

Modeling International Short-Term Capital Flow with Genetic Programming

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Abstract

In this paper, a non-deterministic (portfolio-based) finite-state automaton is proposed to generalize the current financial trading applications of genetic programming from single risky asset to multi risky assets. The GP-evolved trading rules are tested under various settings with respect to search intensity, genetic portfolios, and validating parameters. The rules are compared with performance of a buy-and-hold strategy in a context of international capital flow using data from Taiwan, the U.S., Hong Kong, Japan and the U.K. The GP are evaluated by using both the mean rule and the majority rule. However, by and large, it is found that GP was outperformed by the buy-and-hold strategy in both cases.

Introduction

Based on the survey of the current financial trading applications of genetic programming by Chen and Kuo (2003), GP has been applied to the trading of stocks (Allen and Karjalainen, 1999), foreign exchanges (Neely, Weller and Ditmar, 1997, 1999), and spots and futures (Wang, 2000). However, most trading applications of GP consider only one single risky asset. Wang (2000) is the only exception that considers using GP as a speculation tool by simultaneously trading both in the spots market and the futures market of a stock index.

Similar to that idea of the two-market dimension, this paper addresses an integrated trading design by simultaneously taking into account two stock markets with two foreign exchanges. Doing in this way, this paper can be regarded as a generalization of the early study by Allen and Karjalainen (1999) on the stock market and Neely et al. (1997) on the foreign exchange market. This generalization is originally motivated by the empirical observation of the international flow of hot money, which sometimes moves very quickly among international capital markets. Our original curiosity lies in seeing whether the momentum of capital inflow and outflow can be simulated and hence predicted by using the GP. Therefore, to achieve that goal, we need to develop trading decisions not only on a single capital market (the host capital market), but also on the foreign capital market.

Consequently, the decision on the currency position is not just an independent arbitrage motive, but is also CIEF 2003 (<http://aiecon.org/conference/cief2003.html>).

connected to the previous decision on the participation intensity of different stock markets. These two decisions originally treaded separately by Allen and Karjalainen and Neely et al. are now bound together. In the simplest model, there are a minimum of four markets involved in this general framework, and the trading strategy needs to inform the trader which market to participate at any point in time.

Representation

The design of our finite-state automaton is based on the transition graph given above. There are four states characterizing four assets in the automaton. From the leftmost to the rightmost the four assets are TAIEX, NT\$, US\$, and S&P 500. The current state indicates the market in which the investment is put. For example, if the current state is "TAIEX", it means that money is now flowing into the Taiwan stock market, whereas a state "US\$" refers to a demand for the asset of US\$.

The transition from state to state is governed by the transition table upon the received signal. The transition from one state to the other state follows a sequential order as arranged in the figure. For example, a direct transition from the state "TAIEX" to "S&P500" is prohibited. To get there, the asset in the Taiwan stock market has to be first sold out to get cash in NT\$, and then changed to US\$ before one can finally invest to the US stock index.

At a given state, the moving direction is determined by the received signal generated by GP. The GP considered in this paper has a tree-structure as shown in Figure 1. It is not the standard single parse-tree structure. Instead, it is composed of three subtrees, each of which works independently. Call them from the left to the right Tree A, B, and C. The three trees lie between the two consecutive states (shown in Figure 2), and they instruct what to do if the current position is one of the two consecutive states. For example, if the current state is "TAIEX", then Tree A is the one to consult with; if the current state is "NT\$", then both Trees A and B will be involved. The specific instruction is given by the output of the tree. At a point in time, each tree simultaneously outputs "+1" or "-1", altogether as a 3-bit signal. This 3-bit signal will then decide where to move for the next. The moving direction is shown in the previous figure. Basically, "+1" means a move to the left, and "-1" means a move to the right.

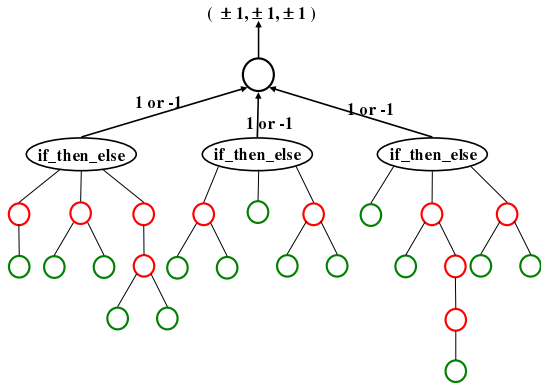


Figure 1: Tree-Structure

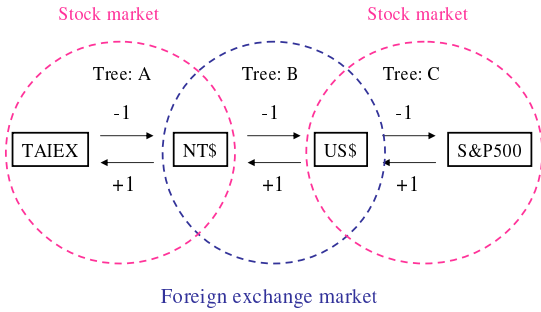


Figure 2: The Four-Asset Finite State Automaton

The transition rules can be described as follows: Initially at any position (state), if the local signals are consistently positive (negative), then move the position one step to the left (right). If it already comes to the leftmost (rightmost) state, then simply stay there. If the local signals are inconsistent, stay there when the moving arrows make the current state a “sink”, and split, moving both to the left and right when the moving arrows make the current state a “source”. A remark is required for the last case, because it is not the common style of the non-deterministic finite state automata. Non-deterministic finite state automata interpret the uncertain situation as a command “or”, “move to the left or to the right”. But, here, we are using “and” rather than “or”, since we are dealing with the allocation of investment, and a way out of an equally competing situation is to diversify the investment as one half for each. This not only distinguishes our finite state automaton from the conventional one, but also enables it to befit the problem of portfolio selection.

Based on the transition rules described above, the transition tables are displayed in the following figure by assuming a different current state.

Data Description

The data used in this paper include the financial time series on exchange rates, stock indices, and interest rates from the following four countries: the USA, Japan, Hong Kong, the UK, and Taiwan. Taiwan is taken as the host country here. The data from 1992, Jan. 1 to 2002, Dec. 31 are downloadable from *Datastream*. The original time

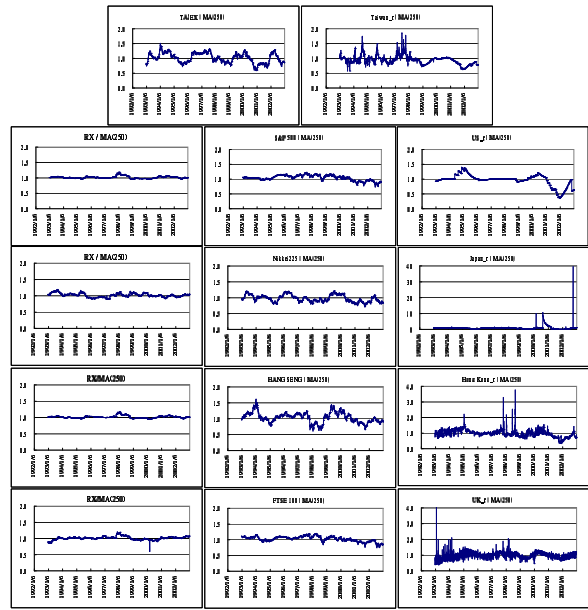


Figure 3: Time Series of Stock Indices, Interest Rates, and Exchange Rates

series data are generally non-stationary. All data are stationarized by dividing them by the 250-day moving average. The adjusted data are shown in Figure 3.

The data are divided into three parts with equal proportion. The first part is used for training. The GP trading rules are extracted from this part. The second part is used to validate the rules learned from the first part. The rules which perform best on this validation set will be kept until they are replaced by the newly found best rules. However, after a number of generations, if no new best rules are found, the program will be terminated. This procedure of validation is proposed by Neely et al. and commonly used in the literature. Evaluations of GP trading rules are, of course, based on the last part of the data.

Experiment Designs

The Use of GP

The *primitives* of GP are given in Table 1. These primitives are motivated by some familiar trading rules, such as the moving average rules and the range break-out rules. Using these primitives, those familiar trading rules become a member of the GP search space, and hence are potentially replicable by GP.

Search intensity is mainly controlled by the product of two factors: *population size (POP)* and *number of generations to evolve (GEN)*. In the examples of chaotic time series, Chen and Kuo (2002) shows the search efficiency of GP may depend upon the combination of the two factors. Motivated by that study, we conduct search intensity with six different combinations of *POP* and *GEN* as shown in Table 1.

Genetic portfolio is defined as the proportion of each genetic operator used in generational replacement. Also motivated by Chen and Kuo (2002), which showed the

Table 1: Tableau of Control Parameters	
Function Set: +, −, *, /, <i>norm</i> , <i>max</i> , <i>min</i> , <i>lag</i> , <i>avg</i> <i>and</i> , <i>or</i> , <i>not</i> , >, <, <i>if – then – else</i>	
Terminal Set:	
<i>Variables</i> exchange rate, stock indices, interest rate	
<i>Numerical constants</i> 100 constant numbers in [0.0, 10.0)	
<i>Boolean constants</i> True, False	
Population: 200, 500, 1000	
Generation: 100, 200	
Fitness: Gross returns	
Validation (ω): 1/2, 1/4	
Selection: Tournament	

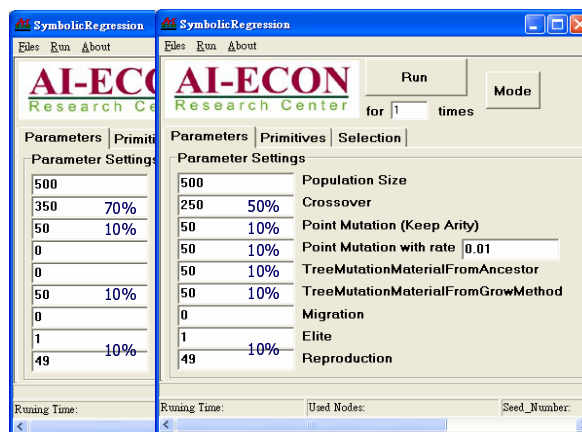


Figure 4: Genetic Portfolio a and b

significance of the genetic portfolio, this paper considers two different genetic portfolios, and they are shown in Figure 4. The first portfolio relies more heavily on the crossover operator, while the second portfolio puts more emphasis on the mutation operator.

The *fitness function* is the *annual return* of the investment. The return is calculated in terms of the foreign currency. Consider the case of the capital flow between Taiwan and the U.S. Let us say we have US\$ 1.00 investment at the beginning, and after a 3-year investment, it end up with US\$ 1.12. Then the total return for the three years is 12%, and hence the annual return is 4%. Notice that penalty for complexity is not explicitly included in our fitness function. The complexity regularization is conducted via the validation scheme as sketched in Section . The validation scheme requires the user to input a *waiting* parameter, i.e., how long to wait for the newly-founded best-performed trading rules before we terminate the training stage. The number of iterations to wait is, of course, less than *GEN*. However, there is no general guidance for the setting of this waiting time. To test whether this parameter is significant, we consider two waiting times in this paper: namely a longer one as one half of *GEN* ($\omega=1/2$), and a shorter one as one fourth ($\omega=1/4$).

Benchmark

Following the convention, the buy-and-hold (**B&H**) strategy is employed as the benchmark by which GP trading rules are evaluated. However, since we have four assets in our application, the **B&H** strategy can be conducted in four different ways: buy TAIEX and hold, buy NT\$ and hold, ..., etc. As a result, what we do here is to assume a *uniform portfolio* over these four **B&H** strategies. The essence of the **B&H** strategy lies in its *simplicity*, and our modification is, therefore, a natural extension of the **B&H** strategy from the interest-bearing asset to the multiple interest-bearing assets.

Experimental Results

Before giving the experimental results, notice that we have all 6 (search intensity) \times 2 (genetic portfolio) \times 2 (waiting time) equal to 24 designs. Other control parameters of GP remains the same over these 24 designs. For each design, 20 independent runs are conducted. This gives us a total of 20 trading rules for each design. The evaluation of each design depends on how to use these 20 rules. Two methods exist in the literature. The first is to assume a uniform portfolio over these 20 rules, and the evaluation is simply to take the average of the gross returns over these 20 rules. The second one is to assume an investment committee comprising these 20 rules, and the investment decision is made by the majority of the committee. The gross returns of the majority rule are then calculated accordingly for evaluation.

Based on the description above, we shall first present the performance of GP using the portfolio method (Table 2), and then the committee method (Table 3). The in-sample performance of GP in both cases will be skipped here, because they are not very interesting even though they unanimously perform quite superior to the uniform **B&H** strategy.

As shown in Table 2, over all the four markets, the performance of the GP trading rules is inferior to that of the **B&H** strategy. The worst cases are the capital flow between Taiwan and U.S. markets, and that between Taiwan and H.K. markets: GP loses to the **B&H** strategy under all the 24 designs. For Japan and U.K. markets, GP is able to beat the **B&H** under some designs. However, despite the existence of some winning designs, there is no indication of what the effective design is.

The results of the majority rule (Table 3) are slightly better. In particular, for the case of the capital flow between Taiwan and Japan, there are some designs leading to a gross return greater than one, which proves that GP can even make profits in a very adverse situation.¹ Nevertheless, situations for other pairs of markets do not show a difference to an exciting degree.

¹Notice that in this testing period, all **B&H** strategies suffer a loss.

	Gen	\ Pop	200	500	1000
USA $\omega=1/2$	100	a	0.6390	0.6436	0.6814
		b	0.6258	0.6477	0.6532
	200	a	0.6283	0.6878	0.6767
		b	0.6668	0.6387	0.7160
$\omega=1/4$ [0.8033]	100	a	0.6792	0.6624	0.6726
		b	0.6297	0.6891	0.7185
	200	a	0.6309	0.6404	0.6287
		b	0.6906	0.6590	0.6850
Japan $\omega=1/2$	100	a	0.8911	0.7037	0.8112
		b	0.7708	0.7793	0.8419
	200	a	0.7015	0.7462	0.8786
		b	0.7469	0.7406	0.8312
$\omega=1/4$ [0.8051]	100	a	0.8514	0.8294	0.7892
		b	0.8062	0.7762	0.7446
	200	a	0.7939	0.7739	0.8386
		b	0.8682	0.7658	0.8118
HK $\omega=1/2$	100	a	0.6175	0.6374	0.6441
		b	0.6224	0.6670	0.6471
	200	a	0.6192	0.6605	0.6562
		b	0.5938	0.6138	0.5511
$\omega=1/4$ [0.7988]	100	a	0.6673	0.6823	0.6411
		b	0.6719	0.7030	0.6882
	200	a	0.6419	0.5943	0.6089
		b	0.6379	0.7483	0.6445
UK $\omega=1/2$	100	a	0.6791	0.7234	0.7608
		b	0.6846	0.8011	0.7217
	200	a	0.7794	0.8491	0.6895
		b	0.6906	0.8647	0.7616
$\omega=1/4$ [0.8121]	100	a	0.7012	0.7382	0.8397
		b	0.7123	0.7909	0.7866
	200	a	0.7280	0.7179	0.8194
		b	0.7082	0.7662	0.6626

The “a” and “b” refers to two different genetic portfolios defined in Figure 4. The number shown in the bracket is the gross return earned by following the buy-and-hold strategy.

Table 2: Gross Returns of GP (the Portfolio Method)

Concluding Remarks

In general, GP did not outperform the simple buy-and-hold strategy. On this point, our finding is similar to Allen and Karjalainen (1999) and Wang (2000). However, by conducting a more extensive test, this paper stands in even a more solid position to answer the following question: *Should the relatively inferior performance of GP be attributed to the market efficiency or the poor use of GP?* In this paper, we have taken into account all the key factors which may affect the performance of GP, such as search intensity, genetic portfolios, validation designs, and different combinations of GP-evolved rules. None of them, however, are significant enough to stand out. This result, therefore, is in favor of market efficiency as a cause for the poor performance of GP.

	Gen	\ Pop	200	500	1000
USA $\omega=1/2$	100	a	0.6002	0.7636	0.6411
		b	0.6348	0.7009	0.6016
	200	a	0.6283	0.6438	0.8697
		b	0.6568	0.6348	0.7306
$\omega=1/4$ [0.8033]	100	a	0.6129	0.6133	0.6974
		b	0.6582	0.6342	0.6735
	200	a	0.6179	0.6274	0.6229
		b	0.6353	0.8233	0.6921
Japan $\omega=1/2$	100	a	0.7680	0.6855	0.8540
		b	1.0706	1.1617	1.1579
	200	a	1.0199	0.6895	1.0456
		b	1.0278	1.0171	1.0199
$\omega=1/4$ [0.8051]	100	a	0.7795	0.8773	0.7057
		b	0.9095	0.6047	1.0333
	200	a	0.8658	1.1220	0.8579
		b	0.9415	1.0227	0.8471
HK $\omega=1/2$	100	a	0.4505	0.4758	0.5849
		b	0.6198	0.6582	0.6692
	200	a	0.4896	0.5666	0.6694
		b	0.5001	0.4523	0.5160
$\omega=1/4$ [0.7988]	100	a	0.6034	0.4753	0.6516
		b	0.7299	0.7836	0.5274
	200	a	0.7685	0.6128	0.4615
		b	0.6988	0.6561	0.4877
UK $\omega=1/2$	100	a	0.6022	0.8478	0.7730
		b	0.8289	0.8300	0.7171
	200	a	0.8646	0.7874	0.8976
		b	0.8240	0.8115	0.8284
$\omega=1/4$ [0.8121]	100	a	0.6199	0.7193	1.0894
		b	0.7971	0.7332	0.8779
	200	a	0.6383	0.6670	0.8720
		b	0.7891	0.7825	0.7868

The “a” and “b” refers to two different genetic portfolios defined in Figure 4. The number shown in the bracket is the gross return earned by following the buy-and-hold strategy.

Table 3: Gross Returns of GP (the Majority Rule)

Of course, these are not final words on the issue. There is always room for enhancing GP performance, as what GP people have been doing over the last decade. From representations, primitives, fitness functions, to the inclusion of domain-specific knowledge and the use of automatic defined functions, it is too early to say that possibilities have run out. Whether the failure of GP is tantamount to the unpredictability of the market remains to be studied.

References

- Allen, F., and R. Karjalainen (1999), “Using Genetic Algorithms to Find Technical Trading Rules,” *Journal of Financial Economics*, Vol. 51, No. 2, pp. 245–271.
- Chen, S.-H., and T.-W. Kuo (2002), “Genetic Programming: A Tutorial with the Software Simple GP,” in

, S.-H. Chen (ed.), *Genetic Algorithms and Genetic Programming in Computational Finance*, Kluwer Academic Publishers, pp. 55–77.

Chen, S.-H., and T.-W. Kuo (2003), “Discovering Hidden Patterns with Genetic Programming,” in S.-H. Chen and P. P. Wang (eds.), *Computational Intelligence in Economics and Finance*, Springer-Verlag, pp. 329–347.

Neely, C., and P. Weller (1999), “Technical Trading Rules in the European Monetary System,” *Journal of International Money and Finance*, Vol. 18, pp. 429–458.

Neely, C., P. Weller, and R. Dittmar (1997), “Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach,” *Journal of Financial and Quantitative Analysis*, Vol. 32, No. 4, pp. 405–426.

Wang, J. (2000), “Trading and Hedging in S&P 500 Spot and Futures Markets Using Genetic Programming,” *Journal of Futures Markets*, Vol. 20, No. 10, pp. 911–942.