# Exploring the Vast Parameter Space of Multi-Agent Based Simulation

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**Abstract.** This paper addresses the problem regarding the parameter exploration of Multi-Agent Based Simulation for social systems. We focus on the principles of *Inverse Simulation* and *Genetics-Based Validation.* In conventional artificial society models, the simulation is executed straightforwardly: Initially, many micro-level parameters and initial conditions are set, then, the simulation steps are executed, and finally the macro-level results are observed. Unlike this, *Inverse Simulation* executes these steps in the reverse order: set a macro-level objective function, evolve the worlds to fit to the objectives, then observe the micro-level agent characteristics. Another unique point of our approach is that, using Genetic Algorithms with the functionalities of multi-modal and multi-objective function optimization, we are able to validate the sensitivity of the solutions. This means that, from the same initial conditions and the same objective function, we can evolve different results, which we often observe in real world phenomena. This is the principle of *Genetics-Based Validation*.

**Keywords:** Multi-Agent Based Modeling, Social Systems, Verification and Validation, Parameter Exploration, Genetic Algorithms.

## 1 Introduction

As Alan Kay stated, *the best way to predict the future is to invent it*. When we use Multi-agent based simulation (MABS) for social systems, we always invent a new world, or a new bird-view-like point, because we are able to design the simulation world as we would like to. Therefore, when we use MABS, we are predicting some future. After several decades of the Allan Kay's statements, we have a new gear for predicting the future: MABS is a new modeling paradigm [1],[2].

MABS focuses from global phenomena to individuals in the model and tries to observe how individuals with individual characteristics or “agents” will behave as a group. The strength of MABS is that it stands between the case studies and mathematical models. It enables us to validate social theories by executing programs, along with description of the subject and strict theoretical development.

In MABS, behaviors and statuses of individual agents are coded into programs by researchers. They also implement information and analytical systems in the

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environment, so the model itself may be very simple. Even when the number or variety of agents increases, the complexity of simulation descriptions itself will not increase very much [13], [14]. Axelrod [1] has emphasizes that the goal of agent-based modeling is to enrich our understanding of fundamental processes that may appear in a variety of applications. This requires adhering to the *KISS principle*, which stands for the army slogan *"keep it simple, stupid."*

Running an agent-based model is an easy task, however, the analysis is not [7]. Even for a simple simulator with the KISS principle, we must cope with vast parameter space of the model. This paper discusses the problem regarding the parameter exploration of Agent-Based Simulation for social systems.

## 2 Coping with the Huge Parameter Spaces

There are no Newton's Laws, or the first principles in social systems. This makes MABS approaches both easy and difficult. The easy face is that we are able to build models as we like, on the other hand, the difficult face is that the models are hardly grounded in any rigorous grounding theories. For example, the application of finance engineering is one of good candidates of MABS approaches. They seem to follow the first principles, however, it is not true. The assumptions of finance engineering often come from the principles of statistical physics, one of the first principles of physics. However, the real data and real phenomena sometimes break the assumptions. This means that the assumptions about social phenomena are not based on the first principles.

The real phenomena in our society and social systems are only collections of instances. Therefore, using social simulation techniques, we are able to generate so many instances of simulation results through MABS. This is the very merit of our MABS approach.

However, even simple models with ten step decisions with ten alternatives in every step have 10**10 parameter spaces. This means that it would take over 10,000 days to complete them, if we could search 10 spaces per second. We must compute so many cases. To overcome the problem, one solution of the issue is to follow the *KISS principle*. Simple convincing models are welcome. However, the simpler the model, more explanatory interpretation of the result has to be, in order to avoid easy explanation such as "We did it and we got it." Actually, several extreme explanations were given to the models discussed in Axelrod or Epstein. When the model is simple, the result seems to be obvious, and the harder we try to understand phenomena, the more complex the model becomes against the KISS principle.

To convince the results of MABS, we are required (i) to rigorously validate the models and simulators, (ii) to examine background social and organizational system theories, and (iii) to overcome the vast of parameters of both agent behaviors and models. Also, (iv) we need multiple good results to design and analyze social complex task domains. Therefore, as another solution, we propose a new method, which employs *Generate and Test* techniques in the simulation process. This follows the principles of *Inverse Simulation* and *Genetics-Based Validation*.

## 3 Principles of Inverse Simulation

In conventional MABS models, the simulation processes are executed straightforwardly: Initially, many micro-level parameters and initial conditions are set, then, the simulation steps are executed, and finally the macro-level results are observed. Unlike in conventional simulation models, in the Inverse simulation, we execute these steps in the reverse order: set a macro-level objective function, evolve the worlds to fit to the objectives, then observe the micro-level agent characteristics. Thus, we solve very large inverse problems. The basic principles are shown in Figure 1. The essential point is that we force to get desired results specified by the macro-level objective functions, then analyze the micro-level structures of the results.

They have thought such brute force approach is infeasible, so far, however, using recent competing genetic algorithms (GAs) [4] has made it possible to get multiple solutions in reasonable times. In our simulators in the following sections, we have employed GAs with tabu-search techniques in Operations Research literatures[5],[6]. The method is able to optimize multi-modal functions [3]. This means that, from the same initial conditions and the same objective function, we can evolve different results, which we often observe in real world phenomena.

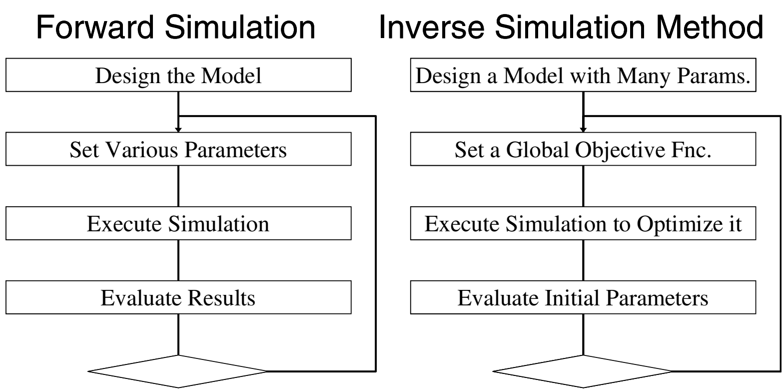


**Fig. 1.** Basic Cycles of Agent-Based Simulation

The agents, their behaviors, and the world are controlled by many parameters. In our settings, genotypes of GAs are corresponding to initial parameters of agents and the initial world we are considering. Phenotypes of GAs to be evaluated are simulation results, which can be measured macro-level evaluation functions. We will carry out so many simulation cycles to get the results. For example. To get one result, we might need several hundred simulation steps per simulation. To evaluate one generation, we might need several hundred populations in parallel, and to converge the macro-level objective functions, also we need several hundred GA generations. The outline is shown in Figure 2.

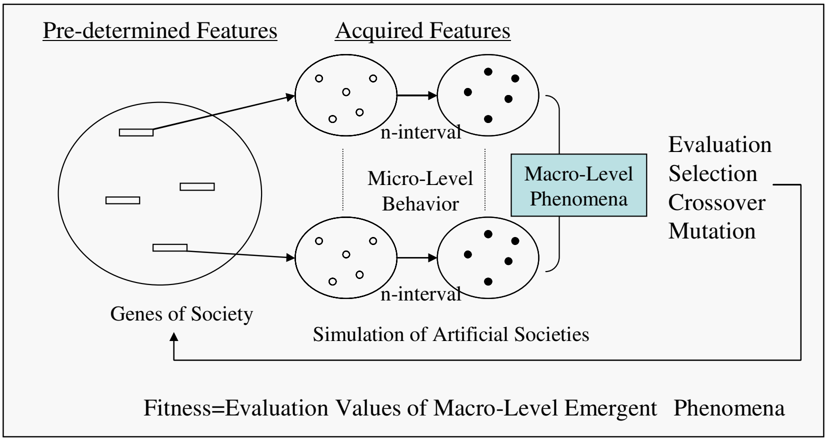


**Fig. 2.** Inverse Simulation

To apply *Inverse Simulation*, we assume that the MABS models have the following properties:

(i) micro-level rich functionalities of agent behaviors, interactions, and the world;
The requirement is important to leap simple models to be analyzed. If the model would be simple, the KISS principle would work better to convince the results.

(ii) macro-level clear evaluation measures to be optimized through the simulation processes;
The requirement is critical to quantitatively evaluate the simulation results. We usually use macro level measures of a social network, e.g., the centrality, agents' population distributions, or GINI index of some welfare of the worlds. The landscape of the objective functions might be very complex in the social phenomena, e.g., multiple peaks and multiple objectives. So, simple GAs are not adequate to get the results.

(iii) Fast execution of single simulation run.
The requirement is necessary to compute the simulation efficiently. Inverse Simulation is computationally high cost. Therefore, the faster the run, the better the results. We are planning to utilize Grid-based computer systems to apply the technique.

## 4 Principles of Genetics-Based Validation

Validation is one of the most critical tasks in MABS approach to convince the results. In this section, we address a new statistical validation method: *Genetics-Based Validation* for the solutions of simulation results. This is a kind of sensitivity analyses of parameters in the experimental system we target. The principle is summarized as follows. When *Inverse Simulation* terminates, using GAs for multiple solutions, if there were multiple solutions in the targeted MABS model, then every important parameter of the model would converge. This means that the objective functions have their peaks. However, non-essential parameters would have various distributed values. It is because the variations of non-essential parameters would not contribute to the values of objective functions. If we would have used conventional GAs, because of the effects of genetic drifts, the non-essential parameters would converge. This is a bad situation for our analysis. Competing GAs with the functionalities to cope with the multiple solutions, they keep diversity of the solutions. We are able to utilize the variance of the parameters to determine whether specified parameters are essential for the results of simulations or not.

In Figure 3, we illustrate the situations. we observe some distribution of simulation results. Initially, simulation results are several values in the sense of the objective functions values. In the final steps, the objective function values converge to the same level, however, the distributions of solutions are different according to the essential and/or non-essential dimensions of parameters. Therefore, applying statistical techniques, we are able to uncover the shape of the landscapes of the results measured by the specified objective functions. For example, to apply the principal component analysis technique, we are able to obtain the distributions of solution values, or simulation results, which will reveal both essential and non-essential dimensions of parameters.. We call the method *Genetics-Based Validation.*

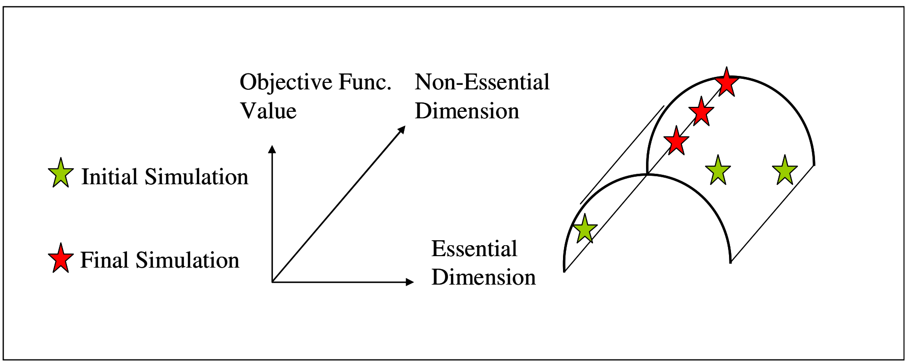


**Fig. 3.** Principles of Genetics-Based Validation

## 5 How Inverse Simulation and Genetics-Based Validation Work

We have applied the proposed techniques: *Inverse Simulation* and *Genetics-Based Validation* to various kinds of agent-based simulation models. In this section, we will briefly describe three of them. The first example is a MABS model for social interaction analysis. The second one is a marketing model of competing firms. The last one is concerned with a MABS model for financial decision making. The three models are too complex to understand from the KISS principle, however, we are able to uncover what have happened in the sense of parameter sensitivity analysis.

### 5.1 Example 1: Social Interaction Analysis [8], [9]

Recently there are so many MABS models from the state-of-the-art literature, they frequently report that simple autonomous agents and artificial worlds are able to evolve global interesting social structures and behaviors.

However, many of the researches seem to report too artificial results, because of the following three reasons:

(I) Although many agent models are developed from the bottom-up, the functions the agents have are so simple that the models can only handle with difficulty to practical social interaction problems.
(II) Although the functions are simple from the viewpoint of simulation experiments, the models have too many parameters that can be tuned and, therefore, it seems as if any good result a model builder desires is already built in.
(III) The results seem to have a weak relationship with emerging phenomena in real-world activities.

Thus, these studies have not yet attained a level necessary to describe the flexibility and practicability of social interactions in real organizations.

To overcome such problems, we have developed a novel multi-agent-based simulation environment TRURL for social interaction analysis.

The basic principles of TRURL can be summarized as follows: To address point (I) above, the agents in the model have detailed characteristics with enough parameters to simulate real world decision making problems; with respect to (II), instead of manually changing the parameters of the agents, we evolve the multi-agent worlds using GA-based techniques; as for (III), we set some socio-metric measures which can be observed in real world phenomena as the objective functions to be optimized during evolution.

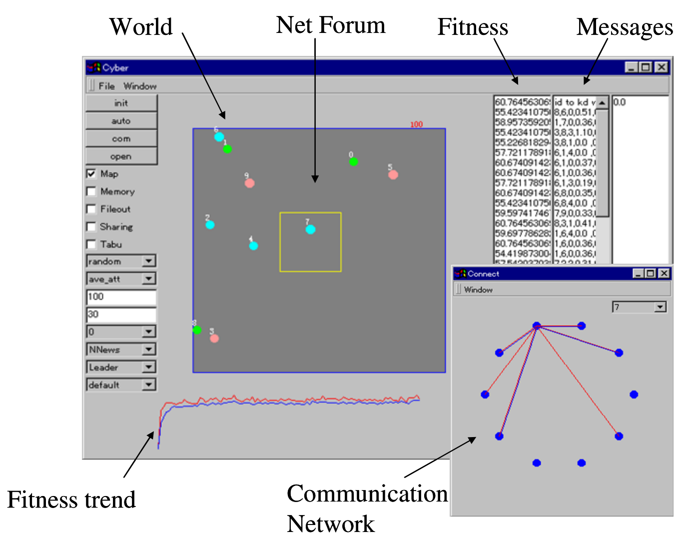


**Fig. 4.** Execution of TRURL

Using TRURL, therefore, we are able to analyze the nature of social interactions, which are based on such real-world activities as e-mail-oriented organizations and electronic commerce markets. We illustrate the snapshot of TRURL execution in Figure 4.

In TRURL, each agent sends and receives messages according to the received knowledge attribute. The a priori attribute of the agent is described as a gene sequence on the chromosome which represents the society. The characteristics of the agent participating in the TRURL artificial society are represented by the speaking probability, the knowledge transfer rate, the comment attitude, and the like:

$$P_p = (c_p, p_s, p_r, p_a, p_c, n, \alpha, \beta, \gamma, \delta, \mu),$$

where $c_p$ denotes the physical coordinates of the agent, $p_s$ is the speaking probability, $p_r$ is the receiving reliability, $p_a$ is the comment attitude, $p_c$ is the additional remark probability, $n$ is the knowledge width, $\alpha$ is the weight transfer rate, $\beta$ is the evaluation value transfer rate, $\gamma$ is the certainty transfer rate, $\delta$ is the metabolism, and $\mu$ is the mutation rate.

The characteristics of the agent participating in the artificial society TRURL are represented by these parameters. What agents are generated in the society depends on the character of the society. Figure 1 shows the relation between the gene structure and agent generation. The agent has the following a posteriori attributes:

$$P_a = (w, e_s, c, c_c, m).$$

Here $w$ is the weight of the knowledge attribute, $e$ is the evaluation value, $c$ is the certainty, $c_c$ is the reliability coordinate of agent, and $m$ is the behavior energy. When an agent is generated, the a posteriori attribute is initialized as a random variable following the normal distribution. When a communication between agents is performed, the a posteriori attribute is modified. The a posteriori attribute differs from the a priori attribute, being a parameter that changes dynamically according to the interaction between agents.

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The information transmission process can be considered as a decision-making process based on alignment behavior. In this model, the change of the knowledge attributeparameter when a message is received is defined for each parameter. The weight $w$, the evaluation value $e$, and the certainty $c$ are defined as follows:

$$\Delta w^i_{kd} = \sum_{j \in S} \alpha(w^j_{kd} - w^i_{kd}) max(0, c^j_{kd} - c^i_{kd})$$

$$\Delta e^i_{kd} = \sum_{j \in S} \beta(e^j_{kd} - e^i_{kd}) max(0, c^j_{kd} - c^i_{kd})$$

$$\Delta c^i_{kd} = \sum_{j \in S} \gamma((1 - 2|e^j_{kd} - e^i_{kd}|) max(0, c^j_{kd} - c^i_{kd}))$$

where, $w_{kd}^{i}, e_{kd}^{i}$, and $c_{kd}^{i}$ are the weight of the knowledge attribute *kd*, the evaluation value, and the certainty, respectively. $\alpha, \beta$ and $\gamma$ are transfer rates. *S* represents the set of sending agents of the messages received by $agent_i$ at period *t*.

The behavior energy *m* changes in proportion to the change of the information content. At the initial stage of generation, *m* is specified at random in accordance with the normal distribution. When information is sent, *m* decreases in accordance with the metabolism $\delta$ ; when valuable information (with a relatively high certainty) is received from another agent, it is increased; and when no communication occurs, *m* decreases regularly according to $\delta$ .

From the viewpoints of *Inverse Simulation*, In TRURL, the individuals are corresponding to the set of initial agent parameters. The multiple objective functions are corresponding to macro-level measures about social interactions, for example, the GINI indices of social welfare measured by the amount of information the agents have. Through *Genetics-Based Validation*, we are able to observe that free-riders in the information networked society have positive effects to the total welfare of the society. From the simulation studies, for example, we have found the information difference between the information rich and information poor is not increased as much as was expected in the net society, and that although free riders are generated, they do not induce the collapse of norms.

### 5.2 Example 2: Model of Competing Firms in Marketing [12]

The second example of ABS is to explore 'optimal' marketing strategies on given specific markets. Conventional research in business strategy literature, they state the importance of translating the strategy of a company into action to get the profit. 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.

As the basis of companies' strategy, we use the concepts of the Balanced Scorecard (BSC) to describe the agent functionality. to describe the agent functionality. The origin of BSC by Kaplan and Norton [15] was a performance measurement system of a company. The system was then extended to the one, which organized around four distinct perspectives – financial, customer, internal, and innovation and learning. Innovative companies used 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 [16].

Based on the background, we employ the idea of Treacy and Wirsema [17] 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. However, the criteria are only descriptive ones. They do not explain which types of companies are how characterized in real market places.

We have determined the seven attributes to the value proposition of a company: (1) price, (2) quality, (3) time, and (4) function; (5) services and (6) relationship among customers; and (7) brand image. The company's decision depends on how to distribute these values among the seven attributes.

In order to model customers, they are divided by the two attributes: price and quality of the goods or services. 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, the attitudes of customers in each category or customers' parameters are determined.

In the simulator, the society contains 40 competing companies. We have tuned 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. 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.

Figure 5 shows the architecture.

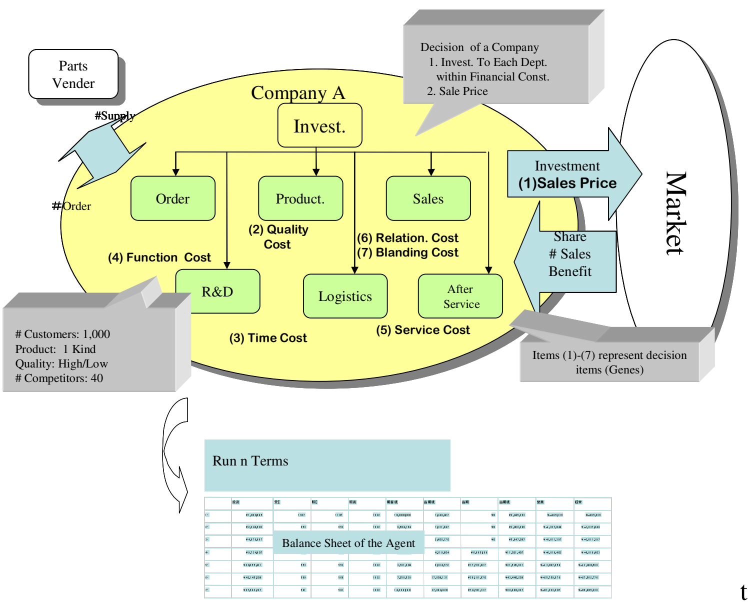


**Fig. 5.** Architecture of the Market Simulator

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.

From the viewpoints of *Inverse Simulation*, In the marketing simulator, the individuals are corresponding to the set of initial parameters of value propositions of a company. The multiple objective functions are corresponding to measures of a company about financial benefits, market share, cash flows, and borrowings. From *Genetics-Based Validation*, we are able to observe that the changes of markets, e.g., the ratio of kinds of customers will cause the changes of the strategies.

From the simulation studies, we have observed 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. 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 with the discussion of some of marketing research results: the operational excellence strategy is the dominated one in the simulation.

### 5.3 Example 3: Investors in Behavioral Finance [10], [11]

The Third example is to investigate the risks of financial markets. We have developed a simulator to clarify microscopic and macroscopic links between investor behaviors and price fluctuations in a financial market. The virtual financial market with 1000 investor agents has been used as the model for this research. They share and risk-free assets with the two possible transaction methods. Several types of investors exist in the market, each undertaking transactions based on their own stock calculations. The market is composed of three major steps, (1) generation of corporate earnings, (2) formation of investor forecasts, (3) setting transaction prices. The market advances through repetition of these steps.

This market consists of both risk-free and risky assets. There is a financial security (as risky assets) in which all profits gained during each term are distributed to the shareholders. Corporate earnings $(y_t)$ are expressed as $y_t = y_{t-1}(1+\varepsilon_t)$, however they are generated according to the process $\varepsilon_t \sim N(0, \sigma_y^2)$ with share trading being undertaken after public announcement of profit for the term. Each investor is given common asset holdings at the start of the term with no limit placed on debit and credit transactions.

Investors in the market calculate transaction prices based on their own forecast for market tendency, taking into account both risk and return rates when making investment decisions. Each investor decides on the investment ratio $(w_t^i)$ of stock for each term based on the maximum objective function of $f(w_t^i) = r_{t+1}^{\mathrm{int},i} w_t^i + r_f(1-w_t^i) - \lambda(\sigma_{t-1}^{s,i})^2 (w_t^i)^2$. In this case, $r_{t+1}^{\mathrm{int},i}$ and $\sigma_{t-1}^{s,i}$ express the expected rate of return and risk for stock as estimated by each investor i. $r_f$ represents the risk-free rate. $w_t^i$ is the stock investment ratio of investor i for term t [2][5].

Expected rate of return for shares $\left(r_{t+1}^{\text{int},i}\right)$ is calculated as $r_{t+1}^{\text{int},i} = \left(1 \cdot c^{-1}\left(\sigma_{t-1}^{s,i}\right)^{-2}\right) / \left(1 \cdot c^{-1}\left(\sigma_{t-1}^{s,i}\right)^{-2} + 1 \cdot \left(\sigma_{t-1}^{s,i}\right)^{-2}\right) r_{t+1}^{f,i} + \left(1 \cdot \left(\sigma_{t-1}^{s,i}\right)^{-2}\right) / \left(1 \cdot c^{-1}\left(\sigma_{t-1}^{s,i}\right)^{-2} + 1 \cdot \left(\sigma_{t-1}^{s,i}\right)^{-2}\right) r_t^{im}$. Here, $r_{t+1}^{f,i}, r_t^{im}$ express the expected rate of return, calculated respectively from short-term expected rate of return, and risk and gross current price ratio of stock etc[2][5].

Short-term expected rate of return $\left(r_t^{f,i}\right)$ is obtained by $r_{t+1}^{f,i} = \left(\left(P_{t+1}^{f,i} + y_{t+1}^{f,i}\right)/P_t - 1\right)\left(1 + \eta_t^i\right)$, $\left(P_{t+1}^{f,i}, y_{t+1}^{f,i}\right)$ being the equity price and profit forecast for term t+1 as estimated by the investor. Short-term expected rate of return includes the error term $\left(\eta_t^i \sim N\left(0, \sigma_n^2\right)\right)$ reflecting that even investors of the same forecast model vary slightly in their detailed outlook.

Expected rate of return for stock $\left(r_t^{im}\right)$ as obtained from stock risk etc. is calculated from stock risk $\left(\sigma_{t-1}^{s,i}\right)$, benchmark equity stake $\left(W_{t-1}\right)$, investors' degree of risk avoidance $(\lambda)$, and risk-free rate $\left(r_f\right)$ in the equation $r_t^{im} = 2\lambda\left(\sigma_{t-1}^{s}\right)^2 W_{t-1} + r_f$.

This analysis looks at (1) forecasting based on fundamental values, (2) forecasting based on trends (4 terms), and (3) forecasting based on past averages (4 terms).

The fundamental value of shares is estimated using the dividend discount model. Fundamentalists estimate the forecast stock price $\left(P_{t+1}^{f,i}\right)$ and forecast profit $\left(y_{t+1}^{f,i}\right)$ from profit for the term $\left(y_t\right)$ and discount rate of stock $(\delta)$ respectively as $P_{t+1}^{f,i} = y_t / \delta, y_{t+1}^{f,i} = y_t$.

Forecasting based on trends involves forecasting next term equity prices and profit through extrapolation of the most recent stock value fluctuation trends. This analysis looks at the 4 terms of 1 day, 5 days, 10 days, and 20 days for trend measurements. Forecasting based on past averages involves estimating next term equity prices and profit based on the most recent average stock value. Average value was measured for the 4 terms of 1 day, 5 days, 10 days, and 20 days.

Stock risk is measured as $\sigma_{t-1}^{s,i} = s_i \sigma_{t-1}^h$. In this case, $\sigma_{t-1}^h$ is an index that represents stock volatility calculated from price fluctuation of the most recent 100 steps, and $s_i$ the degree of overconfidence. The presence of a strong degree of overconfidence can be concluded when the value of $s_i$ is less than 1, as estimated forecast error is shown as lower than its actual value. Transaction prices are set as the price where stock supply and demand converge $\left(\sum_{i=1}^{M}\left(F_t^i w_t^i\right)/P_t = N\right)$.

The architecture is illustrated in Figure 6.

The Inverse Simulation Analysis consists of the following 3 steps. (1) Carry out 100 times a simulation with an investment period of 100 terms. (2) Calculate the index of deviation between transaction prices and the fundamental value for each simulation. (3) Set the calculated index as the adaptive value and select 100 simulation conditions (investors' forecasts, confidence). This analysis is undertaken through repetition of these 3 steps. The index $(q)$ of deviation between transaction prices and the fundamental value expresses the deviation ratio with the fundamental value and is specifically calculated as $q = E[x]^2 + Var[x]$. However, $P_t^0$ represents the fundamental value $x_t = \left(P_t - P_t^0\right)/P_t^0$ for term t.

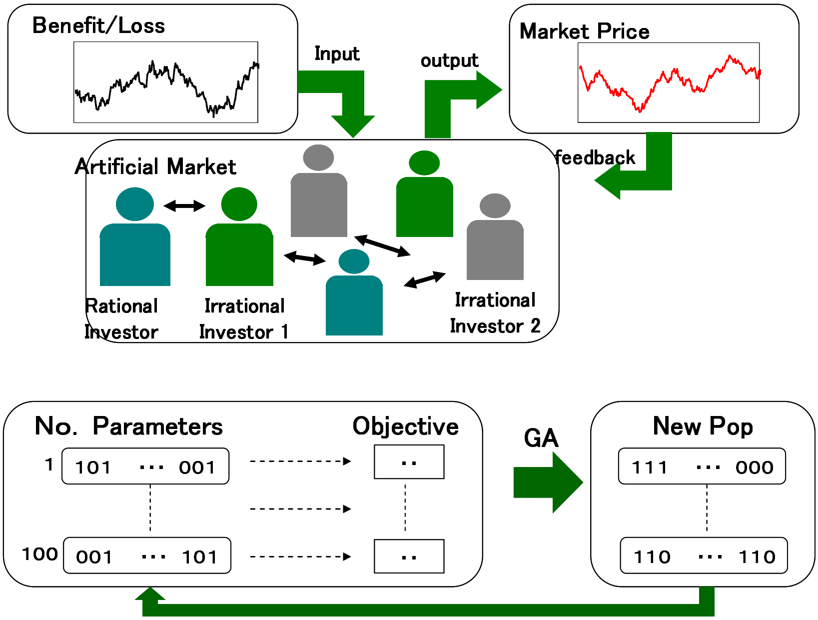


**Fig. 6.** Architecture of the Financial Market Simulator

From the simulation study of the agent-based virtual market, we have found that (1) overconfident investors emerge in a bottom-up fashion in the market, and (2) these overconfident investors have the ability to contribute to the market, in which the trading prices are coincide with theoretical fundamental values.

Traditional finance argues that market survival is possible for those investors able to swiftly and accurately estimate both the risk and rate of return on stock, achieving market efficiency. However, analysis results obtained here regarding the influence irrational investors have on prices suggests a different situation, pointing to the difficulty of market modeling which takes real conditions into account.

## 6 Concluding Remarks

This paper addresses the problem regarding the parameter exploration of Agent-Based Simulation for social systems. In this paper, in order to enhance the power of MABS models, we have discussed the critical issues of validations, background theories, and vast parameter spaces. Then we have explained the principles of *Inverse Simulation* and *Genetics-Based Validation*. After the proposal, to convince the effectiveness of the proposed methods, based on our previous and on-going research projects, we have demonstrated the applications of the principles to MABS models: Social Interaction analysis, Marketing strategies, and Financial decision making.

Future work includes the refinement of the principles to apply the ones to much more complex task domains: (1) Determination of effective objective functions or macro-level evaluation method of the simulation results; (2) Design of micro level agent functionalities including the concepts of distributed artificial intelligence and machine learning; (3) New competing genetic algorithms for the purpose, (4) Development of very large scale simulation environments including grid computing, and (5) Development of validation methods based on the concepts of estimation of distribution algorithms in genetic algorithm literatures.

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## References

1. Axelrod, R.: The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration. Princeton University Press, Princeton (1997)
2. Axtell, R.: Why Agents? On the Varied Motivation for Agent Computing in the Social Sciences. Brookings Institution CSED Technical Report No. 17 (November 2000)
3. Coello, C.A., Van Veldhuizen, D.A., Lamont, G.B.: Evolutionary Algorithms for Solving Multi-Objective Problems. Kluwer Academic Publishers, New York (2002)
4. Goldberg, D.E.: The Design of Innovation, Lessons from and for Competent Genetic Algorithms. Kluwer Academic Publishers, Boston (2002)
5. Yuji, K., Kurahashi, S., Terano, T.: We Need Multiple Solutions for Electric Equipments Configuration in a Power Plant - Applying Bayesian Optimization Algorithm with Tabu Search –. In: Proc. 2002 IEEE World Congress on Computational Intelligence, pp. 1402–1407 (2002)
6. Kurahashi, S., Terano, T.: A Genetic Algorithm with Tabu Search for Multimodal and Multiobjective Function Optimization. In: Proc. the Genetic and Evolutionary Computation Conference (GECCO-2000), pp. 291–298 (2000)
7. Richiardi, M., Leombruni, R., Saam, N., Sonnessa, M.: A Common Protocol for Agent-Based Social Simulation. Journal of Artificial Societies and Social Simulation 9(1) (2006), http://jasss.soc.surrey.ac.uk/
8. Terano, T., Kurahashi, S., Minami, U.: TRURL: Artificial World for Social Interaction Studies. In: Proc. 6th Int. Conf. on Artificial Life (ALIFE VI), pp. 326–335 (1998)
9. Kurahashi, S., Terano, T.: Analyzing Norm Emergence in Communal Sharing via Agent-Based Simulation. Systems and Computers in Japan 36(6) (2005) (Translated from Denshi Joho Tsushin Gakkai Ronbunshi, Vol. J84-D-I, No. 8, August 2001, pp. 1160.1168)
10. Takahashi, H., Terano, T.: Agent-Based Approach to Investors' Behavior and Asset Price Fluctuation in Financial Markets. Journal of Artificial Societies and Social Simulation 6(3) (2003)
11. Takahashi, H., Terano, T.: Exploring Risks of Financial Markets through Agent-Based Modeling. In: Proc. SICE-ICASS Joint Conference 2006 (to appear)
12. Terano, T., Naitoh, K.: Agent-Based Modeling for Competing Firms: From Balanced-Scorecards to Multi-Objective Strategies. In: Proceedings of the 37th Annual Hawaii International Conference on System Sciences 2004 (HICCS 2004), pp.1–8 (January 5-8, 2004)
13. Terano, T., Deguchi, H., Takadama, K. (eds.): Meeting the Challenge of Social Problems via Agent-Based Simulation. Springer, Japan (2003)

14. Terano, T., Kita, H., Kaneda, T., Arai, K., Deguchi, H.: Agent-Based Simulation – From Modeling Methodologies to Real World Applications. Springer, Japan (2005)
15. Kaplan, R.S., Norton, D.P.: The Balanced Scorecard - Translating Strategy into Action -. Harvard Business School Press, Massachusetts (1996)
16. Kaplan, R.S., Norton, D.P.: The Strategy Focused Organization: How Balanced Companies Thrive in the New Business Environment. Harvard Business School Press, Massachusetts (2001)
17. Treacy, M., Wiersema, F.: The Discipline of Market Leaders: Choose Your Customers, Narrow Your Focus, Dominate Your Market. Addison-Wesley, Readings, Massachusetts (1997)