Functional Modularity in the Test Bed of Economic Theory – Using Genetic Programming

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Abstract. In this paper, we follow the model of Chen and Chie (2004), but start with the primeval setup. The implementation of computer simulations show mutation did play an important role in the technology evolution. In a well define simulation world, the producer will exert all of his effort to make the life get better. The parameter of mutation rate is just like the frequency of innovation in the real world. Different mutation rate will shift the model to the different path of history. The path of real world might be represented by one of the mutation rate, but it must be emergent from the different behaviors of the bottom actors.

1 Introduction

Continued from Chen and Chie (2004), we find that the expression power of genetic programming (GP) is a possible way to the model of technology innovation. Considering the using of GP, we face many challenges including which version we should follow, which parameter setting we should start, and how to reconcile our computing constraint with the time limitation.

At present GP has many improved version for many specific purpose. In order to adapt our model, we now couldn't assert what version is most suitable for us, therefore, we start from the simple GP, and then seek the path for the proper solution. In this stage, we will go through some visual and instinctive setup to discuss the proformance of simple GP. In the transation stage, we have tried many possible ways to apply GP; however, the most direct and simple way is the viewpoint of data mining. There are two guidelines including the parameter settings of GP, and the driving forces of fitness function. They will be discuss in the latter section.

In the early paper, we expound this framework as a model of evolving economy. Nevertheless, involving abruptly in a economic system may be not quite judicious. It is sensible to test whether GP will be equal to the problem or not. Therefore, we simplify our economy into one producer versus only one consumer. The producer produce numerous produces to please the consumer, and then refine his products according to the feedback of the consumer. Readers might understand that it may hopeless to know which customer for a producer in the real situations, but here we have to investigate the ability of the GP solver.

Regarding the performance measures, one is how much time taking to find the right solution, and the other is how close of the finding solution with the correct solution in a specific time. The preliminary results showed that the possibility of finding the correct solution was not so high, due to the time and computing constraint, the latter measure of closeness will be taken in this paper.

The structure of this paper is as following; firstly we briefly describe the model in section 2, and followed by the experiments and results in section 3, finally end with the concluding remarks.

2 The Model

2.1 Parameter Settings

First of all, it is important to know the dimension of this model. In order to summarize this key features, we present Table 1 as the guideline for our further movement.

Table 1. Parameters of the model

Parameters	Default Settings
Generations	10,000
Population Size	200
Elite Size	20
Selection Method	Tournament Selection
Tournament Size	10
Crossover Rate	90%
Mutation Rate	20%
Crossover Method	One Point
Mutation Method	Point and Tree (half)
Terminal Sets	1,2,3
Function Sets	1,2,3
Initial Population	Growth Method (d=4)

In the initial stage, it has extremely high diversity in the population. In general, higher population size may help to get the right commodity with higher probability. Unfortunately, due to the immense search space, one may not has the lucky chance to get the cure in limited generations. After few generations, the diversity will go out then the most of the population would get stuck in a local solution. Therefore, if one set a large population, it will only spend vain time on evaluation of the same products.[3]

[3] Instead of population and generation, it is more common to use the term *the number of evaluations* to present the computation loading. It takes about 3 hours per run with Intel Pentium 4 3GHz Processor to our parameter settings.

To articulate the character of *time* is much complicated; however, without doubt, time would be the driving force of evolution. Given a time line of history, the evolution events happened in the path could be treated as a *Poisson Process*. When the events happened more frequently, which means there are more events happened in a given time. It is not a good metaphor to apply generations as the control parameters or rather crossover and mutation are really matter.

Selection with recombination would be the *innovation*, and selection with mutation would be the *continual improvement*. Crossover and mutation plays an important role in the evolution process in Goldberg (2002), so do the technology innovation. Therefore, when the rates of crossover and mutation goes higher, the pace of the system would be also running faster.

That is a globe view of these two rates. If we get into the profile of a producer, and to ask him how about altering his products. He might not feel up to take any risk due to the uncertainty. However, the good strategy for him is to make his products better, when he has extra fund to do research and develop or faces the presses from his competitors. In the long run, the successes are always willing to take risk, and it seems no evidence to the contrary.

Because the tournament size is rather small in this model, we believe that the good solution might be devastated with a bad luck. The good product have to surely prosper in the production schedule, unless he get better idea. It would be desirable to think about the issue on *disturbance avoidance*. Certainly, the producer have no way to evaluate the potential profits of a product which has not provided yet. Therefore, the conventional election operator cannnot be applied easily. Nevertheless, there are other designs, such as *steady-state replacement scheme*, instead of using generational replacement. In our case, the top 10% products, ranked in terms of their profits, will be kept. This idea provides the good production go on, we use the parameter *elite size* to ensure the best few products could get into next generation.

3 Experiments and Results

3.1 Experiment 1

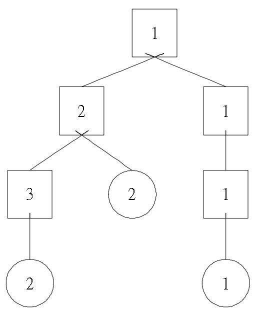
The first experiment is a rather simple setup, and it has only few primitives. We would like to inquire whether the performance with a sample of consumer preference perform good or not. We start with a easy case, the consumer's preference is showed in the Fig. 1. The depth of this preference described by GP tree is 4, and the maximum preference he or she can gain is $2^{4-1} = 8$. To Simplify the corresponds of the preference and the willing to pay of a consumer, we assume the willing to pay of the consumer is exact the same as the preference he or she gain from consuming the product. Table 2 summarizes the parameters of experiment 1.

That the performances measure here are coming from two folds, one is the revenue from the sales, the other is the cost of producing the product. Due to the truthful revealing preference of a consumer then the difference between the

Table 2. The Parameters of Experiment 1

Parameters	Settings
Generations	10,000
Population Size	200
Elite Size	20
Selection Method	Tournament Selection
Tournament Size	10
Crossover Rate	90%
Mutation Rate	20%, 40%, 60%
Crossover Method	One Point
Mutation Method	Point and Tree (half)
Terminal Sets	1,2,3
Function Sets	1,2,3
Initial Population	Growth Method (d=4)

willing to pay and the cost of producing would be the net profit of the producer or the social welfare of the economy.[4]



{1{2{3{-2}}{-2}}{1{2{-1}}}}

Fig. 1. Experiment 1: Consumers' Preference: The Tree Form and The LISP Form

Fig. 1 shows the *parse-tree* and also the *LISP* form representation of the preference of consumer. The square means functions and the round shapes means terminals. In the LISP form, the terminals come with negative sign in from of them. Notice that if the producer produces a perfect commodity just matching the consumer's preference, then the product would be the same as the preference. The revenue measure of this product is just the same as the willing to pay of the consumer which is 8, and the cost is measure by 10% of the length of the

[4] The social welfare can be defined as the sum of consumer surplus and producer surplus. However, in this case, the consumer surplus is exact zero due to he or she did not adopt any bargain strategies of the deal. When the consumers awake to retain their surplus, they would also be the adaptive agents.

LISP string of the commodity. In this case, if the product perfectly match the preference, the cost of this product would be 27*10%=2.7, due to the length of the string "{1{2{3{-2}}{-2}}{1{2{-1}}}}" is 27.

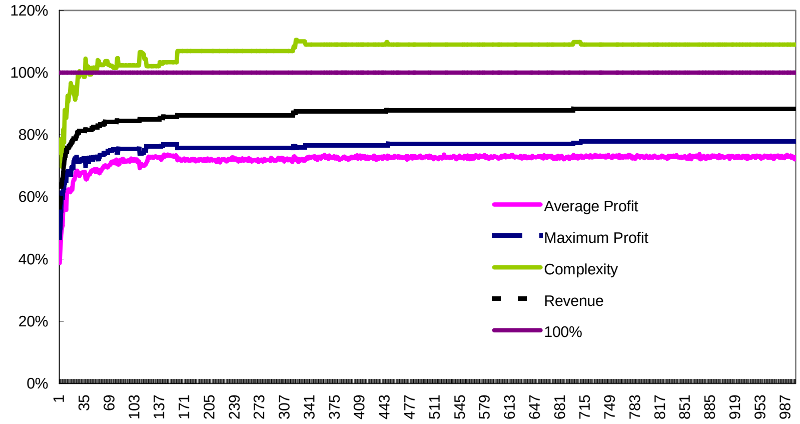


Fig. 2. The Typical Example for the Detail Profit Composition of a Producer

Fig. 2 shows an example of detail information for a producer over 1000 periods. It provides the case with 20% mutation rate over 30 runs, and the value presented here is the average value. The percentage value of vertical axis means the degree compare to the perfect product. One can figure out all the values are less then 100% except the complexity. In the long term all of these lines will converge to the line of 100%.

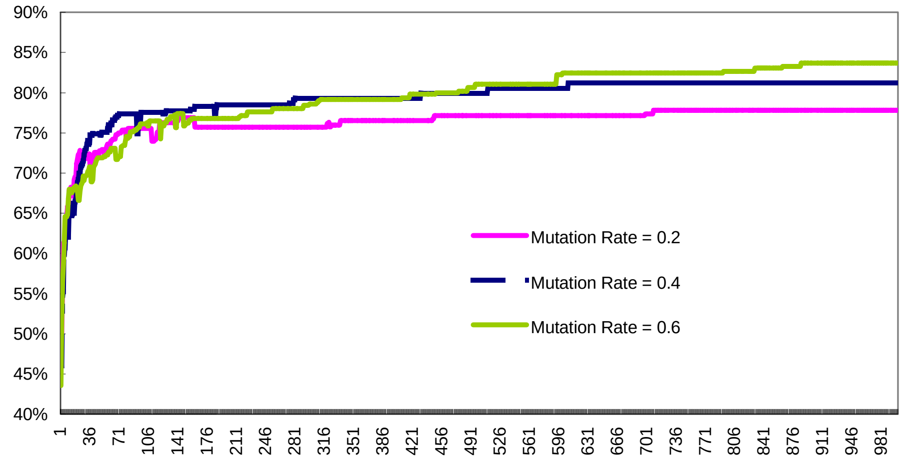


Fig. 3. The Realized Social Welfare of Three Mutation Rates for Experiment 1

Fig. 3 shows the social welfare which is the *Maximum Profit* of a producer showed in Fig. 2. We present it by three mutation rates, and one could observe the progress shapes are much the same as the logarithm function. It goes with highly disturbance in the beginning and later on with fewer jumps to shift the line up. Different mutation rate seems relative to the times of jumps, the higher mutations the more jumps. In about period 100, these three lines shift dramatically, the line with highest mutation rate break through the other two lines, and then get the champion of the race.

How many times does the GP producer require to find the perfect product in the limited periods is a concerned issue. In this simple case GP producer did have chance to find the correct solution perfectly and the summarized is provided below in Table 3. Thirty runs maybe too short to find the entire pattern of the found times; however, the conjecture of the found times is increase and the number of periods for finding is decrease when the mutation rate increase.

Table 3. The Statistics of Found for Case 1

Mutation Rate	0.2	0.4	0.6
Found at period	447	607	224
	709	1135	254
	2153	1264	418
	5691	2846	487
	6886		496
	8744		830
			885
			1331
			1442
Total Found Times in 30 runs	6/30	4/30	9/30
Average Found with Number of Periods	4105	1463	707

3.2 Experiment 2

The preferences in the real situation would be influenced by other consumers and the new products. Nevertheless, it is not a good opportunity to let the preferences evolve over time. We now increase the depth of preference from 4 to 8. In this case, the preference will get much complex and its parse-tree form is showed in Fig. 4, and the LISP from of this preference will be.

$$\{1\{2\{3\{3\{1\{2\{3\{-2\}\}\{1\{-1\}\}\}\{3\{1\{-2\}\}\{2\{-1\}$$

$$\{-3\}\}\}\}\}\{1\{2\{1\{2\{-1\}\}\}\}\}\}\{2\{2\{2\{1\{2\{-3\}\}\{3\{-1\}\{-3\}\}\}\}\}\}\}$$

Notice that the products might be get stuck in the jungle, we add one stop

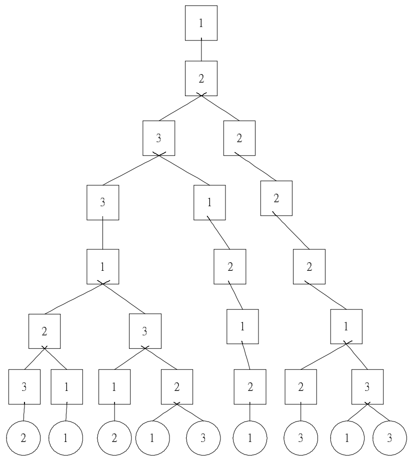


Fig. 4. Experiment 2: Consumers' Preference: The Tree Form

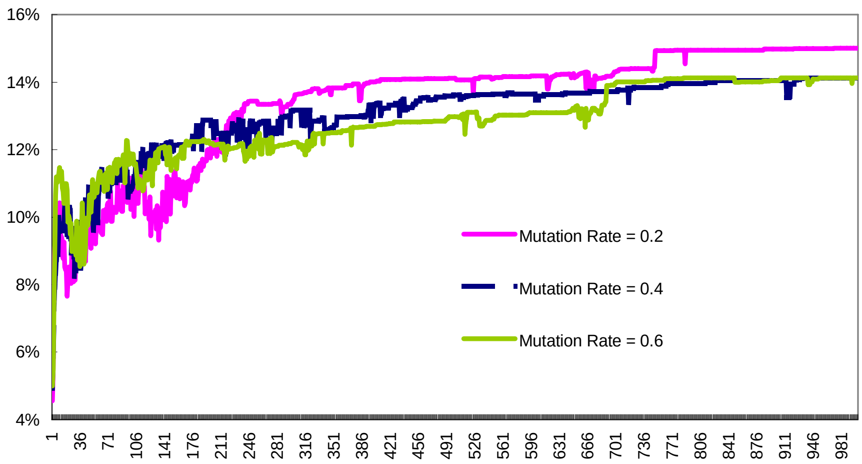


Fig. 5. The Realized Social Welfare of Three Mutation Rates for Experiment 2

criterion to the run of simulation. As the profit did not improve, we would stop the run. The experiment results we report is based on the first 1,000 periods over 30 runs. The realized social welfare is presented in Fig. 5. The total welfare can be realized should be $2^{8-1} - Len(Preference)/10 =$ 128 - 9.9 $=$ 118.1.[5] However, the realized ratio in this figure, is only about 15% at best. The performance is pretty poor and the order is different from the previous case. The lower mutation rate perform well in this complex case, but we cannot make an assertion that the performance would be reversed when the complexity increased.

In order to investigate this puzzle, we look into the complexity and revenue

[5] Len(Preference) means the length of the preference for presenting its complexity.

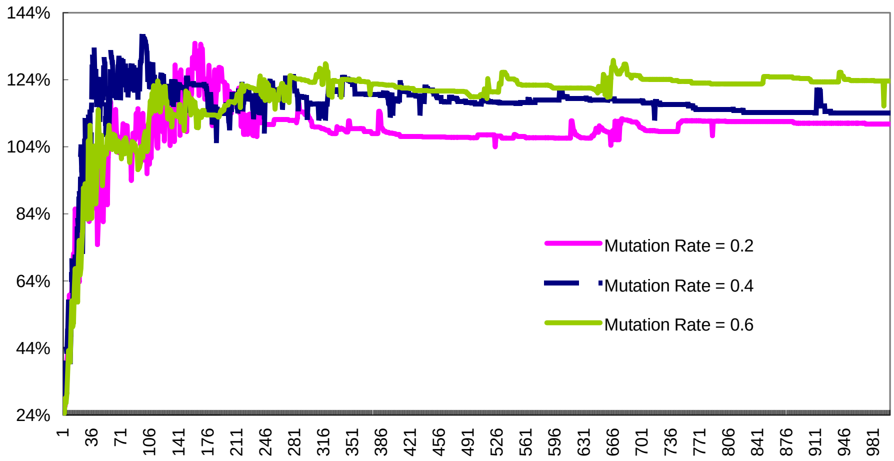


Fig. 6. The Complexity Measure of Three Mutation Rates for Experiment 2

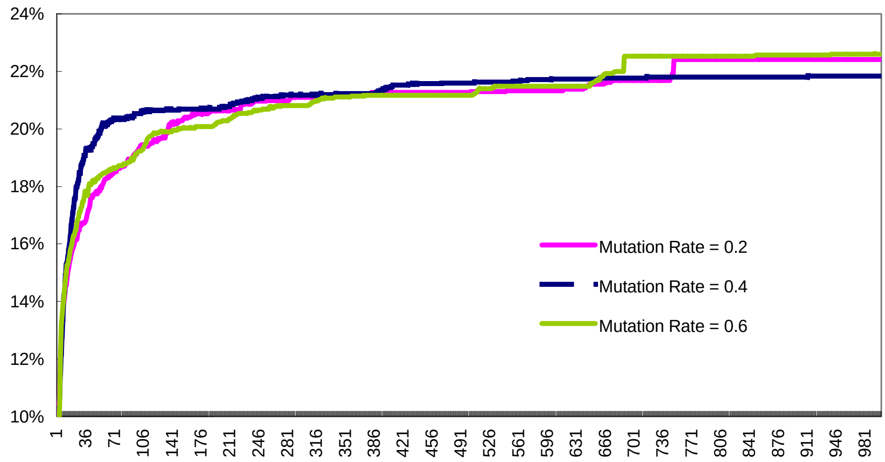


Fig. 7. The Revenue Measure of Three Mutation Rates for Experiment 2

measure of these three mutation cases. The revenue measure in Fig. 7 shows that the most popular commodity is provided by GP producer with highest mutation rate, although the complexity would be uncontrollable. In Fig. 6 shows the pattern, higher revenue may cause higher cost. It seems good *building-block* can be preserved well under the lower mutation, and the main job of crossover is pruning the tree. If the mutation rate goes higher, the good building-block might be adulterate.

This lesson shows us that the mutation rate is not omnipotent in finding new useful stuff. There must be something important which can directly the evolution sensibly.

4 Concluding Remarks

From the observing path of profit, revenue, and complexity, the producer has to meliorate his products and lower the cost (complexity). One may notice that the increased profit results from either the production improvement or the cost down. This ability is that the enterprise of GP is good for this job. GP did has some chance to hit the target in the first experiment. Unfortunately, in the second case, GP did not perform that well. This failure force us to think about what is important to guide the evolution, besides the crossover and mutation.

The first one consideration is to let the mutation rate adapt to the complexity of the population. When it meets high complexity, it is time to lower down it mutation rate, and vice versa. As well as being more complicated then the primitive setup, augmented GP plays a more significant role in the future. The preceding job will attempt to apply a newly design GP, and hopefully to catch the real process of human design and innovation process.

References

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