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AGENT-BASED SIMULATION OF ORGANIZATIONAL DYNAMICS IN CONSTRUCTION PROJECT TEAMS

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ABSTRACT: As construction projects have been getting larger and more complex, a single individual or organization cannot have complete knowledge or the abilities to handle all matters. Collaborative practices among heterogeneous individuals, which are temporarily congregated to carry out a project, are required in order to accomplish project objectives. These organizational knowledge creation processes of project teams should be understood from the active and dynamic viewpoint of how they create information and knowledge rather than from the passive and static input-process-output sequence. To this end, agent-based modeling and simulation which is built from the ground-up perspective can provide the most appropriate way to systematically investigate them. In this paper, agent-based modeling and simulation as a research method and a medium for representing theory is introduced. To illustrate, an agent-based simulation of the evolution of collaboration in large-scale project teams from a game theory and social network perspective is presented.

Keywords: Project Management; Organizations; Simulation Models

1. INTRODUCTION

Large-scale construction projects are so complex that the dynamic nature and nonlinearity underling their production processes are highlighted and they are considered a complex system (Bertelsen 2003). They cannot be completed by a single individual or organization with limited capacity and partial information, but by joint project teams temporarily constituted by scores of heterogeneous organizations. Accordingly, construction project teams need to be re-engineered and re-structured all over the life of a project as it progresses (Ballard 2005) so that they can cope with numerous interdependent tasks. The continuous organizational reengineering could take place through effective communication and coordination among stakeholders. However, teams in large-scale construction projects have not been very effective at being flexible and thus it is not unusual for them to fail. Unique organizational features of construction project teams have resulted in project failure such as cost overruns or schedule slippages which are becoming pandemic in large-scale projects (Morris and Hough 1987).

Nevertheless, current construction management practice does not properly reflect the organizational aspects of projects. *Optimism bias* regarding organizational issues can be broadly found throughout the construction industry, which could result in unrealistic baseline plans leading to negative performance in large-scale projects (Son and Rojas 2010).

Organizational dynamics in project teams should be examined from the active and dynamic viewpoint of how they create information and knowledge rather than from the passive and static input-process-output sequence derived from hierarchical information processing views (Nonaka 1994). However, the later has been the most adopted view in the construction management domain.

Based on these considerations, this paper introduces agent-based modeling and simulation (ABMS) as not only a research method for investigating project organizations as complex systems but also a medium for representing organizational theory. Then, an illustrative example of an agent-based simulation of the evolution of collaboration in large-scale project teams is presented.

2. BACKGROUND

2.1 Organizational Dynamics in Construction Projects

As construction projects have been getting larger and more complex, collaborative practices among project stakeholders have being found to have substantial impacts from the productivity of tasks at the operational level to overall project performance (Shelbourn et al. 2007). The reason for this is twofold. First, most project information that will influence performance is created during pre-construction. Second, such knowledge creation process involves continuous inter-personal and inter-organizational development processes (Fig. 1).

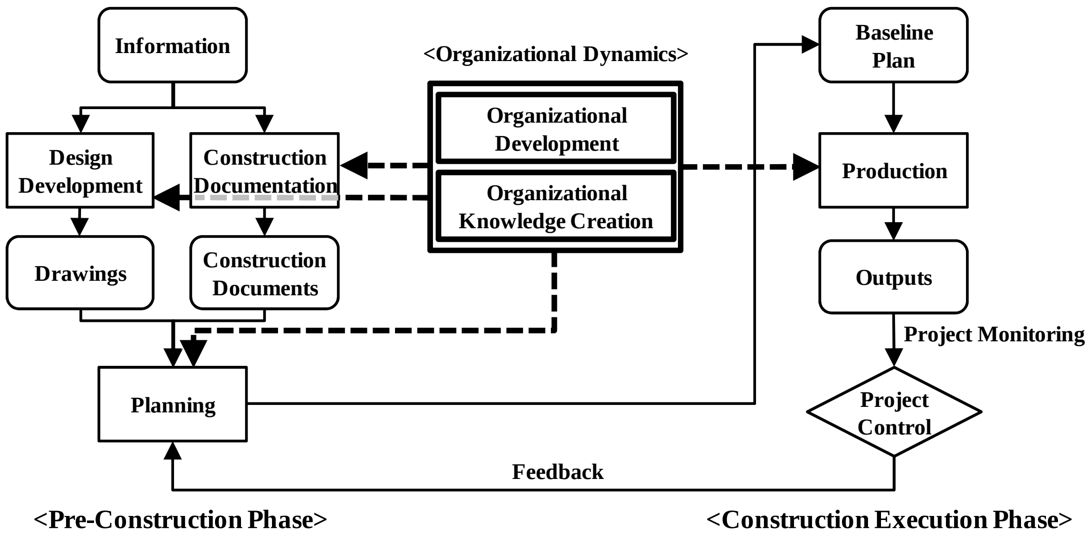


Fig. 1. The Influence of Organizational Dynamics on Construction Planning and Execution

Particularly, the majority of project-related information is generated during the design development phase and the construction documentation phase. The extent to which the information created accurately and comprehensively reflects project conditions results in overall project performance since occurrences of unplanned events such as change orders would result in schedule delays and additional expenses. Most importantly, the quality of information created is determined by how well organizational knowledge creation processes and organizational development processes are executed.

Nevertheless, current planning methods used in large-scale projects do not explicitly consider organizational and information-handling issues. Project planners are likely to have optimism bias for organization and information-handling issues without having explicit reasoning processes. Yet, the reality is often opposed to planners' delusions. People who have limited knowledge and incomplete information in complex large-scale projects often make fallacious decisions. Organizations which have different pieces of knowledge, experiences, goals, and protocols; frequently fail to communicate, share knowledge, and create a team atmosphere. Examples include architects' failure to identify all owners' needs, design professionals' overlooking design defects and conflicts, lack of constructability in design documents, unrealistic duration estimates and logical inconsistencies in an execution plan, an execution plan's disagreement with material delivery schedule, and lack of storage and equipment space.

In consequence, whereas current construction planning and control practices have served project managers for the purpose of preparing project proposals, managing resources, tracking delays and change orders, approving progress payments, and coordinating with subcontractors (El-Bibany 1997), they are not likely to retain sufficient plan reliability (Ballard 2000). Plan reliability refers to the extent to which planned schedule corresponds to the actual task execution. The more the actual operation of activities is consistent with the planned schedule, the higher the plan reliability. High plan reliability cannot be achieved when the schedule is developed through planners' estimation processes separated from operational reality, but when it is integrated with numerous factors in a explicit and systematic manner, which have influence on task productivity. Current construction planning practice; however, does not often secure sufficient plan reliability by overlooking the organizational and information-handling issues that are associated with many productivity factors.

2.2 Organizations as Complex Systems

Several researchers have put forward a new perspective that organizations should be understood as social organisms rather than mechanical systems (Burns and Stalker 1961; Morgan 1997). This *organic organization* perspective is underpinned by the fact that organizations are the entities which are born, grow, develop, decline, and die and they adapt to changing environment (Morgan 1997). Burns and Stalker (1961) have explained the characteristics of organic organizations by contrasting them with those of mechanistic organizations: whereas mechanistic organizations which are governed by top-down instructions in strict hierarchic relations may function the best in stable conditions, organic organizations which are coordinated by distributed lateral communication through various layers networks would fit best in dynamic environments. More differences between mechanistic and organic organizations are presented in Table 1.

The advocacy of the organic organization perspective has something to do with researchers' understanding 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 into simpler or more fundamental parts which systems are composed of, while positing that a whole system is nothing but the sum of its subsystems. Reductionism ignores the effect 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 a 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 - this kind of system is called complex system. Reductionist thinking may be very misleading when trying to understand complex system: even if we can fully uncover the micro-level foundations of behavior, we may still not have a simple way to understand their macro-level implications. Organic organization perspective can be thought of viewing organizations under unexpected and dynamic conditions as complex systems in the sense that it highlights local interactions among members, network characteristics, and emergent properties of organizations.

2.3 Agent-Based Modeling and Simulation

Agent-based modeling and simulation (ABMS) is a new approach to modeling complex systems. ABMS has recently become popular to investigate complex systems in many areas ranging from sociology, biology, and organizational study to economics, business, and military studies. Such increasing use of ABMS is primarily due to its realistic viewpoint of complex systems. Agent-based models are built from the ground-up perspective rather than from a top-down. In particular, developing agent-based models begins by defining agents – representations of individuals or groups - that are identifiable, situated in an environment, goal-directed, autonomous, and have the ability to learn and adapt (Macal and North 2005). This ground-up approach of ABMS is most appropriate to explore systematically collaborative working processes of project teams that are characterized by a high degree of localization and distribution and dominated by discrete decision (Van Dyke Parunak et al. 1998).

The goal in developing a theory is to make the world understandable by finding the right set of simplifications. Depending on domains, how theory is represented varies in terms of explanatory succinctness. In some cases, mathematical models may be most appropriate to represent the structures and the regularities of subjects. If mathematical modeling is not proper, verbal-conceptual models can be considered to describe entities, relations,

Table 1. Mechanistic vs. Organic Organizations (Burns and Stalker 1961)

	Mechanistic Organization	Organic Organization
Appropriate Conditions	*Stable* conditions	*Dynamic* conditions
Type of Corporation	The *specialized* differentiation of functional tasks	The *contributive* nature of special knowledge and experience
Nature of Individual Tasks	The abstract nature of each individual task, which is pursued with techniques and purposes more or less distinct from those of the concern as a whole	The 'realistic' nature of the individual task, which is seen as set by the total situation of the concern
Individual Task Scope Management	The *reconciliation* of these distinct performances by the immediate superiors	The adjustment and continual redefinition of individual tasks through *interaction* with others
Obligation and Rights	The precise definition of rights and obligations and technical methods attached to each functional role	The shedding of 'responsibility' as limited field of rights, obligations and methods
Responsibility	The translation of rights and obligations and methods into the responsibilities of a functional position	The spread of commitment to the concern beyond any technical definition
Organizational Structure	*Hierarchic* structure of control, authority, and communication	A *network* structure of control, authority, and communication
Organizational Knowledge	A reinforcement of the hierarchic structure by the location of knowledge of actualities exclusively at the *top of the hierarchy*	Technical and commercial knowledge may be *distributed* anywhere in the network
Communication Direction	A tendency for interaction between members of the concern to be *vertical*	A *lateral* communication between people of different rank
Management Type	A tendency for operations and working behavior to be governed by the *instructions* and *decisions* issued by superiors	A content of communication which consists of *information* and *advice*
Values	Insistence on loyalty to the concern and obedience to superiors	Commitment to the concern's tasks and to the "technological ethos" of material progress and expansion is more highly valued
Prestige	A greater importance and prestige attaching to internal than to general knowledge, experience, and skill	Importance and prestige attach to affiliations and expertise valid in the industrial and technical and commercial milieux external to the firm

and processes in rather informal languages.

However, large-scale construction projects and project organizations are so complex that the structure and the regularities cannot be expressed by a set of equations or verbal-conceptual models. In this case, computational modeling such as ABMS appears to be the most promising approach and it offers the flexibility and the expressive power that no other approach can match. In consequence, computational models constitute another language for scientific theorizing, somewhat different from either mathematical models or verbal–conceptual models. They can be used to theorize complex systems just as what mathematical models and verbal-conceptual models do for appropriate subjects.

As such, a computation model per se can become part of the theory. Particularly, agent-based modeling proceeds by abstracting the individual agents' properties and behavior in the system into simplified agents and then the system behavior will be emerged by allowing the agents to interact directly with one another using computation. When there is good computational representation of agents' properties and behavior in the simulation, it very much becomes part of the theory.

3. An Illustrative Example: A Model of the Evolution of Collaboration

On the extension of existing studies such as Jackson and Watts (2002), we have developed a game theory model of the evolution of collaboration in project teams of large-scale construction projects and implemented it using ABMS. Promising interdisciplinary research areas including ABMS, game theory, and social network analysis are explored to embody relevance to the target system, project teams.

Game theory is multi-personal interdependent decision theory in which strategic interactions among rational players determine their payoffs. Game theory has been used in many different areas entailing economics, biology, engineering, political science, computer science, and philosophy owing to its advantage of natural and plausible representation of economic, political, sociological, and psychological behaviors of entities. In general, a game is specified by a set of players, a set of possible strategies for each player, and payoffs as the result of their choosing a strategy. When a game plays, it is assumed that all players are rational, maximizing their payoffs, and reasoning strategically to take other players behaviors into account. However, conventional game theory has several limitations that preclude its application under dynamic conditions. Considering that cooperation processes in real life entail learning individuals with bounded rationality, interacting with other learning individuals in a dynamic environment, it seems that the assumptions of game theory need to be revised to accommodate collaborative processes in project teams. Several efforts have been undertaken to overcome the limitations of the conventional game theory. For instance, evolutionary game theory which focuses more on how players reach equilibrium than what the properties of equilibrium states are, has been studied in this regard (Weibull 1995). Furthermore, some have attempted to endogenize the effects of networks in the games (Jackson and Wolinsky 1996).

Social Network Analysis (SNA) is a set of techniques to help understand ecology of social networks by description, visualization, and statistical modeling (van Duijn and Vermunt 2006). A social network is considered a social structure composed of nodes that are connected by one or more specific types of relations such as friendships, firm alliances, and international trade. The traits of a social network can be represented using social network measures including density, diameter, average distance, centrality, and so on. In the last decades, several social network principles have been proposed to enhance the understanding on social phenomena including structural holes, structural equivalence, and cohesive subgroups.

3.1 Model Development

Project teams are viewed as dynamic information processing networks composed of members who are self-interest seeking and myopic to recognize whole networks. Team members, who are modeled as agents possessing individual characteristics such as sociability and familiarity 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.

In each time step t, agents participate in social interactions and meet a candidate partner and choose either to cooperate with or to defect from it. Whether agents cooperate or defect is determined by comparing between the current payoff and the potential payoff which they could achieve by forming a new relation with the candidate. The resulting payoffs are determined by Eq. 1.

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

Where u_i : the payoff of i

g_t : a network at time t

$\omega_{i,t}$: the number of within relations which i agent has at time t

$\beta_{i,t}$: the number of between relations which i agent has at time t

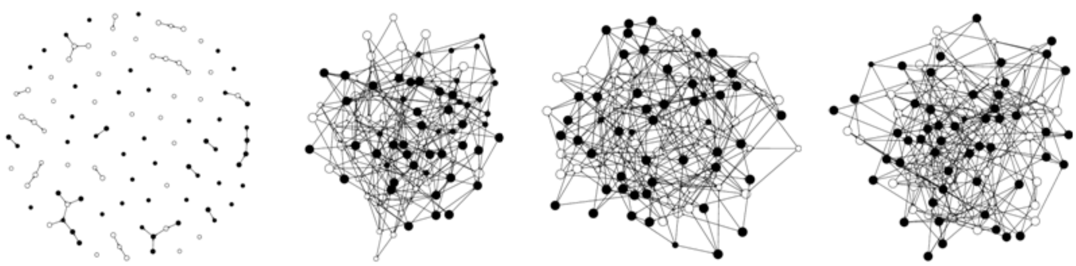
a : the elasticity of $\omega_{i,t}$ to payoff

b : the elasticity of $\beta_{i,t}$ 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 the synergistic effect and the cost to maintain relations. When agents have relations with outsiders as well as insiders at the same time, they end up with higher payoff than others who have relations only with outsiders or insiders. This is grounded in the fact that those who can access diverse task-related information and occupy powerful positions

t=1	t=16	t=38	t=92



# of Relations w/ Insiders*: 0.2438	1.8603	1.4971	1.2591
# of Relations w/ Outsiders*: 0.0829	0.9429	1.5009	1.7409
Payoff *: 1.0712	1.9292	2.166	2.2319

* The average value of 100 simulations
** The color of nodes symbolize the types of nodes
*** The size of nodes represent the payoff they earn

Fig. 3. The Evolution of Networks

connecting divided subgroups in networks could use positional advantages to improve their payoffs (Reagans and Zuckerman 2001)

After the goal-seeking behavior in each time step, mutational partner changes occur with the probability of mutation rate. Stochastic mutations in the network formation process may arise for a variety of reasons (Jackson and Watts 2002). Agents may make a mistake in evaluating payoffs, they may fail to sustain current partners due to the limit of time and the associated cost, or have only partial information and thus they may experimentally change a partner.

Behavioral dynamics of agents and overall network dynamics co-evolve, while interacting with each other (Fig. 2). Particularly, 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 is endogenized in agents' strategic behaviors in this study.

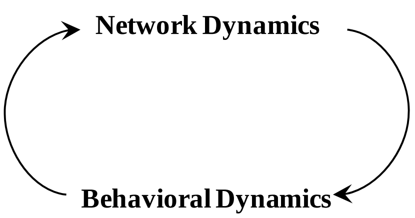


Fig. 2. The Execution

The simulation is implemented using Java programming language in Eclipse, an integrated development environment (http://www.eclipse.org). For brevity, 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 architect firm and a general contractor. The total number of agent (n) in the game is 100. Model parameters are specified. A simulation runs for 200 time steps and it is repeated 100 times for each setting.

3.2 Results

As the simulation progresses, agents start looking for partners and thereby relations among agents are created. 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, Fig. 3 exhibits a representative instance of the evolution of the networks. 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 higher between familiarity show 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 to replace within relations with more beneficial between relations through random social contact arises. Consequently, at time 38, agents have the number of between relations, 1.5009, which is equivalent of 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]. In addition, a tendency of forming local cohesive subgroups was identified. The higher cost an individual have to pay for having relations with outsiders, the stronger tendency of cohesive subgroups.

5. Conclusions

This paper introduces a complex systems perspective to understanding organizational dynamics in large-scale projects. Organizational dynamics cannot be understood by traditional approaches which are based on reductionism. We proposed the use of ABMS as an alternative and explained the strength of ABMS as a research method and a medium for representing theory. Besides, we presented an agent-based simulation of the evolution of collaboration within inter-organization networks in large-scale construction projects, as an illustrative example of ABMS. We were able to achieve the modeling potential of ABMS such as descriptive realism and high relevance to target systems.

REFERENCES

[1] Ballard, G. (2000). "The Last Planner™ System of Production Control," Doctoral dissertation, The University of Birmingham, Birmingham, UK.

[2] Ballard, G. (2005). "Construction: one type of project production system." *Proc., The 13th International Group for Lean Construction (IGLC) Conference*, Sydney.

[3] Bertelsen, S. (2003). "Construction as a complex system." *Proc., 11th Annual Meeting of the International Group for Lean Construction*, Blacksburg, Virginia.

[4] Burns, T., and Stalker, G. (1961). "Mechanistic and organic systems of management." *The management of innovatioon*, Tavistock, London, 96-125.

[5] El-Bibany, H. (1997). "Parametric Constraint Management in Planning and Scheduling: Computational Basis." *Journal of Construction Engineering and Management*, 123(3), 348-353.

[6] Jackson, M. O., and Watts, A. (2002). "The evolution of social and economic networks." *Journal of Economic Theory*, 106(2), 265-295.

[7] Jackson, M. O., and Wolinsky, A. (1996). "A Strategic Model of Social and Economic Networks." *Journal of Economic Theory*, 71(1), 44-74.

[8] Macal, C. M., and North, M. J. (2005). "Tutorial on agent-based modeling and simulation." *Proc., Winter Simulation Conference*, 2-15.

[9] Morgan, G. (1997). *Images of organization*, Sage Publications, Thousand Oaks, Calif.

[10] Morris, P. W. G., and Hough, G. H. (1987). *The anatomy of major projects : a study of the reality of project management*, Wiley, New York.

[11] Nonaka, I. (1994). "A Dynamic Theory of Organizational Knowledge Creation." *Organization Science*, 5(1), 14-37.

[12] Reagans, R., and Zuckerman, E. W. (2001). "Networks, Diversity, and Productivity: The Social Capital of Corporate R&D Teams." *Organization Science*, 12(4), 502-517.

[13] Shelbourn, M., Bouchlaghem, N. M., Anumba, C., and Carrillo, P. (2007). "Planning and implementation of effective collaboration in construction projects." *Construction Innovation: Information, Process, Management*, 7(4), 357-377.

[14] Son, J., and Rojas, E. M. (2010). "The impact of optimism bias regarding organizational dynamics on project planning and control." *Journal of Construction Engineering and Management*, (Posted ahead of print at: http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000260, July 2010).

[15] van Duijn, M. A. J., and Vermunt, J. K. (2006). "What Is Special About Social Network Analysis?" *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, 2(1), 2-6.

[16] Van Dyke Parunak, H., Savit, R., and Riolo, R. L. (1998). "Agent-Based Modeling vs. Equation-Based Modeling: A Case Study and Users' Guide." *Multi-Agent Systems and Agent-Based Simulation*, Springer, Berlin/Heidelberg, 10-25.

[17] Weibull, J. W. (1995). *Evolutionary game theory*, MIT Press, Cambridge, Mass.