JOURNAL OF CIVIL ENGINEERING AND MANAGEMENT
ISSN 1392-3730/eISSN 1822-3605
2015 Volume 21(8): 998–1013
doi:10.3846/13923730.2014.893916

APPLICATION OF AGENT-BASED MODELING AND SIMULATION TO UNDERSTANDING COMPLEX MANAGEMENT PROBLEMS IN CEM RESEARCH

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Received 04 Nov 2012; accepted 21 Feb 2013

Abstract. As construction projects have become larger and more complex, they develop different features than smaller or traditional projects, which characterize them as complex systems. Still, Construction Engineering and Management (CEM) researchers have mostly relied on traditional approaches to investigate complex management problems, which might produce misleading results. This paper introduces Agent-Based Modeling and Simulation (ABMS) as a research method, and addresses how it could be applied to CEM research. With an illustrative example of the application of ABMS to CEM research, the theoretical background as well as the design, development, and test processes of ABMS are presented. We then made a recommendation on the promising research subjects in CEM area to which ABMS could be suitably applied.

Keywords: construction management, computer models, simulation, research methods.

Introduction

Construction projects have become larger and more complex (Chan *et al*. 2004). Not only has the scale of construction projects increased, but their uncertainty and difficulty has also grown, due to the large number of participating organizations and quantities of resources, which are interrelated by contractual, sequential, and managerial relationships. The intertwined and multi-layered interactions among organizations and resources often become a significant factor in determining project outcomes. This adds more complexity to construction projects.

Such large-scale and complex construction projects should be thought of as different entities, termed *complex systems* (Bertelsen 2003). A complex system refers to a system whose system-level behaviors emerge from interactions among sub-elements, and where the emergent properties of a system are greater than the simple sum of its subsystems (Bar-Yam 2000). Complex systems have very different characteristics from other systems, such as emergence, nonlinearity, decentralization, and adaptation. Due to the innate features of complex systems, they cannot be understood by traditional approaches, which rely on reductionism (North, Macal 2007): reductionist thinking may be very misleading when trying to understand a complex system. Even if we can fully uncover the micro-level foundations of a system, we may still not have a simple way to understand their macro-level implications (Miller, Page 2007). Nevertheless, researchers in Construction Engineering and Management (CEM) area have mostly relied on traditional approaches – usually, Operational Research (OR) methods – to investigate management problems in complex construction projects.

Agent-Based Modeling and Simulation (ABMS) is a new computer simulation approach to modeling complex systems. Agent-Based Simulations (ABS) are built from a ground-up perspective, rather than from a top-down perspective. ABMS begins by defining agents, which represent fundamental elements in the system, and evolves as agents locally interact with other agents and the environment according to defined protocols; and eventually, systematic patterns emerge (Macy, Willer 2002). This realistic viewpoint toward complex systems and very natural way to represent the dynamic behavior of complex systems provides new ways of gaining insight and understanding of complex systems (Miller, Page 2007).

In this regard, this paper aims to introduce ABMS as a research method, and address how it could be applied to CEM research and practice. To accomplish the objectives, we first present a new perspective that regards construction projects as complex systems. Then, the theoretical background and practical details of ABMS are explained. The design, development, and test processes

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of ABS are specified. As an illustrative example of the application of ABMS to CEM research, we consider the ABS of construction project teams, which the authors have developed in order to understand the effects of organizational dynamics on project outcomes. The paper concludes with specific recommendations on subjects and areas where ABMS could appropriately be adopted as a research method in the CEM area.

1. Construction projects as complex systems

1.1. Complex system perspective

The world has become increasingly complex. Not only is the number of physical and social systems increasing, but the composition of systems is also becoming more complex. *Complexity* arises when the dependencies among a system's elements become important (Miller, Page 2007). Complex systems have common traits, such as (1) aggregation: allowing groups to form; (2) nonlinearity: this invalidates simple extrapolation; (3) flow: allowing the transfer and transformation of resources and information; and (4) diversity: allowing agents to behave differently from one another, which often leads to the system property of robustness (Holland 1995). The unique characteristics of complex systems often make them hard to examine, and difficult to understand.

It is believed that the system-level behavior of a complex system emerges from the local activities of lower-level components. But the system-level behavior of a complex system is very different from those of its components, and it cannot be reduced to their sum of difference (Blitz 1992). It provides a very powerful organizing force that can overcome a variety of changes to the lower-level components (Miller, Page 2007) – this is termed *emergence*. Emergence is defined as "the arising of novel and coherent structures, patterns and properties during the process of self-organization in complex systems" (Goldstein 1999).

Complex systems cannot be understood by traditional approaches, which rely on "heroic assumption" (North, Macal 2007). Heroic assumption refers to the fact that researchers often simplify the level of detail in systems under investigation, and reduce the ranges of allowed interactions between components – in other words, reductionism. However, even if we fully understand the lower-level fundamentals of a complex system, we may not be able to use that knowledge to reconstruct a higher-level system, because the whole becomes not only more than, but very different from the simple sum of its components (Anderson 1972). For example, in the study of the effect of communication and coordination among team members on team performance, simply assuming that project team members in a large-scale project communicate only through hierarchical relations, and that they all work independently of other team members, would be a heroic assumption. There would exist informal communication channels, such as social networks, and they may need to collaborate with colleagues to achieve results. If a researcher employs mathematical modeling, statistical method, or survey as a research method, and is concerned only with each separate individual to build a model, while abstracting or excluding interrelations among team members, s/he would not be able to understand organizational aspects as a whole, notwithstanding the findings on individuals.

1.2. Complex systems in construction projects

As construction projects have become larger and more complex, due to their scale, uncertainty, number of participating organizations, and quantity of resources, they develop different features than smaller or traditional projects (Table 1).

Several researchers have put forward a new perspective that the production system, construction process, and project teams in a construction project should be understood as a complex system. Bertelsen (2003) stated that the construction sector forms an interwoven network of high complexity and great dynamic due to its contracting practice, and thus the construction production system has the characteristic of a complex system. He gave a detailed explanation of a complex system's characteristics that the construction production system exhibits – autonomous agents, undefined values, and nonlinearity. He also pointed out that the construction process has the properties of a complex system similar to the production system. Particularly, construction has a co-evolution of product development and production processes through self-modification and learning (autonomous agents); project values are established during the initial stages, but they are kept developing further through the project life cycle (undefined values); the process outcome is obviously characterized by the whole being more than the sum of the sub-elements (nonlinearity).

More importantly, construction project teams should be thought of as complex systems. Due to the one-off nature of construction projects, project teams come to have the properties of temporary organizations, and have a purpose, composition, and working method that are unique to the construction industry (Cornick, Mather 1999) (Table 2). Therefore, they need to be re-engineered and re-structured over the life of the project as it progresses, so that they can cope with numerous interdependent tasks (Ballard 2005; Morgan 1997). The program teams working on a project consist of individuals (autonomous agents), and establish values (undefined values) through communication and cooperation among members, which is emergent phenomena (nonlinearity) (Bertelsen 2003).

2. Research methods in CEM research

As described in the previous section, some subsystems comprising large and complex construction projects, such as production system, construction process, and project team, should be considered from a complex system perspective. The advocacy of a complex system perspective has something to do with the researchers'

Table 1. Comparison between large-scale and small-scale construction projects (inspired by Ballard (2005))

	Small-scale/Traditional construction	Large-scale/Complex construction
Product		
Size	Small	Very large
Volume	Massive	Unique
Repetition	Repetitive	One-off
Reliability	High	Relatively low
Complexity	Low	High
Process		
Number of activities	Hundreds	Thousands
Difficulty	Low	High
Uncertainly	Low	High
Interdependency among activities	Low	High
Organization		
Number of involving organizations	Tens	Hundreds
Project team continuation	Temporary	Temporary
Required level of skills	Relatively low	High
Required level of collaboration	Relatively low	High
Management		
Number of resources to be managed	Manageable	Intractable
Primary strategic challenge	Price/Inventory	Bidding/Delivery
Primary operational challenge	(1) Quality (2) Schedule (3) Cost	(1) Schedule/Cost (2) Quality

Table 2. Comparison between construction project teams and traditional manufacturing firms (Cornick, Mather 1999)

	Construction project team	Traditional manufacturing firm
Purpose	Determined by a *client* who is not a part of the design and construction supply side	Determined by the *manufacturing firm*, on the basis of its extensive experience of design, production, and marketing
Composition	Not necessarily selected because of their ability to form a effective team, but because of their *attractive design* and *competitive price* for construction	Comprised of team members who are mostly *in-house employees,* with shared company philosophy
Method of Working	Based on the *conventions* of how each entity, including owners, architects, and contractors, carry out their normal practice through traditional contractual arrangements	Not necessarily hidebound by a convention of how separate organizations work together; no contractual conditions between parties

understanding of the limitations of reductionism, which has been a dominant approach in science, including physics, chemistry and biology, for the last several decades. *Reductionism* or *reductionist thinking* refers to a way of understanding systems by reducing them to simpler or more fundamental parts of which the systems are composed, while positing that a whole system is nothing but the sum of its subsystems. Reductionism ignores the effects of the relations and interactions among subsystems on a whole system. It may be valid for systems where only the total mass of a system matters, or for collections of small weakly interacting particles; however, it is not generally true in systems where the behavior of a system arises from interactions among subsystems, and the emergent properties of a system are greater than the simple sum of its subsystems (Bar-Yam 2000) – e.g. complex systems. Reductionist thinking may be very misleading when trying to understand a complex system (Miller, Page 2007).

Existing CEM research and practice has adopted traditional research methods based on reductionism to study subjects, where they might have produced more useful results using a complex system perspective. However, note that we do not mean that the existing research has constructed wrong knowledge by using inadequate approaches, but rather that they might be able to create more relevant and explicit knowledge using a complex system perspective.

For example, current construction planning practices, usually based on the Critical Path Method (CPM), may be of little value to actual operations, and cause inefficient schedules and poor productivity (Hendrickson, Au 1989). Also, CPM has not been very effective in preventing cost and schedule overruns in large projects (Majid, McCaffer 1998). This is because CPM is not capable of modeling the complex and dynamic processes present in large-scale construction projects (Majid, McCaffer 1998). In particular, CPM does not ensure continuity for the construction crew, relies on data prepared by heuristic decision-making processes, and assumes that interferences and variability rarely occur (Laufer, Tucker 1987). CPM also lacks the capability to manage dynamic and complex feedback caused by iterative error and change, which is common in construction projects (Lee 2006). In addition, CPM is inadequate to cope with non-precedence constraints, such as contract constraints and information constraints. CPM cannot associate schedule information with the description of the physical building; it is unsuitable for analyzing constraints at operational levels (Sriprasert, Dawood 2002). CPM also does not take into account information dependencies among concurrent activities, nor the impacts of actor interactions (Jin, Levitt 1996); and cannot represent the coordination overhead of executing flexible and interdependent activities in parallel (Levitt *et al.* 1999). Consequently, estimating activity durations with CPM often produce unrealistic values, due to its formalized methodology. The duration estimate is achieved by adjusting historical productivity values based on the planner's heuristic learning from prior experience, educated guesses, and advice from colleagues in accordance with project conditions. This methodology might work appropriately for planning and managing small or medium-scale construction projects; however, it often creates a simplistic and static plan that is inadequate to manage large-scale construction projects that involve higher complexity and uncertainty.

Furthermore, there has been considerable effort to understand organizational issues in the construction management field. Research subjects have concentrated on several matters, including organizational performance (Dikmen *et al.* 2005; Cheng *et al.* 2007), partnering (Anvuur, Kumaraswamy 2007; Chan *et al.* 2008; Ozorhon *et al*. 2008), innovation (Gray, Davies 2007; Keast, Hampson 2007), leadership (Hensey 1999), culture (Maloney, Federle 1990), and the learning organization (Chan *et al*. 2005; Chinowsky, Carrillo 2007; Chinowsky *et al.* 2007). These studies present general understandings on the subjects, and have led organizational study in construction management. However, by and large they have relied on research methods, such as statistical analysis, interview, and survey, and therefore have not provided project managers with concrete managerial lessons and analytical ability regarding organizational processes and their effect on project performance from a comprehensive viewpoint.

3. Agent-based modeling and simulation

ABMS is a new approach to modeling complex systems that is comprised of autonomous and interacting agents (Macal, North 2005). ABMS is particularly useful to investigate complex systems where: (1) individual behavior is nonlinear, and can thus be modeled by threshold models, production systems, or differential equations; (2) individual behavior exhibits memory, path-dependence, non-Markovian characteristics, or temporal correlations, including learning and adaptation; (3) interactions among individuals are heterogeneous, and can generate network effects; and (4) the system is linearly stable, but unstable to larger perturbations (Bonabeau 2002).

The idea of ABMS was developed in the late 1940s, and it begun attracting researchers' attention in the early 1990s, because of the development of multi-agent models, which offered the promise of simulating autonomous individuals and the interactions between them (Gilbert, Troitzsch 2005). Prior to the use of ABMS, many different simulation methods had been devised and used. They were mainly discrete-event simulations, or system dynamics simulations. Other methods that have affected the development of ABMS include Simulmatics and Microsimulation. Simulmatics was designed for understanding voter behavior in presidential elections in the 1960s; its idea and formulation was very close to those of the present ABMS. Microsimulation, which thrived in the 1980s, is a simple individual-based simulation based on stochastic processes. Recently, artificial intelligence has had a significant effect on the growth of ABMS. In particular, the area of machine learning in artificial intelligence, which is concerned with how to allow computers to evolve behaviors by learning from empirical data, has developed computational models of human cognition and decision-making.

The increasing use of ABMS is primarily due to its realistic viewpoint toward complex systems. ABS (Agent-Based Simulations) are built from a ground-up perspective, rather than from a top-down perspective. In particular, ABMS begins by defining agents – representations of individuals or groups – that are identifiable, situated in an environment, goal-directed, autonomous, and that have the ability to learn and adapt (Macal, North 2005). An agent-based model (ABM) evolves as agents locally interact with other agents and the environment according to defined protocols, and eventually systematic patterns emerge (Macy, Willer 2002). This ground-up approach is most appropriate to systematically explore complex systems, which are characterized by a high degree of localization and distribution (Van Dyke Parunak *et al.* 1998). The attractive features of ABMS for exploring complex systems are presented in Table 3 and the following paragraphs:

- *Descriptive realism*: An ABM is expressed with unambiguous mathematical and computational formalisms, so that once it has been fully described, its predictions are clear, quantitative and objective

Table 3. Modeling potential (created from Edmonds (2001) and Miller and Page (2007))

Traditional tools	Agent-based models
Abstracted	Descriptive
Little process	Process-oriented
Instructive	Constructive
Regulated	Self-organizing
Precise	Flexible
Reliable	Relevant
Static	Dynamic
Recoverable/Repeatable	
Less contingent	Contingent
Single-level	Multi-level
Optimizing/Perfect rationality	Adaptive/Bounded rationality
Homogenous	Heterogeneous
1, 2, or infinite agents	1, 2, ..., N agents

(Goldstone, Janssen 2005). In other words, it is almost universal that entities being modeled in the target system are mapped onto corresponding agents in the ABM; consequently, the boundaries of the entities and their interactions correspond to those of the agents.

– *Process-oriented*: ABMS requires process-oriented thinking. Every aspect of agent processes, such as how agents recognize the environment, how agents use information, and how agents interact with each other, must be explicitly and well specified. Such issues are often ignored in equation-based models, which rely on only a few parameters to represent problems.
– *Constructive*: ABMS inherently produces constructive proofs to propositions. The ability to fully generate a phenomenon from the bottom-up provides new ways of gaining insight and understanding (Miller, Page 2007).
– *Self-organizing*: Because the models are typically either simple or informed by real-world data, they are appropriately constrained, and cannot fit any conceivable pattern of data (Goldstone, Janssen 2005).
– *Precision* and *flexibility*: ABMS can attain a balanced trade-off between flexibility and precision. Flexibility occurs when the model can capture an extensive class of behaviors; precision requires the model elements to be exactly defined. ABMS is remarkably flexible in its ability to capture a variety of behaviors, and at the same time ABMS also requires a high degree of precision (Miller, Page 2007).
– *Relevance* and *reliability*: Improving the reliability of formal modeling may be accomplished at the expense of its relevance to the target systems, because of the augmented abstraction to the target systems; that is, the more abstract the model, the more reliable, but also the less relevant. ABMS allows the application of formal models to complex systems without the loss of relevance, due to its "descriptive realism" (Edmonds 2001).
– Inherently *dynamic*: Most analytic methods emphasize equilibrium states in systems. However, in the case of complex systems, this approach is like trying to understand running water by catching it in a bucket. ABMS provides a very natural way to represent the dynamic behavior of systems (Miller, Page 2007).
– *Recoverable* and *repeatable*: Whenever anomalies are detected, ABMS can be rerun and re-probed, to identify the cause of the anomalies. This ability facilitates the rapid development and refinement of theoretical ideas. ABMS is also repeatable, in that it allows multiple observations of a system (Miller, Page 2007).
– *Greater contingency* in inference: Because ABMS is indeterministic, path-dependent, and emergent, it can generate a wide range of consequences. Single runs of ABMs are not representative of the systems' general behavior, and thus examining each single run is often required to distinguish what is happening in each, so that one can begin to determine how to classify the simulation trajectories (Edmonds 2001).
– *Multi-level analysis*: ABMS provides true bridging explanations that link two distinct levels of analysis, the properties of individual agents, and the emergent group-level behavior.
– *Adaptive* and *boundedly rational agents*: The flexibility of ABMS and development of computational study such as artificial intelligence enabled ABMS to be suitable for incorporating agents who are boundedly rational and can adapt their behaviors (Miller, Page 2007).
– *Heterogeneous* agent: Many social and economic theories and analytical tools have been developed

with the assumption of homogeneous agents. However, this homogeneity is not a feature that can be observed in the real world, but is rather a necessity imposed on us due to inadequate modeling techniques. ABMS is able to incorporate heterogeneous agents, who have a different set of properties and behave differently (Miller, Page 2007).
– *Scalability*: ABMS can be easily scaled: once the behavior of a single agent is described, it can be easily scaled to a system consisted of agents of an arbitrary size, by simply adding as many agents to the system as desired.

ABMS has recently become popular to investigate complex systems in many areas, such as sociology (Gilbert, Abbot 2005), economics (Tesfatsion 2002), supply chain (Swaminathan *et al.* 1998), management science (Rahmandad, Sterman 2008), anthropology (Kohler *et al.* 2005), and physical science (Troisi *et al.* 2005). Likewise, a few simulation tools in the CEM area have been developed using ABMS. Virtual Design Team (VDT) (Jin *et al.* 1995) is a computational model of project organizations to analyze how activity interdependencies raise coordination needs, and how organization design and the introduction of communication tools may change the coordination capacity of project teams, with resulting impacts on design project performance. Virtual Coach (Rojas, Mukherjee 2006) is an education-purpose situational simulation application, whose main objective is to help learners further develop their decision-making skills in a problem-based learning environment. Kim, K. and Kim, K. J. (2010) developed a multi-agent-based simulation system to evaluate the traffic flow of construction equipment in a construction site. Azar and Menassa (2011) developed an agent-based simulation to model energy consumption in commercial buildings by accounting for the diverse and dynamic energy consumption patterns among occupants. Recently, Du and El-Gafy (2012) proposed the use of agent-based modeling to study the interactions of organizational and human factors and their effects on construction performance.

As such, there have been a few ABMS studies developed for specific purposes, such as analyzing non-value adding activities in construction project execution, optimizing construction operation, and analyzing total energy consumption in building. Still, ABMS is generally not recognized as a research method, despite its merits, and its theoretical background and development process is not well established in the CEM area. In the next section, a typical ABS development process is explained, and the ABS of construction project teams is presented as an illustrative example.

3.1. ABS development process

ABM design and development processes appear quite similar to that of object-orient programming (OOP), because technically, ABMS is rooted in OOP. Thus, ABM is likely to be considered the same as object-orient simulation (OOS). However, while simulated entities in OOS are purely reactive and simple-minded, agents in ABMs have more sophisticated representation of mind and abilities, such as learning ability and goal-oriented decision-making (Davidsson 2001). This makes the ABS development processes more complicated than standard simulation studies, because it requires the following additional steps for building an agent model (Macal, North 2006) (Fig. 1):
– Identify the agent types and other objects (classes), along with their attributes (micro level);
– Define the environment the agents will live in and interact with (macro);
– Specify the methods by which agent attributes are updated in response to either agent-to-agent interactions or agent interactions with the environment (meso level);
– Add the methods that control which agents interact, when they interact, and how they interact during the simulation (meso).

1. Agent's attributes and internal behavior modeling (micro level)

An agent is a fundamental decision-making component in ABMS. Agents in ABMS can be any type of independent components in real worlds, such as software, model, and individual. Agents are defined by abstracting their attributes and behavior, which determine internal and external interaction with other agents and the environment. Agents are heterogeneous and dynamic in their attributes and behavior rules. Behavior rules vary in their sophistication, how much information is considered in the agent decisions, the agent's internal models of the external world including other agents, and the extent of past events the agent retains and uses in its decisions; agents also vary by their attributes and accumulated resources (Macal, North 2005) (Fig. 2).

Macal and North (2005) stated that agents have certain characteristics:
– An agent is *heterogeneous*: it is a discrete individual, with a set of characteristics and rules governing its behaviors and decision-making capability. Agents are self-contained. The discreteness requirement implies that an agent has a boundary and one can easily determine whether something is part of an agent, is not part of an agent, or is a shared characteristic.
– An agent is *situated*: living in an environment with which it interacts with other agents. Agents have protocols for interaction with other agents, such as communication protocols, and the capability to respond to the environment. Agents have the ability to recognize and distinguish the traits of other agents.
– An agent is *goal-directed*: it has goals to achieve (not necessarily objectives to maximize) with respect to its behaviors.
– An agent is *autonomous* and *self-directed*: An agent can function independently in its environment and

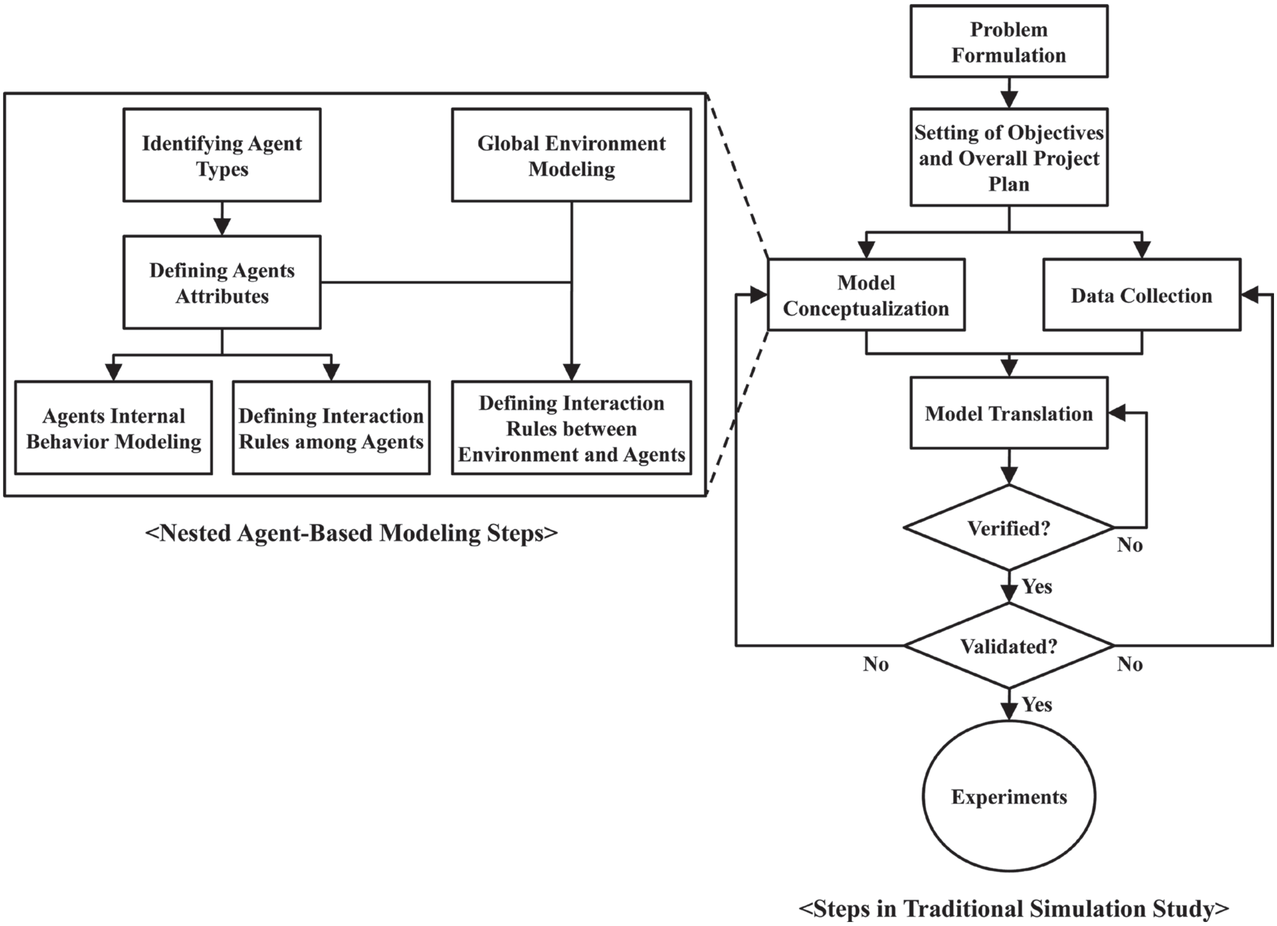

Fig. 1. ABMS process (modified from Banks *et al.* (2004))

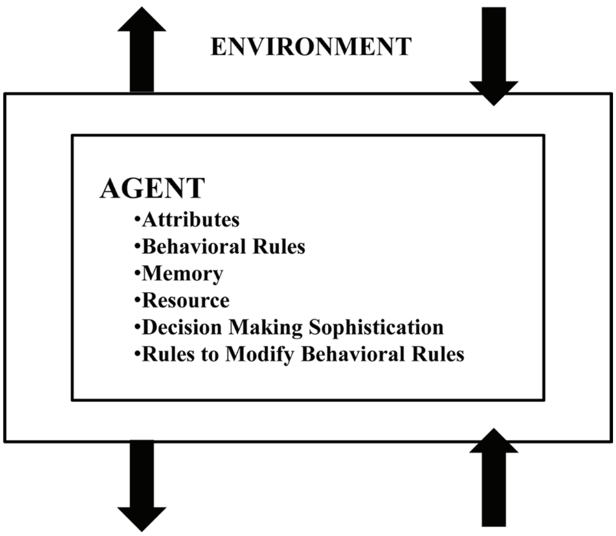

Fig. 2. An agent (Macal, North 2005)

in its dealings with other agents, at least over a limited range of situations.
- An agent is *flexible*, and has the *ability to learn and adapt* its behaviors over time, based on experience. This requires some form of memory. An agent may have rules that modify its rules of behavior.

Abstracting complicated human behavior and mindset, and designing human-like rational agents in the ABMS is one of most significant efforts to generate more plausible behaviors in simulation (Norling *et al.* 2001). ABMs can be built of primitive representations of agents and interaction rules between them at the simplest level. Even a simple ABM can exhibit complex emergent patterns (Reynolds 1987), and provide valuable information about the target systems. Simple rules have several advantages. In particular, simple reactive decision rules allow focusing on core mechanisms, permit models to be quickly developed, shorten verification and validation times, and enable rapid model application (North, Macal 2007). As mechanisms in a model are more succinct, the operation of each rule becomes more apparent. More sophisticated agents, which can perceive the world, make decisions in complex situations, and learn from feedback, can be developed by incorporating advanced techniques or other learning techniques, in order to allow realistic learning and adaptation (Bonabeau 2002); for instance, game theory and machine learning.

2. Defining interaction rules among agents (meso level)

Defining interaction rules among agents is a step that specifies the social behavior of agents. In particular, depending on the purpose of simulation, underlying mechanisms to determine relations among agents are designated, such as how agents get to know each other, how an agent communicates or cooperates with others, and what makes agents communicate and cooperate. As mentioned, there is not an established set of standard formalisms or procedures for model development; defining interaction rules among agents is a context-specific task.

As in the preceding step for defining internal behavior, simple rules or sophisticated mechanisms can be used. In other words, agents could be simple reactive ones as in most existing literature, or socially realistic ones which have features like a myopic view in networks, self-interested and profit-seeking behavior, and forming coherent subgroups. For instance, social processes are often modeled as a few mathematical equations (Yu *et al.* 2008), and relations are regarded as the conduits of material, information, and cash flow between agents (Swaminathan *et al.* 1998). Whereas in some literature, such social processes are represented in more realistic and explicit manner: forming and breaking relations are based on expected marginal benefit, marginal cost, and trust (Hanaki *et al.* 2007). Agents' behaviors are influenced by their indirect relations as well as by direct relations, and having limited information constrains agents to make myopic decisions in the context of dynamic networks (Jackson, Watts 2002). Several theories and methods may help to define interaction rules; for instance, social network analysis (SNA) and game theory.

3. Global environment modeling and defining interaction rules between environment and agents (macro level)

The global environment in an ABM provides agents with essentially an abstracted model of the real world where they play. The target of global environment modeling could be organization (Levitt *et al.* 1999), software development society (Smith *et al.* 2006), supply-chain (Min, Bjornsson 2008), or transportation system (Dia 2002), according to the subject under study. As a result of interaction, not only are agents' properties changed, but also the current states of the environment are updated. In particular, once agents perceive inputs from the environment, they evaluate them, decide what they need to do at the current moment, and then execute the actions they have chosen (North, Macal 2007); these steps are performed by an internal behavior model. The actions taken by agents iteratively influence the properties of themselves and other related agents as well as the states of the environment, as in Figure 3. This is one cycle of ABS; this continues until the end of the simulation.

4. Illustrative example

To convey a clearer idea of ABMS application and development process, an illustrative example is presented. This is a model of the evolution of collaboration in project teams of large-scale projects, which the authors have developed on the extension of existing studies, such as Jackson and Watts (2002), and which was implemented using ABMS. Because the primary purpose of this paper is to explore the possible application of ABMS in the CEM area, and for brevity of discussion, detailed descriptions of the model and technical aspects are not included. For further detail, refer to Son and Rojas (2011).

4.1. Modeling concept

Project teams are viewed as dynamic information processing networks composed of members who are self-interest seeking and myopic to recognizing whole networks (Fig. 4). Team members, who are modeled as agents possessing individual characteristics and network properties, keep seeking maximum payoff through not only dealing with information and decision, but also communicating and coordinating with each other via existing paths in networks. Collaboration processes are modeled as the sequential co-evolution of behavioral dynamics at the micro level, and network dynamics at the macro level. Agents' decisions are influenced by both global

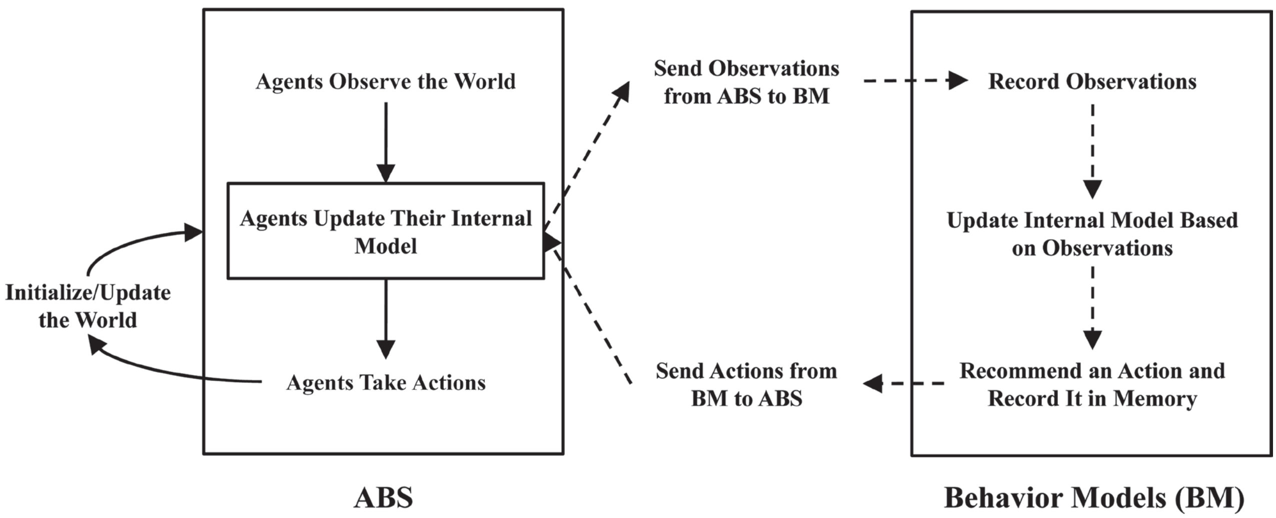

Fig. 3. Integrated cycle of agent-based simulation and behavior models (inspired by Rand (2006))

and local network properties, and the network properties emerge from local interactions among individuals. Consequently, agents' payoffs are determined according to their current network properties, while the work capabilities of agents are assumed to be equal, and thus do not affect payoffs. Equality of work capabilities of agents is later discussed as one of the limitations of this research. However, considering that the primary purpose of this research is to understand how team networks evolve over time and affect performance, the authors argue that this is a valid assumption in order to isolate network effects.

4.2. Agent design

Agents are designed to have different values of *sociability* and *familiarity*. *Sociability* refers to the extent that agents are outgoing, so that they have a chance to meet new candidate partners. *Familiarity* refers to the extent that agents are close to other agents in the network. Agents participate in social interactions with a probability of *sociability*. If agents are not social enough to meet new agents, they seldom have an opportunity to improve their payoff through forming a new relation or replacing an unproductive partner with a promising one. In social interactions that agents are involved, they make new contacts with agents who are not currently in their relations. The likelihood of which agents meet is decided by the probability distribution of *familiarity* to others. Therefore, agents more frequently meet one to whom they maintain higher *familiarity*.

In each time step, agents meet a candidate partner, and choose either to cooperate with (i.e. share information with), or to defect from it. Whether agents cooperate or defect is determined by comparison between the current payoff that they are attaining from the combination of existing partners, and the potential payoff that they could achieve by forming a new relation with the candidate partners and severing least efficient relations. The resulting payoffs are determined by a payoff function (Eqn (1)) inspired by the production function developed by Cobb and Douglas (1928):

$$\text{payoff: } u_i(\mathrm{g}_t) = ((\omega_{i,\mathrm{t}}+1)^a)^{(\beta_{i,t}+1)^b} \times (\beta_{i,t}+1)^b - \sum_{j:ij\in g} c_{ij}, \quad (1)$$

where: ui – the payoff of i; g_t – a network at time t; ω_{it} – the number of within relations which i agent has at time t; β_{it} – the number of between relations which i agent has at time t; a – the elasticity of ω_{it} to payoff; b – the elasticity of β_{it} to payoff; c – cost to maintain a relation.

Yet, having more relations does not necessary result in higher payoff because payoff is also subject to both: (1) the synergistic effect generated from the advantage of having both *within relations* which agents form with others from the same organization – hereafter insiders – and *between relations* that agents form with others from different organizations – hereafter, outsiders – and (2) the cost to maintain relations. When agents have *between relations* as well as *within relations* at the same time, they end up with higher payoff than others who have only *between relations* or *within relations*. This is grounded in the fact that those, who can access diverse task-related information and occupy powerful positions connecting divided subgroups in networks, could use positional advantages to improve their payoffs (Reagans, Zuckerman 2001). Also, sustaining relations incurs a cost

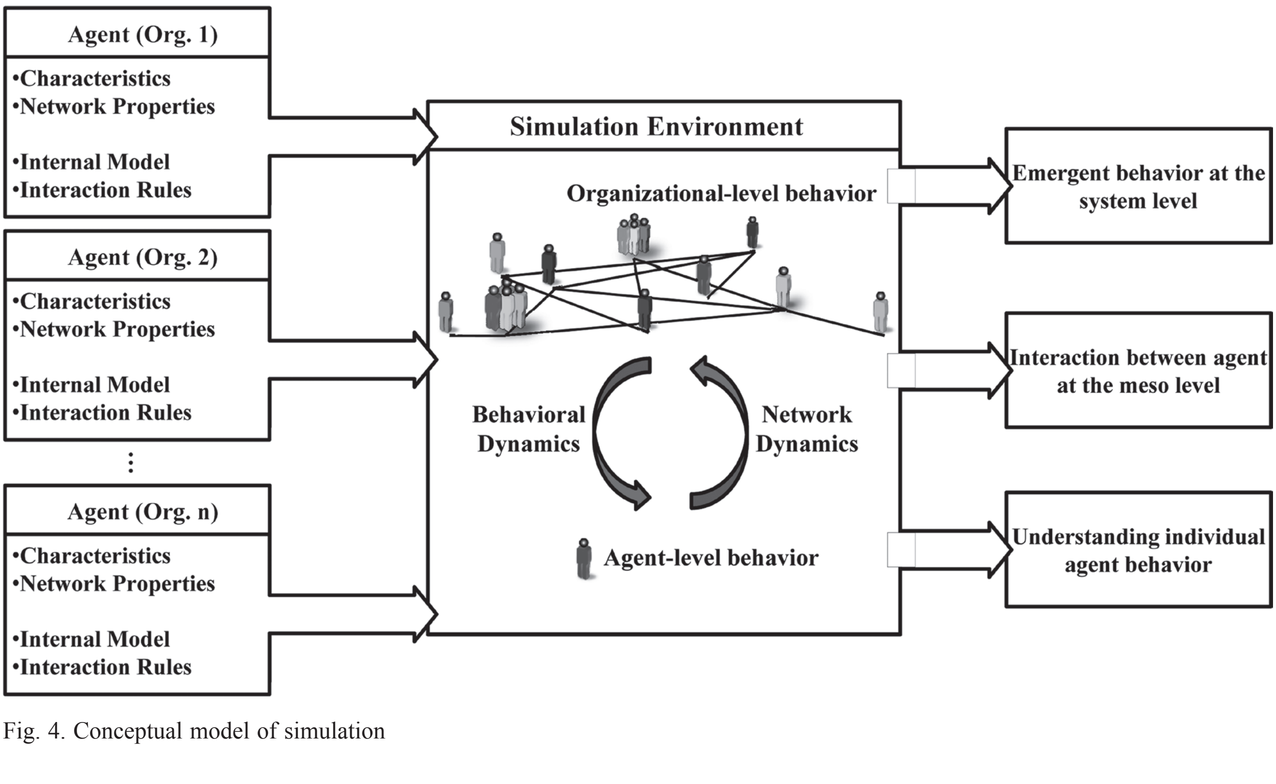

Fig. 4. Conceptual model of simulation

proportional to the number of relations that agents have. The maintenance cost for *within relations* (*within cost)* is assumed to be lower than that for *between relations* (*between cost*).

When meeting new candidate partners, agents compare payoffs of all possible combinations of relations in a network at the next time step and choose the best option available. However, agents cannot have infinite relations, due to limited cognitive capability. Therefore, in this model, it is assumed that the maximum number of partners that agents concurrently collaborate with is limited to three.

Behavioral dynamics of agents and overall network dynamics co-evolve, while interacting with each other. In particular, the properties of the whole network emerge from the goal-seeking behaviors of distributed agents in order to accomplish maximum payoff; while the agents' behaviors are constrained by structural configurations of the network. Unlike a traditional perspective in economics and social network study, where one of these two are regarded as an exogenous factor, the network dynamics are endogenized in agents' strategic behaviors in this study. After some time period, a network reaches a state where no additional relations are formed or severed; this state is called a stable state.

4.3. Implementation

The simulation is implemented using Java programming language in Eclipse, an integrated development environment (http://www.eclipse.org) (Fig. 5).

4.4. Experiments and results

It is assumed that there are two types of agents that can be thought of as two different organizations in project teams, such as an architecture firm and a general contractor. The total number of agents (n) in the game is 100. The values to describe personality and model parameters, such as sociability and familiarity, are initialized as discrete number and appropriate distributions. A simulation runs for 200 time steps, and is repeated 100 times for each setting.

As the simulation progresses, agents start looking for partners, and thereby relations among agents are created. A majority of ordinary agents form relations with partners in several time steps in a way that they increase payoff, and ultimately achieve maximum payoff. For ex-

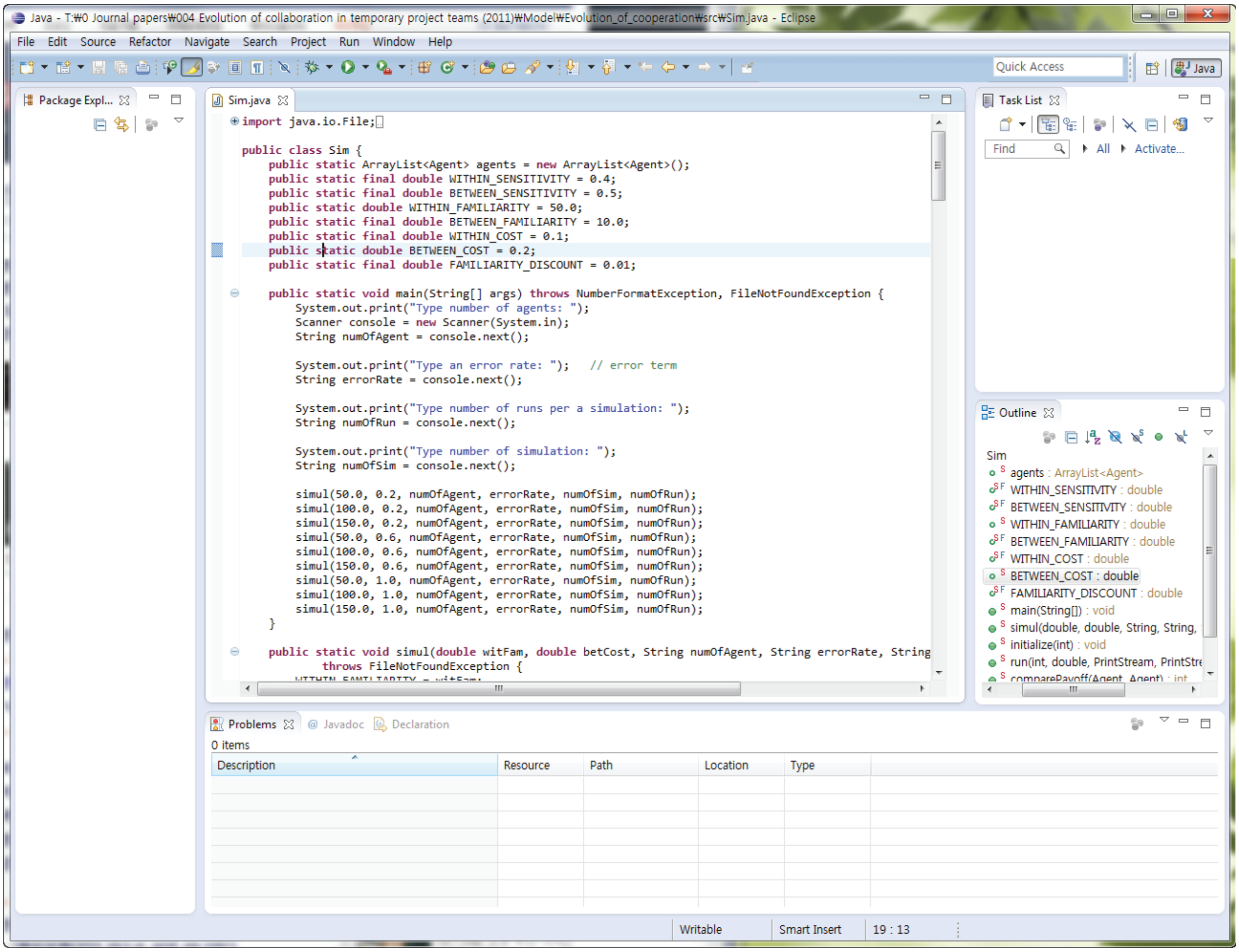

Fig. 5. Simulation implementation

ample, agent 9 accomplished maximum payoff by forming relations with agents 81, 79, and 35 at time 4, 6, and 9, respectively, in the case of *within familiarity* of 50 and *between cost* of 1.0. In the meantime, sociable agents quickly and more frequently join the partner searching process, while less sociable agents are reluctant to participate. Accordingly, sociable agents begin to achieve higher payoff right after a simulation gets started, and also achieve maximum payoff earlier. To illustrate, agent 17 formed a relation at each first three time step, and attained maximum payoff at time 3. On the contrary, agent 29's network development was delayed. It is not until time 19 that agent 29 formed a first relation, and he attained maximum payoff at time 23 (Fig. 6).

While sociable agents quickly and more frequently join the partner searching process, less sociable agents are reluctant to participate. Accordingly, sociable agents begin to achieve higher payoff right after a simulation gets started. For instance, in a simulation with *within familiarity* of 50 and *between cost* of 0.2, the network unfolds as shown in the sociograms shown in Figure 7. At time 1, only 37 agents who are mostly sociable get a partner, and thus they achieve higher payoff [1.2182] than those who do not have a partner [1.0]. Among them, agents who maintain a higher *between familiarity* show a higher payoff [1.2195] by forming a *between relation,* than those who have a *within relation* [1.2142]. Beyond time 16, when agents have the highest number of *within relations*, 1.8603, a tendency arises to replace *within relations* with more beneficial *between relations* through random social contact. Consequently, at time 38, agents have the number of *between relations*, 1.5009, which is equivalent to the number of *between relations*, 1.4971. Then, the network reaches a stable state at around time 92, where all agents attain the maximum payoff [2.2319].

Due to the effect of different *between cost*, the networks come to have remarkably different characteristics. It is noteworthy that the higher the *between cost*, the stronger the tendency of cohesion. In particular, the clustering coefficient increases as the *between cost* gets higher, which implies that local neighborhoods in networks with higher *between cost* are denser than others, and thus there seems to be a stronger tendency to form local cohesive subgroups. Also, networks differ in diameter and average distance; while those values in networks with *between cost* 0.2 and 0.6 are almost equivalent, networks with *between cost* 1.0 exhibit bigger diameter and longer distance. The outcomes represent the fact that overly high *between cost* prevents agents

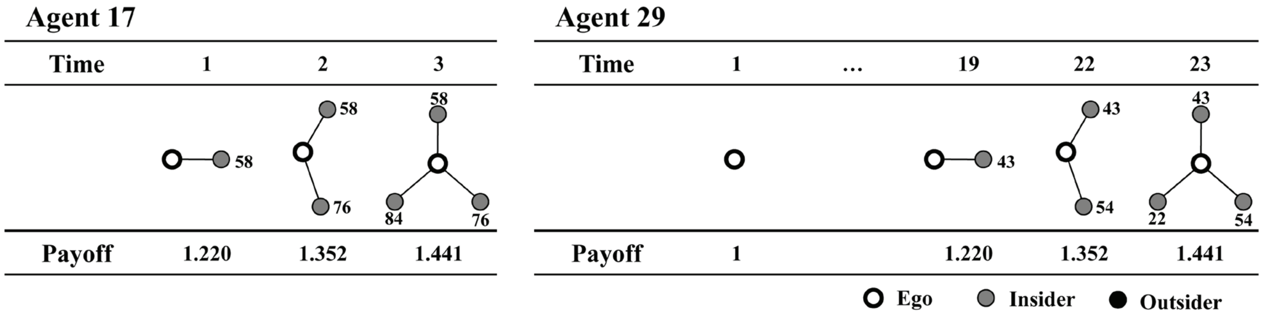

Fig. 6. Individual network development

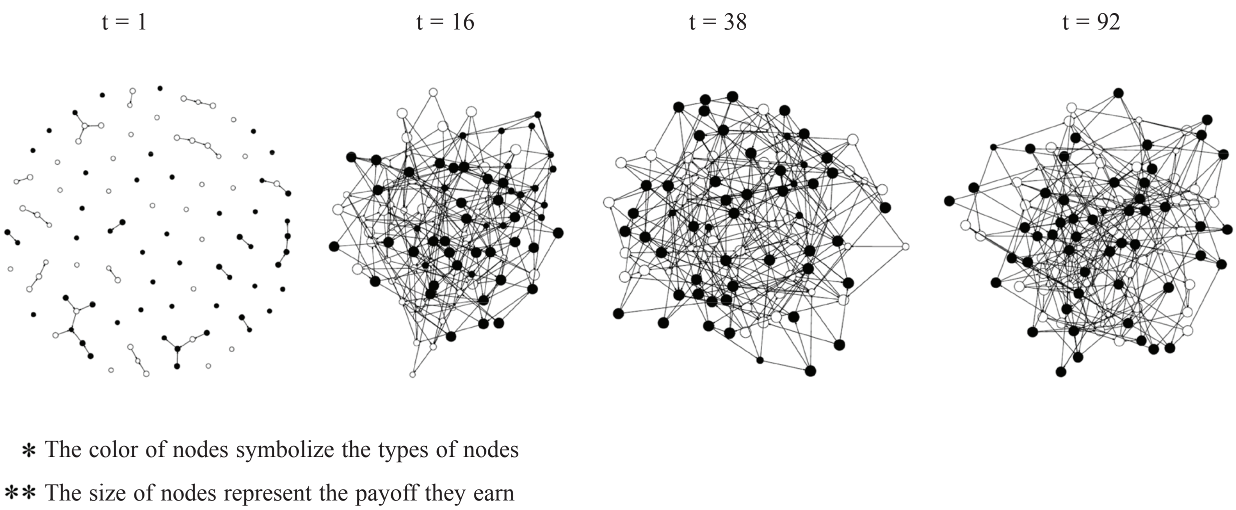

Fig. 7. Evolution of network (within familiarity: 50, between cost: 0.2)

from having *between relations* by fully offsetting the advantage of having *between relations,* whereas moderate *between cost* partially cancels the advantage. The resulting subgroups are visually illustrated in Figure 8.

4.5. Validation

Agent behavior and interaction mechanisms in this research represent real life as closely as possible, in the sense that they are grounded in theories in experimental game theory studies and findings in sociology and economics, such as a production function model (Cobb, Douglas 1928), collaboration (Reagans, Zuckerman 2001), and maintenance cost (Jackson, Wolinsky 1996). In addition, the model is tested with comprehensive sets of plausible variables to see whether they change model results in useful and confident ways to the model purpose – sensitivity analysis. The change in variables changes the numerical values of the results (numerical sensitivity), and the patterns of the model behavior (behavior mode sensitivity).

5. ABMS application for CEM research

In the model of the evolution of collaboration, knowledge creation processes in project teams are modeled and simulated using the ABMS approach. The behaviors of individual team members who are autonomous, goal-directed, and situated in networks are abstracted, and interaction rules among individuals are defined. Consequently, several findings were brought out, while taking advantage of the modeling potential of ABMS, which are embodied in the example. These are summarized in Table 4.

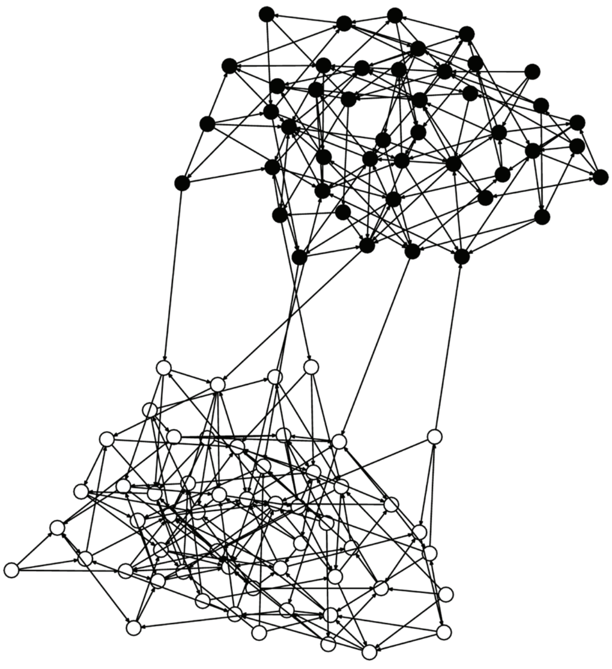

Fig. 8. Sociograms of cohesive subgroups

As in the illustrative example, CEM research can also make use of the unique features and advantages of ABMS to make its research processes and results much more useful. This would especially be the case when they are studying systems that have the properties of complex system explained earlier, such as aggregation, nonlinearity, flow, and diversity – e.g. production systems, construction processes, and project organizations. In the next paragraphs, research subjects in the CEM area that are expected to offer the most promise to apply ABMS as a research method are recommended.

First, a system that involves multi-human or multi-organization decision-making in its transition, and where relations among them are significant factors determining system states, could be effectively investigated with the ABMS approach. Decision-making in the construction industry in general requires extensive information exchange and sharing, communication, and coordination among stakeholders. Also, a decision made by one side would influence a decision to be made by another party, and vice versa. The resultant state of the system would be shaped by how they interact with each other in the global environment, as well as by each individual's decisions. For instance, whether the international construction market grows and shrinks at the macro level emerges from decisions on investment and consumption made by related parities, such as countries and firms at the micro level. They make an effort to obtain as much information as possible via all available sources, in order to make a perfect decision: they are only able to get partial information. In turn, their decisions and updated market information also influence other parties' decisions. International construction market research has been studied through statistical data analysis (Crosthwaite 2000), and by developing a theoretical framework (Ofori 2003). We believe that applying ABMS to subjects in this category – including project organization, knowledge network, learning organization, collective intelligence, and international construction – could considerably contribute to improving our understanding of them.

Next, complex production systems and supply chains in the construction industry could be effectively modeled with ABMS, in the sense that they have distinct properties of complex systems. Heterogeneous members in the production system and supply chain consist of whole networks, where they behave as autonomous agents. The performance of production systems and supply chains arises as the outcome of local interactions among companies, which have limited knowledge of the whole system. In these regards, ABMS has been used in manufacturing to study supply chains (Kaihara 2003; Van der Zee, Van der Vorst 2005). However, the main approaches to study supply chains in construction have been in developing the supply chain management system (Tserng *et al*. 2006; Polat *et al*. 2007) and the performance evaluation matrix (Meng *et al*. 2011). Considering that the main advantage of applying ABMS is multi-level analysis through realistic

Table 4. Modeling potential embodied in the example

Modeling potential	Example
Descriptive realism/Process-oriented	Agents are mapped onto corresponding entities in the target system, project team members. Agents' properties, behaviors, and processes of interactions with other agents and the environment are expressed with mathematical and computational formalisms. This enabled the construction of a model that can be more naturally understood, tested, and expanded, which might not be possible with equation-based approaches.
Constructive/Self-organizing/scalable	The simulation was constructed by defining an agent, and by adding as many agents to the system as was desired. The system behavior emerged from interactions among agents at the micro level, rather than from abstracting system properties. This unique characteristic of ABMS provides ways to understand the target system from the bottom-up.
Precision and flexibility	Since computational or mathematical formalism, or both, were selectively employed as needed to develop the simulation, a variety of agents' behaviors were able to be captured.
Relevance and reliability	The ABMS approach enabled the building of a computational model of project teams, without the loss of relevance to the target system, due to its descriptive realism.
Recoverable and repeatable	Whenever detecting anomalies, the simulation was refined through debugging processes. This facilitated the development process, and helped to verify the model. The completed model was executed as many times as required, with different parameters and settings, in order to obtain multiple observations on a system.
Greater contingency in inference	The simulation runs ended up with a great diversity of networks because of the unique characteristics of ABMS, such as indeterminism, path-dependence, and emergence. Besides, it produced unexpected behaviors; for example, the occurrence of cohesive subgroups, and delayed network development. Therefore, examining each single run was required, to understand what was happening in each.
Multi-level analysis	It was able to identify the behavior of distinct levels of network in the simulation. The behavioral dynamics of each individual agent was observed, and at the same time the overall network dynamics, which emerged from the interactions among agents at the lower level, were obtained.
Adaptive and bounded rational agent	Bounded rational behaviors of agents are incorporated in the simulation. This enhances the credibility of the results, as well as the explanatory power of the model. In particular, agents could not achieve maximum probable payoff in all cases. A primary reason for failing to accomplish maximum probable payoff is their inability to recognize the whole network and the mutational actions – this is not included in this paper; for further detail refer to Son and Rojas (2011).
Heterogeneous agent	Agents, of which each has a different set of properties, are incorporated. This also significantly enhances the explanatory power of the model.

and relevant representation of system components from the bottom-up, it could help managers make better and timely decisions in complex production systems and supply chain management.

Last, disaster response and recovery in urban areas is characterized by complex, dynamic, massive, and unfamiliar work demands, occurring in a widely distributed area. The participation of numerous responders from multiple organizations, such as firefighters, policemen, medical personnel, and government employees, who have different traits, such as role, function, protocol, and work procedure, is required. They need to collect, share, and process information regarding buildings and infrastructures, and communicate with each other during dynamic disaster response operations. The described characteristics of disaster response and recovery bear a close resemblance to those of complex systems. Naturally, ABMS becomes a legitimate approach that reflects all necessary aspects of disaster response and recovery, and thus is useful in developing and testing new response scheme and technologies. While existing research on disaster response and recovery has centered on fragmentary development, such as evacuation operations (Massaguer *et al*. 2006), logistics planning (Yi, Özdamar 2007), and sensor networks (Lorincz *et al*. 2004), ABMS is expected to be a virtual, comprehensive, and economically repeatable test-bed for disaster response and recovery, analogous to a flight simulator in the aviation industry.

Conclusions

As construction projects have become larger and more complex, it becomes difficult to understand them using traditional research approaches, due to the innate features of complex systems. In this study, we suggested ABMS as a complementary alternative to traditional research methods. The realistic viewpoint of ABMS toward complex systems, and its natural way to represent the dynamic behavior of complex systems, is expected to provide new ways of gaining insight and understanding of complex construction projects. How ABMS can be made practical use of in CEM research is explained, by presenting the theoretical background, a development process, and an application example. We then made a recommendation on the promising research subjects in CEM area to which ABMS could be suitably applied.

We concede that developing ABS might be costly, and more time-consuming than before. Researchers might also need to accept some of the drawbacks that ABMS has – e.g. data unavailability, difficulty of validation, lack of generality, causal spread, and greater subjectivity. Despite the expected disadvantages, we argue that ABMS, when applied to appropriate cases in a valid way, would produce useful information and valid insight on the system under study that would more than compensate for the additional investment.

Acknowledgements

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT and Future Planning (No. NRF-2013R1A1A1010562 and No. NRF-2013R1A2A2A04014772).

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