Explorations in the use of artificial intelligence techniques and short-term econometric forecasting in the €-$ market

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Abstract. The paper uses a short-term GARCH multi-equation model, estimated between 1999 and 2007, in order to issue Long/Short trading signals for €-$ day-trading, based on its appreciation/depreciation forecasts. Optimal stopping values, i.e. Stop-Loss (SL) and Take Profit (TP) are determined by two Artificial Intelligence (AI) techniques: a data-mining version of a Genetic Algorithm and a neuro-fuzzy combination of a Fuzzy Controller and a Neural Network. Optimality here consists of getting the highest trading profit consistent with the smallest number of trading Drawdowns (DD) and the smallest amount of losses, originating from them. The two AI methods are used to reach this goal. Both AI protocols are trained for 750 trading days, between 2008 and 2010. They are then used in Testing or Trading mode for 782 days, between 2011 and 2013. The combination of econometric forecasting and AI produces a Profits-DD trade-off locus of the expected positive slope: the higher the profits, the higher the DD. The results indicate a far superior performance, for €-$ day-trading, of our AI-optimized rules with respect of a B&Hold strategy. The same holds true also for cumulative profits obtained with the use of a set of broad consensus TP and SL values among traders. As expected, profits are lower in the Training Set than in the Trading Set for both methods; DD are slightly lower in the Trading Set than in the Training Set, as hoped for. But in ratio terms, the two techniques yield substantially comparable results. In a broad conclusion: (a) the combination of Econometrics and AI is a winning strategy, (b) this result is confirmed by the similar results of our two AI protocols.

Keywords. Foreign exchange trading rules, €-$, news, Neuro-Fuzzy techniques, Genetic Algorithms.

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1 Introduction

This paper is exploratory mainly on one particular issue: how to combine econometric forecasts of exchange rates, for deciding the direction of a trade (buying or selling Euro-Dollar), with optimal stopping rules for it, by using Artificial Intelligence (AI) methods, in a day-trading environment.

The use of econometrics to forecast the short term movements of one exchange rate is used to establish the direction long or short for a day-trade. This approach is not frequent in a market practice which uses mainly charting techniques and automated trading procedures, based on technical movements of the exchange rate (for instance [5]).

AI is used here, in combination with econometrics, to find the best Stop Loss (SL) or Take Profit(TP) for closing the trade. The AI techniques are examined both singularly and jointly. They belong to the families of the Genetic Algorithms (GA), Fuzzy Logic Controllers (FLC) and Neural Networks (NN). In a first, experiment we use a data-mining variant of GA in isolation (a GA-Only). This last definition means that we use some GA procedures employed to find optimal biological matchings. We do not use here the parts of GA programmes aimed at finding the fittest pairs. In a second experiment, a combination of a FLC and of a NN receives some outputs from the first experiment and uses the same type of GA to refine the output data of the latter. We thus have a FLC+NN+GA procedure.

The two main positive results of our exploration are the following. Firstly, we wish to underline the profitable nature of using econometric techniques to forecast the direction of the exchange rate in the very short term, in conjunction with AI methods to find optimal trade-closing procedures. This profitable situation is enhanced by using AI techniques, as shown by the upward-sloping equity lines of our day-trading activity over and above a simple Buy-and-Hold strategy and over a common sense approach, frequently used by traders (see later).

Secondly, the use of both the GA-Only protocol and of the mixed technique made up by a sequence FLC+NN+GA (as more widely described by [10]) yields comparable results. This indicates that the joint use of econometric forecasting models, to establish the trading direction, and of AI techniques, to find the best parameters for closing the trade, can be very promising for day-trading in the forex market.

The similarity of results is due, to some extent, to the common information used by the two AI methods (GA-Only and FLC+NN+GA), notwithstanding their rather different inner logics. In the first place, the day-trading direction (coming from the econometric forecast) is shared by the two protocols. Besides, the FLC+NN+GA gets its initial parameters from the GA Only output, consisting of the optimal parameters found there. So the inputs of the FLC+NN+GA are all conditional on the various extrema, contained between the highest and the lowest (numerically) values used in the GA-Only optimality search.

We left some loose ends in the above brief description of our work. We want to give full details of them all in the paper, as articulated in the following sections.

Section 2 will describe the day-trading decision protocol using the model (to be described in the Appendix). Here we have a description of the trading zones and how they impinge on the trading protocol. Here we will show how a decision is taken for going Long or Short the €-$ with model-based trading signals. We will discuss the role of Stop-Loss (SL) and Take-Profit (TP) plus the role of other parameters relevant for trading in our context. We will highlight the usefulness of AI to spot profit-maximizing values for these parameters.

The AI methods used in this paper will be described in Section 3.

Section 4 will be devoted to describe our results. Here we will describe - in terms of financial analysis - the AI techniques used in the paper and their role. We will show their similarities, as anticipated above. We will describe how cumulative profits evolve by using some of the optimal parameters and will compare them with those coming from a Buy-and-Hold (BH) strategy and a Common Sense (CS) approach. We will show how we implemented AI methods to improve profitability, but also to reduce, as much as possible, the volatility of day-trading results. This latter task consists of forcing our protocols in order to keep as low as possible the amount of drawdowns (DD).

Some Summary and Conclusion lines, with some indication of present and future directions of our work, will be in Section 5.

2 Day-trading with Econometrics and with some Artificial Intelligence techniques

Day-trading has become the most widespread tool in financial markets. In the case of the foreign exchange market, this situation was accelerated - from a scientific viewpoint - by a famous article and a subsequent widespread literature on the failure of the regression model to beat the random walk in forecasting short-term exchange rate movements ([8]).

Other powerful forces brought about this situation: unpredictability of asset price movements in the information era, with the massive amount of web-based online information, risk reduction and the production of a wide spectrum of technical trading tools over the short time span, frequently in automated mode ([4, 5]).

The €-$ investment strategy of this paper is based on construction and use of econometric tools to produce long-short trading signals quite differently from the vast array of technical systems, both automated or not.

The production of trading signals for going long or short the €-$ rate is taken by simulating a three-zone (see Figure 1), news based, GARCH model, described in the Appendix. The decision to go Long or Short the exchange rate is taken only on the basis of the appreciation or depreciation forecast and not of the point forecast.

Frequent use of this approach, by the authors, has shown that the prediction of the exchange rate movements in the first 2-3 hours after the forecast is quite accurate. Then the management of day-trading positions by the whole community of world traders leads to reversals and the initial long/short trading instruction is not necessarily right. Therefore, all it is needed for a successful use of our model-based approach, is finding optimal stopping rules, in terms of Stop-Loss (SL) or Take-Profit (TP), after the initial hours of trading, where the directional advice is generally correct. It is here that AI is very useful.

Figure 1 (hours are at London time) gives a representation of the 24-hour Global Trading Day (GTD), when the market operates.It goes from the closing of Wall Street in the previous day to its present-day closing. The tri-partition of GTD is approximately based on the opening hours of the main financial centres of the three trading zones: Tokyo (Japanese Time Zone, JTZ)[1], London and continental Europe (European Time Zone, ETZ), New York (American Time Zone, ATZ)[2] .

In this paper, the analysis will be carried out in reference to ETZ and ATZ only and we will limit ourselves only to €-$ rate, for space constraint. Each trading zone lasts for eight hours. In our approach a trade is placed at the beginning (or nearly so[3]) of ETZ and ATZ and must be closed by the end of the same trading zone.

The coincidence of time zone and trading zone is precise only for ATZ. Most US macroeconomic data are published at 1:30 (London Time). In the early hours of ATZ, forex trading is then very busy because London and New York operate at the same time. Then, after 4-5PM, Europe closes for the day and trading gets lighter and lighter. It then gets negligible - under ordinary circumstances - after the closing of Wall Street at 9PM (London), waiting for a new GTD and for the moves of the early birds (traders jargon, meaning traders arriving at their desks very early in the morning) in JTZ.

Figure 2 describes our directional trading protocol. For simplicity, we make reference only to ETZ. The model is updated and simulated before 7AM. It goes without saying that, in this simulation, no scheduled and unscheduled news are used as they are unknown ex-ante. Only known variables (at 7AM) are employed in the appreciation or depreciation forecasts. This forecast recommends either a Long trade or a Short trade.

The initial directional information is further refined by watching at the movements of €-$ (ER in the Figure) in the early period, between 7-8AM. If a Long recommendation is issued, the protocol checks whether the ER goes reasonably below a certain threshold (THR^L in the Figure). The expectation here is for a

[1] This definition of JTZ was adopted long ago, when the Japanese market was by far the most important in the region. Today the situation is somewhat different.

[2] This tri-partition was adopted to better evaluate the impact of news on the forex dynamics, in three homogeneous zones. In the Appendix, we see how the model deals with three different currency pairs.

[3] In ETZ, heavy volumes of forex trading get visible at 7AM (not at 5AM), London time, when the main financial centres in Europe open for business.

bounce back and a movement in the right direction[4]. If that happens, the trader takes a Long position and sets a SL^L and TP^L. If the €-$ does not go below the threshold, THR^L, no trading gets underway.

Moving forward to the right in Figure 2, the Long position (recalling that we are following a Long example) is closed when a TP^L or SL^L is reached. If neither one is reached, the trade is closed at 1PM, the end of ETZ. Then ATZ activity gets underway and a lot of US macroeconomic information (frequently macroeconomic surprises) becomes available. A Short signal works very much under the same logics.

From Fig. 2 we see that the direction of the trade is initially based on the Long/Short signal coming from the model. But the final trading outcome is determined by a successful choice of the threshold (THR^L and THR^S) and of the TP^L, TP^S and SL^L, SL^S. In this choice a data mining version of the Genetic Algorithm (GA) is very useful, as shown in Figure 3. Here GA determines, for both Longs and Shorts, the combination of TP^L, TP^S, SL^L, SL^S, THR^L and THR^S for maximum profit.

The GA-Only protocol does not take care of the amount of drawdowns (DD), namely the number of contiguous days where the trading activity loses money. It can be easily imagined that a high and frequent occurrence of DD - and of the losses associated with them - causes deep psychological disturbances to traders, frequently leading to the interruption of this activity.

The functioning of GA-Only protocol, adopted here, starts its search for optimal TP^L, TP^S, SL^L, SL^S, THR^L, THR^S (for both Longs and Shorts) from numerical lower and upper bounds. In this GA-Only procedure we ran 55 optimizations, with lower and upper bounds. Figure 4 shows the behaviour of Profits (in Basis Points, vertical axis) and of the number of DD. Figure 5 does the same but with reference to a ratio Profits/DD. for various combinations of these boundary values. The two charts have various combinations of boundary values in the horizontal axis. They go from 1 to 55. The couples of boundary values start from the couple 0.0010-0.0060 and goes up to 0.0050-0.0150. The metrics of the above numbers consists of basis points of the Euro-Dollar exchange rate. The GA-Only algorithm searches SL, TP, THR, for maximum profits, starting from the above bounds, and gives as an output the thresholds, THR^L THR^S, and the trading stops, TP^L, SL^L, for Longs, or TP^S, SL^S, for Shorts.

The 55 combinations are organized in 5 categories (11 couples each) of search-starting parameters between the vertical bars in Figures 4 and 5. From them, we see that both variables(Profits and Profits/DD) have a downward-sloping trend[5].

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[4] This empirical regularity was observed, before 2008, in the long testing period, with actual trading. Today the same is true, but to a lower extent because of the great expansion of trend-following automated algorithms

[5] This indicates that increasing the lower bound of the 55 couples and leaving the same progression in the upper bound (from 0.0060 to 0.0150) causes a deterioration of the Profit-DD trade-off. The trading mechanism studied here produces always a SL much lower than the TP (a typical strategy of traders, see Tables 2 and 4). In

The use of a more complex Neuro-Fuzzy AI technique (FLC+NN+GA) was aimed at obtaining optimal profits, under the constraint of the smallest DD, inside the same algorithm, among the 74 AI neuro-fuzzy optimizations which we ran. Our aim was to confirm the results obtained with GA-Only. And that happened.

3 The FNC+NN+GA Artificial Intelligence method

In order to obtain the optimal stopping parameters of our trading rules, we used a combination of AI techniques: Fuzzy Logic, Genetic Algorithms and Neural Networks [9]. In Figure 6 is shown the block diagram which combines FL, NN and GA (for FLC+NN+GA).

The AI procedure starts with 3 references values of the profit, p_r, drawdown number, ndd_r (DD), and losses connected with the DD, l_r[6]. These values are shown on the left hand side of the Figure 6, numbered 1,2,3.

These inputs are compared with the 55 values coming from the GA-Only outputs, i.e. the profit p, drawdown number ndd and losses l. That corresponds to the rectangular shapes on the left of the figure.

The beginning values of the Fuzzy Logic part of the AI procedure are computed by the econometric model+directional trading rule (EDT) with suitable values of the inputs TP, SL and THR. Such values are matched with the profit, drawdowns number and losses values, coming from the optimization of the model with GA-Only, in search of closer values of p_r, ndd_r and l_r respectively.

In this way, we obtain the initial values of $TP1_0$, $SL1_0$, $TP2_0$, $SL2_0$ besides $thr1_0$ and $thr2_0$ (where the numbers 1 and 2 in the symbols refer, respectively, to Longs and Shorts),which are given as inputs of EDT, in a second round. EDT produces the outputs p, ndd and l which are compared pairwise with the respective references values (originally derived, as indicated above, by the GA-Only routine) through a series of feedbacks. In others words, we compute the difference between the parameters computed with EDT and the references parameters. Moreover, our method takes into account also the rate of change of this difference. Whenever this difference gets negligible, these parametric quantities are passed onto the FLC, as inputs. See Figure 6.

The inputs of the FLC, obtained as difference, are the errors, e, producing the change in error, de, of p n_{dd} and l, defined by the equations (1) and (2), below, where i comes from the $i-th$ feedback.

$$\begin{aligned} e_p(i) &= p(i) - p_r \\ e_{ndd}(i) &= ndd(i) - ndd_r \\ e_l(i) &= l(i) - l_r \end{aligned} \tag{1}$$

these tables we report only the 7 best (profitwise) boundary combinations, amongst the 55 we computed.

[6] These reference values are supplied by the user of this optimization technique as reasonable or maybe desired values for these quantities.

Table 1. Fuzzy rules

e \ de	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NS	NS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	PS	PS	PM	PB	PB	PB

$$\begin{array}{l} de_p(i) = e_p(i) - e_p(i-1) \\ de_{ndd}(i) = e_{ndd}(i) - e_{ndd}(i-1) \\ de_l(i) = e_l(i) - e_l(i-1) \end{array} \tag{2}$$

The design of the FLCs depends on the knowledge of the initial optimization by GA-Only. In fact, through GA-Only, the optimal values (in terms of profit) of SL, TP and THR are investigated and eventually obtained. By means of this knowledge, the slopes of the membership functions are defined. We define the shape of the membership functions on the base of the specific application.

The shape of the membership functions is triangular/trapezoidal. The membership functions are: NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZE (Zero), PS (Positive Small), PM (Positive Medium) and PB (Positive Big). The fuzzy rules, thus obtained, are shown in Table 1. During the rule-designing-process, we have discovered that increasing the number of rules and of membership functions beyond 49 rules is a futile procedure. In fact, this procedure increases the complexity of the FLC but has no effect on output response of the system.

The combination of the outputs of the FLCs supplies the crisp value *out*. This value is the input value of the block tuning function (see the central part of Figure 6) which adjusts the values of TP, SL and THR on the basis of *out* value. In others terms, it is: $TP^L = TP^L(out)$, $SL^L = SL^L(out)$, $TP^S = TP^S(out)$, $SL^S = SL^S(out)$, $THR^L = THR^L(out)$ and $THR^S = THR^S(out)$.

The tuning function gives as output the five parameters SL^L, TP^L, SL^S, TP^S and THR, which are passed to the trading rules, EDT. The outputs of EDT (profits, p, DD number, ndd, and losses, l) are then fed back again (as feedback signals) in order to be compared with the references values, hypothesized in the beginning of the AI procedure. Once that a threshold value for the AI optimization or the max number of iterations are reached, the updated values of p, ndd and l, resulting as the output values of the FLC part of the programme, are passed to the neural network, NN. See the right part of Figure 6.

The design of neural networks for specific applications is often a trial and error process. This process sometimes depends mainly on previous experience in similar applications. Moreover, the performances and the cost of a neural network depend on the choice of the neurons number, net architecture and learning algorithms.

As widely known, any NN needs a suitable specification of a training set (TNS) and a test set, which in the case of this paper is called a trading set (TRS). The TNS set of our NN has three inputs and ten outputs; the reasons follow.

For each value of the profit, we consider the contribution to the DD number and the connected losses. In particular, the value of the profit p changes with the rate n_{dd}/l (the ratio of the number of DD over the amount of the losses, l). In the same way, the extrema of SL, TP and THR depend on the same rate. Thus, the TNS has three inputs (p, ndd and l) and ten outputs (two for each output parameter: SL, TP, both for Longs and Shorts, and one THR. See Figure 6).

The input layer of the network has three neurons, corresponding to the parameters p, ndd and l. The output layer has ten neurons because there are five range of optimization and each range has two extrema. The neurons number of the hidden layers typically is determined by a specific application. Our hidden layer has seven neurons. The net is trained through a TNS which comes from the experiment at hands. Ours is defined in the second period of next paragraph. The outputs of the neural network, i.e. the optimization ranges (between the upper and lower levels of our 5 optimal stopping parameters), are passed to a new GA [1, 2, 7]. This GA algorithm searches inside the 9 ranges, defined by the 10 extrema described above, the best SL^L, TP^L, SL^S, TP^S and THR which give the maximum profit, consistent with the lowest number of DD. Once the stopping criteria are reached, the algorithm supplies the best stopping parameters. They will then be used in the trading exercises, described in the paragraphs contiguous to this one.

We designed above a NN able to supply the best ranges over which the GA optimizes the trading parameters. However, there are a few other algorithms to optimize parameters. In the future, we will take into account optimization methods as Particle Swarm Optimization [6], Differential Evolution [14] and Gravitational Search Algorithm [13].

4 Findings of the exploration

Lets recap what we saw so far. The use of a news-based GARCH forecasting model gives a Long or Short opening signal in each trading day. Once the trsding signal is issued, there is a number of key parameters which govern any subsequent decisions: thresholds (THR^L, THR^S) and stops, SL^L, TP^L, SL^S, TP^S.

As for every automated trading technique and for the proper use of AI applications, a Training Set (TNS) and a Trading Set (TRS) must be established.

In the TNS, the AI techniques find optimal values of unknown parameters, in our case THR^L, THR^S, SL^L, SL^S, TP^L, TP^S[7]. In this paper the econometric model is estimated between 1999 and 2007, The TNS goes from February 18, 2008 through to December 31, 2010. The TRS goes from January 3, 2011 to December 31, 2013.

Optimal values of the threshold THR and of SL and TP, for the highest Profit, are initially searched via a GA-Only algorithm. This technique does not care about DD, meaning that only profits are optimized. In the FLC+NN+GA protocol optimality aims at the highest profits, consistent with the smallest number of DD and with the smallest amount of losses connected with DD.

The comparison between GA-Only and FLC+NN+GA is carried out by comparing the Profit/DD results (i.e. profits expressed in basis points divided by the number of DD) in the former experiments (GA-Only) with the corresponding ones carried out in the latter (Tables 3 and 5).

The Figures 7 and 8 report scatter-plots of Profit (expressed in Basis Points, on the vertical axis) versus the number of DD (total number of DD[8], in the horizontal axis). The slope must be a positive number: the higher the Profits the higher the DD. A higher slope of the interpolating line indicates a more favourable relation between Profits and DD: for the same number of DD, Profits are higher.

Figure 7 deals with the GA-Only algorithm: in the upper panel we have the TNS, in the lower panel we have the TRS. Straight lines interpolate the scatter-plot. The slopes of the interpolation lines in the upper and lower pannels (0.0084, 0.0051) indicate that a slightly better trade-off relation between Profits and DD is observed in the TNS than in the TRS, as to be expected. This for GA-Only. The same relationship holds true in Fig 8, where we deal with the more complex FLC+NN+GA (slopes of 0.0114 in the TNS and 0.0054).

Tables 2, 3, 4, 5 give more detailed results in the comparison of GA-Only with FLC+NN+GA. Here we do not use the entire number of experiments (55, for GA-Only, and 74, for FLC+NN+GA) but only those yielding better Profits/DD results. They are 7 experiments with the lower and upper bounds for optimization shown in columns a in Table 2 (GA-Only) and in Table 4 (FLC+NN+GA). These extrema are those in the first partition on the left in Figure 4 and 5.

In Tables 2 and 4 we report minimum and maximum boundary values, for GA-Only and for FLC+NN+GA; plus their SL,TP and threshold values. Interestingly, the SL are invariably lower than the TP for Longs and Shorts, for both methods. This is in tune with the most frequent behaviour by traders: they pre-

[7] The TNS/TRS distinction is relevant only for the AI part of the day-trading procedure. The direction of the trade comes from the econometric part of the protocol. That it is true for both the TNS and the TRS. The optimal parameters are computed in the TNS. They are then used in the TRS. Besides, in our optimizations THR^L is equal to THR^S, namely the trading threshold is imposed to be equal for both Longs and Shorts

[8] It is worth pointing out that the highest number of DD is concentrated in the two-day length. Then the number of higher-length DD decrease quite a lot, but in one or two applications the length reached the ten-days DD.

fer to withstand comparatively more small losses in exchange for less frequent, but large, profits.

Table 3 reports, for the GA-Only TNS and TRS, Profits and DD, for each one of the seven experiments. Here the results to be noticed are the sizeable decrease of Profits going from the TNS to the TRS, fortunately accompanied by a comparable decrease of DD. But looking at the third and sixth columns (c), we see a deterioration of the ratio Profits / DD. So the lower Profits seen when moving from TNS to TRS decrease more than the reduction in the number of DD.

Tables 3 and 5 show the same typology of numbers and statistics, for the FLC+NN+GA protocol. Obviously SL, TP and thresholds are different from those of GA-Only, but the same feature of the stop values remain the same: SL are lower than TP. The same result, as for GA-Only, is true by comparing Profits and DD in the TNS and TRS.

Our system for evaluating the comparative performance of GA-Only versus FLC+NN+GA is looking at the Profits / DD ratios. In comparing the relevant numbers in the columns 3 and 6 in Tables 3 and 5 (indicated as c) we see that in the TRS they are basically the same (0.0057 and 0.0057, column 6).

Moving from the simpler GA-Only to FLC+NN+GA, the overall Profits-DD trade-off is comparable, with only marginal differences. That was our goal: confirming the good performance obtained with the GA-Only optimizations with those of FLC+NN+GA.

The next step is looking at our results the same way traders do. How do cumulative profits from our two techniques perform overtime? Traders assess that by drawing cumulative profits charts, which they call equity lines. In this paper we draw cumulative profit lines referred to the TRS for both AI techniques (GA-Only, Figure 9, and FLC+NN+GA, Figure 10). We evaluate our results by comparing the equity lines of the 2 AI experiments (GA-Only and FLC+NN+GA) with those obtained with Common Sense (CS) parameters, typically used by traders (Figures 11 and 13) and with a Buy and Hold (BH) strategy (Figures 12 and 14).

The CS trading strategy uses symmetric SL and TP of 0.0030 (30 Basis Points) and a THR, for both Longs and Shorts, of 0.0007. Similar parameters are quite commonly used and are those we arrived at after a lengthy experimentation of our model, also for proprietary trading. The second benchmark, BH, is standard in assessing trading rules. In our case the BH simulation reflects the trading environment of our exercises: opening occurs at the beginning of a trading zone (nearly so in ETZ) and closing occurs at the end of the time zone.

All the charts show seven equity lines, corresponding to the trades highlighted in Tables 2-5. The equity lines have solidly continuous upward slopes. The last value on the right of each cumulative profit line shows the total profit of the entire trading exercise. Profits on the vertical line are measured in Basis Points (BP). These values correspond to the annualized profits, in percentage form, in Tables 3 and 5 (first columns).

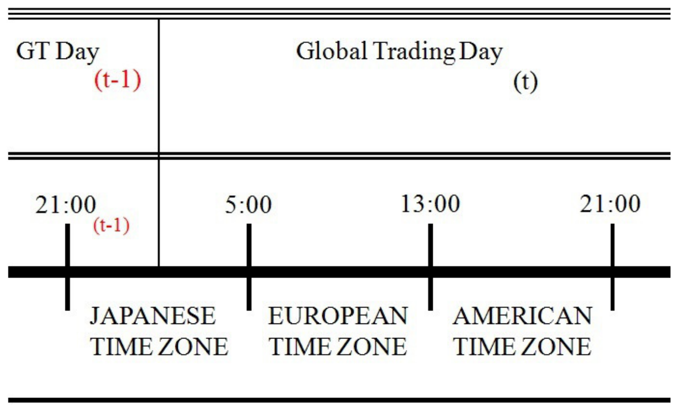

Fig. 1. Three trading zones in the Global Trading Day, GTD

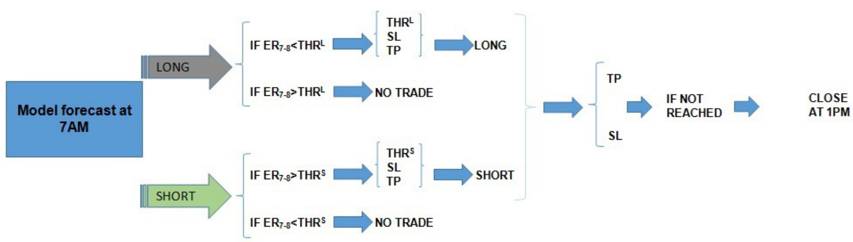

Fig. 2. Directional trading in ETZ

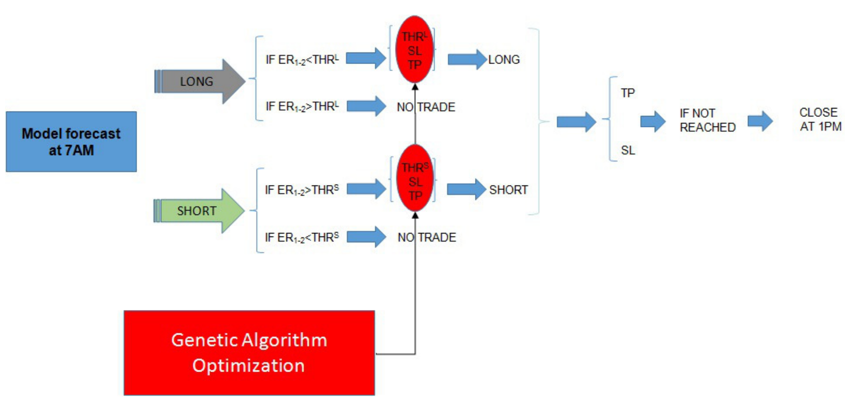

Fig. 3. Directional trading and parameter optimization in ETZ

Looking at the TRS of both AI schemes, all equity lines - based on optimal parameters - beat those of the CS strategy, which are based just on plausible SL, TP, THR parameters. The BH cumulative rotates around zero.

Table 2. GA-only in training and trading set (TNS:Feb.18,2008 - Dec. 31, 2010 TRS: Jan.3,2011 - Dec.31,2013)

PARAMETERS OBTAINED IN THE TRAINING SET					
EXTREMA FEATURES [a]	STOP-LOSS FOR LONGS [b]	TAKE-PROFIT FOR LONGS [b]	STOP-LOSS FOR SHORTS [b]	TAKE-PROFIT FOR SHORTS [b]	OPENING THRESHOLD [b]
0.0010-0.0090	0,0010055	0,0061957	0,0010128	0,0083675	0,00099911
0.0010-0.0105	0,0010003	0,0084723	0,001	0,0096684	0,00078032
0.0010-0.0115	0,0010287	0,0086675	0,0010189	0,010157	0,00098346
0.0010-0.0120	0,0010052	0,010072	0,0011066	0,010025	0,00089725
0.0010-0.0125	0,0010202	0,010622	0,001	0,0109	0,00089452
0.0010-0.0135	0,0010111	0,0084196	0,0010156	0,0099615	0,00098572
0.0010-0.0150	0,001	0,0063015	0,0010212	0,012239	0,0009903
MEAN VALUES	0,0010101	0,0083929	0,0010250	0,0101883	0,000933

[a] This is a group of GA extrema values - in €-$ Basis Points - which operate as lower and upper boundary values where the data mining programme searches for profit-maximizing optimal values of SL and TP.

[b] These are the profit-maximizing SL and TP obtained respectively by the GA-Only.

Table 3. GA-only in training and trading set (TNS:Feb.18,2008 - Dec. 31, 2010 TRS: Jan.3,2011 - Dec.31,2013)

TRAINING SET			TRADING SET		
PROFIT RATES IN TNS [a]	DRAWDOWNS IN TNS [b]	PROF./DRAWD. IN TNS [c]	PROFIT RATES IN TRS [a]	DRAWDOWNS IN TRS [b]	PROF./DRAWD. IN TRS [c]
26,03	102	0,007361	17,65	95	0,005587
24,48	117	0,006035	18,41	101	0,005483
26,43	105	0,007262	18,12	94	0,005797
26,63	109	0,00705	21,19	97	0,006571
24,81	113	0,006335	20,05	96	0,00628
25,36	106	0,006903	17,35	95	0,005493
25,75	103	0,007211	17,67	96	0,00491
25,64[d]	107,86	0,006880	18,63	96,29	0,005732

[a] Starting from profit/loss daily values in Basis Points, these annualized profit numbers are obtained by dividing the total cumulated profit values by the total trading days (750 for TNS and 782 for TRS), multiplied by 260 (the business days in one year).

[b] This is the total number of DD in the seven trading exercises, consisting of the sum of DD of 2 days, 3 days, up the the maximum observable DD lenghth.

[c] This the ratio of profits (in Bassis Points) over the total number of DD.

[d] This is a Mean Value, as all subsequent values in the same line are.

Table 4. FLC+NN+GA in training and trading set (TNS:Feb.18,2008 - Dec. 31, 2010 TRS: Jan.3,2011 - Dec.31,2013)

PARAMETERS OBTAINED IN THE TRAINING SET					
EXTREMA FEATURES [a]	STOP.LOSS FOR LONGS [b]	TAKE-PROFIT FOR LONGS [b]	STOP-LOSS FOR SHORTS [b]	TAKE-PROFIT FOR SHORTS [b]	OPENING THRESHOLD [b]
0.0010-0.0090	0,000915	0,001119	0,003377	0,017717	0,000891
0.0010-0.0105	0,000912	0,001124	0,003198	0,017742	0,000899
0.0010-0.0115	0,000834	0,00102	0,007753	0,012687	0,000894
0.0010-0.0120	0,000823	0,000815	0,008491	0,012641	0,000893
0.0010-0.0125	0,000804	0,000821	0,008491	0,012679	0,000897
0.0010-0.0135	0,000827	0,001102	0,007718	0,012662	0,0009
0.0010-0.0150	0,001005	0,001206	0,002498	0,017669	0,000799
MEAN VALUES	0,0008743	0,0010296	0,0059323	0,0148281	0,0008819

[a] This is a group of GA extrema values - in €-$ Basis Points - which operate as lower and upper boundary values where the data mining programme searches for profit-maximizing optimal values of SL and TP.

[b] These are the profit-maximizing SL and TP obtained by the FLC-NN-GA programmes.

Table 5. FLC+NN+GA in training and trading set (TNS:Feb.18,2008 - Dec. 31, 2010 TRS: Jan.3,2011 - Dec.31,2013)

TRAINING SET			TRADING SET		
PROFIT RATES IN TNS [a]	DRAWDOWNS IN TNS [b]	PROF./DRAWD. IN TNS [c]	PROFIT RATES IN TRS [a]	DRAWDOWNS IN TRS [b]	PROF./DRAWD. IN TRS [c]
25,76	96	0,007739	15,25	93	0,004932
25,84	94	0,007928	15,41	93	0,004985
27,53	110	0,007219	19,53	98	0,005993
28,89	113	0,007375	20,98	98	0,006439
29,13	113	0,007436	21,18	98	0,0065
28,13	108	0,007513	19,59	99	0,0059522
24,53	86	0,008228	14,62	87	0,005054
27,12[d]	102,86	0,007634	18,08	95,14	0,005694

[a] Starting from profit/loss daily values in Basis Points, these annualized profit numbers are obtained by dividing the total cumulated profit values by the total trading days (750 for TNS and 782 for TRS), multiplied by 260 (the business days in one year).

[b] This is the total number of DD in the seven trading exercises, consisting of the sum of DD of 2 days, 3 days, up the the maximum observable DD lenghth.

[c] This the ratio of profits (in Bassis Points) over the total number of DD.

[d] This is a Mean Value, as all subsequent values in the same line are.

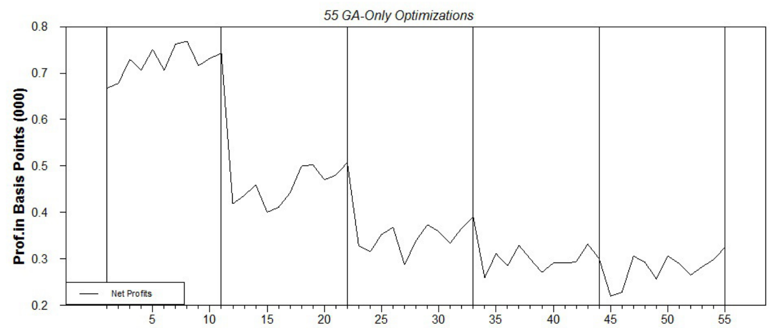

Fig. 4. Net profits per 55 families of GA-Only

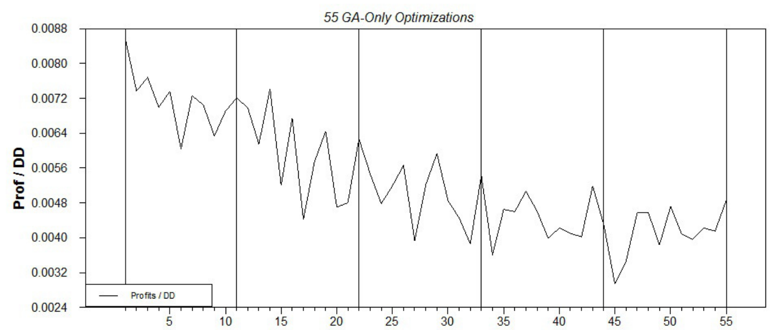

Fig. 5. Profits divided by DD per 55 families of GA-Only

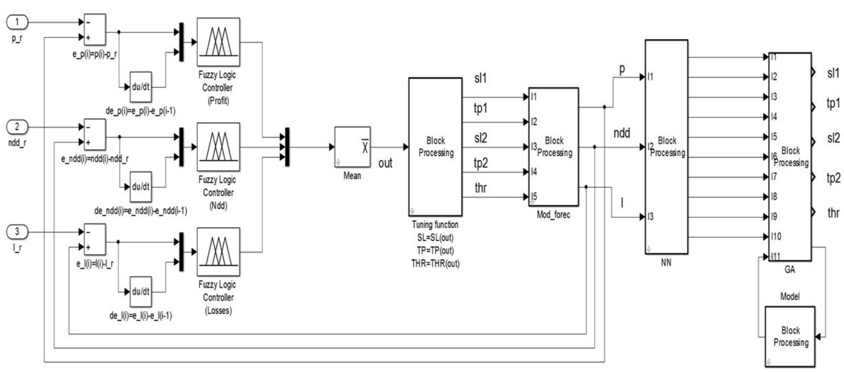

Fig. 6. A feedback FLC+NN+GA based on Model Forecast and Directional Trading (MFDT) technical flowchart

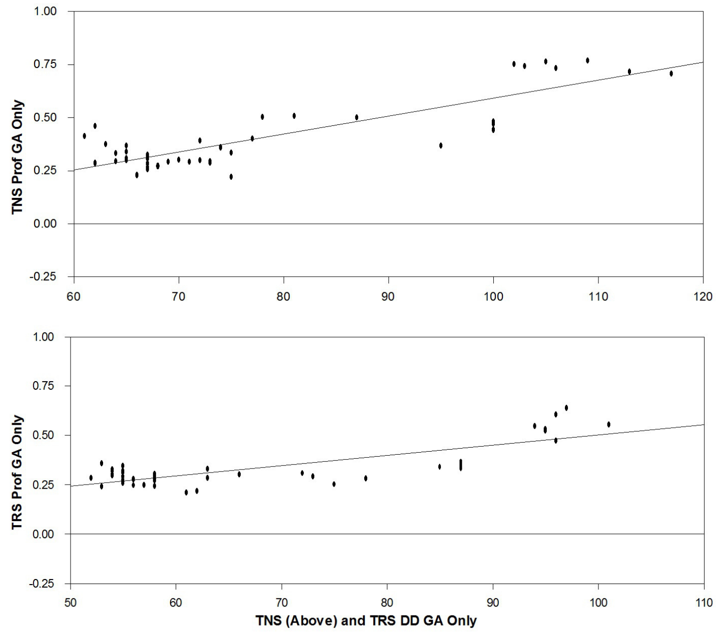

Fig. 7. Relationship between Profits and DD in TNS and TRS, GA only trading rules

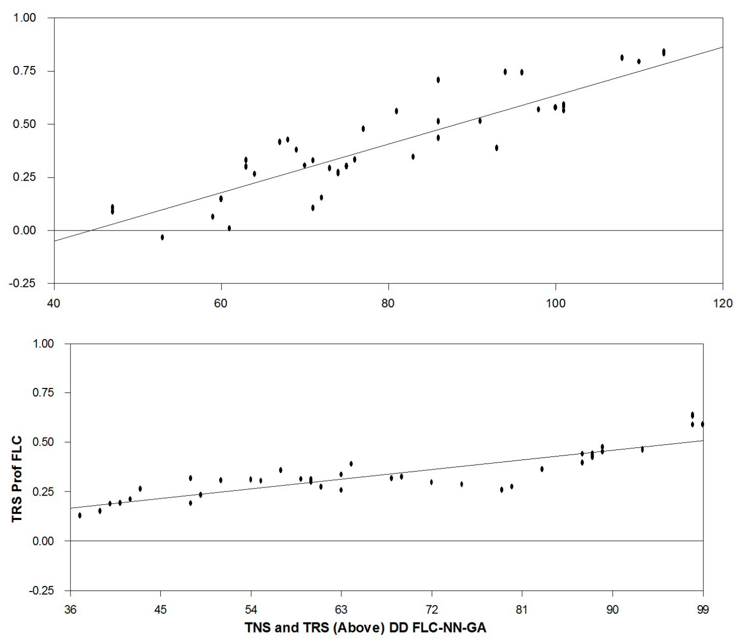

Fig. 8. Relationship between Profits and DD in TNS and TRS, FLC+NN+GA trading rules

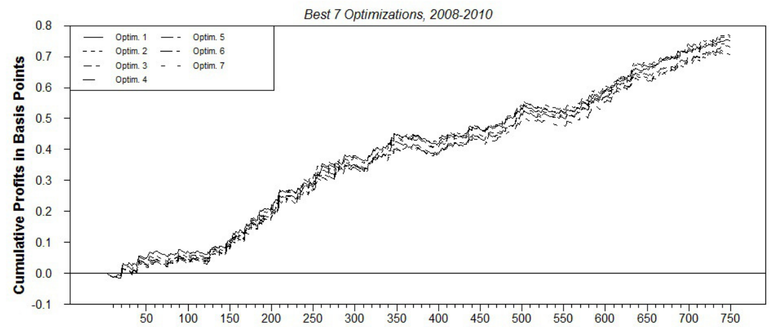

Fig. 9. €-$ Cumulative Profits in TRS with GA-Only

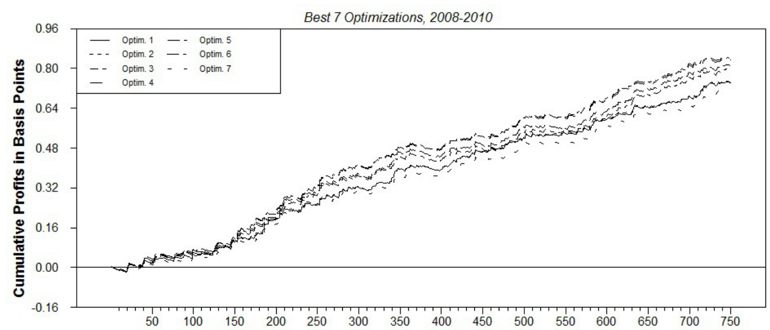

Fig. 10. €-$ Cumulative Profits in TRS with FLC-NN-GA

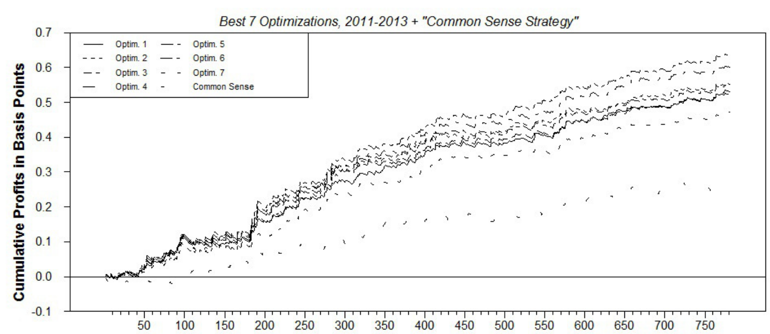

Fig. 11. €-$ Cumulative Profits in TRS with GA-Only, compared with a common sense strategy

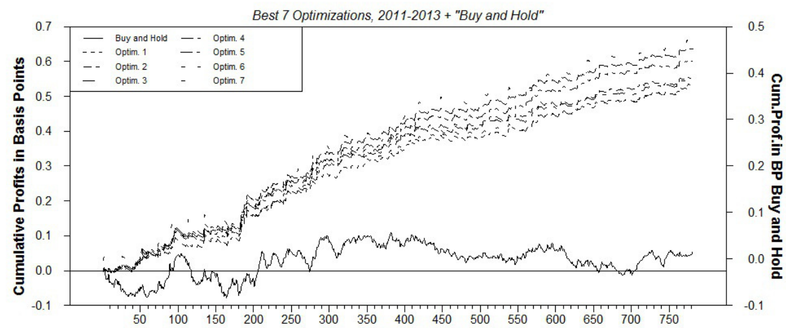

Fig. 12. €-$ Cumulative Profits in TRS with GA-Only, compared with a buy & hold

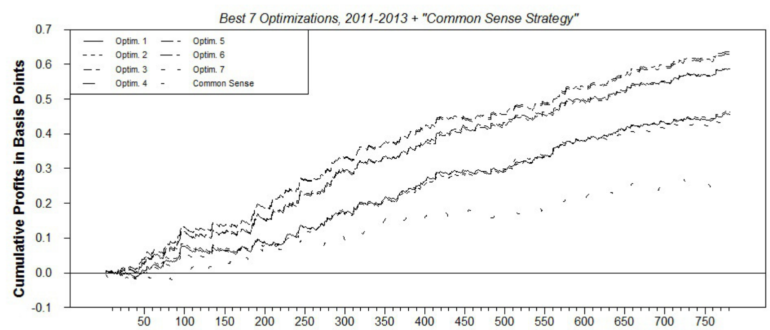

Fig. 13. €-$ Cumulative Profits in TRS with FLC-NN-GA, compared with a common sense strategy

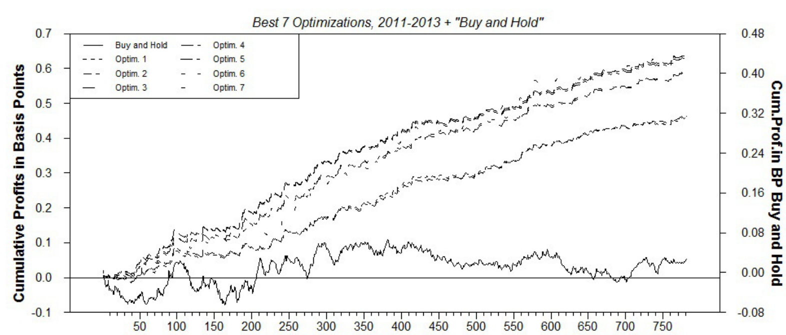

Fig. 14. €-$ Cumulative Profits in TRS with FLC-NN-GA, compared with a buy & hold

Table 6. Stop-loss take-profit and threshold. annualized profits and total drawdowns. GA-only in training set and FLC-NN-GA in trading set (TNS:Feb.18,2008 - Dec. 31, 2010 TRS: Jan.3,2011 - Dec.31,2013)

PARAMETERS OBTAINED IN THE TRAINING SET					
BEST TNS PROF/DD (*) [1]*[a]	STOP-LOSS FOR LONGS [2]**[b]	TAKE-PROFIT FOR LONGS [2]**	STOP-LOSS FOR SHORTS [2]**	TAKE-PROFIT FOR SHORTS [2]**	OPENING THRESHOLD [2]**
0,00832	0,00091	0,002183	0,001214	0,017599	0,000798
0,00796	0,000902	0,009996	0,001007	0,012752	0,000998
0,008008	0,000905	0,006786	0,001021	0,012759	0,000996
0,00845	0,000858	0,0026	0,001101	0,018087	0,0009
0,008052	0,000909	0,006787	0,001007	0,012772	0,000995
0,008501	0,000861	0,002497	0,001117	0,017695	0,0009
MEAN VALUES	0,0007636	0,0044070	0,0009239	0,0130949	0,0007981

[a] They are the best values (in terms of Prof / DD) coming from output values of the GA-Only protocol used in the TNS.

[b] These are the profit-maximizing SL and TP obtained by the GA-Only in the TNS.

5 Summary and Conclusion

No summary of this paper can be more synthetically exhaustive than its Abstract.

Here we want to clarify some elements of our work, which deserve some more attention.

The first word in the title of this paper is "'Explorations"'.

The main result of the exploration is how to combine econometric directional forecasting of short-term exchange rate movements, using it to issue Long/Short signal and apply AI methods to manage the trading position. This seems to be a winning solution.

Our work was based on a limited number of trading experiments: 55 GA-Only optimizations based on different boundary values and 44 simulations with FLC+NN+GA.

Lets further clarify here the experimental outlay. A series of approximately 1500 8-hour ahead forecasts for ETZ and ATZ (750, daily) were made for TNS, 782 daily for the TRS. In the GA-Only, the trading algorithm received exogenously the direction of the trade from model directional forecasts, then AI produced SL, TP and thresholds for the highest profit. No explicit DD constraint was placed here, but we simply computed the number of DD and the losses amount, consistent with each of the 55 optimized Profit results.

The FLC+NN+GA took off from the Profits, DD numbers and losses, explicitly associated with GA-Only boundary values used in the optimizations. That AI neuro-fuzzy system produced several Profits, DD and losses results (now explicitly linked together simultaneously) which were then optimized by a new passage of GA.

Table 7. stop-loss take-profit and threshold. annualized profits and total drawdowns. GA-only in training set and FLC-NN-GA in trading set (TNS:Feb.18,2008 - Dec. 31, 2010 TRS: Jan.3,2011 - Dec.31,2013)

TRAINING SET			TRADING SET		
PROFIT RATES IN TNS [3]****[a]	DRAWDOWNS IN TNS [4]*****[b]	PROF./DRAWD. IN TNS [5]******[c]	PROFIT RATES IN TRS [3]***	DRAWDOWNS IN TRS [4]****	PROF./DRAWD. IN TRS [5]*****
24,22	84	0,00832	14,2	81	0,005274
28,7	104	0,00796	19,34	96	0,006062
28,31	102	0,008008	17,31	96	0,005425
25,51	87	0,00845	14,17	86	0,004956
28,47	102	0,008052	17,43	96	0,00546
25,34	86	0,008501	14,22	85	0,005033
22,94	80,71	0,007042	13,81	77,14	0,004601

[a] Starting from profit/loss daily values in Basis Points, these annualized profit numbers are obtained by dividing the total cumulated values by the total trading days (750 for TNS and 782 for TRS), multiplied by 260 (the business days in one year).
[b] This is the total number of DD in the six trading exercises, consisting of the sum of DD of 2 days, 3 days, up the the maximum observable DD lenghth.
[c] This the ratio of profits (in Bassis Points) over the total number of DD.

A second result of our exploration was finding that two different AI methods (GA-Only and FLC+NN+GA) gave broadly similar results in terms of Profits-DD relations.

A further improvement of our day-trading approach we wish to reach is connecting overtime Profit-DD behaviour with the clustering of good and bad news (macroeconomic surprises and, most of all, unscheduled news) on our currency pair, the €-$.[9].

We believe our approach is an important step forward in the construction of a new kind of automated trading tool, which has the added advantage of being solidly anchored in statistics and in economic-financial theory.

6 Appendix

The trading rules presented in this paper are built on a multivariate GARCH model explaining the variation of (USD-JPY), (EUR-USD) and (GBP-USD) in the three trading zones: JTZ, ETZ and ATZ (see Figure 1). The specification and the coefficients are shown in Tables VI, VII. We will use in this paper only results for for (EUR-USD) in ETZ and ATZ. All the variables are standardized, therefore the coefficients are measure-free and can be compared among them.

[9] This is a less arduous accomplishment as it may appear because estimation of a news-based model implies that we have a pretty broad data base on news (see the Appendix and, for instance, [3, 15, 16])

It must be recalled again that the movements of the exchange rates are modelled across three trading zones in the GTD so the time unit is a period of eight hours and the rates are measured at the end of the zones. The lagged variables do not refer to the previous day but to the value observed at the end of the preceding eight-hour periods.

Let's look at the two models together, as they are represented in Tables VI (second column), and VII (columns 2, 4 and 5, since the ATZ model consists of 3 equations).

The specification of the model in European time (ETZ, here indicated with superscripts E) is in equation (3).

In the notation of the models, the current and lagged exchange rates are scalars. (\$/Y) is (USD-JPY), (E/\$) is (EUR-USD) and (£/\$) is (GPB-USD). The scheduled news, **sk** , representing surprise values of the main market moving macroeconomic variables, refer to their respective countries (UK, GE, US). Unscheduled news variables, **u**, refer, differently, to unexpected events, affecting exchange rates in the three trading areas. Both types of news are contained in partitioned vectors, whose number of elements can be pretty high.

The model in ETZ (superscripts E) is:

$$\begin{bmatrix} (\$/Y)_t^E \\ (E/\$)_t^E \\ (£/\$)_t^E \end{bmatrix} = \sum_{i=0}^{3} B_i^E \begin{bmatrix} (\$/Y)_{t-i} \\ (E/\$)_{t-i} \\ (£/\$)_{t-i} \end{bmatrix} + \\ + \Gamma^{SK,E} \begin{bmatrix} sk_t^{UK} \\ sk_t^{GE} \\ sk_{t-2}^{US} \end{bmatrix} + \\ + \Gamma^{UNSK,E} \begin{bmatrix} u_t^{\$/Y,E} \\ u_t^{E/\$,E} \\ u_t^{£/\$,E} \end{bmatrix} + \varepsilon_t^E \tag{3}$$

The error term vector and variance-covariance matrix is:

$$\varepsilon_t^E N\left(\mathbf{0}, H_t^E\right) \tag{4}$$

$$H_t^E = \Omega^E + \Gamma\left(\varepsilon_t^E\right)^2 B H_{t-1}^E \tag{5}$$

The parameter values of ETZ model (3) in B^E, $\Gamma^{SK,E}$ and $\Gamma^{UNSK,E}$ are reported in Tab. VI (column 2).

The scheduled news terms (**sk** in UK, GE, US) are built as the standardized difference between the actual data announced by the statistical authorities and their values expected by financial markets[10]. The unscheduled news (**u**, for the three currencies in ETZ) are represented by ternary vectors made of 0, when no

[10] The expected values here are produced by Bloomberg, by far the consensus provider today.

news occurs, +1 when a Euro (or Pound, or Yen)-positive news occurs, -1 when there is a negative news. Recall that the scheduled, **sk**, and unscheduled news, **u**, are represented as partitioned vectors.

The model in the American Time Zone is the following one in (6):

$$\begin{bmatrix} DJ_t \\ r_t^{US} \\ (\$/Y)_t^A \\ (E/\$)_t^A \\ (\pounds/\$)_t^A \end{bmatrix} = \sum_{i=0}^{3} B_i^A \begin{bmatrix} (Y/\$)_{t-i} \\ \\ (E/\$)_{t-i} \\ (\pounds/\$)_{t-i} \end{bmatrix} + \\ + \sum_{i=0}^{5} \Theta_i^A \begin{bmatrix} DJ_{t-i} \\ r_{t-i}^{US} \\ r_{t-i}^{UK} \\ r_{t-i}^{EU} \\ r_{t-i}^{JA} \\ \\ \end{bmatrix} + \\ + \Gamma^{SKED,A} \begin{bmatrix} sk_t^{US} \\ sk_{t-1}^{EU} \\ sk_{t-1}^{UK} \end{bmatrix} + \\ + \Gamma^{UNSK,A} \begin{bmatrix} u_t^{\$/Y,A} \\ u_t^{E/\$,A} \\ u_t^{\pounds/\$,A} \end{bmatrix} + \varepsilon_t^A \tag{6}$$

with error vector and covariance matrix as

$$\varepsilon_t^A N\left(\mathbf{0}, H_t^A\right) \tag{7}$$

$$H_t^A = \Omega^A + \Gamma\left(\varepsilon_t^A\right)^2 B H_{t-1}^A \tag{8}$$

The matrices of coefficients in (6), B^A, Θ^A, $\Gamma^{SK,A}$ and $\Gamma^{UNSK,A}$ contain the coefficients in Tab. VII, in the appropriate positions.

The ATZ model (superscripts A) is larger than those in the previous two trading zones because the Dow Jones (DJ) and the 10-year interest rates on Yen, Euro, Pound and Dollar (r^Y, r^E, $r^{\pounds}$, $r^{\$}$) are significant in all the exchange rate equations (Table VII). The basic specifications of $r^{\$}$ and DJ consist of an autoregressive part plus scheduled news. It is interesting to note that the $r^{\$}$ equation contains a pretty large number of them (see Table VII, column 5). The interest rates r^Y, r^E and $r^{\pounds}$ are exogenous in ATZ, as they are quoted earlier in the GTD.

Finally all the estimated coefficient are significant at the 99% level with just a few exceptions (indicated in the tables) and the signs are all correct.

Table 8. The Model in European Time Zone, ETZ

	FUNDAMENTALS	$\Delta(USD-JPY)$	$\Delta(EUR-USD)$	$\Delta(GBP-USD)$
0	Constant	-0.0054*[a]	-0.0655	-0.0144*
1	$\Delta(USD-JPY)_{t-1}$	-0.0482		
2	$\Delta(USD-JPY)_{t-2}$	-0.1035		
3	$\Delta(EUR-USD)_{t-1}$		-0.2552	
4	$\Delta(EUR-USD)_{t-2}$		-0.2068	
5	$\Delta(GBP-USD)_{t-1}$			-0.0637
6	$\Delta(GBP-USD)_{t-3}$			0.0447
7	$\Delta EUR-USD$	-0.1211		0.5597
	SKED.NEWS EUROLAND			
8	German IFO		0.2286	
9	German Unemployment			-0.2115
	SKED.NEWS[b] US			
10	$(Prod.PriceIndex)_{t-1}$	-0.1599	-0.1842	
11	$(PersonalIncome)_{t-1}$	-0.3387		
12	$(Cons.Conf.Michigan)_{t-1}$		-0.1275	
	SKED.NEWS UK			
13	Retail Price Index			0.2392
14	Retail Sales			0.3888
15	Industr. Production			0.2585
16	Visible Trade Bal.			0.1831
	UNSK.NEWS[c] ETZ			
17	BoJ Intervent.	-0.1104		
18	JPY Statements	-0.2141		
19	USD Statements	-0.1029		
20	JPY News	-0.4211		
21	USD News	-0.1934		
22	USD Polarization	-0.1791		
23	EUR-USD Statements		0.2807	
24	EUR-USD News		0.5142	
25	BCE Interventions		0.1649	
26	USD Polarization		0.3239	
27	GBP-USD Statements			0.1161
28	GBP-USD News			0.387
	GARCH			
29	Intercept	0.0315	0.0024	0.0162
30	Squared Error	0.0847	0.0194	0.0526
31	Lagged Volatility	0.8663	0.9765	0.914
32	Squared R Bar	0.38	0.39	0.51

[a] The coefficients with an asterisk are not significant at the 99%

[b] Scheduled news terms are built as the difference between the actual data announced by the statistical authorities and their values expected by financial markets divided by the standard error of this difference. When there are no news of this type, the vectors contain zeros.

[c] Unscheduled news are represented by ternary vectors made of 0, when no news occurs, +1 when a Euro(or Pound, or Yen)-positive news occurs, -1 when there is a negative news.

Table 9. The Model in European Time Zone, ETZ

	FUNDAMENTALS	$\Delta(USD-JPY)$	$\Delta(EUR-USD)$	$\Delta(GBP-USD)$
0	Constant	-0.0054*[a]	-0.0655	-0.0144*
1	$\Delta(USD-JPY)_{t-1}$	-0.0482		
2	$\Delta(USD-JPY)_{t-2}$	-0.1035		
3	$\Delta(EUR-USD)_{t-1}$		-0.2552	
4	$\Delta(EUR-USD)_{t-2}$		-0.2068	
5	$\Delta(GBP-USD)_{t-1}$			-0.0637
6	$\Delta(GBP-USD)_{t-3}$			0.0447
7	$\Delta EUR-USD$	-0.1211		0.5597
	SKED.NEWS EUROLAND			
8	German IFO		0.2286	
9	German Unemployment			-0.2115
	SKED.NEWS[b] US			
10	$(Prod.PriceIndex)_{t-1}$	-0.1599	-0.1842	
11	$(PersonalIncome)_{t-1}$	-0.3387		
12	$(Cons.Conf.Michigan)_{t-1}$		-0.1275	
	SKED.NEWS UK			
13	Retail Price Index			0.2392
14	Retail Sales			0.3888
15	Industr. Production			0.2585
16	Visible Trade Bal.			0.1831
	UNSK.NEWS[c] ETZ			
17	BoJ Intervent.	-0.1104		
18	JPY Statements	-0.2141		
19	USD Statements	-0.1029		
20	JPY News	-0.4211		
21	USD News	-0.1934		
22	USD Polarization	-0.1791		
23	EUR-USD Statements		0.2807	
24	EUR-USD News		0.5142	
25	BCE Interventions		0.1649	
26	USD Polarization		0.3239	
27	GBP-USD Statements			0.1161
28	GBP-USD News			0.387
	GARCH			
29	Intercept	0.0315	0.0024	0.0162
30	Squared Error	0.0847	0.0194	0.0526
31	Lagged Volatility	0.8663	0.9765	0.914
32	Squared R Bar	0.38	0.39	0.51

[a] The coefficients with an asterisk are not significant at the 99%

[b] Scheduled news terms are built as the difference between the actual data announced by the statistical authorities and their values expected by financial markets divided by the standard error of this difference. When there are no news of this type, the vectors contain zeros.

[c] Unscheduled news are represented by ternary vectors made of 0, when no news occurs, +1 when a Euro(or Pound, or Yen)-positive news occurs, -1 when there is a negative news.

Table 10. The Model in American Time Zone, ATZ.

	FUNDAMENTALS	$\Delta_{USD-JPY}$	$\Delta_{EUR-USD}$	$\Delta_{GBP-USD}$	Dow J.	$\Delta(r^{USD})$
0	Constant	0.0251*[a]	0.0469	0.0212*	0.0337*	-0.0008*
1	$\Delta(USD-JPY)_{t-1}$	-0.1024				
2	$\Delta(USD-JPY)_{t-2}$	-0.0642				
3	$\Delta(EUR-USD)_{t-1}$		-0.1646			
4	$\Delta(EUR-USD)_{t-2}$		-0.1006			
5	$\Delta(EUR-USD)_{t-3}$		-0.0679			
6	$\Delta(r^{JPY})_{t-1}$	-0.0657				
7	$\Delta(r^{EUR})_{t}$		0.0731			0.2442
8	$\Delta(r^{EUR})_{t-1}$					-0.1237
9	$\Delta(r^{EUR})_{t-2}$					0.0603
10	$\Delta(r^{USD})_{t}$	0.0709	-0.0947	-0.042		
11	$\Delta(r^{USD})_{t-1}$					0.5387
12	$\Delta(r^{USD})_{t-2}$					-0.113
13	$\Delta(r^{USD})_{t-3}$					-0.1694
14	$\Delta(r^{USD})_{t-4}$					0.1373
15	$\Delta(r^{GBP})_{t}$			0.1449		
16	$\Delta(DowJones)_{t}$		-0.188	-0.0559*		
17	$\Delta(DowJones)_{t-1}$		0.209	0.0473	0.6339	
18	$\Delta(DowJones)_{t-2}$		-0.0644	-0.035	-0.123	
19	$\Delta(DowJones)_{t-3}$			-0.033	-0.14	
20	$\Delta(DowJones)_{t-4}$			0.0447	0.1344	
21	$\Delta(DowJones)_{t-5}$			-0.049	-0.052	
22	EUR-USD	-0.499		0.7673		
	SKED.NEWS US					
23	Non-farm Payrolls		-0.5801			0.487
24	ISM Manufact.		-0.3328			0.5338
25	(GDP)		-0.3517			
26	Industr.Product.				0.1494	
27	Personal Income				0.2011	
28	Unemp.Rate				0.2792	
29	Consumer Conf.					0.146
30	Retail sales					0.3396
31	Consum.Conf. Mich.					0.1523
32	PPI Less Food&Energy				-0.258	0.1613
33	Initial Jobless Claims					-0.13239
34	ISM Manufacturing					0.1971
35	ISM Chicago					0.3061
36	Phila. Business Conf.					0.283
	UNSK. NEWS US ATZ					
37	BoJ Intervent.	-0.0769				
38	JPY Statements	-0.0964				
39	USD Statements	-0.0559	0.1774			
40	JPY News	-0.3247				
41	USD-JPY Polarization	-0.1144				
42	EUR-USD Statements					
43	EUR-USD News		0.4676			
44	EUR-USD Polarization		0.2726			
45	GBP-USD Statements			0.129		
46	GBP-USD News			0.289		
	GARCH					
47	Intercept	0.0023	0.004	0.0074	0.008	0.004
48	Squared Error	0.011	0.0178	0.0317	0.0684	0.0395
49	Lagged Volatility	0.9849	0.9752	0.9489	0.9206	0.9532
50	Squared R Bar	0.32	0.42	0.61	0.33	0.45

[a] The coefficients with an asterisk are not significant at the 99%. For skeduled and unskeduled news see Tables 1,2

Table 11. Acronyms

AI	Artificial Intelligence
ATZ	American Time (or Trading) Zone
B&H	Buy and Hold
BH	Buy and Hold
CS	Common Sense
DD	Drawdown
de	Change in Error
e	Error
EDT	Econometric Model+Directional Trading
ER	Exchange Rate
ETZ	European Time (or Trading) Zone
EU	Eurozone
EUR-USD, E/$	Exchange rate Euro - Dollar, i.e. how many Dollars per one Euro
FLC	Fuzzy Logic Controller
GA	Genetic Algorithm
GA-Only	Use of the Genetic Algorithm Only
GARCH	Generalized AuroRegressive Conditional Heteroschedasticity model in time series econometrics
GBP-USD, /$	Exchange rate UK-Pound - Dollar, i.e. how many Dollars per one UK-Pound
GE	Germany
GTD	Global Trading Day
JTZ	Japanese Time (or Trading) Zone
l	Losses from Drawdowns
MACD	Moving Average Crossover, Convergence-Divergence
MFDT	Model Forecast Directional Trading
ndd	Number of Drawdowns
NN	Neural Network
p	Profits
SK	Scheduled news
SL	Stop-Loss for Longs (L) and Shorts (S)
THR	Threshold where to start trading for Longs (L) and Shorts (S)
TNS	Training Set
TP	Take-Profit for Longs (L) and Shorts (S)
TRS	Trading (or Testing) Set
U	Unscheduled news
UK	United Kingdom
USD-JPY,$/Y	Exchange rate Dollar - Yen, i.e how many Yen per one Dollar

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