Optimization of the Trading Rule in Foreign Exchange using Genetic Algorithm

Akinori Hirabayashi
Hartford Life Insurance K.K.
15th Floor, Shiodome Bldg,
1-2-20, Kaigan, Minato-ku, Tokyo
105-0022, Japan
TEL: +81-3-6219-2417
akinori.hirabayashi@gmail.com

Claus Aranha
Graduate School of Frontier Sciences,
The University of Tokyo
2-11-16, Yayoi, Bunkyo-ku, Tokyo,
113-8658, Japan
TEL: +81-3- 5841-6751
caranha@iba.k.u-tokyo.ac.jp

Hitoshi Iba
Graduate School of Engineering,
The University of Tokyo
7-3-1, Hongo, Bunkyo-ku, Tokyo
113-8656, Japan
TEL: +81-3-5841-7424
iba@iba.k.u-tokyo.ac.jp

ABSTRACT

The generation of profitable trading rules for Foreign Exchange (FX) investments is a difficult but popular problem. The use of Machine Learning in this problem allows us to obtain objective results by using information of the past market behavior. In this paper, we propose a Genetic Algorithm (GA) system to automatically generate trading rules based on Technical Indexes. Unlike related researches in the area, our work focuses on calculating the most appropriate trade timing, instead of predicting the trading prices.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search - *Heuristic methods.*

J.4 [**Social and behavioral sciences**]: Economics.

General Terms: Algorithms, Economics.

Keywords

Genetic Algorithms (GA), Optimization, Finance, Foreign Exchange (FX), Technical Analysis.

1. INTRODUCTION

Nowadays, we can see a growing trend to solve problems in the financial field by mathematical methods [1, 2] –in particular, in the sub-field of active decision-making for stock markets, foreign exchange, and investment credit. The foreign exchange (FX) market is the largest financial market in the world. At its core are exchange rates and market timing. Based on the two, a large variety of financial instruments have been created. Exchange rates are under the influence of a myriad of factors. It is very complicated to predict exchange rates based on fundamental analysis, which studies all relevant economic and financial indicators.

Therefore, technical analysis is a sound alternative to forecast short-term FX market movements [3]. Its advocates do not concern themselves with fundamental values such as account balance or economic conditions, but instead base their ideas on the hypothesis that any factor that truly influences the market will immediately show up in the FX rate. Therefore, this technique only studies indexes and the charts that describe their movements.

To avoid the difficult problem of forecasting the precise exchange rate, we propose a way to optimize FX trading on the timing to make an investment. In this paper, we aim to raise the profit of an investment by buying and selling the foreign exchange in very short periods, assuming that we start off with a certain amount of Japanese Yen. Our GA system searches for the optimal combination of Technical Indexes which will allow us to accurately judge the timing when the exchange rates rise or fall. Furthermore, by actually introducing the concept of leverage in accordance with the settings employed by FX companies in Japan, we also consider the profit generated through application of the proposed method. Our goal is to develop and implement an evolutionary system which is able to learn the nuances of trading rules in FX markets, and to adapt to its changing conditions.

GA is a search technique used to find exact or approximate solutions to optimization and search problems. GA uses techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover [4]. Though our method is to search the preferable trading strategies from the past time series data of FX rate (Data for Learning), simply searching all the patterns requires a great amount of time. The application of GA may achieve a great reduction in the computing time. In addition, the evolutionary operators of GA allow successful rules for past problems to adapt to changes in the market conditions.

This paper is organized as follows. Section 2 explains the system of FX market and introduces some technical indexes used in this paper. Section 3 introduces some related works. The proposed FX trading rule optimization mechanism by GA is discussed in section 4. The experiments and the results are presented in section 5. In addition, comparison with a method that uses a Neural Network is provided in Section 6. Section 7 concludes the paper.

2. BACKGROUND AND TOOLS

2.1 Foreign Exchange Market

The FX market is different from the stock market in some respects. First, individual FX traders can deal 24 hours per business day, due to time differences around the world. Because of this, FX traders have much more chances to deal compared to stock traders who can only deal during local business hours.

Second, FX trading does not require an agreement time. This means that traders can buy or sell foreign currencies at the current rate almost immediately for the major currencies.

Finally, commission fee in FX is relatively cheap, generally. By most FX brokerage companies, the asking price is set little higher than the bidding price. So, trading fees have less influence in FX trading than in stock markets.

2.2 Technical Analysis

Technical indexes are tools to expect and analyze the change of the price in the future, using the change of pricing generated in the past. Here, three typical technical indexes used to forecast and to analyze the stock or FX prices are described [5, 6].

1) RSI (Relative Strength Index)

$$RSI[\%] = \frac{|U|}{|U| + |D|} \times 100 \tag{2.1}$$

$|U|$: Sum of the absolute value of rising width in the past n days

$|D|$: Sum of the absolute value of falling width in the past n days

RSI is one of the typical index which is called "contrary" type, and aims to buy when the currency is sold too much (the price is low), and to sell when it is bought too much (the price is high). It is general to use 9 or 14 as n. As a general guideline, an RSI value below 30 indicates that the currency has been sold too much, while it an RSI higher than 70 indicates that the currency has been bought too much.

2) Moving Average; MA

The moving average is a technique for smoothing the short-term variation of price (longitudinal data), and it can be obtained by calculating the mean value of the past n days' prices. The moving average is used to understand the present trend, and as such it is called a "Trend Following" type of index, opposite to the contrary type. There are several types of Moving Averages, depending on past prices are weighted.

First, the Simple Moving Average (SMA) indicates a simple mean value with identical weights to past prices. Second, the Weighted Moving Average (WMA) is a kind of index which put higher weights on more recent dates' prices. An example of weight assignment would be to give weight n to the price at the current time (time t), weight n-1 to the price at time t-1, n-2 to t-2 and so on.

Finally, we refer to Exponentially Weighted Moving Average (EWMA) which is applied in the proposed method. Contrary to the linear weight putting in WMA, EWMA assigns weights exponentially. One example of weight assignment is shown in (2.2), α is an arbitrary coefficient which takes range of $0<\alpha<1$ [7].

$$EWMA_M = \frac{p_M + \alpha p_{M-1} + \alpha^2 p_{M-2} + \cdots}{1 + \alpha + \alpha^2 + \cdots} \tag{2.2}$$

3) Percent Difference from Moving Average

$$(Difference)[\%] = \frac{(Current\,Price) - (MovingAverage)}{(MovingAverage)} \times 100 \tag{2.3}$$

This index indicates how much the current rate differs from the moving average described in 2). As well as RSI, Percent Difference is one of the "contrary" type indexes. And it is general to use either of the 5 days/25 days/13 weeks/26 weeks as the period n. The experts say that it is sold too much when this is lower than -10%, while it is bought too much when this is higher than +10%.

3. RELATED WORKS

Though we apply Technical Indexes to the FX data in this paper, most of other studies on FX have not focused on Technical Analysis. In this section, some related works are shown as 1.Works on FX, and 2.Works on Technical Analysis.

3.1 Works on Foreign Exchange

As attempts to apply mathematical methods, especially Artificial Intelligence (AI) to the financial problems, most studies have focused on the stock market, and there seems to be little related works on the FX market [8, 9].

However, some works which attempt to analyze the movements in the FX market by the approach of the Artificial Market can be seen [10]. Artificial Market is the virtual market made on a computer, and is applied the concept of complex systems. By using Artificial Market, analysis of economic phenomenon in real world or verification of economic thesis can be put into practice.

3.2 Works on Technical Analysis and GA

Fuente et. al. [11] have presented a work which also attempts to optimize the timing of an automated trader. They use GA to develop trading rules for short time periods, using Technical Indexes, such as RSI, as GA's chromosome. They proposed the use of the developed rules on stocks of Spanish company. However, the description in that work was too preliminary to allow for a comparison with our system to be made.

And also, Schoreels et.al [12] have presented a work which attempts to generate the buying and selling signals against 30 companys' stocks in Germany (DAX30). They use combination of Technical Indexes applied to GA as well as [11], and then rank the stocks according with the strength of signals to restructure the portfolio. However, they don't devise any criterion of profit cashing and loss cutting.

4. PROPOSED METHOD

The overall flow of our proposed technique is shown in Fig.1. Basically, using historical exchange data as the learning data, the system searches for buying and selling rules that return the highest profits. These rules are composed of a combination of Technical Indexes and their parameters, and are used as the GA's genotype. After the training is complete, the acquired rule is applied to a testing set of data, composed of historical data directly posterior to the training data, to validate the efficiency of the proposed method.

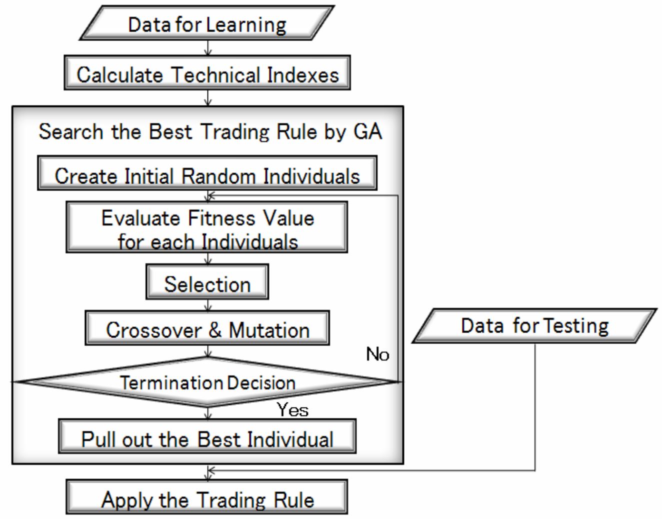

Fig. 1 Flow of the Proposed Method

4.1 Training Data Set

The training data used in this work consists of historical rates of the U.S. Dollar towards the Japanese Yen (USD/JPY) and Euro towards the Yen (EUR/JPY).

For each data set, we use the hourly closing price, and our system analyses the trading signals every hour. The same thing goes for the testing data sets, which are the historical rates immediately following those of the training data set.

4.2 Calculation of Technical Indexes

For each of the foreign exchange data sets previously mentioned, we calculate the following Technical Indexes for use with the trading rules:

1. RSI of the original data [RSI1]

2. Percent Difference from Moving Average of the original data [PD]

3. Rising (Falling) rate from one hour ago of the original data [RR]

4. RSI of Exponentially Weighted Moving Average [RSI2]

Generally, indexes 1, 2, 3 are said to be contrary type. On the other hand, index 4 can be understood as a trend following type, because it is the RSI calculated on current trend. By using both types of indexes, a wider variety of trading patterns can be covered.

4.3 Search the Best Trading Rule by GA

The GA chromosome contains the information needed to build buy and sell rules in our method. It is composed of a binary representation, and can be divided in three main parts (as shown in Fig.2).

The first 65 bits represent the buying rule. The bits are grouped in fives, each grouping representing one of 32 values between the maximum and minimum possible values for the indexes represented by the grouping. For instance, in the case of the RSI, which values range from 0 to 100, each bit pattern in the grouping represents an increment of 3.125.

The first 8 groupings (40 bits), represent lower and higher limits for the 4 above mentioned indexes. If the current value for the indexes is between these limits, it indicates a buying signal. The next 3 groupings (15 bits) represent parameters for the calculation of the indexes (described in the previous section). The final 2 groupings (10 bits) determine the profit cashing and loss cutting values which are used to end transactions.

The next 65 bits represent the selling rule. These bits follow the exact same rules for the buying rule bits.

The final 4 bits indicate the rule that will be used to determine the timing for trading. The fourth bit determines which of rules A, B or C (in Table1) will be used. The first 3 bits determine whether operators 1-3 are AND operators, or OR operators. If the rule is evaluated to a TRUE value, the system realizes the trading. Else, it does not trade in this time period.

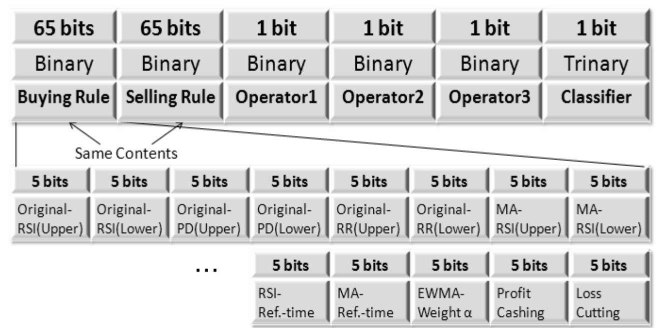

Fig. 2 A Chromosome Design

<u>Step1) Generation of Initial Individuals</u>

Our population size is set to 1500. We initialize these individuals with random chromosomes following the structure in Fig.2 and Table1.

Figure c_1- c_8 in Table.1 correspond to the ranges of Technical Indexes shown in 2nd line bits in Fig.2. And 3rd line bits are parameters to calculate the Technical Indexes.

Table 1. Conditional Equation

[A]	$\{(c_1 < RSI1 < c_2)$ $\boxed{Op.1}$ $(c_3 < PD < c_4)\}$ $\boxed{Op.2}$ $\{(c_5 < RR < c_6)$ $\boxed{Op.3}$ $(c_7 < RSI2 < c_8)\}$
[B]	$\{(c_1 < RSI1 < c_2)$ $\boxed{Op.1}$ $(c_5 < RR < c_6)\}$ $\boxed{Op.2}$ $\{(c_3 < PD < c_4)$ $\boxed{Op.3}$ $(c_7 < RSI2 < c_8)\}$
[C]	$\{(c_1 < RSI1 < c_2)$ $\boxed{Op.1}$ $(c_7 < RSI2 < c_8)\}$ $\boxed{Op.2}$ $\{(c_3 < PD < c_4)$ $\boxed{Op.3}$ $(c_5 < RR < c_6)\}$

<u>Step2) Calculation of Fitness</u>

For each individual generated in Step1), the fitness value is given as the profit gained by trading during the period of the training data set. The flow of investment management is shown in Fig.3.

Every hour, the system checks the current value of the indexes against the conditional equations shown in Table 1. If the ranges of the Technical Indexes calculated at time i satisfy either the buying equation or the selling equation, the trading system buys or sells the foreign currency.

If both equations are satisfied at the same time, the chromosome is invalid, and the individual receives fitness 0 (the lowest value) automatically.

After the system successfully realizes a buy or sell operation, it stays in that position until the profit cash or loss cut conditions are met. These conditions are defined in the chromosome (see section 4.3).

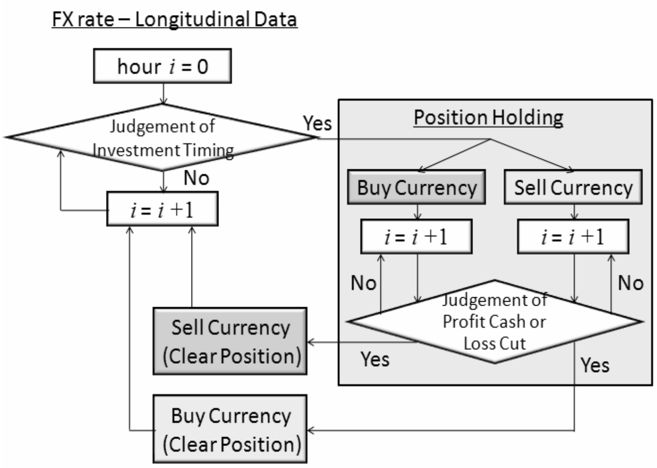

Fig. 3 Flow of the Investment Management

Step3) Selection

We use Tournament selection as the selection method for the GA in our system. This method selects a number of individuals from the population, and performs a "tournament" between them, and the winner is selected to perform the crossover. Selection pressure can be easily adjusted by changing the tournament size. If the tournament size is larger, weak individuals have a smaller chance to be selected. Tournament size is set at 50 in this experiment. Besides, in order to keep high-fitness individuals, the elite 1% (the top 1% individuals in terms of fitness value) are reserved automatically every generation. In addition, the worst peformers (the bottom 30% in our method) are replaced through randomly generated new genes using concept of immigration, an approach previously suggested by Branke, and also applied by Schoreels [12, 13] (see Fig.4).

Step4) Crossover and Mutation

We use two-point crossover as our crossover method. This method chooses two points at random in each parent individuals. All bits between these two points are swapped between the parents, generating two child individuals.

Mutation is a genetic operator used to maintain genetic diversity from one generation of a population of chromosomes to the next. Concretely, mutation is done by converting chromosome's 0 to 1, or 1 to 0, in extremely low-probability. The last trinary part of the genome is not subject to mutation. In this paper, the probability of crossover and mutation are 60% and 1% respectively.

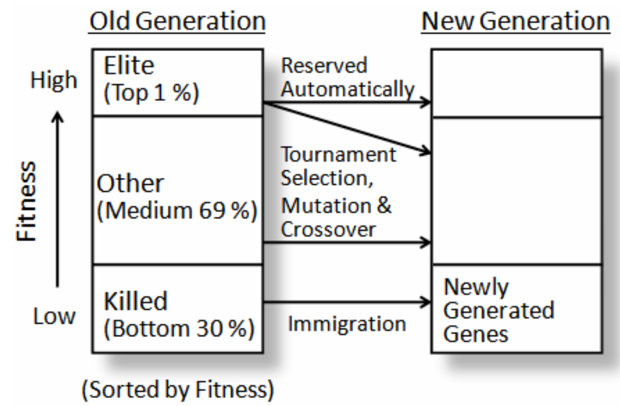

Fig. 4 Image of Making New Generation

After repeating the process of Step2) - 4) for 100 generations, or the fitness of the best individual does not improve for 10 successive generations, the best individual is chosen as the optimized trading rule.

4.4 Testing Data Set

Like described in section 4.1, the data immediately posterior to the training data set is used as the testing dataset, and the individual with best fitness found in the learning step is used as the trading rule.

4.5 Application of Investment Rules

An example of optimized trading rule (buying rule only) is shown in Table2.

Table 2 An Example of Optimized Trading Rule

Range of Technical Indexes to Invest (Buying Rule)	
{(75% <RSI1< 87.5%) || (0.1% <RR< 0.25%)} && {(-0.35% <PD< -0.05%) || (62.5% <RSI2< 97.5%)}	
RSI-Reference Time Length	24 hours
EWMA-Reference Time Length	13 hours
EWMA-Weight α	0.65
Profit Cashing	+ 0.8 Yen/ 1 USD
Loss Cutting	- 1.5 Yen/ 1 USD

Insofar as the sequence of rule application is concerned, as with the training data, we first calculate the four Technical Indexes indicated in Section 4.2 in accordance with the optimized trading rule for the testing data. We then execute foreign exchange trades for a time period that is consistent with the conditional equation for the range of indexes shown in Table 1.

We can now conduct an experiment using leverage. We decided to permit an investment with maximum leverage of 10 times.

1) Application of Leverage

For determining when leve rage should be applied, r, the correlation coefficient of the 24-hour period immediately preceding execution of foreign exchange trades and the subsequent 24-hour periods within the period of the training data, is calculated for all time periods.

$$r = \frac{\sum_{i=1}^{24}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{24}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{24}(y_i - \bar{y})^2}} \quad (4.1)$$

Next, for the periods in the training data for which $r > 0.75$, the tendency of the foreign exchange rate to either increase or decrease immediately after a trade is judged based on calculations using the following equation:

$$F = \sum_{i=1}^{24}(x(t+i) - x(t)) \times (24 - i) \quad (4.2)$$

where F>0 in the case of buying, and F<0 in the case of selling. The relative proportions of buying and selling trades are calculated and leverage is determined based on the calculated proportion, p. Figure 5 shows the correspondence between p and leverage, where the example leverage is a maximum of 5 times.

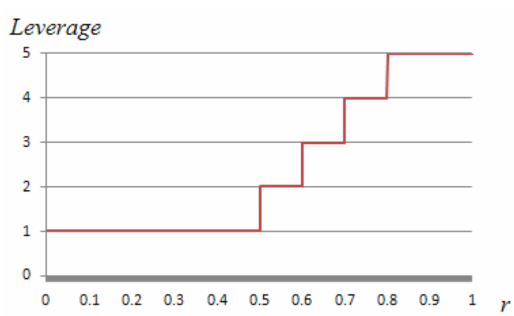

Fig. 5 Determination of Leverage

2) Additional Buying and Selling

In this study, in addition to leverage, when a profit was incurred for a given traded position we decided to add a position further in the same direction. Figure 6 shows a specific example of such additional buying.

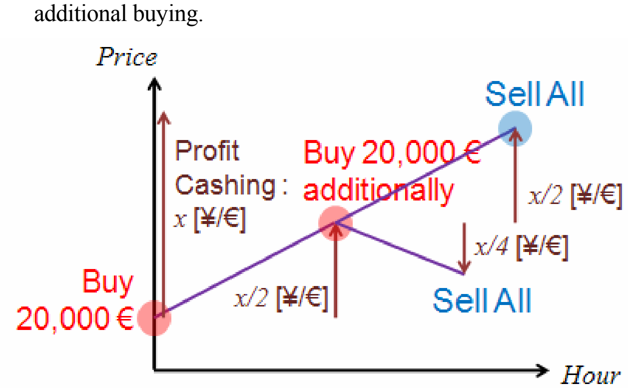

Fig. 6 Image of Additional Buying

Ordinarily, when 20,000 Euros are bought at a certain price, profits are taken when the Euro increases by x above that price [Yen/Euro]. However, under the additional buying rules used in this study, we decided to buy an additional 20,000 Euros at the point where the Euro increased by $x/2$ [Yen/Euro]. Subsequently, if the Euro increases further by $x/2$ [Yen/Euro], then the original profit-taking position is reached, and by selling the entire holding at that time, it is possible to obtain 1.5 times the ordinary profit. Conversely, if after additional buying the Euro falls by $x/4$ [Yen/Euro], then selling the entire holding at that time results in zero profit or loss. Coupled with the application of leverage in 1), leverage reaches a maximum of 10 times.

A similar rule can also be applied in the case of further selling. By applying this further buying and further selling method, we have adopted a strategy aimed at increasing profit while managing risk.

5. EXPERIMENT

5.1 Experiment Conditions & Data Used

1) Trading Fees

In this paper, the investment simulation is held based on a real FX brokerage company in Japan. Spread (the difference between asking price and bidding price) is 0.03 Yen per 1 USD trading, 0.04 Yen per 1 EUR trading, and 0.06 Yen per 1 AUD trading.

2) Initial Capital and Investment Amount

The experiments on USD/JPY, EUR/JPY, and AUD/JPY investment are held independently. The initial capital is 1,250,000 Yen for the USD investment, 1,600,000 Yen for the EUR investment, and 1,000,000 Yen for the AUD investment. In all the cases, the investment amount is n*10,000 (USD or EUR or AUD) per trade operation (either buying or selling), while n is equal to "leverage" defined in section 4.5.

3) Data Used

As the data for testing, the following historical FX rate data sets are used. Each data set contains the hourly closing values for the FX rates.

1. USD/JPY (2005-2008, 4years)
2. EUR/JPY (2005-2008, 4years)
3. AUD/JPY (2005-2008, 4years)

To separate the training and test data, we use a rolling window method. We train with a six month period, and test with a 3 month period. Then for the each subsequent experiment, we move both the training and the testing period 3 months forward (see Fig. 7).

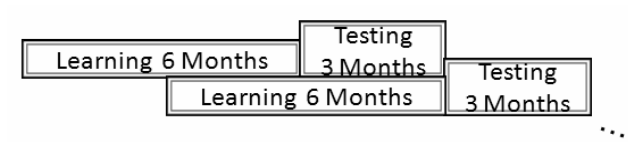

Fig.7 Method of Learning & Testing

5.2 Results & Discussion

1) Results

First, as examples, results of investment management in EUR in 2005 and USD in 2006 are shown (Fig.8, 9). The blue line ("Proposed") shows how the trading rule increases the profit from the asset (Right axis, Retained [JPY]). We also show the results for a method where the leverage rule is not used (Red line, "No leverage").

For reference, the chart of rate (EUR/JPY or USD/JPY or AUD/JPY) is shown in green line.

In a similar way, the result of EUR and AUD in 2008 is shown in Fig.10 and Fig.11.

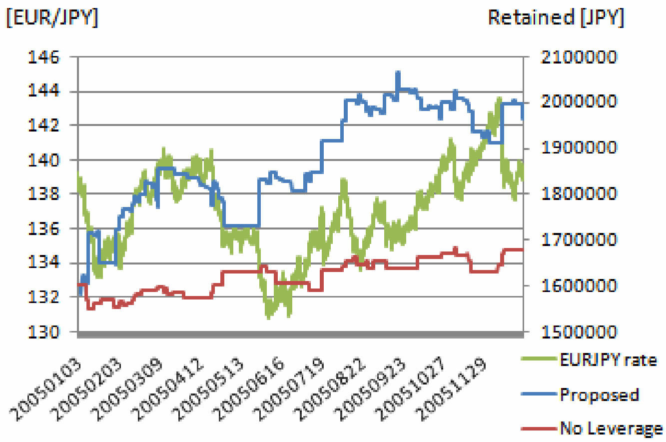

Fig. 8 EUR/JPY Chart in 2005 & Operating Result

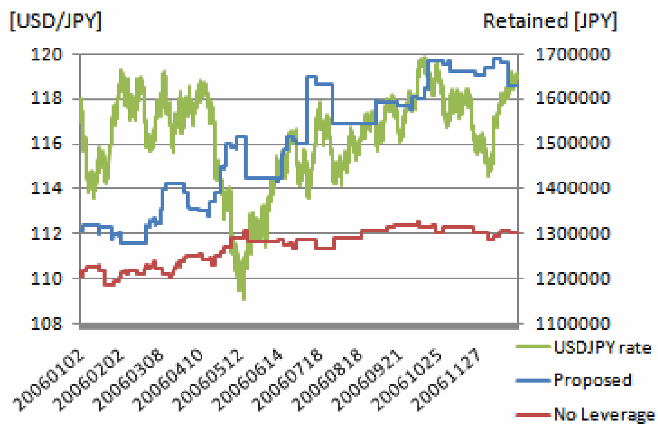

Fig. 9 USD/JPY Chart in 2006 & Operating Result

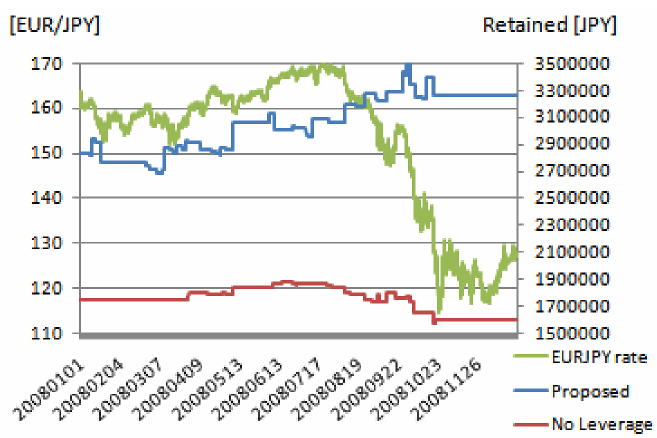

Fig. 10 EUR/JPY Chart in 2008 & Operating Result

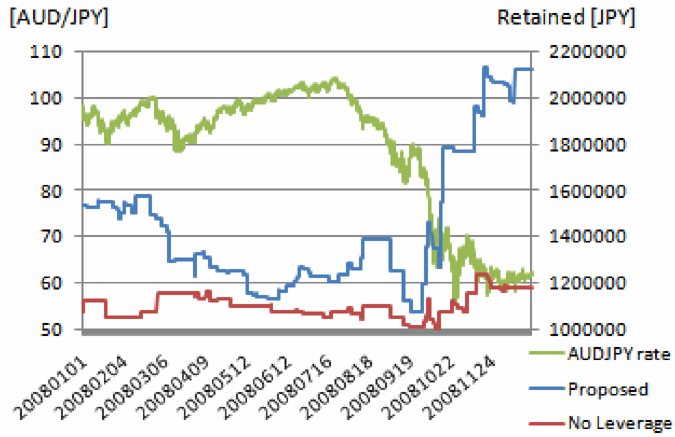

Fig. 11 AUD/JPY Chart in 2008 & Operating Result

Finally, the example of optimized trading rule (buying rule only, from the EUR, period: 2006, 4-9) is shown in Table3.

Table3 An Example of Optimized Trading Rule

Range of Technical Indexes to Invest (Buying Rule)	
{(81.25% <RSI1< 93.75%) && (-0.3% <RR< 0.1%)} || {(-0.15% <PD< 0.7%) && (75% <RSI2< 97.5%)}	
RSI-Reference Time Length	31 hours
EWMA-Reference Time Length	23 hours
EWMA-Weight α	0.7
Profit Cashing	+ 2.3 Yen/ 1 EUR
Loss Cutting	- 1.7 Yen/ 1 EUR

<u>2) Discussion</u>

First, as notably observed in Fig.8 and Fig.9, the movement of the retained amount has a strong tendency to behave similarly to that of original FX rate. However, though the price in the beginning of the year is almost same as that of the end of the year, the proposed method could gain a certain amount of profit, in both cases. In that point, therefore, the effectiveness of the proposed method is shown in some extent.

Next, as we can see Fig.10 and Fig.11, the proposed method gained quite large profit in the price's sharp falling period (caused by Financial Crisis accompanying Lehman Brothers collapse). Especially in Fig.11's AUD case, one having a loss, it gained twice as much profit as the loss.

Seeing these results, we can see that a market with a rapidly falling price is easily understandable to the Machine Learning method, allowing it to extract large profits from it.

Besides, considering the profitable buying rule as shown in Table3, both RSI of original data and RSI of EWMA have tendency to take high value. It implies that when the market price is in rising trend, following the trend have much probability to bring profit, especially in short-period trading.

6. Comparison with Neural Networks (NN)

To confirm the effectiveness of the proposed method using genetic algorithms (GA), we compared the results obtained with NN and provide an overview here [14].

6.1 Learning using Neural Networks

First, as for using the proposed method with GA, we used the four technical indexes as input signals. For the signals, we use the binary numerals 0 and 1 rounded to 32 values. For teacher signals, we use the values calculated using the following equation:

$$Out = \sum_{i=1}^{23} \{x(t+i) - x(t)\} \times (24 - i)] \quad (6.1)$$

where $x(t)$ indicates the exchange rate on day t. As output signals, we use the values obtained by summing the product of a coefficient and the increase in the exchange rate i days later, with the increase in the rate in the 24-hour period immediately following i. In other words, the higher the best-fit value, the greater the tendency is for the exchange rate to increase within the 24-hour period. As with the input signals, we use the binary numerals 0 and 1 rounded to 32 values for the output signals.

We optimize the NN weights by back-propagation (BP) for pairs of a fixed period spanning several minutes of input signals and teacher signals. In addition, we set the intermediate layer unit number at 8, the learning rate at 0.5, and the coefficient of inertia at 0.03.

6.2 Investment Simulation

In the testing period immediately following the learning period, we perform an investment simulation similar to that of the proposed GA method using the weights optimized through the learning period.

On the basis of the technical indexes calculated for each period, t, we take the output calculated using the NN weights as n_t.

We then determine buying and selling times for n_t using the following relations:

Buying time) $n_t > \mu + 2\sigma$ (8.2)

Selling time) $n_t < \mu - 2\sigma$ (8.3)

where μ and σ are the mean values for exchange rates derived from the learning period and the standard deviation, respectively.

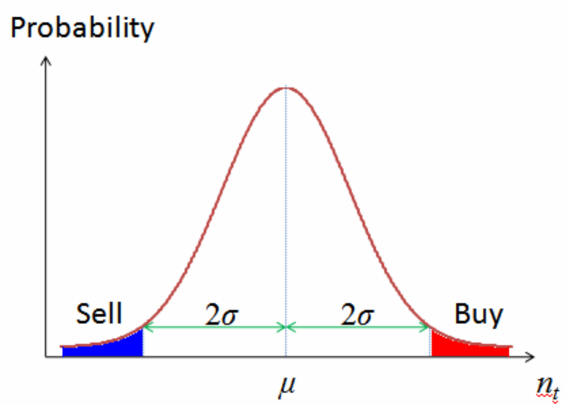

Fig. 12 Image of Buy & Sell Timing

Ordinarily, financial product price fluctuations are considered to conform to a normal distribution, with the timing for buying and selling is considered to fall within the upper (8.2) and lower (8.3) 2.28% bounds of this distribution, respectively.

The results of an investment simulation using the loss cutting and profit cashing settings of the proposed method using GA are shown below.

6.3 Results & Discussion

1) Results

We show the percentage profit (%) on the initial retention of USD, Euro, and AUD in Figs.13-15. We also compare the proposed method with the results obtained using the GA (Proposed), GA (No Leverage), Buy & Hold strategies , and NN (Neural). The results of the GA shown here are the averages of 5 runs. The error-bars in "Proposed" and "No Leverage" represent the value of the standard deviation for each data point. "2005-2007" means the total results of 3 years.

2) Discussion

In almost all the situations, NN's performances are inferior to GA, even compared to that of the Buy & Hold strategy, the performances are not good. In fact, a comparison of the three-year totals for each method reveals that GA performs consistently better than NN.

Next, see the Fig.13's US Dollar case, and compare with the behavior of cases in Fig.10 and 11. The fall of USD price in 2008 was not so fast as the Euro or Australian Dollar, and it became rather difficult to understand the market and achieve profit.

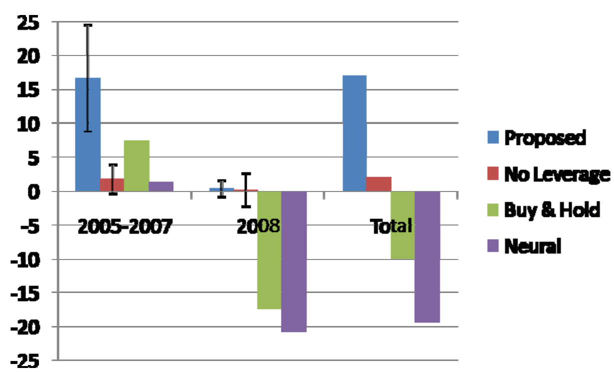

Fig. 13 Comparison of Percentage Profit (USD)

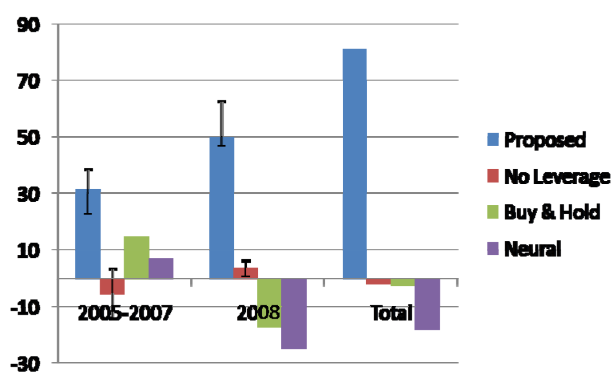

Fig. 14 Comparison of Percentage Profit (EUR)

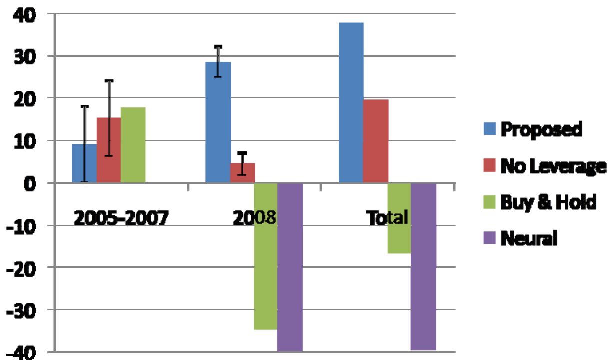

Fig. 15 Comparison of Percentage Profit (AUD)

7. CONCLUSION

In this paper, we proposed a method for the optimization of trading rules in Foreign Exchange using GA. Concretely, using historical exchange rates data with extremely short interval, and applying a variety of Technical Indexes, GA managed to find the most profitable trading rule for the period was searched by GA. This rule was applied in the time period immediately posterior without being re-trained beforehand. As a result, though there is vulnerability to sudden market changes, the effectiveness of the proposed method was shown in some aspects.

As future work, we want to introduce Multi-Objective GA for decreasing the investment risk. Also, we feel that the performance of our system could improve by the use of a smarter representation of the profit cash and loss cut conditions in genomes. This is the current focus of our research.

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9. REFERENCES

[1] T.Hellstrom and K.Holmstrom, "The Relevance of Trends for Predictions of Stock Returns", *International Journal of Intelligent Systems in Accounting, Finance & Management*, Wiley & Sons, 2000, Vol.9, pp.23-34.

[2] A.Lipton-Lifschitz, "Predictability and unpredictability in financial markets", *Physica D*, Elsevier, 1999, Vol.133, pp.321-347.

[3] Shuo Yao, Michel Pasquier, Chai Quek, "A Foreign Exchange Portfolio Management Mechanism Based on Fuzzy Neural Networks". *IEEE Congress on Evolutionary Computation 2007*, pp.2576-2583, 2007.

[4] W.Banzhaf, P.Nordin, R.E.Keller, and F.D.Francone, Genetic Programming – *An introduction: on the automatic evolution of computer programs and its applications*, Kaufmann, San Francisco, 1998.

[5] Bentley College, *Technical Analysis 1* (Hughey Center for Financial Serivices, 2002).

[6] S.B.Achelis, *Technical Analysis from A to Z*, McGraw-Hill Trade, 2000

[7] Pablo Fernández-Blanco, Diego J. Bodas-Sagi, Francisco J. Soltero, J. Ignacio Hidalgo, "Technical Market Indicators Optimization using Evolutionary Algorithms". *GECCO 2008*, pp.1851-1857, 2008

[8] Shu-Heng Chen, *Genetic Algorithms and Genetic Programming in Computational Finance* (Kluwer Academic Publishers, 2002).

[9] Roy Schwaerzel, Tom Bylander, "Predicting Currency Exchange Rates by Genetic Programming with Trigonometric Functions and High-Order Statistics". *GECCO 2006*, Vol.2, pp.955-956, 2006

[10] Kiyoshi Izumi, Kazuhiro Ueda, "Analysis of Exchange Rate Scenarios Using an Artificial Market Approach". *IPSJ SIG Notes.ICS*, vol.2000, No.3, pp. 9-16, 2000

[11] David de la Fuente, Alejandro Garrido, Jaime Laviada, Alberto Gomez, "Genetic Algorithms to Optimize the Time to Make Stock Market Investment". *GECCO 2006*, Vol.2, pp.1857-1858, 2006

[12] Cyril Schoreels, Brian Logan, Jonathan M.Garibaldi, "Agent based Genetic Algorithm Employing Financial Technical Analysis for Making Trading Decisions Using Historical Equity Market Data", IAT04, 2004

[13] J.Branke, "Evolutionary Approaches to Dynamic Optimization Problems – A Survey", *GECCO Workshop on Evolutionary Algorithms for Dynamic Optimization Problems*, 1999, pp.134-137

[14] B.K.Wong and Y.Selvi, "Neural network applications in finance: A review and analysis of literatures (1990-1996)", *Information & Management*, 1998, Vol.34, pp.129-139