Construction of Portfolio Optimization System using Genetic Network Programming with Control Nodes

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ABSTRACT

Many evolutionary computation methods applied to the financial field have been reported. A new evolutionary method named "Genetic Network Programming" (GNP) has been developed and applied to the stock market recently. In this paper a portfolio optimization system based on Genetic Network Programming with control nodes is presented, which makes use of the information from Technical Indices and Candlestick Chart. The proposed optimization system, consisting of technical analysis rules, are trained to generate trading advice. The experimental results on the Japanese stock market show that the proposed optimization system using GNP with control nodes outperforms other traditional models and Buy&Hold method in terms of both accuracy and efficiency, and its effectiveness has been confirmed.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Intelligent agents

General Terms

Algorithms

Keywords

Portfolio Optimization, Genetic Network Programming, Control Node, Reinforcement Learning

1. INTRODUCTION

Nowadays, Evolutionary Computation has become a subject of general interest with regard to the power to solve complex optimization problems. This paper presents an application of Evolutionary Computation method named Genetic Network Programming (GNP) to the problem of portfolio optimization within the field of financial economics.

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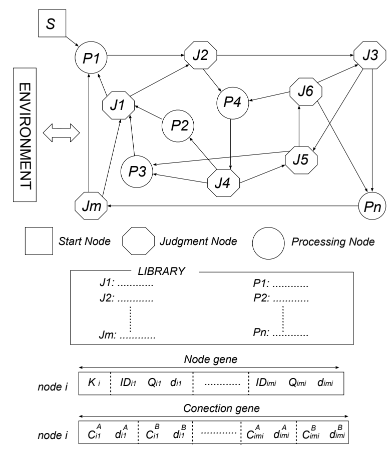

Figure 1: The basic structure of GNP

In this work, we extend our previous research on Genetic Network Programming with Reinforcement Learning (GNP-RL) and propose an algorithm that integrates the GNP-RL and control nodes in order to create an efficient portfolio optimization system. The features of the proposed method compared with other traditional methods are as follows: The GNPcn method makes a stock trading strategy considering the recommendable information of technical indices. Also Candlestick Charts are introduced for efficient trading decision making.

2. GENETIC NETWORK PROGAMMING WITH CONTROL NODES

2.1 Basic Structure of Genetic Network Programming

The traditional GNP is composed of a start node, judgment nodes and processing nodes, which are connected to each other. Fig.1 shows a basic structure of GNP. Judgment nodes have if-then type branch decision functions, which re-

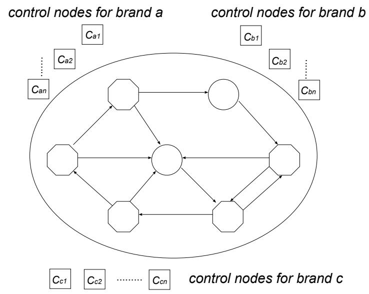

Figure 2: The basic structure of GNPcn

turn judgment results for assigned inputs and determine the next node. Processing nodes take buying and selling actions for the stock trading. The genotype expression of GNP node is also shown in Fig.1. This Figure describes the gene of node i, then the set of these genes represents the genotype of GNP individuals.

2.2 GNP with Control Nodes (GNPcn)

In conventional GNP, since the current node isn't compulsorily transferred to the start node, there is a possibility that some of the nodes are not used. Therefore, in this paper, GNP with control nodes (GNPcn) is proposed to solve this problem. Fig. 2 shows the basic structure of GNPcn. GNPcn has several control nodes, judgment nodes and processing nodes. GNPcn uses one of the groups of control nodes for one brand of stocks, so that GNPcn could deal with multi-brands.

3. PORTFOLIO OPTIMIZATION SYSTEM USING GNPCN

In this section, how to determine the ratio of the initial budget of each brand is described in the dealing of stocks using GNP with control nodes. Portfolio optimization system has been constructed by training phase and testing phase. Especially, the portfolio does not change during the dealing, although it changes generation by generation. We use the GNPcn for determining the portfolio of the stock brands, where each brand corresponds to each set of control nodes like shown in Fig.2. In GNPcn, judgment nodes check the technical indices and candlestick chart patterns, and processing nodes work for buying or selling stocks.

GNPcn individual starts its operation from one of the control nodes, the activated node is transferred to a judgment node or a processing node. At the processing node, the trading is executed using the opening price of the day. The concrete procedure of trading is as follows.

- Calculate the initial budget of each brand whenever the buying signal occurs in the processing nodes during the transition of each brand.
- Do the following for each brand until the end of the trading: If the current node is a judgment node, it determines the next node depending on the judgment result. If the current node is a processing node, after buying or selling stocks, it transits to the next node. When the processing node is executed m times from the last control node, the next node is determined by the next control node.
- Calculate the fitness of each brand at the end of the trading.

Table 1: PROFITS IN THE TESTING SIMULATIONS

	Profit[yen](profit rate[%])		
Brand	GNPcn	GNP-RL	Buy&Hold
NEC	-	43,400(0.9)	-1,026,000(-20.5)
Fuji H.	-	188,800(3.8)	-189,000(-3.8)
East JR	-	418,800(8.4)	477,000(9.5)
KDDI	-	316,233(6.3)	-576,000(-11.5)
Nomura H.	-	638,933(12.8)	-985,500(-19.7)
Shin-Etsu C.	-	133,800(2.7)	-264,000(-5.3)
Sony	-	202,766(4.1)	150,000(3.0)
Tokyo E. P.	-	116,100(2.3)	262,500(5.3)
Hitachi	-	403,366(8.1)	336,000(6.7)
Nissan	-	464,966(9.3)	450,000(9.0)
Average	678,530 (13.6)	292,716 (5.9)	-136,500(-2.7)

4. SIMULATIONS

To confirm the effectiveness of GNPcn for the portfolio optimization system, we carried out the trading simulations using 10 brands selected from the companies listed in the first section of Tokyo stock market in Japan (see Table 1). The simulation period is divided into two periods: one is used for training and the other is used for testing simulation. We suppose that the initial funds is 5,000,000 Japanese yen in both periods, and the order of buy or sell is executed at the opening of the trading day.

Table 1 shows the profits and losses in the testing term using the data in 2004. The values in Table 1 are the average profits of the 30 independent simulations with different random seeds. From the table, the proposed method can obtain larger profits than both Buy&Hold and traditional GNP-RL in the trade of 10 brands. Especially, In the case of conventional GNP, one GNP deals with only one brand, so the profit for each brand can be calculated. On the other hand, GNPcn deals with all of the brands, so only the total profit can be obtained. The advantage of the proposed method is to determine the distribution of the initial capital to each brand automatically, and the brands which obtain larger profit can get the initial capital more than other brands. As a result, by this efficient portfolio optimization system, GNPcn could obtain much profit in the trading of those brands.

5. CONCLUSIONS

In this paper, we proposed a portfolio optimization algorithm by using GNPcn to check the information of tecnical indices and candlestick chart pattern. From the simulation results, it is clarified that GNPcn performs much better in terms of the profit than GNP and Buy&Hold method. It shows the efficiency of the proposed GNPcn method for dealing with the portfolio optimization problem. For the future work, first, the algorithm presented can be further improved by modifying evolutionary operators. Moreover, additional effort should be spent on methods of portfolio validation in order to eliminate unacceptable solutions at the moment of its creation. We will also evaluate the proposed method comparing with other methods in the finantial market.