On the Relationship between Model Complexity and Decision Support in Agent-based Modeling and Simulation

Ruhollah Jamali[1*], Sanja Lazarova-Molnar[2, 1]

[1]Maersk Mc-Kinney Moller Institute, University of Southern Denmark
5230 Odense, Denmark; *ruja@mmmi.sdu.dk

[2]Institute of Applied Informatics and Formal Description Methods
Karlsruhe Institute of Technology, 76133 Karlsruhe, Germany

SNE 34(3), 2024, 177-180, DOI: 10.11128/sne.34.sn.10702
Selected EUROSIM 2023 Proceedings Publication: 2024-06-18
Received Rev. Improved: 2024-08-08; Accepted: 2024-08-10
SNE - Simulation Notes Europe, ARGESIM Publisher Vienna
ISSN Print 2305-9974, Online 2306-0271, www.sne-journal.org

Abstract. Agent-based models can simulate interactions of complex systems that lead to emergent events. This capability enables the exploration of potential outcomes of different assumptions and scenarios, which can support the decision-making process for complex systems. However, identifying the optimal level of detail and granularity of agent-based models is challenging and highly related to the decisions they are intended to support. Detailed and granular models can incorporate more information and potentially provide a more realistic representation of an actual system. However, the more complex models require more time and resources to run and analyze, and their complexity can make the interpretation of simulation challenging. Conversely, simpler and more aggregated models are often easier to interpret and more efficient to run, though they may offer a less accurate representation of the original system. In this paper, we discuss the trade-offs between detailed and aggregated models and review the factors that influence the optimal level of detail and granularity.

Introduction

Agent-based modeling and simulation (ABMS) is a modeling approach that is applied to understand and predict the behavior of complex systems, such as social, economic, and natural systems. Generally, an agent-based model represents the behavior of individual agents (which can represent people, companies, or other entities) and the interactions between them. The collective behavior of the system emerges from the interactions between these agents in the simulation.

ABMS enables the exploration of the potential outcome of different assumptions or scenarios to support the decision-making process in various fields [11, 14, 2, 6]. Schinckus [9] identifies four main approaches to employing agent-based modeling in economics: The deductive approach using perfectly rational agents, the abductive approach with adaptive agents, the metaphorical approach using concepts from physics, and the phenomenological approach that aims to reproduce observed statistical patterns. This diversity of approaches demonstrate the flexibility of ABMS in capturing different aspects of a complex system which make it a unique decision-support tool.

Intuitively, an agent-based model that incorporates more details and granularity of a real-world system will more accurately replicate the behavioral patterns of the original system. However, there are various benefits to employing simpler models, such as model interpretability and required resources. These advantages can outweigh the consequences of lower accuracy of simple models which motivates the modelers to create models with the highest possible level of detail and granularity. However, there are various benefits to employing simpler models, such as model interpretability and reduced resource requirements [13, 10]. These advantages can outweigh the consequences of lower accuracy. Therefore, balancing the incorporation of the highest possible level of detail and granularity in an agent-based model with considerations such as model interpretability and resource requirements is a complex and challenging task for modelers. Besides the trade-off between model complexity and accuracy, it is crucial to understand the complexity of an agent-based model in order to grasp its capabilities and limitations accurately.

Sun et al. [12] explain that a model can be structurally simple yet produce complex behaviors, or it can be very complicated in structure without necessarily generating complex dynamics. The authors emphasize that we must consider both the desired level of structural complicatedness and the intended complexity of model behaviors while designing agent-based models.

Decision support systems can benefit from the use of ABMS, which provides policy-makers and decision-makers with a controlled and transparent way to explore potential outcomes of different decision options. The relationship between the level of decisions and the complexity of a model is often proportional, with more complex models being better suited for supporting higher levels of decision-making.

For instance, simple models may suffice for operational-level decisions based on established rules and procedures, while strategic-level decisions requiring long-term planning and resource allocation may require more complex models to consider a wider range of factors and uncertainties.

The aim of this paper is to discuss the factors that influence the complexity of an agent-based model employed as a decision support tool, taking into account the desired level of decision support. These factors include agents' characteristics, the agent-based model's interaction rules, the user's specific context and decision-making requirements, the availability of resources and expertise, the nature and scope of the decisions being made, the desired level of interpretability of the model, the reliability of the model, and the available resources to run the simulations.

1 Model Complexity vs. Decision-Making

In this paper, the complexity of a model refers to its structural aspect. We consider the complexity of an agent-based model to be strongly dependent on the number of agents, the rules and behaviors attributed to the individual agents (including the degree of interdependence between agents), and the environmental factors affecting agents. A more complex agent-based model typically refers to a greater number of agents, each having a more extensive range of attributes and behaviors, as well as more complex rules governing their interactions with each other and their environment.

Several factors can affect the complexity of an agent-based model such as the multitude and diversity of agents, processes, and interactions, along with their respective attributes [12]. Following the ODD (Overview, Design concepts, and Details) protocol [4], the main factors that affect an agent-based model's complexity are:

Agents: The more agents and the more diverse the types of agents, the more complex the model is likely to be.

Interactions: The more interactions between agents and the more complex those interactions are, the more complex the model is likely to be.

Rules: The more rules for agents' decisions and the more complex those rules are, the more complex the model is likely to be.

The environment: The more features and interaction rules for the environment, the more complex the model is likely to be.

Scheduling: The longer the model's time horizon, the more complex the model is likely to be.

There are several methods to measure the complexity of an agent-based model. One of the most popular methods is Kolmogorov's definition of complexity [7], which is a measurement of the resources needed to specify the model. Moreover, Popovics and Monostori [8] proposed an approach to determine the complexity of discrete event simulation models by combining several parameters.

Agent-based models are used to support a variety of decisions. However, modeling decisions is challenging due to the importance of including the beliefs, desires, and intentions of decision-makers while considering physical, emotional, and social factors [3]. There are multiple studies that focused on modeling human decisions and behaviors in agent-based models [1, 5]. Focusing on business-related decisions, we can categorize the decisions into operational, tactical, and strategic level decisions. *Operational level decisions* are relatively simple decisions and involve the execution of well-defined rules and procedures.

As such, simple agent-based models may be sufficient to support these decisions. *Tactical level decisions* are medium-term decisions that involve the allocation of resources and the coordination of activities. These decisions may be more complex than operational level decisions and may require more sophisticated models to evaluate the potential consequences. Finally, *Strategic level decisions* are long-term decisions that involve the allocation of resources and the formulation of overall goals and objectives. These decisions may be more complex than operational or tactical level decisions and may require more sophisticated models to evaluate the potential consequences.

We propose a further classification of decisions based on their intended purpose into forecasting, demonstration of past decisions, and hypothesis testing. For forecasting decisions, the modeler designs the model as a prediction tool. It may be necessary to use highly detailed and complex models that consider a wide range of factors and processes to make accurate predictions.

However, it is also possible to use simpler models that capture the key processes in a system in order to make more qualitative, non-specific predictions. The complexity of the model needed for predictive purposes will depend on the level of certainty required. The second category is the demonstration of past decisions to understand their cause and effect. Simple models are often suited for this purpose since they are more explainable than complex models, and it is more convenient to understand them.

In hypothesis testing or what-if analysis, the goal is to confirm or challenge a theory. Modeling complex systems is often done by simplifying and generalizing in order to build theories. Simple models that focus on general questions are more effective at developing theories with general validity.

In another perspective, Sun et al. [12] argue that different principles apply depending on the type of agent-based model being developed.

The principle of parsimony should be followed for abstract theoretical models, keeping the model as simple as possible.

For empirically grounded models aimed at prediction or decision support, the ’Medawar zone’ principle applies meaning models should be in an intermediate range of complicatedness, as complicated as necessary but no more so.

The authors also mention that in all cases, modelers should strive to match the level of model complicatedness to the specific research questions being investigated.

2 Summary and Conclusion

Increasing complexity of agent-based models can lead to a more accurate representation of the system being modeled and the behavior of individual agents. For example, if a model of a stock market includes a large number of variables that describe the behavior of individual investors, it is likely to provide more accurate predictions of stock prices.

However, more complex models require more computational resources for simulation and comprehensive datasets for accurate calibration of the model. These challenges potentially limit the practical implementation of large-scale models involving millions of agents with intricate interactions in time-sensitive or resource-constrained decision-making contexts.

Moreover, complex models are less interpretable for stakeholders who are not familiar with the underlying assumptions and relationships between variables. Consequently, this challenge constrains decision-makers ability to effectively employ models and make informed judgments using simulation results. Lastly, complex models are also more prone to errors and inaccuracies, especially if the underlying assumptions or relationships between variables are not well understood. This vulnerability can compromise the reliability and validity of the results and lead to incorrect or misleading predictions and insights.

In conclusion, the design of agent-based models requires an approach that addresses both the demands of the decision-making process and practical implementation. A model that is overly simplistic may not possess the necessary information to facilitate informed decision-making, whereas a model that is excessively complex may prove to be intricate to comprehend. For the future of agent-based modeling in decision support systems, modelers should focus on developing models at both ends of the complexity spectrum, investigating complexity indicators to address the crucial challenge of finding a balance between complexity and simplicity. The goal must be to create models that are simple, yet theory-driven and rich in dynamics to understand the key processes of the system.

Acknowledgement

This work is partly funded by the Innovation Fund Denmark (IFD) under File No. 9065-00207B.

References

[1] An, L.: Modeling human decisions in coupled human and natural systems: Review of agent-based models. Ecological modelling **229**, 25–36 (2012)

[2] Axtell, R.L., Farmer, J.D.: Agent-based modeling in economics and finance: Past, present, and future. Journal of Economic Literature pp. 1–101 (2022)

[3] Conte, R., Paolucci, M.: On agent-based modeling and computational social science. Frontiers in psychology **5**, 668 (2014)

[4] Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F.: The odd protocol: a review and first update. Ecological modelling **221**(23), 2760–2768 (2010)

[5] Groeneveld, J., Müller, B., Buchmann, C.M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., et al.: Theoretical foundations of human decision-making in agent-based land use models–a review. Environmental modelling & software **87**, 39–48 (2017)

[6] Khodabandelu, A., Park, J.: Agent-based modeling and simulation in construction. Automation in Construction **131**, 103882 (2021)

[7] Kolmogorov, A.N.: On tables of random numbers. Sankhyā: The Indian Journal of Statistics, Series A pp. 369–376 (1963)

[8] Popovics, G., Monostori, L.: An approach to determine simulation model complexity. Procedia CIRP **52**, 257–261 (2016)

[9] Schinckus, C.: Agent-based modelling and economic complexity: a diversified perspective. Journal of Asian Business and Economic Studies **26**(2), 170–188 (2019)

[10] Srikrishnan, V., Keller, K.: Small increases in agent-based model complexity can result in large increases in required calibration data. Environmental Modelling & Software **138**, 104978 (2021)

[11] Stieler, D., Schwinn, T., Leder, S., Maierhofer, M., Kannenberg, F., Menges, A.: Agent-based modeling and simulation in architecture. Automation in Construction **141**, 104426 (2022)

[12] Sun, Z., Lorscheid, I., Millington, J.D., Lauf, S., Magliocca, N.R., Groeneveld, J., Balbi, S., Nolzen, H., Müller, B., Schulze, J., et al.: Simple or complicated agent-based models? a complicated issue. Environmental Modelling & Software **86**, 56–67 (2016)

[13] Ward, S.C.: Arguments for constructively simple models. Journal of the operational research society **40**(2), 141–153 (1989)

[14] Zhang, B., DeAngelis, D.L.: An overview of agent-based models in plant biology and ecology. Annals of Botany **126**(4), 539–557 (2020)