Model for Evolutionary Technology

An Automatically Defined Terminal Approach

Bin-Tzong Chie
AI-ECON Research Center
National Chengchi University
Taipei, Taiwan
chie@aiecon.org

Chih-Chien Wang
AI-ECON Research Center
National Chengchi University
Taipei, Taiwan
wrp@nccu.edu.tw

ABSTRACT
This study uses automatically defined terminal (ADT) to keep ready and stable building blocks growing into complex structure. The idea is originated from the functional-modularity approach. ADT is tested in an agent-based innovation model to see how it works and whether there is any improvement in searching new commodities for commercializing in the market; hence the market represents an environment for nourishing the development during innovative process. This paper will not only show how the capable producers with ADT work, but also how market selection plays an important role in the evolution of innovation. In other word, the agent-based modeling approach will present the evolutionary dynamic of interaction between producers and consumers in a commodity market.

Keywords
Automatically Defined Terminal, Agent-Based Modeling

1. INTRODUCTION
Many fields including biology, design, engineering, management science, and complex adaptive system share the same fact of a general awareness that the natural organisms and artificial structures start with very basic and simple modules. However, engineering applications of the functional-modularity approach to evolving a history of technology is just data-mining. In the view point of economics, economic interests give us a clue. The comparison of economic interests to the biological chemical mechanism helps us to understand how the functional- modularity activates.

[11] defined economic innovations as the introduction of a new good, the introduction of a new method of production, the opening of a new market, the conquest of a new source of supply of raw materials or half-manufactured goods, and the carrying out of new organization of any industry. Those economic innovations may be influenced by two effects, which are demand and supply. They need to satisfy consumer preferences on the demand side and lower production costs of products on the supply side. The emergence of new technology results from interactions between many factors within market environment. The success or failure of an introduction of new technology is hoped to be addressed with our model.

GECCO'06, July 8–12, 2006, Seattle, Washington, USA.

In order to express technology explicitly, a product can be represent by the realization of a sequence of the production process, and it is a sequence of combinations of processors and raw materials. When understanding every detail of a product, one can regard innovation as a process of altering and recombination of these processors and materials. However, to evaluate each decomposed processes of functional-modularity is an ideal. It is impossible to take apart every connection between these processors and materials. One of Herbert Simon's contributions is the idea of 'near decomposability' which means that each level of a complex system has a limited amount of autonomy and within those limits can be considered a simple system with only the variety faced by the level to contend with.

Modularity is a notion or a hypothesis that things may be composed of modules. The concept has been used in many fields, for example in biology ([5]; [1]), cognitive science, computer science, economics ([6]; [2]; [3]), and management science [12]. [7] carried out near decomposability idea with his famous NK-model which has also been developed in the field of biology [1], economics ([6]; [10]) and management ([9]). The model has been widely used. Nevertheless, The dimension is too limited to extend to the possible future or unknown fitness landscapes. This will con?ne the possibility of innovation.

[3] proposed a computational economic model of innovation. Genetic programming is a candidate to be applied to describe the production process. They argue that a well defined modular preference and production process using the representation of GP [8]. A commodity can be represented as the associated production process, which is a sequence of combinations of processors and raw materials. In their paper, the associated utility function (preference) represented in the same method which satisfies the well-behaved if and only if it satisfies the monotone, synergy and consistency condition. Therefore, the innovation process can be embodied in the behavior of the producers finding new products

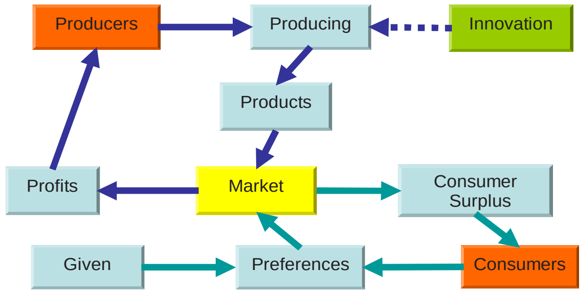

Figure 1: The relationship of the producer and consumer.

to satisfy consumers. In this paper, we provide a well ready agent-based computational economic (ACE) model of technology of evolution to demonstrate the process.

2. THE IMPLEMENTATION OF THE ACE INNOVATION MODEL

According to [4], the model is composed of producers and consumers in a commodity market. The income of consumers and the capital of producers are given. In the beginning, the preference of a consumer is given by a randomly generated GP tree, and it cannot reveal to anyone including herself. The products of a producer are also generated by the same way. The producers produce variety of commodities for consumers. When a consumer enters a shop of the producers, she would try to choose a commodity which could maximize her utility. If not, she would rather keep the money without buying anything. After each consumer enter every shop of producers several times, we call it a day. Producers calculate their profits of the day, and consumers enjoy consuming their commodities.

After a few days trading, producers will adjust their inventory or each commodity and make new goods via recombining his existing patterns of product. The process of how producers reform their patterns of products, the innovation process, is also called research and development (R&D) in the industry. In our model, there is a R&D ratio which is a proportion of producer's working capital. However, this ratio also represents a strategy of the producer. We will allow the ratio to evolve in the future. Here, they will spend the budget of this ratio to produce new commodities. To generate new commodities follows the standard GP crossover, mutation operator, and ADT extraction procedure; however, the number of new commodities is constrained by the R&D budget. We will record the simulated results of the performance of the consumers and producers every single simulation day.

Figure 1 shows the relationship between producers and consumers, and after their trading day in the market, they will both get their rewards. Note that in our model, the preferences of consumers are given. Later we will discuss how this approach develop the idea of near decomposability property.[1]

[1]The formal definition of modular preference and functional-modularity representation of commodity can be seen in [3].

2.1 Representation of Modular Preferences

Figure 2 is the prefix LISP representation. The elements begin with X are the terminals which are the primitive materials, and those begin with F are the functions which represent the primitive processors. Different subscript numbers are the representative of different materials or processors. Figure 2 is an example of the modular preferences of the consumer for the time being. Each consumer may have her own preference which would be varied then. Nevertheless, in this paper, we assume the preference of the consumer would keep constant within the entire experimental period.

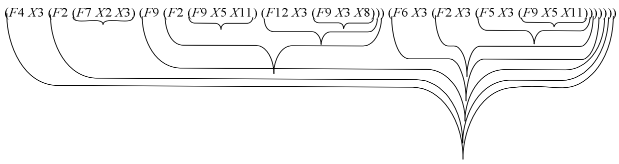

Figure 2: Modular preference: the LISP representation

Table 1 shows the all modular preference ($S_{d,j}$) sorted by their depths (d) of Figure 2. Where j is the index of the subtrees. The utility assigned in Table 1 follows the definition of well-behaved utility function. The raw utility $U(\cdot)$ is generated by the following exponential function with base Z.

$$U(S_{d,j}) = Z^{d-1}, \text{ where } Z \geq 2. \tag{1}$$

Based on these conditions, a consumer would test each product and know how much price he willing to pay for each specific commodity by matching the modular preference and summation of these raw utilities. This price of willing to pay minus the list price will be the consumer surplus. Note that the evaluating process is invisible and can not be told by anyone, but it works in the simulation programs to capture the behaviors of consumers. For instance, a commodity (Y_i) which presented by $(F_7(F_9X_5X_{11})(F_{12}X_3(F_9X_3X_8)))$ is produced. Of course, the consumer couldn't decompose it to see what match her preference. However, the possible way to know how much she likes this commodity is to test what functions it has and feel the textures of it, then, the raw utility comes out. In the case of $Z = 2$, the commodity matches modular preference $S_{3,1}, S_{2,2}$, and $S_{2,4}$. The total raw utility he got is 2+2+4=8.

2.2 The Economic Model

Before introducing the market process, it will be useful, to begin with transactions. Economic motivation is the essential for trading. Earlier, the consumer evaluates her raw utility; nevertheless, this evaluation must be measurable in the market. We apply a parameter "price to utility ratio" (ν) to transfer the raw utility into market value. Here, the market value can be presented by $V = \nu U(Y_i)$, which is willing to pay for commodity Y_i. Suppose the value V is greater than the listed price $P_{i,j}$, which means that consumer will consider to buy this commodity.[2] In this case, the consumer

[2]Where the subscript i and j can refer to the commodity j of producer i.

Table 1: **Modular preferences with $Z = 2$**

d	Subtrees or terminals	Raw utility
1	$X_2, X_3, X_5, X_8, X_9, X_{11}$	1
2	$S_{2,1} = (F_7X_2X_3)$ $S_{2,2} = (F_9X_5X_{11})$ $S_{2,3} = (F_9X_3X_8)$ $S_{2,4} = (F_9X_5X_{11})$	2
3	$S_{3,1} = (F_{12}X_3(F_9X_3X_8))$ $S_{3,2} = (F_5X_3(F_9X_5X_{11}))$	4
4	$S_{4,1} = (F_2(F_9X_5X_{11})(F_{12}X_3(F_9X_3X_8)))$ $S_{4,2} = (F_2X_3(F_5X_3(F_9X_5X_{11})))$	8
5	$S_5 = (F_6X_3(F_2X_3(F_5X_3(F_9X_5X_{11}))))$	16
6	$S_6 = (F_9(F_2(F_9X_5X_{11})(F_{12}X_3(F_9X_3$ $X_8)))(F_6X_3(F_2X_3(F_5X_3(F_9X_5X_{11})))))$	32
7	$S_7 = (F_2(F_7X_2X_3)(F_9(F_2(F_9X_5X_{11})(F_{12}$ $X_3(F_9X_3X_8)))(F_6X_3(F_2X_3(F_5X_3$ $(F_9X_5X_{11}))))))$	64
8	$S_8 = (F_4X_3(F_2(F_7X_2X_3)(F_9F_2(F_9X_5X_{11})$ $(F_{12}X_3(F_9X_3X_8)))(F_6X_3(F_2X_3(F_5X_3$ $(F9X_5X_{11}))))))$	128

will have a positive surplus; however, she will make her decision until she find the one maximizing her surplus, and then consider whether her budget is enough or not. Once she buys it, the producer will make a profit. How to decide the cost and price of a producer will be illustrated later.

In the model, the cost of producing a commodity is measured by its node complexity. Assume the cost of each processor and material is fixed at unit cost c. Suppose a producer has a commodity with node complexity NC_j, the production cost of this commodity is $C_{i,j} = cNC_j$.[3] After the cost is decided, the price of a commodity will be determined. According to the cost of the commodity, he has to decide a mark-up factor (η). Therefore, the listed price of the commodity will be $P_{i,j} = (1 + \eta)C_{i,j}$. When the commodity is sold, the profit will be calculated by $\pi_j = P_{i,j} - C_{i,j}$. If the commodity is not sold, then the profit will be negative because the production cost is assumed to be the sink cost, which cannot be stored to next generation. Then, the profit will be $\pi_j = -C_{i,j}$. Each profit of commodities will be summarized every day, and then the fitness will be evaluate by average profit of each kind of commodities. According to these fitness values, producers can produce new kinds of products in the innovation process.

2.3 The Market Process

During the market process, each consumer enters the market randomly through a probability named call-on rate (γ). When the rate $\gamma = 100\%$, the consumer will visit all the producers in the market; otherwise, she will visit partial of them. When $\gamma < 100\%$, system will automatically form the relationships between she and every producer by simple reinforcement learning. The positive or negative feedback simply depends on whether consumers successfully searching their needs or not. When consumer enter the shop, she will browse and evaluate every commodity, and then she will decide which commodity to buy. If the preferred one has already been sold out, the producer will make a note to remind himself to produce more next generation, and will suggest the consumer to try another one. Fortunately, the consumer will get his commodity, if not, he will get nothing and have a negative feeling to the producer.

[3]The details of production cost can be seen in [4].

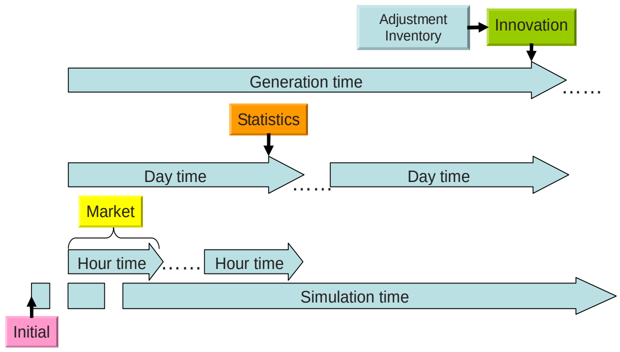

Figure 3: The time line of the simulation

Figure 3 indicates the time line of the simulation. The market process completes every hour time. A day should include HT hours. The statistical data will be summarized every simulation day. Through these data, researchers can analyze and trace the market performance. When it comes to the generation time, each product already had the evaluation of performance and the condition of oversupply or shortage in the market. Producer will adjust the inventory of each product.[4] If there are working capital left, they will spend the budget $\gamma_{R\&D}$ times the capital. This R&D budget will be used to produce new patterns for next trading period.

2.4 The ADT Extraction Process

[8] introduced automatically defined functions in his book of Genetic Programming II. The idea of ADT can be easily borrowed from Koza's notion. The benefits of adapting ADT notion are simplification, encapsulation, and reuse. In this paper, the ADT does not evolve actually, but extract from a simple and identical structure. This structure is defined by a basic binary tree with depth 2. For instance, $ADT_1 = (F_1X_2X_3)$. To determine which structure should be preserved by ADT follows these processes. First, during innovation process, the producer will compare each pare of outstanding commodities amount every selection of tournament population. If he finds that there are the same structures in both commodities, he will extract this subtree into ADT_n, where n is the index number. Second, the innovation process will also examine whether the new ADT already listed in the ADT database to prevent the heavy memory loading. Third, old ADT can be called by new ADT, for example, $ADT_1 = (F_1X_2X_3)$ and $ADT_3 = (F_4ADT_1X_6)$. This representation will not only keep good structures remain intact, but also have more flexibility of reusing the developed modularity.

[4]The adjustment method is based on adaptive learning, that is at generation t, $Q_{j,t} = Q_{j,t-1} + \lambda ED$, where λ is the inventory adjustment parameter, $Q_{j,t}$ is the quantity of product j at generation t, and ED is the excess demand during $t-1$ generation.

Once the ADT list developed, the producer's terminal set will be anatomically extended. He can choose these ADTs for his production materials. Recently, the probability of choosing these terminals is uniform; however, it maybe a bias selection according to their reusable abilities.

2.5 The Real World Application

In the real world application, internet provides producers very good opportunities to extract useful knowledge from their customers. It is a process to discover what the real needs are in people minds. The vivid illustrations are the applications of the human-computer interaction in designing. Our aim is to build an interface that could accommodate human with an automatic and easier way to figure their ideas. Imaging a producer providing a server, and a user can provide her interests in the existing patterns shown in the web browser. Then, after few seconds, the remote server will pass back a set of the new designs for the user to select. Ideally, the process will keep working until finding satisfied designs.

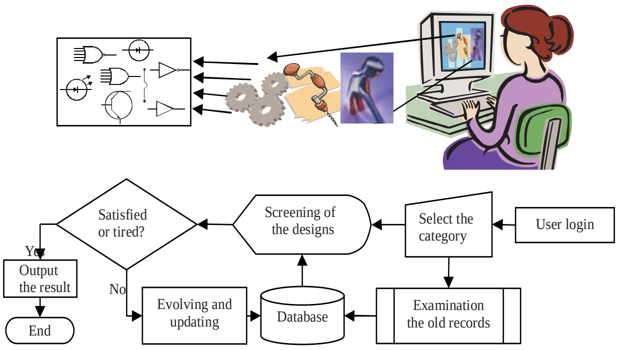

Figure 4: Procedure of finding the satisfied designs

Figure 4 is a typical procedure for the customers. In the future, the latest results of neuroscience would be applied in this procedure. The new equipment will extract the feelings of the user, and then pass the feedback to the evolutionary algorithms. Nevertheless, we are just trying to connect the consumer and producer to provide a possibility of the future blueprint. The simulation designs and results will be presented in the following section.

3. EXPERIMENTAL DESIGN

Table 2 shows the fundamental parameters, types, and the ranges of the model. We will start with some simple setups to demonstrate the reliability of the model. A setup $(n_c, I, d_p, d_c, \nu,\ \gamma,\ n_p,\ K_0,\ K,\ d_{max},\ \lambda,\ \eta,\ \gamma_{R\&D},\ \rho, c, ST,$ $Gen,\ HT,\ P_c,\ R_{TS},\ P_m,\ P_{tm}, \mathrm{A})$ = (100, 125, 9, 9, 10, 1, 1, 100000, 10000, 9, 0.8, 1, 0.1, 9, 1, 800, 5, 3, 0.5, 0.5, 0.05, 0.5, False) which is a basic sample of the market. The distinguishing the feature of this setup is all the preferences of the consumers are identical and there is one monopolistic producer in this market. Each consumer has to visit this producer every day in this market. One can conceive that the producer will get a very strong hint about what to produce because each consumer should want to buy the same product of the producer simultaneously. In the beginning of the trading days, the best product must be sold out in no time. The late coming consumers will find the fact that

Table 2: The types of parameters in the model

Consumer		
Number of Consumer	Integer (n_c)	[1, ∞]
Consumer Income	Integer (I)	[1, ∞]
Total Preference Depth	Integer (d_p)	[1, 17]
Common Preference Depth	Integer (d_c)	[1, d_p]
Price to Utility Ratio	Real (ν)	[0, ∞]
Call on Rate	Real (γ)	[0,1]
Producer		
Number of Producer	Integer (n_p)	[1, ∞]
Initial Capital	Integer (K_0)	[1, ∞]
Working Capital	Integer (K)	[1, ∞]
Product Tree Depth	Integer (d_{max})	[1, ∞]
Inventory Adjustment Rate	Real (λ)	[0, 1]
Mark-up	Real (η)	[0, ∞]
R&D Rate	Real ($\gamma_{R\&D}$)	[0, 1]
Number of Primitive	Integer (ρ)	[1, ∞]
Node Cost	Real (c)	[0, ∞]
Time Schedule		
Simulation Day	Integer (ST)	[1, ∞]
Generation Day	Integer (Gen)	[1, ∞]
Hours in a Day	Integer (HT)	[1, ∞]
GP Operators		
Crossover Rate	Real (P_c)	[0, 1]
Tournament Size Rate	Real (R_{TS})	[0, 1]
Mutation Rate	Real (P_m)	[0, 1]
Tree Mutation Ratio	Real (P_{tm})	[0, 1]
ADT	Boolean (A)	True, False

there is no stock and have to choose the second best. However, the consumer will still make a reservation for the best commodity, and have no choice but to come back to buy next time.

At the end of the evaluating day, the generation day, a producer calculates the profit of each product, and furthermore adjusts the inventory of each product. Finally, the profit provides the producer clues to improving the existing products. A ratio of the capital will be used to serve the R&D department, which is now played by the genetic programming. Next generation, the new products would be available in the market. Hopefully consumers will be satisfied with some of the new products. If the new designs do not please the consumer, those unsold new design patterns will be destroyed before next generation; otherwise, the new patterns will replace the former patterns. We will illustrate how the evolutionary new designs prevail in the market.

Table 3 shows the performance of the producer in the beginning of the 30 simulation days. Let us start with day 1. First column indexes the trading day, every day contains HT = 3 trading hours. Each consumer enters the market at least a time per hour. Therefore, if the call-on rate is 100%, every producer will be visited by every consumer a time an hour. In this case, we have 100 consumers, so the maximum transactions a day will be 100 $\times$ 3 = 300, which just match the number of total sold products in column 4. Next, column 2 is for average cost over total number of the products, which can be obtained by the sum of column 4

Table 3: The daily report of the producer 1 of the first 30 days

Day	avgCost	TotProfit	TotSold	Inventory	The Best Profit Product			Pattern Information			Capital	Max	
					Price	ID	Sold	Number	avgCost	avgProfit	Left	Price	Depth
1	7.52	-94496	300	12993	26	1171	1	13293	7.52	-7.11	2	30	4
2	7.52	-88860	300	12693	28	1264	1	13293	7.52	-6.68	2	30	4
3	7.52	-82720	300	12393	30	6927	1	13293	7.52	-6.22	2	30	4
4	7.52	-76524	300	12093	26	7766	1	13293	7.52	-5.76	2	30	4
5	7.52	-71218	300	11793	28	5322	1	13293	7.52	-5.36	2	30	4
6	6.75	-28763	300	4323	26	14325	1	3124	8.08	-3.43	97559	48	8
7	6.75	-26363	300	4023	8	11638	300	3124	8.08	-3.43	97559	48	8
8	6.75	-23963	300	3723	8	11638	300	3124	8.08	-3.43	97559	48	8
9	6.75	-21563	300	3423	8	11638	300	3124	8.08	-3.43	97559	48	8
10	6.75	-19163	300	3123	8	11638	300	3124	8.08	-3.43	97559	48	8
11	7.58	-35354	300	5315	34	14951	1	2625	7.09	-7.04	167049	46	9
12	7.58	-28154	300	5015	24	13305	300	2625	7.09	-7.03	167049	46	9
13	7.58	-20954	300	4715	24	13305	300	2625	7.09	-7.03	167049	46	9
14	7.58	-13754	300	4415	24	13305	300	2625	7.09	-7.03	167049	46	9
15	7.58	-6554	300	4115	24	13305	300	2625	7.09	-7.03	167049	46	9
16	11.21	-57727	300	5655	52	19101	1	2960	8.89	-8.86	236316	52	14
17	11.21	-48727	300	5355	30	15187	300	2960	8.89	-8.85	236316	52	14
18	11.21	-39727	300	5055	30	15187	300	2960	8.89	-8.85	236316	52	14
19	11.21	-30727	300	4755	30	15187	300	2960	8.89	-8.85	236316	52	14
20	11.21	-21727	300	4455	30	15187	300	2960	8.89	-8.85	236316	52	14
21	14.29	-77870	300	6241	4	20536	0	3544	9.04	-9.03	287868	60	14
22	14.29	-62270	300	5941	52	19101	300	3544	9.04	-9.03	287868	60	14
23	14.29	-46670	300	5641	52	19101	300	3544	9.04	-9.02	287868	60	14
24	14.29	-31070	300	5341	52	19101	300	3544	9.04	-9.02	287868	60	14
25	14.29	-15470	300	5041	52	19101	300	3544	9.04	-9.02	287868	60	14
26	17.06	-65277	300	4488	76	25179	1	3289	12.99	-7.99	384181	76	15
27	17.06	-49667	300	4188	52	19101	184	3289	12.99	-6.15	384181	76	15
28	17.06	-34067	300	3888	52	19101	300	3289	12.99	-6.15	384181	76	15
29	17.06	-18467	300	3588	52	19101	300	3289	12.99	-6.14	384181	76	15
30	17.06	-2867	300	3288	52	19101	300	3289	12.99	-6.14	384181	76	15

and 5. Column 4 is the amount of sold commodity, and column 5 is the unsold stocks which will be destroyed by next generation. Following, column 3 is the total profit of a day, which is the total sales revenue minus the total production cost. Total cost can be calculated via the number in column 2 times the summation of column 4 and 5, therefore, we get $7.52 \times (300 + 12993) = 99998$. Then, the total revenue of the day can be calculated by summation of the total cost and the total profit, which will be $99998 + (-94496) = 5502$. During the first 30 days, this producer was burning the money.

Column 6, 7, and 8 are the information for the best profit product. It details the price, pattern serial number (ID), and sold amounts of the product. These three columns are the key window for us to observe how the innovation processes prevails. From column 8 to 10, which are the pattern information including the number of patterns, average pattern cost, and average profit of pattern. Many products can be duplicated by a pattern, so, the maximum size of pattern will be the number of products, which means every pattern has only a single duplication. This is the situation during the first 5 days, because producer is no way to know which pattern is more likely to be successful in the beginning. To produce with fully-diversified manner is the best strategy. Column 12 is how many working capital left for the producer. The last two columns are the highest price of all commodities, and the deepest depth of product tree of certain products.

3.1 Outcomes of Innovation

Let us go back to column 6, 7, and 8 of Table 3. In the generation 2, which is from day 6 to 10, the best profit product in day 6 is ID 14325. Note that the ID number is greater than 13293, which is the total pattern number in the generation 1. This means ID 14325 is a new product and gets very good profit at generation 2; however, there is only one quantity of ID 14325. Will ID 14325 become the best profit product in the generation 3? The answer is not necessary true. In the following days, ID 11638 becomes the best profit product. Because it has strong demand in the generation 1, it has been adjusted to new quantity to fit in with the demand. In generation 3, we could see ID 14325 because there is another product ID 13305 with lower price and can make consumer has more surplus. The product ID 13305 was invented in the end of generation 1, and now has become a popular product in generation 3.

In general, the invented new product will be tested during next generation, and to see whether it can prevail or not. Let us see a successful case. In generation 4, product ID 19101 stood out at that time. In the following, we see ID 19101 prevailing in the generation 5 and 6. In generation 6, there is a potential competitive product ID 25179. What we know is that the product ID 19101 would not stand out long. The process will keep the price, quality, and cost increasing. What behinds these numbers is the increase of social welfare. The loss of the producer is mitigating and soon the producer will make positive profits. On the other hand, the consumer surplus is increasing. In the following, we will discuss the information of the consumer side.

3.2 The Welfare of Consumers

Table 4: The daily report of the consumer of the first 20 days

Day	Consumer Surplus						Number		Total
	Min	1st	Median	3rd	Max	Avg	Buyer	Trade	Budget
1	236	242	246	254	298	248.98	100	300	94498
2	182	184	188	190	196	187.34	100	300	88862
3	152	152	154	154	158	153.60	100	300	82722
4	138	138	138	138	142	138.54	100	300	76526
5	128	128	128	128	130	128.04	100	300	71220
6	426	426	426	426	620	428.70	100	300	168760
7	426	426	426	426	426	426.00	100	300	166360
8	426	426	426	426	426	426.00	100	300	163960
9	426	426	426	426	426	426.00	100	300	161560
10	426	426	426	426	426	426.00	100	300	159160
11	1008	1008	1008	1008	1332	1011.34	100	300	251944
12	1008	1008	1008	1008	1008	1008.00	100	300	244744
13	1008	1008	1008	1008	1008	1008.00	100	300	237544
14	1008	1008	1008	1008	1008	1008.00	100	300	230344
15	1008	1008	1008	1008	1008	1008.00	100	300	223144
16	1980	1980	1980	1980	1988	1980.08	100	300	314122
17	1980	1980	1980	1980	1980	1980.00	100	300	305122
18	1980	1980	1980	1980	1980	1980.00	100	300	296122
19	1980	1980	1980	1980	1980	1980.00	100	300	287122
20	1980	1980	1980	1980	1980	1980.00	100	300	278122

Table 4 shows the information of consumer welfare. The first column is also indexed by the trading day. From column 2 to 7 are the information of consumer surplus detailed with minimum, first quartile, median, third quartile, maximum, and average value of all consumers. In this case, the performances of these statistics are much alike, because the whole population shares the same preference. From generation 2, there is a slight different in the max value of consumer surplus at the first day of each generation. It means someone consumed the best new product. For instance, during the day 6, each consumer bought three commodities. There was a consumer who bought a most advanced one and made consumer surplus of 620. This surplus includes two popular commodities and a newest one. Therefore, we can infer the surplus of the newest one, which is $620 - 426 \div 3 \times 2 = 336$. Then, one could expect most of the consumer surplus in the next generation will be $336 \times 3 = 1008$ which matches the surplus shows in generation 3.

The value of consumer surplus plus the listed price of the commodity would be the price of willing to pay. This information also leads us to find the price of willing to pay, for example, we already know the maximum consumer surplus in day 6 is 336, which the product is ID 13305 in Table 3. So the willing to pay of ID 13305 is 336 + 24 = 360. Because the willing to pay is utility value times ν which is 10 in our setup, we can infer the utility of the consumer is 360 $\div$ 10 = 36. It means the product already matches some degree of the consumer preference. The reference for raw utility value can be found in Table 1.

3.3 The Performance of ADT

In order to study the role of ADT, we conduct two experimental designs. The only difference is whether the ADT mechanism presents or not. The details of two experimental designs are as follows: $\overrightarrow{E_{NoADT}}=(n_c, I, d_p, d_c, \nu,\ \gamma,\ n_p,\ K_0,\ K,\ d_{max},\ \lambda,\ \eta,\ \gamma_{R\&D},\ \rho, c, ST,\ Gen,\ HT,\ P_c,\ R_{TS},\ P_m,\ P_{tm}, \mathrm{A})$ = (100, 1000, 5, 5, 2, 1, 1, 100000, 1000, 9, 0.8, 1, 0.01, 6, 1, 200, 5, 3, 0.9, 0.2, 0.5, 0.5, False), $\overrightarrow{E_{ADT}}=(n_c, I, d_p, d_c, \nu,\ \gamma,\ n_p,\ K_0,\ K,\ d_{max},\ \lambda,\ \eta,\ \gamma_{R\&D},\ \rho$, c, ST, Gen, HT, P_c, R_{TS}, P_m, P_{tm}, A) = (100, 1000, 5, 5, 2, 1, 1, 100000, 1000, 9, 0.8, 1, 0.01, 6, 1, 200, 5, 3, 0.9, 0.2, 0.5, 0.5, True).

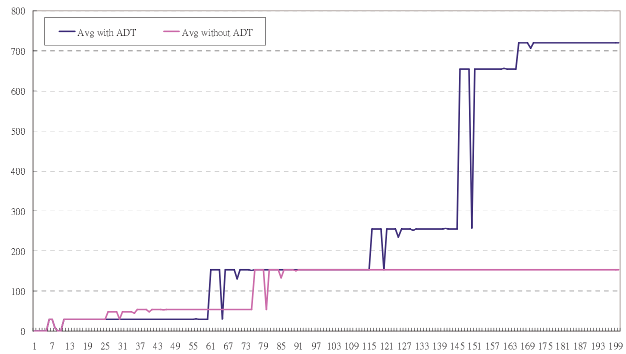

Figure 5: The average welfare of consumers of the experiments

We look at Figure 5. It shows the case with ADT has a better progress than the case without ADT. However, due to the limitation of time, this is the result of only one run, and we will conduct more experimental designs to support the role of ADT. In Figure 5, before day 25, the performances of both experiments are identically patterned. Then $\overrightarrow{E_{NoADT}}$ outperforms $\overrightarrow{E_{ADT}}$ until day 61. After 75 days, $\overrightarrow{E_{NoADT}}$ seems stuck somewhere, and did not get any improvement until the end of the experiment. On the other hand, the case of $\overrightarrow{E_{ADT}}$ gets more stable improvement. We still can not address too much of this single case. The latest and large-scale simulation results will be presented during the conference session.

Since all producers try to discover the preference of consumers, they don't know any directly information about the preference. The clue they have is the profit and cost of product from commodity market. The situation is pretty much as the same as the producers in the real market. Nevertheless, in the real market, it is hopeless to check whether we match with the preference of consumers, and the degree we matched. Through this platform, we have chance to observe the matching process. Fist we take the best profit product of each producer of day 200 for example. The preference of all consumers is shown in Figure 6. The product of producer without and with ADT are shown in Figure 7 and 8.

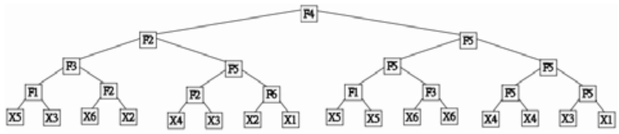

Figure 6: The preference of consumers

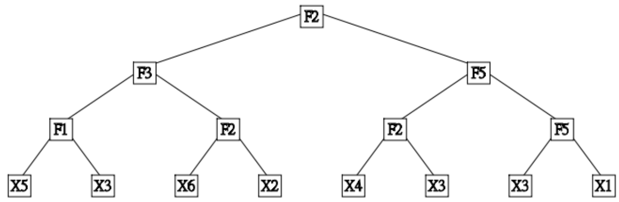

Figure 7: The product of producer without ADT at day 200

When we look Figure 6 and 7, the product of the producer is pretty much like the left subtree of the preference. However, some nodes of it still not match. A closer look of the left subtree leading from F_3, is exactly as the same as the subtree of preference. So, the best match depth so far is depth 3 for the case of no ADT. The production cost of this product is 15, and the price of it is 30. The willingness to pay of consumer is Z^2 for subtree $(F_3(F_1X_5X_3)(F_2X_6X_2))$, Z^1 for $(F_2X_4X_3)$, and $2 \times Z^0$ for X_3 and X_1. If $Z = 4$, the utility level will be $16 + 4 + 1 + 1 = 22$, and the willingness to pay will be $22 \times 2 = 44$. If a consumer buys this product, the welfare or surplus of a consumer will be $44 - 30 = 14$.[5]

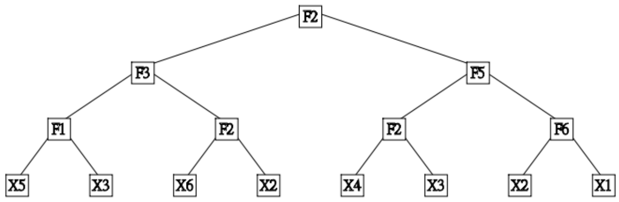

Figure 8: The product of producer with ADT at day 200

Let us look at Figure 8, we are excited that the product match the left subtree leading from F_2 of preference. To calculate the utility of a consumer will be $Z^3 = 4^3 = 64$, and the surplus of consumer will be $64 - 30 = 34$, which is more than twice larger than the value of previous case. If we observe the product of the ADT level, the whole product is enclosed in ADT_{22}. So, the structure is well protected. If we decompose ADT_{22}, we will have $(F_2(F_3ADT_{13}ADT_8)ADT_{18})$. Then, these sub modular, ADT_{13}, ADT_8, and ADT_{18} can still be further decomposed. The concept of functional-modularity is the essence of this research, and we implement it through introducing the ADT.

[5]The average value of Figure 5 has been normalized into [0, 1000] for comparison reason.

4. CONCLUSIONS

This paper shows how the thought of functional-modularity is implemented, and the potential application of this project. Human have already presented their creativity and innovation by improving technologies and science. Some of the human intelligence may be described by artificial intelligence. However, the scalability of artificial intelligence is still a tentative work. ADT is not only an abstraction of the essence of functional-modularity, but also an approach of automatic symbolism. Through ADT, the formation of a concept or a new object can help itself prevailing and sustaining in the system.

We need more evidence to support the idea of ADT, and this paper can be a platform for simulating intensive interactions between consumers and producers. In the near future, we will test the search complexity by increasing function and terminal sets, and the robustness of feature detecting via increasing the diversity of consumers' preference.

5. REFERENCES

[1] L. Altenberg. Evolving better representations through selective genome growth. *Proceedings of The IEEE World Congress on Computational Intelligence*, pages 182–187, 1994.

[2] C. Bladwin and K. Clark. *Design Rules. volume 1: the Power of Modularity*. MIT Press, Cambridge, MA, 2000.

[3] S. Chen and B. Chie. Functional modularity in the fundamentals of economic theory: Toward an agent-based economic modeling of the evolution of technology. *International Journal of Modern Physics B*, 18:2376–2386, 2004.

[4] S. Chen and B. Chie. A functional modularity approach to agent-based modeling of the evolution of technology. *in A. Namatame, T. Kaizouji, and Y. Aruka. (eds.), Lecture Notes in Economics and Mathematical Systems, The Complex Networks of Economic Interactions*, 567:165–178, 2006.

[5] J. A. Fodor. *Modularity of Mind: An Essay on Faculty Psychology*. MIT Press, Cambridge, MA, 1983.

[6] K. Frenken, L. Marengo, and M. Valente. Interdependencies, near-decomposability and adaptation. In *in Brenner, T. (ed.), Computational Techniques for Modeling Learning in Economics*, pages 146–165. Kluwer, 1999.

[7] S. Kauffman. *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford University Press, New York and Oxford, 1993.

[8] J. R. Koza. *Genetic Programming: On the Programming of Computers by Means of Natural Selection*. MIT Press, 1992.

[9] D. Levinthal. Adaptation on rugged landscapes. *Management Science*, 43:934–950, 1997.

[10] L. Marengo, G. Dosi, P. Legrenzi, and C. Pasquali. The structure of problem-solving knowledge and the structure of organizations. *Industrial and Corporate Change*, 9:757–788, 2000.

[11] J. A. Schumpeter. *The Theory of Economic Development*. Harvard University Press, Cambridge, MA, 1934.

[12] K. Ulrich. The role of product architecture in the manufacturing firm. *Research Policy*, 24:419–440, 1995.