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Ultra-short-term trading system using a neural network-based ensemble of financial technical indicators

Theodoros Zafeiriou[1] · Dimitris Kalles[1]

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Abstract

The proposed paper presents the analysis, design, implementation and evaluation of an ultra-short-term frequency trading system for the foreign exchange (FOREX) market, which features all stages of the trading process (Pretrade Analysis, Trend Forecasting, Transaction Execution) substantially exploiting artificial intelligence techniques. Our goal is to simulate the judgment and decision making of the human expert (technical analyst or broker) with a system that responds in a timely manner to changes in market conditions, thus allowing the optimization of ultra-short-term transactions. We designed and implemented a series of technical indicator simulators, which are fed to a novel artificial neural network architecture, to eventually generate the trend forecasting signal. We also designed and implemented a series of customizable ultra-short-term automated trading machines, which receive as inputs the generated forecasting signals and perform real-time virtual transactions. A comparative analysis of the results of both automated trading machines and each machine is carried out for a comprehensive variety of trend forecasting sources.

Keywords Foreign exchange · Technical analysis · Neural networks · Trend forecasting

1 Introduction

The largest share of foreign exchange market profits, especially foreign exchange (FOREX) market profits [1], derives from extended margin-based leveraging [2]. Leverages as high as 1–200 (i.e., someone with an initial capital of 1000 € is allowed to risk a capital of 200,000 €) is a source of high risk for investments of low volatility (on the same day and sometimes between a few minutes). Therefore, it has been argued that it is essential for forecasting models as well as the accompanying systems of algorithmic trading [3] be based on short time periods.

Economists have been trying for several decades to build models for successfully forecasting trends. These efforts gave birth to the field termed as technical analysis. Despite a large number of long and arduous attempts, no indicator or model of a sufficiently generic nature has been developed so far that can forecast with great success the trend of the financial markets. The main reason for this is that technical analysis does not take into account the most recent changes of fundamentals, which have not been yet recorded, nor the effect of breaking news on the psychology of investors. Moreover, examining technical analysis indicators and their usage in trading [4] requires so much time that the appreciation of short-term (sometimes, within seconds) changes in exchange rates is rendered practically impossible. In markets of considerable depth and volume, such as the FOREX one, exploiting micro-changes within a minimum time frame is of paramount importance and can be achieved with ultra-short-term trading [5].

The aim of this work is the design and implementation of a trend forecasting and transaction system in FOREX, which will be able to take into account the micro-changes in the exchange rates and carry out ultra-short-term transactions. To develop trend forecasting, we build a series of appropriately designed and configured simulators of technical indicators [6], which are then fed into an artificial neural network (ANN) [7], based on an earlier architecture [8]. The forecasting signals as well as the technical

✉ Theodoros Zafeiriou
zafiriou.theodore@ac.eap.gr

Dimitris Kalles
kalles@eap.gr

[1] Hellenic Open University, Parodos Aristotelous 18, 26335 Patras, Greece

indicators supply a series of automatic trading machines. Based on a comprehensive simulated experimentation, we review the most successful configurations and associate their maximum (simulated) profits by tracing their performance back to the techniques used for generating the trend forecasts. In doing so, we address the non-trivial problem of integrating a trend prediction mechanism with a transaction one; in the FOREX practice, having access to a quality forecast does not necessarily mean that you will make a good decision based on it (you might postpone a decision expecting your profit to go beyond a point in time where you are no longer able to conclude a transaction or you may hurry towards a decision that will leave you with a loss). So, a particular contribution of this work is that it closes the loop from information to action.

The rest of this paper is structured in four subsequent sections. We first briefly review related work on predicting exchange rates using computational intelligence. Then, we describe the proposed system architecture and we proceed with presenting and analyzing the experimental results, before concluding, in the last section, where we also set out a couple of future work directions.

2 A brief background on predicting exchange rates using computational intelligence

As earlier mentioned, in FOREX, traders use technical analysis tools [6] to predict the exchange rates but higher profits are usually achieved by automated systems [3] which trade huge sums of money based on forecasting models. However, automated systems also tend to follow the "avalanche" model [5] by training each other and thus re-enforce ascending or descending trends. In shallow markets, such models may lead to significant distortions. A typical example is the stock market crash of Monday October 19, 1987 (Black Monday), with the resulting sell-off in the S&P 500 and the Dow Jones generating a price fall in excess of 20%. A particular automated trading system exacerbated the sell-off by attempting to hedge a portfolio of stocks against market risk by short-selling stock index futures and by automatically beginning to sell stocks as stop loss targets were hit, triggering a domino effect of other programs following suit and falling prices triggering further stop loss orders.

Technical analysis methods have resulted both in successes and failures. Failures are usually due to undetected changes in fundamental values and market psychology and forecasting inaccuracies tend to increase with shorter-term forecasting [9].

A demonstration of how to efficiently approach the problem of automated trading with large portfolio strategy that continuously consumes streams of data across multiple diverse markets appears in [10], where a simple scalable trading model that learns to generate profit from multiple inter market price predictions and markets' correlation structure is presented.

Forecasting methods are broadly divided into two categories, traditional and non-traditional. Traditional ones are usually based on static algorithms, which are not altered and are not influenced by input data [11]. Basically, these are econometric models which help us interpret the results. Furthermore, they allow hypothesis control, which is a standard quality assurance procedure in technical analysis [11].

Non-traditional methods include all methods which are based on data and auto-correct themselves [11]. Such methods are based on fuzzy logic [12], on artificial neural networks (ANN) [8], neuro-fuzzy architecture (hybrid systems) [13] and genetic algorithms [14]. Non-traditional methods can be quite competitive to econometric methods, due to the generalized operations they perform [15]. While they can function as general models, they do not guarantee satisfactory results; nevertheless, they are usually better than conventional models where data is associated with linear relationships [15] especially when modeling the market response.

Machine learning-based methods have been extensively used for predicting trading patterns and are considered strong enough to deal with FOREX forecasting based on past trading data [8].

Furthermore, the hidden layers of ANN systems represent an internal representation of relations between variables and, as a result, they do not satisfy certain prerequisites required by palindromic models, such as variability between epochs, smoothness of background noise, etc. Neural networks can also perform quite well in cases of sparse data, as opposed to regression models where serious problems arise [16]. Moreover, neural networks are suited to complex phenomena for which satisfactory performance measures do exist but there is limited knowledge of the relationships between these phenomena. They are also relatively successful for forecasting and prognosis [16]. Additionally, genetic algorithms have been also used to learn trading rules and, then, combined with an echo state network to predict the market trend [14], with results demonstrating better results both on bull and bear markets compared to the usual buying and holding strategy of retail traders.

We now briefly review some key contributions to the field.

Yong et al. [17] examined the closing price as well as the various closing price technical indicators to determine their impact on the FOREX trend provided by a machine learning module.

Abraham et al. [18] attempted to compare the performance of a Takagi Sugeno Type neuro-fuzzy system to that of a neural network to predict the average monthly exchange rate values. The Australian dollar was used as the basis and its exchange rates with the US dollar, the Singapore dollar, the New Zealand dollar, the yen and the pound sterling. It was reported that the proposed models were able to predict average exchange rates but only when dealing with a time horizon of at least one month.

Wang et al. [19] have shown that a neural network with three layers combined with an auto-regressive integrated moving average mode outperforms the global modeling techniques in terms of profit returns.

Vanstone and Finnie [20] presented a methodology for the design of robotic trading systems using artificial neural networks. They outlined the key steps (selecting inputs and outputs, partitioning available data, determine architecture, setting threshold and stop trading signals, real world constraints and benchmarking) for building a neural network to be used in stock trading.

A hybrid model was developed by Ni and Yin [21], consisting of a mix of different neural network models (mostly unsupervised learning) and simulators of technical indicators to predict exchange rates. The model uses some of the most popular technical indicators such as the moving average [6], convergence/deviation, and the relative resistance index (RSI) [6]. A genetic algorithm is used to “mix” the forecastings of the generators and the technical neural networks, producing the overall system forecasting.

The combination of neural networks with technical analysis, and, in particular, the relative resistance index (RSI), has been used to improve the trading systems [22] of the IBEX-35 stock index.

Further experiments with two other indicators, the weighted moving average and the momentum [6], have shown that, when fed into a technical neural network, they produce a better forecast compared to the original (i.e., the forecast produced by the indicator before being introduced into the artificial neural network) [23].

Khirbat et al. [24] studied the forecasting of stock market prices by feeding the time series of stock prices to a multilayer back-propagation neural network which also attempts to deal with other non-deterministic input, such as the Earning per Share value and a public confidence index.

Sermpins et al. [25] used a hybrid neural network optimization and adaptive radial basis function (ARBF-PSO) to implement a leverage negotiation strategy based on the Glosten, Jagannathan and Runkle (GJR) variability forecasts. By comparing the results of the ARBF-PSO with those of three different architectural neural networks, a neighbor neighborhood (k-NN) algorithm, a moving average model (MA) and a moving average convergence/deviation median (MACD) for the EUR/JPY, EUR/GBP and EUR/JPY exchange rates, for the period January 1999–March 2011 (daily closing prices from the ECB), the ARBF-PSO has been shown to be superior to other models in terms of statistical accuracy and transaction efficiency.

In our previous work, we designed and implemented an ANN, which tries to predict market signals in the money market [8] based on an input which consists of a series of econometric models (technical indicators). Essentially, the ANN “corrects” the econometric model, combining the advantages of technical analysis and ANN in causal modeling and case control. It is important to note that the ANN is not trained with a set of data and then tested with another data set but, rather, it is trained in real time and produces its price forecast in real time, being constantly trained throughout its life (at the resolution of one price per minute).

Although the aforementioned works do highlight the advantage of these novel architectures, compared to various previous models and to classic technical indices, they have not been applied to automatic trading systems. Thus, it is unclear whether their implementation can be translated to real market profits.

3 A detailed system description

In this section, we describe how we analyzed, designed and implemented an algorithmic ultra-short-term trading system, comprising all stages of the (price) negotiation process as described in [26]. This system includes the fundamental stages of Pretrade Analysis, Transaction Signal Production (Trend Forecasting), and Transaction Execution.

Our goal is to simulate the judgment of the human expert (technical analyst, broker) with an artificial intelligence system that responds in a timely manner to changes in market conditions making it possible to optimize the efficiency of short-term transactions.

First, at the analysis stage the data mining is carried out and the data used in the subsequent steps are selected.

Then, at the trend forecasting stage, a series of technical indicator simulators [6] were designed and implemented to generate the trend forecasting signal. These signals are fed as inputs to the artificial neural network system (to be described in a subsequent section of this paper), which also yields a trend forecasting signal [27] with appropriate design changes in parameterization to be consistent with the attempted ultra-short-term trading.

At the transaction stage, a series of customizable high-frequency automated trading machines were designed and implemented, which receive as inputs the forecasting signals generated in the previous stage and perform real-time virtual transactions. Next, a comparative analysis of the results of both automated trading machines and each machine is made for the different sources of trend forecasting (the different technical indices and the ANN).

Finally, useful conclusions can be drawn about the suitability of different configurations of automated trading machines according to the trend forecasting source and about the suitability of the modified architecture [8] for ultra-short-term algorithmic trading.

3.1 Selection of the exchange rate and experimental data source

We have selected to experiment with the EUR/USD exchange rate, since this is the world's largest trading currency pair, and its market depth deters lobbies from engaging in price manipulations which might alter its true image.

Truefx [28], which is an industry leader exchange rate data server, and American Integral [29] were selected as the sources of experimental data. The largest institutional service FOREX providers in the world use the prices given by Integral.

We have experimented with the tick-to-tick EUR/USD exchange rate of July, August and September 2020. The data initially consists of over 10 million values, which after pre-processing in order to squeeze out flat areas (where the exchange rate does not change at all).

3.2 Technical analysis indicators simulators

Selecting the most suitable time frame is a decision which us unique to each individual trader. Normally, traders will focus on a time frame and then choose a time frame above and below it to complement the main time frame. So, they will normally use a long-term chart to define the trend, a intermediate-term chart to provide the trading signal and a short-term chart to select the entry and exit points [30]. On the other hand, Shynkevich et al. investigated the dependency of a financial forecasting system's performance on the choice of a forecast horizon and of an input window length, which is a parameter used for calculation of many technical indicators. They used three well-established machine learning techniques, SVM, ANN and k-NN, and concluded that the highest performance was obtained when the input window length was approximately equal to the horizon [31].

After preliminary experimentation, we selected some technical indicators for our experiments [6], which are consistent with the short-term forecast (Fig. 1), namely the arithmetic moving averages (MAs) of 600, 900 and 1800 prices, the RSI-600 oscillator, the CCI-600 oscillator, the Williams-600 oscillator and the Price Oscillator (MA-600, MA-900, MA-1800).

These technical indicators are calculated as described in "Appendix 1".

The system accepts exchange rate, time and date as inputs (Fig. 1) and, based on the predicted trend signal and the configurations of its auto-trading agents, simulates ultra-short-term trading and produces performance logs for simulating profit or loss. We are using the purchase price and the selling price as input to the accuracy of five decimal places, and we also use a tick-to-tick frequency [32]. (This is an upgrade over the four decimal places and the minute-frequency reported in [8].)

We use the purchase price for the stage of forecasting [27]. We can also use the selling price without a big different in our results. Both the purchase price and the selling price is used only at the automated trading stage.

The data serve as input to the technical indicator simulators (Fig. 1) [27].

The output of each technical indicator simulator is a value from the set of values in Table 1.

The outputs of the simulators of the technical indicators are fed to the input neurons of the ANN system.

The prediction system consists of two series of ANNs, which operate in pairs. One ANN of a pair receives as inputs the outputs of the simulators of the corresponding technical indicators and works in conventional error back-propagation mode by trying to match the trend prediction. This ANN works with past values, so we can calculate the error in its prediction This ANN, then, transfers its learned weights to its pairing ANN, which, however, only works in feed-forward mode with present values. All feed-forward ANNs are then combined in an ensemble to produce the final trend forecast [27].

Technical indicators are generated and their predicted trends are sent to the input layer of each back-propagation ANN. A technical indicator corresponds to an ANN, and its calculation reflects its value at time $t - M(x) - 1$, where $t - M(x)$ is the time in which the neural network with index x operates in the past. (For example, M(1) is 30 to indicate that we are interested in confirming the technical indicator's prediction within 30 s; this also means that each ANN is trained on a time-point by time-point basis.) The hidden layer is activated by a tanh-type sigmoid to deliver output values in $[-2, +2]$, while the output layer is linear. The number of hidden layer neurons was set to be 2 times the number of input layer neurons (based on preliminary results). The output layer neurons as well as the corresponding data export the trend signal for each back-propagation ANN (Fig. 1) [27].

Moreover, the algorithm of calculating the real trend is updated using the data from time points $t - 1$ and $t - 1 - M(x)$ and the iteration is activated (Table 2). The real trend algorithm produces a normalized estimated value of the real trend. The output value of the final node is then

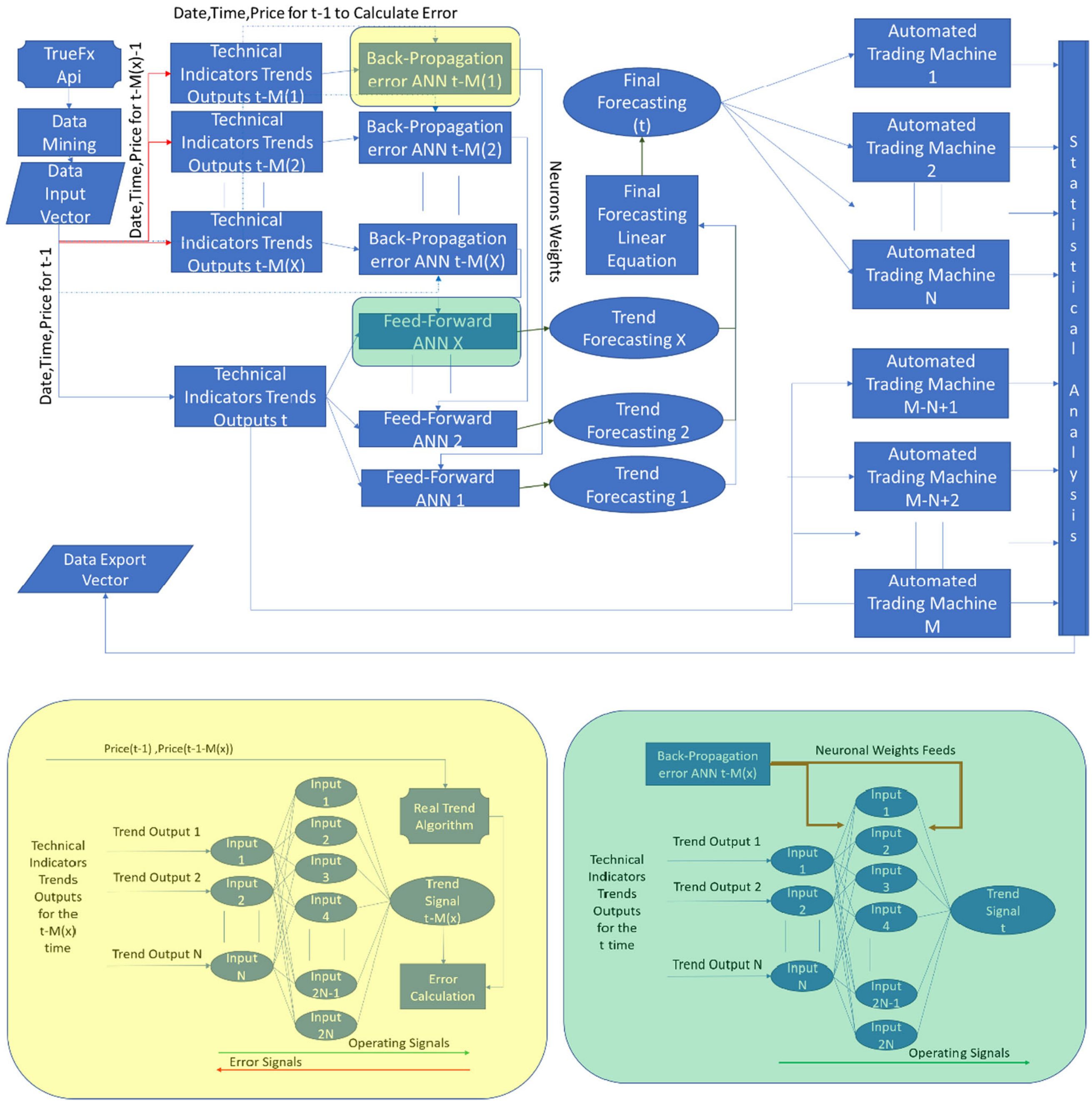


Fig. 1 An overview of the system—architecture

Table 1 Correspondence of arithmetical values to trends

Value	Corresponding trend
+ 2 (− 2)	Absolutely positive (absolutely negative)
+ 1.5 (− 1.5)	Quite positive (quite negative)
+ 1 (− 1)	Positive (negative)
+ 0.5 (− 0.5)	Neutral/positive (neutral/negative)
0	Neutral

compared to the real trend to train the neural network. The actual trend conditions of the actual ANN system forecasting trend signal (Table 2) are selected after preliminary experimentation. These conditions are in line with Take Profit Factory for trend signals (Table 6) [27].

Each back-propagation ANN in the series is characterized by the time in which it operates in the past (t − M(x)). The number of back-propagation ANN is configurable. The number of feed-forward ANN is equal with the number of back-propagation ANN. Each back-propagation

Table 2 Actual trend conditions of the actual ANN system forecasting trend signal (the rules are listed in descending order of priority) which is consistent with ultra-short-term trading

Conditions	Value
price(t − 1)/price(t − 1 − M(x)) > 1,00,090	+ 2
price(t − 1 − M(x))/price(t − 1) > 1,00,090	− 2
price(t − 1)/price(t − 1 − M(x)) > 1,00,060	+ 1.5
price(t − 1 − M(x))/price(t − 1) > 1,00,060	− 1.5
price(t − 1)/price(t − 1 − M(x)) > 1,00,030	+ 1
price(t − 1 − M(x))/price(t − 1) > 1,00,030	− 1
price(t − 1)/price(t − 1M(x)) > 1,00,015	+ 0.5
price(t − 1 − M(x))/price(t − 1) > 1,00,015	− 0.5
Other cases	0

ANN feeds the weights of its neurons into a feed-forward ANN [27].

Technical indicators are generated and their predicted trends (for the time t) are sent to the input layer of each feed-forward ANN. The hidden layer is activated by a tanh-type sigmoid to deliver output values in [− 2, + 2], while the output layer is linear. All the neuron weights are fed of the neuron weights of a back-propagation ANN [27].

Each forecasting trend (FT(x)) from the ANN feed-forward series leads to a linear equation calculating the final forecasting trend (FFT) of the system (Fig. 1).

$$\mathrm{FFT} = \sum_{1}^{X}(\mathrm{FT}(x) * a(x)), \quad \text{with} \sum_{1}^{X} a(x) = 1$$

where $a(x)$ is the weight multiplier for each (x) feed-forward ANN.

The FFT is finally normalized to one of the values shown in Table 1 [27].

3.3 Design of the virtual transaction stage

This part includes a series of high-frequency automated trading mechanisms which perform virtual transactions with real data. It uses as input the forecasting from the previous level, the price of the exchange rate, and it manages a number of simulated transaction machines, each with a different configuration (to be presented below), producing for each of them a detailed log with all (simulated) performed transactions and obtained financial results.

3.3.1 Configuration of the high-frequency automated transaction machines

All input data (date, time, purchase price and sales price, as well as the trend forecasting of the technical indicators simulators and the technical neural network system) are fed to a series of high-frequency automated trading machines.

Automated trading machines only take into account the trend forecasting signals (− 1, + 1, − 1.5, + 1.5, − 2, + 2) to determine their strategy. Each trading machine is described using a set of parameters, as shown below:

1. Machine Class (0 or 1)

A Class "0" machine operates as follows: when it has a long (or short) position [32, 33] and receives a short (or long) predictive signal, closes the position without opening a new position. In other words, if it receives a forecasting signal opposite to an open position it closes the position. Note that if there is more than one open position then the opposite signal closes the earliest one (the one that has been opened before the other) while keeping the remaining positions open. In other words, a counter-forecasting signal closes only the earliest opposed open position and not all opposed open positions. This logic has been chosen so that any individual false predictive signals may not altogether close all opposing open positions leading to loss. Therefore, a balancing logic has been selected for each predictive signal received by the machine.

A Class "1" machine operates as follows: when it has a long (or short) position and it receives a short (or long) forecasting signal, it does not close the long (or short) position but, instead, opens a new short (or long) position. In other words, if the machine receives an opposite forecasting signal from an open position, it opens a new position (as long as the other machine parameters allow it) and manages both positions separately.

2. Sensitivity (1000–0)

This parameter refers to the sensitivity of each machine to open new positions when it receives short or long [32, 33] forecasting signals within a short time frame. The higher the value of the parameter, the lower the sensitivity of the machine to open new positions.

For example, if the sensitivity value is X and the machine accepts a long (or short) trend forecasting by opening the corresponding position, then an uninterrupted sequence of X new long (or short) trend forecasting values will not lead the machine to open a new position. In other words, two positions of the same (short or long) signal cannot be less than X data values apart.

3. Source of Trend Forecasting Signals (0–7)

Each machine has a single source of trend forecasting signals to open and close its positions. This source is defined based on the values of this parameter:

0. The machine receives trend forecasting values from the ANN system.
1. The machine receives trend forecasting values from the CCI oscillator.
2. The machine receives trend forecasting values from the long-term MA.
3. The machine receives trend forecasting values from the Williams oscillator.
4. The machine receives trend forecasting values from the medium-term MA.
5. The machine receives trend forecasting values from the oscillator.
6. The machine receives trend forecasting values from the short-term MA.
7. The machine receives trend forecasting values from the RSI oscillator.

4. Take Profit factor

The take profit factor allows a position to be closed automatically when the desired profit has been achieved. This parameter is defined by applying a multiplier (or divisor) to the position opening value for long (or short) positions.

For example, let us assume that the earnings factor for the ± 1 signal strengths of an automated trading machine is 1.006. Let us say we have an open long position with an opening value of 1.36110. If the exchange rate reaches or exceeds 1.36110 * 1.0006 = 1.36192 then the position will be closed.

It should be noted that the condition to close a position is '>=' of the desired profit and not '=' because in tick-to-tick frequency transactions price fluctuations can be larger than the minimum allowed price difference, especially in days with intense fluctuations (for example, the price can change from 1.36190 to 1.36196 without ever taking the value of 1.36192).

5. Stop Loss Factor

It is the maximum level of losses allowable for each position. This parameter is defined by applying a multiplier (or divisor) to the position opening value for short (or long) positions.

For example, let us assume that the maximum allowable losses coefficient of an automated trading machine is 1.0018. Let's say we have an open long position with an opening value of 1.36110. If the exchange rate is equal to or less than 1.36110/1.0018 = 1.35865 then the position will be closed.

6. Take Profit Factor Revision Time

This is the time that the previously defined Take Profit Factor is revised. If an open position does not close within that time period, the Take Profit Factor is redefined since the prediction that led to the opening of the position has not been confirmed. The aim of this parameter is to close an open position even with limited profit or loss. This parameter is defined by a number of exchange rate values entered into the system after the opening of the specific position.

7. Revised Take Profit Factor

The Revised Take Profit Factor is activated and replaces the Take Profit Factor after the revision time as described in 6. The Revised Take Profit Factor may be even lower than one if its objective is to limit possible losses.

For example, let's assume that the desired Take Profit Factor for the ± 1 signals of an automated trading machine is 1.0006, the Revised Take Profit Factor is equal to 1 and the revision time is 1800. Suppose we have an open long position [32] at a market price of 1.36110. If after 1800 prices after opening the position the position is not closed, then the Take Profit Factor is revised to 1. Therefore, in order to close the position, it is sufficient that Selling Price >= 1.36110.

8. Maximum Waiting Time

This is the maximum length of a sequence of values for which any position is allowed to stay open.

9. Total Investment Capital

This is the total Investment Capital in USD for all period.

10. Investment Capital per Transaction

This is the Investment Capital per transaction in USD.

11. Maximum Leverage Ratio

This is the maximum Leverage Ratio. For example, a maximum leverage ratio of 1:30 means that an individual with a margin deposit of 10,000 USD can initiate a maximum leverage trading positions of up to 300,000 USD.

3.3.2 Operation and transaction logging of the high-frequency automated transaction machines

Automated trading machines display in real time the following data for each transaction.

1. The opening time of the transaction position with the accuracy of a second.
2. The opening price of the transaction position.
3. The Type of position (short or long) [32, 33]

4. The intensity of the trend forecasting signal (− 1, + 1, − 1.5, + 1.5, − 2, + 2) based on the opening of the position.
5. The time of closing the position with the accuracy of a second.
6. The closing price of the transaction position.
7. The profit or loss of the transaction.

It is worth noting that the opening of a long position [32, 33] takes place at the buying price and its closing at the selling price. Correspondingly, the opening of a short position [32, 33] takes place in the sale price and its closing at the buying price. In other words, the result of the ultra-short-term simulated algorithmic transactions include the spreads [1] between the buying and selling prices of the exchange rate.

3.4 System development and use

The system has been developed in Java using the NetBeans IDE 8.2.

The application is fully parameterizable by means of an appropriately labeled Type parameter file (.fxipf standing for FX Intelligence Parameter File), whose contents are shown in "Appendix 2".

When launching the application, we select the parameter file and the main application screen {1} is displayed.

Figure 2 shows a desktop snapshot when executing the application. In the left side {2}, we view nine of the activated automated trading machines, while in the right-hand upper section we view the central simulation screen {1} and just below it we view the summary of aggregated results of automated trading machines {3}.

The central simulation screen features the date, time, purchase price, sales price, spread of these two prices (which is the transaction provider's commission), CCI oscillator forecast, medium-term MA, the long-term MA, the Williams oscillator, the value oscillator, the short-term MA, the RSI oscillator, and the forecast of the ANN system.

The forecast is displaying at the bottom of the screen correspond to the values: [− 2: SHORT, − 1.5: SHORT, − 1: Short, − 0.5: Short, 0: NEUTRAL, + 0.5: Long, + 1: Long, + 1.5: LONG, + 2 LONG].

On the displays of automated trading machines, we see in real time the transactions and all their data and elements.

In addition to these screens, the aggregated results screen is also minimized. This screen consists of as many rows as automated trading machines. Each row displays the name of the machine and updates in real time the transactions, the profit or loss and the maximum theoretical profit that could have been achieved if the position had closed at the best possible time, within the maximum open position waiting time, as defined in the system configuration file.

At the end of the simulation, all transaction records are exported and stored in the data folder.

4 Experimentation and results

We have experimented with the tick-to-tick EUR/USD exchange rate of July, August and September 2020.

The values of the parameters selected for all neural networks (back-propagation series and feed-forward series) of the application are shown in Table 3.

The selection of parameters from 1 to 7 was based on earlier work [8]. The choice of the 10-values ASM as well as the value 1 in the actual trend selection parameter was confirmed by preliminary experimentation. Limiting the number of epochs in ANN training to 10 may look as if we are imposing an unusually tight constraint, but it is a realistic trade-off between the need to provide training without spending too much time on it. (We remind the reader that we have set our system to be trained every second.)

The series of back-propagation and feed-forward ANNs consist of three ANNs each. We have also six parameters of each back-propagation ANN as shown in Table 4.

The parameter values selected for the technical analysis simulators are shown in Table 5.

The Price Oscillator period is based on three moving averages (line 7 in Table 5).

There are thirty-two (32) parameterized automated trading machines in the experimentation, evenly allocated to the '0' class (opposite signals close each other's position) and '1' class (opposite signals do not close each other's position). In class "1" machines, the maximum waiting time should be limited; otherwise, we are at risk of staying with several positions open at the end of the session. Half of the machines of each class (0 or 1) are of a higher sensitivity (value 1) and the other half of a lower sensitivity (value 10), giving rise to four combinations, overall, which are codified as machines of type I through IV (numbering in 1atin).

Based on the above, we group the machines into four general configurations (general machines or machine types) that we will now call general machines (or just machine Types). Each technical indicator simulator (there are seven altogether) and the forecasting machine of the ANN feeds a separate forecasting signal to a machine of each Type. Therefore, we activate 4 x (7 + 1) = 32 automated trading machines to simulate.

All values of the parameters of the thirty-two automated trading machines to be used in the context of experimentation are shown in Table 6. Theses parameters were

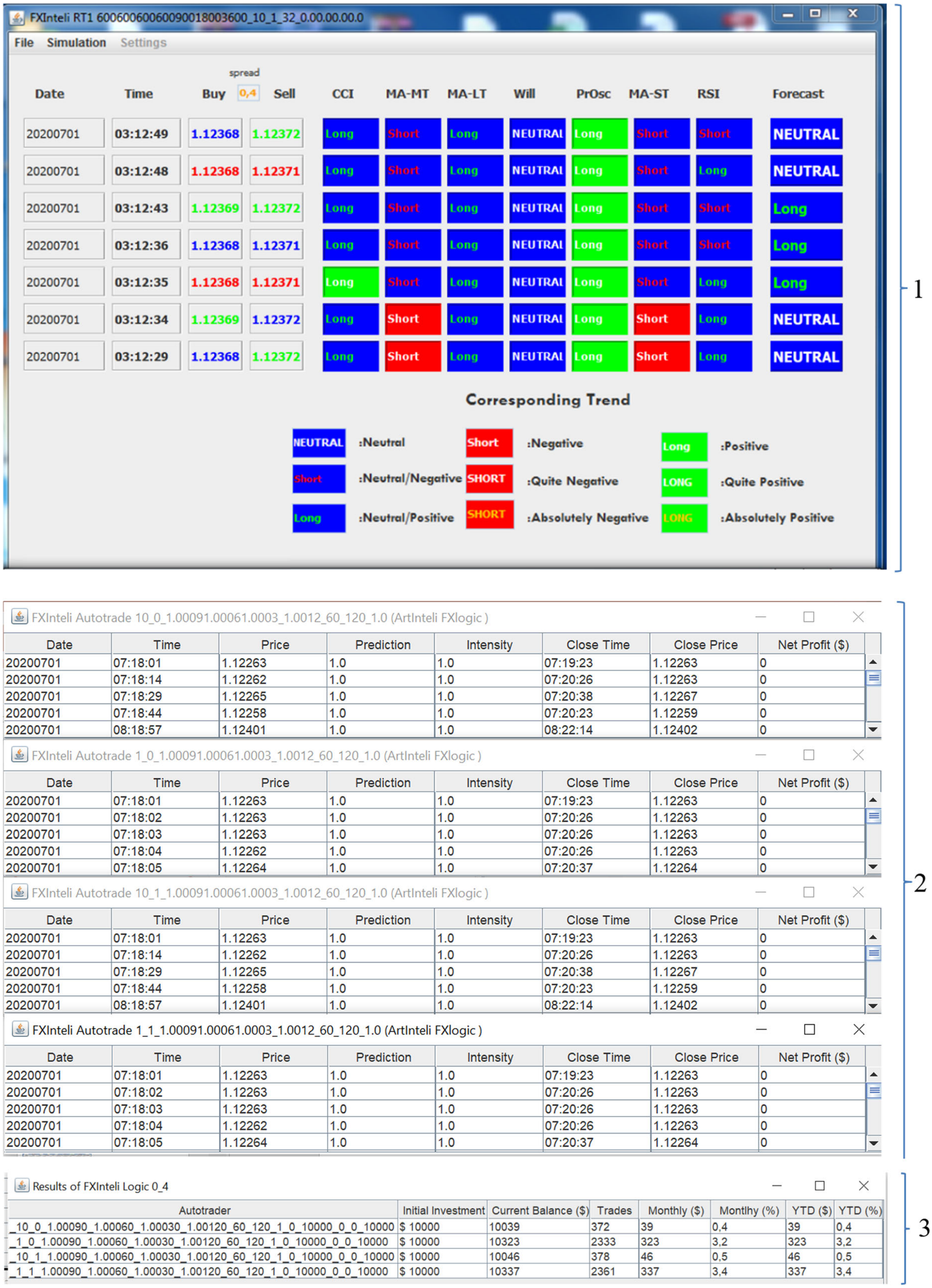


Fig. 2 A snapshot of the simulation

Table 3 ANN parameterization

A/A	Parameter	Value
1	Number of ANN Epochs	10
2	Number of ANN hidden neurons	14
3	Learning rate of synapses between hidden layer neurons and input layer neurons (LR-Inputs)	0.001
4	Learning rate of synapses between hidden layer neurons and output layer neurons (LR-Output)	0.001
5	Number of hidden layers	1
6	Number of output neurons	1
7	Number of input neurons	7
8	Period (ιn a number of values) of auxiliary MA	10
9	"Actual Trend" Algorithm Selection Parameter (1: Based of table 3.4 or 2: Based of table 3.3)	1

Table 4 Parameterization of back-propagation ANN's

A/A	Parameter	ANN-1	ANN-2	ANN-3
1	M(x) (In a number of prices approx. 1 price = 1 s)	30	60	90
2	Trend Value $\pm$ 2	1.0090	1.0090	1.0090
3	Trend Value $\pm$ 1.5	1.0060	1.0060	1.0060
4	Trend Value $\pm$ 1	1.0030	1.0030	1.0030
5	Trend Value $\pm$ 0.5	1.0015	1.0015	1.0015
6	$a(x)$	0.50	0.25	0.25

Table 5 Parameterization of technical indicators simulators

A/A	Parameter	Value
1	Period (ιn a number of values) Oscillator RSI	600
2	Period (ιn a number of values) Oscillator Williams	600
3	Period (ιn a number of values) Oscillator CCI	600
4	Period (ιn a number of values) Short-Term MA	600
5	Period (ιn a number of values) Mid-Term MA	900
6	Period (ιn a number of values) Long-Term MA	1800
7	Auxiliary Moving Averages of Price Oscillator	(600, 900, 1800)

selected after some preliminary experimentation with technical indicators to reflect a combination of real market conditions.

The typical leverage on forex trading institutions ranges from 50 to 400 times [1].

In our experimentation, we choose the minimum leverage ratio for our transactions, so as to minimize the risk of capital loss. We note that the maximum leverage ratio occurs rarely within the experimental period. Since we experiment with more than one open position at any time, we exploit leverage by allowing multiple open positions (instead of just one position with a much larger value; however, positions do not open simultaneously, but may overlap temporally). In the case of machines with general type I and II, the maximum number of open positions is 30 while in the case of machines with general type III and IV it is 5. In all cases, the invested capital per transaction is $ 10,000. That is, we do not use leverage for each transaction separately.

4.1 Presentation and analysis of results

We note that the below take into account spread between purchase and sell price so the transaction cost is included on our calculations.

We notice that the best performance in absolute profit ($ 9032) is achieved by the Type I machine which uses the ANN as a source of forecasting, followed by the Type II machine, again with the ANN as a forecasting source ($ 8506) (Fig. 3).

Table 6 Parameterization of automated transaction machines

N/A		General Type I	General Type II	General Type III	General Type IV
1	Machine Sensitivity (1000–0)	1	1	10	10
2	Machine Class (0 or 1)	0	1	0	1
3	Take Profit Factor for trend signals of very high intensity ± 2	1.00090	1.00090	1.00090	1.00090
4	Take Profit Factor for trend signals of high intensity ± 1.5	1.00060	1.00060	1.00060	1.00060
5	Take Profit Factor for trend signals of normal intensity ± 1	1.00030	1.00030	1.00030	1.00030
6	Stop Loss factor	1.0012	1.0012	1.0012	1.0012
7	Revision Time of Take Profit factor	60	60	60	60
8	Maximum Waiting Time	120	120	120	120
9	Revised Take Profit Factor	1	1	1	1
10	Total Investment Capital ($)	10,000	10,000	10,000	10,000
11	Capital per Transaction ($)	10,000	10,000	10,000	10,000
12	Maximum Leverage Ratio	1:30	1:30	1:5	1:5
Forecasting trend sources		Price	Price	Price	Price
ANN—> 0, PriceOsc(600,,900,1800)- > 1, CCI-600—> 2, Williams-600—> 3, RSI-600—> 4 MA-600 —> 5, MA-900—> 6, MA-1800 —> 7		0–7	0–7	0–7	0–7
Total machines		8	8	8	8

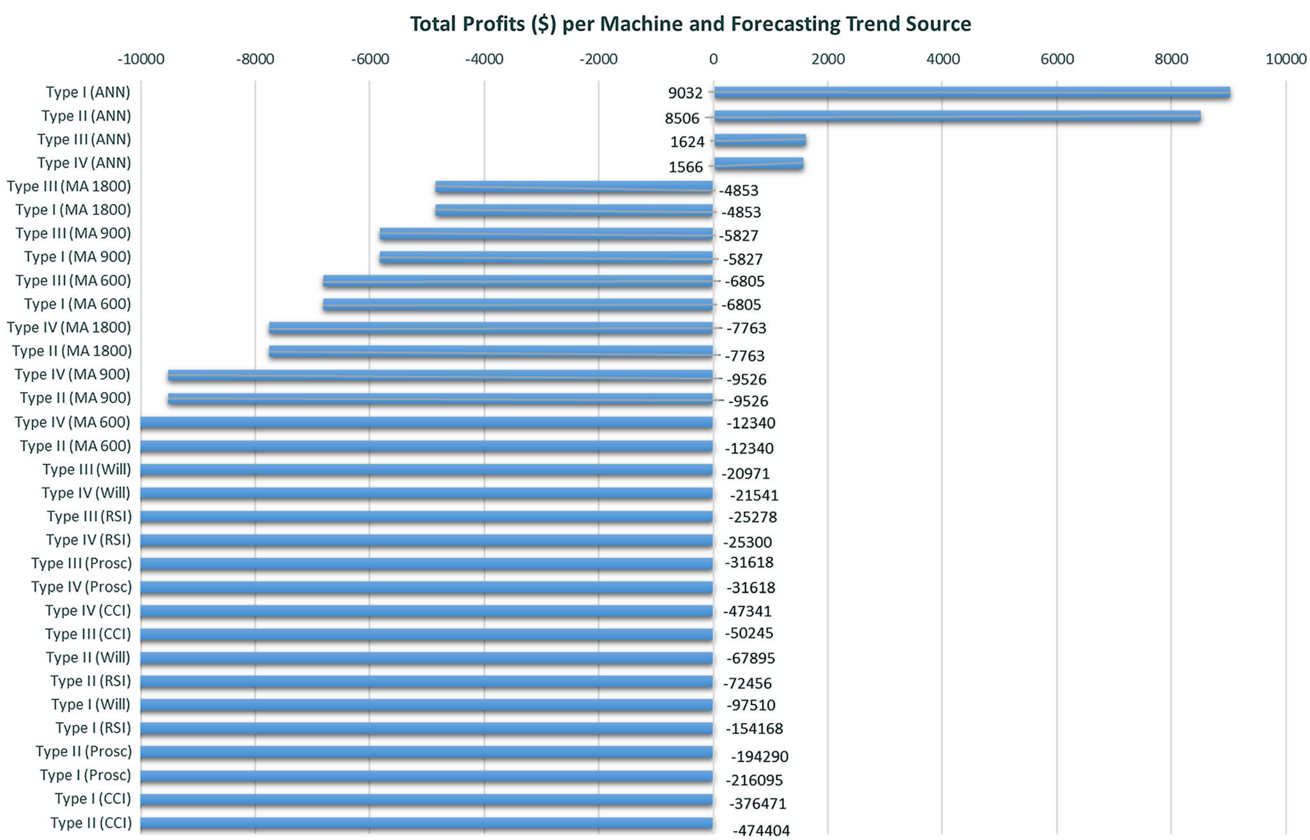


Fig. 3 Total experimental results per machine and forecasting trend source in descending order

Among the top four, we observe the Type III and Type IV machines with the ANN as forecasting source.

It is noteworthy that the first places in terms of performance are occupied by the ANN. All the others forecasting sources fare quite badly. We notice that all machines with oscillators as a forecasting source lost all of the investment capital.

In general, we observe that Type I and II machines (sensitivity parameter set to 1) with ANN are superior to the corresponding Type III and IV machines (sensitivity parameter set to 10). This is to be expected, since machines I and II have a maximum leverage ratio of 6 times compared to machines II and III. Moreover, we observe that type 0 machines perform slightly better than type 1 machines.

In terms of average earnings per transaction, the best performance is achieved by the Type III machine with ANN ($ 0.193 per transaction), followed by the Type IV machine with ANN ($ 0.181 per transaction) (Fig. 4).

The last entries to the top four are the Type I machine with ANN, the Type II machine with ANN.

We notice that all machines with any other technical indicator have loses.

In general, we notice that Type III machines (machine class 0 and low leverage) outperform in terms of average profit per transaction.

Type III and IV machine with ANN predictor are profitable for the largest number of days within the total period of experimentation (49/78) (Fig. 5).

Figure 6 shows the total profit per forecasting source for all machines, in total pips and at average profit per transaction. ANN turns out to be the most efficient with $ 20,728. All the technical indicators underperform and lost the entire investment capital.

In terms of average profits, the ANN ($ 0.17/transaction) outperform the profit of all others in absolute figures.

Figure 7 shows the total profit per machine Type and the average profit per transaction for the ANN forecasting source.

The most efficient generic machine Type appears to be of Type I ($ 9032) followed by Type II ($ 8506). This was to be expected, since the I and II engines have the highest sensitivity (using the highest leverage). If we take into

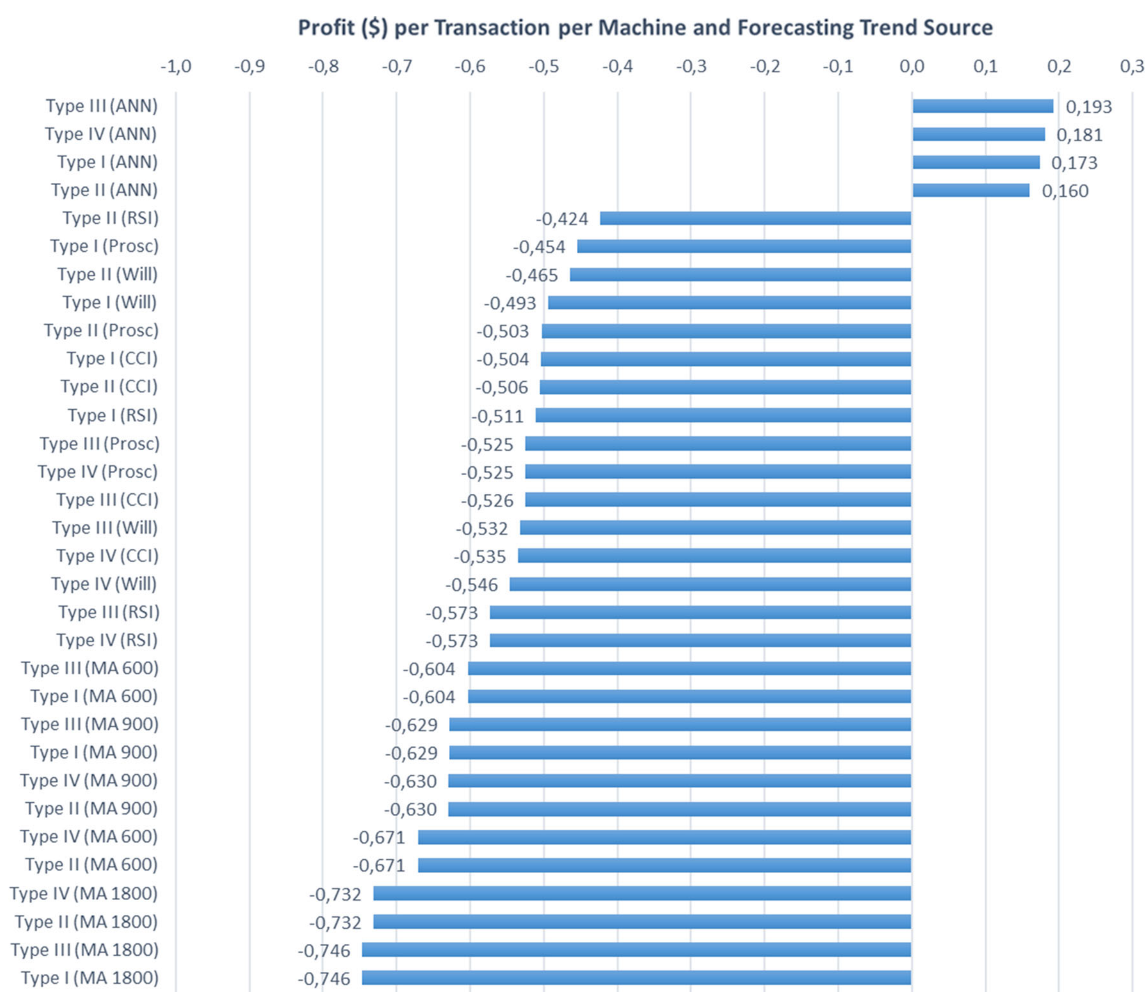


Fig. 4 Total monthly experimental results per transaction per machine and forecasting trend source in descending order

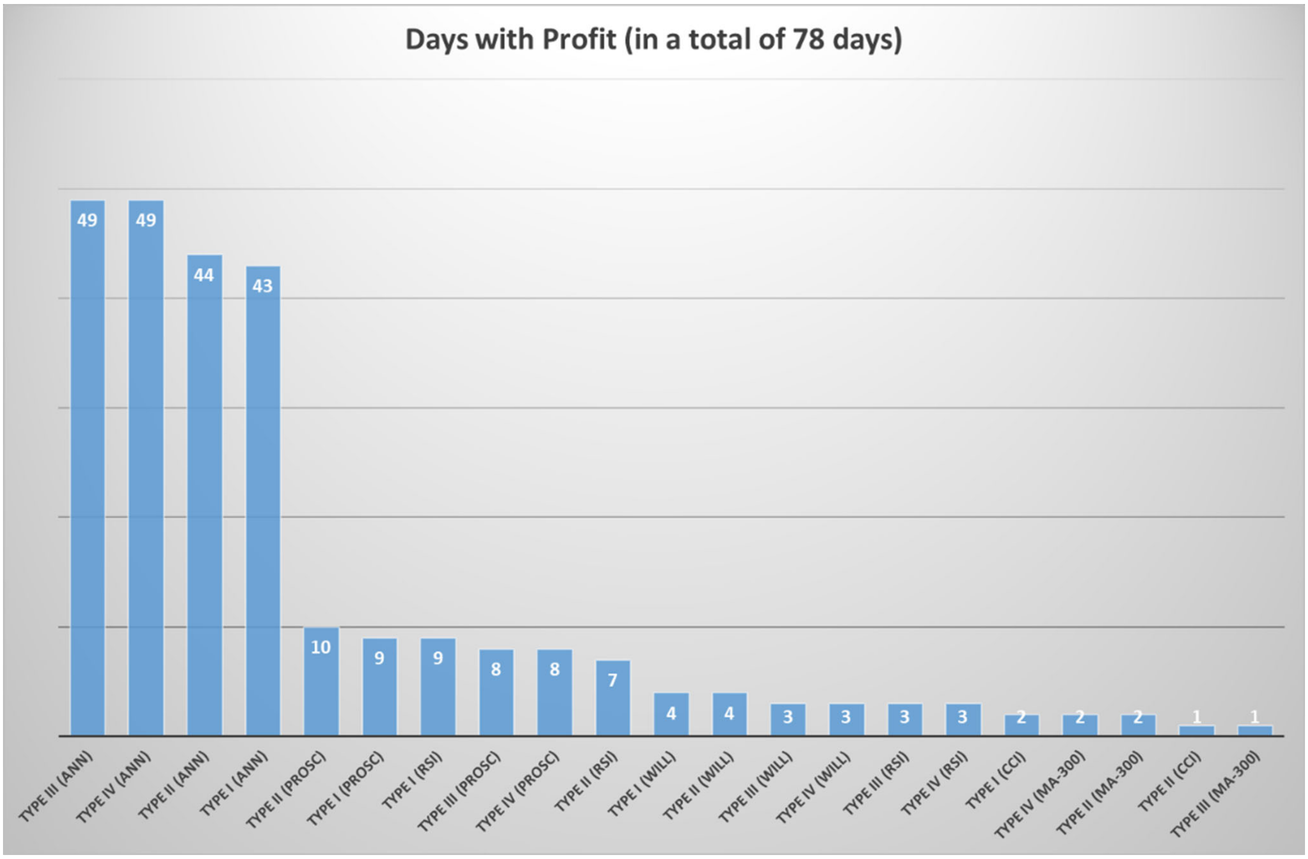


Fig. 5 Days with profit per machine in descending order

account the earnings per transaction (which are independent of the leverage since each transaction has invested the same initial capital, i.e., $ 10,000), we notice that the most efficient is the general type III machine (Low leverage and class 0). Among the high leverage machines (type I and II machines), the type I machine (general type 0) is more efficient.

Figure 8 shows the comparative daily yields of the four general Types of automated trading machines. We notice that machines with the highest sensitivity (I and II) are more prone to lose heavily but also to profit strongly. Also, among machines of the same sensitivity (I and II or III and IV), we notice that class "1" machines (as described in paragraph 3.3.1) are, also, more prone to such gaps in performance compared to class "0" ones. Therefore, in terms of decreasing tendency to register large profits but also large losses, we could rank the machines as follows: II > I > IV > III. By calculating the standard deviation of daily/period returns, we see that this rank has not been disturbed by considering a risk-adjusted measure.

"Appendix 2" features the detailed results of the experimentation per day, machine and source of forecasting.

If we focus on ANN-based machines, the most efficient with the fewest loss-making days is the Type III machine. We also note that loss-making days appear more often in the early days of the period of the experimentation. This observation, which is confined to ANN-based machines, suggests that as an ANN is trained over time, it improves the quality of its forecasting.

Figure 9 shows the cumulative profit for each general machine Type and the forecasting signal of ANN. Regarding the generic machine I and II, the sequence of ANN cumulative profitability has been increasing throughout the period of the experimentation, and particularly so in the second half of it, apparently due to improved network training.

The ANN in the general type IV machine behaves identically to the Type III machine.

Figure 10 shows the comparative monthly profit percentages of the four general types of ATMs based on the ANN forecast.

As expected, machines with high sensitivity (high leverage) show higher percentage monthly profits. A back-of-the-envelope comparison between all machines involves some leverage balancing, i.e., an $\times$ 6 multiplication of leverage per transaction for the 1:5 machines (to map them

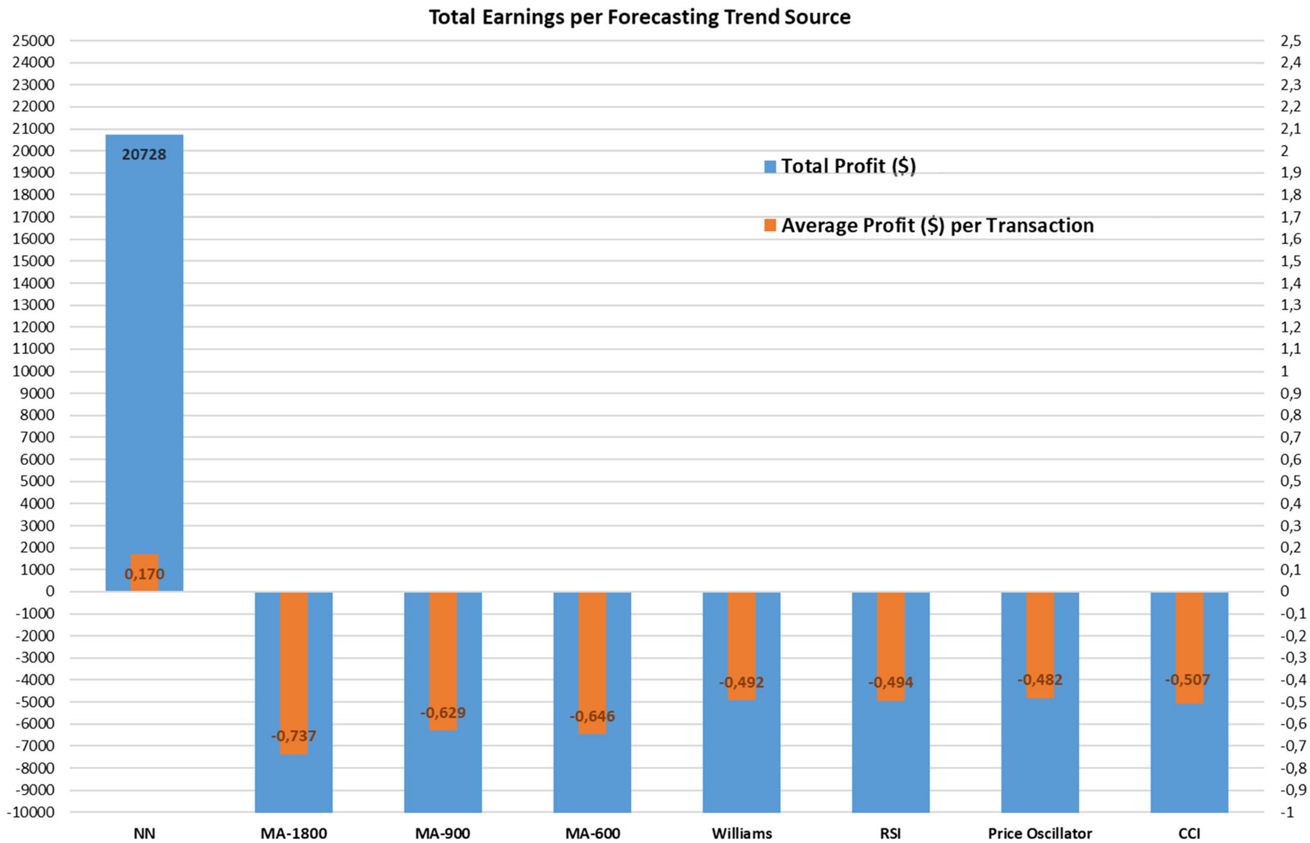


Fig. 6 Total profit per forecasting source in all machines (total pips vs. average profit per transaction)

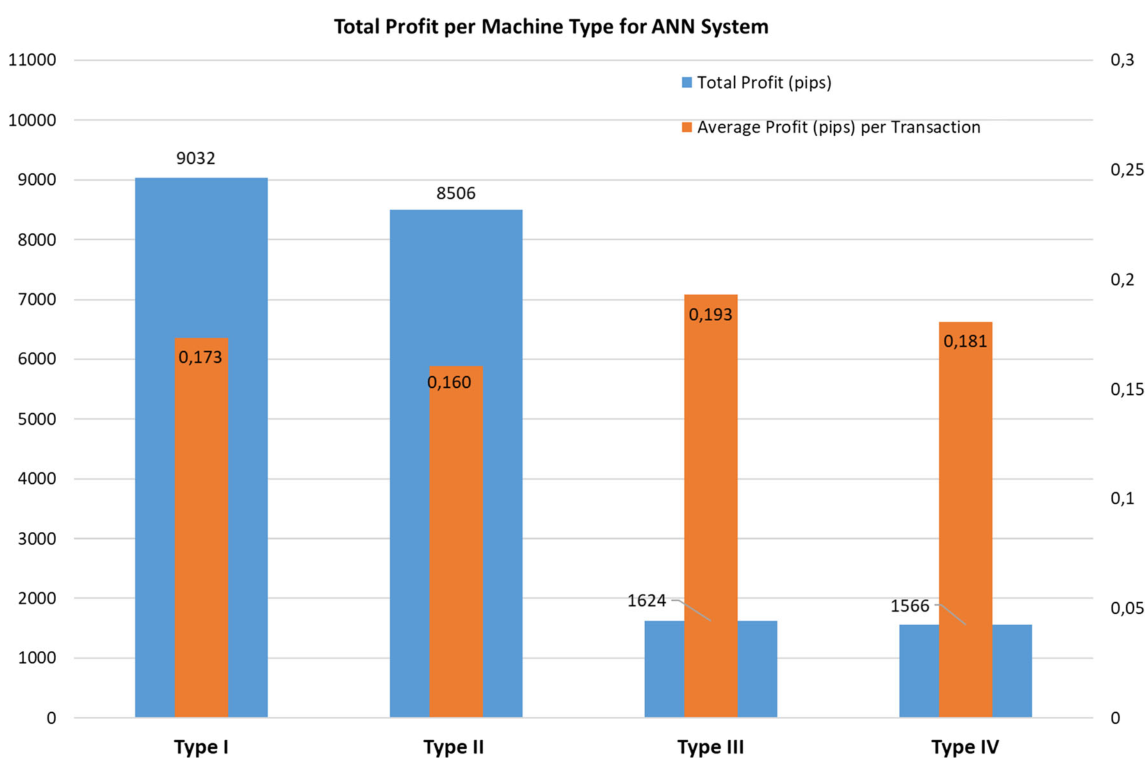


Fig. 7 Total profit per machine type (total pips vs. average profit per transaction)

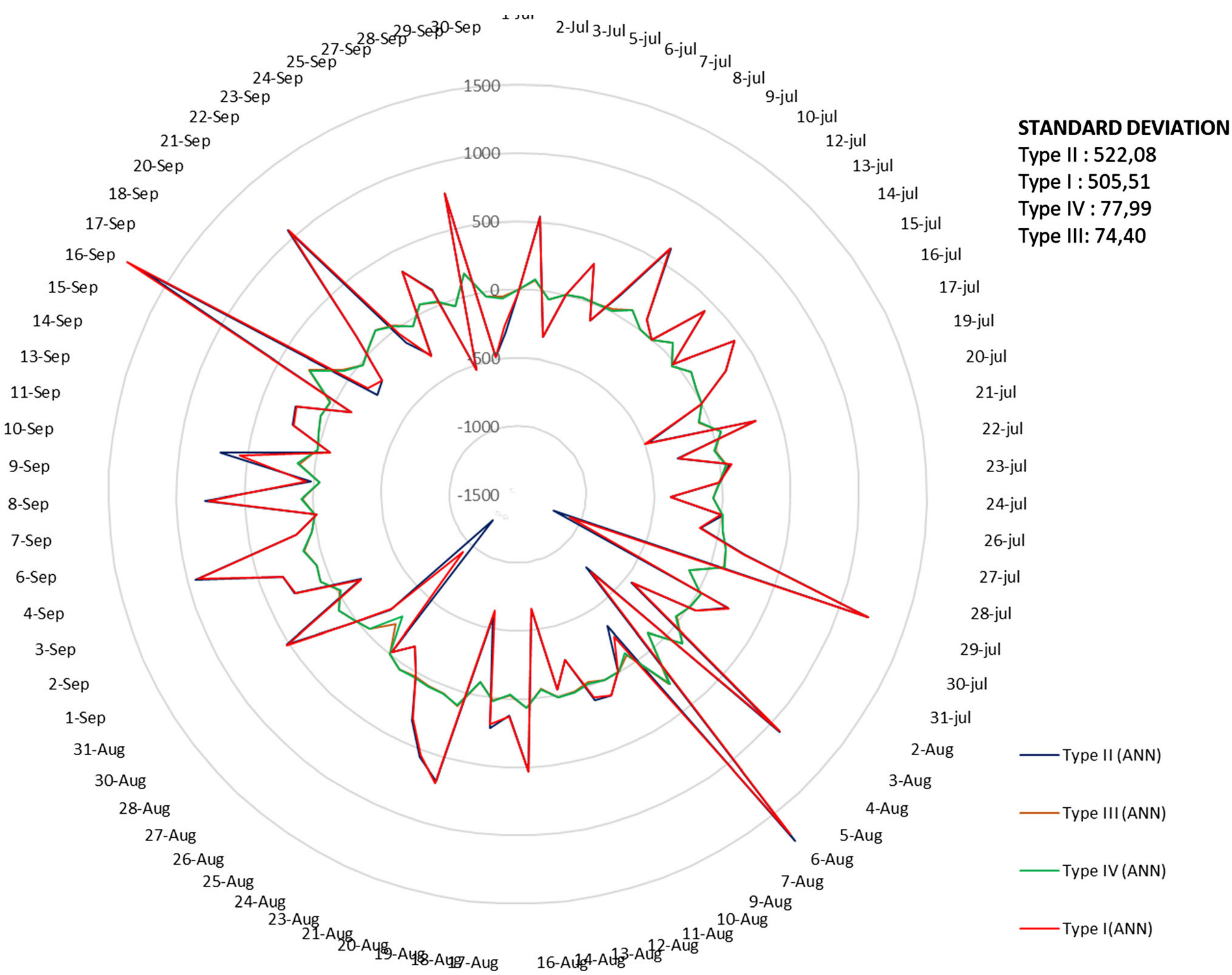


Fig. 8 Comparative daily yields ($) and standard deviation of the four general types of automated trading machines

to a 1:30 leverage) and suggests that lower sensitivity machines are overall more efficient (Fig. 11).

In the case of leverage balancing, the maximum invested capital leverage between the 4 machines is the same.

4.2 A brief discussion of the results

Reviewing the results above, we can attempt to draw conclusions on a number of important topics.

On selecting the most suitable combination of machine (Type) and forecasting source, with reference to the percentage of profit in investment capital with balancing leverage, a Type III machine with ANN prevails, followed by (in that order) Type IV with ANN, Type II with ANN and Type I with ANN.

On selecting the most profitable forecasting source regardless of machine Type, we clearly observe the superiority of the ANN, where machines with all other forecasting sources lost all the investment capital.

On selecting the most profitable forecasting source regardless of predictive source, after balancing the leverage, we note the relative superiority of a Type III one followed by a Type IV one. So, it seems that if we do not consider the source of the prediction signal, generic type machines with the lowest sensitivity seem to be more profitable. We have also noticed (see Fig. 8) that high sensitivity machines (I and II) are associated both with higher losses and higher profits and that between machines of the same sensitivity (I and II or III and IV), we observe that machines of class “1” are more unstable than those of “0” class. So, in terms of decreasing instability one would rank machines as follows: III > IV > I > II. Additionally, we observe that, in general, machines which are less unstable (to high profits and high losses) are more profitable regardless of the source of forecasting; as a result, using low sensitivity machines (of Types III, IV) should be preferred, if we are uncertain of the forecasting source.

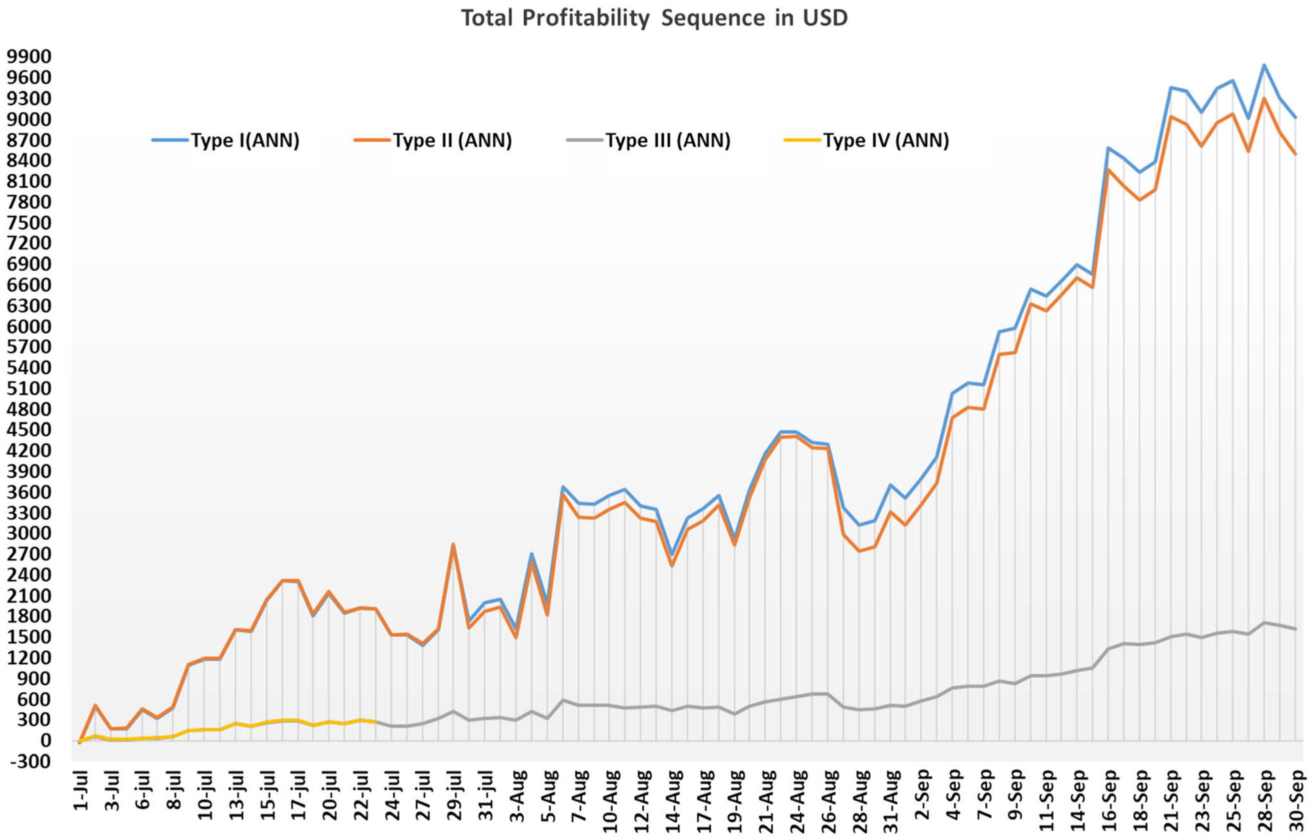
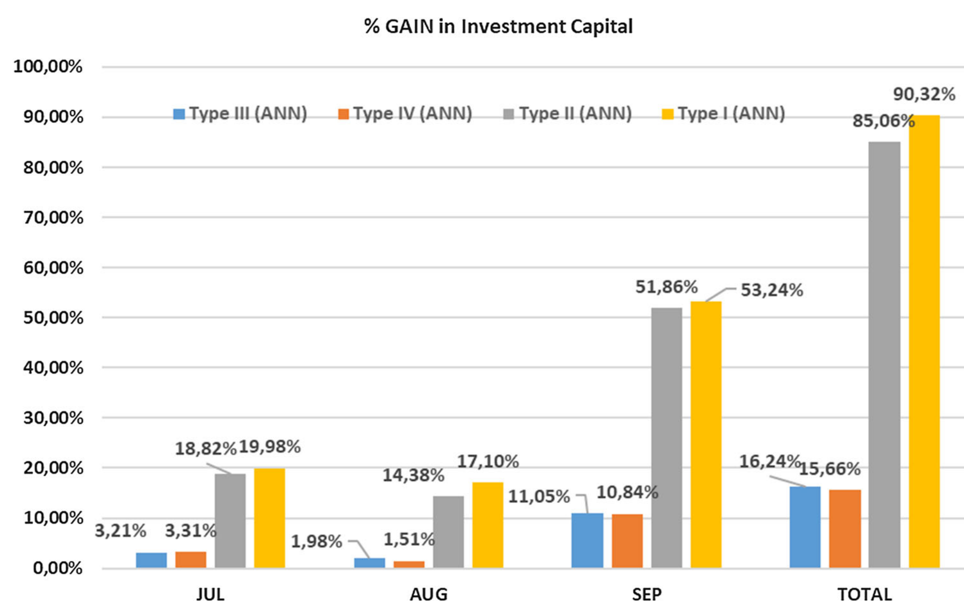


Fig. 9 The comparator sequences for each general machine type in relation to the source of the forecasting trend signal

Fig. 10 Percentage gain in investment capital



On associating efficient machine Types with forecasting sources, we have observed that the high sensitivity machines (Types I and II) are better suited to most effective sources of forecasting. Specifically, a Type I or II machine is better suited to ANN forecasting. On ultra-short-term transactions, the high sensitivity is a desirable feature (i.e., being able to quickly open and close positions) if it is accompanied by high profitability, as this reduces margin and leverage, which is otherwise great due to the nature of these transactions. By limiting leverage, we reduce the likelihood of automatic liquidation of our positions (by the

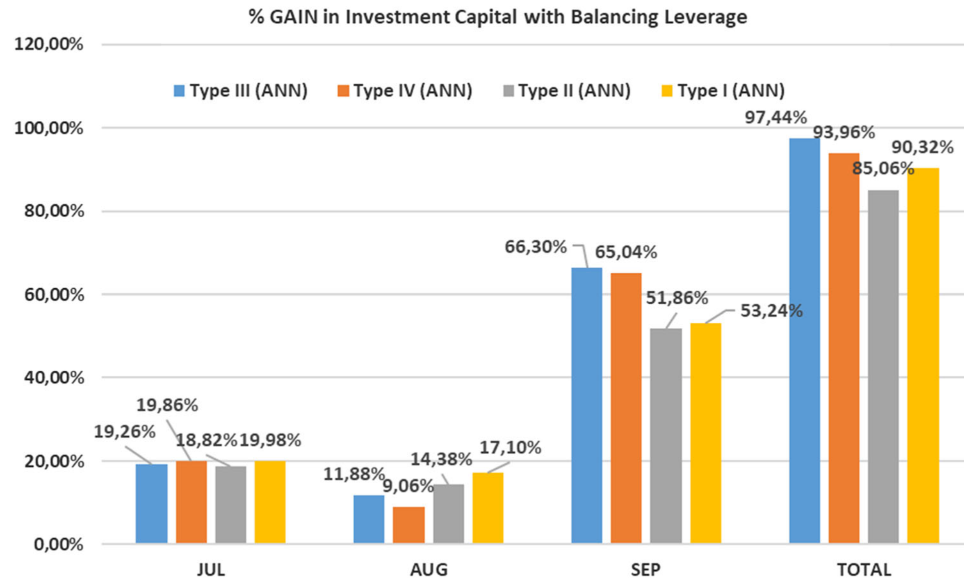


Fig. 11 Percentage gain in investment capital with balancing leverage

broker, in cases where the specified margins have been exceeded).

If we attempt a comparative discussion of the forecasting sources, we have experimented with, as regards their apparent suitability for use in ultra-short-term transactions in FOREX, we note that the ANN system had the best overall performance, but it also surpassed all other sources on all machines. Based on the analysis of daily earnings per machine and the examination of comparative profit aggregates, for each Type of machine, it appears that, over time, the ANN system can be effectively trained to improve the quality of the forecast. All other indicators led to the loss of all invested capital.

5 Conclusions

We have designed and built a tick-to-tick ultra-short-term trading system, which includes all stages of the trading process, namely pretrade analysis, production of the transaction mark (trend prediction) and execution of transactions, for ultra-short-term transactions in the FOREX market. The system is fully customizable and has been built using a lean object-oriented approach. This has allowed us to simultaneously test a large number of automated trading machines, which, in turn, drew predictive data from a series of technical indicator simulators, as well as from a neural network system attempting to online learn how to correctly forecast a new technical indicator. The dataset consisted of over 10 million data points, and we have fed it through a set of 32 automated trading machines, each one featuring a different combination of forecasting signal source and trading parameters.

Based on the results of our extensive experimentation, we have concluded that, for a large collection of appropriately set parameters, the implemented algorithmic trading system performs fully autonomously at a (simulated) profit when tested with real data.

More aggressive (more sensitive) automated trading machines for opening new positions seem to be better suited to using reliable forecasting signals (such as the ANN introduced in this paper). If the forecasting signal is of lower quality, one would be better off with less sensitive machines.

Future work should focus on examining alternative ANN training techniques as well as investigating the exploitation of conventional fundamentals, break events and news which affect the FOREX market and might be announced at any time point during a 24-h day. Such data can be harnessed from the internet in real time. Also, different neural networks models, with various input data set combinations (such as the technical indicators) will be considered and compared.

Additionally, it would be extremely interesting if we could build a closed system of virtual transactions, which would also simulate the trade-based setting of the exchange rate (as opposed to retrieving it from an online source). The objective of such an experimentation (which, undoubtedly, would have to be properly designed and computationally budgeted for) would be to examine the relative quality of the auto-trading machines, if they are all based on the same quality forecasting source (the ANN, for example), and their ability to evolve their ability to counter quality trading opponents, over time.

It is evident that by opening up our implementation and our research in such a way, one expects that we can pursue research at a variety of levels: We can investigate how one produces industrial-quality trend prediction, while also researching how one can utilize such trend predictions, either for profit-making enterprises or as a tool for tilting a market towards an equilibrium for hedging purposes.

Appendix 1: Parameterization of system

Simulators of moving averages

Conditions	Trend forecasting signal
MA_M(t) < MA_10(t) && MA_M(t-1) ≥ MA_10(t-1)	+ 1
MA_M(t) > MA_10(t) && MA_M(t-1) ≤ MA_10(t-1)	− 1
MA_M(t) < MA_10(t)	+ 0.5
MA_M(t) > MA_10(t)	− 0.5
Other cases	0

MA_M(t): Moiving Average of M values, MA_10: Moving Average of 10- values

Oscillators simulators

	Trend forecasting signal
Conditions of CCI	
CCI(t) < -150 && CCI(t) < CCI(t-1) && CCI(t-1) < CCI(t-2) && CCI(t-2) < CCI(t-3)	+ 2
CCI(t) > 150 && CCI(t) > CCI(t-1) && CCI(t-1) > CCI(t-2) && CCI(t-2) > CCI(t-3)	− 2
CCI(t) < -150	+ 1.5
CCI(t) > 150	− 1.5
CCI(t) < -100	+ 1
CCI(t) > 100	− 1
CCI(t) < CCI(t-1) && CCI(t-1) < CCI(t-2) && CCI(t) < 0	+ 0.5
CCI(t) > CCI(t-1) && CCI(t-1) > CCI(t-2) && CCI(t) > 0	− 0.5
Other cases	0
Conditions of Williams	
WILL(t) < -99 && WILL(t) < WILL(t-1) && WILL(t-1) < WILL(t-2) && WILL(t-2) < WILL(t-3)	+ 2
WILL(t) > -1 && WILL(t) > WILL(t-1) && WILL(t-1) > WILL(t-2) && WILL(t-2) > WILL(t-3)	− 2
WILL(t) < -99	+ 1.5
WILL(t) > -1	− 1.5
WILL(t) < -98	+ 1
WILL(t) > -2	− 1
WILL(t) < -80	+ 0.5
WILL(t) > -20	− 0.5
Other cases	0
Conditions of RSI	
RSI(t) < 5 && RSI(t) < RSI(t-1) && RSI(t-1) < RSI(t-2) && RSI(t-2) < RSI(t-3)	+ 2
RSI(t) > 90 && RSI(t) > RSI(t-1) && RSI(t-1) > RSI(t-2) && RSI(t-2) > RSI(t-3)	− 2
RSI(t) < 5	+ 1.5
RSI(t) > 90	− 1.5
RSI(t) < 15	+ 1
RSI(t) > 85	− 1
RSI(t) < 30	+ 0.5
RSI(t) > 70	− 0.5
Other cases	0
Conditions of price oscillator	
PROSC(t) < -12	+ 2
PROSC(t) > 12	− 2
PROSC(t) < -9	+ 1.5
PROSC(t) > 9	− 1.5
PROSC(t) < 6	+ 1
PROSC(t) > -6	− 1
PROSC(t) < 0	+ 0.5
PROSC(t) > 0	− 0.5
Other cases	0

Content of the system's configuration file

Line	Parameter	Value
1st	Number of ANN epochs	10
2nd	Number of ANN Hidden Neurons	14
3rd	Learning rates between synapses of Neurons of Hidden Layer with Input Neurons (LR-Inputs)	0.001
4th	Learning rates between synapses of Neurons of Hidden Layer with Output Neurons (LR-Output)	0.001
5th	Number of ANN Hidden layers	1
6th	Number of Exit Neurons	1
7th	Number of Import Neurons	7
8th	Period (in a number of values) of Oscillator RSI	600
9th	Period (ιn a number of values) of Oscillator Williams	600
10th	Period (ιn a number of values) of Oscillator CCI	600
11th	Period (ιn a number of values) of Short-Term MA	600
12th	Period (ιn a number of values) of Mid-Term MA	900
13th	Period (ιn a number of values) of Long-Term MA	1800
14th	Period (ιn a number of values) of auxiliary MA (used instead of a pair of instantaneous values so that there is no possible momentary deviation of values due to tick to tick data)	10
15th	Number of ANN pairs	3
16th	M(x) (In a number of prices approx. 1price = 1 sec)	30
17th	Trend Value ± 2	1.00090
18th	Trend Value ± 1.5	1.00060
19th	Trend Value ± 1	1.00030
20th	Trend Value ± 0.5	1.00015
21th	a(x)	0,5
22th	Number of Automated Trading Machines	32
23th	Machine Sensitivity (1000–0). Paragraph 3.4.1	1
24th	Machine Class. Paragraph 3.4.1	0
25th	Take Profit Factor for trend signals of very high intensity ± 2. Paragraph. 3.4.1	1.00090
26th	Take Profit Factor for trend signals of high intensity ± 1.5. Paragraph. 3.4.1	1.00060
27th	Take Profit Factor for trend signals of normal intensity ± 1. Paragraph. 3.4.1	1.00030
28th	Stop Loss Factor. Paragraph. 3.4.1	1.0012
29th	Revision Time of take profit factors. Paragraph. 3.4.1	60
30th	Maximum Waiting Time. Paragraph. 3.4.1	120
31th	Revised Take Profit Factor. Paragraph. 3.4.1	1
32th	Source of Trend Forecasting Signals (0 έως 7). Paragraph. 3.4.1	0
33th	Total Investment Capital	$ 10,000
34th	Capital per Transaction	$ 10,000

Lines 16 through 21 are repeated as many times as the number of ANN pairs as set on the 15th line

Lines 23 through 34 are repeated as many times as the number of machines as set on the 22th line. So each machine has its own exclusive parameterization

Appendix 2: Analytical results of experimentation per day, machine and source of forecast (July, August and September 2020)

	1-Jul	2-Jul	3-Jul	5-Jul	6-Jul	7-Jul	8-Jul	9-Jul	10-Jul	12-Jul	13-Jul	14-Jul	15-Jul
Type III (ANN)	− 6	71	− 55	4	15	10	23	88	5	0	88	− 29	53
Type I (ANN)	− 31	530	− 331	2	276	− 123	158	617	90	0	419	− 15	448
Type IV (ANN)	− 6	77	− 55	4	16	10	14	93	5	0	88	− 29	53
Type II (ANN)	− 31	541	− 331	2	279	− 123	149	620	90	0	419	− 15	448
Type III (PROSC)	− 261	− 483	− 261	− 31	− 294	− 123	− 553	− 287	− 298	− 89	14	− 316	− 306
Type I (PROSC)	− 2523	− 3860	− 2230	− 182	− 2558	− 594	− 5041	− 2234	− 3005	− 858	856	− 2168	− 2079
Type IV (PROSC)	− 261	− 483	− 261	− 31	− 294	− 123	− 553	− 287	− 298	− 89	14	− 316	− 306
Type II (PROSC)	− 2523	− 3860	− 2230	− 182	− 2558	− 594	− 5041	− 2234	− 3005	− 858	856	− 2168	− 2079
Type III (CCI)	− 664	− 950	− 483	− 23	− 707	− 564	− 921	− 702	− 386	− 270	− 1016	− 533	− 684
Type I (CCI)	− 5507	− 7825	− 3878	− 135	− 6321	− 4287	− 8524	− 5510	− 3174	− 2432	− 8512	− 4264	− 6156
Type IV (CCI)	− 691	− 963	− 629	− 23	− 703	− 591	− 946	− 709	− 388	− 270	− 1036	− 600	− 755
Type II (CCI)	− 5602	− 7835	− 4736	− 135	− 6305	− 4444	− 8613	− 5525	− 3158	− 2438	− 8607	− 4581	− 6274
Type III (WILL)	− 138	− 178	− 259	1	− 291	− 271	− 295	− 181	− 114	− 83	− 260	− 176	− 237
Type I (WILL)	− 706	− 895	− 1071	13	− 1647	− 702	− 1437	− 720	− 614	− 351	− 863	− 956	− 1297
Type IV (WILL)	− 138	− 176	− 279	1	− 290	− 275	− 295	− 181	− 114	− 83	− 265	− 224	− 239
Type II (WILL)	− 712	− 893	− 1124	13	− 1646	− 719	− 1437	− 720	− 613	− 351	− 868	− 1042	− 1303
Type III (RSI)	− 178	− 401	− 136	− 1	− 36	− 56	− 252	− 252	− 20	− 109	− 110	− 250	− 123
Type I (RSI)	− 877	− 3038	− 366	− 6	296	− 169	− 1626	− 1674	− 74	− 719	− 324	− 1379	− 269
Type IV (RSI)	− 178	− 401	− 136	− 1	− 36	− 56	− 252	− 252	− 20	− 109	− 110	− 250	− 123
Type II (RSI)	− 877	− 3038	− 366	− 6	296	− 169	− 1626	− 1674	− 74	− 719	− 324	− 1379	− 269
Type III (MA600)	− 83	− 30	− 142	− 5	− 82	− 144	− 46	− 73	− 63	− 7	− 68	− 92	− 71
Type I (MA600)	− 83	− 30	− 142	− 5	− 82	− 144	− 46	− 73	− 63	− 7	− 68	− 92	− 71
Type IV (MA600)	− 148	− 134	− 202	− 3	− 140	− 183	− 76	− 119	− 96	− 7	− 209	− 193	− 128
Type II (MA600)	− 148	− 134	− 202	− 3	− 140	− 183	− 76	− 119	− 96	− 7	− 209	− 193	− 128
Type III (MA900)	− 76	− 40	− 108	− 3	− 78	− 93	− 60	− 45	− 39	− 9	− 25	− 68	− 98
Type I (MA900)	− 76	− 40	− 108	− 3	− 78	− 93	− 60	− 45	− 39	− 9	− 25	− 68	− 98
Type IV (MA900)	− 109	− 82	− 157	− 2	− 109	− 286	− 77	− 113	− 87	− 9	− 70	− 112	− 132
Type II (MA900)	− 109	− 82	− 157	− 2	− 109	− 286	− 77	− 113	− 87	− 9	− 70	− 112	− 132
Type III (MA1800)	− 38	− 33	− 121	− 13	− 37	− 22	− 60	− 38	− 27	− 5	− 56	− 96	− 89
Type I (MA1800)	− 38	− 33	− 121	− 13	− 37	− 22	− 60	− 38	− 27	− 5	− 56	− 96	− 89
Type IV (MA1800)	− 58	− 69	− 169	− 21	− 54	− 27	− 96	− 53	− 43	− 7	− 125	− 100	− 184
Type II (MA1800)	− 58	− 69	− 169	− 21	− 54	− 27	− 96	− 53	− 43	− 7	− 125	− 100	− 184

	16-Jul	17-Jul	19-Jul	20-Jul	21-Jul	22-Jul	23-Jul	24-Jul	25-Jul	26-Jul	27-Jul	29-Jul	30-Jul	31-Jul
Type III (ANN)	23	0	− 72	55	− 21	46	− 19	− 67	3	28	76	101	− 126	27
Type I (ANN)	274	− 4	− 494	322	− 292	85	− 21	− 378	− 2	− 141	217	1220	− 1085	257
Type IV (ANN)	23	0	− 69	55	− 25	42	− 18	− 67	9	30	77	105	− 128	27

(continued)

	16-Jul	17-Jul	19-Jul	20-Jul	21-Jul	22-Jul	23-Jul	24-Jul	25-Jul	26-Jul	27-Jul	29-Jul	30-Jul	31-Jul
Type II (ANN)	274	− 4	− 478	321	− 302	68	− 14	− 380	13	− 138	219	1223	− 1216	248
Type III (PROSC)	− 732	− 257	− 214	− 410	− 594	6	− 151	60	− 159	− 1088	− 794	− 540	− 524	− 674
Type I (PROSC)	− 6148	− 2324	− 2208	− 2862	− 4966	410	− 821	618	− 1585	− 8777	− 6487	− 4765	− 4705	− 6470
Type IV (PROSC)	− 732	− 257	− 214	− 410	− 594	6	− 151	60	− 159	− 1088	− 794	− 540	− 524	− 674
Type II (PROSC)	− 6148	− 2324	− 2208	− 2862	− 4966	410	− 821	618	− 1585	− 8777	− 6487	− 4765	− 4705	− 6469
Type III (CCI)	− 1214	− 449	− 228	− 820	− 1001	− 670	− 978	− 713	− 199	− 1698	− 1344	− 857	− 1439	− 1012
Type I (CCI)	− 10,503	− 3867	− 1879	− 7284	− 9093	− 5560	− 8352	− 5260	− 1839	− 14,809	− 11,650	− 6473	− 12,374	− 8450
Type IV (CCI)	− 1219	− 451	− 228	− 853	− 1050	− 682	− 1094	− 750	− 228	− 1872	− 1337	− 858	− 1460	− 1004
Type II (CCI)	− 10,550	− 3944	− 1879	− 7498	− 9226	− 5675	− 8973	− 5379	− 1885	− 15,552	− 11,660	− 6445	− 12,406	− 8452
Type III (WILL)	− 501	− 174	− 99	− 137	− 448	− 207	− 342	− 42	− 57	− 700	− 377	− 212	− 471	− 218
Type I (WILL)	− 1911	− 711	− 668	− 781	− 2106	− 727	− 1925	− 63	− 106	− 3403	− 1955	− 956	− 2342	− 764
Type IV (WILL)	− 501	− 174	− 99	− 137	− 480	− 212	− 456	− 42	− 57	− 744	− 378	− 212	− 471	− 218
Type II (WILL)	− 1911	− 711	− 668	− 782	− 2137	− 734	− 2243	− 63	− 106	− 3447	− 1956	− 965	− 2342	− 760
Type III (RSI)	− 434	− 32	− 73	− 7	22	− 175	− 315	− 10	− 38	− 418	− 601	− 325	− 183	− 238
Type I (RSI)	− 3175	48	− 481	526	440	− 1433	− 1697	− 3	− 21	− 2009	− 3817	− 2196	− 642	− 802
Type IV (RSI)	− 434	− 32	− 73	− 7	22	− 175	− 315	− 10	− 38	− 418	− 601	− 325	− 183	− 238
Type II (RSI)	− 3175	48	− 481	526	440	− 1433	− 1697	− 3	− 21	− 2009	− 3817	− 2196	− 642	− 802
Type III (MA600)	− 98	− 40	− 2	− 116	− 3	− 10	− 89	− 75	− 92	− 82	− 80	− 90	− 48	− 61
Type I (MA600)	− 98	− 40	− 2	− 116	− 3	− 10	− 89	− 75	− 92	− 82	− 80	− 90	− 48	− 61
Type IV (MA600)	− 216	− 93	4	− 155	− 63	− 153	− 141	− 135	− 114	− 164	− 230	− 200	− 95	− 115
Type II (MA600)	− 216	− 93	4	− 155	− 63	− 153	− 141	− 135	− 114	− 164	− 230	− 200	− 95	− 115
Type III (MA900)	− 89	− 28	− 4	− 112	− 68	− 26	− 37	− 55	− 69	− 85	− 128	− 85	− 46	− 62
Type I (MA900)	− 89	− 28	− 4	− 112	− 68	− 26	− 37	− 55	− 69	− 85	− 128	− 85	− 46	− 62
Type IV (MA900)	− 151	− 64	− 3	− 119	− 116	− 55	− 88	− 91	− 70	− 158	− 154	− 146	− 94	− 123
Type II (MA900)	− 151	− 64	− 3	− 119	− 116	− 55	− 88	− 91	− 70	− 158	− 154	− 146	− 94	− 123
Type III (MA1800)	− 43	− 35	4	− 79	− 9	− 8	− 19	− 19	− 17	− 100	− 53	− 109	− 12	− 22
Type I (MA1800)	− 43	− 35	4	− 79	− 9	− 8	− 19	− 19	− 17	− 100	− 53	− 109	− 12	− 22
Type IV (MA1800)	− 121	− 53	4	− 131	− 36	− 39	− 57	− 32	− 29	− 144	− 63	− 131	− 61	− 76
Type II (MA1800)	− 121	− 53	4	− 131	− 36	− 39	− 57	− 32	− 29	− 144	− 63	− 131	− 61	− 76

	2-Aug	3-Aug	4-Aug	5-Aug	6-Aug	7-Aug	9-Aug	10-Aug	11-Aug	12-Aug	13-Aug	14-Aug	16-Aug
Type III (ANN)	3	168	116	136	295	209	12	49	150	135	114	90	16
Type I (ANN)	16	1088	765	842	1948	1362	72	283	830	733	616	598	138
Type IV (ANN)	3	171	116	141	314	217	12	50	154	139	115	93	18
Type II (ANN)	16	1096	766	865	2014	1395	72	284	836	741	617	601	145
Type III (PROSC)	38	1233	1093	1205	1465	946	17	798	1466	1035	982	703	21
Type I (PROSC)	360	11,452	10,185	11,176	13,732	8800	152	7332	13,504	9369	8933	6514	157
Type IV (PROSC)	38	1233	1093	1205	1465	946	17	798	1466	1035	982	703	21
Type II (PROSC)	360	11,452	10,185	11,176	13,732	8800	152	7332	13,504	9369	8933	6514	157
Type III (CCI)	35	2005	2123	1959	2202	1956	65	1674	2241	2059	1950	1679	79
Type I (CCI)	325	17,483	18,766	17,305	19,211	16,651	443	14,638	19,569	17,777	16,922	14,605	688
Type IV (CCI)	35	2012	2138	1964	2210	1986	75	1686	2256	2077	1969	1703	88
Type II (CCI)	325	17,524	18,853	17,328	19,247	16,798	481	14,691	19,640	17,852	17,005	14,738	728
Type III (WILL)	9	618	660	671	702	544	16	560	716	660	608	477	29
Type I (WILL)	46	3095	3364	3454	3714	2698	56	2696	3722	3301	3077	2370	125
Type IV (WILL)	9	618	662	671	702	544	18	561	717	661	608	479	32
Type II (WILL)	9	618	662	671	702	544	18	561	717	661	608	479	32
Type III (RSI)	3	511	640	587	733	415	534	744	460	469	391	23	432
Type I (RSI)	12	3514	4354	4110	5533	2712	3907	5226	2933	3102	2863	155	3181
Type IV (RSI)	3	511	640	587	733	415	534	744	460	469	391	23	432
Type II (RSI)	3	511	640	587	733	415	534	744	460	469	391	23	432
Type III (MA600)	2	184	160	162	181	223	11	131	170	181	173	139	6
Type I (MA600)	2	184	160	162	181	223	11	131	170	181	173	139	6
Type IV (MA600)	2	312	256	263	294	380	19	209	276	291	281	235	10
Type II (MA600)	2	312	256	263	294	380	19	209	276	291	281	235	10
Type III (MA900)	1	138	139	128	132	188	6	104	135	163	120	102	4
Type I (MA900)	1	138	139	128	132	188	6	104	135	163	120	102	4
Type IV (MA900)	1	225	226	207	214	322	9	161	222	257	195	167	6
Type II (MA900)	1	225	226	207	214	322	9	161	222	257	195	167	6
Type III (MA1800)	3	82	88	94	93	108	12	79	94	115	94	117	5
Type I (MA1800)	3	82	88	94	93	108	12	79	94	115	94	117	5
Type IV (MA1800)	5	132	145	154	147	184	19	131	150	181	160	202	8
Type II (MA1800)	5	132	145	154	147	184	19	131	150	181	160	202	8
	17-Aug	18-Aug	19-Aug	20-Aug	21-Aug	23-Aug	24-Aug	25-Aug	26-Aug	27-Aug	28-Aug	30-Aug	31-Aug
Type III (ANN)	57	136	165	182	158	16	57	84	87	374	200	12	97
Type I (ANN)	268	828	1161	1108	1051	69	281	498	540	2617	1229	75	631
Type IV (ANN)	58	142	174	186	159	17	58	85	87	403	210	12	98

(continued)

	17-Aug	18-Aug	19-Aug	20-Aug	21-Aug	23-Aug	24-Aug	25-Aug	26-Aug	27-Aug	28-Aug	30-Aug	31-Aug
Type II (ANN)	270	839	1211	1119	1054	72	282	499	540	2768	1259	75	635
Type III (PROSC)	647	891	910	1034	953	17	549	857	805	1505	1259	34	717
Type I (PROSC)	5954	4030	910	1034	953	17	549	857	805	1505	1259	34	717
Type IV (PROSC)	647	891	910	1034	953	17	549	857	805	1505	1259	34	717
Type II (PROSC)	5954	8202	8227	9506	8685	122	4753	7689	7378	14,181	11,573	320	6395
Type III (CCI)	1603	1793	1958	2155	1818	79	1571	1929	1832	2162	2107	118	1891
Type I (CCI)	13,993	15,651	17,071	18,901	15,697	696	13,723	16,925	15,950	18,966	18,555	933	16,140
Type IV (CCI)	1623	1813	1965	2167	1838	80	1603	1938	1851	2179	2117	128	1914
Type II (CCI)	14,120	15,750	17,125	18,966	15,809	698	13,886	16,983	16,055	19,073	18,623	998	16,258
Type III (WILL)	507	555	550	691	590	26	495	593	581	691	643	46	596
Type I (WILL)	2633	2715	2749	3405	2891	154	2369	2896	3048	3494	3252	216	2917
Type IV (WILL)	507	555	551	693	592	26	497	593	582	693	643	49	598
Type II (WILL)	507	555	551	693	592	26	497	593	582	693	643	49	598
Type III (RSI)	409	394	610	476	12	407	457	530	652	613	13	501	11,016
Type I (RSI)	2592	2573	4093	3293	40	2768	2955	3809	4612	4215	85	3560	76,197
Type IV (RSI)	409	394	610	476	12	407	457	530	652	613	13	501	11,016
Type II (RSI)	409	394	610	476	12	407	457	530	652	613	13	501	11,016
Type III (MA600)	144	152	182	188	138	7	134	147	183	209	190	12	187
Type I (MA600)	144	152	182	188	138	7	134	147	183	209	190	12	187
Type IV (MA600)	228	234	297	309	219	12	213	239	317	356	312	18	311
Type II (MA600)	228	234	297	309	219	12	213	239	317	356	312	18	311
Type III (MA900)	126	144	160	142	123	3	125	115	132	163	169	19	145
Type I (MA900)	126	144	160	142	123	3	125	115	132	163	169	19	145
Type IV (MA900)	202	228	267	225	201	4	207	177	229	270	282	30	239
Type II (MA900)	202	228	267	225	201	4	207	177	229	270	282	30	239
Type III (MA1800)	111	128	105	106	81	6	83	90	69	97	80	5	89
Type I (MA1800)	111	128	105	106	81	6	83	90	69	97	80	5	89
Type IV (MA1800)	182	208	169	167	130	9	137	136	114	160	132	10	138
Type II (MA1800)	182	208	169	167	130	9	137	136	114	160	132	10	138

	1-Sep	2-Sep	3-Sep	4-Sep	6-Sep	7-Sep	8-Sep	9-Sep	10-Sep	11-Sep	13-Sep	14-Sep	15-Sep
Type III (ANN)	163	144	137	170	4	12	181	112	271	70	13	28	62
Type I (ANN)	1062	824	756	1030	25	57	1075	668	1707	470	105	145	383
Type IV (ANN)	166	149	138	180	4	12	187	119	290	70	14	29	63
Type II (ANN)	1067	837	757	1073	25	57	1123	695	1784	470	114	149	384
Type III (PROSC)	1247	1157	1041	794	13	258	973	624	871	583	49	368	392
Type I (PROSC)	11,555	10,599	9448	7129	47	2362	8999	5418	7802	5246	430	3091	3563
Type IV (PROSC)	1247	1157	1041	794	13	258	973	624	871	583	49	368	392
Type II (PROSC)	11,555	10,599	9448	7129	47	2362	8999	5418	7802	5246	430	3091	3563
Type III (CCI)	1996	2041	2067	1932	98	1237	1968	1818	1995	1637	56	1546	785
Type I (CCI)	17,516	17,813	17,898	16,917	661	10,366	17,121	15,822	16,954	14,318	533	13,215	6681
Type IV (CCI)	2005	2050	2082	1942	113	1262	1984	1843	2016	1658	57	1558	1651
Type II (CCI)	17,569	17,857	17,980	16,971	695	10,489	17,220	15,944	17,102	14,413	536	13,243	7630
Type III (WILL)	652	688	576	562	21	371	598	476	534	479	25	464	485
Type I (WILL)	3407	3491	2925	2823	103	1810	2891	2413	2674	2272	127	2251	2328
Type IV (WILL)	652	688	577	562	23	372	598	476	534	479	25	464	485
Type II (WILL)	3408	3491	2927	2823	108	1812	2891	2413	2674	2272	127	2251	2329
Type III (RSI)	593	517	489	440	14	321	486	325	440	420	30	351	254
Type I (RSI)	4129	3342	3312	3046	65	1960	3380	2096	2977	2925	209	2148	1455
Type IV (RSI)	593	517	489	440	14	321	488	325	440	420	30	351	254
Type II (RSI)	4129	3342	3312	3046	65	1960	3387	2096	2977	2925	209	2148	1455
Type III (MA600)	179	162	186	197	16	149	208	190	204	150	3	133	182
Type I (MA600)	179	162	186	197	16	149	208	190	204	150	3	133	182
Type IV (MA600)	289	264	294	324	24	247	342	315	330	233	3	220	300
Type II (MA600)	289	264	294	324	24	247	342	315	330	233	3	220	300
Type III (MA900)	151	157	158	147	21	124	159	152	159	138	5	97	129
Type I (MA900)	151	157	158	147	21	124	159	152	159	138	5	97	129
Type IV (MA900)	243	259	258	238	32	205	262	255	256	221	7	154	206
Type II (MA900)	243	259	258	238	32	205	262	255	256	221	7	154	206
Type III (MA1800)	93	112	80	93	10	93	95	124	119	99	6	69	96
Type I (MA1800)	93	112	80	93	10	93	95	124	119	99	6	69	96
Type IV (MA1800)	149	185	134	142	12	159	156	211	199	162	9	115	155
Type II (MA1800)	149	185	134	142	12	159	156	211	199	162	9	115	155

	16-Sep	17-Sep	18-Sep	20-Sep	21-Sep	22-Sep	23-Sep	24-Sep	25-Sep	27-Sep	28-Sep	29-Sep	30-Sep
Type III (ANN)	223	155	38	6	123	155	119	115	64	18	70	94	138
Type I (ANN)	1290	955	231	37	716	979	770	753	361	105	419	608	779
Type IV (ANN)	244	159	38	6	124	160	120	118	65	18	70	95	142

(continued)

	16-Sep	17-Sep	18-Sep	20-Sep	21-Sep	22-Sep	23-Sep	24-Sep	25-Sep	27-Sep	28-Sep	29-Sep	30-Sep
Type II (ANN)	1396	975	231	37	722	994	772	764	363	105	419	609	794
Type III (PROSC)	1181	1172	507	8	927	1107	894	972	533	84	616	773	1106
Type I (PROSC)	10,880	10,591	4501	29	8687	9860	8046	8819	4793	785	5476	7128	10,146
Type IV (PROSC)	1181	1172	507	8	927	1107	894	972	533	84	616	773	1106
Type II (PROSC)	10,880	10,591	4501	29	8687	9860	8046	8819	4793	785	5476	7128	10,146
Type III (CCI)	10,880	10,591	4501	29	8687	9860	8046	8819	4793	785	5476	7128	10,146
Type I (CCI)	10,880	10,591	4501	29	8687	9860	8046	8819	4793	785	5476	7128	10,146
Type IV (CCI)	1839	2230	1759	76	1989	2123	2131	2188	1735	80	1713	1673	2172
Type II (CCI)	1839	2230	1759	76	1989	2123	2131	2188	1735	80	1713	1673	2172
Type III (WILL)	598	695	498	14	588	656	591	640	458	43	577	529	688
Type I (WILL)	3048	3446	2429	69	2903	3126	2719	3112	2112	275	2916	2696	3604
Type IV (WILL)	598	695	499	14	589	656	593	641	458	43	578	529	690
Type II (WILL)	3051	3446	2430	69	2905	3126	2724	3115	2112	275	2917	2697	3606
Type III (RSI)	520	586	414	15	474	495	482	541	282	43	402	501	628
Type I (RSI)	3454	4133	2632	34	3173	3162	3072	3913	1798	307	2592	3362	4459
Type IV (RSI)	520	586	414	15	474	495	482	542	282	43	402	501	628
Type II (RSI)	3454	4133	2632	34	3173	3162	3072	3914	1798	307	2592	3362	4459
Type III (MA600)	170	190	156	14	182	205	172	197	161	11	170	166	180
Type I (MA600)	170	190	156	14	182	205	172	197	161	11	170	166	180
Type IV (MA600)	278	320	262	22	296	346	281	315	265	18	284	283	290
Type II (MA600)	278	320	262	22	296	346	281	315	265	18	284	283	290
Type III (MA900)	162	152	120	7	147	147	126	167	149	8	146	132	155
Type I (MA900)	162	152	120	7	147	147	126	167	149	8	146	132	155
Type IV (MA900)	272	250	196	12	244	249	193	274	245	12	244	215	260
Type II (MA900)	272	250	196	12	244	249	193	274	245	12	244	215	260
Type III (MA1800)	78	119	72	4	112	130	106	123	114	2	113	84	107
Type I (MA1800)	78	119	72	4	112	130	106	123	114	2	113	84	107
Type IV (MA1800)	124	194	118	7	183	219	173	205	190	2	184	138	177
Type II (MA1800)	124	194	118	7	183	219	173	205	190	2	184	138	177

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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