Agent-based simulation in management and organizational studies: a survey

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Abstract

Purpose – The purpose of this paper is to provide a comprehensive survey of the literature about the use of agent-based simulation (ABS) in the study of organizational behavior, decision making, and problem-solving. It aims at contributing to the consolidation of ABS as a field of applied research in management and organizational studies.

Design/methodology/approach – The authors carried out a non-systematic search in literature published between 2000 and 2016, by using the keyword "agent-based" to search through Scopus' business, management and accounting database. Additional search criteria were devised using the papers' keywords and the categories defined by the divisions and interest groups of the Academy of Management. The authors found 181 articles for this survey.

Findings – The survey shows that ABS provides a robust and rigorous framework to elaborate descriptions, explanations, predictions and theories about organizations and their processes as well as develop tools that support strategic and operational decision making and problem-solving. The authors show that the areas that report the highest number of applications are operations and logistics (37 percent), marketing (17 percent) and organizational behavior (14 percent).

Originality/value – The paper illustrates the increasingly prominent role of ABS in fields such as organizational behavior, strategy, human resources, marketing and logistics. To-date, this is the most complete survey about ABS in all management areas.

Keywords Complexity, Agent-based simulation, Decision making, Organizational simulation, Simulation as a method, Organizational studies

Paper type Research paper

1. Introduction

Today's markets and organizations are complex systems (CS). CS are made up of heterogeneous elements that interact with each other and the environment, generating interdependencies across multiple spatial and temporal scales that are difficult to understand, predict and control (Boisot and Child, 1999). A distinctive feature of CS is their ability to exhibit complex emergent properties, i.e. counterintuitive aggregate properties

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(Mitchell, 2009). Their environment is characterized by dynamic, fast-paced changes across different domains that make them prone to uncertainty, systemic risks and networked effects (Helbing, 2013). To be able to cope, organizations must create mechanisms to learn, adapt and coevolve under such circumstances.

Most phenomena relevant to current organizations entail uncertainty and complexity. Understanding and managing the intrinsic complexity in organizations requires strategies that go beyond intuition (Bonabeau, 2003) and traditional analytical methods (Andriani and Mckelvey, 2007). Therefore, new theoretical and methodological frameworks are needed.

Over the past two decades, agent-based simulation (ABS) has emerged as a new research and management paradigm within organizational theory (Wall, 2016). However, ABS has not been as widely adopted in management as in other domains, leaving its potential to manage organizations far from realized. We believe that this is in part due to a lack of knowledge about what has been done in the field or what are the most promising areas for future application. Hence, the goal of this paper is to provide a comprehensive survey of the literature about ABS in business and management. Such overview contributes to the establishment of a dialogue among scholars and the consolidation of ABS as a field of research in management and organizational studies. To help demarcate this field, we use the term agent-based organizational simulation (ABOS) to refer to any of the applications of ABS in business and management.

ABS allows researchers to recreate interactions between individuals in an organization or between organizations in a market to evaluate the aggregate outcome of their behavior (Fioretti, 2012). As a result, SBA can be used to study organizational behavior (Secchi and Neumann, 2016) and manage complexity within organizations and their environments (Terna, 2008).

ABS provides a robust framework that enables elaborate descriptions, explanations, predictions and theories about organizations and their processes (Fioretti, 2012). It also aids in the development of tools that support strategic and operational decision making and problem-solving (North and Macal, 2007).

2. The paradigm of ABS

Understanding ABS requires distinguishing between three interrelated concepts: agent-based complex systems (ABCS), agent-based models (ABMs) and ABSs. An ABCS (Grimm *et al.*, 2005) is a portion of reality in which basic components interact with each other and the environment in non-linear ways producing emergent, global patterns. These patterns could be structural, behavioral or functional (Gómez-Cruz, 2013). Examples of ABCS are the brain, ant colonies, organizations and economies (Mitchell, 2009).

ABCSs are tightly coupled with their environments. They display sensitivity to initial conditions and path-dependence. These elements cause network effects and interdependency at different scales, often leading to cascading failures that limit our ability to control and predict these systems (Helbing, 2013). Models help us overcome such limitations.

An ABM is an abstraction of a system's components, their actions, interactions and environment (Wilensky and Rand, 2015). An ABM architecture, therefore, includes three components: agents, an environment and agent-agent/agent-environment interactions.

An agent is an autonomous computational entity that has its own behavior and attributes (Rand, 2013). Agents represent social actors or institutions that make up the system. In the context of organizations and markets, agents can be consumers, employees, companies, clusters or countries. Agents can be simple or complex – their intricateness depends on the problem at hand.

Each agent can be modeled with a different set of properties that include perception, communication, reactivity, proactivity, flexibility, learning and adaptation (Crooks and Heppenstall, 2012). There are different ways to model the cognitive ability underpinning decision making in agents (Balke and Gilbert, 2014). These include simple probabilistic models;

if-then decision rules; decision trees; reasoning and planning mechanisms derived from cognitive science and artificial intelligence, and bio-inspired (meta)heuristics.

The most distinctive feature of ABMs is that they explicitly model the interactions among agents and between agents and the environment (Macal, 2016). These interactions make the system inherently dynamic and can be direct, i.e. agent-agent, or indirect, i.e. mediated by the environment or artefacts. The communication through chemicals that takes places in ant colonies is an instance of indirect interaction mediated by the environment. An example of indirect interaction mediated by artefacts is the communication that occurs in social networks like Facebook and Twitter.

Modeling interactions between agents requires the specification of who is linked to whom and the definition of interaction strategies. The first task refers to the model topology; the second, to the mechanisms of interaction. Diverse interaction topologies are used in the literature (Macal and North, 2009): rigid topologies, Euclidean spaces, network topologies, non-spatial models or realistic geospatial landscapes using GISs. Rand (2012) highlights the implications of this last topology in business.

Regardless of the topology, interactions and information transmission are local – agents have limited visibility of the system as a whole. In ABS there is no global communication or information. This allows a more realistic representation of the complex nature of organizational and economic systems.

Finally, the environment is the space within which agents "live" and interact. ABS can depict natural and artificial environments (Cioffi-Revilla, 2014). Natural environments may include topological, climatic, biological and hydrological elements while artificial ones encompass manmade systems like roads, and power and telecommunications networks.

ABS links agents' micro-behaviors to macro-patterns that emerge from their interactions. The transition between local and global is achieved through computational simulation (Gómez-Cruz, 2017). ABS is, therefore, the computational implementation of the system and the "visualization" of its dynamics over time.

Several frameworks and platforms have been developed for this end. Some of the most widely used are NetLogo, Repast, Simphony, Swarm and MASON (Railsback *et al.*, 2006). For methodological details of ABS see Wilensky and Rand (2015).

ABS can be considered an approach to modeling, a computational tool, a methodological framework or an analytic method. However, it is better understood as a new paradigm of computational thinking that is decentralized, interactive, dynamic, generative and emergent (Wilensky and Rand, 2015; Epstein, 2007). Its foundations are not so much technical or technological, but scientific and philosophical. In consequence, ABS is technically simple but conceptually deep (Bonabeau, 2002).

3. ABOS: scope and applications

The use of simulation in management and organizational studies is not new (Berends and Romme, 1999). The novelty of ABOS derives from the use of agents for understanding and managing complexity and uncertainty in organizations. ABOS uses ABMs and simulations in the domain of organizations, their problems and environment. From the conceptual and epistemological point of view, ABOS is rooted in computational social science (Cioffi-Revilla, 2014), generative social science (Epstein, 2007), computational organization theory (Frantz *et al.*, 2013) and computational management[1].

ABOS overlaps with growing fields like agent-based computational economics (Tesfatsion and Judd, 2006) and agent-based computational sociology (Squazzoni, 2012). ABOS's specificity relies on the use of ABS in domains of organizational life that lend themselves to management and control. While other fields emphasize the comprehension and explanation of systems and processes, ABOS emphasizes decision making and problem-solving.

We present a non-systematic survey of the main areas in ABOS encompassing articles published between 2000 and 2016. Paper selection was conducted following two strategies: First, articles where filtered using the "agent-based" keyword in Scopus' business, management and accounting database. Then, additional search criteria were devised using the articles' keywords and the categories defined by the Academy of Management (AOM, 2017) (See Table I). Selected books and conference proceedings were included as well. From 436 articles, 181 were selected, based on titles, abstracts and keywords (see Table I). Figure 1 shows that most applications are in operations and logistics (37 percent), marketing (17 percent) and organizational behavior (14 percent).

3.1 Organizational behavior

The study of organizational behavior underscores the versatility of ABS. It has been used to understand behavior of organizations in a market and the behavior of agents within an organization. Thus, organizations can be considered agents or environments.

Organizations as agents have been studied in business networks and innovation. Prenkert and Folgesvold (2014), for instance, found that in an international business network the topology of the net affects the intensity of commercial relationships. Other publications focused on innovation found that companies with similar technological conditions can occupy very different market positions. Particularly, Ciarli *et al.* (2007) showed that companies focusing on specific innovations over long periods of time increased their short-term competitiveness, but faced long-term technological lock-in.

Literature on organizations as agents encompasses areas such as analysis of market conditions, the knowledge society (Mollona and Hales, 2006) or the study of populations of companies. Odehnalová and Olsevcová (2009) addressed development processes in family business, and Wu *et al.* (2009) examined organizational adaptability in terms of agility, robustness, resilience and survival.

Application field	Subfield	Number of papers reviewed
Organizational behavior	Organizational change	4
	Organizational learning	3
	Organizational design	5
	Organizational psychology	1
	Unclassified	12
Strategic management and decision making	General topics	13
Research and development	General topics	15
Operations and logistics	Operations	9
	Healthcare logistics	3
	Production	11
	Supply networks	32
	Transportation	11
Marketing	Traditional marketing	4
	Digital marketing	4
	Social marketing	1
	Diffusion of innovations	12
	Other topics	10
Human resources	General topics	4
Education in management	General topics	6
Other categories	Examples: project management, public administration, social responsibility, entrepreneurship	21

Table I.
SBA applications in organizations and management

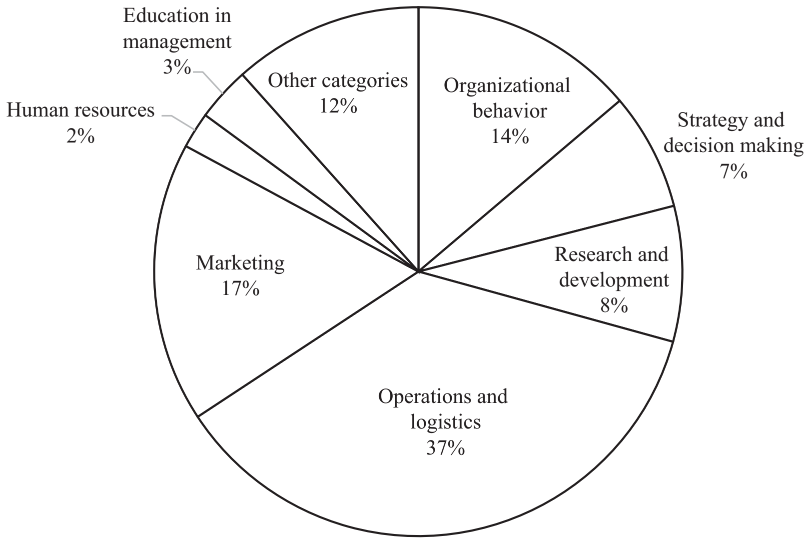

Figure 1.
Percentage of identified works by application area

The use of ABS to study interactions within organizations has been centered around the diffusion of knowledge (Wang *et al.*, 2009) or opinions (Rouchier *et al.*, 2014) among institutional actors. It has also been used to study the result of these diffusion processes, for example, the emergence of a changing organizational identity (Rousseau and Van der Veen, 2005). Jiang *et al.* (2010) explored the link between employees' behavior and task assignment. They implemented a simulation that allowed them to determine that a collaborative environment in which learning is encouraged and tasks are dynamically assigned, employees' capabilities can be increased.

Contributions in organizational psychology (Hughes *et al.*, 2012), organizational design (Heyne and Mönch, 2011) and organizational architecture (Rodríguez *et al.*, 2011) we also found.

3.2 Strategic management and decision making

We found several applications on organizational decision making. Sun and Naveh (2004) computationally recreated organizational dynamics that have been studied empirically for decades. The simulation showed that decisions made in non-hierarchical teams have better outcomes than those made in hierarchical structures. Similarly, they show that organizations with free access to information perform better than those with restricted access.

Forkmann *et al.* (2012) studied the link between strategic decision making and the position of power held by an agent. They found that although dominant strategies are favored by CEOs, these strategies do not necessarily yield the best results over time. This shows that the mismatch between empirically derived decisions made by managers and the effect that these strategies have on their businesses. These results underscore the need for decision-making tools. Kodia *et al.* (2010), on the other hand, study the impact of local interactions and cognitive behavior of investors in stock markets. Under different market conditions, the simulations show the effect of the investors' decision making on the price fluctuation in the market.

North *et al.* (2010) discuss the need to develop holistic models that represent interdependences between consumers, retailers and producers in consumer markets to aid in decision making. This is exemplified by an ABM that addressed different organizational problems in Procter & Gamble. The model helped guide organizational decisions leading to significant savings in operation costs. Other areas of applications of ABS in decision-making systems include the value chain (Hilletofth and Lättilä, 2012), logistic and manufacturing systems (Nilsson and Darley, 2006) and the integration of technical and business aspects in the oil sector (Hu *et al.*, 2012).

3.3 Research and development

ABS has been used in R&D to understand innovation as a collective process that emerges from the interaction of different actors. It has provided some evidence of some pitfalls in previous approaches to the process of innovation, such neglecting human subjectivity.

Mild and Taudes (2007) presented a model that showed that guided-search methods in which the companies decide hierarchically the features of a new product, are less successful that decentralized strategies such as trial and error. The model suggests that a larger knowledge-base of prototypes or alternatives, the more likely it is to develop new products. Similarly, Zhong and Ozdemir (2010) claimed that group structure affects the speed of innovation processes.

Zhang *et al.* (2013) used a task assignment model based on agents' preferences to provide important insights regarding the effect of human elements in the innovation process. Finally, Maisenbacher *et al.* (2014) exemplified the use of ABS in product-service systems (products that also provide services). They also laid out the most promising lines of research regarding the use of ABS for product development.

3.4 Logistics and operations

Applications in logistics are some of the earliest used of ABOS. The first models date back to the early 1990s (Santa-Eulalia *et al.*, 2012). Then, perhaps unsurprisingly, most ABS in business and management are to-date in this area.

ABS used to add dynamism to the implementation of the productive processes. The work of Renna (2011) proved that, in a dynamic context, an ABS performs better that traditional methods regarding throughput time, throughput, work in process, machines average utilization and tardiness. Rolón and Martínez (2012) incorporate dynamicity from the perspective of production automatization. Their work determined that agents' ability to learn provided significant advantages in the new era of automatization of manufacturing systems.

ABS has increased its popularity in the transportation. Currently, there are some ABS platforms built exclusively to deal with transport tasks. The most popular, according to Zheng *et al.* (2013), are: TRANSMISMS; Multi-Agent Transport Simulation Toolkit (MATSim); Sacramento Activity-Based Travel Demand Simulation Model (SACSIM); Simulator of Activities, Greenhouse Emissions, Networks, and Travel (SimAGENT); Open Activity-Mobility Simulator (OpenAMOS) and Integrated Land Use, Transportation Environment (ILUTE).

ABS had a great impact in this area because traditional approaches do not capture the complexities of current logistic markets. They are unable to account for external perturbations, such as changes in policy or traffic flows (Cavalcante and Roorda, 2013). ABS provide a way to overcome these problems, thanks to its flexibility (Kavicka *et al.*, 2007) and its ability to deal with diversity –a feature that is common in freight transportation around the world (Holmgren *et al.*, 2013).

In air logistics, Bouarfa *et al.* (2013) use a hybrid ABS and a Monte Carlo simulation to identify uncommon emergent behaviors in air transport systems. Their work showed that some high-level risks in air safety cannot be identified or managed with traditional warning systems. Other applications in transportation and logistics are cross-docking optimization (Suh, 2015) and the implementation of shared parking strategies to reduce traffic and pollution in a food transport network (Boussier *et al.*, 2011).

Risk management in supply networks is also a common topic in the literature. Chen *et al.* (2013) elaborated a review of ABS applications for the management of value chain risks. According to these authors, the volatility of the environment and its increasing complexity has made that up to 75 percent of the operation costs depends on the management of the supply network.

Analogously, some authors have studied the impact of local processes on global economic behavior, focusing on dynamics and systemic risks that affect the value chain (Mizgier *et al.*, 2012). Others suggest that ABS helps increase value chain visibility and improve communication between different actors (Hilletofth and Lättilä, 2012).

There are also several ABS applications in healthcare logistics. Friesen and McLeod (2014) describe the most common application in this domain and also provide some suggestion regarding its use. In turn, Denton (2013) surveys several case studies and provides a more comprehensive review of ABS and other methods used in healthcare logistics. Most ABS in this direction focuses on optimization. There are, however, many other applications. Liu and Wu (2016), develop a model about a payment model that increases accountability in health organizations.

Finally, some of the most recent applications seek to provide common logistic frameworks. Long and Zhang (2014) implemented a model to analyze the global behavior of the supply network. This model integrates production, inventory and transportation, enabling the exploration of the system at different levels and granularity. The model is reusable and scalable, reducing computational costs and computing time.

3.5 Marketing

ABS has been used in marketing, both inside and outside academia (Rand, 2013). Hence, there are two major trends in the literature: case studies documented by consultants and academic research encompassing theory and practice.

Case studies published by consultants (e.g. Icosystem o Ignite Technologies) include organizations in different economic sectors. Most studies are made for large organizations, such as Procter & Gamble, Telecom Italia, Urban Outfitters o Toyota. The former has used simulation to quantify the release of several products on media and social networks. In order to protect clients, consultants often restrict access to sensitive information but publish most of their results. Concentric – an ABS consulting firm – claims that it was able to predict the number of subscriptions for a video streaming website with less than 1 percent error. It used detailed data from previous years to calibrate the model. The company has also implemented a simulation for a coffee firm experiencing a decrease in sales in which market dynamics were replicated with less than 2.2 percent error. With this model, it was able to determine that the best strategy was to improve the product experience and increase marketing in stores. Similarly, Ignite Technologies increased the return on investment of a packed goods company by 15 percent using the same principle.

A literature review by Negahban and Yilmaz (2014) included 80 articles, out of 11,200, in which ABS was used. It discusses emergent phenomena and the overall results of using ABS for market research. According to these authors, the ABS literature in marketing can be divided in three categories: conventional marketing, digital marketing and diffusion of innovations. We add social marketing as fourth category.

Conventional marketing focuses on scenarios in which clients find out about new products through conventional channels, like catalogues or at the store. Hassan and Craft (2012) evaluated the effectiveness of market segmentation based on the customers' perception. The authors concluded that basic market features, such as consumer decision-making rules and preference variability determine the performance of segmentation strategies, even in cases in which those strategies are closely linked. Roozmand *et al.* (2011) also built a model focused on segmentation dynamics. The model addresses the processes of decision making, validating the results with information from European countries. It sought to overcome the lack of realism in the decision-making heuristics of traditional models. Therefore, they included element like identity, extroversion, affability and openness in the agents' cognitive structure. They also included the social status and social responsibility. This shows that ABS allows for agents as complex and realistic as the problem demands. Even though there is not a full correspondence between the results of the model and the empirical data, the model was able to determine that the cultural dimension of agents is particularly relevant for the purchase of vehicles.

The digital market category studies scenarios in which the clients are influenced through non-traditional means, such as online reviews, blogs or social networks (Negahban and Yilmaz, 2014). Chang *et al.* (2010), for example, analyze the effect of a strategic alliance between two small search engines to better compete with the company with the largest market share. The model assumes that the decision to advertise in a search engine depends on the advertiser's individual preferences and the disposition to follow others' decisions. Even though market share of the biggest company is larger than the share of the two small companies, the simulation reveals that the alliance allows the two companies to take over the bigger company. This category also involves digital markets in which producers and clients meet and interact online. ABS could be used, for instance, to study the impact of e-commerce on organizational structures (Siggelkow and Levinthal, 2003) or supply chains (Zhang and Bhattacharyya, 2010).

Diffusion of innovations pertains to the uptake of new products and innovations. Most applications found by Negahban and Yilmaz (2014), 37 articles, are on this topic (here we consider 12). Diffusion models study adoption behavior and social influences to understand the role of heterogeneity, interaction dynamics, network effects and promotion strategies. Recent models analyze the effect of word-of-mouth on the perception of product attributes (Goldenberg *et al.*, 2001). Other applications include models that provide time-price strategies for new products releases in the mobile phone market (Lee *et al.*, 2014).

The last category, social marketing, is less developed than the other three and is not considered by Negahban and Yilmaz. Nonetheless, it is an important category that should be included in this survey. Marketing goods or services is different from "marketing" a cause or idea.

The model by Pérez-Mujica *et al.* (2014) about an ecotourism campaign for a zone of wetlands conservation is an instance of these kind of models. Results suggested that the ecological state of the wetlands depends on the design of the social marketing campaign.

3.6 Human resources

ABS is not commonly used in human resources. Yet, there are applications that focus mostly on the performance of teams. Rojas and Giachetti (2009), for example, explored collaboration processes in teams that carry out non-structured tasks. The model implements a shared and distributed mental model among agents, according to which each agent has only partial understanding of the skills, knowledge and role of other members. The model provides insights into collaboration dynamics in teams.

Singh *et al.* (2012) study social learning and its impact on team performance. Their results show that the success of different social learning strategies partially depends on how familiar members are with each other, and that the contribution of social learning to team performance is higher in personal interactions, followed by interactions about completed tasks.

SBA has recently been used to study team configurations that were uncommon until recently, due to technological limitations. Some simulations explore the behavior of teams working remotely through complex technological systems. According to Sullivan *et al.* (2015), the operation of these teams requires new structures of shared leadership. The authors suggest, however, that there is not enough knowledge about the time-space interaction that leads to the emergence of such structures. Hence, they develop a model that integrates current knowledge about leadership, networks and innovation, to specify the generative mechanisms through which decentralized forms of leadership emerge. Finally, Siebers *et al.* (2011) move away from team work dynamics, seeking instead to research the practices of personnel management in a wholesale chain.

3.7 Teaching in management

In comparison to other simulation approaches, ABS gives students a wider perspective of market dynamics (Baptista *et al.*, 2014). Simulations allow students to create and generatively identify behavioral patterns exhibited by social systems (Wilensky, 2014).

According to Baptista *et al.* (2014), ABS increases the transparency of a simulation, because it provides students with more information about the workings of the model. Similarly, the work of Tanabu (2010) concluded that ABS does not only improve learning in subjects such as value chain management, it also facilitates the role of teachers managing the simulation. Tanabu's conclusions were drawn after an ABS was implemented as an alternative to traditional simulators in more than 70 Japanese universities.

4. The scope of ABOS

ABS cannot answer all research questions. Problems with features like linearity, causality, statistical averages, and controlled environments are better tackled with analytic methods. Problems involving the comprehension, prediction and control of complex phenomena must be approached with alternative techniques that are better suited for this task (Sayama, 2015). Game theory, network theory, Monte Carlo simulations or Dynamic Systems theory are a few examples. In general, ABS is useful when (Gómez-Cruz, 2017; Wilensky and Rand, 2015; Rand, 2013; Bonabeau, 2002):

- The system under study has multiple autonomous and heterogeneous components.
- Agents act in a local, parallel and distributed manner, without global knowledge. Interactions are non-linear, discontinuous and asynchronous. Small actions can propagate through the entire system, triggering network effects and amplifying fluctuations (Helbing, 2013).
- The system is structured in spatial-temporal scales.
- The system's global dynamic is self-organizing and emergent, i.e. it exhibits properties such as memory, path-dependence, temporal correlations, learning, adaptation and evolution (Bonabeau, 2002). Such dynamics cannot be understood through normal distributions, or by using law of large numbers or as the sum of the parts (Andriani and Mckelvey, 2007).
- The environment is uncertain and often includes a non-reducible spatial component.

4.1 General purposes of ABOS

Theory and practice of organizational studies can be divided in two: the meta scale, which includes academic and scientific aspects of organizations and management and the specific or pragmatic scale, which supports decision making and problem-solving. Fioretti's (2012) work is a good introduction to ABOS on the meta scale. To-date, the use and impact of ABOS is increasing on the pragmatic scale. We outline the main goals of the pragmatic scale using Davidsson and Verhagen's (2013) categories.

Understanding observed dynamics, processes and systems. ABS is often used to deepen understanding where no theory is available. In organizations, it is particularly useful in the development diagnostic or risk management models. In all these scenarios, decision making critically depends on the available knowledge about the problem at hand. Thus, an ABS could provide new insights about the phenomenon of interest.

Designing or engineering of processes or systems. ABS can be used to identify design criteria or to test engineering concepts in *in silico* experimental environments. The design and implementation of an engineering system could have potential negative ethical, economic, social and legal implications that are not easy to predict for an organization. Testing under diverse conditions is supported by ABS enabling managers to better estimate their impact. It also helps to evaluate complex man-machine interactions, typical of socio-technical systems.

Managing a system or process. ABS is able to answer what if questions that can significantly support strategic and operational decision making. It can be used to identify failures, underutilized resources, bottlenecks and the design of organizational policies.

Formulating theory and explanatory models. ABS is an operational platform in which assumptions, theories and models can be translated into testable hypotheses. It is also an experimental laboratory in which, through the manipulation of pre-specified parameters, it is possible to develop theories, models or new hypotheses about the world (Conte and Paolucci, 2014).

Prediction. ABS explores the structural, dynamic and functional possibilities of a system. This approach does not aim at long-term prediction, as it happens with classical methods, but acknowledges the irreducible limitations of predicting the behavior of CS (Nicolis and Nicolis, 2012). Agent-based monitoring systems working on real time help managing organizational uncertainty.

Optimizing resources, capabilities and processes. ABS has been used in areas where traditional and heuristic methods are limited. Particularly, problems that are distributed, heterogeneous and unstable. There are several hybrid applications combining ABS with heuristic and metaheuristic methods. These combined models have been used to solve problems in scheduling, logistics, supply chain planning, manufacturing and packing (Barbati *et al.*, 2012).

4.2 Advantages of ABS

Interaction is a fundamental feature of complex economic and organizational systems. Complexity is not possible without interaction. In this regard, ABS significantly departs from other analytical techniques because it is able to model agents' interactions independently (Macal, 2016). It is does not establish links between fundamental variables, rather it directly models interacting agents that influence each other. Recreating the interactions between members of an organization, between organizations or economies, enables researchers to uncover the effects of individual decisions on the global system. Due to its interaction-based approach to modeling, using ABS has several advantages.

Unlike equation-based models, ABS provides descriptions that closely resemble the system under study (Squazzoni, 2012). Thinking in terms of actors, their features and interactions makes ABS more suitable for the description of markets or organizations.

ABS captures the logic of emergence (Wilensky and Rand, 2015). Agent-based systems exhibit patterns at a global scale that result from interaction of the micro-components, yet are not easily deducible, reducible or predictable from these micro-components alone (Gómez-Cruz, 2013). The price dynamics in a stock market, for instance, are an emergent pattern resulting from the actors' decisions to buy and sell.

A large part of socio-technical systems can be conveniently modeled as networks of interconnected elements. Production and supply networks, organizational clusters, social networks and international trade networks are a few common instances. ABS is the bridge between ABMs and network-based models (Namatame and Chen, 2016). In an ABM, agents represent nodes and interactions represent edges. Therefore, ABS is useful not only for the study of structural, but also functional aspects of complex networks in the organizational domain (Skvoretz, 2002).

Another distinctive aspect of ABS is its flexibility (Helbing and Balietti, 2012). ABS makes it easy to add or delete agents without a need to re-program the model. It is also possible to alter agent and environmental properties to see the effect of such changes. Time can be compressed or expanded to manipulate the speed of the phenomenon simulated.

Finally, ABS can be articulated with other methods (Helbing and Balietti, 2012) to improve realism, explanatory power or problem-solving capabilities. Among the long list of methods that have been paired with ABS is network analysis, fuzzy logic, genetic algorithms, neural networks, swarm intelligence and GIS (Rand, 2012).

4.3 Limitations of ABS

ABS is not without limitations. The validity of a model depends on the assumptions built into the model. Given the inherent complexity of organizational systems, it is not possible to abstract these assumptions completely or univocally. ABS can have programming errors or might not adequately capture the essence of the target system. There are no standardized models that guarantee verification and validation in ABS, in spite of recent efforts (Yilmaz, 2006). Also, interpreting the results of an ABS is hard when they are counterintuitive or when there is stochasticity involved. Finally, the acquisition of technical skills by managers and organizational researchers is still not widespread, and outside academia ABS is rather uncommon.

Despite its limitations, ABS is one of the most promising and generalized approaches to study complexity and emergence (Sayama, 2015).

5. Conclusions

In this paper we provided an overview of impact of ABOS with the intent to consolidate its standing as a field of research. ABOS proved to have a rich variety of practical and theoretical approaches to management and organizational studies (Secchi and Neumann, 2016; Wall, 2016; Fioretti, 2012; Chang, 2006).

There have been many independent efforts to build ABS frameworks and agent architectures focused on organizations (Moise or Thomas); create consultancy firms that make use of ABS (Icosystem, Concentric or ABM Analytics); develop simulation platforms (AnyLogic) and publish academic literature and patents that use this method. We believe the time is ripe to embark on an agenda-setting endeavor and promote an effective dialogue among scholars. We hope that this paper is a step in that direction.

ABOS gives way to a generative view of organizations and their processes. It supports high-level abstractions, aimed at explaining and formalizing organizational dynamics. Further, it gives managers and decision-makers detailed models that can be empirically calibrated to support decision making, prediction and optimization in strategic, tactical or operational scenarios.

From a theoretical point of view, ABS is a third way of approaching reality, along with induction and deduction (Axelrod, 1997). From the practical point of view, integrating ABOS with data science, machine learning, complex network analysis and bio-inspired computation will become increasingly common. We believe that the development of hybrid technologies mediated by ABS is the future of decision making and organizational problem-solving tools.

Note

1. See the journal *Computational Management Science* and the series *Advances in Computational Management Science*, both published by Springer-Verlag.

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