; Chen, Yanga, & Abraham, 2006; Cheng, 1994; Chenoweth & Obradovic, 1996; Enke & Thawornwong, 2005; Fernandez-Rodriguez, Gonzalez-Martel, & Sosvilla-Rivebo, 2000; Halliday, 2004; Harvey, Travens, & Costa, 2000; Hassan, Nath, & Kirley, 2007; Jang, 1992; Kim & Chun, 1998; Kim, 1998; Kimoto, Asakawa, Yoda, & Takeoka, 1990; Koulouriotis, Diakoulakis, & Emiris, 2001; Kuo & Cohen, 1998; Leung, Daouk, & Chen, 2000; Lendasse, De Bodt, Wertz, & Verleysen, 2000; Phylaktis & Ravazzolo, 2004; Ucenic & Atsalakis, 2005a; Walezak, 1999; Wang & Chan, 2007; Wong, 1991; Wu, Fung, & Flitman, 2001; Yiwen, Guizhong, & Zongping, 2000). Neuro-fuzzy based techniques for stock market prediction include (Abraham et al., 2005; Bouqata, 2000; Cao, Karyl, & Schniederjans, 2005; Doesken, Abraham, Thomas, & Paprzycki, 2005; Kosaka, Mizuno, Sasaki, Someya, & Hamada, 1991; Kuo, 1998; Kuo & Xue, 1998; Lin, Khan, & Huang, 2002; Lin & Lee, 1991; Nayak, Sudheer, Rangan, & Ramasastri, 2004; Siekmann, Gebhardt, & Kruse, 1999; Wikowska, 1995). Neuro-fuzzy and neural network techniques have been used for time series prediction by many researchers (Atsalakis, 2006; Atsalakis & Valavanis, 2006; Atsalakis & Ucenic, 2006a, 2006b, 2006c; Atsalakis, 2005, 2005a; Atsalakis, Ucenic, & Plokamakis, 2005, 2005; Atsalakis & Ucenic, 2005b; Ucenic & Atsalakis, 2003, 2005a, 2005b).

2.1. Remarks

Most of the reported papers refer to forecasting of financial markets in well developed countries. However, several recent articles do show that return predictability is also possible when dealing with emerging financial markets (of under development countries). Ferson and Harvey (1993) has studied eighteen international stock markets of both kinds demonstrating evidence of return predictability. Harvey (1995) has examined emerging markets by looking at the returns of more than 800 stocks from 20 emerging stock markets. It is demonstrated that the degree of predictability in emerging stock markets is higher than that found in well developed ones. In addition, it is shown that local information plays a much more important role in predicting returns in emerging stock markets than in well developed ones.

The proposed methodology in this is paper has focused and been applied to an emerging market, the ASE, and to a well developed stock market, the NYSE, for generalization purposes. The overall superiority of the proposed methodology is demonstrated via case studies and comparisons.

3. The proposed methodology

Predicting stock market trends requires capturing and modeling actions and reactions of stock market players, while observing, studying and evaluating past/historical data. Stock prices rise or fall reacting to 'inside' information or publicly available information, because traders themselves react to such news by buying or selling stocks, accordingly. To approximate the real stock market process model requires, among other factors, taking into consideration how traders – human beings – actually learn, process information, and make decisions (McNelis, 2005).

The methodology presented in this paper considers historical/past stock prices as inputs (predictors) to create a forecasting system that captures the underling "laws of the stock market price motion", thus, predicting next day's trend of a stock. The proposed neuro-fuzzy model uses an ANFIS technique, which is superior in modeling time series data as shown in Abraham et al. (2005), Jang et al. (1997).

A block diagram of the proposed neuro-fuzzy system, during the training and the application–evaluation phase, is shown in Figs. 1a and 1b.

The CON-ANFIS controller controls the plant model, in this case, the stock market process model, PR-ANFIS, and forecasts the stock trend one-step-ahead (next day). In the discrete time domain, the overall system is governed by the process and controller equations applicable to both phases:

$$y(k+1) = f(y(k), u(k)) \quad (1)$$

$$u(k) = g(y(k)) \quad (2)$$

where $y(k+1)$ is the stock price at time $k+1$, $y(k)$ is the stock price at time k, $u(k)$ is the control signal (action) at time k. The control problem is to find the mapping $\phi(\cdot)$ for the controller such that the resulting overall system exhibits certain desired behavior. Detailed description of the controller and process models during the training phase follows.

3.1. CON-ANFIS controller – training phase

The CON-ANFIS controller is trained based on the inverse learning technique also known as general learning (Jang et al., 1997). In the learning phase, an off-line technique is used to model the inverse dynamics of the process. In the application–evaluation phase the obtained neuro-fuzzy model, representing the inverse dynamics of the process, is used to generate control actions that drive the stock market process model (plant). These two phases may function simultaneously; hence this design method fits perfectly well with classical adaptive control schemes.

The stock market process model is described by (1). In general (Jang et al., 1997):

$$y(k+n) = F(y(k), U), \quad (3)$$

where n is the order of the process, F is a multiple composite function of f, and U is the control actions from k to $k+n-1$. Eq. (3) points out the fact that given the control input u from time k to $k+n-1$, the stock price will move from $y(k)$ to $y(k+n)$ in exactly n time steps. Furthermore, it is assumed that the inverse dynamics of the stock market process model do exist, that is, U can be expressed as an explicit function of $y(k)$ and $y(k+n)$:

$$U = G(y(k), y(k+n)). \quad (4)$$

Eq. (4) states that there exist unique input sequences U, specified by the mapping G, which can drive the stock prices from stock price $y(k)$ to $y(k+n)$ in n time steps. Thus, the inverse mapping G must be found. An ANFIS controller may be used with $2n$ inputs and n outputs to approximate the inverse mapping G according to the generic training data sets $[y(k)^T, y(k+n)^T; U^T]$. The stock price (output) at $y(k+1)$ is a function of the previous stock price at $y(k)$ and

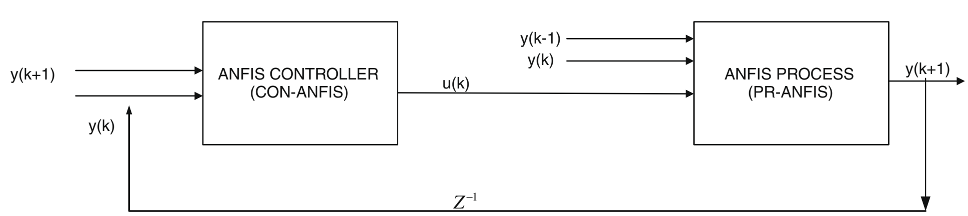

Fig. 1a. Control system during the training phase.

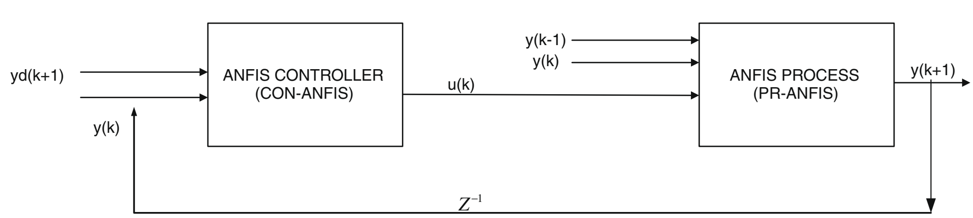

Fig. 1b. Control system during the application–evaluation.

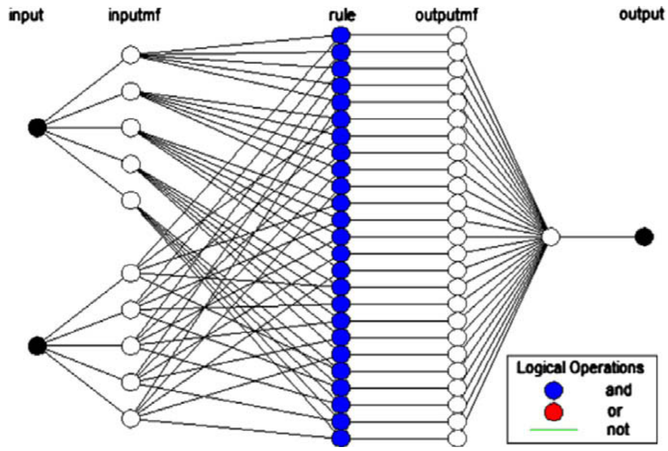

Fig. 2. Graphical representation of the structure of the CON-ANFIS controller using MATLAB (Jang & Gulley, 1995).

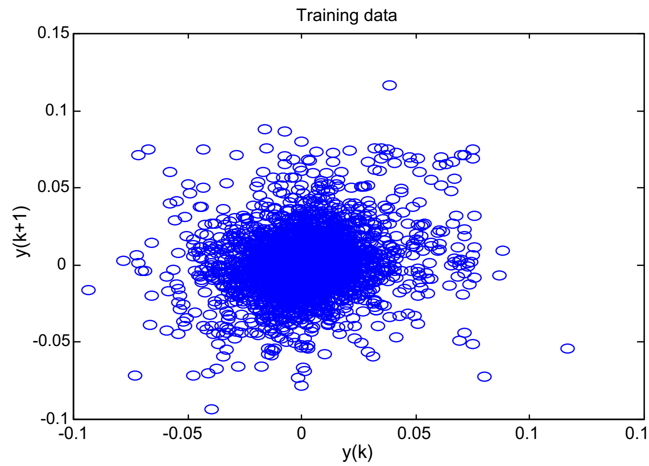

Fig. 4. Scatter plot of the training data of the CON-ANFIS controller.

the input $u(k)$. After the training phase, the ANFIS controller imitates the input–output mapping of the inverse dynamics G. Then, given $y(k)$ and the desired future stock price $y_d(k+n)$ the ANFIS controller will generate an estimated $\widehat{U}$:

$$\widehat{U} = \widehat{G}(y(k), y_d(k+n)). \tag{5}$$

After n steps, this control sequence will bring $y(k)$ close to the desired $y_d(k+n)$, as the function $\widehat{G}$ is exactly the same as the inverse mapping G. When $\widehat{G}$ is not close to G, the control sequence $\widehat{U}$ cannot bring $y(k)$ close to $y_d(k+n)$ in exactly the next n time steps. As more data sets are used to refine the parameters in the ANFIS controller, $\widehat{G}$ will get closer to G and the control will be more accurate as the training process goes on. However, the future desired $y_d(k+n)$ is not available in advance during the application phase.

In the proposed methodology, as shown below, instead of using $y_d(k+1)$ for the next day's desired trend that is unknown, it was decided after trail-and-error efforts to use the rate of change of three-day stock price moving average.

The specific structure of the CON-ANFIS controller for the training phase is shown in Fig. 2. The ANFIS model is a Sugeno first order model with two inputs $y(k+1)$ and $y(k)$ and one output. Five Gaussian-2 membership functions correspond to each input, *very small, small, medium, big* and *very big*. The combination of two inputs and five membership functions creates twenty five rules (5^2) of the form:

If $y(k+1)$ is very small and $y(k)$ is very small, then (u) is $f_1 = p_1 \cdot y(k+1) + q_1 \cdot y(k) + r_1$ where $\{p_i, q_i, r_i\}$ is a parameter set with values calculated and optimized during the learning phase. The reason for using a Sugeno first order model is because of the r_i parameter, used to approximate better real values. The parameters of the first part (premise) of the rule are optimized using the error back propagation gradient descent method and the parameters of the second part (consequent) are optimized using the least square error method.

To train the CON-ANFIS controller, training data sets are used of the form $[y(k), y(k+1); u(k)]$. $y(k)$ is referred to the price change at time k of a specific stock, $y(k+1)$ is referred to the price change of a specific stock at time $k+1$, and $u(k)$ is the always positive control action calculated as:

$$u(k) = \sqrt{(y(k) - y(k+1))^2}. \tag{6}$$

The chosen training data sets for a stock under consideration concern daily changes of a stock price over the period 2 January 1986–31 March 2005 (4,775 observations). A graphic representation of a part of the training data is shown in Fig. 3 and a scatter plot of the observed data is shown in Fig. 4.

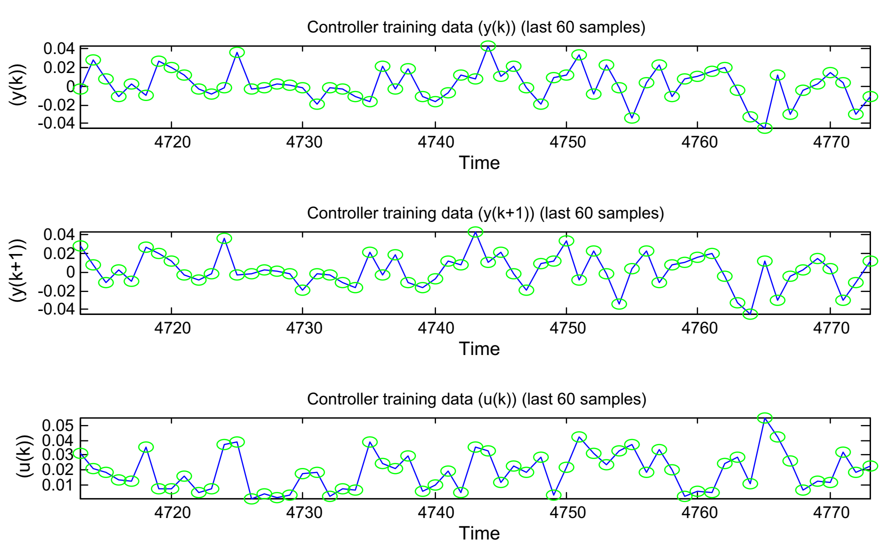

Fig. 3. A part of the training data of the CON-ANFIS controller (60 observations).

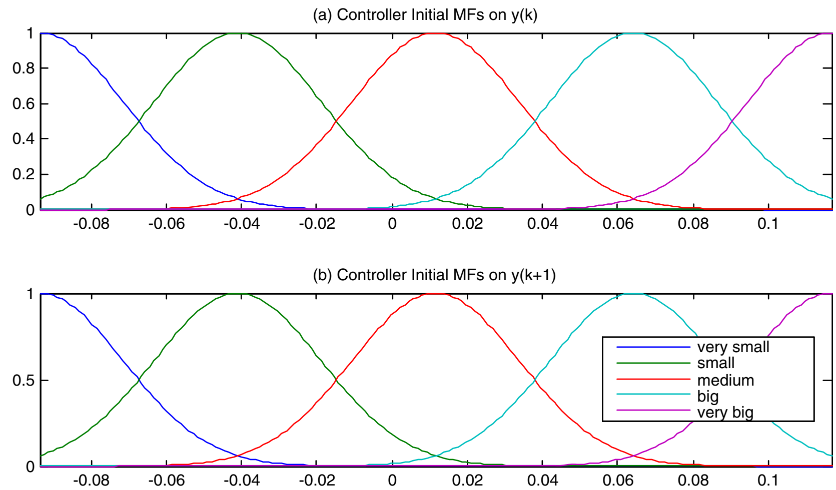

Fig. 5. The membership functions before the training of the CON-ANFIS controller.

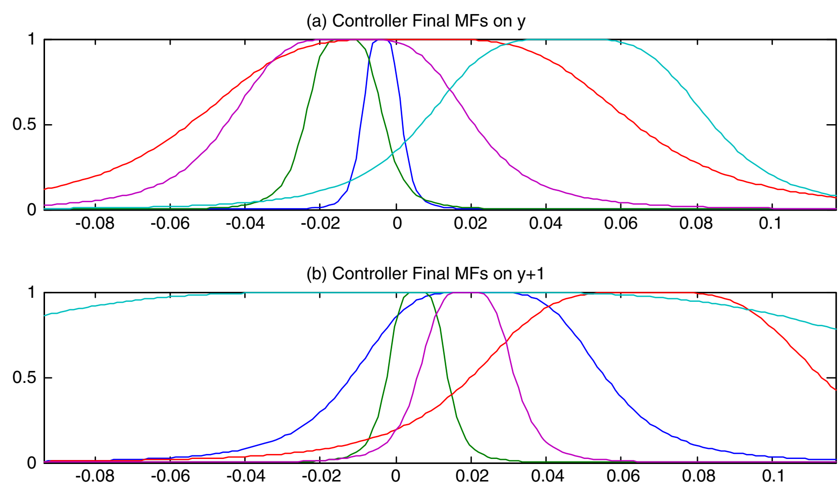

Fig. 6. The membership functions after the training of the CON-ANFIS controller.

Fig. 5 presents the initial membership functions before training for both inputs. Fig. 6 presents the final membership functions once training is complete. The number of epochs is 400 and the step size is 0.1. Fig. 7 shows the evolution of the RMSE and the step size according to the number of epochs. After many trial and error attempts it was determined that when using 400 epochs the RMSE was the lowest (more epochs did not reduce the RMSE further). Fig. 8 represents the control surface of the CON-ANFIS. Fig. 9 offers a visual in-sample evaluation of the CON-ANFIS controller, according to which the actual stock price change and the predicted one are almost identical.

3.2. PR-ANFIS – training phase

The (nonlinear) stock market process model is approximated via identification methods based exclusively on measured data. An ANFIS model is also used. The stock market process model is trained to generate a one-step-ahead prediction of a stock (next day's price change). Inputs to the model are the current and previous outputs of the actual stock price changes and the control action obtained from the CON-ANFIS controller:

$$y(k+1) = f(y(k), y(k-1), u(k)). \tag{7}$$

It is assumed that the dynamics of the stock market process are unknown. Training is based on a first order ANFIS that maps $[y(k-1), y(k), u(k)]$ to the forecasted stock price change at $y(k+1)$. The structure of the PR-ANFIS is shown in Fig. 10.

The PR-ANFIS model is a Sugeno first order model with three inputs and one output. Three Gaussian-2 membership functions *small*, *medium*, and *big* correspond to each input, for a total of twenty seven (3^3) rules of the form:

If $y(k-1)$ is small and $y(k)$ is small and (u) is small, then $y(k+1)$ is f_1

$$f_1 = p_1 \cdot y(k+1) + q_1 \cdot y(k) + s_1 \cdot u(k) + r_1,$$

with the $\{p_i, q_i, s_i, r_i\}$ parameters optimized as previously stated.

Training data sets $[y(k-1), y(k), u(k); y(k+1)]$ are used. Training data concern daily changes of a stock price for the period of 2 January 1986–31 March 2005 (4,775 observations). Fig. 11 is a graphic representation of part of the training data. A 2-D scatter plot of the data is presented in Fig. 12 and a 3-D scatter plot of the training data is shown in Fig. 13. Fig. 14 presents the initial membership functions before training for the three inputs and Fig. 15 presents the final membership functions once training is complete. The number of epochs is 100 and the step size is 0.1. Fig. 16 shows the evolution of the RMSE and the step size according to the

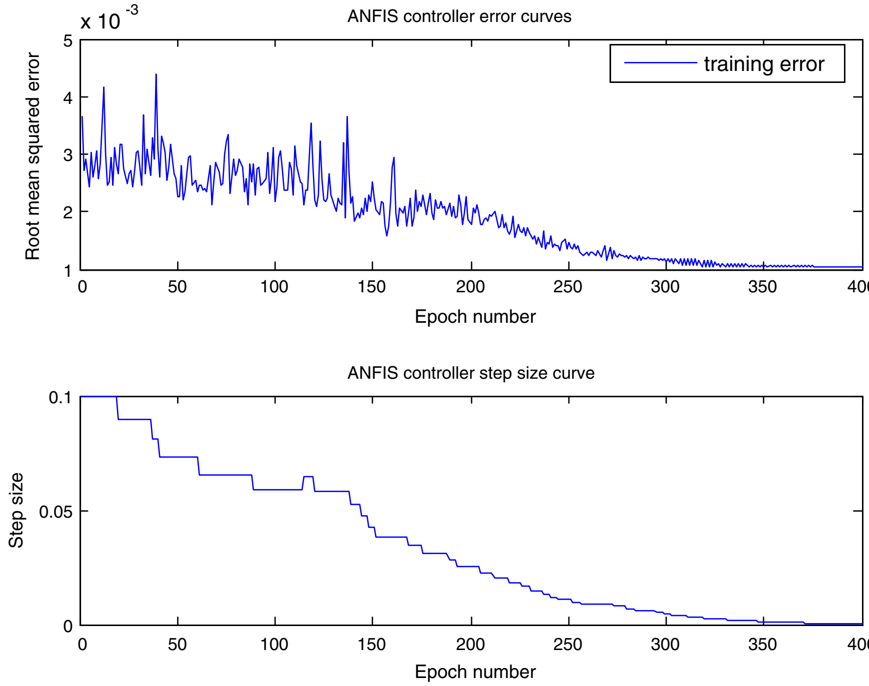

Fig. 7. The error curve and the step size during the training of the CON-ANFIS controller.

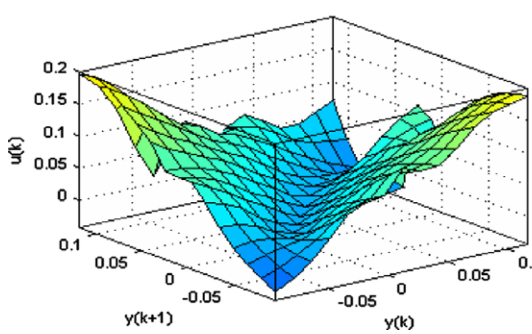

Fig. 8. The control surface of the CON-ANFIS controller.

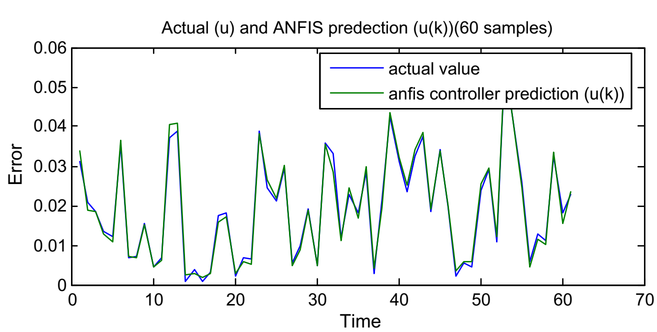

Fig. 9. Actual value and CON-ANFIS controller value of u(k) for 60 observations.

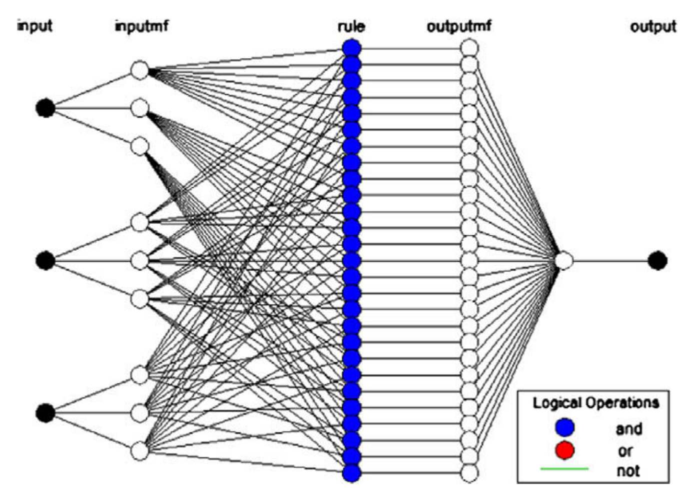

Fig. 10. The structure of the PR-ANFIS using MATLAB (Jang & Gulley, 1995).

number of epochs. After many trial and error attempts the number of epoch is defined to be 100, returning the lowest RMSE. Fig. 17 represents the 3-D surface of $y(k)$ and $y(k-1)$, while Fig. 18 that of $y(k-1)$ and $u(k)$. Fig. 19 presents the 3-D surface of $y(k)$ and $u(k)$. An in-sample evaluation of the stock market process is illustrated in Fig. 20; the predicted stock price trend follows the actual direction of the price in most cases. The in-sample trend forecasting accuracy is 93.20%. However, this accuracy is without important for the practitioners as they are interesting for the out of sample only forecasting accuracy. However, the training error (over the in-sample data) is really important because it indicates the level of model accuracy.

4. System evaluation through case studies

After training is complete, forecasting/ one-step-ahead prediction follows. According to Norgaard, Ravn, and Poulsen (2003), since the CON-ANFIS controller input $y(k+1)$ is unknown, the desired input $y_d(k+1)$ may be used, instead. The CON-ANFIS controller will drive the system output at time $k+1$ towards the desired $y_d(k+1)$.

In the proposed methodology, $y_d(k+1)$ has been defined after trail-and-error efforts to be the rate of change of three-day stock

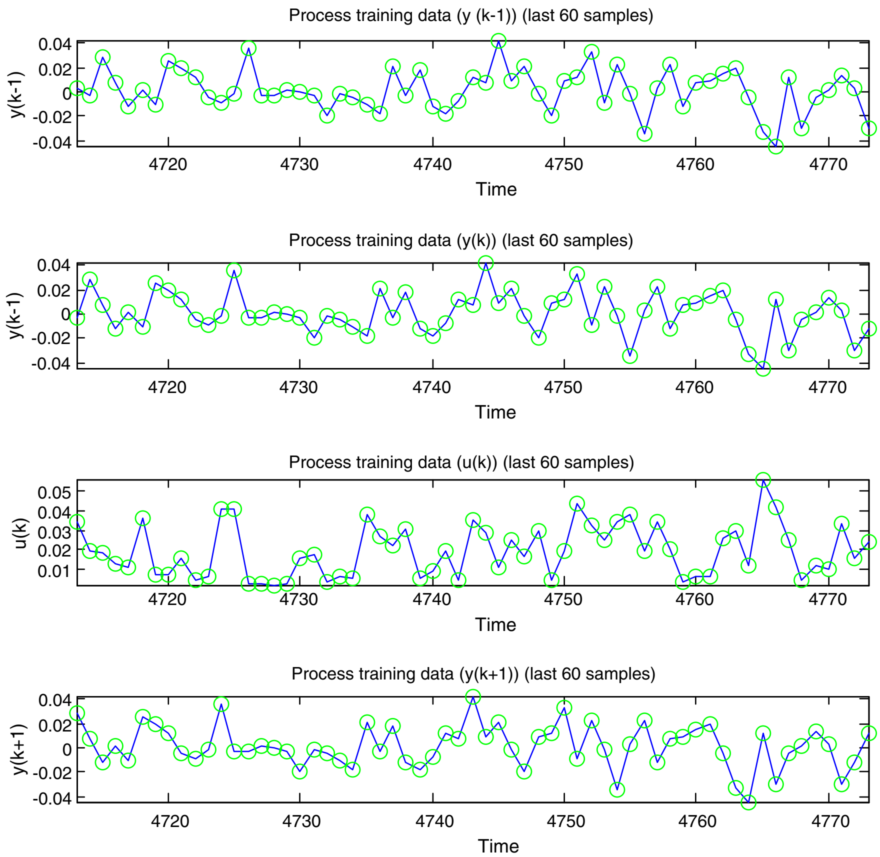

Fig. 11. A part of the training data of the PR-ANFIS (60 observations).

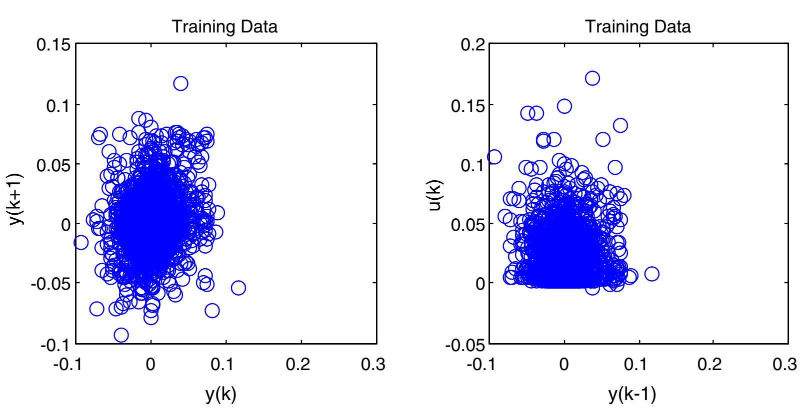

Fig. 12. A scatter plot of the training data of the process.

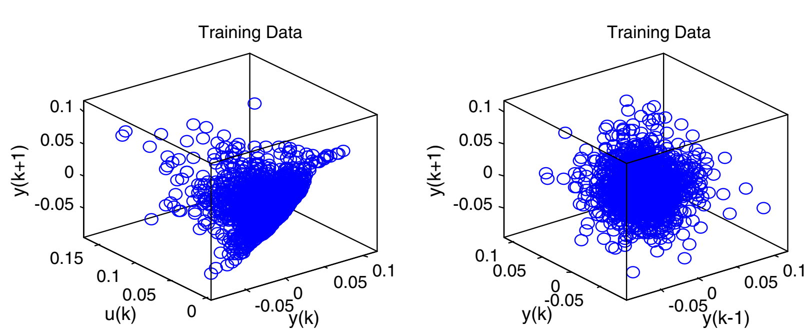

Fig. 13. Three dimension presentation of the training data of the process.

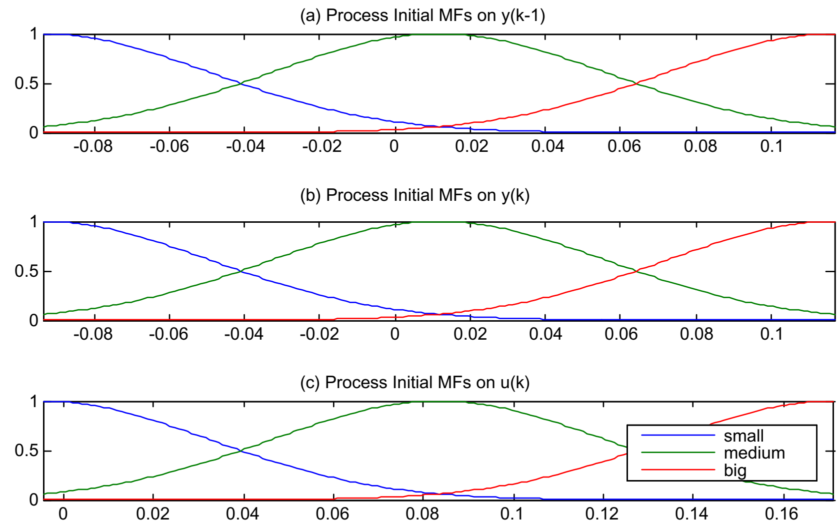

Fig. 14. Initial membership functions of the process PR-ANFIS before training.

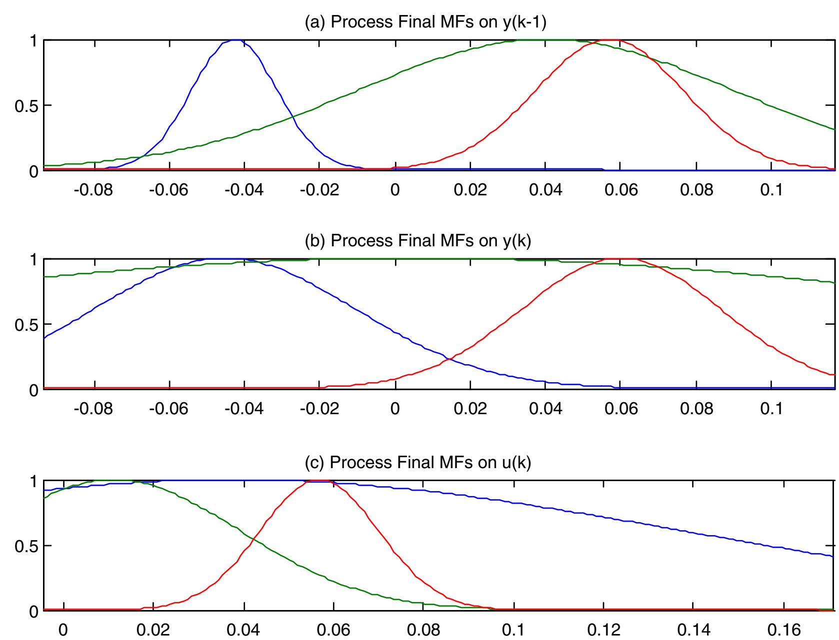

Fig. 15. Final membership functions of the process PR-ANFIS after training.

price moving average. As such, the moving three-day average and the corresponding rate of change are calculated as:

$$SMA(k) = \frac{\text{Sum of close price, day } k, k-1, k-2}{3} \tag{8}$$

$$\text{mooving average rate } = \frac{SMA(k) - SMA(k-1)}{SMA(k-1)} \tag{9}$$

The evaluation data sets (out of sample) relate to three approximately 60 day periods (sessions): 5 April 2005 to 30 June 2005, 4 November 2005 to 31 January 2006, and 28 February 2006 to 31 May 2006. The five stocks evaluated are the National Bank of Greece (NBG), Alpha Bank (ALPHA), Commercial Bank (CB), Titan (TITAN) and Aluminum of Greece (ALGR), all listed in the Athens Stock Exchange, an emerging market. Additional evaluations have been performed for the General Electric (GE), Caterpillar, General Motors (GM), International Business Machine (IBM) and Kodak stocks, all listed in the NYSE, a well developed market.

Results of the proposed methodology are evaluated in terms of the hit rate (trend), comparison against the B&H strategy, comparison against 13 other forecasting trend models, and based on statistical performance measures, as shown below.

4.1. Hit rate

The hit rate of a stock is calculated as:

$$\text{Hit rate } = \frac{h}{n} \tag{10}$$

where h denotes the number of correct predictions of the stock trend and n denotes the number of tests, 60 sessions in this case. Table 1 summarizes forecasting accuracy for the five stocks in the ASE. The range of the forecasting accuracy is between 58.33% and 68.33% with a mean forecasting accuracy of 63.21%. Fig. 21 illustrates, as an example, the actual and predicted price change of the NBG stock.

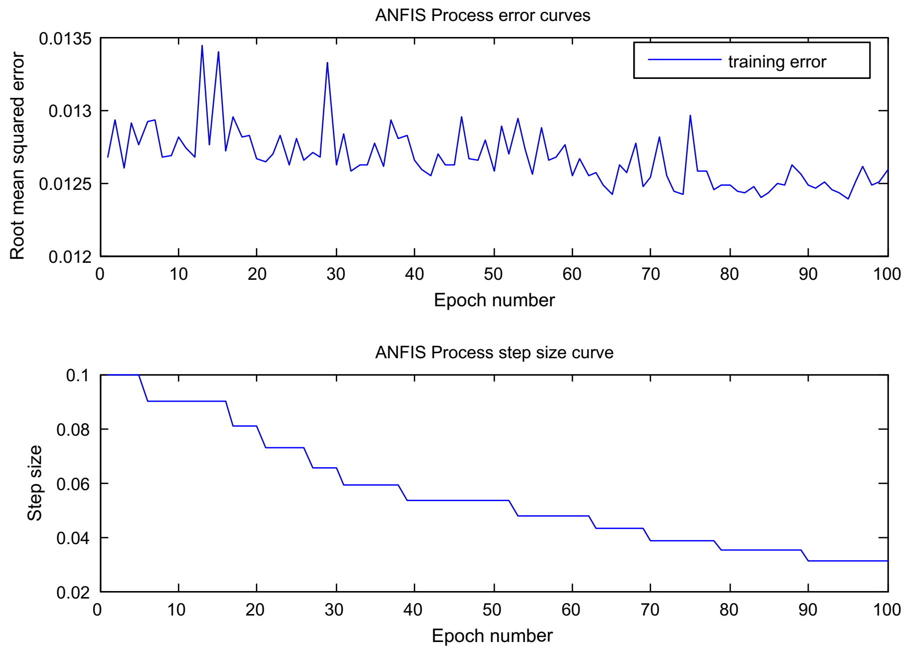

Fig. 16. Error curve and step size during the training of the PR-ANFIS.

Table 2 shows similar results for the NYSE stocks. Forecasting accuracy varies between 56.60% and 68.33% with an average of 62.32%.

4.2. Comparison against the Buying and Hold (B&H) strategy

For further evaluation of the proposed system, a comparison with the B&H is performed. In the B&H strategy the investor invests an amount of money and holds the investment until the end of the simulation horizon (approximately 3 months, 60 sessions). Using the proposed system, the investor allocates assets to the stock when there is a predicted up-trend for the next day, and sells when there is a predicted down-trend for the next day. Regardless of the fact that in stock market trading one may have a long (earnings produced from up-trend of the prices) or a short (earnings produced from the down trend of the stock prices)

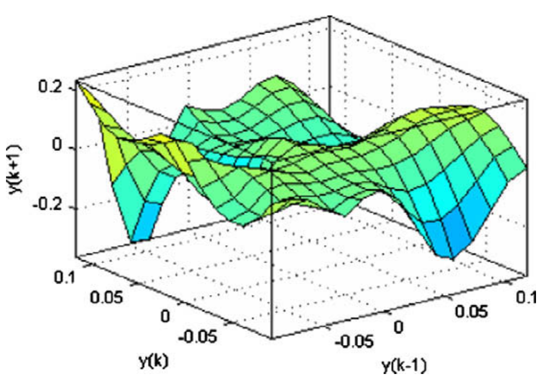

Fig. 17. The control surface of PR-ANFIS.

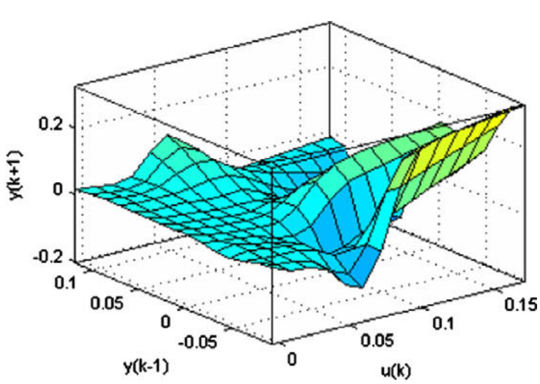

Fig. 18. The control surface of PR-ANFIS.

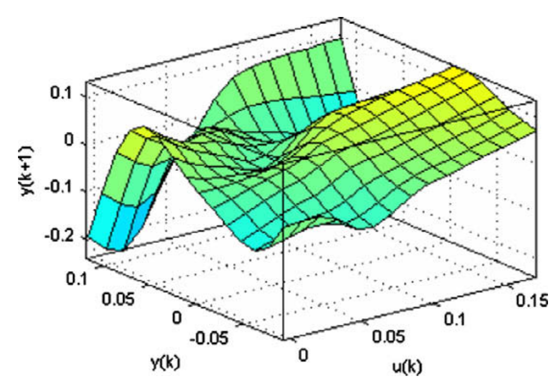

Fig. 19. The control surface of PR-ANFIS.

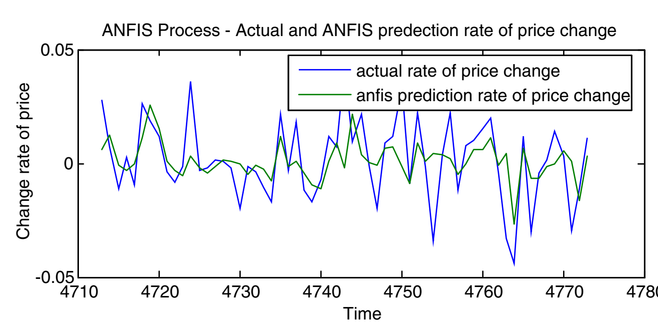

Fig. 20. Results of in-sample evaluation of PR-ANFIS.

Table 1
Forecasting accuracy of the five stocks listed in ASE.

	NBG	ALPHA	CB	TITAN	ALGR
Time period	5/4/05–30/6/05				
Hit rate %	**68.33**	59.32	64.41	61.66	61.66
Time period	4/11/05–31/1/06				
Hit rate %	66.66	60	65.00	60.00	58.33
Time period	28/2/06–31/5/06				
Hit rate %	66.66	68.33	65.00	63.33	60.00

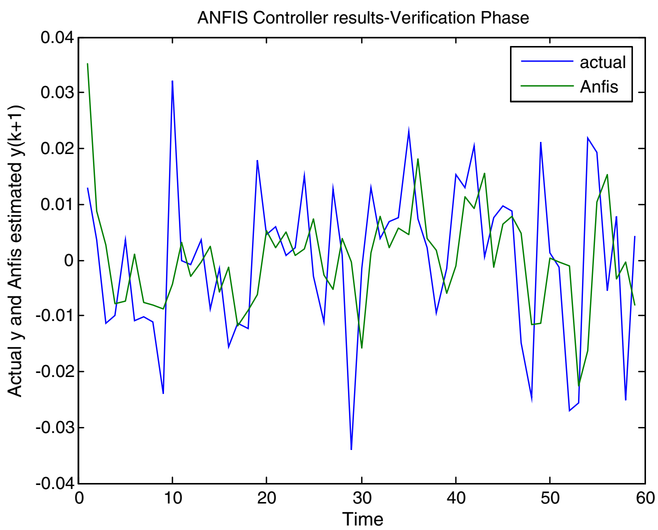

Fig. 21. Actual and predicted price change, NBG stock.

Table 2
Forecasting accuracy of five stocks listed in NYSE.

	GE	Caterpillar	GM	IBM	Kodak
Time period	05/4/05–30/6/05				
Hit rate %	63.33	60.00	65.00	61.66	61.66
Time period	4/11/05–31/1/06				
Hit rate %	66.66	60.00	63.33	63.33	58.33
Time period	28/2/06–31/5/06				
Hit rate %	68.33	63.33	65.00	56.60	58.33

position, in this paper it is assumed that only long positions are taken. An indicative amount of 10,000 € is allocated as an initial investment. The net gain in assets and the rate of return (ROR) over the out of sample forecasts are shown in Table 3. The ROR is calculated as follows:

$$ROR = \frac{\text{net gain in stock}}{\text{initial investment}} \tag{11}$$

The results demonstrate clearly that the proposed system ROR outperforms by far the B&H strategy based return. For example, the NBG stock has an ROR of 12.48% (reaching 11,190 €) after the three month sessions, an improvement of 11.19% over the B&H strategy that returns 1.29% over the same period. Performance is equally impressive for the other four stocks, too.

However, it must be stated that better returns could have been obtained had the investor allocated assets to the risk-free government bonds once the predicted stock return turned negative. This is what is known as asymmetric outcomes of the stock markets. Stock market asymmetric outcomes must be accounted for when calculating investment returns. It is also important to consider that the loss when predicting an upward trend as a downward one is not the same with the loss when predicting a downward trend as

Table 3
Comparison of the ROR with the B&H strategy, ASE stocks.

	NBG	ALPHA	CB	TITAN	ALGR
Time period	5/4/05–30/6/05				
Proposed System ROR %	**12.48**	**15.97**	**45.31**	**10.07**	**25.69**
B&H strategy ROR %	1.29	−3.03	22.43	−3.84	13.72
Performance difference %	11.19	19.00	22.88	13.91	11.97

an upward one. In the first case the investor suffers a loss; in the second case the investor, if he has allocated assets to risk-free government bonds, will still have some positive returns (interest). Further, correct prediction of the stock price direction does not refer to the 'magnitude' of the stock price movement. This means that gains from correct predictions and losses from incorrect predictions may vary. The trading simulation shown in Table 3 demonstrates the potential of the proposed system in predicting the stock price direction. In a real environment, it should be combined with more sophisticated trading strategies and hedging activities to reduce return variance.

4.3. Evaluation by comparing to 13 other models

A comparative study is reported to evaluate percentages of prediction correctness of stock price trends. The study compares the proposed neuro-fuzzy system to similar and/or very relevant reported approaches briefly summarized below. However, this study aims at demonstrating prediction accuracy levels of different techniques, and in particular the highest level, as applied to specific respective stocks, not to the same one.

Armano, Marchesi, and Murru (2004b) have created a hybrid genetic-neural architecture system for forecasting next day's trend of the S&P500 index. They have compared two forecasting systems, a neural XCS and a recurrent artificial neural network. Lin et al. (2002) have created a neuro-fuzzy model for predicting next day's direction, comparing performance of four models, a regression model (REG), a Garch_M model (GM), a neural network model and a neuro-fuzzy model. Fernandez-Rodriguez et al. (2000), Perez-Cruz, Rodrıguez, and Giner (2003) have developed a neural network system for predicting the next day's stock price direction in the Madrid stock exchange. Harvey et al. (2000) and Halliday (2004) have developed a neural network for forecasting the direction of a stock price in the NYSE. Lendasse et al. (2000) derived a neural network to forecast stock price directions in the next session of the Belgium stock exchange. Doesken et al. (2005) developed a Mamdani fuzzy system and a Takagi-Sugeno fuzzy system to forecast the direction of a stock in NYSE. Zhang, Patuwo, and Hu (1998) created a neural network to forecast direction of stock

Table 4
Comparison of various models that forecast the trend in the stock market.

Author	Model	Hit rate (%) next day
Lin et al. (2002)	REG	52.47
Lin et al. (2002)	GM	52.83
Lin et al. (2002)	NN	55.77
Lin et al. (2002)	NF	58.03
Fernandez-Rodriguez et al. (2000)	ANN	58.00
Harvey et al. (2000)	NN	59.00
Perez-Cruz et al. (2003)	MLP	57.00
Lendasse et al. (2000)	RBFN	57.20
Zhang et al. (1998)	NN	56.30
Doesken et al. (2005)	M-FIS	53.31
Doesken et al. (2005)	TS-FIS	56.00
Halliday (2004)	NN	55.57
Atsalakis (2006)	ATS-Anfis	60.00
Atsalakis, (proposed)	Neuro-Fuzzy	68.33

Table 5
Comparative study of error-based performance of five stocks listed in ASE.

	NBG	ALPHA	CB	TITAN	ALGR
Time period	5/4/05–30/6/05				
MSE	0.00020	0.000287	0.000507	**0.000148**	0.000315
RMSE	0.01440	0.016900	0.022500	**0.012200**	0.017700
MAE	0.01090	0.013000	0.016900	**0.010200**	0.014100

Table 6
Comparative study of error-based performance of five stocks listed in NYSE.

	GE	Caterpillar	GM	IBM	Kodak
Time period	05/4/05–30/6/05				
MSE	0.0027	0.0062	**0.0025**	0.0076	0.0078
RMSE	**0.0101**	0.0127	0.0504	0.0133	0.0133
MAE	**0.0081**	0.0104	0.0249	0.0109	0.0110

prices in the Shanghai stock exchange. Atsalakis and Valavanis (2006) has proposed a neuro-fuzzy model to evaluate and forecast stock price directions in the next session of the ASE.

Table 4 tabulates and illustrates the best results in terms of forecasting accuracy of the respective systems when applied to the respective stock markets.

It may be observed that the proposed system returns the highest level of prediction for next session's stock movement direction.

4.4. Evaluation by statistical performance measures

Forecasting results are also reported for the same stocks from the ASE and the NYSE, based on three types of error measures. Forecasting accuracy results are presented in Tables 5 and 6 using as measures the mean square error (MSE), the root mean square error (RMSE) and the minimum absolute error (MAE), defined below, respectively as:

$$MSE = \frac{1}{N}\cdot\sum_{t=1}^{N} e_t^2, \quad RMSE = \sqrt{\frac{\sum_{t=1}^{N} e_t^2}{N}}, \quad MAE = \frac{1}{N}\cdot\sum_{t=1}^{N} |e_t|$$

From Table 5, it is observed that the smaller error corresponds to the TITAN stock, despite that it ranks 3rd according to the forecasting trend accuracy. Leung et al. (2000) have referred to similar situations, too; this is evidence confirming that it is most important to measure if a prediction system succeeds or fails to predict the stock trend than comparing its performance using the above errors.

5. Conclusions

A neuro-fuzzy adaptive control system has been developed to forecast next day's stock price trends. The proposed system has been presented and described from conceptual and technical perspectives, justifying its modeling aspects. Obtained results challenge the weak form of the EMH, by demonstrating that when using historical data, accurate predictions of stock price trends are achievable. This statement has been supported by several case studies of different stocks from the ASE (an emerging market) and the NYSE (a well developed market).

The proposed system has performed very well in trading simulations, returning results superior to the B&H strategy. Comparisons with 13 other similar soft computing based approaches do demonstrate solid and superior performance in terms of percentage of prediction accuracy of stock market trend. Reported case studies do not consider commission and tax liabilities; this means that actual returns will be less than those reported. Nevertheless, the proposed system clearly demonstrates the potential of neuro-fuzzy based modeling for financial market prediction.

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