

Incremental Self-Evolving Framework for Agent-Based Simulation

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Abstract—This paper presents a self-evolving scheme of an agent-based simulation to improve agent simulation models to fit real world data in an incremental way without human intervention by machine learning techniques. The proposed method can solve problems of traditional optimization methods of the agent-based simulation by the incremental optimization of agent simulation models. In this paper, we introduce requirements, the structure and internal functions of the self-evolving agent-based simulation framework for social simulation.

Keywords—self-evolving; agent; simulation; incremental; machine learning

I. INTRODUCTION

Agent-based simulation techniques have been adopted for many areas because macroscopic and microscopic simulation results can be derived simultaneously. However, it is hard to get exact simulation models due to modeling errors between simulation models and real world systems in agent-based simulation. Especially, in complex systems like socio-economics or welfare problems of social simulations, there are lots of latent and non-stationary driving factors in terms of system dynamics [1]. Furthermore, microscopic agent-based simulation requires more adequate modeling because they are used to explain microscopic behaviors of systems. We should adjust many parameters in order to reduce modeling errors of many agent models from the real world system. And, it is hard to predict overall emergent behavior of agents. Therefore, traditional manual verification of agent simulation models is not enough and it is necessary to apply a kind of optimization technique to solve the problem of reducing modeling errors in the agent-based simulation.

There have been many kinds of approaches to optimize the simulation models of agent-based simulation. Reinforcement learning was applied to make each agent or a group of agents learn its or their behavior actions [2]. However, because some kinds of indirect rewards are used in learning, it is hard to modify agent models to fit real world data. Evolutionary algorithms like genetic algorithm and swarm optimization were applied to make agent properties and behavior rules in an evolution way [3]. Because evolutionary algorithm approach requires total simulation process to get the fittest selection among candidates in every generation, it takes long time to get optimized results incrementally. Data assimilation techniques like the Kalman filter and the Particle filter

were applied to utilize real world data to modify agent properties [4]. However, many social simulation problems cannot be converted into mathematical equations which are easy to apply the filters to.

In spite of many optimization techniques for agent-based simulation, there were few studies to consider the properties of latent or non-stationary driving factors of real world system dynamics like socio-economics in social simulation. Because of dynamic properties of agent simulation modeling, the modification of models should be performed in an incremental way.

II. REQUIREMENTS FOR SELF-EVOLVING AGENT-BASED SIMULATION FRAMEWORK

The self-evolving agent-based simulation is the simulation scheme to improve and optimize agent-based simulation models automatically to fit data from real systems in an incremental way by using a machine learning technique. In this section, some functional requirements are described for the self-evolving agent-based simulation framework.

A. Incremental Modification of Simulation Models

Because the self-evolving agent-based simulation should consider the latent and varying factors of real systems, the simulation framework can modify simulation models incrementally. That means that at every moment to arrive new real world data, the simulation framework can modify simulation models with partial simulation process not with full simulation process. In terms of incremental modification of simulation models, classical evolutionary algorithm approaches cannot be applied directly because full simulations are required to get the fitness values of candidates of simulation models.

B. Data Assimilation

The self-evolving simulation framework should modify the simulation model by using data from real systems. In case of traditional data assimilation, mathematical models are modified through filters like Kalman filter, etc. However, because many social simulation problems cannot be transferred to the mathematical models, other methods are required for data assimilation.

C. Modification of Structures of Agents

Even when the agent-based simulation can be converted to mathematical equations, traditional data

assimilation method can modify only parameters of models. That means that it is hard to consider latent factors of real systems by only parameter modification. Therefore, the self-evolving framework should modify structures of agents to encompass the latent driving factors more correctly.

III. PROPOSED FRAMEWORK FOR AGENT-BASED SIMULATION

A. Structure and Functions of Modules

The proposed incremental self-evolving framework for agent-based simulation is composed of the modules as shown in Fig. 1. The data and model management modules manage data and models of simulation via database and storage systems. The simulation engine executes the simulation process and makes simulation results. When new real data arrive, the self-evolving module detects change of the validity of the current simulation models. If the current simulation models become invalid, the framework initiates data assimilation process and configures structures and parameters of models. The modification of models is called incremental because only invalid periods of real data are used and all of real data are not used.

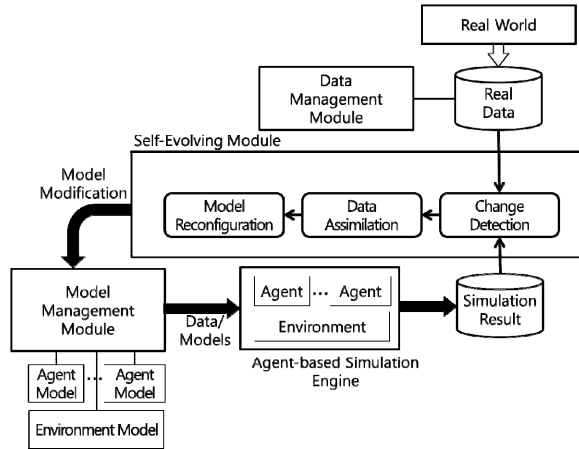


Figure 1. Structures of the self-evolving framework of agent-based simulation.

B. Detection of Change from Models and Real Systems

To find effects of latent and time-varying factors of real system, the validity change of models from real systems should be detected via difference between simulation results and real data or via direct finding of latent factors of real systems [5].

C. Data Assimilation and Simulation Model Reconfiguration

The data from real systems can be used to configure the structures and parameters of simulation models. The evolutionary algorithm is used to select the optimized simulation model as shown in Fig. 2. The phenotypes of the evolutionary algorithm are the parameters and

structures of the simulation models. For the fast and efficient evolution, appropriate genotypes and phenotypes should be designed. In order to consider the data assimilation, the fitness value for selection is formulated by adding the error factors between simulation results and data from the real system.

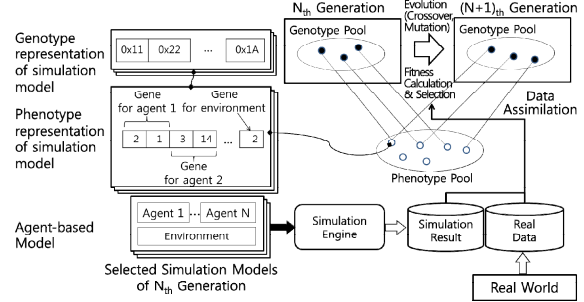


Figure 2. Data assimilation by using evolutionary algorithm.

IV. CONCLUDING REMARKS

In this paper, an incremental self-evolving framework for agent-based simulation was proposed. To solve problems of traditional optimization approaches of agent-based simulation, the simulation framework was proposed for incremental modification of simulation models with data from real systems. The change detection of models from real systems initiates model modification incrementally. The latent and time-varying factors of real system can be considered and more correct simulation models can be derived. For future research, we will examine effects of types of fitness equations for data assimilation and validate the concept of the proposed method by application to real socio-economics simulation.

ACKNOWLEDGMENT

This research was supported by the ICT R&D program of MSIP/IITP, [R7117-16-0219, Development of Predictive Analysis Technology on Socio-Economics using Self-Evolving Agent-Based Simulation embedded with Incremental Machine Learning].

REFERENCES

- [1] Y. Yan, et al., "A multi-agent based evolutionary algorithm in non-stationary environments," Proc. of Evolutionary Computation, 2008, pp. 2967–2974.
- [2] C. Bone and S. Dragicevic, "Simulation and validation of a reinforcement learning agent-based model for multi-stakeholder forest management," Computers Environment and Urban Systems, vol.34, no.2, pp. 162–174, 2010.
- [3] A. Janeczek and T. Jorddan, F. B. Lima-Neto, "Swarm/evolutionary intelligence for agent-based social simulation," Proc. of IEEE Congress on Evolutionary Computation, 2014, pp. 2925–2932.
- [4] M. Wang and X. Hu, "Data assimilation in agent based simulation of smart environments using particle filters," Simulation Modelling Practice and Theory, vol.56, pp. 36–54, 2015.
- [5] W. Lee, Y. Lee, H. Kim and I. Moon, "Bayesian Nonparametric Collaborative Topic Poisson Factorization for Electronic Health Records-Based Phenotyping," Proc. of International Joint Conference on Artificial Intelligence, 2016, pp. 2544–2552.