Iranian Journal of Management Studies (IJMS) *http://ijms.ut.ac.ir/*
Vol. 11, No. 4, Autumn 2018 *Print ISSN: 2008-7055*
pp. 659-692 *Online ISSN: 2345-3745*
DOI: 10.22059/IJMS.2018.261178.673190

A Review of Agent-based Modeling (ABM) Concepts and Some of its Main Applications in Management Science

Hossein Sabzian[1], Mohammad Ali Shafia[1*], Ali Bonyadi Naeini[1], Gholamreza Jandaghi[2], Mohammad Javad Sheikh[3]

1. Department of Progress Engineering, Iran University of Science and Technology, Tehran, Iran
2. Faculty of Management and Accounting, College of Farabi, University of Tehran, Qom, Iran
3. Faculty of Humanities, Shahed University, Tehran, Iran

(Received: May 13, 2018; Revised: October 2, 2018; Accepted: October 7, 2018)

Abstract

We live in a very complex world where we face complex phenomena such as social norms and new technologies. To deal with such phenomena, social scientists often use reductionism approach where they reduce them to some lower-lever variables and model the relationships among them through a scheme of equations. This approach that is called equation based modeling (EBM) has some basic weaknesses in modeling real complex systems so that assumptions such as unbounded rationality and perfect information are strongly emphasized while adaptability and evolutionary nature of all engaged agents along with network effects go unaddressed. In tackling deficiencies of reductionism, the complex adaptive system (CAS) framework has been proven very influential in the past two decades. In contrast to reductionism, under CAS framework, complex phenomena are studied in an organic manner where their agents are supposed to be both boundedly rational and adaptive. As the most powerful methodology for CAS modeling, agent-based modeling (ABM) has gained a growing popularity among academics and practitioners. ABMs show how agents' simple behavioral rules and their local interactions at micro-scale can generate surprisingly complex patterns at macro-scale. Despite a growing number of ABM publications, those researchers unfamiliar with it have to study a number of works to understand (1) why and what of ABM, (2) its differences with EBM (3) its main functionalities in scientific studies and (4) some of its applications in management science. So, this paper's major contribution is to help researchers particularly those unfamiliar with ABM to get insights regarding its philosophy and use and gain a big picture of it.

Keywords

Complexity, Reductionism, Equation-based modeling, Complex adaptive system, Agent-based Modeling.

---

* **Corresponding Author, Email**: Omidshafia@iust.ac.ir

Introduction

A large number of social phenomena such as cultural changes, cooperation formation, innovation, norm formation, technology diffusion, and even evolution of states happen not just due to separate choices by constituent individuals but mainly because of dynamic interactions among them over time. As a matter of fact, such phenomena have a nature entirely different from their constituents. Modeling the formation of these collective phenomena has been a great target for mainstream socio-economic modeling approach but it has not captured it sufficiently. This mainstream modeling approach which often called equation-based modeling (EBM) has been frequently used in different disciplines of social sciences. However, EBMs lack a needed functionality in explaining how the interactions among micro-components of a system can lead to an interestingly different macro-behavior for that system. In fact, they perform very poorly in modeling the emergent properties of real-life systems, namely how a whole arises from the interactions among its simpler and lower-level parts so that it exhibits properties that its simpler and lower-level parts can never exhibit. For tackling such a limitation, the agent-based models (ABMs)[1] have been developed. An ABM is a kind of computational model which explores systems of multiple interacting agents which are spatially situated and evolve over time. ABMs are highly effective in explaining how complex patterns emerge from micro-level rules during a period of time. In contrast to EBMs that are based on deductive reasoning, ABMs properly work not only as an inductive reasoning technique where a conclusion is formed from a series of observations but also as a pure form of abductive reasoning where the best explanation for the phenomena under study is inferred via simulation[2]. ABMs have become a major modeling trend in a large number of domains ranging from the spread of epidemics (Situngkir, 2004) and the threat of bio-warfare (Caplat, Anand, & Bauch, 2008) to the formation of norms (Axelrod, 1986),

1. In ecological sciences ABMs are called individual-based models (IBMS).
2. The purpose and function of models, the difference between mathematical model (e.g. equation-based modeling) and computational model (e.g. ABMs), and the relationship between real world and models are very beautifully discussed in (Weisberg, 2012).

supply chain optimization (Van Dyke Parunak, Savit, & Riolo, 1998) and collaboration in project teams (Son & Rojas, 2010).

In contrast to EBMs which majorly focus on the relationship among macro-variables of a system in top-down manner, ABMs try to model how local and predictable interactions among micro-components of a system can generate a complex system-level behavior (Macy & Willer, 2002). ABM methodology is rooted in complexity theory and network science. In terms of complexity theory, ABMs are developed to explain how simple rules generate complex emergence (i.e. a process model) and in terms of network science ABMs are used to analyze the pattern that arises from agents' interactions over time (i.e. a pattern model)(Wilensky & Rand, 2015).

In this paper, we want to explore ABMs systematically and show their great potentiality for modeling a large number of real world problems (with a special focus on social problems) that contemporary methods cannot model properly.

The rest of this paper is organized as follows: section 2 deals with why and what of ABMs. The unique characteristics of ABMs in comparison to EBMs are discussed in section 3. Section 4 is concerned with main uses of ABMs. ABM building blocks are discussed in section 5. ABM development process is unraveled in section 6. Some critical considerations are offered in 7. Two applications of ABMs are presented in section 8 and a conclusion is provided in section 9.

Why and what of ABMs

We are living in complex world which itself includes an unlimited number of complexities ranging from highly micro-level complexities such as interacting atoms to highly macro-level ones such as nations. With an eye to socio-economic organizations like banks, insurance companies, hospitals and automobile producers, it becomes clear that all of these organizations are in turn a type of complex system so that each of them owns a distinguished whole (or ensemble) beyond its constituent parts (or components). Complex systems should be considered different from complicated systems. Actually, a complex system includes multiple interacting components forming a whole irreducible to its parts; therefore, it doesn't lend itself to divide-and-conquer logic while a complicated system is composed of multiple related components forming a whole reducible to its parts and can be understood by divide-and-conquer logic. When a complex system is studied, the uncertainty of its outcomes never decreases to zero but as soon as a complicated system is analyzed and understood, the certainty of its outcomes increases to a large degree (Snyder, 2013).

One example for illustrating the difference between a complex system and a complicated one is Fig. 1 and Fig. 2. A car engine is assembled by several number of parts. When it is well understood by a team of experts, it can be decomposed and integrated over and over again without losing any of its expected functionalities. In contrast, a team including a number of interacting persons can show a surprisingly unexpected performance even if the experts disarrange it from its initial conditions and rearrange it completely the same as its prior initial conditions[1].

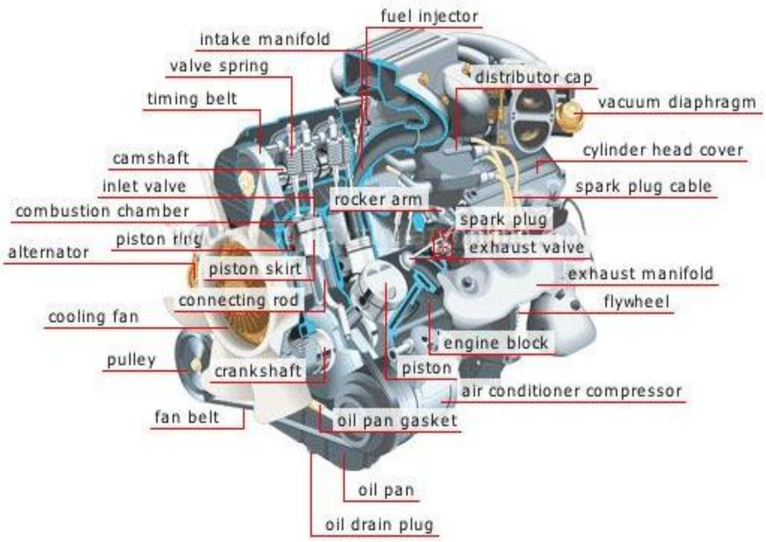

Fig. 1. A car engine[2] as a complicated system

1. It can be inferred that what Merton calls "unintended consequences" can just be observed in complex systems such as society (Merton, 1936)
2. https://supamac.co.za/looking-inside-your-car-engine/

Fig. 2.A team[1] as a complex system

Complexity theory (CT) is an interdisciplinary field studying complex systems ranging from biophysical complex systems such as molecules and organs to socio-economic complex systems such as small firms and multi-national corporations. According to CT, complex systems which absorb information from surrounding environment and accumulate knowledge that can help action are usually called complex adaptive systems (CASs). A CAS represents the notion of a system where "The whole is more than the parts". Actually, these are systems where multiple and perhaps very simple parts interact in a nonlinear and non-trivial manner to give rise to global often unpredictable behaviors observable and discoverable at a higher level of abstraction (Holland, 2002). Table 1 has been constructed to list fundamental characteristics of CASs through which the readers can distinguish CASs from other types of systems.

1.http://www.parstimes.com/soccer/players.html

Table 1. Fundamental characteristics of CASs

Characteristics	Description
Multiplicity and heterogeneity of constituent components	It is composed of a number of components usually called ” agent” (Holland, 2002; Wilensky & Rand, 2015). These agents can be very heterogeneous.
Non-linear interactions	Its agents interact with each other in a non-linear (non-additive) way (Holland, 2002; Wilensky & Rand, 2015).
Learnability and adaptability	Its agents can adapt or learn (Holland, 2002) so agents can experience and accumulate knowledge.
Non-ergodicity	It is non-ergodic (Kauffman, 2000; Moss, 2008).Therefore, it is highly sensitive to initial conditions.
Self-organization	It self-organizes and its control is intensely distributed among its agents(Chan, 2001; Wilensky & Rand, 2015)
Emergence	It exhibits emergence (Chan, 2001; Holland, 2002; Wilensky & Rand, 2015). It means, from the interactions of individual agents arises a global pattern or an aggregate behavior which is characteristically novel and irreducible to behavior(s) of agent(s).
Co-evolution	Its agents can co-evolve and change the system’s behavior gradually (Kauffman, 1992).
Far from equilibrium	It shows “far from equilibrium” phenomenon (Nicolis & Prigogine, 1989). Isolated systems have a high tendency towards equilibrium and this will cause them to die. The “far from equilibrium” phenomenon shows how systems that are forced to explore possibilities space will create different structures and novel patterns of relationships (Chan, 2001)[1].
Time asymmetry and irreversibility	It is time asymmetric and irreversible. One characteristic of a CAS is that it is time-asymmetric. Asymmetry in time happens when a system passes a point of bifurcation, a pivotal point where a choice is taken over another or others, resulting in irreversibility of time. Irreversibility signifies that the system cannot be reversed — run backwards or rewound—so as to get to its original initial conditions. Systems that, when run in reverse, do not necessarily or typically back to their exact initial state are said to be time-asymmetric (Prigogine & Stengers, 1997), and time asymmetry is a crucial factor in testing for a CAS. If a system time-symmetric, it is reversible, and cannot be regarded as CAS but a deterministic system. CASs are time-asymmetric, irreversible and naturally nondeterministic. So, in a CAS if one has an infinite deal of information regarding system’s initial conditions, it is impossible to predict or “retrodict”, since the system itself “chooses” its forward path that its “choice” is indeterminate and a function of statistical probability distribution rather than certainty (Rogers, Medina, Rivera, & Wiley, 2005).
Distributed control	The behavior of a CAS is not controlled by a centralized mechanism, rather, it is completely distributed among its constituent parts. The interactions of these constituent parts cause a CAS to exhibit a coherent macro-level behavior(Chan, 2001).

1. In thermodynamics, systems that do not have any exchange of energy and matter with their surrounding environment are called “isolated systems”. Such systems have a tendency to evolve towards equilibrium. But, our surrounding is enriched by phenomena arising from conations far from equilibrium. Some examples can be turbulences, fractals and even life. (Jaeger & Liu, 2010).

In the domain of CASs modeling methodologies[1], ABMs as micro-scale computational models[2] have shown a much better performance than equation-based models (EBMs) such as analytical models and statistical modeling methods, (Eliot R. Smith, 2007; M. A. K. Niazi, 2011; Y. Sun & Cheng, 2005; Van Dyke Parunak et al., 1998; Wilensky & Rand, 2015). Developed from the fields of complexity, cybernetics, cellular automata and computer science, ABMs have gained lots of popularity in the 1990s and show a growing migration not only from equation based models (EBMs) such as econometric models, analytical models and statistical modeling techniques but also from the more classical simulation approaches such as the discrete-event simulation (Heath & Hill, 2010; Siebers & Aickelin, 2008; Siebers, Macal, Garnett, Buxton, & Pidd, 2010). ABMs have a wide range of application domains ranging from biological systems (Caplat et al., 2008; Situngkir, 2004) to engineered ones (Olfati-Saber & Murray, 2004). The primary reason widely held by ABM practitioners is its very high strength in modeling complex adaptive systems (CAS) in comparison with other modeling methods.

The philosophy of agent-based modeling comes directly from the idea that a CAS can be effectively modeled and explained by creating agents and environment, characterizing behavioral rules of agents, and specifying interactions among them (Wilensky & Rand, 2015). Modeling a CAS needs a specific type of methodology. EBMs such as statistical modeling techniques or PDEs lack a needed functionality for this purpose because they just decompose a system into its main parts and model the relationship among them (a top-down approach) while neglecting the fact that the system itself is an entity beyond its constituent parts and it needs to be analyzed as an emergence of its constituent parts (a bottom-up approach).

1. CAS modeling methodologies have been comprehensively discussed in (Niazi, 2011)
2. Microscale models form a broad class of computational models that simulate fine-scale details, in contrast with macroscale models, which amalgamate details into select categories. Microscale and macroscale models can be used together to understand different aspects of the same problem (Gustafsson & Sternad, 2007, 2010).

Unique characteristics of ABMs in comparison with EBMs

EBM and ABM have stemmed from two distinct epistemological frameworks. The former is grounded on reductionism approaches such as neoclassical economic theories (NET) where the issues such as unbounded rationality, perfect information, deductive reasoning and low-rate heterogeneity are discussed, while the latter is built upon complexity theory (CT) where the issues such as bounded rationality, information asymmetry, network interaction, emergence and inductive reasoning are taken into consideration (Al-suwailem, 2008; Moss, 2008). This has made ABMs specifically advantaged in modeling CASs. Some of these advantages can be summed as Table 2.

Table 2. Major advantages of ABM over EBM

Advantage	Description
Bounded rationality	The context in which agents interact is very complex and unbounded rationality is not a viable assumption for it (Al-suwailem, 2008; Wilensky & Rand, 2015); agents have limited possibilities not only for receiving information but also for its processing. AB modelers contend that complex socio-economic systems have an innately non-stationary nature, because of continuous novelty (e.g., new emerging patterns of aggregated behavior) intrinsically introduced by the agents themselves (Windrum, Fagiolo, & Moneta, 2007). Therefore, it is extremely difficult for agents to learn and adapt in such a turbulent and endogenously changing environment. On this basis, AB researchers argue that assumption of unbounded rationality is unsuitable for modelling real world systems and agents should not only have bounded rationality but also adapt their expectations in different periods of time.
Exhibition of emergence	Since ABMs can model how micro-dynamics result in a high-level macro-dynamic, they can be used as the best method for exhibiting emergent properties. On this basis, ABM does not need knowledge of the aggregate phenomena; in fact, researchers do not need to be aware of what global pattern emerges out of the individual behavior. When modeling an independent variable with EBM, one needs to possess an adequate understanding of the aggregate behavior and then test out his or her hypothesis against it (Wilensky & Rand, 2015)
	A macro-system is an emergence of the way its constituent sub-systems interact so the properties of macro-dynamics can only be thoroughly figd out as the outcome of micro-dynamics including basic agents (Tesfatsion, 2002). This is in stark contrast with the top-down nature of EBMs (i.e., traditional neoclassical models), where the bottom level generally embodies a representative individual

Table 2. Major advantages of ABM over EBM (Continiouse)

Advantage	Description
Bottom-up perspective	and is bound by strong consistency requirements related with assumptions of unbounded rationality and equilibrium (Eliot, 2007; Macy & Willer, 2002). Contrarily, ABM developers specify highly heterogeneous agents living in complex environments that evolve through time (Kirman, 2010; Kirman, 1997). So, global properties are deciphered as an outcome of continuous interactions among simple local agents rather than from rigid assumptions of equilibrium and rationality exerted by the modeler (Dosi & Orsenigo, 1994)
Heterogeneity and discrete nature	An ABM can nicely model a population with high heterogeneity, while EBMs basically have to make assumptions of homogeneity. In many models, most notably in social science models, heterogeneity plays a key role. Furthermore, when you model individuals, the interactions and results are typically discrete and not continuous. Continuous models do not always map well onto real-world situations (Wilensky & Rand, 2015)
Networked interactions	Interactions among agents are both direct and essentially non-linear (Fagiolo, 1998; Silverberg, Dosi, & Orsenigo, 1988). Agents have direct interactions because their current decisions directly rely, via adaptive expectations, on the previous decisions made by other agents of population. These may include structures, such as cliques or local networks of some agents. In such structures, members have more similarity than others. Such structures of interaction can themselves intrinsically change over time, because the agents individually decide with which agent to interact based on their cognitive scheme (i.e., expected payoffs).(Lane, 1993a, 1993b).
Comprehensiveness	Results generated by ABMs are far more detailed than those made by EBMs. ABMs can abundantly provide both individual and aggregate level details at the same time. Because ABMs run by modeling each individual and its decisions, it is possible to study the life and history of each individual in the model, or collective behavior and observe the overall results. This “bottom-up” approach of ABMs is most often in contrast with the “top-down” approach of many EBMs, which tell you only how the global system is behaving and tell you nothing about its local individuals. Many EBMs assume that one aspect of the model directly influences, or causes, another aspect of the model, while ABMs allow indirect causation via emergence to have a larger effect on the model outcomes (Lee et al., 2015; Patel, Abbasi, Saeed, & Alam, 2018; Wilensky & Rand, 2015).
Randomness and indeterminacy:	One essential characteristic of agent-based modeling, and totally of computational modeling, is that randomness can be easily incorporated into models. Many EBMs and other forms of modeling need that each decision in the model be deterministically made. In ABMs this doesn’t apply; instead, the decisions can be made according to a statistical probability (Siebers & Aickelin, 2008; Wilensky & Rand, 2015).

With regard to Table 2, it makes sense that social structures such as teams, organizations, governments and nations or even galaxial systems are few examples of CASs each of which can exhibit a number of emergent properties. For instance, organizations are a type of CAS out of which phenomena such as cooperation, aggregation of core competencies or even the ways employees interactively reinforce or weaken organizational routines emerge (Wall, 2016). In a wider economic system, macro-level phenomena such as inflation, stagflation, stock markets dynamics and economic inequality are aggregates (complex problems) emerging out of the economic systems. In recent years, the literature about complexity economics has been developed in so many areas including evolutionary models built by Nelson and Winter (1982) and Hodgson (1998), Brock and Durlauf's research of social interactions (Brock & Durlauf, 2001), Axtell's study of firm size (Axtell, 2001), Alan Kirman and his colleagues' studies of financial markets (Kirman, Foellmer, & Horst, 2005) and the agent-based simulation of general equilibrium (Gintis, 2006a, 2006b).[1] The importance of ABM in studying macroeconomic issues has been well discussed by (Battiston et al., 2016; Farmer & Foley, 2009) and great reviews of ABM applications in studying financial markets have been offered by (Chen, Chang, & Du, 2012; Mizuta, 2016; Todd, Beling, Scherer, & Yang, 2016).

However, regarding complex nature of real world, it goes clear that EBMs (such as constrained optimization models used in econometrics) cannot capture the behavior of complex adaptive systems. This is an essential departure from the presumptions existing in conventional economic theories. Such systems should be analyzed 'in' time and this limits the way that mathematics can be used. Standard economic theory includes the application of an ahistorical body of logical clauses to display attitudes perceived in the historical domain. In opposition, complex adaptive system theory copes directly with the fundamental principles that rule the behavior of systems in history. Therefore, it can be said that thinking about the economy and its sub-components as complex adaptive systems can allow us to

1. For an extensive overview of computational models in complexity economics, look at Amman et al. (1996) and Tesfatsion (2002).

evade such scientific impasses. In economic thought, Schumpeter's contributions toward the process of "creative destruction" conform to complex adaptive systems theory (Foster, 2001).

However, the core idea of Agent-Based Modeling is rooted in the fact that a CAS can be productively modeled with agents, an environment, and the rules of interactions among them. An agent is a computational autonomous entity with particular properties, behaviors, and even goals. The environment is a landscape over which agents have interactions and can be spatial, network-based, or a mixture of them. The interactions can be non-linear and quite complex. Agents can have interaction with other agents or with the environment and they can not only change their interaction rules but also can change the strategies used to decide what behavior to do at a particular time. (Wilensky & Rand, 2015). So, ABMs can be considered as a revolutionary methodology for modeling and simulating systems (i.e. real-world CASs) that are tremendously difficult and often impossible to be studied by EBMs (Bankes, 2002).

Main functionalities of ABMs

ABMs can be used in *description and explanation*. Like all models, an AMB is a simplification of a real world system which doesn't entail all of its aspects so it is distinguishable from real world system and can help its understanding. The exploratory nature of ABM indicates that they can be used to pinpoint the essential mechanisms underlying the phenomena under study. a subject matter expert (SME) can use an AMB as a proof that his or her hypothesized mechanisms sufficiently account for the aggregate behavior under study. (Wilensky & Rand, 2015). Explanation is strongly believed to be a major function of ABMs because it helps understand how simple rules generate complex structures. ABMs' explanatory power is highly generative, especially in social sciences due to the fact that it explains which macro-structures such as epidemic dynamics or social evolutions emerge in population of heterogeneous agents that interact locally and in non-trivial way under a set of tenable behavioral rules(Epstein, 2008).

ABMs facilitate the *experimentation process*(Leal & Napoletano, 2017). They can be run repetitiously to discern changes in their dynamics and outputs (Wilensky & Rand, 2015). Some models show very small changes during several runs. Some have a path-dependency nature(Brown, Page, Riolo, Zellner, & Rand, 2005) and some exhibit tremendous variations from run to run. Through experimentation, system modelers get informed of how input parameters affect model's outputs. Therefore, they can make various scenarios for achieving the targeted behavior.

ABMs are sometimes used for *prediction* purposes. SMEs frequently use models to get a picture of possible future states. Like every model, the quality of ABMs' prediction relies on the accuracy of its input parameters and since society is a complex system with an unspecified degree of uncertainty and very high sensitivity to small-scale events, no prediction can be deemed as absolutely right (Moss, 2008; Wilensky & Rand, 2015). Prediction differs from description where the modeler describes the past or present states of the system, for example when a modeler describes what changes first occurred in the system. Moreover, prediction is also district from explanation, for example Plate tectonics definitely explains earthquakes, but does not help us to predict the time and place of their occurrence or evolution is commonly accepted as explaining speciation, but it is impossible to predict next year's flu strain(Epstein, 2008). Nonetheless, when SMEs claim to have used ABMs for the purpose of prediction, they actually use ABMs either for description or explanation (Wilensky & Rand, 2015).

ABMs has a high functionality for education and analysis (Blikstein & Wilensky, 2009; Sengupta & Wilensky, 2009; Wilensky & Reisman, 2006). Educators can develop models for people that they have never seen before. For example, educators can model some examples of mutualism between individuals of different species when both individuals benefit[1]. Moreover, models can simulate a system that may not be directly available from real-world observations; therefore, they can be very thought-provoking and enable learners to go beyond their observations and conduct experiments just like scientists.

1. An interesting example can be the mutualism between a goby and a shrimp. The shrimp digs a burrow in the sand and cleans it up where both species can live. Since the shrimp is almost blind, it has a high vulnerability to predators outside the burrow. When the shrimp is under dangerous conditions the goby goes over to warn the shrimp by touching it with its tail. This causes both the shrimp and goby quickly back into the burrow (Helfman, Collette, Facey, & Bowen, 2009).

When a SME is going to gain a deeper understanding of a phenomenon about which there is not enough theory, *thought experiment* can be very useful. Though experiment is another suitable area for ABMs, this type of experiment is done to achieve its purpose without the benefit of execution (Sorensen, 1998). Thought experiment is conducted when the real-world experiments are neither affordable nor possible to execute (Rangoni, 2014). It has a wide application in social and natural sciences. Through this method, researchers can get awareness of the logical consequences of their hypotheses. For example, what will happen if the personnel of a company all telework on Monday, Wednesday and Friday? ABMs can be very useful in thought experiments (Elsenbroich & Gilbert, 2014), especially when people want to deal with complex systems such as organization and society. Such systems are far from a real-word laboratory where it is possible to control some variables (as control group) and measure the effect of test on other variables (as treatment group). As a matter of fact, in such systems, there are numerous causal factors that are mainly interdependent over which we have a very limited control (Savona, 2005). So real-world experiments can rarely be executed in such systems. This has led researchers of social fields to utilize the potential of thought experiment in simulating the consequences of their hypothesized mechanism.

Applications of ABMs in management science

ABM has shown a highly effective performance in various scientific domains from biological and health sciences (El-Sayed, Scarborough, Seemann, & Galea, 2012; Grimm & Railsback, 2005; Kanagarajah, Lindsay, Miller, & Parker, 2010), engineering sciences (Davidsson, 2002; Hao, Shen, Zhang, Park, & Lee, 2006; Park, Cutkosky, Conru, & Lee, 1994), sociology (Axtell, 2000; Bianchi & Squazzoni, 2015; Macy & Willer, 2002), political sciences (Cederman, 2002; de Marchi & Page, 2014; Lustick, 2002), economic sciences (Al-suwailem, 2008; Tesfatsion, 2002) and management sciences (Gómez-Cruz, Loaiza Saa, & Ortega Hurtado, 2017; North & Macal, 2007; Wall, 2016) to only name a few. In this part, the application of this methodology is discussed in the domain of management science.

Most of phenomena in managerial sciences are complex and infused with uncertainty. In fact, it is notoriously difficult to understand this complexity just through personal judgments and intuition (Bonabeau, 2002). Whereas EBMs are not good at overcoming the organization's complexity (mainly due to their reductionism approach), ABMs enables management scientists to understand its underlying dynamics and mechanisms and the way it evolves and affects the total organizational performance over a number of time periods.

On a study on organizational structures and environmental changes, Sigglekow and Levinthal (2003) developed a computational ABM to analyze ways through which organizations can organize themselves after they face an environment change. This work was focused on showing the impact of e-commerce on organizational changes (Siggelkow & Levinthal, 2003). Sun and Naveh (2004) simulated organizational dynamics. The result of their work revealed those decisions that are made by non-hierarchical teams are better than those made in a hierarchical team structure. Moreover, they proved that when there is a free access to information, human resources show a better performance than when they have limited access (Sun & Naveh, 2004). Ciarli et al. (2007) showed that companies which invest on a specific set of innovations in a long time are very likely to gain a good level of competitiveness in the short time but they are very prone to have a technological lock-in over time (Ciarli, Leoncini, Montresor, & Valente, 2007).

As a very practical work, North et al (2007) developed a set of ABMs to study the interactions among suppliers, retailers and consumers of a market. This work resulted in a powerful decision-making tool. One of the major applications of this work was in Proctor & Gamble which led to huge savings in operation costs (North & Macal, 2007). Odehnalová and Olsevicová (2009) used an ABM to understand how family businesses develop over time (Odehnalová & Olsevicová, 2009). Wu et al. (2009) developed an ABM based on some factors such as resilience, agility, robustness and survival to simulate the degree of organizational adaptability (Wu et al., 2009) Schwartz and Ernst (2009) developed an ABM to study scenarios affecting diffusion of three water-saving technologies (i.e., showerheads, toilet flushes and rain harvesting) on households of Southern Germany. Their work revealed that these technologies will be diffused even without promotion. In addition, they could develop some scenarios for relating households' lifestyles to innovation (Schwarz & Ernst, 2009).

Chang et al. (2010) studied the effect of alliance of two small search engines on competing with a big search engine company. The result of their simulation showed that individual preferences and a tendency towards following others are the core structures underlying the behavior of advertisers. Their study also illustrated that in spite of a small market share occupied by two small engines (i.e. alliance), they can gradually acquire the bigger one (Chang, Oh, Pinsonneault, & Kwon, 2010).The effect of group structure on the speed of innovation was studied through an ABM developed by (Zhong & Ozdemir, 2010). Jiang and Wang (2010) analyzed the relationship between the behavior of employees and task assignments through a computational ABM. The simulation revealed that in organizational context where learning is persuaded and tasks are assigned in a dynamic manner, the capability of employees increases (Jiang, Hu, & Wang, 2010).

Rand and rust (2011) used ABM to extend Bass classical diffusion model by exploring network effects in it. Moreover, they provided a systematic framework for the rigorous development of ABMs in marketing studies (Rand & Rust, 2011). In a work on human resources, the effect of social learning on organizational performance was studied. The simulation results illustrated that the familiarity level of individual agents with each other can majorly affect their learning strategies. It was also clarified that social learning has a large positive effect on improving interpersonal relationships (Singh, Dong, & Gero, 2012). Bouarfa et al. (2013) conducted an empirical work in air transportation logistics. They developed an ABM and Monte Carlo simulation to pinpoint unpredictable emergent aggregated behaviors in air transportation systems. Their work showed that traditional warning systems were not able to detect such emergent high-level risky behaviors in air safety (Bouarfa, Blom, Curran, & Everdij, 2013). Forkman et al. (2012) studied the power position of individual agents and the effectiveness of their strategy. The results revealed the strategies formulated and dictated by organization's CEO may not necessarily yield good results. Therefore the positions of employees don't necessarily secure an effective strategy (Forkmann, Wang, Henneberg, Naudé, & Sutcliffe, 2012). In a study conducted by

Prenkert and Følgesvold (2014), they simulated how the network structure of commercial interactions among some international organizations can influence those interactions (Prenkert & Følgesvold, 2014). Some very rich review works have been done on modeling diffusion of renewable energy technologies (Rao & Kishore, 2010) and energy-efficient technologies in residential places (Moglia, Cook, & McGregor, 2017). This work discusses the major technology, management studies that have used ABM to problem modeling and scenarios development

ABM building blocks

ABMs include three building blocks of (1) agents, (2) environment and (3) interactions (J. M. Epstein & Axtell, 1997; M. A. K. Niazi, 2011; Wilensky & Rand, 2015). As the first building block of ABMs, agents are the basic computational units of agent-based models. They are defined by two main aspects of (1) ***propertie*s** and (2) ***behaviors*** (or actions). Agent's properties are internal or external states that can be changed by its behaviors (actions). Suppose you want to model an economic system including individual human agents. Some properties for these agents can be the status of employment, income level, number of bank account and age or even if necessary blood type! Actions of such agents can be searching for a job, opening a bank account, taking a loan and so on. As it is sensible, actions affect properties, for example, when a person opens a new bank account, the number of his or her bank accounts increases. Or when a person finds a job, his or her status of employment is changed and subsequently his or her income level is positively influenced. As the first building block of any ABM, agents are in three specific types of ***mobile*** agents, ***stationary*** agents and ***connecting*** agents. Mobile agents have the capability of movement; for example, a human is a type of a mobile agent. Stationary agents are those static agents that have no moving capability. For example, an organization or in wider sense, an environment is a type of stationary agent. Connecting agents are those agents that connect agents together. One clear example of this can be "links" among agents (Fig. 3). Additionally, in modeling agents, two major factors have to be taken into consideration; the first factor is about the ***granularity*** (grain-size) of agents. For example, when you want to model an economic system, do you choose to model the individual actors or prefer to model institutions? The second important factor deals with the ***cognitive level of agents***. In fact, how much is the capability of agents to observe (and sense) the surrounding world and make decisions?

According to the cognitive level of agents, they can be classified into four types of (1) reflective or myopic agents, (2) utility-based agents, (3) goal-based agents, (4) adaptive agents (Wilensky & Rand, 2015). The reflective agents are very simple if-then agents so that if they face situation A, they immediately do action B. Utility-based agents are very similar to reflective ones but there is a utility function that they do want to maximize it under all conditions. Goal-based agents are more advanced form of utility-based function so that they have a goal that dictates their actions. The most advanced form of agents are adaptive agents. They have enough cognitive capabilities to change their actions in similar conditions based on prior experience. Namely, if they do action A in situation B and lose some payoffs, when they face situation B again, they don't do action A according to their prior experiences[1].

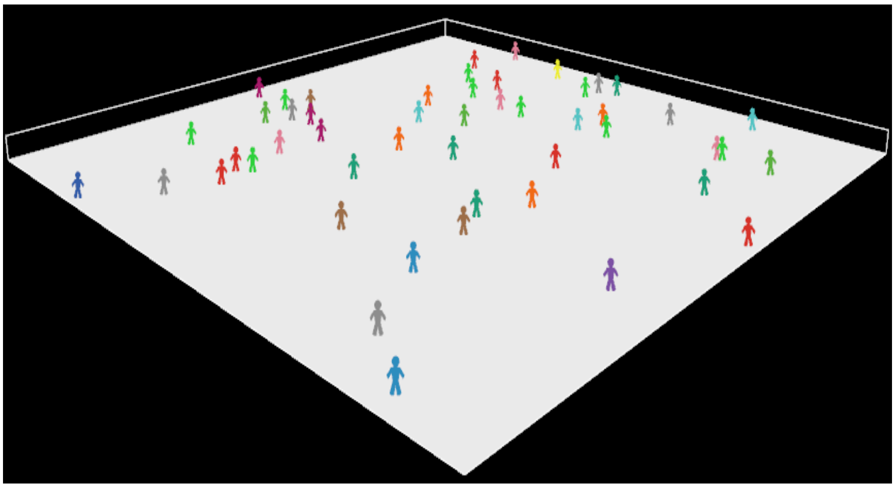

Fig. 3. Building blocks of ABM

1. For a more comprehensive study of agent cognition, look at (Russell & Norvig, 2016)

As the second building blocks of ABMs, the environment is composed of all conditions surrounding the agents as they interact within the model. In other words, the environment is where an artificial social life unfolds (J. M. Epstein & Axtell, 1997). Environments can come into three different major forms of (1) spatial environment, (2) networked environment and (3) mixed environment. The spatial environment is often a discrete environment including several discrete points[1]. The most common form of spatial environment is lattice structure which can be two or three dimensional as visualized[2] in

Fig. 3. In spatial environments, when agent A (here one of the agents near the middle) reaches a border on the far right side of the environment (i.e., the world) and wants to go farther right, boundary conditions of the environment come to play. The topology of an environment deals with such boundary conditions. For a spatial lattice structure such as

Fig. 3, there can be three types of topologies. The first type is a toroidal topology where agent A reappears in the far left side of the lattice. The second type is bounded topology where agent A cannot move farther right and finally, the third type is infinite plane topology where agent A can keep going right for ever (Wilensky & Rand, 2015). In real world situations, such as socio-economic settings, agents have more networked interactions than spatial (geographical) interactions. In two different stock markets, a rumor spreads through the individual agents of a network. Therefore, an environment can be in a network form where the mobile agents are “nodes” and the connections among them are “links”. There are several types of networks that three of them are widely used which are “random networks” (Erdös & Rényi, 1959), “Watts-Strogatz small-world” (Watts & Strogatz, 1998) and “ scale-free networks”(Albert & Barabási, 2002).[3] All these networks have been visualized in Fig. 4, Fig. 5 and Fig. 6, respectively.

1. It can also be continuous, see (Wilensky & Rand, 2015)
2. All visualizations have been implemented by Netlogo 6.0.1
3. For a more comprehensive study of networks, look at (Newman, 2010; Wasserman & Faust, 1994).

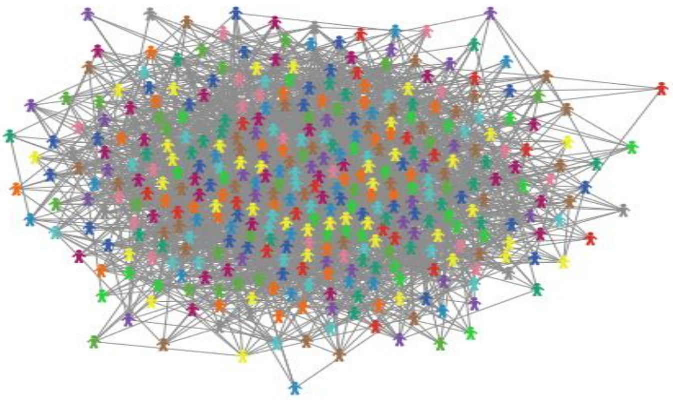

Fig. 4. Random network

Using network structures as an ABM environment provides lots of opportunities to synthesize social network theory (SNT) with ABM. As a matter of fact, ABMs are developed to explain how simple rules generate complex emergence (i.e. a process model) and in terms of network science ABMs are used to analyze the pattern that arise from agents' interactions over time (i.e. a pattern model) (Wilensky & Rand, 2015). When spatial environment and networked environment come together, they form a mixed environment where some agents have links whereas some have no links.

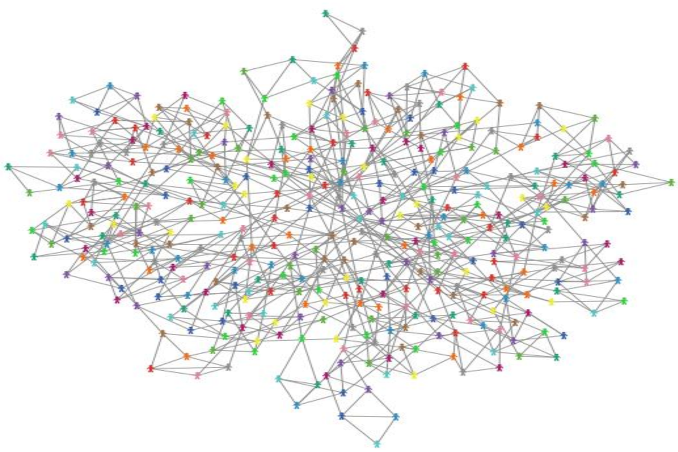

Fig. 5. Small-world network

As the third building blocks of ABMs, interactions refer to rules of behaviors for both agents and the environment (J. M. Epstein & Axtell, 1997). Actually, these rules enable agents to interact with both themselves and others. There are five basic classes of interactions: agent-self, environment-self, agent-agent, environment-agent, environment-environment. In agent-self interactions, an agent checks its internal states and decides according to them. Environment-self interactions are when areas of the environment alter or change themselves. For instance, they can change their internal state variables as a result of some calculations. Agent-agent Interactions are usually the most important type of action within ABMs. Agent-Environment Interactions happen when the agent manipulates or examines an area of the world in which it exists, or when the environment in some way observes or alter the agent's internal states. Environment-Environment Interactions between different areas of the environment are probably the least commonly used interaction type in ABMs(Wilensky & Rand, 2015).

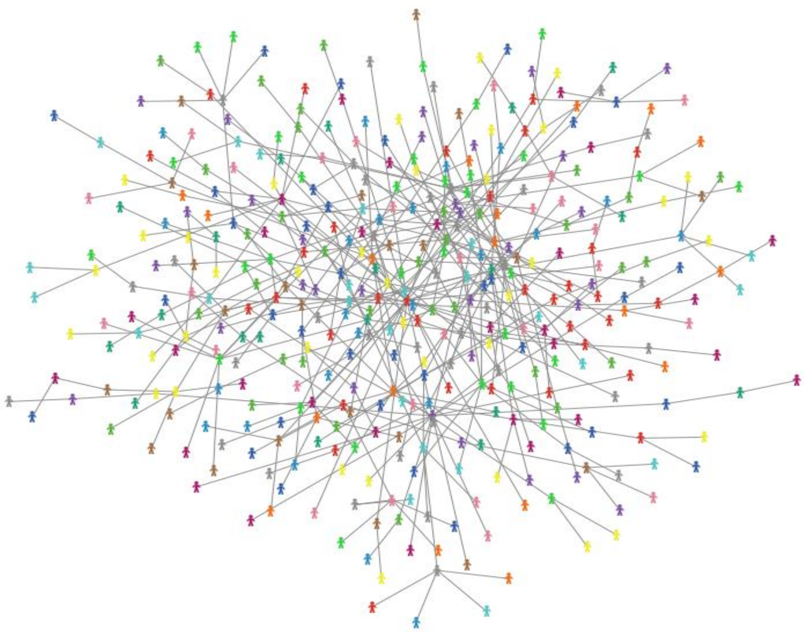

Fig. 6. Scale-free network

Emergence modeling: a critical consideration

Complex adaptive systems (CASs) are real world systems which have a number of characteristics as discussed in Table 1. In contrast, Agent-based models (ABMs) are a type of computational methodology believed to be very promising in modeling CASs. Every developed ABM only shows one or some aspects of a CAS and not all of its aspects. Therefore, what ABM practitioners produce via simulating a CAS (e.g., a society) is a simplified and artificial picture of that CAS as it is visualized in Fig. 7. CASs exhibit emergent properties (Chan, 2001; Holland, 2002; M. A. Niazi & Hussain, 2012; M. A. K. Niazi, 2011; Rogers et al., 2005). A property of a CAS, that emerges out of non-linear and non-trivial interactions among its constituent components so that it is beyond and irreducible to them, is called "emergence[1]". In comparison to other simulation techniques such as discrete event simulation (DES), system dynamics (SD) or even game theory, one of the greatest advantages of ABM is its outstanding prowess in showing the emergent properties of CASs.

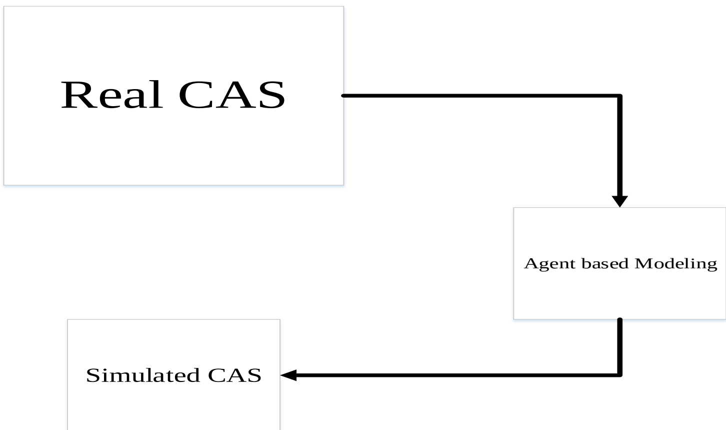

Fig. 7. A real CAS and a simulated CAS

1. According to classical British emergentism, the emergent phenomena were believed to be unexplainable in nature, whereas agent based modeling approach takes an opposite look at emergence; therefore, ABM is incompatible with the basic interpretation of classical British emergentism. This has been deeply discussed in (J. M. Epstein, 1999)

Our world exhibits several observable CASs; in biological sciences, molecules emerge out of interacting atoms, organelles emerge out of interacting molecules, cells emerge out of interacting organelles. Organs emerge of interacting cells and finally body emerges out of interacting organs. Such examples of emergent properties of our body indicates that it is a biological CAS full of interesting emergent properties such as consciousness (Clayton, 2004). In a sociological perspective, there are also several examples of CAS; as an instance, the society can be interpreted as an emergent property of interacting actors or even norms can be studied as the emergent property of social system (Elsenbroich & Gilbert, 2014). In organizational sciences, it also makes sense that organizational routines emerge out of their interacting personnel(Gao, Deng, & Bai, 2014).The emergence is very difficult to forecast and completely depends on the observation (Gilbert, 2006). In facing the challenge of emergence, two kinds of thinking styles can come to play named " integrative thinking" and "differential thinking" (Martin, 2009; Showers, 1992; Sill, 1996; Wilensky & Rand, 2015).

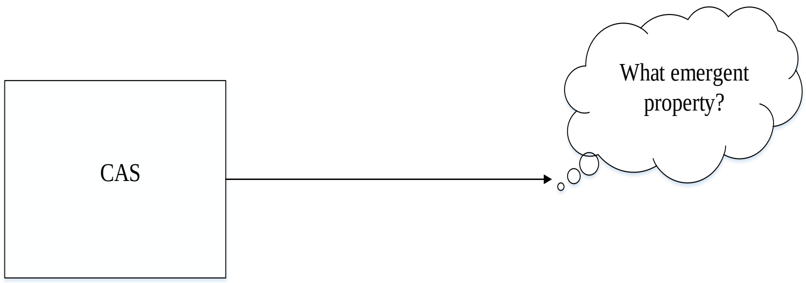

Fig. 8. Integrative thinking

As shown in Fig. 8, integrative thinking refers to when the subject matter experts (SMEs) have a CAS in mind (e.g., an organization into which a number of people with different religious backgrounds and specialties work), but they don't know its targeted emergent property (e.g., the pattern of cooperation or formation of hierarchy). In contrast, when SMEs have an observable emergent property but don't know its CAS (i.e., from which CAS that property emerged), they are facing differential thinking as visualized in Fig. 9.

Fig. 9. Differential Thinking

Essentially, the core of integrative thinking style is to discern what properties will emerge out of the CAS under study, while differential thinking style is used to grasp what CASs can lead to the emergent property under study.

Conclusion

Agent-based modeling (ABM) has a high potentiality for modeling systems that are very hard or often impossible to capture by traditional modeling techniques such as partial differential equations (PDEs), ordinary differential equations (ODEs) and even statistical modeling methods. In addition, ABM has shown a performance far better than a number of simulation methods such as discrete-event simulation (DES) and system dynamics (SD). A number of works have been published on this subject most often each of which has particularly dealt with one aspect of ABMs. For example, some have only dealt with why and what of ABMs (R. Axtell, 2000; Chattoe-Brown, 2013; J. M. Epstein, 1999; J. M. Epstein & Axtell, 1997; Heath & Hill, 2010; Macy & Willer, 2002), some works have only discussed the difference between ABM and EBM (Y. Sun & Cheng, 2005; Van Dyke Parunak et al., 1998) and a number of works have just been conducted on major uses of ABMS (Blikstein & Wilensky, 2009; Elsenbroich & Gilbert, 2014; Leal & Napoletano, 2017; Moss, 2008; Rangoni, 2014; Wilensky & Rand, 2015; Wilensky & Reisman, 2006).Therefore, the major focus of this paper has been to help social sciences researchers particularly those unfamiliar with ABMs to get insights regarding their philosophy, functionalities and some major applications in organizational and management sciences and gain a clear-cut big picture of them. However, like any scientific work, this work has had some limitations. The first limitation is that no development framework has been proposed for ABMs designing, simulating and analysis. So a systematic study about this issue accompanied by some practical implementations can be a very good subject for future studies. The second limitation refers to the fact that a number of toolkits have been so far developed for programming and simulating ABMs each of which has some advantages and disadvantages. But this point has not been discussed here and can be pursued by future works.

References

Al-suwailem, S. , O. (2008). Islamic economics in a complex world: Explorations in Agent-based Simulation. *The Islamic Research and Teaching Institute,* 1–106 Retrieved from http://www.irti.org/English/Pages/Publications.aspx

Albert, R., & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, *74*(1), 47.

Amman, H. M., Tesfatsion, L., Kendrick, D. A., Judd, K. L., & Rust, J. (1996). *Handbook of computational economics* (Vol. 2). Elsevier.

Axelrod, R. (1986). An evolutionary approach to norms. *American Political Science Review*, *80*(4), 1095–1111.

Axtell, R. (2000). Why agents?: on the varied motivations for agent computing in the social sciences.

Axtell, R. L. (2001). Zipf distribution of US firm sizes. *Science, 293*(5536), 1818–1820.

Bankes, S. C. (2002). Agent-based modeling: A revolution? *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7199–7200.

Battiston, S., Farmer, J. D., Flache, A., Garlaschelli, D., Haldane, A. G., Heesterbeek, H., … Scheffer, M. (2016). Complexity theory and financial regulation. *Science*, *351*(6275), 818–819.

Bianchi, F., & Squazzoni, F. (2015). Agent-based models in sociology. *Wiley Interdisciplinary Reviews: Computational Statistics*, *7*(4), 284–306. https://doi.org/10.1002/wics.1356

Blikstein, P., & Wilensky, U. (2009). An atom is known by the company it keeps: A constructionist learning environment for materials science using agent-based modeling. *International Journal of Computers for Mathematical Learning*, *14*(2), 81–119.

Bonabeau, E. (2002). Agent-based modeling: methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences, 99*(suppl. 3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Bouarfa, S., Blom, H. A. P., Curran, R., & Everdij, M. H. C. (2013). Agent-based modeling and simulation of emergent behavior in air transportation. *Complex Adaptive Systems Modeling*, *1*(1), 15.

Brock, W. A., & Durlauf, S. N. (2001). Discrete choice with social interactions. *The Review of Economic Studies*, *68*(2), 235–260.

Brown, D. G., Page, S., Riolo, R., Zellner, M., & Rand, W. (2005). Path dependence and the validation of agent-based spatial models of land use. *International Journal of Geographical Information Science*, *19*(2), 153–174.

Caplat, P., Anand, M., & Bauch, C. (2008). Symmetric competition causes population oscillations in an individual-based model of forest dynamics. *Ecological Modelling*, *211*(3–4), 491–500.

Cederman, L.-E. (2002). Endogenizing geopolitical boundaries with agent-based modeling. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7296–7303.

Chan, S. (2001). Complex adaptive systems. In *ESD. 83 research seminar in engineering systems* (Vol. 31, p. 1).

Chang, R. M., Oh, W., Pinsonneault, A., & Kwon, D. (2010). A network perspective of digital competition in online advertising industries: A simulation-based approach. *Information Systems Research*, *21*(3), 571–593.

Chattoe-Brown, E. (2013). Why sociology should use agent based modelling. *Sociological Research Online*. https://doi.org/10.5153/sro.3055

Chen, S.-H., Chang, C.-L., & Du, Y.-R. (2012). Agent-based economic models and econometrics. *The Knowledge Engineering Review*, *27*(2), 187–219.

Ciarli, T., Leoncini, R., Montresor, S., & Valente, M. (2007). Innovation and competition in complex environments. *Innovation*, *9*(3–4), 292–310.

Clayton, P. (2004). Mind and emergence: From quantum to consciousness.

Davidsson, P. (2002). Agent-based social simulation: A computer science view. *Journal of Artificial Societies and Social Simulation*, *5*(1).

de Marchi, S., & Page, S. E. (2014). Agent-Based Models. *Annual Review of Political Science*, *17*(1), 1–20. https://doi.org/10.1146/annurev-polisci-080812-191558

Dosi, G., & Orsenigo, L. (1994). Macrodynamics and microfoundations: an evolutionary perspective. *Economics of Technology//Amsterdam: North-Holland*, 91–123.

El-Sayed, A. M., Scarborough, P., Seemann, L., & Galea, S. (2012). Social network analysis and agent-based modeling in social epidemiology. *Epidemiologic Perspectives & Innovations*, *9*(1), 1.

Eliot R. Smith, F. R. C. (2007). Agent-Based Modeling: {A} New Approach for Theory Building in Social Psychology. *Personality and Social Psychology Review*, *11*(87), 1–56.

Elsenbroich, C., & Gilbert, N. (2014). *Modelling norms*. *Springer*. Springer. https://doi.org/10.1007/978-94-007-7052-2

Epstein, J. (2008). Why model? *Journal of Artificial Societies and Social …*, *11*(4), 6. https://doi.org/10.1080/01969720490426803

Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, *4*(5), 41–60. https://doi.org/10.1002/(SICI)1099-0526(199905/06)4:5<41::AID-CPLX9>3.3.CO;2-6

Epstein, J. M., & Axtell, R. (1997). Artificial societies and generative social science. *Artificial Life and Robotics*, *1*(1), 33–34.

Erdös, P., & Rényi, A. (1959). On random graphs, I. *Publicationes Mathematicae (Debrecen)*, *6*, 290–297.

Fagiolo, G. (1998). Spatial interactions in dynamic decentralised economies: A review. In *The Economics of Networks* (pp. 53–91). Springer.

Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. *Nature*, *460*(7256), 685.

Forkmann, S., Wang, D., Henneberg, S. C., Naudé, P., & Sutcliffe, A. (2012). Strategic decision making in business relationships: A dyadic agent-based simulation approach. *Industrial Marketing Management*, *41*(5), 816–830.

Foster, J. (2001). Competitive selection, self-organisation and Joseph A. Schumpeter. In *Capitalism and Democracy in the 21st Century* (pp. 317–334). Springer.

Gao, D., Deng, X., & Bai, B. (2014). The emergence of organizational routines from habitual behaviours of multiple actors: An agent-based simulation study. *Journal of Simulation*, *8*(3), 215–230. https://doi.org/10.1057/jos.2014.1

Gilbert, N. (2006). When does social simulation need cognitive models?. *Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation*, 428–432.

Gintis, H. (2006a). The economy as a complex adaptive system.
Gintis, H. (2006b). The emergence of a price system from decentralized bilateral exchange. *Contributions in Theoretical Economics*, *6*(1), 1–15.
Gómez-Cruz, N. A., Loaiza Saa, I., & Ortega Hurtado, F. F. (2017). Agent-based simulation in management and organizational studies: a survey. *European Journal of Management and Business Economics*, *26*(3), 313–328. https://doi.org/10.1108/EJMBE-10-2017-018
Grimm, V., & Railsback, S. F. (2005). Individual-based Modeling and Ecology:(Princeton Series in Theoretical and Computational Biology).
Gustafsson, L., & Sternad, M. (2007). Bringing consistency to simulation of population models–Poisson Simulation as a bridge between micro and macro simulation. *Mathematical Biosciences*, *209*(2), 361–385.
Gustafsson, L., & Sternad, M. (2010). Consistent micro, macro and state-based population modelling. *Mathematical Biosciences*, *225*(2), 94–107.
Hao, Q., Shen, W., Zhang, Z., Park, S.-W., & Lee, J.-K. (2006). Agent-based collaborative product design engineering: An industrial case study. *Computers in Industry*, *57*(1), 26–38.
Heath, B. L., & Hill, R. R. (2010). Some insights into the emergence of agent-based modelling. *Journal of Simulation*, *4*(3), 163–169.
Helfman, G., Collette, B. B., Facey, D. E., & Bowen, B. W. (2009). *The diversity of fishes: biology, evolution, and ecology*. John Wiley & Sons.
Hodgson, G. M. (1998). The approach of institutional economics. *Journal of Economic Literature*, *36*(1), 166–192.
Holland, J. H. (2002). Complex adaptive systems and spontaneous emergence. In *Complexity and industrial clusters* (pp. 25–34). Springer.
Jaeger, H. M., & Liu, A. J. (2010). Far-from-equilibrium physics: An overview. *ArXiv Preprint ArXiv:1009.4874*.
Jiang, G., Hu, B., & Wang, Y. (2010). Agent-based simulation of competitive and collaborative mechanisms for mobile service chains. *Information Sciences*, *180*(2), 225–240.

Kanagarajah, A. K., Lindsay, P., Miller, A., & Parker, D. (2010). An exploration into the uses of agent-based modeling to improve quality of healthcare. In *Unifying themes in complex systems* (pp. 471–478). Springer.

Kauffman, S. A. (1992). The origins of order: Self-organization and selection in evolution. In *Spin glasses and biology* (pp. 61–100). World Scientific.

Kauffman, S. A. (2000). *Investigations*. Oxford University Press.

Kirman, A. (2010). *Complex economics: individual and collective rationality*. Routledge.

Kirman, A., Foellmer, H., & Horst, U. (2005). Equilibrium in financial markets with heterogeneous agents: A new perspective. *Journal of Mathematical Economics*, *41*(1–2), 123–155.

Kirman, A. P. (1997). The economy as an interactive system. In *Santa Fe Institute Studies in The Sciences of Complexity of Complexity-proceedings, Volume* (Vol. 27, pp. 491–532).

Lane, D. A. (1993a). Artificial worlds and economics, part I. *Journal of Evolutionary Economics*, *3*(2), 89–107.

Lane, D. A. (1993b). Artificial worlds and economics, part II. *Journal of Evolutionary Economics*, *3*(3), 177–197.

Leal, S. J., & Napoletano, M. (2017). Market stability vs. market resilience: Regulatory policies experiments in an agent-based model with low-and high-frequency trading. *Journal of Economic Behavior & Organization*.

Lee, J. S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmooei, B., Stonedahl, F., Lorscheid, I., … Parker, D. C. (2015). The complexities of agent-based modeling output analysis. *Jasss*, *18*(4), 1–26. https://doi.org/10.18564/jasss.2897

Lustick, I. (2002). PS-I: A user-friendly agent-based modeling platform for testing theories of political identity and political stability. *Journal of Artificial Societies and Social Simulation*, *5*(3).

Macy, M. W., & Willer, R. (2002). From factors to factors: Computational Sociology and Agent-based Modeling. *Annual Review of Sociology*, *28*(1), 143–166. https://doi.org/10.1146/annurev.soc.28.110601.141117

Martin, R. L. (2009). *The opposable mind: Winning through integrative thinking*. Harvard Business Press.

Merton, R. K. (1936). The unanticipated consequences of purposive social action. *American Sociological Review*, *1*(6), 894–904.

Mizuta, T. (n.d.). A Brief Review of recent Artificial Market Simulation (Agent-Based Model) Studies for Financial Market Regulations and/or Rules.

Moglia, M., Cook, S., & McGregor, J. (2017). A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency. *Sustainable Cities and Society, 31*, 173–182.

Moss, S. (2008). Alternative approaches to the empirical validation of Agent- based Models. *Journal of Artificial Societies and Social Simulation*, *11*(15), 16. Retrieved from http://jasss.soc.surrey.ac.uk/11/1/5.html

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Harvard University Press.

Newman, M. (2010). *Networks: an introduction*. Oxford University Press.

Niazi, M. A., & Hussain, A. (2012). *Cognitive agent-based computing-I: a unified framework for modeling complex adaptive systems using agent-based & complex network-based methods*. Springer Science & Business Media.

Niazi, M. A. K. (2011). *Towards A Novel Unified Framework for Developing Formal , Network and Validated Agent-Based Simulation Models of Complex Adaptive Systems*. University of Stirling.

Nicolis, G., & Prigogine, I. (1989). Exploring complexity.

North, M. J., & Macal, C. M. (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation*. Oxford University Press.

Odehnalová, P., & Olsevicová, K. (2009). Agent-based simulation of development stages of family businesses. *E+ M Ekonomie a Management*, (4), 77.

Olfati-Saber, R., & Murray, R. M. (2004). Consensus problems in networks of agents with switching topology and time-delays. *IEEE Transactions on Automatic Control*, *49*(9), 1520–1533.

Park, H., Cutkosky, M. R., Conru, A. B., & Lee, S.-H. (1994). An agent-based approach to concurrent cable harness design. *AI EDAM*, *8*(1), 45–61.

Patel, M. H., Abbasi, M. A., Saeed, M., & Alam, S. J. (2018). A scheme to analyze agent-based social simulations using exploratory data mining techniques. *Complex Adaptive Systems Modeling*, *6*(1), 1. https://doi.org/10.1186/s40294-018-0052-8

Prenkert, F., & Følgesvold, A. (2014). Relationship strength and network form: An agent-based simulation of interaction in a business network. *Australasian Marketing Journal (AMJ)*, *22*(1), 15–27.

Prigogine, I., & Stengers, I. (1997). *The end of certainty*. Simon and Schuster.

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, *28*(3), 181–193. https://doi.org/10.1016/j.ijresmar.2011.04.002

Rangoni, R. (2014). From informal thought experiments to Agent-based Models: A progressive account of modeling in the Social Sciences. In *Model-Based Reasoning in Science and Technology* (pp. 471–478). Springer.

Rao, K. U., & Kishore, V. V. N. (2010). A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews*, *14*(3), 1070–1078.

Rogers, E. M., Medina, U. E., Rivera, M. A., & Wiley, C. J. (2005). Complex adaptative systems and the diffusion of innovations. *The Innovation Journal*, *10*(3), 1–26.

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited,.

Savona, P. (2005). On the definition of Political Economy and on the metbod of investigation proper to it: Reflections on the bicentennial of the birth of John Stuart Mill. *Journal of European Economic History*, *34*(3), 573–598.

Schwarz, N., & Ernst, A. (2009). Agent-based modeling of the diffusion of environmental innovations—an empirical approach. *Technological Forecasting and Social Change*, *76*(4), 497–511.

Sengupta, P., & Wilensky, U. (2009). Learning electricity with NIELS: Thinking with electrons and thinking in levels. *International Journal of Computers for Mathematical Learning*, *14*(1), 21–50.

Showers, C. (1992). Evaluatively integrative thinking about characteristics of the self. *Personality and Social Psychology Bulletin*, *18*(6), 719–729.

Siebers, P.-O., & Aickelin, U. (2008). Introduction to Multi-Agent Simulation. *SSRN Electronic Journal*, 1–25. https://doi.org/10.2139/ssrn.2827970

Siebers, P.-O., Macal, C. M., Garnett, J., Buxton, D., & Pidd, M. (2010). Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation*, *4*(3), 204–210.

Siggelkow, N., & Levinthal, D. A. (2003). Temporarily divide to conquer: Centralized, decentralized, and reintegrated organizational approaches to exploration and adaptation. *Organization Science, 14*(6), 650–669.

Sill, D. J. (1996). Integrative thinking, synthesis, and creativity in interdisciplinary studies. *The Journal of General Education*, *45*(2), 129–151.

Silverberg, G., Dosi, G., & Orsenigo, L. (1988). Innovation, diversity and diffusion: a self-organisation model. *The Economic Journal*, *98*(393), 1032–1054.

Singh, V., Dong, A., & Gero, J. S. (2012). Computational studies to understand the role of social learning in team familiarity and its effects on team performance. *CoDesign*, *8*(1), 25–41.

Situngkir, H. (2004). Epidemiology through cellular automata: case of study avian influenza in Indonesia. *ArXiv Preprint Nlin/0403035*.

Snyder, S. (2013). The simple, the complicated, and the complex: Educational reform through the lens of Complexity Theory. *OECD Education Working Papers*, (96), 1–33. https://doi.org/http://dx.doi.org/10.1787/5k3txnpt1lnr-en

Son, J., & Rojas, E. M. (2010). Evolution of collaboration in temporary project teams: An agent-based modeling and simulation approach. *Journal of Construction Engineering and Management*, *137*(8), 619–628.

Sorensen, R. A. (1998). *Thought experiments*. Oxford University Press on Demand.

Sun, R., & Naveh, I. (2004). Simulating organizational decision-making using a cognitively realistic agent model. *Journal of Artificial Societies and Social Simulation*, *7*(3).

Sun, Y., & Cheng, L. (2005). A Survey on Agent-Based Modelling and Equation-based Modelling. *Citeseerx*.

Tesfatsion, L. (2002). Agent-based computational economics: Growing economies from the bottom up. *Artificial Life*, *8*(1), 55–82.

Todd, A., Beling, P., Scherer, W., & Yang, S. Y. (2016). Agent-based financial markets: A review of the methodology and domain. In *Computational Intelligence (SSCI), 2016 IEEE Symposium Series on* (pp. 1–5). IEEE.

Van Dyke Parunak, H., Savit, R., & Riolo, R. L. (1998). Agent-based Modeling vs. Equation-based Modeling: A case study and users' guide. *Lecture Notes in Computer Science*, *1534*, 10–25. https://doi.org/10.1007/10692956_2

Wall, F. (2016). Agent-based modeling in managerial science: an illustrative survey and study. *Review of Managerial Science, 10*(1), 135–193. https://doi.org/10.1007/s11846-014-0139-3

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge University Press.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world'networks. *Nature*, *393*(6684), 440.

Weisberg, M. (2012). *Simulation and similarity: Using models to understand the world*. Oxford University Press.

Wilensky, U., & Rand, W. (2015). *An Introduction to Agent-Based Modeling_ Modeling Natural, Social, and Engineered Complex Systems with NetLogo*. *MIT Press*.

Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modeling approach. *Cognition and Instruction*, *24*(2), 171–209.

Windrum, P., Fagiolo, G., & Moneta, A. (2007). Empirical validation of agent-based models: Alternatives and prospects. *Jasss*, *10*(2). https://doi.org/Article

Wu, J., Hu, B., Zhang, Y., Spence, C., Hall, S. B., & Carley, K. M. (2009). An agent-based simulation study for exploring organizational adaptation. *Simulation*, *85*(6), 397–413.

Zhong, X., & Ozdemir, S. Z. (2010). Structure, learning, and the speed of innovating: a two-phase model of collective innovation using agent based modeling. *Industrial and Corporate Change*, *19*(5), 1459–1492.