Comparative Studies of Modeling of Agent's Behavior in Artificial Stock Market Focusing on GA and GP Approach

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1 Introduction

The theory and practice of agent has been a major focus of economic research in recent years, understanding the causal connections relating structure, behavior and welfare outcomes in market comprised of bounded rational agents who learn imperfectly from the past. It is obvious that actually traders are bounded in their information processing abilities and it can be considered reasonable allowing traders to be less rational. Usually there is one way to be fully rational, but there are many ways to be less rational. Loosing the assumption that agent can always behavior optimally can broaden our modeling methodology and as a result, through these unanalytical methodology, better explanation power could be achieved against some puzzles, having not gained satisfactory explanation.

As we all know, in fact participants in real market base their current behavior partly on their past experience and partly on perceived market characteristics, which their past individual behavior has helped determine. This feedback loop can lead to intricate relationship between behavior and outcomes that are difficult to understand and predict by standard analytical and statistical tools[13]. Fortunately, recently advances in computer-based modeling techniques and AI (Artificial Intelligence), specifically machine learning, offer new possibility[3]. In this paper, we will focus on a so-called Agent-Based Computational Modeling (ABC Modeling), which provides a powerful research tool completely different from the standard ones we are familiar with.

ABC Modeling can be applied to model a so-called complex adaptive system in which many adaptive and heterogeneous agents exist. In ABC Modeling, it is allowed that agents lack the behavior sophistication necessary to derive optimal solutions, however that ability is assumed basically in traditional theories. This is referred as a dilemma. Instead, in ABC Modeling it is postulated that adaptive mechanism driven by market forces, leads the agents to act as if they were optimizing.

An agent is said to be adaptive if the actions of the agent can be assigned a value (utility, pay-off etc.), and the agent behaves in order to increase his value over time[3]. Another characteristic of agent is heterogeneity. The use of heterogeneous agents is not new to finance, and there is a long history to build heterogeneous agent rational expectations models. What is attempted in this set of computational method is attacking the problem of very complex heterogeneity, which leaves the boundary of what can be handled analytically. Agents are made up from a very diverse set of types and behavior. To make the situation more complex, the population of agent types, or the individual behavior are allowed to change over time in response to changing environment[11]. A complex adaptive system is such a system which consists of a network of interacting adaptive agents and therefore, exhibits dynamic aggregate behavior emerging from the individual activities of agents.

Many economic systems can be identified as complex adaptive system, especially the stock market, in which heterogeneous agents interacting with other agents and at the same time with environment, based on their internal behavior rules and their past experience. These agents may have a rich internal cognitive structure and more autonomy than conventional modeled economic agents. Consequently, this economic system can exhibit self-organization. And agents and economic system are co-evolving in the way that natural selection pressure in the evolutionary process of economic system induces agents to engage in continual exploration with new behavior rules.

Through ABC Modeling, economic system can be computationally constructed. ABC Modeling has the ability to explore a wide range of phenomenon, involving learning and adaptation. By constructing agent-based computational laboratory, hypothesis can be experimentally studied. ABC Modeling has been proved to be a powerful modeling technique, retaining much of flexibility and synchronously combining the precision and consistency imposed by computer language[3]. By executing the ABC models on a computer, we gain the following three-fold advantages.

(1) With complete control of all conditions in the experiment format, we can explore the system dynamics freely.

(2) We can check expectation and learning of each agent carefully and the various unfolding behavior of the model can be revealed step by step.

(3) Additionally, the infinite patience of agents implies that large-scale computational experiment can be conducted with a very low cost.

ABC Modeling has been applied in various specific types of market, such as financial market, labor market and electricity market etc. In this paper, we are specifically interested in one of the most important application of ABC Modeling, namely application in artificial stock market. The use of ABC Modeling of stock market is driven by a series of empirical puzzles[10], which are still hard to explain using traditional representative agents structures.

Among these puzzles are issues of time series predictability using both technical and fundamental information and issues of volatility persistence. Although some theoretical explanations have been provided for these puzzles, most of the explanation still remains controversial and general theory for all these features are out of reach. Better explanation power might be gained by allowing agents to form their expectations in accordance with the way investors do in real stock market. Actually the image of artificial stock market as groups of interacting agents, continually adapting to new information and updating their expectation model, seems like an accurate image of how real stock market operates.

The core of the ABC Modeling is how to model the agents' interaction, learning, adaptation and herd behavior effectively. On the basis of several research papers, we can see that different methods have been applied to model the complex behavior of agents in the artificial stock market, such as Genetic Algorithm (GA), Genetic Programming (GP) and Fuzzy method etc[1)10)12)]. In this paper, we introduce these methods first and then make some suggestion about the future enhancement.

In the following, in section 2, we make a glance of basic model of artificial stock market. In section 3, we introduce three different schemas, having been proved very effective to model the behavior of agents. In section 4, we make some comparison and analysis, then give some suggestion about future enhancement.

2 Basic model of artificial stock market

It is assumed that the market structure is set up to be a traditional neoclassical two-asset market, but deviating from that model by allowing agents to form their expectations not completely rationally. Traders make predictions about the future, namely the expectation of future return and risk, and then buy and sell stock in corresponding with their expectation. Stock prices to clear the market are set endogenously[1)10)12)].

There are two assets traded, a stock with price P_t that pays an uncertain dividend D_t and a risk-free bond that pays a constant interest rate r_f. The dividend D_t is assumed to follow AR (1) process as follows,

$$D_t=\bar{D}+\rho(D_{t-1}-\bar{D})+\epsilon_t \tag{1}$$

where ϵ_t is Gaussian noise (i.i.d and $N(0,\ \sigma_\epsilon^2)$) and $\bar{D},\ \rho$ are constants. For simplicity, there are N stocks and N heterogeneous agents in market, and each agent initially endowed with a fixed number of stocks. Agents are assumed to have CARA (Constant Absolute Risk Aversion) utility function as follows,

$$U(W)=-exp(-\lambda \mathrm{W}) \tag{2}$$

where W represents wealth and λ is degree of relative risk aversion. And agents are assumed to be myopic to endeavor maximizing their expected utility.

Agents are heterogeneous in terms of their individual expectation of future stock price and dividend. Assuming that agent i's expectation about stock price and dividend at time $t+1$ is distributed with mean $\hat{E}_{i,t}[P_{t+1}+\mathrm{D}_{t+1}]$ and variance $\hat{\sigma}^2_{i,t}$. Under the assumption that stock price and dividend are Gaussian, agent i's preferable stock demand $X_{i,t}$ can be gained by the following equation.

$$X_{i,t}=\frac{\hat{E}_{i,t}[P_{t+1}+D_{t+1}]-P_t(1+r_f)}{\lambda\hat{\sigma}^2_{i,t}} \tag{3}$$

A stock price to clear the market can be found by balancing the demand and the fixed supply of stock, therefore satisfying the following equation.

$$\sum_{i=1}^{N}X_{i,t}=N \tag{4}$$

The behavior sequence of each agent at time t is as follows. Agents form their expectations $\hat{E}_{i,t}[P_{t+1}+D_{t+1}]$ and variance $\hat{\sigma}^2_{i,t}$ based on all current information (including historical dividend and price time series) first. Then according to equation (3), they calculate their desired stock demand and finally, the price to clear the market will be decided endogenously.

Here it is obvious that the key issue is how heterogeneous agents form individual expectation $\hat{E}_{i,t}[P_{t+1}+D_{t+1}]$ and variance $\hat{\sigma}^2_{i,t}$. In this decision process, it is just the complex behavior (learning, adaptation, herd etc.) of agents that results what expectation will be achieved. We will discuss this issue in detail in next section.

3 Modeling of agent's complex behavior

A wide range of computer-based algorithms existing can be applied for this objective, including classifier system, Genetic Algorithm (GA), Genetic Programming (GP), neural network etc. From many literatures related to application of ABC Modeling in artificial stock market, we recommend three important research papers, in which three different schemas, namely GA method with rule base , Fuzzy method combined with GA and GP method with 'school' have been applied to model the complex behavior of agents and proved to be effective. In this section, we summarize these schemas in detail first.

3.1 GA method with rule base

As addressed in reference [10], despite the complexity of the environment forces, agents always use simple rules of thumb in their attempts of optimization. These rules are not static, but continually reevaluated and updated according to their performance. No agent will continue using suboptimal rules when better one has been discovered. Agents not only update their linear prediction models, but also make selections as to what information is relevant to their forecast at the same time.

Each agent contains a table of 100 of their own rules, so-called rule base. These rules map states of market into forecast parameters and are referred as condition-action rules, specifically meaning that if the condition vector is satisfied then the forecast parameter can be determined. These rules govern agent's behavior in trading and can evolve in a learning process that occurs at a low frequency than trading, which is similar to the condition in real stock market. But it is a pity that interaction relationship among agents is not constructed in their computational model.

The condition part of the rule represents the states of the market, summarized in a binary vector, for example 12 bits long as shown in Table 1. If the state condition is satisfied, then the value of the bit is 1, otherwise is 0. The set of bit 1 to bit 6 corresponds to fundamental information (dividend price ratio), for example, bit 1 means that 'if price*interest/dividend>1/4', whereas the set of bit 7 to bit 10 corresponds to technical information (moving average of historical price), for example, bit 7 means 'if price>5-period MA'. Agents are allowed to select these bits arbitrarily.

Bit	Condition
1	price*interest/dividend>1/4
2	price*interest/dividend>1/2
3	price*interest/dividend>3/4
4	price*interest/dividend>7/8
5	price*interest/dividend>1
6	price*interest/dividend>9/8
7	price>5-period MA
8	price>10-period MA
9	price>100-period MA
10	price>500-period MA

Table 1. Condition bit 1 to bit 10

The action part of rules accounts for two forecast parameters $a_{i,j}$, $b_{i,j}$ and helps convert the matched set of bits into a linear forecast model as follows, with i representing the index of agent and j representing the index of rule in rule base.

$$\hat{E}_{i,j,t}[P_{t+1}+D_{t+1}]=a_{i,j}(P_t+D_t)+b_{i,j} \tag{5}$$

At the ending of each trading period, agents will evaluate the forecast accuracy of the matched rules by calculating an exponentially weighted average of squared forecast error as follows, denoted as $e_{i,j,t}$. Then $\hat{\sigma}_{i,j,t}$ can be estimated using $e_{i,j,t}$ as shown in equation(7).

$$e^2_{i,j,t}=(1-w)e^2_{i,j,t-1}+w((P_t+D_t)-(a_{i,j}(P_{t-1}+D_{t-1})+b_{i,j}))^2 \quad (6)$$

$$\hat{\sigma}_{i,j,t}=e_{i,j,t} \quad (7)$$

As we can see from reference [10], through the application of GA, agent's complex behavior including learning and adaptation can be simulated effectively.

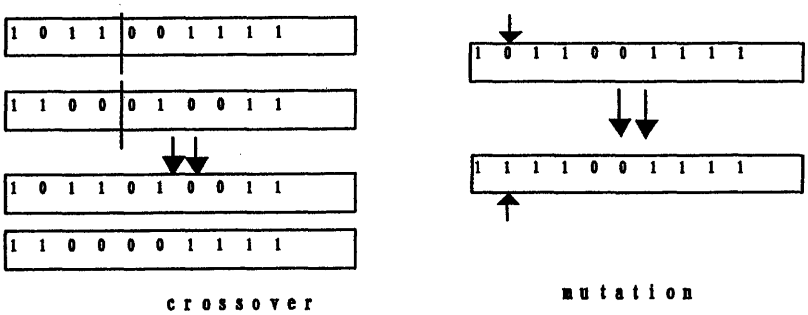

Fig. 1 Genetic operation in GA

In GA, each individual (forecast model) is represented as a string and must be evaluated and assigned a fitness value according to its forecast accuracy. In order to enhance the fitness of the population (rule base), genetic operations (crossover and mutation) are implemented (actually, GA is very similar to GP in many aspects, so we suggest interested readers refer to APPENDIX). In crossover operation, two fit parents are chosen and then swapped, as a result new rules being formulated. In mutation operation, one parent is chosen and then bits of the condition part are flipped at random and the value of forecast parameters also are modified at random (see examples in Fig.1). As a result using GA, poorly performing rules ($e_{i,j,t}$ is undesirable large) are eliminated, and instead new forecast rule will be generated by crossover and mutation operation, and added to the existing rules population. We can see that this is just the same result of agent's learning and adaptation behavior.

3.2 Fuzzy method combined with GA

As addressed in reference [12], they conjectured that agents in the stock market exhibit limitations in their ability to process information and must rely on some form of reasoning, which can be described as an inductive process. The core of the reasoning process herein modeled is an inductive reasoning schema, in which agents rely on fuzzy decision-making rules to make an expectation.

Evidence has been found that human's ability to process an immense amount of information efficiently is the outcome of applying fuzzy logic as part of thought process. Consequently, agents are assumed to have the ability to compress information into a few fuzzy notions and the induction of agents can be modeled by application of fuzzy logic. Specifically, each agent is allowed to form his expectation using his own genetic-fuzzy classifier system, in which a set of conditional forecast rules that guide expectation exist.

These fuzzy rules also involve a condition-action format but they differ from the rules described in the above section in that fuzzy terms rather than precise term describe the conditions and actions. The format of fuzzy rule can be described like 'if specific conditions are satisfied in a relative sense, then the value of forecast parameters can be defined in a relative sense'. For example, a fuzzy rule can be described as 'if price*interest/dividend is low, then $a_{i,j}$ is low and $b_{i,j}$ is high'.

The states of market, here called market descriptors, are summarized into 5 bits, namely $P_t{}^*r_f/D_t$, $P_t/MA(5)$, $P_t/MA(10)$, $P_t/MA(100)$, $P_t/MA(500)$, clearly the first bit is a fundamental bit, whereas the remaining are technical bits. And the action part of rules is summarized into two bits, namely $a_{i,j}$, $b_{i,j}$. These bits are all coded 1, 2, 3, 4 for 'low', 'moderately low', 'moderately high', and 'high' respectively.

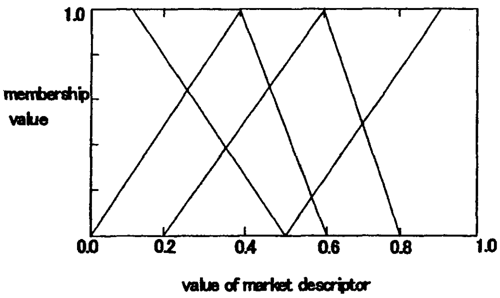

Fig. 2 Fuzzy set of market descriptor

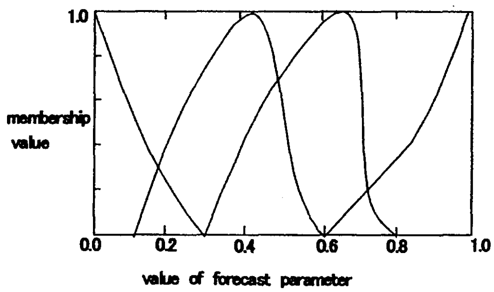

Fig. 3 Fuzzy set of forecast parameter

The corresponding relationship between precise value and the fuzzy set is necessary to be defined previously. One example of fuzzy membership function is described in Fig.2. It is assumed that each market descriptor has the possibility of falling into four alternative states, 'low', 'moderately low', 'moderately high' and 'high', which can be presented by a set of four membership functions associated with a specific shape. For example, state 'moderately low' is associated with a triangle shaped membership function with the precise range from 0 to 0.6. If the precise value of descriptor is 0.4, it may fall into state 'low', 'moderately low' and 'moderately high' with different membership value. Similarly, as described in Fig.3, the fuzzy set of forecast parameter $a_{i,j}$, $b_{i,j}$ are labeled respectively, 'low', 'moderately low' (Gaussian-bell curve), 'moderately high' (Gaussian-bell curve) and 'high'.

Now give an example of how the fuzzy rule works and the objective is to gain the precise value

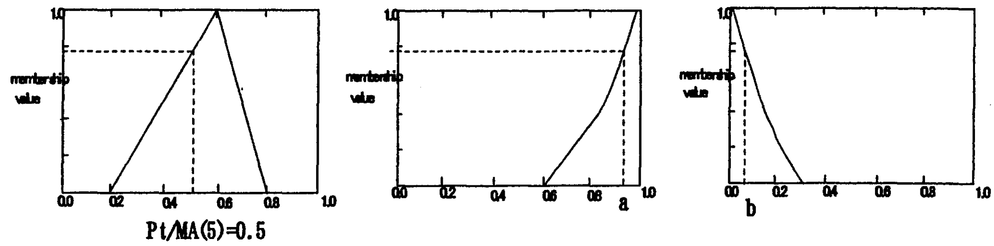

Fig. 4　Example of how fuzzy rule works

of forecast parameters. Consider a rule that 'if $P_t/MA(5)$ is moderately high then a_{ij} is high and b_{ij} is low'. Suppose $P_t/MA(5)=0.5$. Then as described in Fig.4, we can gain the value of a_{ij} and b_{ij} very quickly.

Inside this classifier system, it is also GA responsible for evaluating all existing rules, eliminating bad rules and generating new rules.

3.3　GP method with 'school'

As written in reference [1], social learning in the form of imitation of strategies is important in stock market context, but it is a pity that the standard modeling of stock market does not model this behavior. Unfortunately, in reality, strategies (forecast models) are in general not observable and what is observable is only the trading action. To tackle this problem, namely how can unobservable strategies be imitable, an additional social learning mechanism referred as 'school' was recommended. Actually, the school can be regarded as a public rule base whoever can visit. Through this structure, the observability and imitability of strategy can be ensured.

Different from the linear expectation model described above, they assumed the following expectation model.

$$\hat{E}_{i,t}(P_{t+1}+D_{t+1})=(P_t+D_t)(1+\theta_1\ tanh(\theta_2\ f_{i,t})) \tag{8}$$

As addressed in reference [1], the population of function $f_{i,t}$ need to be determined through GP (see details in APPENDIX). The operator set of the tree is $+$, $-$, $\times$, /, *sin*, *cos*, *exp* and terminal set is defined as P_t, P_{t-1},..., P_{t-10}, $P_{t-1}+D_{t-1}$, ..., $P_{t-10}+D_{t-10}$. The elements in the terminal set can be combined with operator selected from the operator set completely randomly, however it is necessary to make sure that the tree is able to represent a mathematical function correctly. Of course, at some time very complex functions without explicit practical meanings can be formulated through GP, which are difficult to understand but perhaps have good forecast accuracy.

The school consists of many faculty members, each having a forecast model. Each forecast model will be evaluated under a specified schedule. Beyond evaluation, through genetic operations, bad forecast model will be discarded and newly generated forecast model will be added to the existing population of forecast models. Therefore, the school can adapt to the market dynamics and evolve gradually.

On the other hand, the adaptive process of agents can be described as a sequence of two decisions. First, an agent must make a decision whether to go back to school, and if going back to school, he must decide whether to follow the model learned at the school or not. For simplicity, let $r_{i,t}$ be the probability that agent i will decide to go back to school. The class-taking behavior of agent is assumed as follows. The agent will select one forecast rule in school randomly with a uniform distribution. He will then validate this selected forecast rule to fit the historical price and dividend data and compare the forecast accuracy with his original forecast rule. He will apply this new one into practice if this new one is proved to be more successful than his old one (certainly on history data) and discard the old one. Otherwise, he will start another random selection. Therefore, agent's learning and adaptation behavior can be modeled by explicit schooling process and searching process.

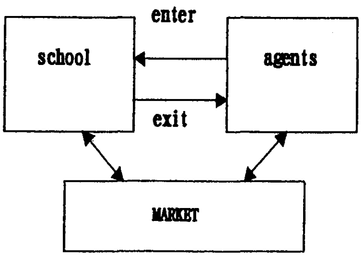

Fig 5. Schema of stock market

By introducing this co-evolution model, the interaction between 'school' and the market can be explicitly modeled. Specifically, the evolution of school must adapt to market dynamics and at the same time, the knowledge gained by agents in school may have further impact on market dynamics. The schema of the model is shown in Fig.5.

4 Comparison and Discussion

The computational experiments based on three different schemas introduced in section 3, have demonstrated rich dynamics of stock price and return which are similar to the characteristics of real stock market. For example, several phenomenon can be replicated, including fundamental and technical predictability, volatility persistence and leptokurtosis. The behavior of the learning and adaptive agents was interested in, not the equilibrium selection and convergence properties.

The reason why a simple artificial stock market can manifest many characteristics of real stock market is that either of GA and GP method can model the complex behavior of agent very effectively, as mentioned in section 3.

First, GA has been proved to be a powerful method to locate improvement in complicated higher-dimensional spaces. Each agent has his own rule base and under a certain schedule, he will eliminate some rules proved to be invaluable according to his evaluation of past performance of rules, while considering some new rules into his rule base. The objective to do this is that agents want to adapt to the market optimally in a dynamic fashion, through maintaining good rules and discarding bad ones through learning process.

But it is a pity that agent's interaction with each other is not dealt with at all. An agent depends only on his own past experience and the historical data entirely, without interacting with other one else. This is a type of individual learning, however the important social learning has been ignored completely.

The condition part of condition-action rule represents the states of market, including both fundamental information and technical information. It is a very important and valuable point, since the combination of these information helps model two typical types of investor's behavior. Two typical investor types are defined as follows, the fundamentalists, expecting prices to return to their fundamental values, and chartist or technical analysts, using simple technical trading rules and extrapolating trends in past prices. Agents switch between fundamentalist belief and simple technical trading rules.

If the agent's selected rule has only fundamental information, this means that he is fundamentalist at this time. On the other hand, if he only uses technical information, the agent is a chartist. But sometimes, the agent may make expectation depending on both fundamental and technical information. The change from one type to another type is allowed in this model.

Secondly, combined with GA method, the application of fuzzy method makes the agent behavior more like the participant in real market. Agent's thought process is modeled as follows. They compress information into fuzzy notions first, and then their induction process is modeled by application of fuzzy logic. Because of this enhancement, the experimental result seems to be enhanced to some extent.

Thirdly, in the schema of GP with school, there exists no rule but a forecast model represented by the tree in GP. Each agent owns only one forecast model, not a rule base and school can be regarded as a public rule base. The forecast model has a more flexible form than the condition-action rule, but sometimes can not be understood easily. The most valuable point in this schema is that a kind of social leaning can be modeled effectively. An agent going back to school could select a preferable forecast rule and through the public facility school, then agents can implement social learning. Furthermore, the school is not static and the forecast rules in school are always evaluated, so that the most powerful rules are maintained and invaluable rules are discarded.

Despite the comparison above, we can not draw a conclusion which schema is the best one. But we noticed one problem that only modeling the learning and adaptation behavior of agents is not enough at all. The more the artificial agents behave like the participants in real market, the more powerful explanation ability will be achieved. In real stock market, agent's other behavior, such as the speculation, herd behavior etc. can also be found. The fact shows that agents become much less rational with this type of behavior than the artificial agents modeled which are found in recent research papers. In other words, the artificial agents modeled here are still too rational.

Another problem remained is that the agent's heterogeneity is bounded too strictly, namely in the way that they are heterogeneous only at their forecast parameter expectation making, however with the same linear forecast models entirely. This restriction will influence the explanation power of ABC model of artificial stock market also.

5 Conclusion

In this paper, we focused primarily on the modeling of agent's complex behavior in artificial stock market, which is the core of ABC Modeling. We viewed three schemas with application of GA, GP and Fuzzy methods respectively and gave some comparison of these schemas. Over the past few years, GA as well as GP has gradually become a major tool in ABCE (Agent-Based Computational Economics).

The computational experiments, which are based on ABC Modeling with these three schemas, have demonstrated rich dynamics of stock price and return similar to which real stock market can generate. Through these discussions, the effectiveness of these schemas to model the complex behavior of agents can be proved, therefore.

We must admit that ABC Modeling is not intended as a substitute, but beyond complementing current theoretical and empirical works, ABC Modeling offers the potential of extension of current theories. With the development of ABC Modeling, it would become to be a standard tool, just like the tools as field study, human-subject laboratory study and even more nowadays as economist's toolkit. Furthermore, as we can see, ABC models of artificial stock market just move the level of complexity one step closer to reality. We must admit that validation whether artificial stock market is able to be proved to be successful in helping explain the dynamics of real stock market remains a critical issue.

Finally, in this paper based on the comparison of these three schemas to model the complex behavior of agents, we also made some important suggestions, which could construct the basis of our future research. And our future research in this field will continue, specifically in the co-evolution mechanism based on the GP schema.

APPENDIX : Introduction of GP

The GP is an extension of the conventional GA in which each individual in the population (pool of individuals) is a computer program composed of the arithmetic operations, standard mathematical expressions and variables[2)4)-9)].

In the GP, the forecast equations are represented in the tree structure (called individuals). The prefix representation is approved in [6], based upon the comparative study with other representation such as pointer based implementation and the postfix approach. In the parse tree the node non-terminal are taken from some well-defined functions such as binomial operation $+$, $-$, $\times$, $/$, and the operation taking the square root of variable. Terminal nodes consist of arguments chosen from set of constants and variables.

The prefix representation follows traditional representation by using the Lisp syntax. For example, we have the next prefix representation.

$$(6.43\times x_1-x_2)\times(x_3-3.54)\rightarrow\times-\times 6.43x_1x_2-x_3 3.54$$

The equation represented by using the prefix is interpreted based upon the stack operation. We begin to scan the prefix representation, and if we meet the terminal (operand) then we push down the term into the stack.

For checking the validity of underlying parse tree, the so-called stack count (denoted as *StackCount* in the paper) is useful [6]. The *StackCount* is the number of arguments it places on minus the number of arguments it takes off from the stack. The cumulative *StackCount* never becomes positive until we reach the end at which point the overall sum needs to be 1.

By using the *StackCount* we can see which loci in the prefix expression are available to cut off the tree for the crossover operation, and we can validate whether the mutation operation is allowed.

If final count is 1, then the prefix representation (tree) corresponds properly to a mathematical equation. Otherwise, the tree structure is not relevant to represent the equation. Usually, we calculate the forecast accuracy and then use it as the fitness. By selecting a pair of individuals having higher fitness, the crossover operation is applied to generate new individuals.

By using the measure of fitness to evaluate each individual, we apply the genetic operation to the population to derive better fitness.

Crossover operation

Contrary to the operation in GA, the crossover operation in GP is applied to restricted cases. Then, we can not choose arbitrary loci in the string of individuals and replace the parts of two tree structures.

To keep the crossover operation always producing syntactically and semantically valid equations, we look for the part which can be a subtree in the crossover operation and check for no violation. By using the *StackCount* already mentioned, we know the subtrees which are the candidate for the crossover operation. The basic rule is that any two loci on the two parents genomes can serve as crossover points as long as the ongoing *StackCount* just before those points is the same. The crossover operation creates new offsprings by exchanging sub-trees between two parents (see example in Fig.6).

Mutation

The goal of the mutation operation is the reintroduction of some diversity in a population. Two types of mutation operation in GP are utilized to replace a part of the tree by another element.

(Global mutation : G-mutation)

Generate an individual I_S, and select a subtree which satisfies the consistency of prefix representation. Then, select at random a terminal in one selected individual, and replace the terminal by the subtree of the individual I_S.

(Local mutation : L-mutation)

Select at random a locus in a parse tree to which the mutation is applied, we replace the place by another value (a primitive function or a variable) (see example in Fig.6).

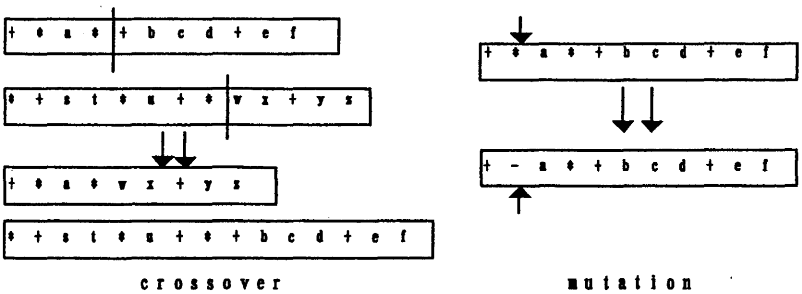

Fig. 6 Genetic operation in GP

We iteratively perform the following steps until the termination criterion has been satisfied.

(Step 1)

Generate an initial population of random composition of possible functions and terminals for the problem at hand. The random tree must be syntactically correct equation.

(Step 2)

Execute each individual (forecast model) in population and then assign it a fitness value according to its forecast accuracy. Then, sort the individuals according to the fitness S_i.

(Step 3)

Select a pair of individuals with a probability p_i based on the fitness. The probability p_i is defined for the ith individual as follows.

$$p_i=(S_i-S_{min})/\sum^{N}(S_i-S_{min}) \tag{8}$$

where S_{min} is the minimum value of S_i, and N is the population size.

Then, create new individuals (offsprings) from the selected pair by genetically recombining randomly chosen parts of two existing individuals using the crossover operation applied at a randomly chosen crossover point. Iterate the procedure several times to replace individuals with lower fitness.

(Step 4)

With certain probability, mutation operation is implemented on some randomly selected individuals, then new individuals are generated.

(Step 5)

If the result designation is obtained by the GP (the maximum value of the fitness becomes larger than the prescribed value), then terminate the algorithm, otherwise go to Step 2.

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