SEA-SF : Design of Self-Evolving Agent based Simulation Framework for Social Issue Prediction

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***Abstract*— Simulation is the imitation of the operation of a real-world process or system over time. Actual real world expectation is expensive and impossible because the modern society is complex and various. Therefore, simulation can be carried out to take proper measures for the problem which may be happened in the future. Agent based model (ABM) models each individuals and interactions among them. ABM mostly defines behaviors based on rule. However, ABM simulation has the weak point that simulation error is accumulated. If long term simulation is conducted, the simulation result will be highly inaccurate because of error accumulation. To overcome error accumulation, the model should be reconfigured using the real data recursively. In this paper, we propose the self-evolving agent based simulation framework (SEA-SF). The SEA-SF is consisted of data management, change recognition, model evolvement, ABM reconfiguration, user interface and ABM simulation environment. The SEA-SF should mitigate the long-term simulation error. Therefore, the SEA-SF performs change recognition between real data and simulation result. And then autonomously, it updates model parameters or the model configuration to increase accuracy of simulation. The proposed framework can be applied to solve the social issue problems because the social issue problems are happened through a long period. Therefore, the social issue simulation, such as the house policy and supply, can be performed using the proposed SEA-SF.**

Keywords-Simulation; Agent Based Model; Self-Evolvement.

I. INTRODUCTION

Simulation is the imitation of the operation of a real-world process or system over time [1]. Simulation is used for predicting future in various fields. Simulation can be carried out to take proper measures for the problem which may be happened in the future. For example, the birthrate, the rearing of children, income, employment and education may be simulated in the field of society. So, various features of social members can be predicted. The policy of social security service can be established using the result of simulation which predicts socio-demographic characteristic. Therefore, the social problem, such as low birthrate and aging, can be prevented.

Social issue prediction has been accomplished both macrosimulations and microsimulations. The macro simulation predicts the overall tendency of the social issue using the stochastic approach of entire social structures and characteristics. However, the microsimulation could predict the behavior and characteristic of each member related with the social issue. Therefore, the cause of social phenomena could be analyzed variously by the microsimulation. Therefore, population dynamics is simulated by microsimulation to analyze various social features recently.

Actual population expectation is expensive and impossible because the modern society is complex and various. Therefore, microsimulation modeling (MSM) and agent based modeling (ABM) are used for modeling and simulation. Microsimulation models the individuals with real data and defines behaviors based on transition probabilities derived from micro data. ABM models individuals and interaction between the individuals. ABM mostly defines behaviors based on rule. However, these technologies have the weak point that simulation error is accumulated. If long-term simulation is conducted using these technologies, the simulation result is highly inaccurate because of error accumulation.

To overcome error accumulation, the model should be evolved using the real world data recursively. In this paper, we propose the self-evolving agent based simulation framework.

The rest of the paper is organized as follows. Section II describes related work. In Section III, we describe the architecture of self-evolving agent based simulation framework. In Section IV, we describe the proposed framework for social issue prediction, and some concluding remarks are finally given in Section V.

II. RELATED WORK

Most social issues, such as a lower birthrate problem and an aging phenomenon, relate with population dynamics. Therefore, the microsimulations of population dynamics have been performed for a long time. A MSM describes a system at the micro-level and the system is consisted of micro units. G. H. Orchtt [2] proposed a new type of model, MSM, of a socio-economic system in 1957. He described the model which was consisted of various sorts of interacting units. The outputs of each unit were related to prior events and were the result of a series of random drawings from discrete probability distributions. The appropriate probability distributions were determined by inputs into the unit and the operating characteristics of the unit. The units of this new type of model might be large aggregates, such as markets or industries, but they were elemental decision-making entities,

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such as individuals, families, firms, labor unions, and governmental units. He represented individual units in the socio-economic system and analyzed the units' behaviors. MSM could facilitate and improve prediction about socio-economic aggregates and could be used either for short-run or long-run forecasting by appropriate selection of initial conditions and by altering the number of periods the model is run. A. Harding [3] described that dynamic population MSM provided one of the most useful available modelling tools for projecting the future distributional consequences of possible policy changes. He contended that the construction of a reliable dynamic population MSM for use in social policy formulation is a very demanding multi-year project. Nowadays, a lot of countries have implemented the dynamic population microsimulation models for predicting the future population and preparing a countermeasure. For example, the dynamic simulation of income model (DYNASIM3) was developed by USA for designing to analyze the long-term distributional consequences of retirement and ageing issues [4]. The dynamic microsimulation model (DYNAMOD 1 & 2) was developed by Australia for modeling economic and demographic change in the Australian population over time, such as superannuation, age, education, health, and housing policy [5][6].

An agent is a micro unit that can decide its own behaviors based on environment, its own state, and interaction with other agents. Therefore, each agent independently acts according the rules of the simulation and their own preprogrammed behaviors. And more, each agent is free for activity with the ability to make independent decisions [7]. ABM means that individuals have characteristic of the agent. T. C. Schelling [8] proposed the segregation model using ABM in 1971. He described a model that individual members of two recognizable groups distribute themselves in neighborhoods defined by reference to their own locations. The most previous works in the field of ABM have been proposed on dynamic demography, such as household demography [9] and population dynamics [10]. However, the previous ABMs are not able to evolve the structure and parameters of model autonomously. Therefore, when long-term simulation is performed, the simulation error is accumulated, according as times go on. In this reason, we propose the self-evolving agent based simulation framework (SEA-SF) to reduce the long-term simulation error.

III. SEA-SF ARCHTECTURE

The SEA-SF is an agent based simulation framework in order to reduce long-term simulation error. Therefore, the SEA-SF should perform change recognition between real data and ABM simulation result. And then autonomously, it should change model parameters or the model configuration to increase accuracy of simulation using the change recognition result. In the SEA-SF, there are some component modules as shown in Fig 1. First of all, the data management module (DMM) collects domain data and saves the data in database (DB). So, the domain data digitization and DB management are required in this module. Second, the change recognition module (CRM) estimates the difference between real world data and simulation result. So, data trace and change recognition is required in this module. Third, the model evolvement module (MEM) defines the strategy how to evolve the present model autonomously. The machine learning is required to micro-level and macro-level model evolvement. Forth, the ABM reconfiguration module (ARM) changes the model parameters or structure according to the evolving strategy. So, the agent should be consisted of the components. And the ARM also includes the ABM simulation engine to execute ABM simulation. Fifth, the user interface module designs the initial model and visualizes a simulation result. And more, simulation is conducted in distribution and parallel computing environment to improve simulation performance.

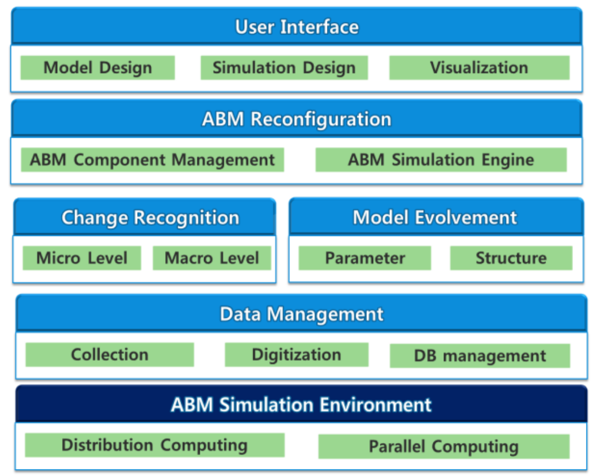

Figure 1. SEA-SF Architercure.

In these modules, the essential modules are CRM, MEM, and ARM. Therefore, these important modules are described more detail below.

A. *Change recognition*

Change recognition detects the difference between the real world data and the simulation result as shown in Fig. 2. The CRM is consisted of the data trend analysis (DTA), feature point extraction (FPE), error estimation (EE) and change recognition (CR) function.

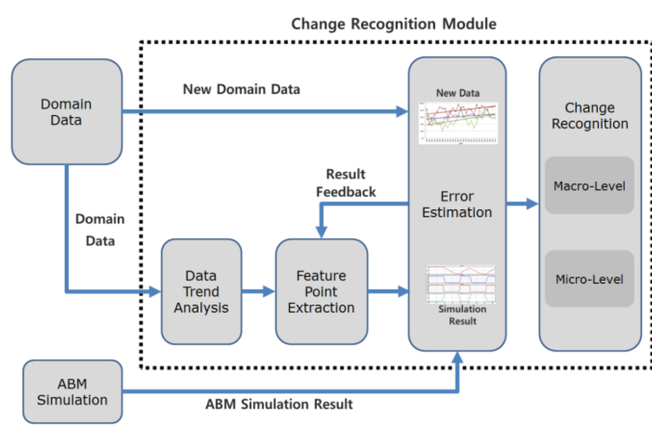

Figure 2. Change recognition.

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The domain data are received from DMM, and then the DTA analyzes these data for detecting data trend using machine learning, such as Hidden Markov Model. The FPE extracts the comparison point for EE using the results of DTA and the feedback from EE. The EE estimates error between the ABM simulation result and new domain data, and then the result of EE is sent to the FPE and CR. The CR estimates whether the change is detected or not. Whenever the change is recognized either micro-level or macro-level, the CRM informs the MEM of the result of CR.

B. Model evolvement

MEM performs micro-level and macro-level evolvements to make agent evolvement strategy and environment transition strategy as shown in Fig. 3.

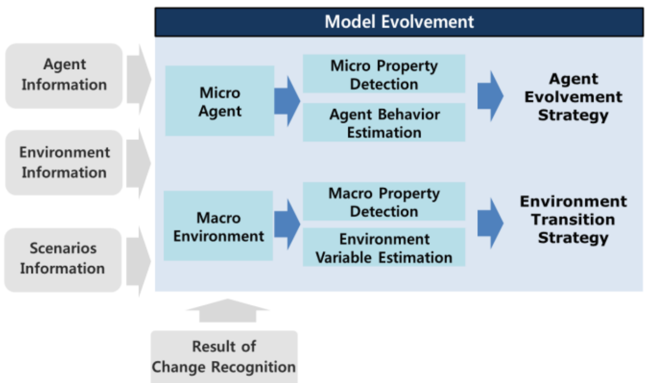

Figure 3. Model Evolvement.

The MEM receives data, such as agent information, environment information, scenarios information and the result of CR, from the DMM and CRM to perform model evolvement. The MEM is consisted of micro agent and macro environment function. The micro agent's property and the agent's behavior are estimated to make the agent evolvement strategy. The macro property of environment is detected and the environment variable is estimated to set out the change recognition direction of environment. This module informs ARM of the agent evolvement and environment transition strategies.

C. ABM reconfiguration

The ARM reconfigures ABM using component, previous ABM, and model evolvement strategy as shown in Fig. 4.

ABM is consisted of agents, environments and interaction among these. The component of ABM means the behavior of agent, property of environment and interaction among agents and environment. For ABM reconfiguration, ABM should be componentized because structure and parameter of ABM are reconfigured using these components autonomously. The previous ABM is the ABM before reconfiguration is performed. ABM based simulation is conducted using this model and produces the simulation result in CRM. The model evolvement strategy (MES) is the result of MEM to reconfigure the ABM.

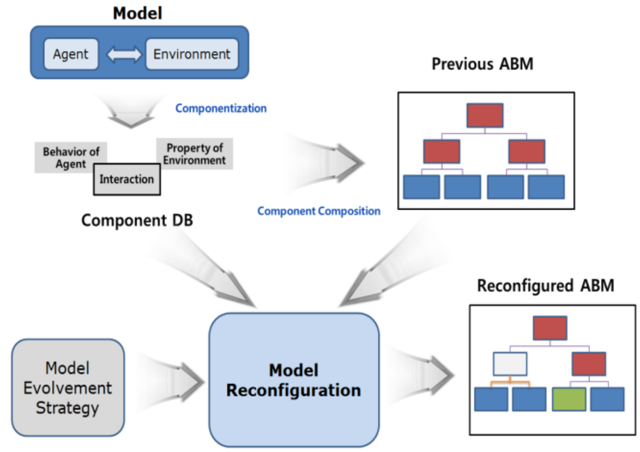

Figure 4. ABM reconfiguration.

Whenever the ARM receives the MES from the MEM, it reconfigures model using the component information, its own present ABM and MES. According to the request of MES, the model is reconfigured at parameter level or structure level.

IV. SEA-SF FOR SOCIAL ISSUE PREDICTION

The proposed framework can be applied to solve the social issue problems because the social issue problems are happened through a long period. Among the social issue problems, this framework can be applied to the house policy and supply. That is, the effect of government policy, such as house policy, is analyzed macro-level and micro-level on socio-economics, such as house supply, as shown in Fig. 5.

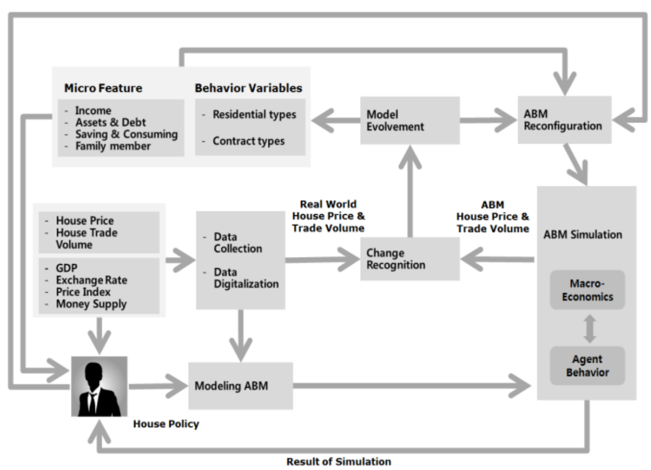

Figure 5. Social issue, house policy and supply, simulation using the SEA-SF.

The leading economic indicators related to the house price and trade volume are gross domestic product (GDP), exchange rate, price index and money supply. These economic data, such as GDP and house price, are collected and digitalized. The ABM is designed using these data and the policy decision factors, such as interest rate, rebuilding and rental house. The ABM simulation is performed using

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economic data, agent behavior and interaction. The CRM receives real world data and ABM simulation result about the house price and trade volume. Whenever this module recognizes the difference between these data, it notifies the result to MEM. The MEM evolves the present ABM using machine learning approach. It changes the micro features of agent, such as income, assets, debt, family member, saving and consuming, and agent behavior variables, such as residential types and contract types. The ARM reconfigures previous ABM using the changed ABM parameters and structure autonomously. The decision maker can also change the present policy to reconfigure the ABM. The result of evolved ABM simulation is compared with real world data at the CRM. These processes are repeated recursively. Therefore, the long-term simulation error can be reduced by SEA-SF.

V. CONCLUSION AND FUTURE WORK

This paper addressed the design of SEA-SF for social issue prediction. The simulation result may be inaccurate in a long-term simulation because the simulation error is accumulated. In this reason, the model of simulation should be evolved using change recognition method. We describe the architecture of the SEA-SF. It is consisted of DMM, CRM, MEM, ARM, user interface and ABM simulation environment. Among these modules, CRM, MEM and ARM conduct essential role of the self-evolving ABM. CRM detects the difference between the real world data and the simulation result and informs MEM of it. The MEM performs micro-level and macro-level agent based model evolvement. The ARM reconfigures ABM using component, previous ABM, and MES. The proposed framework can be applied to solve the social issue problems, such as house policy and supply, because the social issue problems are happened through a long period.

We will implement the proposed framework to simulate a social issue problem, such as house price of South Korea.

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