Electronics and Communications in Japan, Vol. 97, No. 8, 2014
Translated from Denki Gakkai Ronbunshi, Vol. 132-C, No. 12, December 2012, pp. 2019–2032

Portfolio Strategy Optimizing Model for Risk Management Utilizing Evolutionary Computation

KOKI MATSUMURA[1] and HIDEFUMI KAKINOKI[2]
[1]Tottori University, Graduate School of Engineering, Japan
[2]Mitsubishi Electric Corp., Himeji Works, Japan

SUMMARY

This paper proposes a new optimizing system for stock portfolios that uses evolutionary computation techniques to derive a highly suitable combination and investment ratio of brands as well as an appropriate trading-strategy tree. Accurately predicting price trends in the stock market is a difficult task to achieve with the result that investors often suffer great losses. Because stock portfolios are thought to be a valid means of avoiding such risks in terms of financial engineering, they have the effect of reducing risk by diversifying investment into several different brands. Based on this, it was attempted to determine an optimal combination of brands that constitute a portfolio and to derive the investment ratio using a multiobjective genetic algorithm, and also to optimize a trading strategy tree using genetic programming. When a performance evaluation was carried out, the system was found to generally obtain the operative results by making it possible to obtain stable profits using a combination of low risk brands. The system was also able to realize low risk investments in all test periods. © 2014 Wiley Periodicals, Inc. Electron Comm Jpn, 97(8): 45–62, 2014; Published online in Wiley Online Library (wileyonlinelibrary.com). DOI 10.1002/ecj.11587

Key words: portfolio; evolutionary computation; risk management; strategy optimizing; genetic programming; genetic algorithm.

1. Introduction

Increasingly many individual investors are becoming involved in trading of financial products due to the spread of the Internet and other factors. Transactions has become simpler and faster, and stock price movements have become larger and faster. Such conditions provide opportunities for making large profits in a short time period, while the risks of great loss also increase. Thus, one can face great losses and disasters unless risk management is performed thoroughly.

In this situation, some means are required to prevent risks, thus providing safety and loss reduction [1, 2]. In practice, investors (market participants), watching market trends from the standpoint of risk management, work out certain strategies for appropriate judgment about trading timing, and conduct investment activities based on such strategies.

In this context, we propose in this study a new method of building strategy trees for stock investment decisions based on technical indices [3], aiming at strategies that provide appropriate investment decisions in the stock market [4, 5]. Effective methods have been proposed for this purpose, such as building decision trees to predict trading timing by means of genetic programming (GP) [6], and a heuristic algorithm that classifies indices in a binary tree structure by clustering [7]. These methods produce a certain effect when applied to investment in individual brands, which suggests the possibility of building investment strategies by evolutionary computation.

However, with such strategy trees obtained to predict trading timing, it is difficult to manage risks related to stock price movements because such movements can differ at different times, even under the same conditions. One of the factors of this variation is that individual brands are characterized by specific circumstances and arbitrary movements. Thus, we assumed that trading focused on a single brand poses high risks. We therefore adopted the portfolio approach, in which investment is diversified among multiple brands for better risk control and higher return rates, and assumed that optimal strategies must be found to construct a portfolio with optimal allocation of high-return stocks.

Risk control is the most important issue in the field of financial engineering, and the portfolio plays the central role in terms of risk management, being an effective means along with options, a form of derivatives that function as insurance [8, 9].

The portfolio has the advantage that capital is not invested in a single brand but is distributed among multiple brands, thus reducing risk. To put it simply, when capital is distributed among multiple brands, even if some brands decline in price, causing a loss, this loss can be compensated by gains from other brands that rise. Thus, the probability of a large overall loss can be reduced. In addition, depending on the correlation in price movement among different brands in the portfolio, risk can be reduced at the same expected return, or the expected return can be increased at the same risk.

Thus, in this investigation we attempted to optimize trading strategies based on the creation of an efficient portfolio using evolutionary computation, aiming at risk control in stock trading.

First, we determined the optimal combinations and investment ratios for the brands constituting the portfolio from past stock market data by using a multiobjective genetic algorithm (GA) [10], which is a form of evolutionary computing. Each brand was assigned an investment ratio, and the portfolio evaluation indicators "risk" and "return" were evolved as fitness measures. The effectiveness of the resulting portfolio for an unknown period is verified in terms of risk and return.

We then tried to find an efficient trading strategy for the optimal portfolio. For this purpose, we composed a strategy tree, to serve as a transaction decision criterion, from technical indices and trading actions, and optimized the strategy tree by using GP for portfolio trading at appropriate timing. We then evaluated the possibility of stable profit.

Below we describe the proposed method, that is, portfolio strategy optimization, and verify its effectiveness by experiments.

2. Portfolio Theory

The portfolio evaluation criteria "risk" and "return" are expressed by the mean return rate and its variance on the basis of mean variance analysis [8, 9].

2.1 Mean variance analysis

Future values of risky brands fluctuate stochastically, and therefore one must know the stochastic characteristics of such fluctuations in order to make rational investment decisions. Ideally, one would like to know the probability distribution of the return rate for every individual brand, but this is unrealistic. Thus, the expectation and variance of the return rate are used as evaluation criteria for return and risk as follows:

$$Return = \sum_{i=1}^{N} r_i x_i, \tag{1}$$

$$Risk = \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_{ij} x_i x_j, \tag{2}$$

where N is the number of brands, r_i is the daily mean return rate of brand i, x_i is the investment ratio of brand i, and σ_{ij} is the covariance of brands i and j.

In addition the correlation factor ρ_{ij} of brands i and j is calculated as follows:

$$\rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j}, \tag{3}$$

where σ_i is the standard deviation of brand i, $-1 \leq \rho_{ij} \leq 1$.

2.2 Risk reduction due to correlation among brands

When a portfolio is composed of two brands, the fluctuations of the combined stock price are almost the same as those of the individual brands in case of a positive correlation in stock price movements, and are much smaller in case of a negative correlation. This is because price movements cancel each other in the case of two brands with opposite tendencies. Thus, the portfolio effect becomes particularly pronounced in the case of a combination with negative correlation.

Figure 1 shows the relation between the risk and return of a two-brand portfolio when the correlation coefficient is $\rho = 1$ (positive correlation), $\rho = 0$ (no correlation), and $\rho = -1$ (negative correlation). As can be seen from the graph, risk can be reduced without a significant decrease in return by selecting brand combinations with due regard for the correlation coefficient.

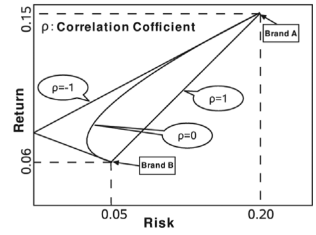
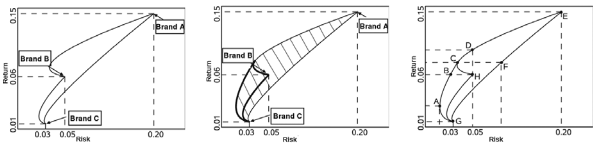


Fig. 1. Relation between risk and return based on correlation coefficients.



(a) In two brands (b) In three brands (c) Efficient frontier

Fig. 2. Relation between risk and return in multiple brands.

2.3 Risk reduction effect by multiple investment and the efficient frontier

Now let us extend the portfolio to three brands. The relation between risk and return for two of three brands is shown in Fig. 2(a). In the graph, the curves represent investable sets.

The relations for all three brands are illustrated in Fig. 2(b). In the graph, the investable sets are shown by the hatched area. The wider the area, the lower the risk. Compared to the curves in Fig. 2(a), the risk is reduced with the same return. Thus, risk can be reduced by portfolio diversification.

When an investor selects a portfolio from the investable set in Fig. 2(b) in terms of risk avoidance, it is usually desirable to choose high-return brands at the same risk, and low-risk brands at the same return. Consequently Fig. 2(c) (which is redrawn from Fig. 2(b) in terms of risk and return) provides the investor with a borderline consisting of points A, B, C, D, and E (the efficient frontier). Therefore, one can expect a reduction of risk and an increase of return when the investment ratio of constituent brands is adjusted to the efficient frontier.

3. Evolutionary Computation Method

Evolutionary computation is a technique simulating the evolution of living organisms [11]. An outline of evolutionary computation is given below.

3.1 Individual structure and optimization

In evolutionary computation, data or procedures associated with the solution structure are represented as arrays, trees, and other genotypes. Individuals with high fitness are selected and subjected to crossover, selection, mutation, and other genetic operations repeated up to a preset number of generations. The surviving high-fitness individuals are adopted as final solutions.

3.2 Procedure of evolutionary computation

The processing flow of evolutionary computation is shown in Fig. 3. In the diagram, a series of genetic operations including evaluation, selection, crossover, and mutation is considered as one generation, and is repeated through a preset number of generations (termination condition).

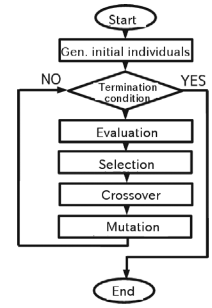


Fig. 3. Procedure of evolutionary computation.

(1) *Generation of initial individuals* The gene values are selected at random and a preset number of individuals are generated to obtain the initial population.

(2) *Evaluation* Evaluation is performed by calculation of the fitness of individuals. The fitness is a quantity expressing the ability to adapt to the environment, and is used to select individuals in crossover and other genetic operations. It is an important factor governing the direction of evolution.

(3) *Selection* There are various methods of selection, including random selection, roulette selection, and elitist selection. In particular, in case of elitist selection, several individuals with the best fitness survive into the next generation. Thus, the best individuals can be made to survive into the next generations.

(4) *Crossover* In crossover, multiple individuals are chosen and new structures are generated by partial replacement of genes. After evolving to some extent, individuals have efficient structures, and new individuals adjusted to the environment are generated by combining these structures by crossover. Examples of crossover are given in Fig. 4(a) for the GA and in Fig. 4(b) for GP.

(5) *Mutation* In mutation, some of the individual's genes are freshly generated. If only crossover is applied, the proportion of individuals with similar structure increases in the course of evolution; thus mutation is used to maintain the diversity of individuals. Examples of mutation are given in Fig. 5(a) for the GA and in Fig. 5(b) for GP.

4. Portfolio Strategy Optimization

As shown in Fig. 6, the portfolio strategy optimization proposed in this study includes (1) brand selection, (2) determination of the investment ratio, and (3) strategy tree optimization.

(a) GA. (b) GP.

Fig. 4. Crossover.

(a) GA. (b) GP.

Fig. 5. Mutation.

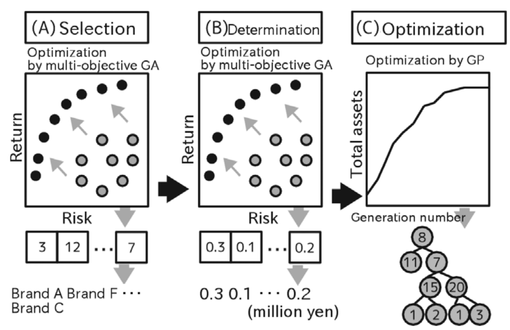


Fig. 6. Flow of proposed method: (A) Selection of brands, (B) Determination of ratio, and (C) Optimization of strategy tree.

4.1 Brand selection

A combination of brands is selected to make up a portfolio. The brands were selected from among 56 stocks listed in the Nikkei 225 (see Table A1 in the appendix).

Considering a realistic number of investments, the number of constituent brands was set to 10. The total number of combinations of 10 brands out of 56 is ${}_{56}C_{10}$ = 35,607,051,480. Thus we applied a multiobjective GA to derive stock combinations offering low risk and high return.

The structure of the individual in the multiobjective GA is shown in Fig. 7. The genes of every individual store numbers corresponding to the stock brands. These brand numbers are modified by crossover and mutation to find highly fit individuals. Specifically, we set the learning period as 1997 to 1999, and verified the results in every year from 2000 to 2008. The Investment ratio was set to 0.1 for each brand.

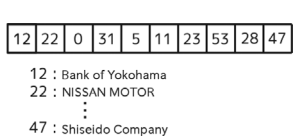


Fig. 7. Structure of individual in optimization of brand selection.

4.1.1 Fitness in brand selection

The fitness was defined as the risk and return in the period of interest, using Eqs. (1) and (2). The mean rate of return r_i of each brand and the covariance σ_{ij} between two brands are as follows:

Mean rate of return r_i:

$$\begin{aligned} &\mathit{current\_day\_rate\_of\_return} \\ &= \frac{(\mathit{current\_day\_closing\_price} - \mathit{previous\_day\_closing\_price})}{(\mathit{previous\_day\_closing\_price})} \end{aligned} \tag{4}$$

$$\begin{aligned} &\mathit{sum\_of\_rates\_of\_return} \\ &\quad = \sum_{k=1}^{N} (\mathit{current\_day\_rate\_of\_return}_k) \end{aligned} \tag{5}$$

$$\begin{aligned} &\mathit{mean\_rate\_of\_return}\ r_i \\ &\quad = \frac{(\mathit{sum\_of\_rates\_of\_return})}{(\mathit{days\_in\_period\_of\_interest})}. \end{aligned} \tag{6}$$

Covariance σ_{ij}:

$$\begin{aligned} &\mathit{sum\_of\_deviations} \\ &\quad = \sum_{k=1}^{N} \{(\mathit{rate\_of\_return\_of\_brand\_i\_on\_day\_k} \\ &\qquad - \mathit{mean\_rate\_of\_return\_of\_brand\_i}) \\ &\qquad \times (\mathit{rate\_of\_return\_of\_brand\_j\_on\_day\_k} \\ &\qquad - \mathit{mean\_rate\_of\_return\_of\_brand\ \_j})\} \end{aligned} \tag{7}$$

$$\mathit{covariance}\ \sigma_{ij} = \frac{(\mathit{sum\_of\_deviations})}{(\mathit{days\_in\_period\_of\_interest})}. \tag{8}$$

4.1.2 Brand selection algorithm

The optimization procedures of step (A) are shown in Fig. 8. Each step is explained below.

(1) Data related to the opening price, high price, low price, closing price, and trading volume of the 56 brands are entered.

(2) A preset number of initial individuals are generated. The brand numbers in each individual's gene are set at random.

(3) The number of generations is checked against the maximum number. If the latter has been reached, the algorithm is terminated; otherwise the genetic operations are repeated.

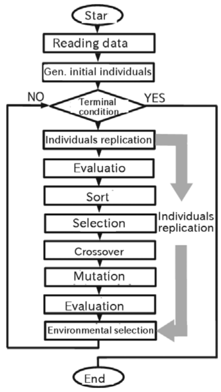


Fig. 8. Flow of selection of brands.

(4) The generations are copied and saved. The replicated populations are used later for environment selection.

(5) The fitness is calculated. The risk and return are calculated for each individual.

(6) The individuals are sorted in descending order of return for even generations, and in ascending order of risk for odd generations.

(7) Two individuals are chosen at random for crossover.

(8) Single-point crossover is performed as shown in Fig. 4(a). Two individuals are generated by one-time crossover. Selection and crossover are repeated until a preset number of individuals is reached. If an individual includes the same brand numbers, that individual is rejected and the genetic operations are repeated.

(9) Mutation is applied to each individual at a probability of 5%. The genes for mutation are chosen at random. Just as in crossover, if an individual includes the same brand numbers, that individual is rejected and the genetic operations are repeated.

(10) The fitness is calculated. The risk and return are calculated for each individual.

(11) In environment selection, the individuals to survive to the next generation are selected from the replicated generations and those obtained by genetic operations. Pareto ranking and end cutting are used for this purpose; see the next section for details.

4.1.3 Environment selection

Pareto ranking and end cutting are used to select the individuals to be transferred to the next generation from the replicated generations and those obtained by genetic operations [10]. The individuals for the next generation are selected by a fitness criterion. The fitness of an individual in this case is calculated as the number of individuals with higher return and lower risk. For example, the individual numbered 4 in Fig. 2(a) has a fitness of 4. Individuals with a fitness of 0 are superior to the other individuals in terms of both return and risk.

In environment selection, the low-fitness individuals to survive into the next generation are chosen as described below.

(1) The number of individuals with a fitness of 0 is smaller than a preset number.

(2) The number of individuals with a fitness of 0 is larger than a preset number.

In case (1), the individuals for the next generation are selected in the order of fitness; those having a lower risk than nonzero fitness individuals are selected preferentially.

In case (2), end cutting is applied. End cutting is the technique of deleting the individuals closest to those with zero fitness; this procedure is repeated until a preset number of individuals remains. Specifically, the following steps are performed.

(1) The distances between individuals are first calculated.

(2) As shown in Fig. 9(b), the two closest individuals are found, and one of these two individuals is eliminated.

(3) The distances to the individuals nearest to the individual in question is calculated, and nearest individual is eliminated.

Due to this end cutting, well-balanced individuals without a bias toward risk or return are continued into the next generation.

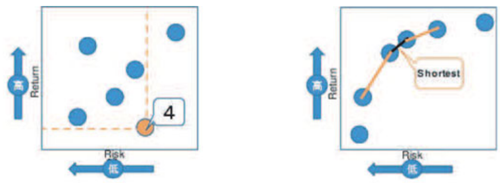
4.2 Determination of investment ratio

We optimize the investment ratio for the combination of brands with the lowest risk among those selected as explained above. Here too, the optimization is based on the criteria of risk and return, and hence the multiobjective GA is used in a similar way. Thus, the individuals with the investment ratios offering the best risk and return are found. In this experiment, 1-year learning was performed and the resulting investment ratios were verified in the next-year test period.

The structure of the individuals optimized by the multiobjective GA is shown in Fig. 10. One individual is composed of 10 elements, each storing a value from 0 to 1.0. These values express the investment ratios of the brands. The sum of the 10 values is 1.0.

4.2.1 Fitness in determination of investment ratio

As in brand selection, the fitness is determined by two indices, risk and return. These indices and the mean rate of



(a) Pareto ranking method (b) End cutting method

Fig. 9. Algorithms of selection of brands. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

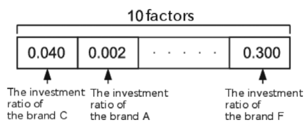


Fig. 10. Structure of individual in optimization of investment ratio.

return r_i of each brand and the covariances σ_{ij} of pairs of brands are calculated as explained above.

4.2.2 Algorithm for determination of investment ratio

This algorithm is basically the same as that for brand selection. The different parts are described below.

(1) Data on the opening price, high price, low price, closing price, and trading volume of the 10 selected brands are collected.

(2) A preset number of initial individuals are generated. The order of the gene elements in the initial individuals is set so as to minimize the difference in investment ratio. In accordance with the order thus determined, the investment ratio is set at random from 0 to 1.0. For example, if the investment ratio of the first element of a gene is set to 0.3, then the value of the second element is chosen at random from 0 to 0.7. The smallest increment of the investment ratio is 0.001. This procedure is repeated for a preset number of individuals.

(3) The investment ratio is a real number, and hence BLX-α crossover [12] is employed.

First, one child individual is generated from two parents as follows:

$$x_i^c = \frac{x_i^1 + x_i^2}{2} + \left(x_i^2 + x_i^1\right)(0.5 + \alpha)(2\xi_i - 1), \quad (9)$$

where ξ_i is a uniform random number from 0 to 1, α is the recommended value of 0.5, x_i^c is the i-th element of the child individual, and x_i^1 and x_i^2 are the i-th elements of parents 1 and 2, respectively. Thus child individuals are generated by random numbers from a hypercube region obtained by two-sided α-fold extension of each variable in the real-valued vectors of the parent individuals. In addition, when the parent individuals are far from each other in the state space, the child individuals are generated over a wide range; when the parent individuals are close to each other, the child individuals are generated in the neighborhood of the parents. Thus the search efficiency increases from the middle stage to the final stage.

(4) Mutation was not used in the determination of the investment ratio. This is because BLX-α generates child individuals somewhere between the parent individuals, thus maintaining diversity, and consequently embodies the effect expected from mutation.

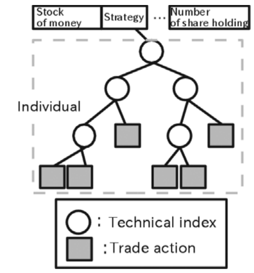


Fig. 11. Key map of strategy tree.

4.3 Strategy tree optimization

Strategy trees are optimized so as to increase their fitness, defined as total assets. The results are then verified during the test period by using the best individuals of the final generation.

Here, the strategy trees are optimized using the optimal combinations of brands and their investment ratios obtained by brand selection and investment ratio determination, and verification is conducted during the test period (an unknown period). Here, we aim at risk reduction, and thus the transactions are started with the initial investment amounts allocated according to the investment ratios of the individuals with the lowest risk among the results of brand selection and investment ratio determination. The initial funds are assumed to be 1 million yen. For example, if the optimized investment ratios are 0.2, 0.1, 0.4, 0.1, ..., then the initial funds are allocated among the respective brands as 200,000, 100,000, 400,000, 100,000, ...

4.3.1 Strategy tree

For stock trading, a strategy tree contains supplementary data, namely, the cash balance and number of shares held, as shown in Fig. 11. Under these conditions, the daily trade actions are determined according to the strategy tree. As shown in the diagram, a strategy tree consists of technical indices and trade actions. Three trade actions are set at the terminal node of a strategy tree: sell all, buy all, and do

Table 1. Terminal nodes of strategy tree.

Number	Functions	Summary
1	act_buy_all	Buying with all funds at closing price.
2	act_sell_all	Selling all stocks at closing price.
3	none	No action (Standby).

nothing. The strategies are numbered as shown in Table 1. The strategy tree is optimized by GP.

4.3.2 Technical indices

Technical indices are tools used to predict future stock prices from past price movements. Technical indices can be divided into three groups: trend indices, oscillator indices, and volume indices. The respective features of these indices are as follows:

(1) Trend indices
These indices, expressing trends in stock prices, are used for mid-term mainstream transactions.
(2) Oscillator indices
These indices, expressing the magnitude of stock price fluctuations, are used to judge excessive movements of current stock prices.
(3) Volume indices
These indices are often used as an aid to trend indices and oscillator indices. Usually, trade volumes increase when the stock is in an uptrend and decline when the stock is in a downtrend.

While they are helpful as described above, these indices have the following disadvantages.

(1) Trend indices
Buy or sell orders may be issued belatedly.
(2) Oscillator indices
Often deceptive.
(3) Volume indices
Order timing is not very accurate.

The technical indices and their branching rules actually used in strategy tree optimization are described in Table 2.

4.3.3 Fitness in strategy tree optimization

Here, the fitness is defined as the final amount of total assets obtained after trading using a strategy tree in the learning period and the test period. If a stock remains on the last day of a period, all the stock is sold. The total assets are calculated as follows, where i is the brand number:

$$\begin{aligned} daily\_total\_assets(\text{yen}) &= cash\_balance(\text{yen}) \\ &\quad + \sum_{i=1}^{10}(closing\_price_i(\text{yen}) \\ &\quad \times number\_of\_shares\_held_i) \quad (10) \end{aligned}$$

4.3.4 Algorithm of strategy tree optimization

The procedures of strategy tree optimization are illustrated in Fig. 12; each step is explained below.

(1) Data on the opening price, high price, low price, closing price, and trading volume of the 10 selected brands are collected.

(2) The investment ratios determined for the 10 brands are collected.

(3) The weighted stock price average is calculated so that the 10 brands can be traded simultaneously. The weighted average stock price is calculated using the number of shares that could be bought on the day preceding the first day of the learning period, as follows:

$$\begin{aligned} &daily\_weighted\_stock\_price\_average(yen) \\ &\quad = cash\_balance(yen) + \Sigma_{i=1}^{10}(closing\_price(yen) \\ &\qquad \times shares\_held), \end{aligned}$$

where closing_price$_i$ is the daily closing price of brand i and X_i is the number of shares that could be bought on the day preceding the first day of the learning period in accordance with the investment ratio. By using the weighted average stock price rather than the arithmetic mean stock price, stock prices can be calculated closer to the actual portfolio prices.

(4) The technical indices are calculated. The resulting values are used in the branching rules on the nonterminal nodes of strategy tree.

(5) A preset number of initial individuals are generated. The initial individuals (strategy trees) are complete binary trees with a depth of three (number of nodes: seven). For each individual, the nonterminal nodes are set to a random value of between 6 and 37, and the terminal nodes are set to a random value between 1 and 3.

(6) The number of generations is checked against the maximum number. If the latter has been reached, the algorithm is terminated; otherwise, the genetic operations are continued.

(7) The fitness (total assets) is calculated for each individual based on transactions within the designated period.

(8) The individuals are arranged in descending order of fitness (total assets).

Table 2. Nonterminal nodes of strategy tree

Number	Functions	Summary
6	if_kairi_3	Divergence of 25 days moving average > 7%
7	if_kairi_4	Divergence of moving average of 25 days > −7%
8	if_bollinger_3	Bollinger bands > 25-day moving average +2σ
9	if_bollinger_4	Bollinger bands < 25-day moving average −2σ
10	if_percent_r_1	%R of 3 days before < 50, %R of 2 days before ≥ 50, %R of 1 day before ≥ 50
11	if_percent_r_1	%R of 3 days before > 50, %R of 2 days before ≤ 50, %R of 1 day before ≤ 50
12	if_stochastics_1	%D of 2 days before > Slow%D, %D of 1 day before ≤ Slow%D
13	if_stochastics_2	%D of 2 days before < Slow%D, %D of 1 day before ≥ Slow%D
14	if_stochastics_3	%D of 1 day before ≥ 80
15	if_stochastics_4	%D of 1 day before ≤ 20
16	if_macd_1	MACD of 2 days before > signal, MACD of 1 day before ≤ signal
17	if_macd_2	MACD of 2 days before < signal, MACD of 1 day before ≥ signal
18	if_macd_3	Long-term smooted index average of 3-day index is in downtrend
19	if_macd_4	Long-term smoothed index average of 3-day index is in uptrend
20	if_dead	Short moving average < long moving average after deadcross
21	if_golden	Short moving average ≥ long moving average after goldencross
22	if_roc_1	ROC of the day before ≥ 7%
23	if_roc_2	ROC of the day before ≤ −7%
24	if_mfi_1	MFI of the day before ≥ 80%
25	if_mfi_2	MFI of the day before ≤ 20%
26	if_rci_1	RCI of the day before ≥ 80%
27	if_rci_2	RCI of the day before ≥ −80%
28	if_move_ave_1	Long term moving average for 3 days is decreasing
29	if_move_ave_2	Long term moving average for 3 days is increasing
30	if_rsi_1	RSI of the day before ≥ 80%
31	if_rsi_2	RSI of the day before ≤ 20%
32	if_gran_1	Granville's law. Closing price of 2 days before > long term moving average and closing price of 1 day before ≤ long term moving average
33	if_gran_2	Granville's law. Closing price of 2 days before < long term moving average and closing price of 1 day before ≥ long term moving average
34	if_gran_3	Granville's law. Closing price of 3 days before ≤ long term moving average, and closing price of 2 days before > long term moving average, and closing price of 1 day before ≤ long term moving average
35	if_gran_4	Granville's law. Closing price of 3 days before ≥ long term moving average, and closing price of 2 days before < long term moving average, and closing price of 1 day before ≥ long term moving average
36	if_gran_5	Granville's law. Closing prices of 3 days, 2 days, and 1 day before are below long term moving average, and the uptrend has reversed since 1 day before
37	if_gran_6	Granville's law. Closing pric of 3 days, 2 days, and 1 day before are above long term moving average, and the downtrend has reversed since 1 day before

(9) First, a certain number of elite individuals are preserved for the next generation. Then crossover is applied in order to generate as many individuals as the total number of individuals minus the number of elite individuals. Pairs of individuals for crossover are chosen by tournament selection: the two individuals are chosen at random from the parent population, and the one with higher fitness is selected as a parent. One more parent individual is also chosen by tournament selection.

(10) Single-point crossover (Fig. 4(b)) is performed and two individuals are generated. The series of tournament selection and crossover is repeated until the needed number of individuals has been generated.

(11) Mutation (Fig. 5(b)) is applied to the individuals other than the best ones preserved as elite, namely, those remaining after elitist selection and those generated by crossover. The mutation probability is set to 5%. The nodes of the individuals to be manipulated are also chosen at random. The selected nonterminal nodes are set to a random value from 6 to 37, and the terminal nodes are set to a random value from 1 to 3.

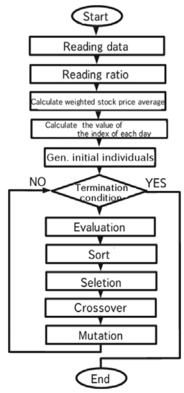


Fig. 12. Flow of optimization of strategy tree.

Table 3. Experimental periods in brand selection

Learning period	Test period
1997.1 ~1999.12	2000.1~2000.12
1997.1~1999.12	2001.1~2001.12
1997.1~1999.12	2002.1~2002.12
1997.1~1999.12	2003.1~2003.12
1997.1~1999.12	2004.1~2004.12
1997.1~1999.12	2005.1~2005.12
1997.1~1999.12	2006.1~2006.12
1997.1~1999.12	2007.1~2007.12
1997.1~1999.12	2008.1~2008.12

5. Experiments

5.1 Market model

In order to obtain many correlations between brands, we built a market model using 56 brands selected from the Nikkei 225 stocks, two for each of 28 industries.

Actual daily data on the 56 brands for the period from January 1997 to December 2008 were used as the market data. These data consisted of the year, month, day, opening price, high price, low price, closing price, and trading volume. The 56 target brands were not split during the 12-year experimental period. We assumed that every brand was traded in units of one share, regardless of the actual lots. In addition we assumed that the total investment capital was 1 million yen.

In order to compare performance of the optimized portfolios, we used the Nikkei Stock Average, a price-weighted index of 225 companies.

5.2 Experimental periods

The learning periods and test periods used in the experiments with brand selection are listed in Table 3. In these experiments, the learning period was set to 3 years, from January 1997 to December 1999, and the learning results were then verified every year.

Table 4. Experimental periods in determination of investment ratio

Learning period	Test period
1999.1~1999.12	2000.1~2000.12
2000.1~2000.12	2001.1~2001.12
2001.1~2001.12	2002.1~2002.12
2002.1~2002.12	2003.1~2003.12
2003.1~2003.12	2004.1~2004.12
2004.1~2004.12	2005.1~2005.12
2005.1~2005.12	2006.1~2006.12
2006.1~2006.12	2007.1~2007.12
2007.1~2007.12	2008.1~2008.12

The learning periods and test periods used in the determination of the investment ratios are listed in Table 4. In these experiments, the learning periods of 1 year were set from January 1997 to December 2007, and the respective test periods were set to the following years.

The learning periods and test periods in the experiments with strategy tree optimization were set the same as in the experiments with determination of the investment ratios (Table 4).

5.3 Parameter setting in evolutionary computation

The parameters of the genetic operations used in the experiments are given in Table 5(a) to (c), respectively, represent the multiobjective GA in brand selection, the multiobjective GA in investment ratio determination, and GP in strategy tree optimization.

6. Results and Discussion

Here, we consider the results of all experiments.

6.1 Results of brand selection

Figure 13 shows relation between the risk and return of individuals in the 0-th generation and the 1000-th generation. As can be seen from the graph, the risk is decreased and the return is increased by optimization of combinations by the multiobjective GA. These results indicate that during the learning period, the individuals evolved efficiently in terms of risk and return.

The brand combination of the individual that offered the lowest risk in the 1000-th generation in Fig. 13 is given

Table 5. Parameters of genetic operations

(a) Brand selection	
Population	100
Generation	1000
All number of brands	56
Number of brands	10
Duplicate individual	100
Generation by crossover	100
Mutation rate(%)	5
(b) Ratio determination	
Population	200
Generation	1000
Number of brands	10
Duplicate individual	200
Generation by crossover	200
Mutation rate(%)	None
(c) Optimization of tree	
Population	100
Generation	2000
Depth of initial tree	3
Nonterminal nodes	32
Terminal nodes	3
Elite preservation	2
Generation by crossover	98
Mutation rate(%)	5

Table 6. Brands with high return and low risk

(a) Brands in individuals with minimal risk

Industry	Code	Company	No.
Power	9501	Tokyo Electric Power Company	54
	9503	Kansai Electric Power	55
Chemicals	4452	Kao	46
	4911	Shiseido	47
Gas	9531	Tokyo Gas	3
Food	2502	Asahi	49
Transport	9064	Yamato Japan	6
Electricity	6991	Panasonic Living	53
Precision	7752	Richo	50
Machinery	6367	Daikin Industries	27

(b) Brands in individuals with maximum return

Industry	Code	Company	No.
Precision	7733	Olympus Corporation	51
	7752	Ricoh	50
Chemical	4452	Kao	46
Fiber	3404	Mitsubishi Rayon	42
Service	9737	CSK HD	0
Security	8601	Daiwa Securities Group Inc.	11
Automotive	7203	Toyota Motor Corporation	23
Medical	4502	Takeda Pharmaceutical Company	38
Machinery	6367	Daikin Industries	27
Transport	9064	Yamato Japan	6

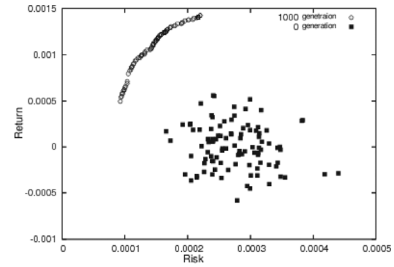


Fig. 13. Evolution of individuals in learning period.

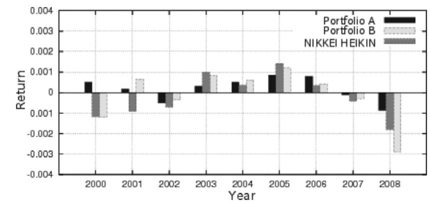


Fig. 14. Return with optimal combination of brands.

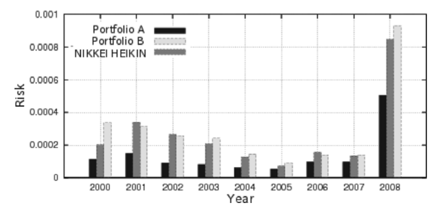


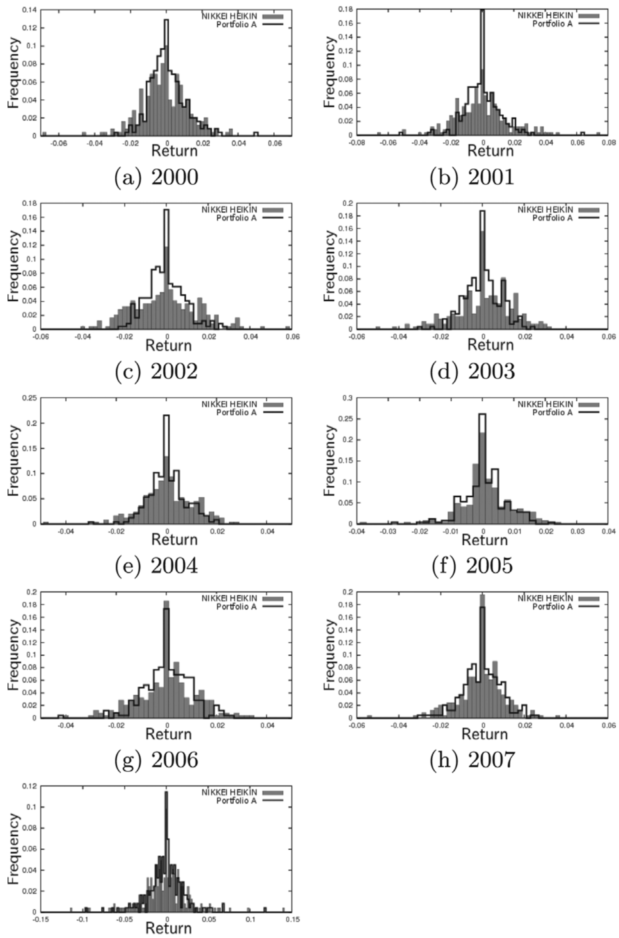
Fig. 15. Risk with optimal combination of brands.

in Table 6(a). This portfolio includes stocks in the electric power industry, gas industry, and other industries. These 10 brands were relatively stable in the past, and thus were assumed to contribute to risk reduction. The 10 brands of the individual that offered the highest return are given in Table 6(b). These brands do not involve the electric power industry or gas industry, but represent blue chips with relatively high profitability. That is, high returns were achieved in stock trading in the learning period.

The bar graphs in Fig. 14 show, from left to right, the yearly returns of the 10 brands in Table 6(a) (Portfolio A), the 10 brands in Table 6(b) (Portfolio B), and the Nikkei Average. As can be seen from the diagram, Portfolio A did not incur significant losses, even compared to the Nikkei Average (average of 225 Nikkei brands). In particular, a profit was gained in 2000 and 2001, unlike the Nikkei Average.

Portfolio B achieved high returns during the learning period (Fig. 13); however, the returns were much lower in the test periods. In particular, large losses were incurred in 2008.

Figure 15 shows the risks calculated in the same way as in Fig. 14. As can be seen from the diagram, the risks of Portfolio A are lower than those of the Nikkei Average



(a) 2000 (b) 2001 (c) 2002 (d) 2003 (e) 2004 (f) 2005 (g) 2006 (h) 2007 (i) 2008

Fig. 16. Distribution of daily return in each year.

in every test period. In the very unfavorable year 2008, the risks were about 2/3 as great as those of the Nikkei Average.

In addition, Figs. 14 and 15 indicate that the returns tend to be high in years of low risk. Thus, one can assume that making investment decisions on the basis of the risk magnitude is an effective strategy.

Figure 16 shows the daily returns in every test period. The rate of return and the frequency are plotted on the horizontal and vertical axes, respectively. In the diagrams, the bar graph represents the Nikkei Average and the broken line represents Portfolio A. Here, Portfolio A shows a smaller spread in the rate of return than the Nikkei Average in almost every test period.

Figure 17 shows how the return (time-weighted rate of return) varied when the stock was held for the long period from January 2000 to December 2008. The curves in the diagram represent, from top to bottom, Portfolio A, Portfolio B, and the Nikkei Average. The diagram indicates that Portfolio A performed well for 9 years. This can be explained by the differences among 2000, 2001, and 2008 in Fig. 14. In these 3 years, Portfolio A performed more

Fig. 17. Comparison of time-weighted returns.

steadily than the Nikkei Average and Portfolio B, and despite the loss suffered in 2008, the final return was positive.

The closing prices of all assets and their simple sum when 100,000 yen is invested in each brand of Portfolio A and the portfolio is held unchanged for a year (buy-and-hold strategy) are shown in Table 7. As indicated by the table, the stock prices rise and fall every year but in no year do all assets drop below 100,000 yen. This can attributed to the portfolio effect.

Similar buy-and-hold results for the Nikkei Average are shown in Table 8. As can be seen from the table, the Nikkei Average suffered great losses in 2000 to 2002 and 2008. In the same periods, portfolio investment performed more steadily, as can be seen from Table 7, which confirms the risk reduction effect.

6.2 Results of investment ratio determination

Figure 18 shows the relation between risk and return for the investable set of Portfolio A (Table 6) and the individual brands constituting Portfolio A (shown by ×) in every learning period (1999 to 2007). As can be seen from the diagrams, the investable area and the area of low risk and high return are expanded by creating portfolios.

Figure 19 presents results obtained by optimizing the investment ratios during the learning periods. The use of multiobjective GA resulted in low-risk high-return frontiers (shown by heavy lines).

In addition, Fig. 20 shows the results obtained in every test period (2000 to 2008) using the optimized investing ratios in Fig. 20. Here, 21 ratios for the learning periods are used, namely, the first, tenth, 20th, ..., 200-th in ascending order of risk. As can be seen from the diagram, the investment ratios offering low risk in the learning periods concentrate in the central part of the investable sets in the test periods with low risk.

On the other hand, high-risk investment ratios produced low returns in the test periods. This is because high-risk investment ratios have a bias toward certain brands.

Table 7. Investment results of buy-and-hold strategy for each brand (principal of each brand: 100,000 yen)

Brand	1999	2000	2001	2002	2003
Ricoh	187,397	102,400	122,950	77,653	107,400
Daikin Industries	121,402	154,810	94,375	88,040	129,016
Kao	118,000	115,470	82,165	94,960	84,230
Tokyo Gas	86,160	145,686	106,992	110,030	101,056
Panasonic Living	89,528	128,611	84,712	67,150	128,595
Shiseido	104,830	85,729	95,813	129,736	83,872
Tokyo Electric Power	99,100	94,555	97,280	81,460	103,010
Asahi	69,561	105,130	104,984	66,484	122,875
Kansai Electric Power	74,211	107150	94100	95112	103850
Daiwa Securities Group	250,696	53,500	117,860	62,800	79,726
Total for 10 brands	1,200,885	1,093,041	1,001,231	873,425	1,043,630
Brand	2004	2005	2006	2007	2008
Ricoh	94,689	104,150	117,040	84,400	57,364
Daikin Industries	116,770	115,840	116,800	151,360	42,000
Kao	119,125	119,240	102,480	103,300	83,500
Tokyo Gas	108,806	123,836	119,364	80,750	90,846
Panasonic Living	93,240	123,632	120,445	88,924	66,904
Shiseido	112,996	148,106	117,325	102,090	69,845
Tokyo Electric Power	106,720	113,845	135,000	72,750	109,540
Asahi	129,886	112,792	131,671	99,116	86,896
Kansai Electric Power	107,548	122,080	125,740	79,150	104,400
Daiwa Securities Group	121,680	127,820	92,100	87,094	73,855
Total for 10 brands	1,111,460	1,211,341	1,177,965	948,934	785,150

Table 8. Investment results of buy-and-hold strategy for Nikkei Average

Brand	1999	2000	2001	2002	2003
Nikkei Average	1,408,332	728,716	770,196	791,428	1,223,896
Brand	2004	2005	2006	2007	2008
Nikkei Average	1,061,088	1,394,998	1,052,704	883,378	603,492

6.3 Results of strategy tree optimization

6.3.1 Learning periods

Figure 21(a) shows the evolution of the fitness during the learning periods. In every case, the fitness of the strategic tree (best individuals) shown by the upper curve and the population-average fitness shown by the lower curve show some increase over generations as a result of learning.

In addition, in Figs. 20(b) and (c) the horizontal axis shows the days of year (about 250); the curve in (b) represents stock price variation (daily), and the curve in (c) shows daily assets when transactions are made according to the strategy tree. The bar graphs in diagrams (b) and (c) show the number of shares held. The actual transactions were based on buy or sell decisions made by technical analysis using the closing prices before the previous day; thus, transactions were made only once a day at most. As a result, the stock is bought in an uptrend, as can be seen from the bar graphs and stock price movements in diagram (b). The assets tend to grow as shown in diagram (c).

6.3.2 Test periods

Figure 22 presents the results of transactions made in the test periods using the strategy trees obtained in the learning periods. As in Fig. 21, the diagrams show the daily changes of the assets (b) and of the portfolio stock price (a). From these results, we can conclude that variation of the portfolio stock price provides information about how profit can be gained by using stock price movement or how losses can be reduced, thus providing clues for evaluating the operations and functions of the strategy trees.

Here too, efficient transactions were made in 2000 and 2003 to 2006, although the buy signal timing was slightly off in some periods. In particular, the stock price

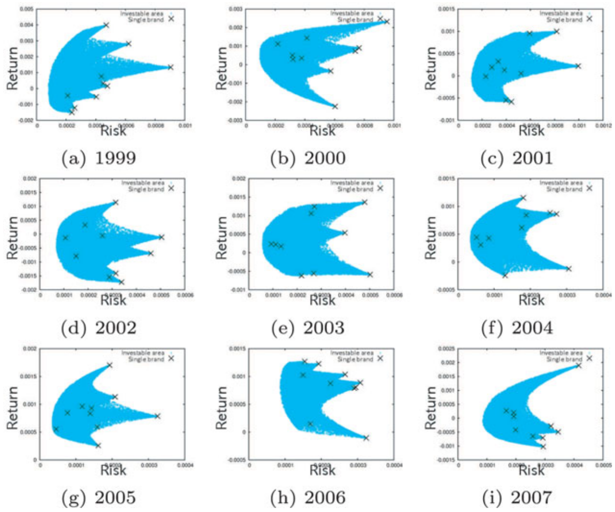


Fig. 18. Investable set and relation between risk and return for each brand. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

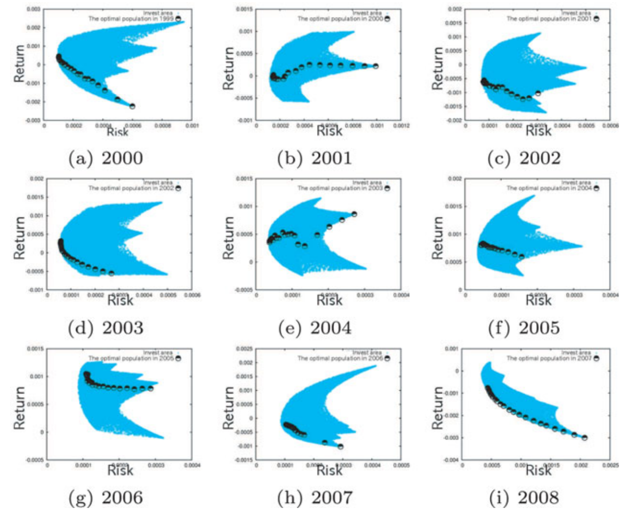


Fig. 20. Verification of optimum investment ratio. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

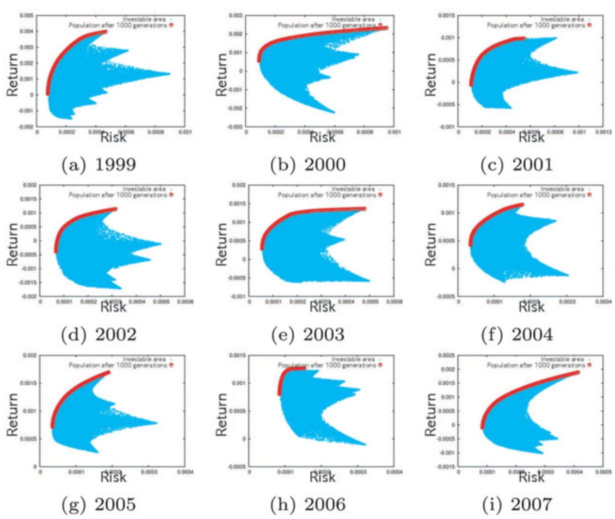


Fig. 19. Investable set and relation between risk and return for brand combination optimized by 1,000 generations. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

showed a strong downtrend on the 100 to 130-th days of 2003, but the assets increased. As can be seen from the bar graphs, transactions were made frequently in that period. The assets increased due to the adept use of small fluctuations in stock price by buying in downtrends and selling in uptrends.

In 2004, steady profits were gained by holding shares in uptrends and unloading shares in downtrends. As regards investment performance in 2008, the assets fell below the initial capital but the overall loss was reduced by timely unloading of shares when prices plunged. These results show that the proposed method allows the strategic optimization of trade actions based on past data.

6.3.3 Comparison with buy-and-hold strategy

Table 9 gives the rates of return for all test periods in Fig. 22 and the rates of return for the same periods in the case of a buy-and-hold strategy (the rate of change of the weighted stock price average). As can be seen from the table, the strategy trees produce higher annual rates of return in many periods, as well as a higher 9-year average.

However, in the case of a bull market without large dips, as in 2005 and 2006, the buy-and-hold strategy performs slightly better. This means that when the market is bullish, it is better to buy and hold shares, without concern about daily fluctuations.

On the other hand, when the market is flat, as in 2001, or a downturn trend appears as in 2002, diligent transactions based on a strategy tree contribute to higher profits. Such effects of strategy trees are especially pronounced when the market is generally in a slow rise, as in 2003 and 2004; more profit than with a buy-and-hold strategy can be gained by taking the opportunity to make frequent transactions.

However, in strongly bearish periods such as 2007 and 2008, neither strategy would bring a profit. However, more detailed consideration shows that the stock price movement in 2007 was much different from that in 2006 (the learning period of the strategy tree) so that the learning effect was poor; on the other hand, in 2008, due to the experience of plummeting stock prices once in 2007 (part of the learning period), the strategy tree helped to limit losses

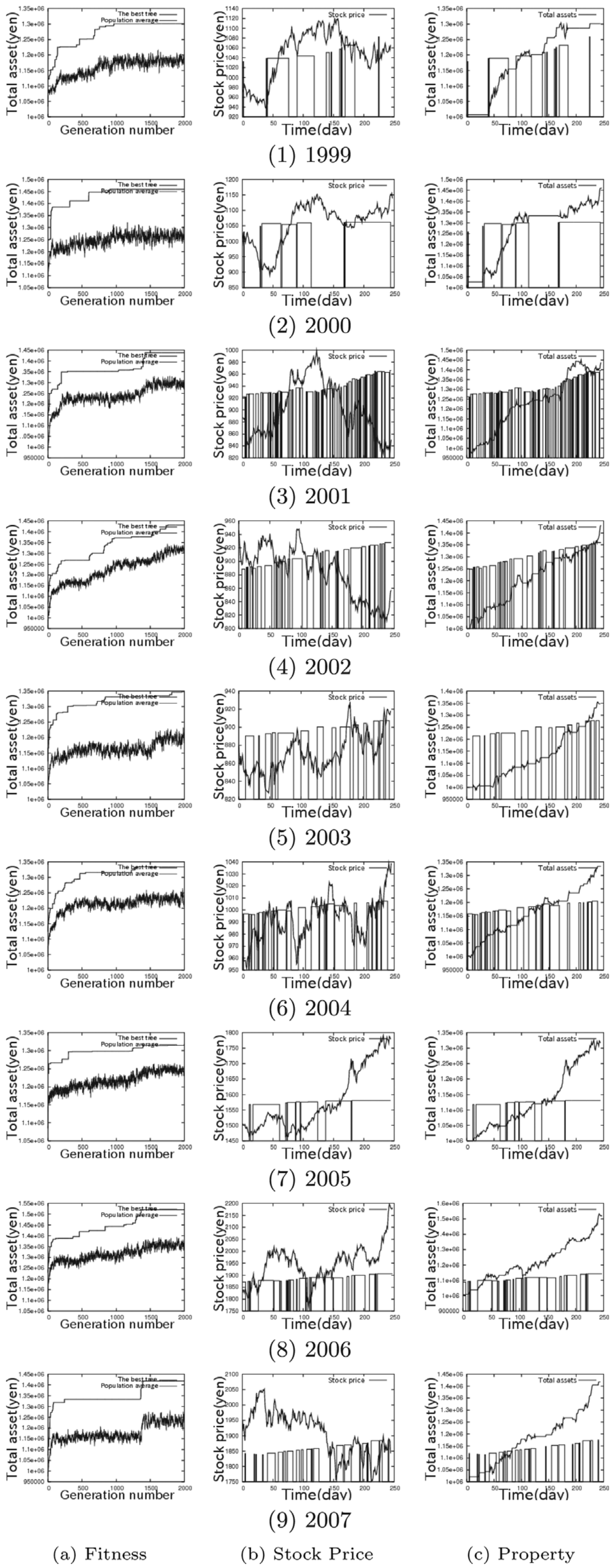


Fig. 21. Learning periods: 1999–2007.

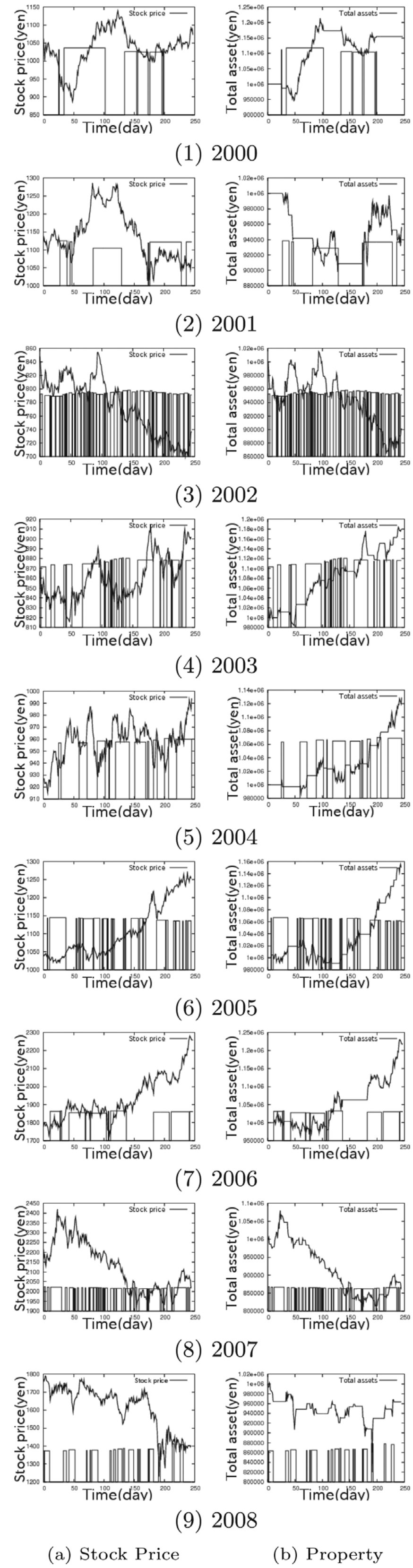


Fig. 22. Test periods: 2000 to 2008.

Table 9. Comparison of rates of return

	Rate of return (%)	
Year	Buy & Hold	Strategy tree
2000	100.9	115.4
2001	95.4	95.6
2002	86.9	90.1
2003	103.9	117.9
2004	107.2	112.8
2005	119.0	115.5
2006	123.6	123.0
2007	91.0	88.0
2008	78.9	96.3
Average	100.8	106.1

compared to the buy-and-hold strategy, so that almost all of the initial investment was preserved.

Based on the above results, considering that it is not easy to predict bullish or bearish trends or trend reversals, sharp dips, and other market events, one can expect that the use of an appropriate strategy tree, such as that obtained in the proposed method, is likely to reduce risk and provide safe trading.

6.3.4 Efficiency of strategy tree

A strategic tree that contributes to profits is assumed to include efficient components. By the example of this study, we consider its major indices and examine the effectiveness of successful strategy trees obtained by GP.

In particular, we consider the strategic tree of 2003, which demonstrated high performance by considerable profit enhancement in the test period, as noted in Section 6.3.2. The structure of the tree is shown in Fig. 23. In the diagram, the first line of each tree node shows the index number, and the second and third lines show the numbers of days that branched right and left during the learning period and test period, respectively. The route numbers (Table 10) are shown at the top of the terminal node frames.

At the first-level nodes, Granville's selling rule (index 32) is set. This is a useful index of sell signals; however, depending on the specific case, the sell conditions are not necessarily satisfied. This can be also seen from the tree, where buy or sell conditions are set regardless of the specific case. Therefore, this index is combined with other indices, and optimal actions are taken under the resulting compound conditions.

In order to clarify this issue, Table 10 shows the routes toward terminal nodes. The leftmost column gives the route numbers, and the figures in the table are index numbers (L and R represent right and left branching, respectively).

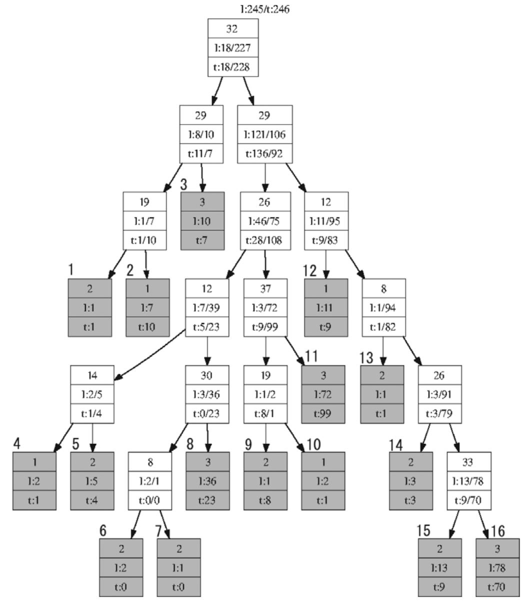


Fig. 23. Strategy tree learned in 2003.

Table 10. Routes of strategy tree

No.	Route	Pass				
1	32L	29L	19L	2		
2	32L	29L	19R	1		
3	32L	29R	3			
4	32R	29L	26L	12L	14L	1	
5	32R	29L	26L	12L	14R	2	
6	32R	29L	26L	12R	30L	8L	2
7	32R	29L	26L	12R	30L	8R	2
8	32R	29L	26L	12R	30R	3	
9	32R	29L	26R	37L	19L	2	
10	32R	29L	26R	37L	19R	1	
11	32R	29L	26R	37R	3		
12	32R	29R	12L	1			
13	32R	29R	12R	8L		2	
14	32R	29R	12R	8R	26L	2	
15	32R	29R	12R	8R	26R	33L	2
16	32R	29R	12R	8R	26R	33R	3

As can be seen from the table, routes 1 and 2 contain the same indices under the same conditions down to the second level, then branch at index 19 immediately before the terminal nodes where the actions are stored. Index 29 at the second level expresses whether the long-term moving average increases for three consecutive days. The moving average is an important trend factor, but it has been pointed out that the moving average itself is not sufficient for a final decision on buying or selling. Thus, the branching of routes 1 and 2 was determined by the immediately preceding index 19 (MACD: branching to left if the long-term smoothed index average increases for three consecutive days). That is, route 1 issues a buy signal providing that Granville's selling condition (32) is satisfied, the long-term moving average grows continuously (29), and the long-term smoothed index average grows continuously (19). When the conditions of these three indices are satisfied, the stock price is usually rather high, and it may either rise further or drop back. We may assume that when many learning data involve such situations, the system concludes that it is better to sell stocks at a profit. This constitutes a complex advanced strategy of cautious selling based on the combination of the three indices; such a strategy is confirmed by the fact that expert investors act in the same way based on the results of technical analysis.

Regarding route 2, it appears that the system learned to purchase stock when the MACD condition (index 19) is not satisfied but the moving average increases, thus indicating a strong bullish market.

In addition index 19 acts in the same way on routes 9 and 10, which indicates high reliability of this branching condition. Index 37 (Granville's buying rule) is on the level immediately above this index 19; even if Granville's condition is satisfied, the buy signal of index 19 is given priority and the profit is taken. However, if index 19 is negative, then stock is purchased according to Granville's buying rule in index 37.

On route 11, which branches from route 2, Granville's buying condition (index 37) is not satisfied, and hence no action is taken.

On route 3, the condition of index 29 is not satisfied, and the system has learned to take actions maintaining the current state, or no action at all.

As regards routes 4 and 5, the node preceding trade actions decides whether the current stock price tends to rise too high at index 14 (stochastics). If this trend is confirmed, then bearish sentiment usually prevails, which is not the case here. It is the only example of not following technical indices in this strategy tree.

Both routes 6 and 7 result in selling; that is, the immediately preceding index 8 (Bollinger bands) is ignored, and the upper index 30 (RSI: Relative Strength Index) takes effect. Usually an RSI above 80% is considered as a sign of overbuying, and the stock is sold. Therefore, if index 30 is satisfied, the tree results in selling, as in routes 6 and 7; otherwise, the current state is maintained as in route 8.

On route 12, %D of index 12 (stochastics) drops on the preceding day compared to the day before; therefore overselling is recognized and the stock is bought. If this condition is not satisfied, the following routes 13, 14, 15 result in selling. As regards route 16, all conditions are unsatisfied, and hence the current state is maintained.

Here, we have presented just a few examples of strategy tree functions; however, many successful strategy trees that bring profits show similar operations based on effective rule setting due to technical analysis in the course of learning.

From the above we can conclude that strategic trees obtained by GP perform efficiently because they closely follow efficient indices set by technical analysis to improve profits. Therefore, the proposed method using GP has produced convincing and rational results. This can be attributed to stable profits secured by building a portfolio.

On the other hand, strategies obtained by the proposed method do not go beyond conventional technical analysis, and in this sense our results can be considered as routine. However, such strategies based on conventional technical analysis have been cultivated through many years of experience, and the fact that a system produces the same conclusions seems meaningful. That is, these routine results were obtained by the system by acquiring knowledge from a massive body of raw data followed by learning and evolution. Thus, the proposed method functions properly as an independent system, and may be further developed into an intelligent system in the future.

In addition, we can expect even more accurate strategy trees as a result of detailed analysis of combinations. This requires quantitative analysis of more cases and comprehensive discussion. The result is likely to be advanced strategies, more accurate than those known so far. We plan to continue investigation of these issues.

7. Conclusions

In this paper, aiming at risk management in stock trading, we attempted to build efficient portfolios and to optimize trading strategies using evolutionary computation.

First, by applying a multiobjective GA to past data on stock prices, we selected the best brand combinations and investment ratios to build a portfolio.

We next built strategy trees composed of technical indices and trade actions as a basis for making trade decisions, and optimized these trees by GP so as to trade a portfolio at the appropriate timing.

The proposed system was trained and optimized using real past market data, and the performance of the system was evaluated using real unknown data. We obtained the following results.

(1) Efficient learning resulting in risk reduction and increased return was implemented in brand selection, investment ratio determination, and strategy tree optimization.

(2) Portfolios developed by learning to minimize risks performed efficiently in the test periods, avoiding great losses even in periods of sharp decline, and gaining more stable profits than other portfolios.

(3) Generally, returns tend to increase when risk decreases; thus we assumed that the evaluation of stock quality by risk magnitude is an effective strategy.

(4) Efficient frontiers with low risk and high return were obtained using investment ratios optimized by learning.

(5) In some cases, investment ratios that showed high risk in the learning periods were the least profitable in the test periods. Such investment ratios had a bias toward particular brands.

(6) The optimized strategies tended toward holding of shares during uptrends, and unloading of shares during downtrends. This suggests that more stable and efficient trading is achieved than in the buy-and-hold strategy.

(7) The strategic trees obtained by GP performed efficiently because they closely followed effective indices established by technical analysis so as to improve profits.

The above results indicate that low-risk investments can be implemented by optimization of portfolio trade strategies by using evolutionary computing. Robust portfolio strategies resistant to market trends are a topic for future research.

REFERENCES

1. Kahneman D, Versky AT. Prospect theory of decisions under risk. Econometrica 1979;47:263–291.
2. Tabata Y. Introduction to financial engineering, Economist Press; 2002. (in Japanese)
3. Murphy JJ. Technical analysis of the financial markets, New York Institute of Finance; 1986.
4. Matsumura K, Kuniya Y, Kimura S. Agent based trader model utilizing genetic programming approach. IPSJ 2006;47(9):2869–2886. (in Japanese)
5. Matsumura K. Optimization model of strategy tree in stock investment based on evolutionary computation applied by clustering. IPSJ 2008;49(1):457–475. (in Japanese)
6. Koza J. Genetic Programming: On the programming of computers by means of natural selection, MIT Press; 1992.
7. Holland JH. Adaptation in natural and artificial systems. The University of Michigan Press; 1975.
8. Hibiki N. Financial engineering and optimization. Asakura Shoten; 2001. (in Japanese)
9. Markowitz H. Portfolio selection. J Financ 1952;7(1):77–91.
10. Watanabe S, Hiroyasu T, Miki M. Neighborhood cultivation genetic algorithm for multi-objective optimization problems. IPSJ 2002;43(SIG10 (TOM7)):183–198. (in Japanese)
11. Munetomo M. Genetic algorithms: theory and high technique, Morikita Shuppan; 2008. (in Japanese)
12. Eshelman LJ, Schaffe JD. Real-coded genetic algorithms and interval-schemata. Found Genet Algorith 1993;2:187.

Appendix

Table A1. The target brands

Construction	1802	Obayashi Corporation
	1925	Daiwa House Industry Co. LTD.
Food	2502	Asahi
	2802	Ajinomoto Co. Inc.
Fiber	3103	Unitika LTD.
	3404	Mitsubishi Rayon
Pulp	3861	Oji Paper Co. LTD.
	3864	Mitsubishi Paper Mills Limited
Chemical	4452	Kao
	4911	Shiseido Company
Medical	4151	Kyowa Hakko Kirin Co.Ltd.
	4502	Takeda Pharmaceutical Company Limited
Medical	4151	Kyowa Hakko Kirin Co.Ltd.
	4502	Takeda Pharmaceutical Company Limited
Oil	5001	Nippon Oil Corporation
	5002	Sowa Shell Sekiyu K.K.
Rubber	5101	The Yokohama Rubber Company, Limited
	5108	Bridgestone Corporation
Pottery	5201	Asahi Glass Company, Limited
	5233	Taiheiyo Cement Corporation
Steel	5401	Nippon Steel Corporation
	5405	Sumitomo Metal Industries, Ltd.
Metal	5706	Mitsui Mining & Smelting Company, Ltd
	5715	Hurukawa Co.LTD.
Machinery	6367	Daikin Industries
	7011	Mitsubishi Heavy Industries, Ltd.
Electricity	6902	Denso Corporation
	6991	Panasonic Living
Shipbuilding	7003	Mitsui Engineering & Shipbuilding Co.
	7012	Kawasaki Heavy Industries, Ltd.
Car	7201	Nissan Motor
	7203	Toyota Motor Corporation
Precision	7733	Olympus Corporation
	7752	Ricoh
Manufactures	7912	Dai Nippon Printing Co., Ltd.
	7951	Yamaha Corporation
Trading	8001	Itochu Corporation
	8058	Mitsubishi Corporation
Retail	8233	Takashimaya Company, Limited
	8270	Uny Co., Ltd.
Banking	8331	The Chiba Bank, Ltd.
	8332	Bank of Yokohama
Security	8601	Daiwa Securities Group Inc.
	8606	Mizuho Financial Group, Inc.
Estate	8801	Mitsui Fudosan Co., Ltd.
	8815	Tokyu Land CorporationN
Railroad	9001	Tobu Railway Co., Ltd.
	9009	Keisei Electric Railway Co., Ltd.
Transport	9062	Nippon Express Co., Ltd.
	9064	Yamato Japan
Marine	9101	Nippon Yusen Kabushiki Kaisha
	9107	Kawasaki Kisen Kaisha, Ltd.
Power	9501	The Tokyo Electric Power Company, Inc
	9503	Kansai Electric Power
Gas	9531	Tokyo Gas
	9532	Osaka Gas Co., Ltd.
Service	9681	Tokyo Dome Corporation
	9737	CSK HD

AUTHORS (from left to right)

Koki Matsumura (member) completed the doctoral program at Osaka City University in 1978 and became an associate professor at Ibaraki University (Faculty of Engineering), then a professor at Konan University (Faculty of Science); since 2002 professor at Tottori University (Graduate School of Engineering). He holds a D.Eng. degree. Research interests include evolutionary computation, financial engineering, management information engineering, and other fields. He is a member of IPSJ, IEEJ, IEICE, and JASMIN.

Hidefumi Kakinoki (nonmember) completed the doctoral program at Tottori University (Graduate School of Engineering) in 2010 and is now employed by Mitsubishi Electric Corporation (Himeji Works). Research interests include financial engineering and evolutionary computation. He is a member of IEICE.