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Incorporating Markov decision process on genetic algorithms to formulate trading strategies for stock markets

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ABSTRACT

With the arrival of low interest rates, investors entered the stock market to seek higher returns. However, the stock market proved volatile, and only rarely could investors gain excess returns when trading in real time. Most investors use technical indicators to time the market. However the use of technical indicators is associated with problems, such as indicator selection, use of conflicting versus similar indicators. Investors thus have difficulty relying on technical indicators to make stock market investment decisions.

This research combines Markov decision process and genetic algorithms to propose a new analytical framework and develop a decision support system for devising stock trading strategies. This investigation uses the prediction characteristics and real-time analysis capabilities of the Markov decision process to make timing decisions. The stock selection and capital allocation employ string encoding to express different investment strategies for genetic algorithms. The parallel search capabilities of genetic algorithms are applied to identify the best investment strategy. Additionally, when investors lack sufficient money and stock, the architecture of this study can complete the transaction via credit transactions. The experiments confirm that the model presented in this research can yield higher rewards than other benchmarks.

1. Introduction

Increased globalization has led the government to open numerous investment channels. However, as opportunities have increased, so too has risk. How to grasp opportunity and avoid risk thus has become a major issue in industry and academia.

Stock investment is what most individuals choose for their personal investment. Television broadcasts increasingly numerous equity investment analysis programs. Regardless of the state of the economy, provided investors make good decisions equity analysis can still be profitable.

Correct timing and risk-aversion have always been important in investment. Previous studies mostly use fundamental or technical analysis to solve these key issues. The stock market is an open market, and numerous external factors can affect stock prices. Internal messages, government industrial policy or the financial conditions of individual firms can all influence corporate stock prices. Thus it is important to build a profitable and accurate investment model.

With the recent rapid development of science and technology, artificial intelligence has achieved significant progress. Scholars began to apply artificial intelligence financial management research. Artificial intelligence theories have been effectively applied to investment and become human decision-making tools. Famous techniques include neural networks [30], genetic algorithms [32], genetic programming [16], fuzzy theories [17] and decision trees [39].

Two forms of stock investment analysis exist, one is a mathematical theory-based approach that tries to represent stock trading behavior by creating a stock market model to identify an interpretable profit. However, traditional mathematical theories are inadequate to explain the problem of non-linear, complex, and multi-targeted models and thus successfully profit from the stock market. Another method is based on artificial intelligence studies that forecast stock values via machine learning to construct a model and help investors make investment decisions, such as artificial neural networks [48]. However, input factors of artificial neural networks are difficult to define and select.

The implied parallel processing space search capabilities offer fast speed, high reliability, and flexibility due to the space search speed of genetic algorithms, and thus offer entirely new computational methods [26]. Based on their powerful search skills and combinatorial optimization solving ability, genetic algorithms can

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help solve complex problems such as portfolio selection and capital allocation in relation to stock investments. The Markov decision process involves the use of mathematical theory to achieve a forecast by sequential derivation function in the Markov chain. Markov decision process, which is capable of prediction, is suitable to solve stock investment problems [19].

Previously, most studies on stock timing focused on technical analysis, but the use of technical indicators frequently is often problematic. For example, investors can encounter difficulty in choosing the type or number of technical indicators and how to resolve similarity or contradiction between technical indicators. Most previous literature on the stock market considers only reactions to general transactions while ignoring credit transactions, and cannot take into account whether trading on margin is permitted or ownership is insufficient. This investigation thus combines Markov decision-making and genetic algorithms to help investors make the best decisions, such as those regarding selection, timing and capital allocation, when facing stock market uncertainty. This paper also considers credit transactions.

This study combines the Markov decision process and genetic algorithms available to investors in the stock investment strategy and uses them to develop a decision support system. This predicts the results of applying the Markov decision process with real-time computational power to help investors devise correct timing and trading strategies. This study thus uses the excellent genetic algorithm parallel space searching ability to provide investors with the optimal stock selection strategy and capital allocation, and combines them with both constructs to solve the portfolio problem and improve return on investment for investors.

2. Literature review

The stock market requires investors to consider risk and return. To diversify their investment risk, investors may allocate their funds among different targets. A complete investment strategy should incorporate stock selection, timing and capital allocation.

Timing aims to identify the best opportunity to buy or sell a stock. Korczak et al. [35], Allen et al. [1], Chang chien et al. [7], Jiang et al. [29] Huang et al. [27], Bao [3] and Badawy et al. [4] combined the genetic algorithms and other methods, such as technical analysis, regression and support vector machine, to identify the optimal stock market trading opportunities, through experiments that intended to demonstrate a good return. Kimoto et al. [33], Jang et al. [28] and Yang et al. [53] created an intelligent stock transaction system by using neural networks to predict stock prices and stock market trends. Additionally, some scholars use evolutionary systems to resolve the slow convergence and low learning efficiency of neural networks [40]. Taking advantage of genetic algorithms to optimize the stock index prediction model is also effective [2,15,18,31,50,51].

Selection strategy aims to pick out better investment targets from among numerous investment stocks, considering the return and risk of stock investment and then identifying the optimal portfolio. Gold et al. [21] combined artificial intelligence and fundamental analysis for portfolio optimization and to verify the feasibility of the application of artificial intelligence to investment. Oh et al. [41] and Chun et al. [12] applied genetic algorithms with a new fitness function design to select investment targets based on stock price. Regardless of whether the stock market increases or decreases, this method can gain stable returns. Chiu et al. [13] combined genetic algorithms, regression and technical analysis to devise a stock selection model and identify stocks offering high returns as investment targets. To correctly predict stock prices Cheng et al. [10] proposed a hybrid forecasting model that integrated genetic algorithms with rough set theory to improve the accuracy of stock price predictions. This model can obtain higher returns than either the buy and hold strategy or general genetic algorithms.

Capital allocation is intended to help investors maximize portfolio return through the allocation of funds among investment targets. Shoaf et al. [46] proposed a new method of encoding the genetic algorithm to do capital allocation. Soleimani et al. [47] combined with various heuristic and non-heuristic algorithms to propose a portfolio optimization model for solving the nonlinear portfolio optimization problem and improving rate of return. Chen et al. [8] proposed a relational genetic algorithm guided by new mutation operations to increase the evolution efficiency and solve a comprehensive portfolio optimization problem.

Besides examining single investment issues, previous studies have also examined multiple investment issues. With regard to selection and timing strategy, Orito et al. [42], Chang et al. [6] and Papadamou et al. [44] considered selection and timing issues to employ genetic algorithms to optimize investment portfolio and achieve a stable profit. Ng et al. [43] combined fuzzy theory and genetic algorithms to identify stock trading rules able to determine matters of timing and target selection. The experiments verify that this method outperformed the buy and hold strategy.

With regard to timing and capital allocation, Rafaely et al. [45] and Gorgulho et al. [22] proposed the use of genetic algorithms for stock selection and capital allocation strategies. Some scholars used neural networks for stock selection, and used genetic algorithms to solve the capital allocation problem [37]. Chen et al. [9] integrated genetic algorithms and the pattern search method for capital allocation and stock selection. Such experiments yielded common selection methods include roulette wheel good results. Leu et al. [38] used fuzzy time series to predict investment return then used genetic algorithms to identify the optimal investment strategy. Experimental results showed this method to outperform the Taiwan 50 Index and Taiwan market Index. Dastkhan et al. [14] and Bermúdez et al. [5] combined genetic algorithms and fuzzy theory to simultaneously solve problems of investment capital allocation and stock selection.

With regard to timing and capital allocation, Laura [36] and Hoklie et al. [24] applied genetic algorithms combined with technical indicators and considered investment return and risk to devise a stock trading system. Genetic algorithms can help identify the best combination of technical indicators and can yield better results. Ko et al. [34] used genetic algorithms to assess stock price range, and then determine capital allocation using a cubic spline curve. The experimental results outperform a buy and hold strategy.

Markov chain has been widely used to analyze continuous data and related areas such as speech recognition [52], DNA sequence [11] and so on. Since the Markov decision process was used to analyze continuous data with good results, some research has started to apply this process to investment by analysis of historical transaction data in the stock market and derived good results. Ghezzi et al. [20] used a Markov chain model to establish a stock value estimation model based on dividends and stock price. The Markov decision process is also used combined with other theories on stock investment with good effect. For example, Hassan [23] combined hidden Markov chains and fuzzy theory to devise a model to predict stock market volatility, and find the best fuzzy rules. Wang et al. [49] applied Markov chain and fuzzy theory to create a predictive model for the stock market index. Following data validation, the results not only demonstrate the ability to improve return on investment, but also to stop losses. Hsu et al. [25] integrated the Markov chain, gray theory and Fourier series to forecast turning points of the stock market weighted index. These studies can demonstrate the ability of the Markov decision process to improve equity portfolio returns.

The above literature review demonstrates that stock portfolio optimization focuses on selection of investment targets, when to

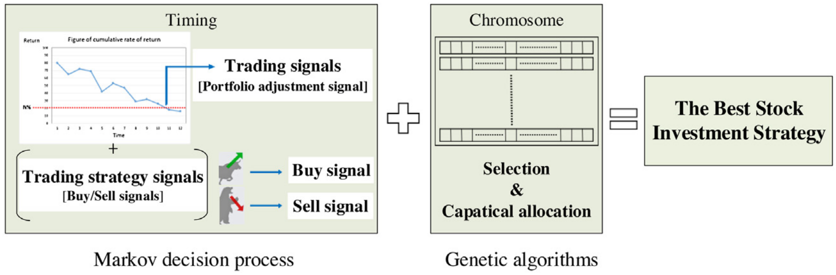

Fig. 1. Research architecture. P_1 = Average return based on all cumulative declines over a month P_2 = Average return based on all cumulative rises over a month

buy or sell stocks and the sums invested in individual investment targets. However, discussion of the past literature reveals that few studies can solve these three issues simultaneously, and most can solve only one or two. Additionally, how to improve returns and reduce risk is also important.

3. Research framework

This research proposed a new analytical framework for the general portfolio stock trading. Calculation using the expected profit can yield timing signals for portfolio adjustment and develop a daily strategy regarding stocks to buy, sell or hold. When combined with genetic algorithms, this transaction system can perform stock selection and capital allocation. That is this study encoded the capital allocation (0%–100%) for each stock for portfolio into the chromosome of the genetic algorithm. By evolution process, the genetic algorithm can get the optimal weight of stocks (optimal capital allocation) and make the selection decision in the portfolio.

The proposed new analytical framework is a general framework. This study also found the optimization parameter setting of the new model for Taiwan's stock market. For example, this research found the optimization number of state variable for Markov decision process, genetic algorithms' parameter . . .. et al. This study apply the new analytical framework on Taiwan's stock market to prove the validity of the new research framework. Whether the stock market is in a bull market, the bear market or market correction. The new model can be applied in different stock markets to get high return just finding the new optimization parameter setting.

Investors invest in the stock market seeking maximum returns and minimum risk. But investment targets have different levels of risk and return. To diversify risk and increase their returns, investors must diversify their investments. The objective is to maximize the expected risked return of a portfolio, which may be calculated using formula (1)

$$\text{Max}\frac{E\left(R_p\right)-R_f}{\sigma_p}\,\ldots.. \qquad (1)$$

s. t. *Criteria* 1
Criteria 2
Criteria 3
. . ..
Criteria n
$E(R_p)$: The expected rate of return on portfolio p
R_f: Risk-free interest rate
σp: Risk of portfolio p

There are several kinds of classifications for the stocks of Taiwan's stock market. There is a usually familiar classification are eight categories of stocks. All stocks in Taiwan's stock market can be classified into eight categories, commonly known as eight categories of stocks. This investigation integrates the Markov decision process and genetic algorithms to propose a stock investment trading decision support system, as shown in Fig. 1. First, the

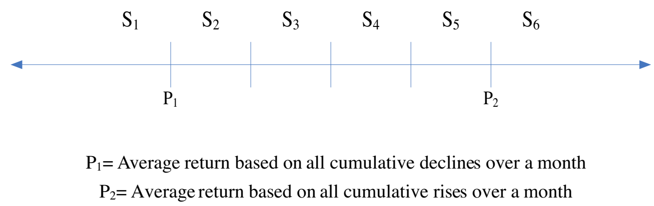

Fig. 2. Cumulative return state variables.

proposed system used the daily closing prices for eight industrial stocks listed on the Taiwan Stock Index to calculate the likelihood of a state transition matrix. Then it calculated the expected profit of these probability transition matrixes. Calculation using the expected profit can yield timing signals for portfolio adjustment and develop a daily strategy regarding stocks to buy, sell or hold. When combined with genetic algorithms, this transaction system can perform stock selection and capital allocation. Through varying capital allocation the system can carry financing and margin and obtain the best investment strategy. The following describes timing (trading signals, trading strategy signals), stock selection and capital allocation (financing, margin).

3.1. Trading signals (portfolio adjustment signal) – cumulative rate of return

Stock timing strategy is based on the cumulative of return for eight industrial stocks and uses the Markov decision process. A market timing signal occurs where the state (S_1 or . . .. . . S_n) predicted by the cumulative of return (S_i) selects whether to adjust the portfolio for investors. If the cumulative of return is below a preset N%, investors must perform portfolio adjustment rather than the other way round. Markov decision process must define state variables, and transfer the probability matrix, decision variables and return expectations. A rule of thumb sets the state variable to S_1. . . . . . S_6, and these six states are based on the cumulative of return of the Taiwan market index during the past year. The floor of cumulative return P_1 is expected to decrease based on monthly averages. The ceiling of cumulative return P_2 is the average rise in the cumulative return for the month. Moreover, the segment between P_1 and P_2 divides equally into four sections. After many experimental test. If the number of states is less than 6, the state transition of Markov decision process is not obvious. There is no even the case of state transition occurs. State transition delayed. If the number of states is greater than 6, the state transition of Markov decision process is too frequently and not easy to find out rules. That is not easy to find the exact status metastasis. So there are 6 states for Markov decision process. The upper and lower limits were exceeded taking a section. Fig. 2 shows six states. Each section was represented by the middle value of the cumulative rate of return. The cumulative rate of return migration probability matrix must be calculated from historical data. For example, a state transition frequency of

	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	0	0	0	0	0
S_2	0	0	0	0	0	0
S_3	0	0	1	0	1	0
S_4	0	0	1	1	0	0
S_5	0	0	0	1	5	2
S_6	0	0	0	0	2	4

Fig. 3. Cumulative returns migration times matrix.

	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	0	0	0	0	0
S_2	0	0	0	0	0	0
S_3	0	0	0.5	0	0.5	0
S_4	0	0	0.5	0.5	0	0
S_5	0	0	0	0.125	0.625	0.25
S_6	0	0	0	0	0.33	0.66

Fig. 4. Cumulative returns migration probability matrix.

the cumulative rate of return is shown in Fig. 3. From Fig. 3, the migration from S_5 to S_4 occurs once, S_5 remaining in S_5 occurs five times, and migration from S5 to S6 occurs twice. Thus eight total migrations occur. The probability of migration from S_4 to S_5 thus equals $1/(1+5+2)=12.5\%$. Fig. 4 shows the cumulative rate of return migration probability matrix.

Volatility refers to the variation of the portfolio's return which generated every day. Expectations of volatility are calculated as the cumulative volatility expected for the portfolio's return known as cumulative volatility of portfolio's return. When the cumulative volatility below the investor's minimal return level, it means that investors need to adjust their portfolios. Suppose that the investor's minimal return level is 20%. When the cumulative volatility below 20%, trading signal appears 1 and represents the portfolio of the investor required adjustment. As the cumulative volatility is still keep above 20%, then trading signal appears 0 and represents the portfolio do not need to do adjustment.

Expectations of volatility are calculated as the cumulative volatility expected for the rate of return of the next day, which equals the probability multiplied by the volatility, which is multiplied by each state migration probability matrix that corresponds to the state of the fluctuating amplitude. The intermediate values of the amplitude range represent degree of fluctuation. Based on the definition of state variables, this study calculates the cumulative rate of return migration probability matrix, followed by the expected value of fluctuation. The expected fluctuation is used to

	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	2	3	0	3	2
S_2	1	0	2	0	0	2
S_3	1	2	3	1	1	0
S_4	1	1	0	1	0	0
S_5	0	1	0	0	0	0
S_6	1	0	1	0	1	1

Fig. 6. Next day return migration times matrix.

determine the trading signal and these market timing signals can be integrated into the genetic algorithms.

3.2. Trading strategy signals (buy/sell signals) – expected next-day return

According to the Markov decision process, expected next day rate of return is used for the buy, sell or hold trading strategy. Because the experimental subjects are eight categories of stocks, there are eight trading strategy signals. Forecasts of daily expected rate of return are based on the actual state of expected return for the previous day. When expectations are for a high rate of return then investors should seek to buy low and sell high.

Markov decision processes must define state variables, transfer probability matrix, decision variables and expectations. Since the Taiwan Stock Exchange prescribed that stock price daily rate of change should not exceed ±7%, each 1% increase or decrease can be considered an interval. The expected next day rate of return thus comprises 14 state variables, S_1...... S_{14} etc. as shown in Fig. 5. S_1 represents the interval that was decreased by 6–7% from the previous day. Moreover, S_2 represents the interval that was decreased by 5–6% from the previous day. The calculation of the expected value for S_1 is −6.5%, which is midway between −6% and −7%, the remaining interval and so forth. The migration probability matrix is based on historical data analysis of the calculated probability of each state migration, and then deposited into the migration probability matrix of the expected return for the next day. For example, from Fig. 6, the migration from S_4 to S_1, S_2, and S_4 occurs once, and the probability of the migration occurring to each of the three potential destinations is 1/3, so the migration probability index for the next day return, involves migration from S_4 to S_1, S_2, S_4 with probability 33.33%, and thus can be calculated as shown in Fig. 7.

Trading strategy decision variables include buy, sell or continue to hold. Expectations represent next day volatility for expected return. The expected value equals the probability multiplied by the volatility, which is multiplied by the probability of each state and corresponds to the fluctuating migration status. Based on the definition of state variables to calculate next day return migration probability matrix, the expected value is calculated, and the decision variables are determined based on expectations. Trading

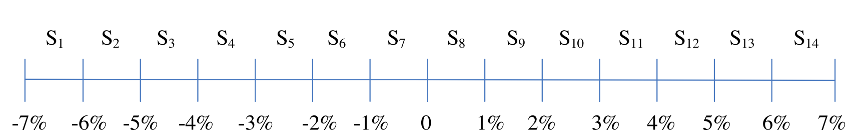

Fig. 5. State variables of the expected return for the next day.

	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	0.2	0.3	0	0.3	0.2
S_2	0.2	0	0.4	0	0	0.4
S_3	0.125	0.25	0.375	0.125	0.125	0
S_4	0.333	0.333	0	0.333	0	0
S_5	0	1	0	0	0	0
S_6	0.25	0	0.25	0	0.25	0.25

Fig. 7. Next day return migration probability matrix.

1	0	1	0	0	1	......	1	0	1	1	1	0

Fig. 8. Chromosome coding.

strategy signals can combine with genetic algorithms to identify the best investment trading strategy.

3.3. Stock selection and capital allocation- buy long transaction, short sale transaction

This study uses genetic algorithms to optimize the capital allocation, and uses Markov decision process to solve the timing and selection strategies. Genetic algorithms combined with trading signals and trading strategies, through chromosome evolution, identify possible portfolios and calculate the fitness value. Once convergence is achieved, high value adaptation chromosomes (portfolio) are filtered out. The funds will be invested in good targets selected using the stock selection function.

Capital allocation involves splitting capital into 50 equal parts, each comprising 2% of the total capital. These investment funds are then invested in a portfolio of different stocks, and the optimal capital allocation is determined via genetic algorithms. If there is no money to buy stocks or there is no stock can be sold by the investment strategy, the stocks must implement buy short sale transaction and long transaction. As shown in Fig. 8. Chromosome is encoded by eight 1s and 50 0s. The number of 0s between two 1s denotes the capital invested in corresponding stocks. A 0 represents 2% of the capital. There are nine intervals. There is no 0s in front of the first 1, which means there should be no investment

Parent Chrom.A 0 1 1 0 |1 0 0 0 0 0 0 1 1 0 1 1 0| 1...

Parent Chrom.B 0 0 1 0 |0 1 0 1 1 0 1 1 0 0 1 0 1| 0...

Offspring Chrom.A 0 1 1 0 |0 1 0 0 0 0 0 1 0 0 1 1 1| 1...

Offspring Chrom.B 0 0 1 0 |1 0 0 1 1 0 1 1 1 0 1 0 0| 0....

Parent Chrom.A: The set of 1's position P_A={1, 8, 9, 11, 12}

Parent Chrom.B: The set of 1's position P_B={2, 4, 5, 7, 8, 11, 13}

$P_A \cup P_B$={1, 2, 4, 5, 7, 9, 12, 13}

Fig. 9. Crossover.

in the corresponding stocks during the first interval. The second interval contains one 0 that represents 2% of the funds invested in the second stocks. Meanwhile, the third interval contains two 0s, and indicates 4% of the funds invested in the third stocks. Finally, the number of 0s in the last interval shows that the ninth interval portion of cash reserves comprises 2% of funds.

Genetic algorithms perform three main operations, namely selection, crossover and mutation. Selection involves the use of fitness function to select good chromosomes that continue to evolve. Common selection methods include: roulette wheel method, elite law and competition law. Crossover selects one gene segment from two chromosomes for exchange. Crossover is intended to produce another new offspring that may inherit the advantages of their parent, as shown in Fig. 9. Based on mutation rate, mutation randomly changes one gene of a chromosome to obtain new features not possessed by the parents. This operation can reduce the number of answers that fall in the local optimal region. This study used two point mutation. Fig. 10 shows the situation before and after chromosomal mutation].

3.4. Investment trading strategies

This investigation combined the trading signals and trading strategy obtained using Markov processes with genetic algorithms to identify the optimal investment strategy. First, trading signals based on cumulative rate of return were generated using the Markov decision process to help investors decide whether to adjust the portfolio. The expected next day for the Markov decision pro-

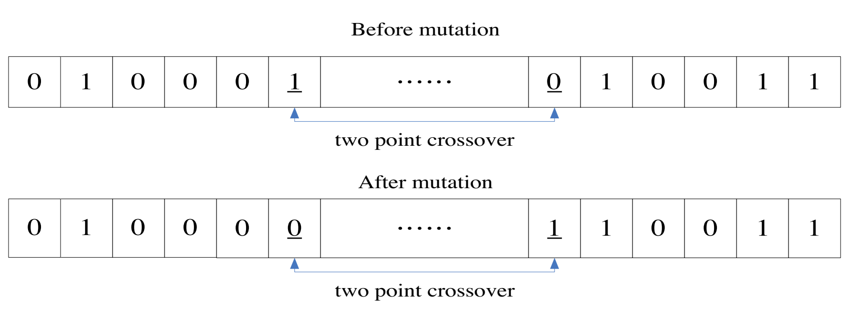

Fig. 10. Mutation.

Table 1
Capital allocation adjustment.

	Cash reserves	1st stocks	2nd stocks	3rd stocks	4th stocks	5th stocks	6th stocks	7th stocks	8th stocks
Trading signals		adjust	adjust	adjust	adjust	adjust	adjust	adjust	adjust
Buy/Sell signals		Sell	Buy	Buy	Buy	Buy	Sell	Buy	Buy
Capital allocation	30%	10%	10%	0%	20%	0%	10%	10%	10%
Adjustment capital allocation	50%	0%	10%	0%	20%	0%	0%	10%	10%

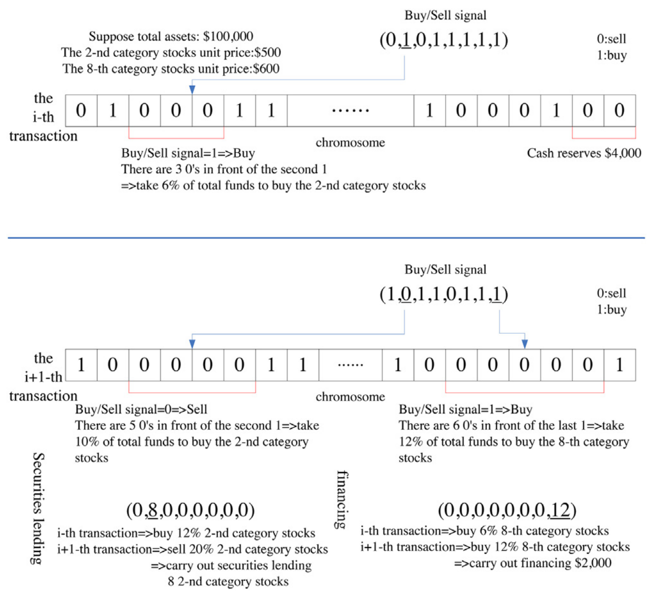

Fig. 11. Trading signals, trading strategy signals and capital allocation.

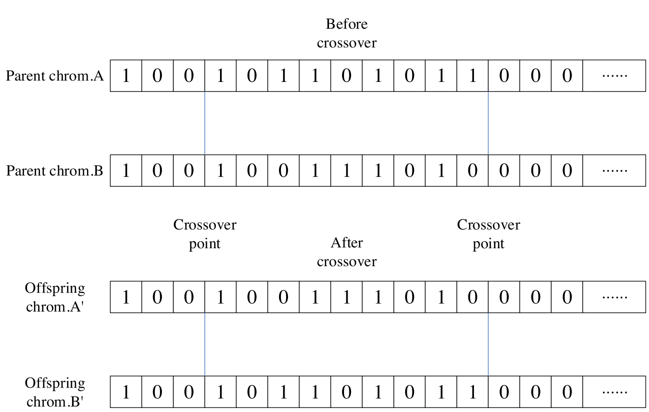

Fig. 12. Crossover of SGA.

cess generated a trading strategy able to make buy or sell decisions, and this strategy was then integrated with genetic algorithms to evolve and obtain the best chromosomes.

To maintain total investment capital of 100%, the capital allocation of chromosomes must be adjusted in accordance with the trading signals and trading strategy signals, as shown in Table 1. For example, assuming system displays the portfolio adjustment signal. Moreover, regarding trading strategy signals (buy/sell signals) the signals for the first and sixth stocks is sell, while that for the second, third, fourth, fifth, seventh and eighth stocks is buy. The trading signals and trading strategy signals based approach adjusts

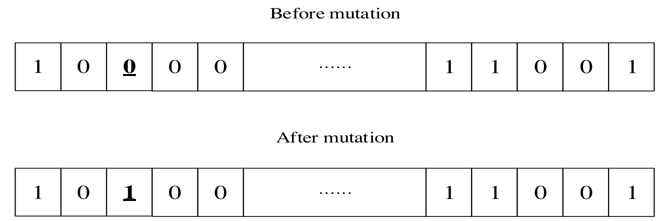

Fig. 13. Mutation of SGA.

the chromosome. The capital allocation ratios of the stock that must be sold migrate to cash reserves. The fourth stock comprised 20% of total funds while the second, seventh and eighth stocks comprised 10% of total funds.

Chromosomes are evaluated based on the three criteria of Sharpe ratio, the proportion of funds invested in electronics stocks and cash reserved. Offspring are reproduced according to level of fitness. Following crossover and mutation in sequence, the final optimal allocation of funds was calculated and the best chromosomes were selected for use in the stock investment strategy.

Before stock transactions the trading signal should be checked: 0 represents “do not adjust the portfolio today” and 1 represents “the portfolio must be adjusted today”. Eight trading strategy signals correspond to eight categories of stocks. The numbers of 0s in front of the n-th 1 for chromosomes represent the capital allocation of the n-th categories of stocks. Moreover, the numbers of 0s behind the eighth 1 represent cash reserves. This study assumes that one 0 represents 2% of the total funds. The chromosome is a string that comprises 50 0s and eight 1s.

Trading strategy signals and corresponding capital allocation can be used to determine trading behavior and volume. When the existing funds or holding stocks cannot meet the transition needs, it is possible to perform financing and lending transactions. The timing for securities lending trading is such that when no stocks can be sold, then according to government regulations that require the maximum payment of 90% of the margin, these stocks can be traded on 100% margin. Fig. 11 shows that in the i-th transaction with trading signals 1, the second category stock trading strategy signal is 1 and means buy. There are three 0s in front of the second 1, which means 6% of the total funds are required to buy the second category stocks. If the total asset value is $100,000, then $6000 must be spent to buy 12 s category stocks whose unit price is $500. In an i + 1 transaction, the second category stock trading strategy signal is 0 and denotes sell. There are five 0s in front of the second 1 which means 10% of the total funds should be used to sell the second category stocks. Thus 20 s category stocks must be sold, with a unit price of $500. However, the second category stocks in hands only have 12 stocks which were purchased in the last transaction. There are insufficient volumes of the eight stocks in hand to sell, so it is necessary to perform securities lending transactions. Investors thus must pay $3600 (90% of the value of the stock) as a security deposit to borrow the eight stocks.

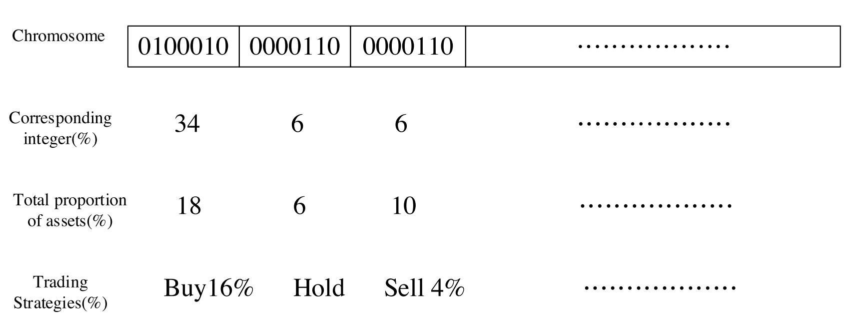

Fig. 14. SGA trading strategy.

Table 2
The chromosome encoding for the SGA.

	1st stocks	2nd stocks	......	8th stocks	Cash reserves
chromosome	0010100	0100110	......	0001110	0000110
integer	20	38	......	14	6

Financing transactions occur when cash on hand is insufficient for the desired transaction. According to government regulations the maximum financing rate is 60%, meaning prospective traders must possess 40% of the funds needed to buy stocks. Thus 40% of the stock can be used as collateral to finance 60% funding from financial institutions. For example, in a subsequent transaction, the eighth category stock trading strategy signals is 1 and denotes buy. There are six 0′s in front of the eighth 1 which means 12% ($12,000) of the total funds are needed to buy the eighth category stocks. Given $4000 cash in the hand, investors must secure finance of $2000 to buy the eighth category stock with a unit price of $600. This allows an investor to buy a total of 20 stocks. The above approach integrates trading strategy signals and trading signals in capital allocation with financing and securities lending relationships.

4. Experimental analysis

This study apply the new analytical framework on Taiwan's stock market to prove the validity of the new research framework. In the experiments, the eight categories listed in the index can serve as investment targets to simulate the stock trading process. Markov decision process can identify the timing of the adaptive portfolio and determine the trading strategies. The Markov decision process combined with genetic algorithm can solve capital allocation problems. The experimental results were compared with the returns derived from the buy and hold strategy, Taiwan market index, Taiwan top 50 Index and the simple genetic algorithm (SGA).

Experimental data obtained from the Taiwan Economic Journal sources (TEJ) covered the period 2003 to 2014. By the sliding window concept, this study take advantage of the previous three months data of the stock market to predict the fourth month fluctuation of return. After several trials. If the sliding window size is too short (<3 months), the forecasting process can not eliminate irregular variation on prediction. If the sliding window size is too long (>3 months), the prediction process will produce increasing or decreasing trend. That is the prediction may generate moderate fluctuations situation. The three experimental evaluation criteria include Sharpe ratio, the proportion of funds invested in electronics stocks and cash reserves ratio. The final experimental results were obtained by running the experiment ten times to ensure statistical accuracy. This section first describes the general approach of genetic algorithms, then presents the comprehensive appraisal results.

4.1. Simple genetic algorithms (SGA)

The chromosomes of simple genetic algorithms use binary encoding. Based on eight categories of stocks and cash reserves, the chromosomes are divided into nine sections. Each section comprises 7 bits, so the total code length is 63 bits. Moreover, each section can be converted from binary to integer to become the capital allocation for each category of stocks as listed in Table 2. The coding of the first stocks is 0010100, which corresponds to the integer 20, and so on for the remainder.

The genetic algorithms involve tree operands, selection, crossover, and mutation. Genetic algorithms generally mate using a dual-point exchange, two randomly selected crossover points and an exchange for the crossover point in the middle part. Fig. 12 shows that the parent chromosomes A, B were mated to produce offspring A' and B'. Mutation is intended to avoid the chromosome preventing the optimal solution. Mutation can achieve advantages that the parent chromosomes are unable to. General genetic algorithms generally use a single point mutation. In Fig. 13, the value of the third bit from 0 becomes 1.

Table 3
Average rate of return for 2003–2014.

average rate of return / time	TWN50	TAIEX/Trend		Buy & Hold	SGA	M_GA
1. 2003.01~06	2.26	1.88	Bull market	1.88	2.31	2.30
2. 2003.07~12	3.68	3.33	Bear market	4.65	6.12	4.41
3. 2004.01~06	-0.42	-0.01	Market correction	1.14	1.65	6.20
4. 2004.07~12	1.01	0.94	Bull market	2.05	0.95	3.30
5. 2005.01~06	0.26	0.33	Bear market	-1.45	0.11	0.35
6. 2005.07~12	0.92	0.92		0.25	0.48	1.72
7. 2006.01~06	0.54	0.47	Bull market Bear market	3.07	2.64	1.70
8. 2006.07~12	2.12	2.66	Bull market	3.78	3.08	5.89
9. 2007.01~06	2.11	2.20	Bear market	1.86	2.17	3.11
10. 2007.07~12	-0.61	-0.55	Bull market	0.11	0.76	7.27
11. 2008.01~06	-1.52	-1.64	Market correction	-0.12	-0.07	-0.63
12. 2008.07~12	-7.79	-7.58		-7.53	-5.14	3.62
13. 2009.01~06	5.45	6.25		7.97	7.13	11.62
14. 2009.07~12	4.01	4.25		3.40	3.87	4.99
15. 2010.01~06	-2.07	-1.71		-1.46	-2.80	0.41
16. 2010.07~12	3.73	3.50		4.46	3.25	3.94
17. 2011.01~06	-0.62	-0.55		-0.10	-1.37	2.49
18. 2011.07~12	-2.60	-3.13		-3.23	-1.32	1.27
19. 2012.01~06	0.30	0.64		0.58	1.32	3.55
20. 2012.07~12	1.27	0.99		1.60	1.56	4.26
21. 2013.01~06	0.69	0.78		0.94	1.20	2.56
22. 2013.07~12	0.78	1.12		1.57	1.51	3.03
23. 2014.01~06	1.95	1.48		0.08	2.35	4.25
24. 2014.07~12	0.39	-0.12		-0.40	0.63	2.68
average	0.66	0.69		1.05	1.35	3.51

Table 4
2003–2014 Average convergence generation and average execution time.

	SGA		M_GA	
	Average Convergence Generation	Average execution time (in s)	Average Convergence Generation	Average execution time (in s)
2003.01–06	4552	156.01	4058	119.78
2003.07–12	4580	155.43	4490	121.21
2004.01–06	4480	156.09	4140	116.90
2004.07–12	4373	151.50	4123	120.95
2005.01–06	4396	152.91	4103	121.00
2005.07–12	4202	151.34	4019	119.59
2006.01–06	4082	148.71	4040	120.18
2006.07–12	3863	146.11	4365	124.64
2007.01–06	4060	149.42	4103	120.18
2007.07–12	4783	156.10	4038	120.66
2008.01–06	4446	153.62	3985	118.99
2008.07–12	4382	152.57	4131	121.78
2009.01–06	4340	151.37	4401	124.63
2009.07–12	4274	153.32	4029	119.85
2010.01–06	4021	149.50	4378	122.86
2010.07–12	4225	151.39	4250	122.50
2011.01–06	4016	149.02	4011	121.27
2011.07–12	4047	149.18	3956	118.02
2012.01–06	4365	152.23	4069	119.12
2012.07–12	4526	156.20	4116	121.40
2013.01–06	4153	150.46	3995	119.02
2013.07–12	4222	152.75	4201	121.97
2014.01–06	4651	159.25	4155	121.69
2014.07–12	4165	150.68	4036	118.30
average	4300	152.30	4133	120.69

There are three chromosome fitness evaluation criteria. Criterion 1 is the Sharpe ratio for eight categories. Criterion 2 is the proportion of funds invested in the electronic sector, which needs to be between 10% and 30%. According to the transaction records of Taiwan Stock Exchange, the most common trading for investors is the electronics sector. So this research adopt criterion 2 to do the experiments. Criterion 3 is the cash reserves, which must be between 5% and 10%. Because of the different units for various criteria, regularization must be performed to remove the effects of various units.

For each transaction, the chromosome can be decoded to facilitate comparison with the proportion of total assets following the last transaction. Comparison of the results obtained can determine the trading strategy.

The corresponding integer for the first chromosome stocks is 34, and the proportion of total assets after the last transaction was 18, 34–18 = 16, and the representative trading strategy involves purchasing the first stocks with 16% of total capital. The corresponding integer of the second stocks for the chromosome is 6, and the proportion of total assets following the last transaction is 6, 6–6 = 0, representative of the investment ratio remaining unchanged for the second stocks. The corresponding integer of the third stocks for chromosome is 6, and the proportion of total assets following the last transaction is 10, 6–10 = –4, which indicates the optimal trading strategy is to sell 4% of total capital invested in the third stock, as shown in Fig. 14.

This study was based on a rule of thumb, and the actual experiments to decide the parameter setting. Experimental parameter settings for M_GA and SGA:

Initial population is 100

Convergence occurs when the value of the continuous adaptation was no changes for 3000 generations.

Crossover rate is 1

Mutation rate is 0.01/Per Chromosome

4.2. Experimental comprehensive appraisal

This study integrates the Markov decision process and genetic algorithms (M_GA) to propose an investment strategy model. Experiments for M_GA are compared with the simple genetic algorithm (SGA), TWSE Taiwan 50 Index (TWN50), Taiwan stock index (TAIEX) and the buy and hold strategy (Buy & Hold). Experimental data from 2003 to 2014 are encoded on the basis of six-month periods, meaning twelve years divide into twenty four periods, as shown in Table 3. Taiwan's stock market has experienced five bull market, four bear market and two market correction in these twenty four periods. No matter what kind of state of the market, M_GA methods are able to beat the market and the TWN50. During the bull market, M_GA can have a ratio of 70% (7/10) beat Buy and Hold strategy, TAIEX and TWN50. In the bear market, M_GA method can defeat Buy and Hold strategy, TAIEX and the TWN50 with a ratio of 77% (10/13). During the market correction, M_GA can have a ratio of 91% (10/11) beat Buy and Hold strategy, TAIEX and the TWN50.

The average rate of return changes at six-monthly intervals in Fig. 15. In Fig. 15, there are 20 sections, among which M_GA is the best performing. Moreover, in sections 12, 15, 17 and 18, even if the TWN50, TAIEX, Buy and Hold and SGA offer a negative rate of return, the M_GA method can still obtain a 1.95% return on investment. For total average rate of return of up to 3.51%, M_GA exhibits the best performance. This confirms that the integration of genetic algorithms and Markov decision process can help improve return on investment. Table 4 lists the average convergence generation and average execution time for M_GA experiments over the past twelve years. The total average convergence generation of M_GA is less than that of SGA. Moreover, the average execution time of M_GA is 120.69 s faster than that of SGA. The integration of Markov decision process into genetic algorithms can improve their performance and shorten execution time.

Investment in stocks is one of the most common forms of investment that people undertake. However, numerous factors can affect stock market fluctuations. In the face of changeable economic situations, a rigid and inflexible investment strategy is inappropriate. From February 2003 to June 2003, affected by the SARS crisis, the Taiwanese stock market plummeted. This time was not suited to an inflexible buy and hold strategy. After all, a buy and hold strategy is the optimal investment path in bull markets. In booming markets under poor conditions, investors easily suffer losses. The integra-

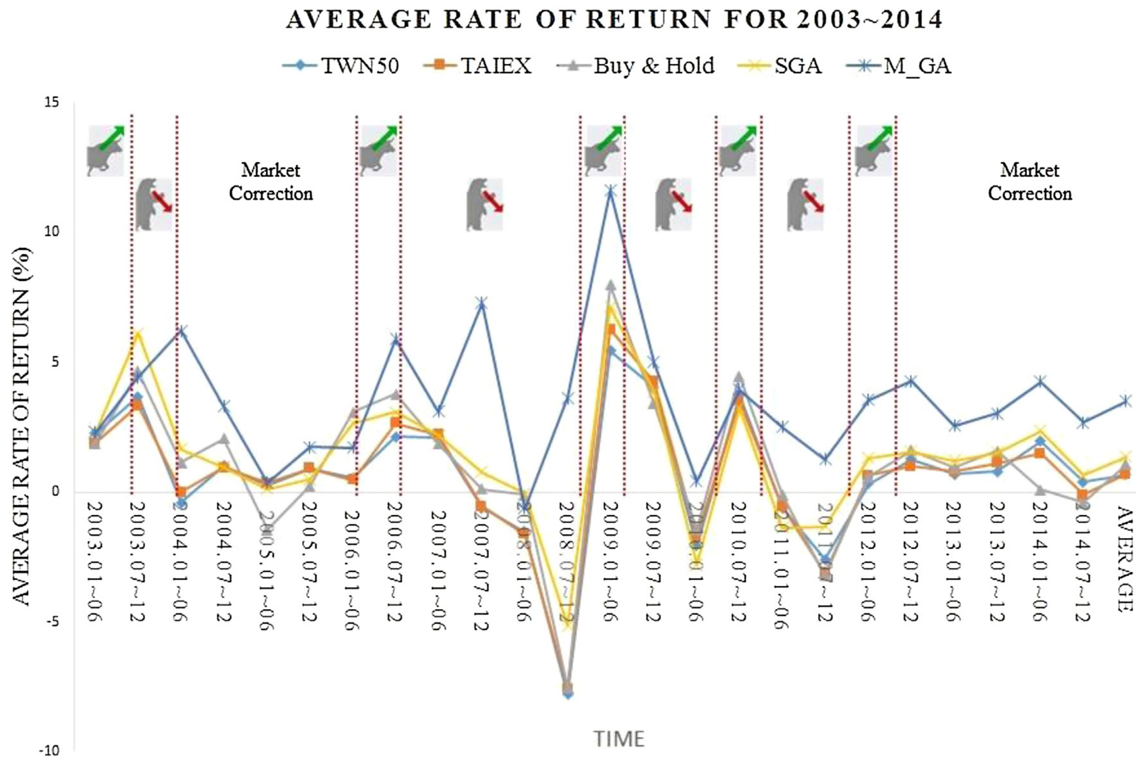

Fig. 15. Average rate of return diagram for 2003–2014.

Table 5
Average rate of return for 2003.2–2003.6.

	Feb-03	Mar-03	Apr-03	May-03	Jun-03	Average rate of return
TWN50	−11.55	−1.29	−1.15	9.83	6.83	0.53
TAIEX	−11.61	−2.5	−4	9.83	6.94	−0.27
Buy & Hold	−15.10	−3.32	−9.88	10.77	4.90	−2.53
SGA	−15.86	−1.52	−2.62	8.84	6.47	−0.94
M_GA	−5.64	−2.01	−2.28	7.67	7.98	1.14

Table 6
Average rate of return for 2008.9–2009.2.

	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Average rate of return
TWN50	−15.77	−16.40	−10.23	3.10	−7.86	7.96	−6.53
TAIEX	−18.83	−14.83	−8.42	2.93	−7.47	7.27	−6.56
Buy & Hold	−23.91	−12.64	3.40	1.43	−8.00	2.42	−6.22
SGA	−12.94	−12.92	−0.67	2.35	−11.18	5.14	−5.04
M_GA	−4.7	−1.58	19.9	6.15	−9.11	4.96	2.60

tion of genetic algorithms and Markov decision process can achieve a 1.14% average monthly rate of return during this period, and outperforms the TWN50, TAIEX, a buy and hold strategy and SGA, which obtain average monthly returns of 0.53%, −0.27%, −2.53% and −0.94%, see Table 5.

In September 2008, the bankruptcy of Lehman Brothers occurred, making the outbreak of a global financial crisis that severely impacted stock markets. The Taiwan stock market also suffered heavy losses, and its value shrank from 22.37 trillion to 12.65 trillion. Simultaneously, the stock market index fell below the 5000 point mark. In February 2009, U.S. President Barack Obama signed a US$ 787 billion plan to revitalize the economy and stabilize the situation, and these measures helped to contain the serious financial storm. M_GA achieved an average monthly return of 2.6% during this period, significantly better than the TWN50, TAIEX, a buy and hold strategy and SGA, which has achieved average monthly returns of −6.53%, −6.56%, −6.22% and −5.04%, as listed in Table 6.

In 2010, the European debt crisis began to spread through the euro zone. Taiwan was also affected during this period, the M_GA

Table 7
Average rate of return for 2010.1–2011.12.

Time	TWN50	TAIEX	Buy & Hold	SGA	M_GA
Jan-10	−5.78	−6.68	−7.30	−7.85	−11.34
Feb-10	−3.00	−2.67	−1.45	0.9	6.38
Mar-10	4.77	6.5	6.35	3.58	5.23
Apr-10	1.49	1.06	0.00	−3.15	−2.91
May-10	−8.22	−7.87	−7.55	−10.8	−2.75
Jun-10	−1.69	−0.6	1.21	0.51	7.87
Jul-10	6.10	5.88	7.28	9.76	9.69
Aug-10	−1.98	−1.86	1.28	−2.09	2.93
Sep-10	7.96	8.16	8.27	6.29	8.16
Oct-10	0.80	0.59	2.42	−0.69	−0.74
Nov-10	1.31	1.03	0.81	−0.91	−1.06
Dec-10	8.18	7.16	6.67	7.18	4.67
Jan-11	2.96	1.92	−0.51	3.17	7.71
Feb-11	−6.23	−5.96	−6.88	−8.69	−5.6
Mar-11	1.27	0.97	2.92	−0.27	−1.27
Apr-11	4.11	3.73	5.36	2.6	−2.49
May-11	−1.05	−0.21	−0.15	−2.57	7.96
Jun-11	−4.80	−3.74	−1.36	−2.46	8.65
Jul-11	−0.88	−0.09	4.38	2.16	−2.67
Aug-11	−9.05	−10.44	−12.33	−11.79	7.16
Sep-11	−5.87	−6.66	−9.54	0.76	4.06
Oct-11	5.04	5.01	6.69	9.81	7.07
Nov-11	−7.94	−9	−10.80	−10.9	−10.7
Dec-11	3.09	2.43	2.24	2.04	2.74
Average rate of return	−0.39	−0.47	−0.08	−0.56	2.03

has average monthly return of 2.03%, and is one of the investment strategies that is profitable in terms of all benchmarks. Buy & Hold profit was −0.8%, while the rest all showed negative rate of return. Based on the above experiments it is possible to learn about how the integration of genetic algorithms and the Markov model can effectively help investors increase their investment returns, for further detail see Table 7.

5. Conclusions and future research directions

This investigation combines the Markov decision process and genetic algorithms to provide a stock investment decision support system for stock market investment. The Markov decision process can help investors solve timing problems. This method differs from the technical indicators traditionally used to forecast market timing. Markov chain can predict whether investors must adjust their portfolios and the optimal trading strategy. Genetic algorithms have powerful spatial parallel search capabilities. Such algorithms can be coupled with Markov process and genetic algorithms to improve stock selection and capital allocation for stock investment strategy. This study proposes a stock trading model that also includes financing and financial securities and can take advantage of financial leverage to obtain excess returns.

The experimental results demonstrate that the Markov decision process, combined with genetic algorithms investment strategy model proposed in this study, obtains better rate of return than the buy and hold strategy, the Taiwan market index and TWN50. Taiwan's stock market has experienced five bull market, four bear market and two market correction from 2003 to 2014. No matter what kind of state of the market, the study proposed method are able to beat the market and the TWN50. Furthermore, M_GA have the ratio of 83% (20/24) can beat Buy and Hold strategy. And the average reward for M_GA method is more about 2.46% than the buy and hold strategy's average remuneration. Under an investment environment characterized by special conditions, such as during SARS, the global financial and economic crisis and the European debt crisis, even the most professional investment fund managers cannot avoid losses, but the proposed method is still effective for preserving returns. Moreover, the proposed method can obtain a satisfactory solution faster than the simple genetic algorithm. Numerous experiments demonstrate that this investment model is an effective investment tool, and can provide investors with an effective investment strategy.

This study uses one day as the transaction time unit. In the future, other units can be used, such as an hour or half hour, to achieve real-time computation. This would enable investors to avoid missing ideal trading opportunities. Experiments involved focusing on eight categories of stock as investment targets. Buying or selling of these eight categories stock was performed to simulate stock investment transactions. Future investigations can use a general stock or fund as the investment targets, and to identify the optimal investment strategy model. Markov decision processes can also be combined with other methods, such as: simulated annealing, artificial neural networks or ant colony algorithm for performance testing.

Evaluation of the genetic algorithm is based on the three criteria of Sharpe ratio, electronic cash ratio and cash reserves. The future may add further criteria or incorporate the concept of hedging to adjust the total asset ratio. In this investigation, Markov decision processes only use the cumulative rate of return and single day return to predict future returns. The addition of other multivariates for the Markov decision process may also be considered. It may consider adding a user-oriented fitness function to the proposed model for the purpose of customization.

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