Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

COMPLEX SYSTEMS MODELING AND ANALYSIS

Claudia Szabo

School of Computer Science
The University of Adelaide
North Terrace
Adelaide, 5000, AUSTRALIA

ABSTRACT

Undesired or unexpected properties are frequent as large-scale, complex systems with non-linear interactions are being designed and implemented to answer real-life scenarios. Modeling these behaviors in complex systems, as well as analysing the large amounts of data generated in order to determine the effects of specific behaviors remains an open problem. In this tutorial, we explore three main complex systems properties and how they can be modelled in well known scenarios.

1 INTRODUCTION

Social networks, supply chains, health-care networks, smart-cities, the 'Internet of Things', and the Internet (Niazi 2013; North et al. 2013) are all examples of complex systems where entities and the environment interact to achieve (mostly desired) emergent properties (Holland 2006; Mittal 2013; Özmen et al. 2013; Mittal 2013; Szabo and Teo 2013).

Three critical properties of complex adaptive systems are self-organization, adaptability, and emergence. Self-organization occurs when entities interact to achieve some goal, or to move into a different collective state (Holland 2006; Mittal 2013; Dekkers 2015). Adaptability drives entities to a particular beneficial state (Walker et al. 2004; Chira et al. 2010; Mobus and Kalton 2015). The identification of system states where self-organization and adaptability occur is crucial to understanding complex system behavior and its causes.

While emergent properties have been the focus of research since the 1970s (Gardner 1970; Cilliers 1998; Holland 1999; Seth 2008), very few methods for their identification, classification, and analysis exist (Kubik 2003; Chen et al. 2007; Seth 2008; Szabo and Teo 2012; Brown and Goodrich 2014). Moreover, existing methods are usually employed only on simplified examples that are rarely found in real life. For example, the flock of birds model suggests that flocks result from the birds obeying three rules, as opposed to the myriad rules that affect flocking in real life. Approaches can be classified broadly from two orthogonal perspectives. In the first perspective, approaches propose to identify emergence as it happens (Kubik 2003; Szabo and Teo 2012), and aim to use formal or meta-models of calculated composed model states. Towards this, a key issue remains in the identification of variables or attributes that describe the system components, or the *micro-level*, and the system as a whole, or the *macro-level*, and the relationships and dependencies between these two levels. These definitions allow the specification of emergence as the set difference between macro-level and the micro-level but are difficult to capture and computationally expensive to calculate.

In contrast, the second perspective uses a definition of a known or observed emergent property and aims to identify its cause, in terms of the states of system components and their interaction (Chen et al. 2007; Seth 2008). A key issue when using this *post-mortem* perspective is that a prior observation of an emergent property is required, and that emergent properties need to be defined in such a way that the macro-level can be reduced or traced back to the micro-level. Moreover, current approaches (Kubik 2003; Chen et al. 2007; Seth 2008; Brown and Goodrich 2014) are demonstrated using simple models such as Flock of Birds or Predator-Prey, which have limiting assumptions and constraints when applied to more complex systems. For example, most approaches do not consider mobile agents (Kubik 2003), assume unfeasible a-priori specifications and definitions of emergent properties (Szabo and Teo 2012), or do not scale beyond models with a small number of agents (Teo et al. 2013). In the multi-agent systems community, approaches focus more on the engineering of systems to exhibit beneficial emergent behavior and less on its identification (Bernon et al. 2002; Jacyno et al. 2009; Salazar et al. 2011). Moreover, approaches that engineer emergent behavior do not ensure that no other side-effects occur as a consequence.

In this tutorial, we study emergence, self-organization and adaptability in two models and we discuss how the modeling techniques could be used in more realistic systems.

2 COMPLEX SYSTEMS PROPERTIES

2.1 Emergence

Emergence occurs when entities organize to behave collectively leading to the creation of an unpredictable *macro* state that cannot be decomposed into its *micro* components (Szabo and Teo 2013). However, some systems exhibit emergence without the presence of self-organization, such as a stationary gas (Mittal 2013). Emergence is present in many complex systems such as communities forming in social networks, formation of ant colonies, and rigid cellular structures (Chan 2011; Toole and Nallur 2014; Birdsey et al. 2015).

Bedau (1997) states that an emergent property can be defined as "a property of assemblage that could not be predicted by examining the components individually." Emergence can be seen in many real-world systems such as technological and nature-driven systems. For example, the neurons in the brain individually fire impulses but together form an emergent state of consciousness (Odell 2000). The flocking of birds is a well-known example of emergent behavior in nature. Independent birds aggregate around an invisible center and fly at the same speed for flock creation. The birds, come together to create something that would be entirely indiscernible by studying only one or two birds. Two key examples of systems where emergent behavior is caused by interactions are the Flock of Birds model (Reynolds 1987), and the cellular automata Game of Life model (Gardner 1970). The former achieves its emergent properties through each bird flocking around a perceived flock center, while in the latter model the emergent properties are achieved by the patterns that are formed by the cells transitions between states. Studies that propose various processes of detecting and identifying emergent behavior mainly use either one or both of these systems to prove the validity of their proposed approach (Seth 2008; Chan et al. 2010; Chan 2011).

Multi-agent systems are a useful formalism to model complex systems. The components present in a complex system can be modeled as agents that perform their respective actions and interactions. The modeling of these components as agents, allows for unnecessary information to be abstracted away leaving only the actions and interactions needed for a particular outcome. These agent-based models are then used in simulations to assist with research and analysis (Johnson 2006). Multi-agent systems can be engineered to exhibit emergent properties (Fromm 2006; Savarimuthu et al. 2007). Several formalisms have been proposed to obtain or engineer emergent behavior, such as the DEVS extension proposed by (Mittal 2013; Birdsey et al. 2016), but they have yet to be employed in practice. By creating models where emergence is an easily attainable product derived from agents interactions, users are relieved from having to model every aspect of the complex system under study. Multi-agent systems which have been designed to exhibit emergence are usually engineered to focus on self-organization and co-operation between agents. These systems generally rely on a system expert to identify the emergent behavior (Savarimuthu et al. 2007; Jacyno et al. 2009; Salazar et al. 2011). For example, human societies and the myriad ways that emergent properties can arise are generally modeled using this approach in order to study aspects such as norm emergence (Savarimuthu et al. 2007; Jacyno et al. 2009).

Chan et al. (2010) highlight that agent-based simulation is the most suitable method for modeling systems containing unexpected or emergent behaviors, because it emphasizes that the actions and interactions between agents are the main causes for emergent behaviors. Several works support the use of agent-based modeling for studying emergent behaviors (Banks et al. 2000; Fromm 2006; Serugendo et al. 2006; Salazar et al. 2011; Pereira and Santos 2012). In addition to the Flock of Birds and Game of Life models, Chan et al. (2010) show that other complex systems such as social networks and electricity markets, implemented within an agent-based simulation, can exhibit emergent properties, which can then be identified. The methods in Chan et al. (2010) for detecting emergence rely upon the presence of a system expert, who can identify the emergent behavior.

Considerable research has been done in developing methods for the detection of emergence, and as discussed above existing methods assess emergence in either a *post-mortem* setting or a *live* setting (Szabo and Teo 2012). *Post-mortem* analysis methods are applied after the system under study has finished executing, and use data that was recorded during the execution (Szabo and Teo 2012). In contrast, *live* analysis methods are used while the system under study is executing (Chan 2011; Szabo and Teo 2012). Most existing works focus on *post-mortem* analysis methods (Chen et al. 2009; Tang and Mao 2014). In addition to *post-mortem* and *live* analysis, methods can be classified into three main types (Teo et al. 2013): *grammar-based* (Kubik 2003; Szabo and Teo 2013), *event-based* (Chen et al. 2007), or *variable-based* (Seth 2008; Szabo and Teo 2013; Tang and Mao 2014).

Some forms of *live* analysis involve *grammar-based methods*. These attempt to identify emergence in multi-agent systems by using two grammars, L_{WHOLE} and L_{PARTS}. Kubik (2003) defines that L_{WHOLE} describes the properties of the system as a whole and L_{PARTS} describes the properties obtained from the reunion of the parts, and in turn produces emergence as the difference between the two solutions. L_{WHOLE} and L_{PARTS} can be easily calculated as the sets of words that are constructed from the output of agent behavior descriptions. This method does not require a prior observation of the system in order to identify possible emergent properties or behaviors, which therefore makes it suitable for large-scale models where such observations are notoriously difficult (Teo et al. 2013). However, as grammars require a formation of *words*, the process through which these words are formalized can suffer badly as the model grows in scope, leading to computational issues, especially for large scale systems (Kubik 2003; Teo et al. 2013). To address this, some works attempt to identify *micro* level properties and model interaction, and performing reconstructability analysis on this data (Szabo and Teo 2013), however this analysis is required to take place in a *post-mortem* context.

Some forms of *post-mortem* analysis involve *event-based methods*, in which behavior is defined as a series of both simple and complex events that changed the system state, as defined by (Chen et al. 2007). Complex events are defined as compositions of simple, atomic events where a simple event is a change in state of specific variables over some non-negative duration of time. These state changes, or state transitions, are also defined by a set of rules. Each emergent property is defined manually by a system expert as a complex event. It is the particular sequence of both complex and simple events in a system that lead to emergence occurring in the system. However, this method relies heavily on the system experts and their specific definitions. Furthermore, it can suffer from both agent and state space explosion making it unsuitable for large systems.

In *variable-based methods*, a specific variable or metric is chosen to describe emergence. Changes in the values of this variable signify the presence of emergent properties (Seth 2008). The center of mass of a bird flock could be used as an example of emergence in bird flocking behavior, as shown in Seth (Seth 2008). Seth's approach uses Granger causality to establish the relationships between a macro-variable and micro-variables and proposes the metric of G-emergence, a near-*live* analysis method. This has the advantage of providing a process for emergence identification that is relatively easy to implement. However, the approach requires system expert knowledge as observations must be defined for each system. Szabo and Teo (2013) proposed the use of reconstructability analysis to determine which components interacted to cause a particular emergent property (defined through a set of variables). They identified the interactions that cause birds to flock (Reynolds 1987), the cells that cause the glider pattern in Conway's Game of Life (Gardner 1970), and the causes of traffic jams. However, their method is heavily dependent on the choice of the variable set that represents the micro and macro levels and requires the intervention of a system expert.

Variable-based methods from other fields, such as information theory and machine learning, have been adapted with the goal of emergence detection. Information theory approaches for detecting emergence have also been proposed by using such techniques as Shannon Entropy (Prokopenko et al. 2009; Gershenson and Fernández 2012; Tang and Mao 2014) and variety (Yaneer 2004; Holland 2007). These have advantages over other *variable-based methods* in that they can process large amounts of data efficiently. Tang and Mao (2014) propose measures of relative entropy that depend on the main emergent property of a system under study. However, these methods require the input of a system expert because they rely on the emergent property of a system being classified along with a specific function to be defined for that particular property. Machine learning classification techniques have also been proposed as a way of detecting emergence. A variant of Bayesian Classification (Brown and Goodrich 2014) has been used to successfully detect swarming and flocking behavior in biological systems such as the flock of birds model (Reynolds 1987). This approach involves identifying *key features* of an agent, such as how many neighbors an agent has, and uses this information to determine the likelihood that a random set of agents is exhibiting emergence. Other methods from machine learning have been utilized, such as Conditional Random Fields, and Hidden Markov Models in (Vail et al. 2007), but with the goal of activity recognition in domain specific contexts. Vail et al. used Conditional Random Fields and Hidden Markov Models somewhat successfully to determine if agents were performing a particular distinct action based on their relational position to other agents.

Analyzing and determining how complex systems attain emergence can not only help system experts gain a a deeper understanding of the system's behavior, but can allow them to configure them to encourage or discourage that particular form of emergence. Detection of emergence in complex systems has been performed significantly over the years (Szabo and Teo 2013; Birdsey and Szabo 2014; Toole and Nallur 2014). Szabo and Teo (2013) analyze emergence from a post-mortem perspective using reconstructability analysis. Birdsey and Szabo (2014) developed an architecture that requires a system expert to analyze snapshots of previous system executions and mark them if they exhibit emergence or not. These snapshots are then compared against when running the system, and various metrics are used to determine if the executing system exhibits emergence. Toole and Nallur (2014) proposed using correlation methods to detect downwards causation while utilizing a decentralized approach.

2.2 Stability

Stability occurs when the system has reached some form of equilibrium (Miller and Page 2009; Chan 2011). Equilibrium is defined differently for each system, but can be characterized as either the system entering a stationary state, or a cycle. Systems that exhibit stability possess beneficial properties such as resilience and resistance (Mobus and Kalton 2015). In particular, resilience is a desired property as it allows a system to endure significant external input without major change, such as obstacles in the path of a large flock of birds, or large scale failures in a distributed system.

2.3 Criticality

Criticality is the single instance or sequence of time, before the system enters a stable, unstable, or emergent state (Ito and Gunji 1992; Miller and Page 2009). In many systems, criticality is observed at the edge of chaos or a bifurcation point (Mobus and Kalton 2015). Determining when entities are involved in self-organization or when self-organization has finished allows system experts to analyze its causes and design complex systems that encourage or discourage it.

2.4 Adaptability

Adaptability can be seen as either a precursor process to self-organization, e.g. adapting to a desirable state before self-organization can begin, or a sub-process, e.g. adapting to enhance current self-organization. Agents adapting allow the system to attain desirable states such as resilience and flexibility, and their adaptability can drive the system as a whole towards new states (Walker et al. 2004; Grisogono 2005; Miller and Page 2009).

3 EXPERIMENTAL MODELS

In this tutorial, we'll look at the implementation of three models in NetLogo. We will analyse the emergent behavior exhibited by the models, as well as how they self-organise and adapt. We will also attempt to identify criticality. We present the three models below.

3.1 Flock of Birds

The Flock of Birds model (Reynolds 1987) captures the motion of bird flocking and is a seminal example in the study of emergence. At the macro level, a group of birds tends to form a flock. Flocks have aerodynamic advantages, obstacle avoidance capabilities and predator protection, regardless of the initial positions of the birds. At the micro level, each bird obeys three simple rules (Reynolds 1987):

1. Separation - steer to avoid crowding neighbors
2. Alignment - steer towards average heading of neighbors
3. Cohesion - steer towards average position of neighbors

We model this as a multi-agent system in which each bird is an agent that has the three movement rules defined above. Other bird attributes include initial position and initial velocities. In our experiments, the initial bird positions can be either fixed or assigned randomly at start up. Bird velocities are assigned randomly. The model parameters can also influence emergent behavior analysis. As such, we collect and analyze interaction graphs of Flock of Birds models with sizes of 20 and 50 birds, with fixed and randomly assigned position values, and randomly assigned velocity values.

3.2 Game of Life

Conway's Game of Life model (Gardner 1970) represents cells that interact with their neighbors to determine in what state they should be at the next time step, either alive or dead. At the macro level, patterns emerge between groups of cells, such as the Pulsar pattern as shown in Figure 1. At the micro level, the rules for each cell are as follows, where X, Y, and Z are the parameters for the Game of Life model (Gardner 1970; Chan et al. 2010):

1. A live cell with at least X and at most Y live neighbors will remain alive in the next time step
2. A dead cell with exactly Z live neighbors will become alive in the next time step
3. Otherwise, the cell will die in the next time step where $0 \leq X, Y, Z \leq \varepsilon$ and $X \leq Y$, where ε is the maximum number of neighbors, which in a 2-dimensional configuration is 8

Certain combinations of X,$Y$and Z settings can reveal emergent behavior such as patterns, like the glider (Szabo and Teo 2013), and shapes appearing in the cellular structure (Chan et al. 2010).

We model the Game of Life as a multi-agent system where each cell is an agent. A 2-dimensional grid of cells, of size $n \times n$, is established and the initial state of each cell is either fixed or chosen at random on start up. The attributes recorded for each cell are the cell state and the states of the cell's eight neighbors at the start of the time step. Snapshots are taken of Game of Life models with sizes of both 20×20 cells and 15×15 cells are collected and analyzed, each cell having a total of two possible states. Their initial

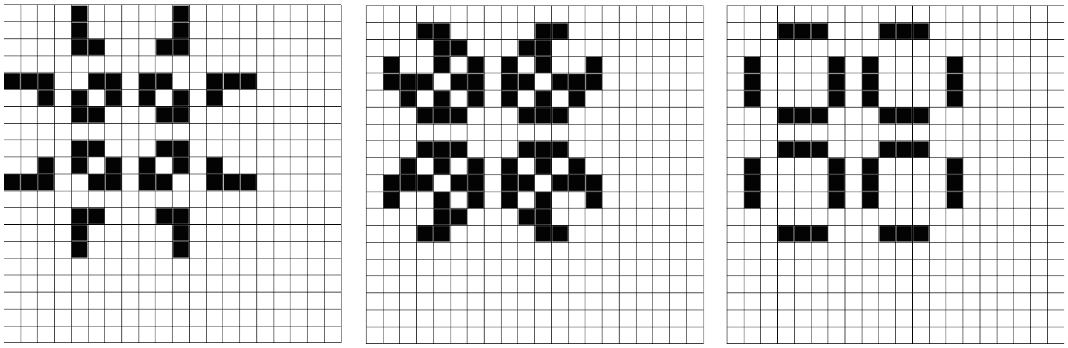

Figure 1: Game of Life with Pulsar pattern.

states are either randomized or set to allow the creation of a particular pattern (Chan et al. 2010). For our experiments, we followed Conway's initial X, Y and Z rules, which are 2, 3, and 3 respectively.

3.3 Predator-Prey

The Predator-Prey model has been used in studying emergent behavior, with varying rule-sets (Chen et al. 2007). The Predator-Prey model has two types of agents, namely, Predators and Prey. As in nature, both types of agents wish to survive to create a new generation. Survival for the Predators is to eat whereas survival for the Prey is to avoid being eaten. The main difference of this model from the previous two is that agents can be added to or removed from the system during execution, and that the different agent types obey different rules. Specifically, Predators obey four rules while the Prey obeys two rules. The rules of the Predators are:

1. If a Prey is detected within distance *d*, kill the Prey with probability *p(predKill)*. If successful, the Prey is removed from the system immediately
2. If some Prey is killed, a new Predator is born at the Prey's location, after one time-step has passed
3. If a Predator is not within distance *d*, it dies with probability *p(predDeath)*
4. Move one step in any random direction if no Prey was killed and the Predator hasn't died

The rules of the Prey are:

1. Move one step in any random direction
2. Give birth to a new Prey at a random location with probability *p(preBirth)*

In our implementation, Predator and Prey are assigned initial random positions. Their velocities are also randomized at initialization as well as for each time step. The three rule probabilities, *predKill*, *predDeath* and *preBirth* are pre-defined. Both agent types have a common set of states, life and procreation, but the Predator has extra states to indicate if it has seen and/or killed some prey. If an agent is removed from the simulation, i.e. upon death, their life state is set to "dead". This is to ensure that no information generated by the system is lost as it may prove valuable to a particular metric.

4 CONCLUSION

In this tutorial, we will discuss complex systems properties using three well-known models of Flocks of Birds, Predator-Prey and Game of Life. We will visualise the execution of these models in NetLogo and discuss how complex systems properties appear in other real-life systems. We will discuss how these properties can be modelled, considering issues of validation and accuracy. Lastly, the metrics used to determine whether an emergent property has appeared are critical for the validation of complex systems where these properties are inherently likely to appear. We discuss the implementation and suitability of a number of emergent behavior metrics.

REFERENCES

Banks, J., J. S. Carson, B. L. Nelson, and D. M. Nicol. 2000. *Discrete-Event System Simulation*. 3rd ed. Upper Saddle River, USA: Prentice-Hall, Inc.

Bedau, M. 1997. "Weak Emergence". *Nous* 31(11):375–399.

Bernon, C., M.-P. Gleizes, S. Peyruqueou, and G. Picard. 2002. "ADELFE: a methodology for adaptive multi-agent systems engineering". In *International Workshop on Engineering Societies in the Agents World*, 156–169. Berlin, Heidelberg: Springer.

Birdsey, L., and C. Szabo. 2014. "An Architecture for Identifying Emergent Behavior in Multi-Agent Systems". In *Proceedings of The 13th International Conference on Autonomous Agents and Multiagent Systems*, 1455 – 1456. New York, USA: Association for Computing Machinery, Inc.

Birdsey, L., C. Szabo, and K. Falkner. 2016. "CASL: A Declarative Domain Specific Language for Modeling Complex Adaptive Systems". In *Winter Simulation Conference*, edited by T. M. K. Roeder, P. I. Frazier, R. Szechtman, and E. Zhou, 1241–1252. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc Press.

Birdsey, L., C. Szabo, and Y. M. Teo. 2015. "Twitter Knows: Understanding The Emergence Of Topics In Social Networks". In *Proceedings of the Winter Simulation Conference*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 4009–4020. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc Press.

Brown, D. S., and M. A. Goodrich. 2014. "Limited Bandwidth Recognition of Collective Behaviors in Bio-Inspired Swarms". In *Proceedings of The 13th International Conference on Autonomous Agents and Multiagent Systems*, 405 – 412. New York, USA: Association for Computing Machinery, Inc.

Chan, W., Y. S. Son, and C. M. Macal. 2010. "Simulation of Emergent Behavior and Differences Between Agent-Based Simulation and Discrete-Event Simulation". In *Proceedings of the Winter Simulation Conference*, edited by B. Johansson, S. Jain, and J. Montoya-Torres, 135–150. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc Press.

Chan, W. K. V. 2011. "Interaction Metric Of Emergent Behaviors In Agent-Based Simulation". In *Proceedings of the Winter Simulation Conference*, edited by S. Jain, R. Creasey, and J. Himmelspach, 357–368. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc Press.

Chen, C., S. B. Nagl, and C. D. Clack. 2007. "Specifying, Detecting and Analysing Emergent Behaviours in Multi-Level Agent-Based Simulations". In *Proceedings of the Summer Computer Simulation Conference*, 969–976. New York, USA: Association for Computing Machinery, Inc.

Chen, C.-C., S. B. Nagl, and C. D. Clack. 2009. "A Formalism for Multi-level Emergent Behaviours in Designed Component-based Systems and Agent-based Simulations". In *From System Complexity to Emergent Properties*, 101–114. Berlin, Heidelberg: Springer.

Chira, C., A. Gog, R. I. Lung, and D. Iclanzan. 2010. "Complex Systems And Cellular Automata Models in the Study of Complexity". *Studia Informatica Series* 55(4):33–49.

Cilliers, P. 1998. *Complexity & Postmodernism*. Abindgon-on-Thames, UK: Routledge.

Dekkers, R. 2015. "Complex Adaptive Systems". In *Applied Systems Theory*, edited by R. Dekkers, 169–190. Switzerland: Springer.

Fromm, J. 2006. "On Engineering and Emergence". *arXiv preprint nlin/0601002*.

Gardner, M. 1970. "The Fantastic Combinations of John Conways New Solitaire Game Life". *Scientific American* 223:120–123.

Gershenson, C., and N. Fernández. 2012. "Complexity and Information: Measuring Emergence, Self-Organization, and Homeostasis at Multiple Scales". *Complexity* 18(2):29–44.

Grisogono, A.-M. 2005. "Co-Adaptation". In *Microelectronics, MEMS, and Nanotechnology*, 603903/1–603903/15. International Society for Optics and Photonics.

Holland, J. 1999. *Emergence, From Chaos to Order*. Oxford, UK: Basic Books.

Holland, J. H. 2006. "Studying Complex Adaptive Systems". *Journal of Systems Science and Complexity* 19(1):1–8.

Holland, O. T. 2007. "Taxonomy for the Modeling and Simulation of Emergent Behavior Systems". In *Proceedings of the 2007 Spring Simulation Multiconference*, 28–35. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc Press.

Ito, K., and Y. P. Gunji. 1992. "Self-Organization Toward Criticality In The Game Of Life". *BioSystems* 26(3):135–138.

Jacyno, M., S. Bullock, M. Luck, and T. R. Payne. 2009. "Emergent Service Provisioning and Demand Estimation Through Self-organizing Agent Communities". In *Proceedings of the International Conference on Autonomous Agents and Multiagent Systems*, 481–488. New York, USA: Association for Computing Machinery, Inc.

Johnson, C. W. 2006. “What are Emergent Properties and How Do They Affect the Engineering of Complex Systems?”. *Reliability Engineering and System Safety* 12(1):1475–1481.

Kubik, A. 2003. “Towards a Formalization of Emergence”. *Journal of Artificial Life* 9(1):41–65.

Miller, J. H., and S. E. Page. 2009. *Complex Adaptive Systems: An Introduction To Computational Models Of Social Life*. Princeton, USA: Princeton University Press.

Mittal, S. 2013. “Emergence in Stigmergic and Complex Adaptive Systems: A Formal Discrete Event Systems Perspective”. *Cognitive Systems Research* 21(1):22–39.

Mobus, G. E., and M. C. Kalton. 2015. *Principles of Systems Science*. NY, USA: Springer.

Niazi, M. A. 2013. “Complex Adaptive Systems Modeling: A Multidisciplinary Roadmap”. *Complex Adaptive Systems Modeling* 1(1):1–14.

North, M. J., N. T. Collier, J. Ozik, E. R. Tatara, C. M. Macal, M. Bragen, and P. Sydelko. 2013. “Complex Adaptive Systems Modeling With Repast Simphony”. *Complex Adaptive Systems Modeling* 1(1):15–23.

Odell, J. 2000. “Agents and emergence”. *Journal of Object Oriented Programming* 12(9):34–36.

Özmen, Ö., J. Smith, and L. Yilmaz. 2013. “An Agent-based Simulation Study Of A Complex Adaptive Collaboration Network”. In *Proceedings of the Winter Simulation Conference*, edited by R. Pasupathy, S.-H. Kim, and A. Tolk, 412–423. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc Press.

Pereira, L. M., and F. C. Santos. 2012. “The Emergence of Commitments and Cooperation”. In *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*, 559–566. New York, USA: Association for Computing Machinery, Inc.

Prokopenko, M., F. Boschetti, and A. J. Ryan. 2009. “An Information-theoretic Primer of Complexity, Self-organization and Emergence”. *Complexity* 15:11–28.

Reynolds, C. W. 1987. “Flocks, Herds and Schools: A Distributed Behavioral Model”. In *Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH ’87, 25–34. New York, USA: ACM.

Salazar, N., J. A. Rodriguez-Aguilar, J. L. Arcos, A. Peleteiro, and J. C. Burguillo-Rial. 2011. “Emerging Cooperation on Complex Networks”. In *Proceedings of the International Conference on Autonomous Agents and Multiagent Systems*, 669–676. New York, USA: Association for Computing Machinery, Inc.

Savarimuthu, B., M. Purvis, S. Cranefield, and M. Purvis. 2007. “Mechanisms for Norm Emergence in Multiagent Societies”. In *Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems*, AAMAS ’07, 173:1–173:3. New York, USA: Association for Computing Machinery, Inc.

Serugendo, G. D. M., M. P. Gleizes, and A. Karageorgos. 2006. “Self-Organisation and Emergence in MAS: An Overview.”. *Informatica (Slovenia)* 30(1):45–54.

Seth, A. K. 2008. “Measuring Emergence via Nonlinear Granger Causality”. In *Proceedings of the Eleventh International Conference on the Simulation and Synthesis of Living Systems*, 545–553. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc.

Szabo, C., and Y. Teo. 2012. “An Integrated Approach for the Validation of Emergence in Component-based Simulation Models”. In *Proceedings of the Winter Simulation Conference*, edited by C. Laroque, R. Pasupathy, and J. Himmelspach, 2412–2423. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc Press.

Szabo, C., and Y. M. Teo. 2013. “Post-mortem Analysis of Emergent Behavior in Complex Simulation Models”. In *Proceedings of the 2013 ACM SIGSIM Conference on Principles of Advanced Discrete Simulation*, 241–252. New York, USA: Association for Computing Machinery, Inc.

Tang, M., and X. Mao. 2014. “Information Entropy-Based Metrics for Measuring Emergences in Artificial Societies”. *Entropy* 16(8):4583–4602.

Teo, Y. M., B. L. Luong, and C. Szabo. 2013. “Formalization of Emergence in Multi-Agent Systems”. In *Proceedings of the 2013 ACM SIGSIM Conference on Principles of Advanced Discrete Simulation*, 231–240. Montreal, Canada: ACM.

Toole, E. O., and V. Nallur. 2014. “Towards Decentralised Detection of Emergence in Complex Adaptive Systems”. In *International Conference on Self-Adaptive and Self-Organizing Systems*, 60–69. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Inc.

Vail, D. L., M. M. Veloso, and J. D. Lafferty. 2007. “Conditional Random Fields for Activity Recognition”. In *Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems*, AAMAS ’07, 235:1–235:8. Honolulu, Hawaii: Association for Computing Machinery, Inc.

Walker, B., C. S. Holling, S. R. Carpenter, and A. Kinzig. 2004. “Resilience, Adaptability and Transformability in Social–Ecological Systems”. *Ecology and Society* 9(2):5–10.

Yaneer, B.-Y. 2004. “A Mathematical Theory of Strong Emergence using Multiscale Variety”. *Complexity* 9(6):15–24.

AUTHOR BIOGRAPHIES

CLAUDIA SZABO is an Associate Professor in the School of Computer Science at the University of Adelaide. Her research interests lie in the area of complex systems and on using simulation to identify and validate their emergent properties. Her email address is claudia.szabo@adelaide.edu.au.