A Trading Method in FX using Evolutionary Algorithms

Extensions Based on Reverse Trend and Settlement Timing

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ABSTRACT

In foreign exchange (FX) markets, the key issues to achieve profitable trading rules are the combination of the indicators, selection of their parameters, and decision of the trade timing for orders and settlements. In this paper, we present a trading system using a combination of genetic algorithm (GA) and genetic programming (GP). Unlike related researches on this problem, our work focuses on two aspects. First, a calculation of appropriate settlement timing is proposed, to make more profits and less losses. Second, reverse trend data are generated using in-sample data, to overcome the overfitting problem and suppress the risk of loss. To examine the effectiveness of the method, we employed simulations using real-world trading intraday data. It is verified the enhanced capability of our method to make consistent gain out-of-sample and avoid large draw-downs.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods and Search—*Heuristic method*; J.4 [**Social and behavioral sciences**]: Economics

General Terms

Algorithms, Economics

Keywords

Genetic Algorithm (GA), Genetic Programming (GP), Finance, Foreign Exchange (FX), Optimization, Technical Analysis

1. INTRODUCTION

For FX market traders, it is important to predict future price changes, or find appropriate trade timing of orders and settlements. Technical Analysis is a mainstream methodology in such issues, which studies only technical indicators as captures of the price behavior and data patterns extracted from the markets. In this paper we propose a hybrid trading system combining GA and GP to generate trading rules based on Technical Analysis.

GAs have been used to obtain parameters of indicators [3, 4], and to find ingredient indicators of trading rules [5]. GPs have been used to generate trading rules expressed in tree forms [6]. Our proposal works in a two-phase fashion: first optimize the parameters of the indicators separately as if they are applied independently, then look for trading rules in tree structures by GP. The search space is divided, and computational efficiency could be improved. In addition, a technique of reverse trend training is suggested, to overcome the overfitting problem which is common in GA/GP based trading systems.

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2. PROPOSED METHOD

As the base of the method, a set of indicators are selected. They are mathematical formulas that turn raw price data into buy or sell signals, and some are widely used. In this work 9 indicators are used: (MA, MACD, SS, RSI, CCI, MO, PO, BB, LW). These are fully described in [1].

Based on a common fitness function *profit factor* [2], defined $Gain/Loss$, we designed ours. Exception is added that when $Gain = 0$, fitness is no longer 0 but $-Loss$. This brings into account the differences of losses.

The flow of our method is as follows: first generate reverse trend data from training data set; then for each indicator, run a GA to optimize its parameters; finally how to select and combine the indicators is searched by GP.

Trading rules make losses when the trend of test data differs from that of training data. Overfitting makes it even worse. To overcome this, we generate reverse trend data by reversing the price axis of training data as shown in figure 1. This part of data brings the opposite trend to that of original data, and thus can avoid bias. The result is used with a weighing factor in the final fitness, as shown in (1).

$$Fitness = \frac{Gain + P_{reverse} * rGain}{Loss + P_{reverse} * rLoss} \quad (1)$$

To give the parameters, we assume the indicators work independently and optimize the parameters separately. In the GA chromosomes, each parameter of the indicator is represented with 6 bits and the range would include the common value of the parameter. For an example in the case of MA_{short}, 3 to 66 is the value range. Both buy/sell signals are considered. In this evolution the population size is set to 100. In selection tournament with size 20 is applied, and the worst 10 individuals are replaced by random new ones. After repeating last 3 processes for 100 generations, the individuals in the final generation are chosen as candidates. We also apply a hill-climbing method to each candidates, each 100 steps, to find local maximums.

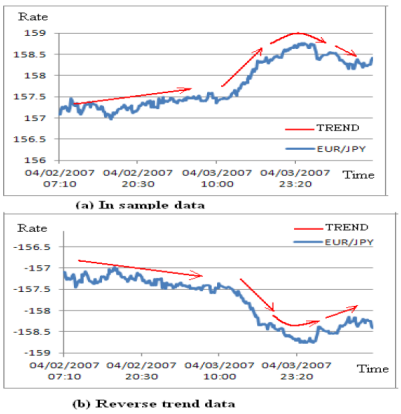


Figure 1: Reverse trend data

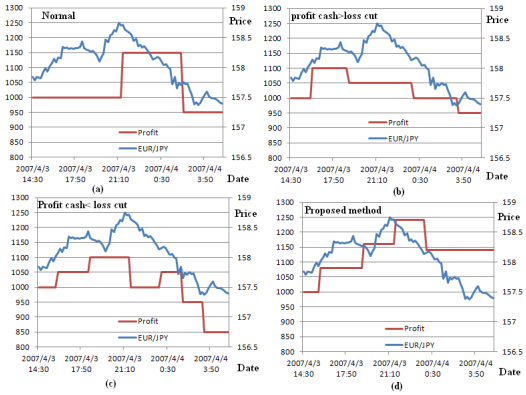


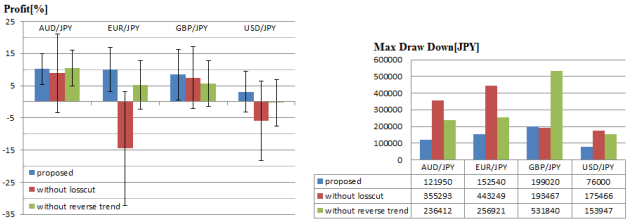
Figure 2: Profit cash and loss cut

Then with GP we look for a buy rule and a sell rule. A rule is in form of a binary tree linked by AND/OR with leaves of indicator signals: MA, MACD, SS, etc. The maximum depth is limited to 5. In this evolution, the population size is 300, in all 200 generations crossover rate 0.8 and mutation rate 0.01 are used.

Furthermore, it is difficult to decide when to make an order and when to settle an order. If we delay this it may lead to great losses. If we do it frequently we need to pay more commission fee. We try to tune this "settlement time" by using concept of "profit cash", "loss cut", and adding "reverse signal" to avoid risk of loss. Hirabayashi et al [5] introduced *profit cash* and *loss cut*. In this method we extend this idea. We analyze the property of those thresholds. In figure (2) the relation of the *profit cash* and *loss cut* is shown. When either of them is absent, the profit and loss depend on how much trading rule fits in test data (2.a). When *profit cash* $>$ *loss cut*, the amount of loss trades becomes greater than number of profit trades (figure 2.b). When *profit cash* $<$ *loss cut*, the amount of profit trades becomes greater than number of loss trades (2.c). In figure 2.(d) it is our proposal. When a loss occurs in a trade we wait for a reverse signal. For example if an order used the buy rule then we wait for the signal of the sell. It decreases the number of loss trades.

3. EXPERIMENT

Actual transaction of 10-minute data from Gaitame. dot is used for the experiment. 4 currencies against the JPY



	AUD/JPY	EUR/JPY	GBP/JPY	USD/JPY
proposed	121950	152540	199020	76000
without losscut	355293	443249	193467	175466
without reverse trend	236412	256921	531840	153947

Figure 3: Percentage profit and Max Draw Down

(AUD, EUR, GBP, USD) are used, and the period is 2007/04/02 to 2009/04/02. The spread is 0.02 Yen per 1 USD trading, 0.09 Yen per 1 GBP trading, and 0.05 Yen per 1 AUD trading and 1 EUR trading. The initial asset is 1000000 Yen for the USD, 2000000 Yen for the GBP and 1500000 Yen for the AUD and the USD investment. We used a rolling window method. The 5040 (5 weeks) data points were used for training, and 4032 (4 weeks) were used for testing. The investment amount is 10000 (AUD or EUR or GBP or USD) per trade. If an order is not settled by the end of a testing period, the settlement is taken to the next testing period. We performed 20 tests for each currency. The evaluation criteria were percentage profit, standard deviation and Max draw down. The final comparison with a conventional GA is shown in figure. 3. It can be observed that with reverse trend training and our settlement timing technique, both profit and max draw down get better.

4. CONCLUSIONS

In this paper, we proposed a trading system using a combination of GA and GP. We introduced an appropriate settlement timing and a reverse trend training technique. Experiments show that using a reverse trend data makes trading rule more robust to overfitting problem and suppresses the substantial danger of loss. The settlement timing gives a great improvement in profitability and stabilization.

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