Improving the profitability of Technical Analysis through intelligent algorithms

Danilo Pelusi, Massimo Tivegna, Pierluigi Ippoliti

Abstract The profitability of Dual Moving Average Crossover (DMAC) rule can be improved through suitable trading systems. However, Artificial Intelligence techniques can increase the profit performance of technical systems. In this paper, two intelligent trading systems are proposed. The first one makes use of fuzzy logic techniques to enhance the power of genetic procedures. The second system attempts to improve the performances of fuzzy system through Neural Networks. The target is to obtain good profits, avoiding drawdown situations, in applications to the DMAC rule for trading the euro-dollar in the foreign exchange market. The results show that the fuzzy system gives good profits over trading periods close to training period length. Viceversa, the neuro-fuzzy system achieves the best profits over trading period less or much greater than training period length. Both systems show an optimal robustness to draw-down.

1 Introduction

The trading performance of Technical Analysis (TA) can be improved using intelligent data mining techniques. Among the main procedures, intelligent methods such as Fuzzy Logic and Genetic Algorithms (GA) have frequently achieved good results. In many cases, the combination of these techniques produces relevant findings. Allen and Karjalainen [1] used a genetic algorithm to learn technical trading rules for the S&P 500 index using daily prices. They concluded that the GA application finds little evidence of economically significant technical trading rules. This

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happens, most likely, because their pioneering experiment aims at discovering randomly, through GA methods, technical rules not necessarily ever used by a human trader. However, good results are found in [4] where the behaviour of traders tends to adapt the chosen algorithm to market conditions, by dropping trading rules as soon as they become loss-making or when more profitable rules are found. A Genetic Algorithm is applied here to a number of indicators calculated on a set of US Dollar/British Pound exchange rates, selecting rules based on combinations of different indicators at different frequencies and lags. Moreover, strong evidence of economically significant out-of-sample excess returns to technical trading rules are found using genetic programming techniques by [6]. A relatively new approach to genetic procedures application to TA is introduced in [9]. The authors use Genetic Algorithms (GA) to obtain optimal (and constrained optimal) parameters for high profit in a very popular trading rule, the Dual Moving Average Crossover (DMAC). This is a mathematically well-defined rule and GA is able to hit at least a good local optimum there.

In this paper, we design a Neuro-Fuzzy system for trading in the Euro-Dollar foreign exchange market, using a DMAC trading rule (described in Section 2). The fuzzy logic is good for decisional problems, whereas the Neural Networks (NN) have the capability to learn from data and trading results. The idea is using the constrained algorithms of [9] to define the Membership Functions (MF) and the fuzzy rules of the trading system (Section 3). Moreover, in order to achieve the best performance of the overall fuzzy logic-GA-enhanced DMAC, the weights of fuzzy rules are computed by a suitable Neural Network (Section 4). Such procedures have been good results in different fields [12], [13], [11], [10], [14]. The target is to achieve optimal profits with DMAC in the euro-dollar exchange rate market, avoiding drawdown situations [9]. The intelligent model is programmed in Matlab with Fuzzy Logic and Neural Network tools. We use hourly time series (1999-2012) of the Euro-Dollar exchange rate supplied by the US data provider CQG (with an extensive work to filter out errors).

2 The DMAC rule

Technical Analysis is a forecasting method of price movements for trading. It includes the decision rule, expressed in mathematical form, and the study of chart patterns using pattern recognition algorithms. A pattern recognition algorithm to optimally match training and trading periods for TA rules is proposed in [15].

A technical trading system consists of a set of trading rules which depend on technical parameters. The rule generates trading signals according to its parameter values. The most well-known types of technical trading systems are moving averages, channels and momentum oscillators [8]. Among such technical rules, the DMAC rule is considered. The Dual Moving Average Method is one of the few technical trading procedures that is mathematically well defined. The DMAC system generates trading signals by identifying when the short-term trend rises above or below the long-term trend.

Let p_t be the hourly foreign exchange rate at time t. We define the Fast Moving Average (FMA) A_f over n hours and the Slow Moving Average (SMA) A_s over m hours the quantities: $A_f(t) = \sum_{i=1}^{n} \frac{p_{t-1-i}}{n}$ and $A_s(t) = \sum_{i=1}^{m} \frac{p_{t-1-i}}{m}$, with $t \geq m > n$.

The trading rules are: If $A_f(t) > A_s(t)$ than go long (i.e. buy the asset) at p_{t+1} and If $A_f(t) < A_s(t)$ than go short (i.e. sell the asset) at p_{t+1}. The FMA computes a moving average over a number of hours smaller than in the SMA. The FMA picks up the short-term movements of the rate whereas the SMA draws the longer term trend of it. Trading signals are obtained by their contemporaneous movements. A trade is opened if one of two trading rules holds. In other words, if the Fast Moving Average curve crosses the Slow Moving Average curve than a trade (long or short) is opened. Such trade is closed when a suitable threshold is reached. For both longs and shorts we have two thresholds: a Take Profit (TP), if the exchange rate went in the direction established by your DMAC, a Stop Loss (SL), if the direction was the opposite.

In the DMAC rule, the technical parameters to be optimized are the Fast Moving Average, the Slow Moving Average, the Take Profit and the Stop Loss. Practitioners choose the values of these parameters according to experience, market trends, volatility and their personal trading styles. They also frequently prefer to base decisions on a mix of technical indicators. The techniques we proposed in [9] and propose here can offer further information to professional and non-professional traders.

3 Design of decisional model

In order to obtain good profits from the application of DMAC rule, a suitable choice of the technical parameters - FMA, SMA, TP and SL - is necessary. Our methodology starts with the definition and actual individualization of two features (among the many possible ones) of the euro-dollar exchange rate behaviour overtime. The first one is the slope of trend (as representing the longer term direction of the exchange rate), whereas the second one is the number of crossings of the exchange rate curve around its time trend (as representing the volatility of the rate). As standard in the evaluation of trading rules (in order to avoiding data snooping), the profitability of our trading protocol is analyzed by dividing the available sample into a Training Set (TNS) and a Trading Set (TRS).

A Fuzzy Logic Controller (FLC) characterizes the slope values and the crossings number. In fact, with the help of this technique it is possible to define suitable scaling parameters of the inputs. The proposed FLC has two fuzzy inputs (slope and crossings number) and four fuzzy outputs (TP, SL, FMA and SMA). To define the Membership Functions (MF) number and the relative scaling factors, we consider the results obtained in [9].

The first fuzzy input (trend) is characterized by five MF: Fast Decreasing (FD), Slow Decreasing (SD), Lateral Trend (LT), Slow Increasing (SI), Fast Increasing

(FI). The crossings number and the fuzzy outputs have three MF: Low (L), Medium (M), High (H). To establish the MF scaling factors, the methods defined in [9] are used. A constrained algorithm is applied to the DMAC rule, avoiding losses greater than four per cent in one month. This constraint avoids draw-down situations during the trading and reduces losses.

As customary in the literature, the choice of training and trading sets length is a delicate issue [1], [7]. We analyze the profitability of our technical rule considering a TNS length of four months (various ones) between 1999 and 2007. Once the training periods is chosen, slope and crossings number are computed. Over such periods, the DMAC rule is applied. Through genetic procedures, the best values of TP, SL, FMA and SMA are found [9]. This means that the GA searches the parameters which give optimal profits.

Using trial and error procedures, we establish the ranges of FD, SD, LT, SI, FI Membership Functions (see Fig. 1) normalized between $[-1,1]$. Moreover, according to the literature, we choose the triangular/trapezoidal shape for our MF. The Membership Functions scaling parameters of fuzzy input crossings number and fuzzy outputs are defined according with the genetic procedures results. Such MF are shown in Fig. 2, where the unit of measurement of TP and SL are the basis points of the Euro-$ exchange rate, the so-called pips in the traders jargon. Note that the Take Profit scale is greater than Stop Loss scale by ten factor. This choice comes from the genetic procedures results and - as a matter of fact - it is frequent (on a much smaller scale) among traders.

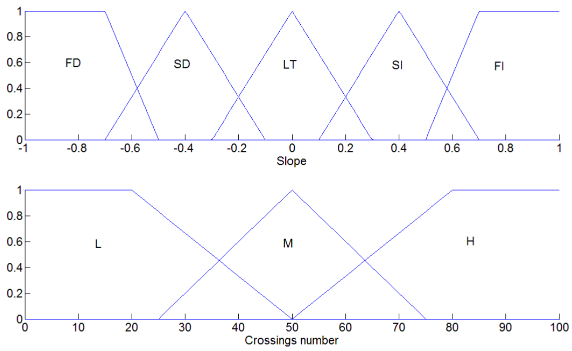

Fig. 1 Fuzzy inputs

The next step to define the fuzzy model is the fuzzy rules definition. Because we have one input with 5 MF and the second one with 3 MF, then $5 \times 3 = 15$ rules can be used. An example of fuzzy rule is: If slope is FD and crossings number is L, then TP is H and SL is L and FMA is L and SMA is M. By exploiting the information of the constrained algorithms, suitably adjusted for our trading aims, the rules base is defined. In other words, the knowledge introduced in the fuzzy system comes

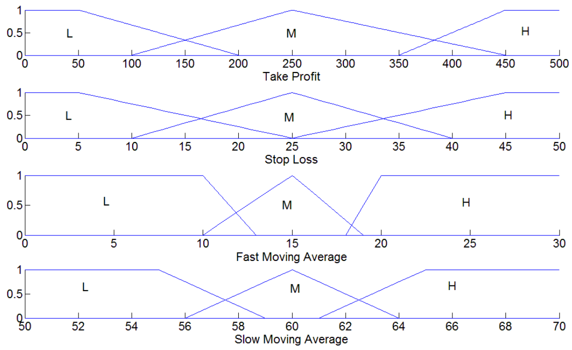

Fig. 2 Fuzzy outputs

Table 1 Fuzzy rules base

$S \setminus N_c$	L	M	H
FD	$H;L;L;M$	$H;M;L;H$	$M;L;H;L$
SD	$M;M;H;H$	$H;L;L;M$	$H;M;M;L$
LT	$H;H;L;M$	$H;M;M;L$	$L;H;M;M$
SI	$L;H;L;M$	$M;H;L;H$	$H;L;L;M$
FI	$H;L;L;L$	$M;L;L;L$	$H;L;L;H$

from genetic-constrained investigations. Denoting the slope input with S and the crossings number with N_c, the fuzzy rules are shown in Table 1.

Notice, at this point, that all the fuzzy rules are defined to have the same weights values in the choice of the parameters of DMAC. To improve the trading decision model, the most profitable rules must be spotted. This means that the fuzzy rules which give good profits must have higher weights values in determining the best DMAC parameters. To solve this problem, we design a suitable Neural Network.

4 Neuro-fuzzy algorithm

Once defined the fuzzy sets and the rules base, the next step is the optimization of rules weights. To do this, a Neuro-Fuzzy algorithm is proposed. First of all, we design a training set for the Neural Network. The patterns are characterized by 2 inputs and 15 outputs. The two inputs are the slope S and the crossings number N_c, whereas the outputs are the weights of fuzzy rules, as reported in Table 1. Such training set for NN is designed with the following algorithm.

Step 1. Select $m = 100$ training period of four months length. For each period, compute the slope S and the crossings number N_c.

Step 2. For each (S, N_c) pair, generate $n = 15$ random values between 0 and 1 which correspond to fuzzy rules weights w_i $(i = 1, 2, ..., n)$, with $w_i \varepsilon [0, 1]$.
Step 3. Compute TP, SL, FMA and SMA according fuzzy inputs S, N_c and weights w_i.
Step 4. Calculate the DMAC profits p_j, $j = 1, 2, ..., l$ (with $l = mn$) and compute the max profit.
Step 5. Select the weights w_i, $i = 1, 2, ..., 15$ associated with max profit.

In this way, a training set of 100 patterns to train the NN is designed. The patterns are composed by the inputs S and N_c and the weights w_j as outputs. A blocks diagram of training set selection is shown in Fig. 3. The FLC receives the fuzzy inputs S and N_c and the weights w_i from NN. The parameters S and N_c are also inputs of NN. The Fuzzy Logic Controllers gives the outputs TP, SL, FMA and SMA which serve as inputs to the DMAC rule.

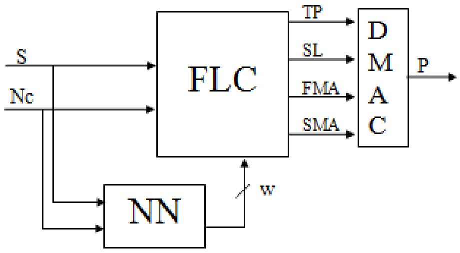

Fig. 3 Blocks diagram of Neuro-fuzzy system

The architecture of a Neural Network very much depends on the kind of application under investigation. Because we have two fuzzy inputs, the input layer of NN is composed by 2 neurons, whereas the output layer has 15 neurons, as the number of fuzzy weights. Because there are no fix rules to establish the hidden layer neurons number, trial and error procedures are used. This number sometimes depends on specific application. For instance, some indications can be found in [16]: he proposes an algorithm able to obtain the number of necessary hidden neurons of single-hidden-layer feed forward networks for different pattern recognition application tasks. The hidden layer of our NN is made up by 3 neurons (see Fig. 4).

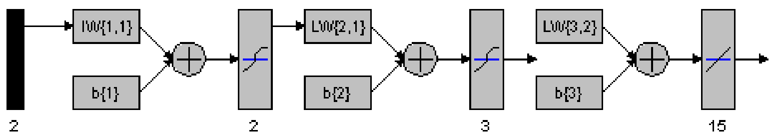

Fig. 4 Neural Network architecture

In order to design the NN architecture, the Matlab Neural Network tool is used. Establishing an epochs number of 250 and a goal of 0.02, the net achieves a performance index of 0.00266812.

Once trained the NN, the intelligent system is ready for trading the euro-dollar exchange rate in the foreign exchange market.

5 Experimental results

Our intelligent algorithm works on hourly foreign exchange rate. The TNSs go from 1999 to 2007, whereas the TDSs go from 2008 to 2012. We consider four-month TNSs length and test the algorithm on monthly, two-months, three-months, four-months, six-month and annual TDSs lengths. Matlab was used for computations.

In all the experiments, the same drawdowns are roughly obtained with the fuzzy controller only and its neuro-fuzzy extension (see, for instance, all the charts in the paper and Table 2, column 3, where only one number is reported). The more the relative frequency of draw-down number, R, is small, the best is the intelligent system performance. The neuro-fuzzy system, though, improves the cumulative profit in four experimental typologies out of six.

Table 2 Draw-down number and cumulative profits for fuzzy and neuro-fuzzy systems.

Period	N_p^*	N_{dd}^*	R^*	P_f^*	P_{nf}^*	$\Delta = P_{nf} - P_f$
Monthly	55	2	0.0364	0.5590	0.7367	0.1777
Two-month	27	2	0.0741	0.6477	0.7529	0.1052
Three-month	18	1	0.0556	0.2702	0.3415	0.0713
Four-month	13	1	0.0769	0.8013	0.6401	-0.1613
Six-month	9	0	0	0.3498	0.2421	-0.1077
Annual	4	0	0	0.3342	0.4032	0.0689

$^*N_p$ is periods number. N_{dd} is the draw-down number. $R = \frac{N_{dd}}{N_p}$ is the relative frequency of draw-down number. P_f is the fuzzy cumulative profit. P_{nf} is the neuro-fuzzy cumulative profit.

Table 2 also shows the cumulative profits achieved with fuzzy and neuro-fuzzy models. It can be noticed note that the fuzzy procedures seem to fare better than neuro-fuzzy ones for medium period lengths respect to TNS length. In fact, fuzzy cumulative profit P_f is greater than neuro-fuzzy cumulative profit P_{nf} over the four-month and six-month periods. Viceversa, the neuro-fuzzy algorithms give better results than fuzzy methods over period lenghts smaller and relatively bigger than TNS length. Remind that the chosen Training Set length is four-month.

We decided - for space limitations - to show only six charts (monthly, bi-monthly and six-month experiments for fuzzy and neuro-fuzzy trades), which give information on the performance overtime of our techniques. All the charts have the same structure (see Fig. 5, 6, 7, 8, 9, 10) and show the profit performance for the period (left axis), the cumulative performance (right axis)and the drawdown horizontal line (referred to the left axis). The time profiles of profit results (single period and cumulative) are not dramatically different for monthly and bi-monthly fuzzy and neuro-fuzzy experiments. More difference is observed in the six-month case for fuzzy and neuro-fuzzy. The cumulative performance line remains always above zero and shows a more subdued profile in the first part of the sample (roughly corresponding to the sub-prime crisis in 2008-09) than in the second. Our algorithms seem to be disturbed more by the subprime crisis (2008-09) than by the European sovereign debt crisis (2010-12).

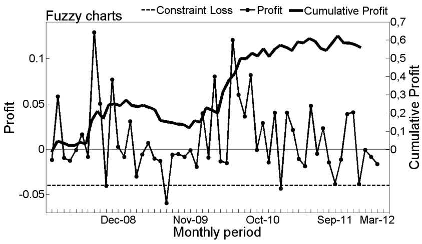

Fig. 5 Monthly profits and cumulative profits of fuzzy system

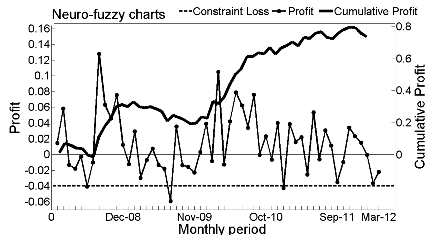

Fig. 6 Monthly profits and cumulative profits of neuro-fuzzy system

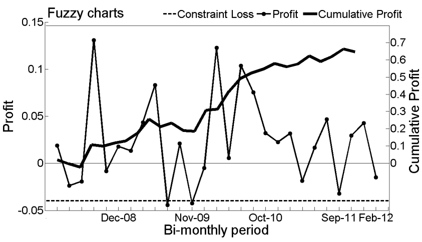

Fig. 7 Bi-monthly profits and cumulative profits of fuzzy system

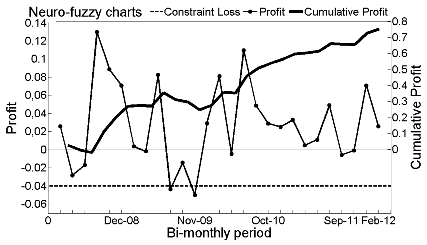

Fig. 8 Bi-monthly profits and cumulative profits of neuro-fuzzy system

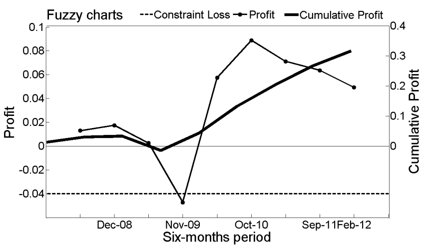

Fig. 9 Semestral profits and cumulative profits of fuzzy system

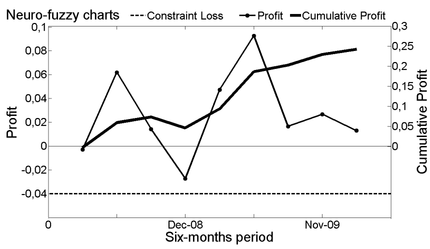

Fig. 10 Semestral profits and cumulative profits of neuro-fuzzy system

6 Conclusions

The profitability of Technical Analysis is a very open issue in foreign exchange market [5], [8]. Technical rules are still the obstinate passion for traders in the foreign exchange market. Among these rules, the DMAC is the most popular technical indicator. To simulate the behavior of market agents, artificial intelligence techniques can be applied. This paper proposes two intelligent systems based on fuzzy and neuro-fuzzy features. The first one is designed with the help of genetic constrained algorithms, whereas the second one is based on a suitable Neural Network architecture. The results show that the fuzzy system is profitable over trading period length close to the four-month training period length. Viceversa, the neuro-fuzzy model improves upon the fuzzy system over periods with length lower or much greater than the training period length. Moreover, both fuzzy system and neuro-fuzzy system give small drawdown numbers. The aggregate profit rates over more than four years (2008-2012), in Table 2 columns 4 and 5, give reasonable numbers also for annual rates.

Going into future planned research on the work in this paper, probably the most useful line of activity for traders is replicating our results with higher frequency data: tick or one-minute. This would indicate how to manage TNS and TDS with a timing much closer to the actual functioning of todays forex market. Another useful step will be the definition of intelligent systems also for others technical rules, such as momentum, oscillators and channel rules. The main future challenge will be the design of neural networks able to reduce to a minimum the drawdown number.

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