Translating Agents' Actions to Strategic Measures: Agent-Based Modeling with Genetic Algorithms to Analyze Competing Companies

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Abstract. Agent-based simulation has become one of the promising gears for computational social sciences including business management strategy studies. This paper addresses a novel technology of agent-based modeling with genetic algorithms. Our method is characterized by (1) Decision making agents or competing companies with strategic parameters to be optimized; (2) A multiobjective optimization framework to evolve the artificial simulated society; (3) Grounding the simulation conditions with marketing survey data in the real world, and (4) Validating the strategic parameters of the agents after simulation via statistical analysis of the individual genes. The proposed method enables us to investigate the strategic measures or balanced scorecards of competing companies from the agents' actions in the simulator.

1 Introduction

Recent progress of computer technology makes it possible to analyze social and economics systems via simulation studies. Among them, agent-based approaches are promising: we are able to make social sciences operational, communicable, and experimental [3],[5],[25],[26].

In this paper, we will focus our attention to business management domains [6]. So far, researchers in marketing management sciences have used either macroscopic statistical techniques from survey data on targeted companies [10],[21] or microscopic case studies to describe the business affairs they have interested in [12],[27]. We believe agent-based modeling will provide the third way. By agent-based modeling, we mean such a methodology that we implement individual agents as software objects with internal state and rules, run the agents to let them interact, then monitor what happens to analyze emergent phenomena from collective behaviors of individuals. That is, as Axtell has stated, executing the model – spinning it forward in time is all that is necessary in order to '*solve*' it. Furthermore, when a particular instantiation of an agent-based model, call it *A*, produces result *R*, one has established a sufficiency theorem, that is, the formal statement *R* if *A* [2].

Running an agent-based model is an easy task, however, the analysis is not. We often meet such difficulties: First, the model becomes too complex to be manually tuned up; second, the results are difficult to interpret even if we optimize the model; third, there are few relations between the simulation results and real world phenomena; and forth, the parameters of the models are hard to validate after the simulation.

To overcome the difficulties, Axelrod claims the importance of "Keep-It-Simple-Stupid" (KISS) principle to let the models simple and clear for the researchers [1]. Instead of the KISS principle, in this paper, we will employ the following methodologies:

- About the first issue, we automatically tune up the agents' parameters via genetic algorithms (GAs) to improve their performance.
- To utilize GAs, we must determine an objective function beforehand. However, in the business management domain, a single clear objective is rare, thus, about the second issue, we formulate our agent-based models as multiobjective ones.
- About the third issue, to ground the simulation results, we set simulation conditions with surveys of consumer behaviors about electric appliances in Japan. This provides us the external validity of the model.
- About the forth issue, we carry out statistical analysis of individual genes in order to discuss the internal validity of the model.

The main contribution of the paper is to show genetic algorithms enable us to develop new real world applications, that is, agent-based social simulation for business management domains. This is achieved by both a multiobjective framework to optimize the artificial societies and a new validation method to analyze genes distributions via statistics.

The remaining parts of the paper are organized as follows: In Section 2, we describe the characteristics of the domain we address. In Section 3, we formulate the model to multiobjective optimization problems. In Section 4, we explain GA-based techniques employed in the modeling. In Section 5, we carry out intensive experiments and discuss the results then finally concluding remarks will follow in Section 6.

2. Task Domain Description

The objective of our agent-based modeling is to explore 'optimal' marketing strategies on given specific markets. Competing companies will thrive their organizations by choosing their customers, narrowing their focus, and dominating their markets [27]. We will uncover which type of companies will provide how good value proposition of customers from their activities. Conventional research in business strategy literature, they state the importance of translating the strategy of a company into action to get the profit [12]. In our study, on the contrary, we will observe agents' action or companies' activity in the artificial society with given conditions and investigate the agents' or companies' strategy. To model this, we must specify both company and customer models.

2.1 Company Model

As the basis of companies' strategy, we use the concepts of the Balanced Scorecard (BSC) to describe the agent functionality. The origin of the Balanced Scorecards by Kaplan and Norton [12] was a performance measurement system of a company. The system was then extended to the BSC, which organized around four distinct perspectives – financial, customer, internal, and innovation and learning. Innovative companies used the BSC not only to clarify and communicate strategy, but also to manage strategy. This means that BSC evolved from an improved measurement system to a core management system [12].

Based on the background, we employ the idea of Treacy and Wirsema [27] about the strategy of a company on the value proposition of customers: (a) operational excellence, (b) customer intimacy, and (c) product leadership. These three criteria determine the company type. Figure 1 shows the outline of the company model. However, the criteria are only descriptive ones. They do not explain which types of companies are how characterized in real market places.

Figure 1. Value Proposition Model of Competing Companies

On the other hand, Kaplan and Norton [13] defined the seven attributes to the value proposition: (1) price, (2) quality, (3) time, and (4) function (attributes about products and services); (5) services and (6) relationship among customers (attributes about customer relationship); and (7) brand image (branding). These seven attributes are more operational than the ones in [27], thus, we have used the attributes to determine the characteristics of a company or agent.

To each attribute we give ten values (1, …, 10) to represent the investment level of a company. In the market, each competing company will make decisions by identifying the seven attribute values based on strategy selection models of value propositions about customers. In our model, to determine the value proposition is to determine the attribute set and their values based on the company strategy [15]. The sum of the attribute values is between 14 and 49, which means the constraints of the total investment. The company's decision depends on how to distribute these values among the seven attributes.

The company in the model is assumed to be a typical consumer production one, which has the six divisions: ordering, production, sales, R&D, logistics, and after services. It produces one kind good with high or low quality and sell it to initial 1,000 customers with different characteristics described below. At each time step in the simulation, a company makes decision about investment to each division and sales prices, and get the information on the number of sales, the market share, and the benefit from the market. Figure 2 shows the outline. The items with numbers (1)-(7) in the figure represent corresponding genes.

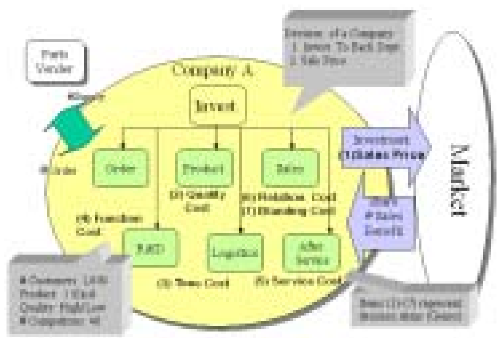


Figure 2. Decision Structure of a Company

2.2 Customer Model

We have various kind of customers in real markets. To simplify the model, we employ the classification of customers by Ikeo [28]. Customers are divided by the two attributes: price and quality of the goods or services. Thus, the four clusters are (A) price sensitive and quality sensitive (the lower price and the higher quality the better); (B) price sensitive and quality insensitive; (C) price insensitive and quality sensitive; and (D) prince insensitive and quality insensitive. From survey studies in [28], purchasing attitudes of customers in each category or customers' parameters are summarized in Figure 3. This is the answer to the third difficulty in Section 1.

Table 1. The Number of Purchased Goods in Each Cluster (Survey Results)[28]

	Cluster (A)	Cluster (B)	Cluster (C)	Cluster (D)	Sum
TV Set Market	31 (46%)	21 (31%)	12 (18%)	3 (5%)	67
Radio Cassette Market	12 (15%)	8 (10%)	38 (49%)	20 (26%)	78
Electric Shaver Market	3 (6%)	1 (2%)	9 (18%)	37 (74%)	50

The number of customers are different if the targeting market is different. We again employ the ratio of customer classes based on the survey by Ikeo [28]. He studies three kinds of electric appliance markets in a local area in Japan. Table 1 shows the summary. We use the ratio to represent the market characteristics of our artificial society.

Figure 3. Customer Preferences in Cluster

3. Agent-based Modeling and Evolutionary Computation

3.1 Basic Decision Making and Simulation Steps

Based on the discussions in Section 2, we develop an agent-based simulator. The society contains 40 competing companies. At the current stage, the only one of them is our concern, that is, we will tune up the attributes of a company (1) to (7) as genes of GAs and the attributes of the remaining 39 companies are set to random values and do not change during the simulation.

The basic idea of the application of GA is similar to the one described in [24]. The technique in the paper is rather straightforward, because the agent-modeling is much more complex than the one in [24]. However, using GAs, we avoid bothering work of parameter tuning in the artificial society. This is the answer to the first difficulty in Section 1.

Customers clusters are determined against the market conditions and remain constant during the simulation.

The simulation is carried out via the following steps:

Step 1: Based on the attribute values, determine the amount of investment to each division

Step 2: Determine the sales goal based on the previous market demand and sales

Step 3: Calculate the logistic and material cost per good based on the amount of the products.

Step 4: Calculate the cash expenditure and determine the excess to borrow.

Step 5: Calculate the market demand in each cluster of customers.

Step 6: Calculate sales amount as the minimum values of sales stocks and market demands.
Step 7: Generate the corresponding balance sheet to be evaluated.
Step 8: If the current term is 10 then stop, else increase the step.

When the simulation reaches term 10, the four objective values are evaluated by the BSC information: Benefit, Market Share, Cash flow, and Borrowing. This means that the target society is evaluated by independent four objective functions: Max_benefit, Max_market-share, Max_cash-flow, and Min_borrowing. This is the answer to the second difficulty in Section 1.

3.2 Genetic Algorithm Cycle

To solve the multiobjective problem, we utilize VEGA [20] as a basic algorithm and extend VEGA with a hybrid GA with a tabu-list [14], [16]. The basic idea of the alogorithm is described in the next section. We apply the following GA parameters to evolve the artificial society with one company to be optimized.

Selection method: Size 2 Tounament Selection
Crossover rate: 1.0
Mutation rate: 0.1
Number of Tabu-Lists: 5 (4 for each objective and 1 for Pareto evaluation)
Length of each Tabu-List: 5
Population size: 100
Number of GA-cycles: 100-1500

The simulation method is illustrated in Figure 4.

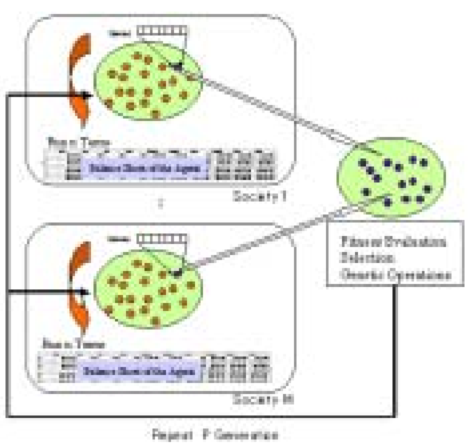


Figure 4. Application of a Genetic Algorithm to the Social Simulation

4. GA with Tabu-Search, and Statistical Validation

4.1 Brief Description of Tabu Genetic Algorithm for Multiobjective Problems

The integration of genetic algorithms, simulated annealing, tabu search, and/or heuristics have been studied for long years to let GAs more powerful to solve complex optimization problems. Most of the conventional methods utilizes GAs to explore global candidates and the other additional algorithms to exploit local optimal points [7],[19].

Tabu Genetic Algorithm in [16] and its extension [14] directly stores individuals into multiple tabu lists. The tabu lists have roles of
(i) storing superior individuals in the previous generations,
(ii) reusing the individuals as the elites
(iii) maintaining diversity of the population, and
(iv) inhibiting individual from converging local minima
as is found in conventional Tabu search methods.

Therefore, hence the optimization proceeds within the dynamical changes of the solution landscape, the tabu-GA will be easier, more robust, and more powerful than the conventional hybrid methods.

The idea of the algorithms is to store the best solutions of each generation into short-term and longt-term tabu lists. The short-term tabu list inhibits the individuals from being selected more than *n* times. The tabu lists or tabu constraints depress the possibility to local convergence in the early stages of the iterations. This enables the candidates to explore new solution spaces to get better and/or various solutions. On the other hand, the long-term tabu list contains best solutions as long as the memory size permits. The final results are accumulated in the long term tabu list. This feature is also useful to analyze our simulation results and to check the validity.

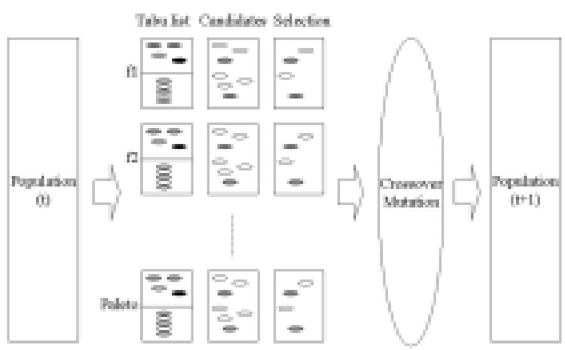


Figure 5. Genetic Algorithm with Tabu-Search for Multiobjective Problems

When applying GAs to multiobjective problems, they reports that the optimization processes for one objective functions will be of use for generating the better

Pareto optimals. The multiclass tabu lists are prepared to correspond with each objective function. We also prepare another tabu list, which corresponds with the Pareto optimals. The structures of the tabu lists are the same with the above long- and short-term tabu lists. Furthermore, applying the methods to multiobjective problems, in order not to converge into one peak, we first measure Hamming distances between the individuals of the current generation and the ones in the tabu lists, then omit the individuals within the distance *d*. In this study, we set *d* = 1.

Figure 5 shows the outline of the algorithm [16].

4.2 Statistical Validation of the Simulation Results

The internal validation of agent-based simulation is quite important to convince the results to various audiences. To address the issues, we have developed a new method for multiobjective problems. The basic principles is that when the results converge or when we have 'desired' results, the variances among the genes in the population are statistically evaluated in the sense of sensitivity analyses.

If the GAs are designed to find one single peak, then each gene will converge to a single value because of the genetic drift phenomena. However, when we cope with multiobjective problems, because of the Pareto optimality characteristics of the algorithms, the genes show some variances: if a specific gene is important, then the value generally have one value, and if it is not important, the corresponding value will show wide variances. This means that statistical analysis is useful to the validation tasks.

In our simulator, we will carry out statistical analysis of the individuals in the tabu-lists, which represent ‘good’ converged ones in the total population. This is the answer to the forth difficulty in Section 1.

In the GA literature, such variations of genes are often used to improve the algoritm performance. The methods in competent GAs such as Linkage Learning, GEM GA, and/or Bayesian Optimization uses statistical information for population-to-population mapping [8]. However, they do not use these information for validation tasks. The similar idea is only found in [17].

5. Experiments

In this section, we report how the simulation results converge on the television set market using the date in Table 1. Figure 6 shows the convergence of each objective function. About benefit cash flow, and borrowing objectives, we obtain good values within 100 generations and about the share objective, it takes 300 generations.

Table 2 shows the results of the statistical validations. We have analyzed the genes of the five individuals stored in the tabu-lists. Genes 1-7 correspond to the attributes of the value proposition: (1) price, (2) quality, (3) time, (4) function, (5) services, (6) relationship, and (7) brand image.

From the table of the television set market data, we observe that 1) the price and service are important for benefit and cash flow maximize and strategies; 2) about the share maximization, there are few dominate strategies; and 2) on the other hand, price and time will affect for borrowing strategy.

About the other two markets, the variances of genes show the similar tendency. From the table, we can explain that about the share of the market, the TV set market has the smallest effect about the cost. About the radio cassettes market, time is important factor. About the electric shaver market, function is critical. The results partly coincide the discussion of [27] in Figure 1: the operational excellence strategy is the dominated one in the simulation.

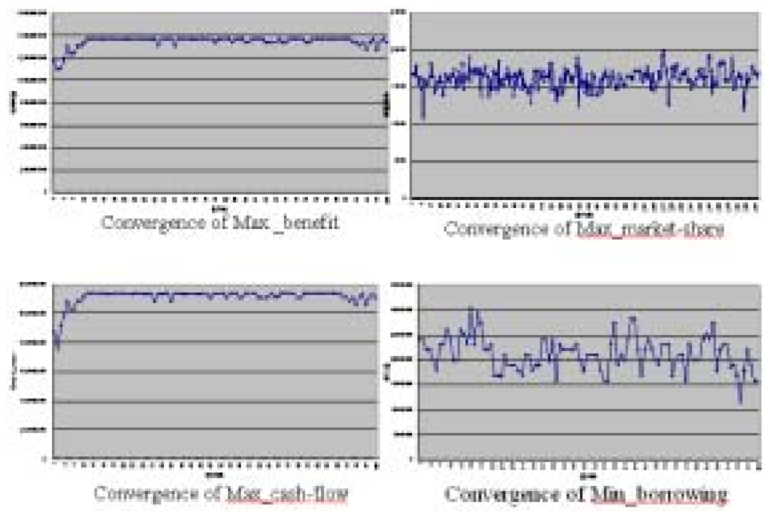
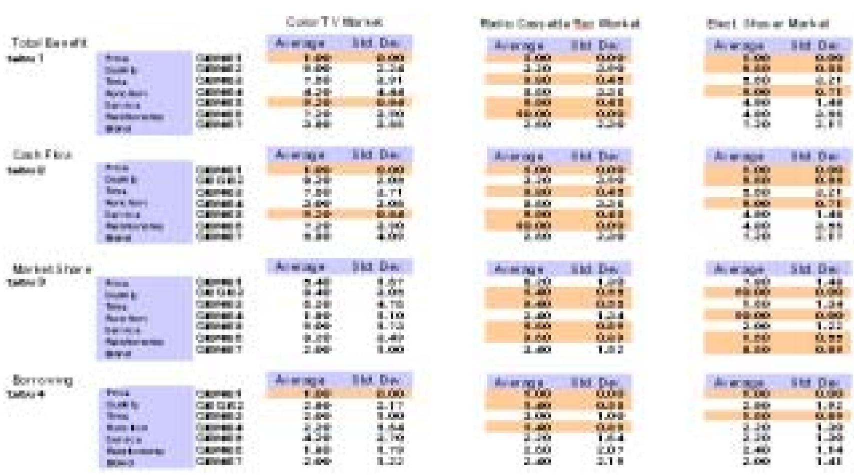


Figure 6. Solving the Multiobjective Problem

Table 2 Summary of Statistical Validation of the Results



			Color TV Market		Radio Cassette Tape Market		Elect. Shaver Market	
Total Benefit			Average	Std. Dev.	Average	Std. Dev.	Average	Std. Dev.
	Price	GENE01	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Quality	GENE02	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Time	GENE03	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Function	GENE04	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Service	GENE05	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Relationship	GENE06	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Brand	GENE07	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cash Flow			Average	Std. Dev.	Average	Std. Dev.	Average	Std. Dev.
	Price	GENE01	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Quality	GENE02	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Time	GENE03	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Function	GENE04	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Service	GENE05	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Relationship	GENE06	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Brand	GENE07	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Market Share			Average	Std. Dev.	Average	Std. Dev.	Average	Std. Dev.
	Price	GENE01	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Quality	GENE02	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Time	GENE03	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Function	GENE04	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Service	GENE05	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Relationship	GENE06	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Brand	GENE07	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Borrowing			Average	Std. Dev.	Average	Std. Dev.	Average	Std. Dev.
	Price	GENE01	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Quality	GENE02	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Time	GENE03	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Function	GENE04	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Service	GENE05	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Relationship	GENE06	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Brand	GENE07	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

6. Concluding Remarks

This paper has described an agent-based modeling with genetic algorithms for business management domain. We have modeled competing companies with the Balanced Scorecards principle and examined the Value Proposition strategies for customers. The proposed method is characterized by (1) Decision making agents or competing companies with strategic parameters to be optimized; (2) A multiobjective optimization framework to evolve the artificial simulated society; (3) Grounding the simulation conditions with marketing survey data in the real world, and (4) Validating the strategic parameters of the agents after simulation via statistical analysis of the individual genes.

The experiments now still continue to investigate more quantitative results on the effects of strategies and other environmental conditions. Future work include (1) to introduce financial engineering frameworks to the decision models, in e.g, [23], [18], and [21]; (2) to implement more sophisticated agent architecture e.g., in [22]; and (3) to discuss the roles of decision making and rationality of the agents [49], and to extend our modeling to experimental economic framework [11], that is, human-agent mixed simulation models.

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