An intelligent statistical arbitrage trading system

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Abstract. This paper proposes an intelligent combination of neural network theory and financial statistics for the detection of statistical arbitrage opportunities in specific pairs of stocks. The proposed intelligent methodology is based on a class of neural network-GARCH autoregressive models for the effective handling of the dynamics related to the statistical mispricing between relative stock prices. The performance of the proposed intelligent trading system is properly measured with the aid of profit & loss diagrams, for a number of different experimental settings (i.e. sampling frequencies). First results seem encouraging; nevertheless, further experimentation on the optimal sampling frequency, the forecasting horizon and the points of entry and exit is necessary, in order to achieve highest economic value when transaction costs are taken into account.

Keywords: statistical arbitrage, intelligent trading systems, neural networks, GARCH models.
JEL codes C14, C22, G11

1 Introduction

In the last few years, a substantial amount of computational intelligent methodologies have been applied to the development of financial forecasting models that attempt to exploit the dynamics of financial markets. A great majority of intelligent approaches employ a network learning technique, such as feedforward, radial basis function or recurrent NN [13, 17], although certain paradigms such as genetically-evolved regression models [5, 8, 11, 14] or inductive fuzzy inference systems [9] are also encountered in the literature. Forecasting experience has shown that predictability in data can be increased if modelling is directed to a combination of asset prices rather than (raw) individual time series. Combinations can be seen as a means of improving the signal-to-noise ratio and hence enhancing the predictable component in the data[3].

Statistical arbitrage is an attempt to profit from pricing discrepancies that appear in a group of assets. The detection of mispricings is based upon the identification of a linear combination of assets, or else a "*synthetic*" asset, whose time series is *mean-reverting* with finite variance. For example, given a set of assets $X_1,...,X_n$, a statistical mispricing can be considered as a linear combination $\omega = (w_1, w_2, ..., w_n)$ such that

$$w_1X_1 + w_2X_2 + \cdots + w_nX_n \sim \text{mean reverting}\,(0, \sigma_t^2), \quad \sigma_t^2 < \infty$$

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where in the above definition we also allow for time-dependent volatility σ_t^2. The vector ω represents actual proportions of each asset to be held in the trading portfolio (the minus sign means selling the corresponding asset). The requirement of mean-reversion is to ensure that mispricings eventually "die out" and do not grow indefinitely. If they did, it would be impossible to control the risk exposure of the trading portfolio.

The standard approach to identify statistical mispricings is to run a regression of the values of one asset, say X_{1t}, against the others X_{2t}, ..., X_{nt} and test the residuals for mean-reversion. Several tests have been developed for this purpose in the econometric literature, the most famous of which are the Dickey-Fuller and Phillips-Perron (see e.g. [6]). Note that the residuals of the regression model represent the mispricing at each time t of X_{1t} relatively to $\{X_{2t},...,X_{nt}\}$. The next step is to create a model that describes the *dynamics* of mispricings, i.e. how errors of different magnitude and sign (positive/negative) are corrected over time. To take advantage of predictability, price forecast need to be incorporated into a dynamic trading strategy. An arbitrage trading system identifies the "turning points" of the mispricings time-series and takes proper positions on the constituent assets when mispricings become *exceptionally* high (i.e. ω for a positive and -ω for a negative mispricing). An arbitrage strategy as described above is not without risk; although profitable in the long run, its instant profit depends heavily on the ability of market prices to return to the historical or predicted norm within a short period of time. Generally, the weaker the mean-reversion the higher the probability of observing adverse movements of the synthetic.

Several authors have suggested approaches that attempt to take advantage of price discrepancies by taking proper transformations of financial time-series; see e.g. [2, 3, 16] for stocks of FTSE 100 Stock Index, [4, 10] for equity index futures and [12] for exchange rates. Amongst them, [3, 4, 12] employ a neural network model to describe the dynamics of statistical mispricings. In this paper, we propose a new intelligent methodology for the identification of statistical arbitrage opportunities. Our approach deviates from the main trend in that it attempts to detect nonlinearities *both* in the mean and the volatility dynamics of the statistical mispricing. For this purpose, we use a newly proposed class of combined *neural network*-GARCH volatility models. The methodology is applied to the detection of statistical arbitrage opportunities in a pair of two Indian stocks.

The rest of the paper is organised as follows: In section 2 we describe the application data, including intraday quotes of stock prices. Section 3 presents the methodology for detecting price discrepancies between stocks and section 4 details the NN-GARCH model used to forecast the dynamics of the statistical mispricing. In section 5 we present two arbitrage trading systems based on a high- and low-frequency predictive model. Section 6 concludes the paper and discusses directions for further research.

2 Sample data

For the application and testing of the trading strategy we chose the stocks of Infosys Technologies Ltd and Wipro Ltd, both Application Software companies from the Indian stock market. We did so for two reasons:

1. We plan to further deploy the system onto a larger set of stocks with sector neutrality so we chose two active names from the Technology/Software sector. Choosing stocks from the same industry sector usually results in better mean-reversion behavior. In addition, both companies have active ADR issues in the US which adds some interesting interactions and influences.
2. We are in the process of investigating the extension of statistical arbitrage equity strategies into developing and emerging markets. We are also interested in studying in detail the execution intricacies of the various markets and thus we will be paying special attention to trading costs in follow-up work.

Both stocks trade in the National Stock Exchange of India, headquartered in Mumbai, India. The NSE trading system is a fully automated order-driven market. The market trades from 09:55 to 15:30 hours with a closing session held between 15.50 hours and 16.00 hours. We are using tick-by-tick data, time and sales as well as best bid and offer and corresponding sizes for the historical period from February 1, 2005 until November 8, 2005. We have run a specialized filtering algorithm to remove any spurious trades that deviate significantly from the actual market. Subsequently the tick data is consolidated into 1-minute bars that include the open, high, low and close price, the total share and tick volume and the VWAP price. We have appropriately adjusted the price and volume data for dividend and split actions. We plan to use the tick data information to work out our trading-cost models in subsequent studies.

3 Identifying statistical mispricings

Figure 1 shows hourly closing prices of Infosys and Winpro from February 2 to November 8[3]. As a first attempt to construct a synthetic asset, we ran a regression of Infosys against Winpro, hence forth X_2 and X_1 respectively, over the first 200 sample observations and we then used the regression coefficients to compute the statistical mispricing. The resulting series is depicted in figure 2. Observe that the estimated combination is weakly mean-reverting especially in the first 600 observations. The Phillips-Perron (PP) test statistic over the whole sample period is -2.0183, which is below (in absolute terms) the 1, 5 and 10% critical levels (-3.8803, -3.3585 and -3.0380 respectively). Hence, the hypothesis of mean reversion cannot be accepted.

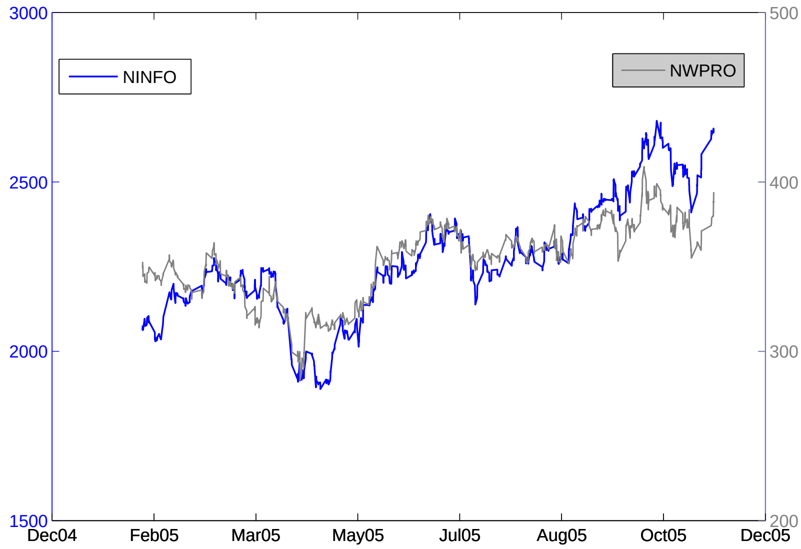

Fig. 1. Hourly data of Infosys and Winpro from 02/02/2005 to 08/11/2005.

[3] Prices in this diagram are adjusted for splits and dividends.

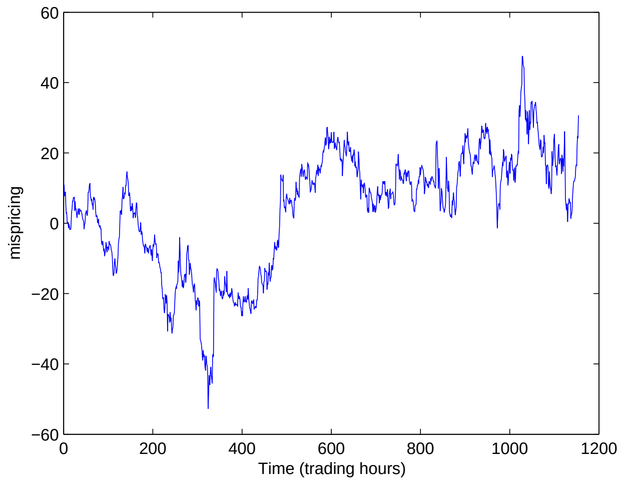

Fig. 2. The synthetic asset constructed from a static regression.

In order to control the non-stationarity of the synthetic asset, we adopt an adaptive estimation scheme in which the coefficients of the linear combination are periodically re-calculated. In particular, we define the mispricing as

$$Z_t = X_{2,t} - \alpha_{t-1} - \beta_{t-1} X_{1,t}$$

where α_t, β_t are estimated on the basis of a window of length W, $\{X_{1,j}, X_{2,j},\ j = t - W + 1, ..., t\}$. Instead of using linear regression, we adopt a slightly different procedure for calculating α's and β's: we define β as the mean price ratio between the two stocks over the specified window and we subsequently choose α so as to minimize the total variation of Z_t within the window, i.e.

$$\beta_t = \text{mean}\,(X_{2j}/X_{1j},\ j = t - W + 1, ..., t)$$

and

$$\alpha_t = \text{mean}(X_{2j},\ j = t - W + 1, ..., t) - \beta_t\,\text{mean}(X_{2j},\ j = t - W + 1, ..., t)$$

This procedure has been experimentally found to give more reasonable estimates of the synthetic vector that also show more stability over time. In figure 3 we show the synthetic time series resulting from a different choice of the window length. Observe that the more often the values of α and β are updated, the stronger is the mean-reversion of the synthetic and hence the more abrupt are the corrections of mispricings. All series are found mean-reverting; the PP test statistic over the whole sample is -10.0852 for $W = 10$, -6.4869 for $W = 30$ and -4.5622 for $W = 100$, which are above common critical levels. In subsequent experiments, we report results obtained for a synthetic calculated on the basis of a window of 10 observations.

4 Modelling the dynamics of the statistical mispricings

To describe the dynamics of the statistical mispricings we use autoregressive models relating the current value of Z_t to its own lags. This gives us an idea of how mispricings of different size and sign (positive/negative)

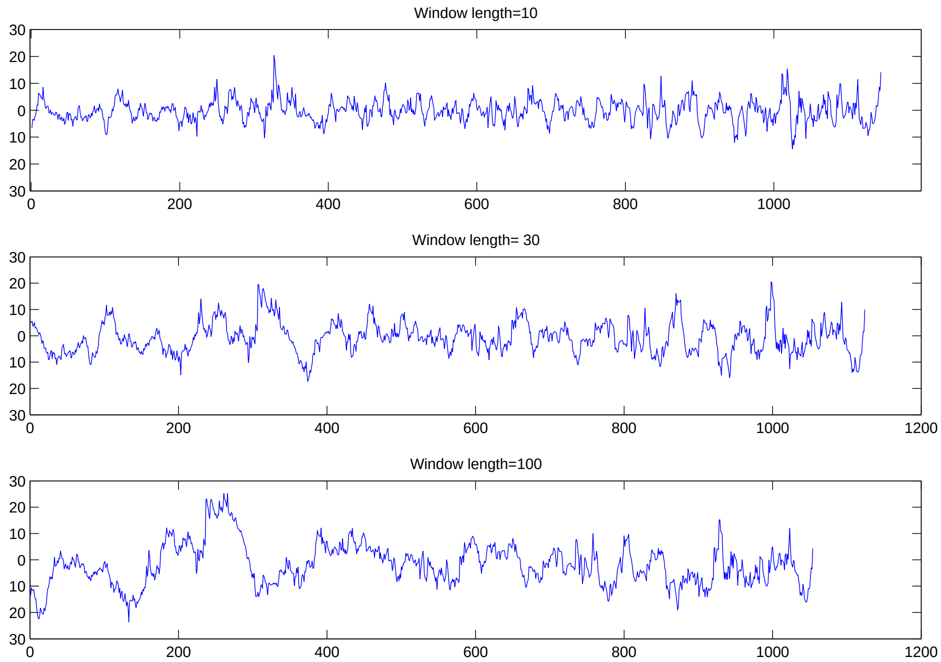

Fig. 3. The synthetic time series obtained from an adaptive estimation scheme for a window length of 10, 30 and 100, respectively.

are corrected over time. We also go one step further to model *both* the mean and the volatility structure of the statistical mispricings. This is because in high sampling frequencies (intra-day data), we find that the volatility of Z_t (i.e. the average uncertainty about the realised value) is not constant over time but strongly depends on the history of Z_t. In particular, large (positive or negative) shocks to Z_t are on average followed up by large shocks of either sign. This "clustering" of volatility, typical in most financial time series, is termed in the literature as *Autoregressive Conditional Heteroskedasticity* (ARCH). Any changes in the short-term volatility level of Z_t deserve special attention from a modelling point of view, as they have important implications for the risk control of the statistical arbitrage. Until today, the most popular models for the volatility dynamics of a time series are the class of ARCH/GARCH models[1, 7]. A GARCH model shows how a sudden negative or positive mispricing affects the future volatility of mipricings.

In our approach, we attempt to model both nonlinearities in the correction of mispricings as well as volatility spill-overs. For that purpose, we use a recently proposed class of joint neural network-GARCH models[15] that is intended to capture both effects. In this framework, an autoregressive model for the conditional mispricing takes the general form:

$$Z_t = \phi_0 + \phi' \mathbf{Z}_t + f(\mathbf{Z}_t; \theta) + \epsilon_t \tag{4.1a}$$

$$\epsilon_t | \mathcal{I}_{t-1} \sim N\ \ 0, \sigma_t^2 \tag{4.1b}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j \epsilon_{t-j}^2 \tag{4.1c}$$

where $\phi_0 \in \mathbb{R}$, $\mathbf{Z}_t$ is a vector of lags of Z_t ($\mathbf{Z}_t = (Z_{t-1}, Z_{t-2}, ..., Z_{t-n})' \in \mathbb{R}^n$), ϵ_t is the innovation term, $\phi \in \mathbb{R}^n$ and $f(\mathbf{Z}_t; \theta)$ is a feedforward neural network with a single hidden layer and l neurons, i.e.

$$f(\mathbf{Z}_t; \theta) = \sum_{j=1}^{l} \lambda_j F(w_j' \mathbf{Z}_t - c_j)$$

where $F(z) = \frac{1}{1+e^{-z}}$ is the logistic function, $c_j, \lambda_j \in \mathbb{R}$ and $w_j \in \mathbb{R}^n$. With $\mathcal{I}_{t-1}$ we denote the information available up to time t, including the history of mipricings Z_t, shocks ϵ_t and volatilities σ_t^2. Note that in the above specification, ϵ_t is assumed conditionally normally distributed with volatility σ_t^2 that depends on past σ_t^2's as well as (the magnitude of) past *unexpected* mispricings. Equation (4.1c) is called a GARCH(p,q) model.

In [15] we propose a complete model-building cycle for NN-GARCH models that comprises the following stages: a) *specification of the model* (e.g. determining the number of neurons in the hidden layer, the connections from inputs to hidden neurons, etc), b) *estimation* and c) *in- and output-of-sample evaluation*. This is a simple-to-complicate modelling approach that starts from a linear model and gradually complicates the specification if the data indicate so. The procedure is roughly as follows:

1. Estimate a linear model with no GARCH component and choose the optimal set of input variables by means of AIC of SBIC.
2. Test the null hypothesis that the true data-generating process is a linear model against the alternative of a neural network model with a single hidden neuron. If linearity is not rejected at a given confidence level then stop. Otherwise, estimate a NN model with a single neuron and test it against a NN model with an additional neuron. Repeat the above procedure until first acceptance of the null.
3. Once the mean model (4.1a) is specified, test the null hypothesis of no GARCH effects in the volatility of the residuals of the model against the hypothesis that residuals follow a GARCH process of a given order. If null is not rejected then stop. Otherwise, jointly estimate a NN-GARCH model.

There are two important things to note about the above procedure. First, the decision of whether to add an extra neuron or not is not based on heuristic arguments but rather on statistical hypothesis testing of "neglected nonlinearity". Such tests are available in the framework of Maximum Likelihood Theory. Second, the procedure presented above does not directly estimate a NN-GARCH model but chooses the *most suitable* specification given the data complexity (linear or nonlinear, with or without a GARCH component). Hence, it is aimed to produce non-redundant models that are less likely to overfit the data.

5 Application: statistical arbitrage between the two Indian stocks

Our methodology for exploiting statistical arbitrages consists of the following steps:

1. *Constructing a "synthetic asset" and testing for mean-reversion in the price dynamics*. Synthetics are calculated for various sampling frequencies.

2. *Modelling the mispricing-correction mechanism between relative prices.* For this purpose we use the general framework of NN-GARCH models (4.1).
3. *Obtaining 1- and h-step-ahead forecasts for the future value of the mispricing.* Forecasts are given in the form of a *conditional probability density* from which confidence bounds on the future value of the mispricing are derived. The estimation of an h-step ahead conditional density is based on the simulation of 800 error scenarios. Errors are calculated as $\sqrt{h_t}u_t$, where u_t are sampled with replacement from model's *standardised* residuals (the residuals divided by the estimated variance obtained by the GARCH model). In that way, we avoid restrictive assumptions on the distribution of the error-generating process.
4. *Implementing a trading system to exploit the predictable component of the mispricing dynamics.* The trading strategy is roughly as follows: buy (long) the synthetic asset if $Z_t < \hat{Z}^{L,\alpha}_{t+h}$ and sell (short) the synthetic asset if $Z_t > \hat{Z}^{H,\alpha}_{t+h}$, where $\hat{Z}^{L,\alpha}_{t+h}$ $\hat{Z}^{H,\alpha}_{t+h}$ denote the $(1-\alpha)\%$ low and high confidence bound on the value of the mispricing h steps ahead[4]. In our approach the confidence interval is a decision variable, which has to be adjusted so that profit is maximized.

5.1 Experiment A: a high-frequency model

In this section, we give an example of a *microscopic* model, which is calculated from 1-minute closing prices of stocks. The values of the synthetic from August 2 to 19, a total of 5000 observations approximately, are used for the specification of the mispricing-correction model and the sample observations from August 29 to September 22 for out-of-sample evaluation. In this sampling frequency, we find both nonlinear corrections of mispricings and ARCH volatility effects. The specified NN-GARCH model includes lags 1-10 in the linear part, 1 hidden neuron with variable Z_{t-10} connected to it and a GARCH(1,1) equation.

We report results from a trading system that is based on 5-minute-ahead forecasts. Figure 6 shows the performance of arbitrage trading strategies by varying the confidence level. Observe that as the interval gets narrower ($1-\alpha$ is decreased) the accumulated profit becomes higher, although the number of trades put in the synthetic is almost exponentially increased. Hence, the average profit per trade gets lower. Figure 7 shows several trading instances of a system with bounds set at 40% confidence. Circles represent entering points of trades. Note the effect of the GARCH component of the model, which is to dynamically adjust the confidence bounds, or else the uncertainty about the future realised value, whenever large unexpected mispricings occur. This in general prevents trading in periods of high volatility and risk (see e.g. the first 50 observations of the lower "snapshot" of figure 7). In figure 4 we give the profit& loss diagram of the afore-described trading system for the period September 23 - October 11. The total number of trades is 823 and the average trade per profit is 78.793/823=0.096. Although from a forecasting point of view the system is statistically correct, it still remains unprofitable as the average profit per trade is below the transaction costs, which in this market are of the order of 3 rupies. The profitability of this high-frequency system is severely limited by the fact that positions are necessarily closed at the end of the 1-minute interval[5]. It is important to note that keeping a trade open for a time interval grater than 1 minute is equivalent to not adjusting α's and β's until the trade is closed. The final outcome of such trades is strongly based upon how well the two synthetic time series, the every 1-min adjusted and that calculated from unchanged estimates of α's and β's, locally resemble each other. It is certain that as the values of the mispricing calculated from unchanged estimates of α's and β's have not been "seen" by the model, the performance of open trades will be unpredictable in the long-run. However, the extend of unpredictability has yet to be evaluated on an experimental basis.

[4] Longing (shorting) the synthetic means buying (selling) 1 stock of X_2 and selling (buying) β_t stocks of X_1.

[5] Recall that the synthetic time series depicted in figure 7 (solid line) assumes periodic recalculation of α's and β's.

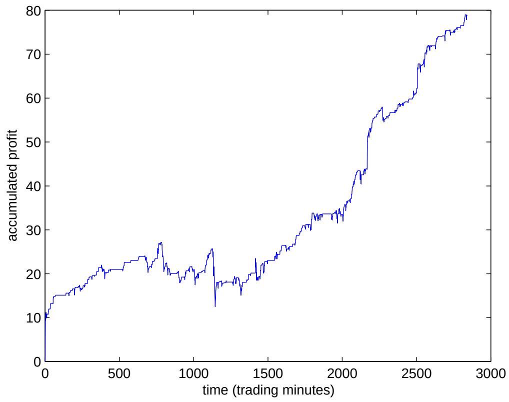

Fig. 4. The profit & loss diagram of the arbitrage trading system described in Experiment A for the sample period September 23 - October 11.

5.2 Experiment B: a lower-frequency model

As a next experiment, we calculate mispricings on hourly averages of stock prices. We use a sample of 804 observations, extending from February 8 to August 19, to specify and estimate the mispricing-correction model and we evaluate the performance of the resulting arbitrage strategies in the period August 29 - October 11. Noticeably significant ARCH effects were not detected on hourly synthetic prices, although nonlinearities were present. The final error-correction model was thus a pure NN including lags 1-8 in the linear part and 1 hidden neuron with lags 1, 4 and 6-9 attached to it.

The obvious advantage of low-frequency compared to high frequency models is that arbitrage trading positions, while they last longer, allow for larger profit opportunities. However, one should bear in mind that as predictions are available not until the next hour, the course of the synthetic within this time interval is largely undetermined. This of course affects the profitability of arbitrage positions. Figure 8 illustrates the point.

The solid line shows the mispricing every 1 minute as computed by the hourly estimates of α and β and the dotted lines represent a 30% confidence bound obtained by 2-hour-ahead forecasts. The placing of a trade is based upon the position of the *1-hour ahead* confidence bounds. The encircled areas are typical examples of cases where the synthetic moves in a direction adverse to the trading decision. The first (second) marker denotes the point where the synthetic crosses the lower (upper) prediction bound, thus signaling a long (short) position on the synthetic. Note that although these trading decisions are right in the long run, their riskiness is increased when the synthetic experiences high volatility in the first area and hits the upper bound in the second one. Generally, this performance is unavoidable and does not depend on the specific choice of the confidence bounds; it is mainly the result of basing trading decisions on a macroscopic model that overlooks short-term adjustments. In our implementation of trading strategies we decided to stop a trade if it hits the opposite bound somewhere in the time interval. Of course, this strategy is not globally optimal but it is a way to restrict losses due to adverse price movements.

Figure 9 shows the performance of arbitrage trading strategies in the sample period August 29 - September 22 for varying confidence intervals. Overall, this trading system is more profitable than the one based on 1-minute closing prices: the number of trades is consistently lower and the average profit per trade is increased at all levels. For wide confidence bounds ($1-\alpha > 80\%$), trading becomes marginally profitable as the average profit exceeds the benchmark transaction cost of 3 rupies.

In figure 5 we show the profit & loss diagram of the 80%-bounds trading system in the sample period September 23 - October 11. The chosen confidence level corresponds to a relatively conservative arbitrage-exploiting policy, which takes a position whenever large mispricings occur. The total number of trades put by the system is 9 and the average profit per trade is 55.5996/9=6.1777, above the one reported in the previous sample period for the same confidence level.

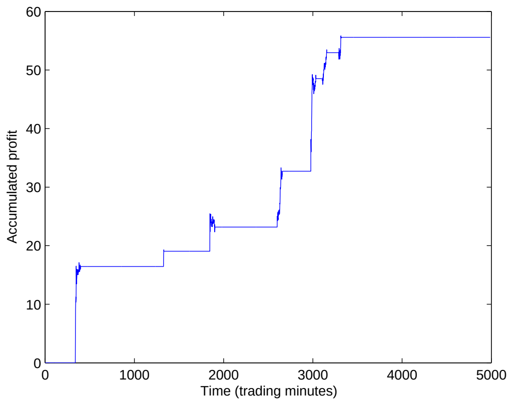

Fig. 5. The profit & loss diagram of a macroscopic arbitrage trading system with confidence bounds set at 80% (sample period: September 23 - October 11).

6 Discussion-Further research

This paper introduced a new computational intelligent framework for detecting and exploiting statistical arbitrage opportunities in a group of assets. Contrary to other intelligent approaches, we do not base the arbitrage trading strategies on point forecasts but on the conditional probability density for the future value of the mispricing. We obtain more realistic confidence bounds on the value of the synthetic that take into account short-term changes in volatility of mispricing movements. Our approach shows also a satisfactory degree of *adaptivity* and *robustness*. It adjusts the combination of the assets so as to control the mean reversion of the synthetic time series and also detects shifts in equilibrium levels of the time series and adapts to the new stationary combinations.

Experiments presented above show that our models are good detectors of arbitrage opportunities, as the profit& loss diagrams of trading strategies statistically increase. However, the profitability of these trades in a real market environment is still questionable given the various trading costs and market "frictions". At present, we are conducting further research on the optimal tuning of the parameters of our trading system, stop-loss criteria as well as the possibility of combining forecasts from various sampling-frequency models so as to track both the long- and short-term behaviour of the mispricing time series. First results from the latter approach are rather encouraging.

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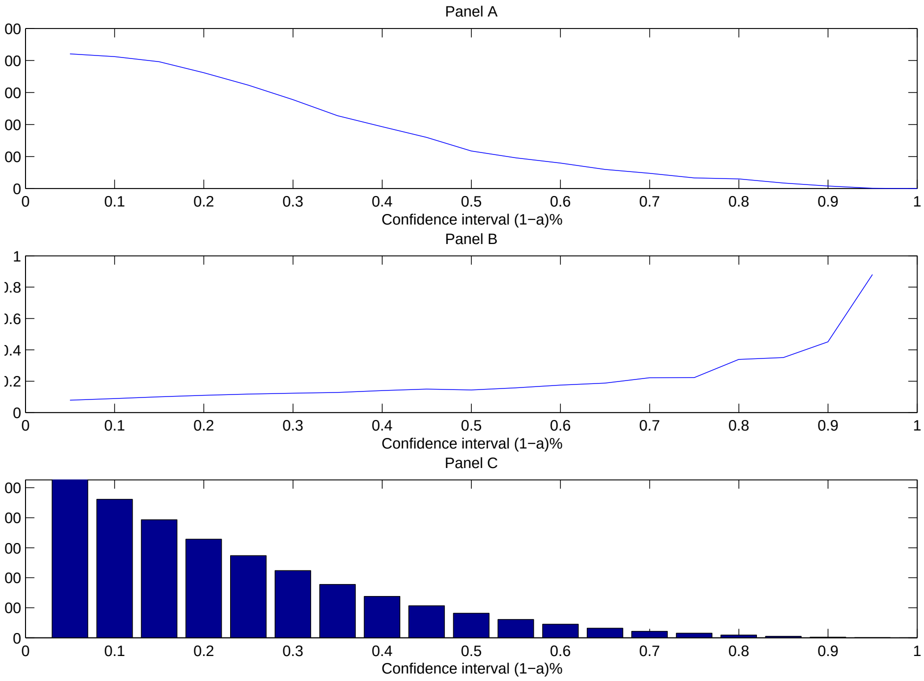

Fig. 6. The performance of arbitrage trading strategies designed in the framework of the microscopic trading system of Experiment A as a function of the confidence level (sample period: August 29-September 22). Panel A shows the accumulated profit achieved by trades, panel B the average profit per trade and panel C the total number of trades in the specified period.

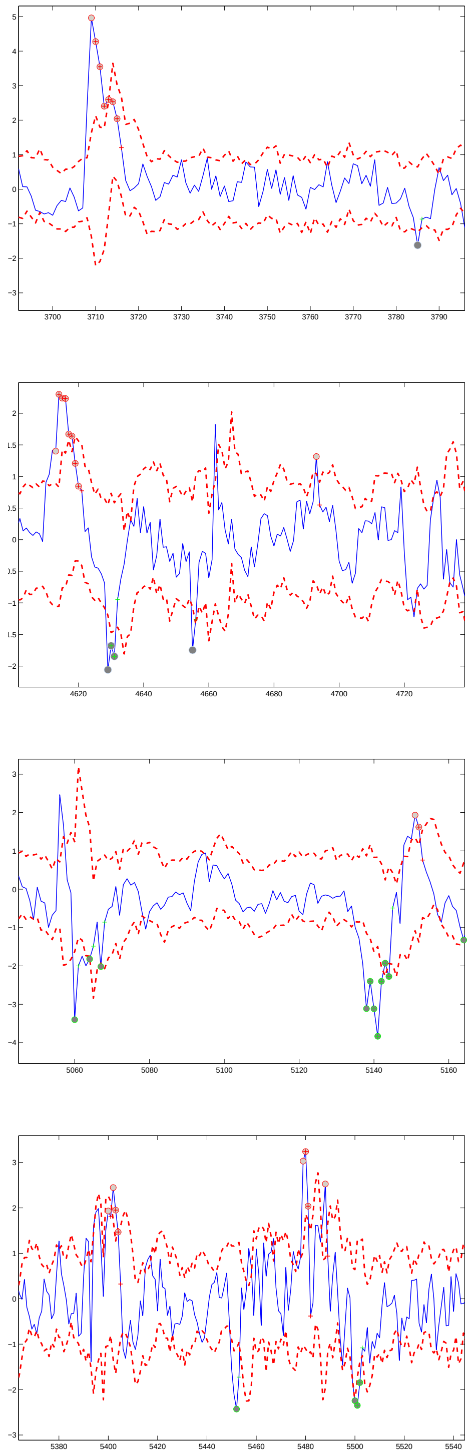

Fig. 7. Trading instances of a microscopic mispricing-detection model that has been estimated on a series of 1-min mispricings. Dotted lines represent a 40% confidence “envelope” for the value of the mispricing. The decision of a trade is taken with respect to 5-minute-ahead forecasts.

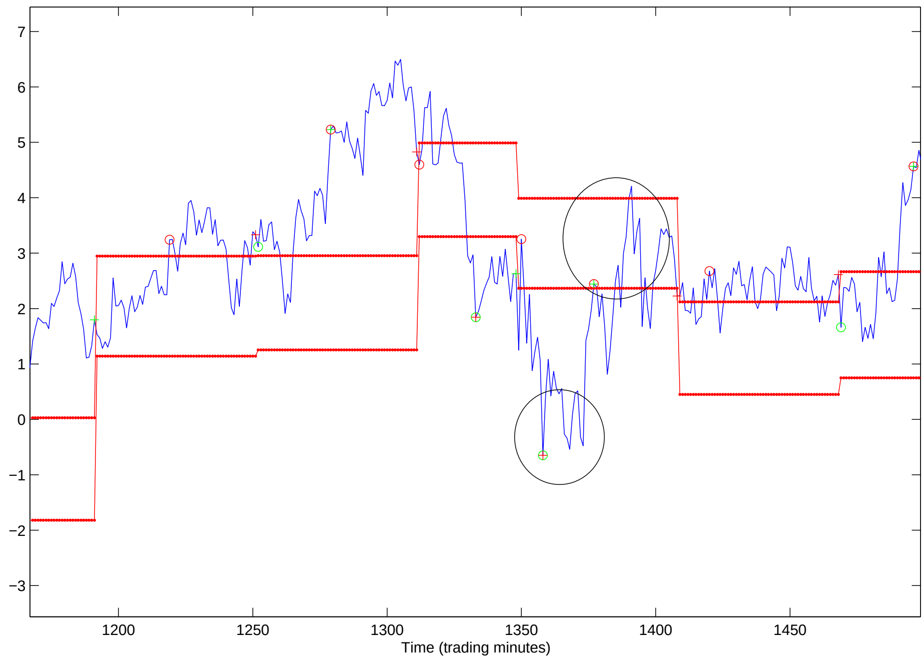

Fig. 8. A trading instance of an arbitrage system based on the macroscopic (1 hour) prediction model of Experiment B. The solid line shows the mispricing every 1 minute calculated from the hourly estimates of α and β and the dotted lines represent a 30%-confidence envelope obtained by 2-hour-ahead forecasts. The decision of a trade is based upon the position of the *following* 1-hour time interval confidence bounds.

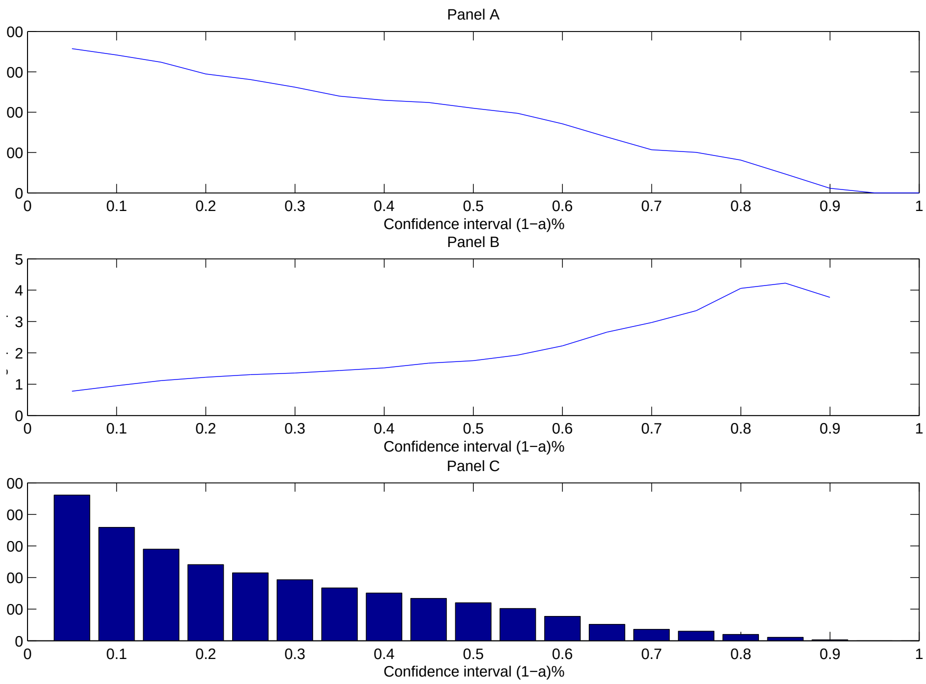

Fig. 9. The performance of arbitrage trading strategies designed in the framework of the macroscopic trading system of Experiment B as a function of the confidence level (sample period: August 29-September 22). Panel A shows the accumulated profit achieved by trades, panel B the average profit per trade and panel C the total number of trades in the specified period. .