01 Jan 2003

Emergence and Artificial Life

Nil H. Kilicay

Cihan H. Dagli
Missouri University of Science and Technology, dagli@mst.edu

Recommended Citation

N. H. Kilicay and C. H. Dagli, "Emergence and Artificial Life," *Proceedings of the Engineering Management Conference, 2003. IEMC '03. Managing Technologically Driven Organizations: The Human Side of Innovation and Change*, Institute of Electrical and Electronics Engineers (IEEE), Jan 2003.
The definitive version is available at https://doi.org/10.1109/IEMC.2003.1252340

Emergence and Artificial Life

Nil H. Kilicay
Engineering Management Dept., University of Missouri-Rolla, Rolla, MO, USA
email nkilicay@umr.edu

Cihan H. Dagli
Engineering Management Dept., University of Missouri-Rolla, Rolla, MO, USA
email dagli@umr.edu

Abstract

The study of complex systems provides powerful tools and concepts for analysis of information about the world. For example, the process of technology innovation and diffusion, group dynamics, culture, communication in the global enterprise, change management and many other concepts crucial to today's important management decisions in technology-driven organizations display emergence and a dynamics shaped by local interactions of individuals with imperfect information. Besides, creative processes that lead to innovation result from generation of new combination of interactions. The interesting and counterintuitive characteristic of complex systems, emergence, is of interest for this paper.

Emergent phenomena result from the local interactions among many individuals. Individuals not only differ in their characteristics but they also evolve over time resulting in unanticipated behaviors to emerge. Therefore, human social systems exhibit emergent behavior as well as react to emergent behavior. The phenomena can not be reduced to the system's parts because of the interactions between the parts. This characteristic of the emergent phenomena makes them difficult to understand and predict and is a challenge for scientists. Many of the problems ranging from the control of economies to understanding consciousness involve emergent phenomena and most of the time emergence can be seen as an impassable barrier. Understanding emergence has been mostly through using heuristics which is a vague and unsatisfying method. Using analytical methods that focus on averages or system equilibriums are also not suitable for studying emergent patterns. Model building is the most important tool in the study of emergence. Unfortunately, tools for building effective models that represent complex systems are limited because small body of mathematics deals directly with nonlinearity.

A growing number of scientists, dissatisfied with the traditional methodologies are seeking new methods for exploring the complexities of human system dynamics. One of the developments is the use of agent-based modeling and simulation to examine how emergent phenomena are created and maintained. These models, diverse in their applications and approaches attempt to create micro worlds or commonly called artificial life to understand real complex systems' dynamics and emergent phenomena arising from them.

Agent-based modeling is a computational methodology that allows the analyst to model and simulate the behavior of system' units mainly called agents, their interactions with other agents and interactions with their environment and captures the emergent behavior from the bottom up. It can incorporate neural networks, evolutionary algorithms and other learning techniques to allow a more realistic representation of learning and adaptation of agents. This nature of Agent-based modeling makes it a suitable method for modeling and simulating emergent phenomena and human systems. Agent-based models and artificial life experiments are becoming the center stage in the effort for understanding the emergent behavior of groups, organizations, cities and nations.

This paper focuses on emergent phenomena and the utilization of computer simulations, basically agent-based modeling to understand emergent phenomena. Agent-based simulation models have a promising future in the social sciences, from management to economics, political science, sociology and anthropology. This paper attempts to realize their full scientific potential by reviewing recent applications in engineering management and addresses the set of challenges confronted by this method. Common methodology for constructing an agent-based model is also discussed with the aim of highlighting how artificial life and management can be brought together to develop decision making aid tools.

Keywords

Management of complex systems, emergence, adaptive agent-based models

INTRODUCTION

Patterns can be observed in every aspect of the life. Emergent patterns rise in everywhere from ant colonies, the Internet, the global economy to network of neurons. A simple observation is that large scale patterns that we encounter in our lives are usually the result of interactions of large number of smaller pieces that combine in surprisingly ways to create large scale patterns. Phenomena that emerge from interactions at a lower level or scale are called emergent phenomena. Complex adaptive systems exhibit emergence. In these systems behavior of the whole is much more complex than the behavior of the parts [6]. Sudden appearance of new patterns and dynamic behaviors within complex systems are complicated to understand and predict by looking only at deterministic interactions of the system's units.

Model building is the most important tool in the study of emergence. One of the developments in model building is the use of agent-based modeling and simulation to examine complex adaptive systems. These models aim to create micro worlds or commonly called artificial life to understand real complex systems' dynamics and emergent phenomena arising from them.

This paper will first focus on emergence where order forms out of local interactions. Then it will continue by focusing on why agent based modeling is preferred over other modeling methods, will provide an outline commonly used for building agent based models and will briefly review some applications related to engineering management. The paper will conclude by criticizing the drawbacks of this new modeling method and will highlight the effect of artificial life experiments on future management problems.

EMERGENCE

Emergence is one of the characteristics of a complex system where new and coherent structures, patterns in a complex system are derived due to interactions between the elements of the system over time [3]. Flock of birds flying in the sky, colony of ants carrying food or audience clapping in a stadium are simple examples that show patterns of emergence. Emergence can be observed in systems with well understood components as well as in systems with few clearly defined rules such as ethical systems, spread of knowledge in organizational systems, etc. In both types of systems small numbers of rules or laws generate systems of surprisingly complexity [6]. The complexity rises not just because of the complex random patterns but because of simple interactions among participants in the system.

Holland [6] provides an outline of the characteristics of emergence:

- Emergence occurs in systems composed of small components that obey simple laws.
- The interactions between the parts are nonlinear so the overall behavior cannot be predicted by summing the behaviors of the isolated components. Therefore the famous definition "The whole is more than the sum of the parts" holds for these systems.
- The context in which emergent pattern is embedded determines its function. Well defined system architecture is preserved over time but its function changes according to context. This dynamic changing that makes it hard to induce emergent phenomena.
- Complexity of the system increases as the number of interactions increase.
- Persistent patterns always satisfy macro laws.

Most of the tools used by experts to analyze complex systems and emergence are not effective enough. Recent computational modeling tools are being developed for scientists to explore systems of many interacting parts that can exhibit emergent behavior. Next section focuses on the characteristics of the new modeling method used to create artificial worlds to analyze and understand complex systems.

ARTIFICIAL LIFE

Model building is the most important tool in the study of emergence. The critical steps in constructing a model are selection of salient features and the laws governing the model's behavior. Emergence and innovation cannot be understood without models. Unfortunately, tools for building effective models that represent complex systems are limited because small body of mathematics deals directly with nonlinearity. Almost all the well established tools of mathematics, partial differential equations, probability theory are built on assumptions of linearity, homogeneity, normality and stationary. Computer based models and simulations deal regularly with nonlinearity. They have the rigor of mathematical models without the generality while allowing the selection and repeatability of good critical experiments without the enforced connection to reality. In social sciences computer simulation may allow more aggressive exploration of the implications of imperfect rationality, the effects of learning and information and social and institutional structure. Therefore, currently computer models are the main tools for understanding of emergence.

In particular agent based models and genetic algorithms are powerful and fascinating computer simulations increasingly used to observe and understand emergent phenomena in diverse settings.

Compared to other modeling techniques ABM provides a natural description and formalism for social science. Global patterns emerge from the bottom-up by the local interactions of autonomous agents. Agents are self-organizing that is agents interact without a central authority or direction. Therefore, once the agent types, their interactions with other agents and their environment are modeled an artificial word representing real life problems can be architected to be used as decision making aid tools. ABM is used in a wide variety of domains. Four main areas related to engineering management where emergent patterns can arise and ABM is used are [3]:

- Flow: evacuation, traffic, super markets
- Diffusion: diffusion of innovation and adaptation dynamics
- Organization: organizational design, organizational learning, operational risk
- Markets: stock market, electronic auctions, ISP market

For example fire escape situation in a confined place is created using ABM [3] in order to find a solution for increasing outflow. Counter intuitively by changing the conditions of this artificial situation it is found out that placing a column just behind the exit increased the outflow. Similarly ABM is used to mimic traveling and driving behavior of real people on a transportation network. This artificial world is used to analyze how changes in transportation policy might affect activities and trips. An artificial theme park is created [3] to analyze the waiting time of customers at an attraction. ABM is used to find strategic solutions for reducing inventory and out-of stock problems [10]. The effect of regularity changes on the financial market under various conditions, the effect of short and long term memory traders on the financial market are some cases where artificial worlds are created for analysis and strategy building in financial markets[7]. Innovation arises from the local interactions thus ABM is used to understand the dynamics of the diffusion of innovation [3]. These studies show how ABM can be used as an effective decision making aid tool for managers.

BUILDING ABMS

A generic methodology can be used to construct agent based models. After analyzing the fitness of the application area for agent based modeling the researchers can start by defining the objective and scope of the design such as defining the problem. Then the next step is identifying the agents of the system. Agent's independent behavioral rules, their interaction with other agents and their interaction with their environment are drawn out of observational studies. Once the agents' characteristics are profiled, related algorithms for coding are selected and programmed. The programming incorporates evolutionary learning, neural networks, and adaptation mechanisms into the model. Then the simulation is run for a specified time and common characteristics are identified in order to find out emergent phenomena. At this point it is important that system parameters are calibrated and validated using empirical data or power laws. Then simulation process is backtracked in order to identify the agent behavior that generates emergent phenomena. This will allow the modeler to observe the effect of emergent phenomenon on agent behavior since human systems exhibit emergence as well as react to emergent phenomenon. This study will allow the researcher to derive correlations between the emergent phenomenon and individual agent behavior which will lead to strategy building for researchers. The final strategy can be focused on agent behavior, agent interaction or environment. Agent based modeling brings out the effect of agents on generation of emergence but also the effect of emergence on agent behavior comprehensively. Figure 1 outlines the generic methodology of designing an agent-based model.

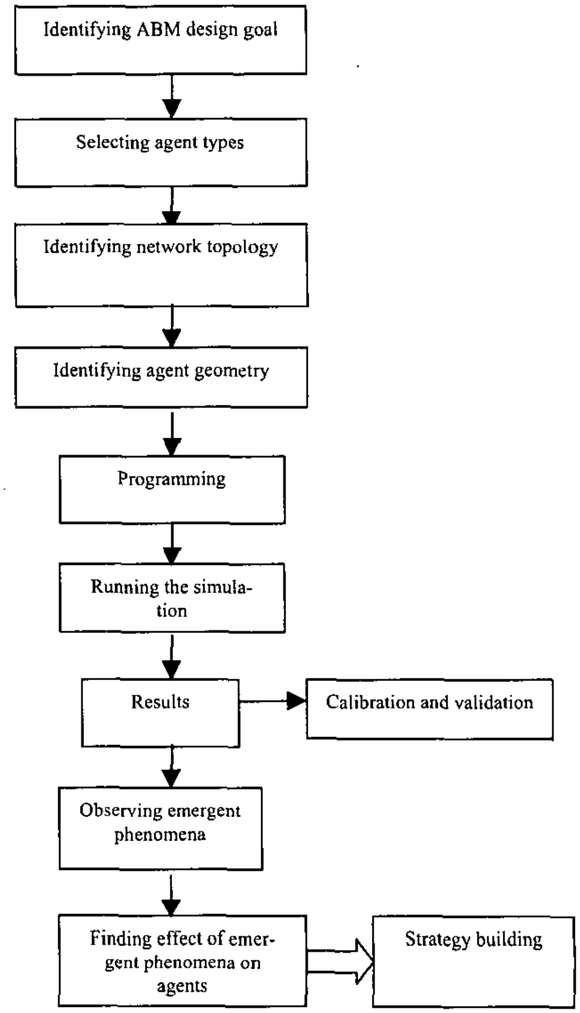

Figure 1. Designing an ABM

Results of agent based models differ depending on the model designs. Conflicting results emerge because of different design methodologies [8]. Global or local interaction, elective or interaction forced tie formation, evolution or learning based adaptation, prediction or analyses based design are some of the parameters that makes differing artificial lives and thus differing results. Table 1 summarizes these design features that affect simulation results.

Table 1. Model design features and types

ABM's design goal			
testing predicted differences		testing robustness	
agent level parameters	population level parameters		
Interaction type			
global		local	
		spatial network	social network
Tie formation			
elective by movement		interaction forced	
Adaptation			
learning		evolution	
imitating other agents	agent behavior	competition for survival	social influence

ABMs have a promising future but there are some potential drawbacks that a modeler should be aware of. Results obtained from agent-based simulations should not vary as the critical set of assumptions, parameters changes. System size, agent geometry, network topology, time calibration, phenomenological calibration, structural stability, power laws are such set of assumptions and parameters that a modeler should ask questions about [4]. Whether changes in the number of interacting agents have an effect on simulation results or not should be considered by conducting sensitivity analyses of the results with respect to system size. Agent geometry defines the number of interaction opportunities and affects the simulation results. Therefore, agent geometry should be selected so that it is closer to referent geometry while balancing not to lose system simplicity. It is likely that interaction structure between agents (network topology) have some effect on resulting processes and emergent behavior. It is also important to determine the equivalence of one simulation run in terms of a physical calendar time such as hours, days, years, etc. This can be achieved by using empirical statistics of duration or empirical frequency of related phenomena. Also magnitude of phenomena in agent-based simulation results should be calibrated using empirical observations. Empirical social processes organize themselves as power laws. These laws such as Pareto's law of income, Richardson's law of war can be used to validate agent-based simulations. However, to what extent power laws are present in the emergent behavior of agent-based simulations can be discussed as to the reliability of this validation method.

Sensitivity of decision rules, selection criteria for initial conditions, types of random distributions also affect the emergent patterns in the model. These are some of the factors that affect results of the simulation and the modeler should take into consideration while architecting the artificial system.

CONCLUSION

Creating artificial worlds using agent based modeling is a new tool for analyzing emergent phenomena and complex systems at the relational level. This methodology has a promising future because it is a bridge between rigorous mathematical tools and experimental studies. It allows us to understand the relationship between micro and macro level behavior generated by complex systems. However, agent based models are highly abstract and this derives a confusion about the appropriate standards for constructing and evaluating agent based computational models. Therefore future research should focus on finding common standards for building agent based models. Many researchers remain highly skeptical about the validity of agent-based simulation results when computational models are used for theoretical exploration rather than empirical prediction. Validation is a major challenge for ABM because emergent phenomena will change based on the input characteristics of the agents and their interactions. Therefore different assumptions in the design phase will affect the results and emergence of the model. Currently, real life data and heuristics are used to validate such models. Future research should focus on finding more robust validation methods for models where there is not a chance to obtain real data. This can increase the value of agent based modeling for managers to test different scenarios and observe the affect of their decisions on the complex systems they manage. If ABM is to achieve its potential there are topics that need to be addressed such as case loading, uncertainty analysis, calibration of models to data, methodologies for using models to answer specific questions or to solve problems.

As discussed in this paper ABMs have the power to demonstrate emergent phenomena. However, computer graphics and attractive demonstrations are found enough to show that emergence is observed at a system. Human observers declare emergence have occurred based on graphical computer outputs. Quantitative tests should also be developed to show the emergent behavior of systems. This will advance and increase confidence in agent based modeling.

For all simulation models including agent based models, the famous systems architecting KISS (keep it simple, stupid!) rule applies. Making agents more cognitively sophisticated results in models that are so complex that they are as difficult to interpret as natural phenomena. Therefore, modeler should be careful in selecting the necessary elements of the system for modeling. Otherwise, researchers will undermine the value of simulation. Modelers should not rely only on biological metaphors and should test the robustness of their model. As this computational technique advances artificial life experiments will be a usual part of engineering management as a reliable tool.

REFERENCES

[1] Axtell R. L., Epstein J. M., *Growing Artificial Societies: Science from the Bottom-up*, MIT Press, 1996

[2] Berry B., Kiel L., Elliott E., *Adaptive agents, intelligence, and emergent human organization: Capturing complexity through agent-based modeling*, Proceedings of the National Academy of Sciences, (2002), Vol.99

[3] Bobabeau E., *Agent based Modeling: Methods and techniques for Simulating Human Systems,* Proceedings of the National Academy of Sciences, (2002), Vol.99

[4] Cioffi-Revilla C., *Invariance and universality in social agent-based simulations*, Proceedings of the National Academy of Sciences, (2002), Vol.99

[5] Gilbert N., Troitzsch K. G., *Simulation for the Social Scientist*, Open University Press, (1999)

[6] Holland J. H., *Emergence*, Addison-Wesley (1997)

[7] Lempert R., *A new decision sciences for complex systems,* Proceedings of the National Academy of Sciences, (2002), Vol.99

[8] Macy M. W., Willer R., *From Factors to Actors: Computational Sociology and Agent-Based Modeling,* Annual Review of Sociology, (2002), Vol.28

[9] Pavard B., Dugdale J., *An Introduction to Complexity in Social Science,* http://www.irit.fr/COSI/training/complexity-tutorial/complexity-tutorial.htm

[10] Siebel F., Kellam L., *The Virtual World of Agent-based Modeling: Procter &Gamble's Dynamic Supply Chain,* http://community.cgrey.com/focus/fcd/Technology15/en_index.jsp