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A recent overview of the integration of System Dynamics and Agent-based Modelling and Simulation

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Abstract: Modelling and simulation aim to reproduce the structure and imitate the behavior of real-life systems. For complex dynamic systems, System Dynamics (SD) and Agent-based (AB) modelling are two widely used modelling paradigms that prior to the early 2010's have traditionally been viewed as mutually exclusive alternatives. This literature review seeks to update the work of Scholl (2001) and Macal, (2010) by providing an overview of attempts to integrate SD and AB over the last ten years. First, the building blocks of both paradigms are presented. Second, their capabilities are contrasted, in order to explore how their integration can yield insights that cannot be generated with one methodology alone. Then, an overview is provided of recent work comparing the outcomes of both paradigms and specifying opportunities for integration. Finally, a critical reflection is presented. The literature review concludes that while paradigm emulation has contributed to expanding the applications of SD, it is the dynamic combination of the two approaches that has become the most promising research line. Integrating SD and AB, and even tools and methods from other disciplines, makes it possible to avoid their individual pitfalls and, hence, to exploit the full potential of their complementary characteristics, so as to provide a more complete representation of complex dynamic systems.

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Keywords: System Dynamic· Agent-Based Modelling · Hybrid Models · Complex Dynamic Systems · multi-paradigm approach · Literature Review

1 Introduction

Modelling and simulation of complex social systems aim at increasing the understanding of the system and testing policies with the objective to support decision-making and at times policy implementation (Meadows and Robinson, 2002). The advantage of computational models are their capability to embrace complex real-life systems characterized by dynamic nonlinear relationships. Another substantial benefit is that what-if scenarios can be tested, but intervention in reality is not required.

Agent-based (AB) modelling and System Dynamics (SD) are two widely used methodologies in modelling complex dynamic system. While System Dynamics has a long tradition since it was founded in the late 1950s by Forrester (1958), AB is as yet in its infancy - implying that its complete potential has not yet been utilized (Bonabeau, 2002). Both approaches have been applied to many socio-economic problem domains including health care (Demarest, 2011; Figueredo, Aickelin, & Siebers, 2011; Figueredo, Siebers, Aickelin, Whitbrook, & Garibaldi, 2015; Kirandeep, Eldabi, & Young, 2013; Mellor, Smith, Learmonth, Netshandama, & Dillingham, 2012), supply chains (Angerhofer & Angelides, 2000; Georgiadis, Vlachos, & Iakovou, 2005; Gjerdrum, Shah, & Papageorgiou, 2001; Tako & Robinson, 2012; Xue, Li, Shen, & Wang, 2005) and technology adoption (Chen, 2011; Fisher, Norvell, Sonka, & Nelson, 2000; Moser & Barrett, 2006; Schwarz & Ernst, 2009; C Swinerd & McNaught, 2014; Zhang & Nuttall, 2007).

More than a decade ago, Scholl (2001) made a call for joint research between SD and ABM by comparing and contrasting both approaches, and more recent works have enriched those comparisons (Lättilä et al., 2010; Macal, 2010). However, during the last decade, and particularly during the last five years, an explosive growth in computational capacity has enabled the emergence of more, and more diverse, joint research in the field of modelling and simulation (Pruyt, 2015).

This article seeks to update the work of Scholl (2001) and Macal (2010) by providing an overview of attempts to integrate SD and AB over the last ten years, with an emphasis on hybrid SD-AB models published over the last five years. The research strategy comprised a systematic literature review. Combinations of the following key words were used: *agent-based modeling*, *combining*, *differential equations models*, *system dynamics*, and *hybrid models*. The objective was to compile literature related to the ongoing discussions on the complementary potential of integrating SD and ABM, and to provide an overview of recent case studies. The research question was formulated as:

What are the potential benefits of integrating System Dynamics and Agent-based and what is the state-of-the-art in its application?

The reviewed literature was retrieved from several research databases, including ACM Digital Library, Elsevier, Springer-link, EBSCO Host, and IEEEXplore. The works by Scholl (2001), Lättilä et al. (2010), Macal (2010), Schieritz and Grobler (2003) and Behdani (2012) were used as a guide in structuring the research process.

The remainder of this paper is ordered as follows: Section 2 gives a short overview about the SD and AB paradigms, including theories behind the paradigms and building blocks and characteristics of the resulting models. Section 3 contrasts the capabilities of SD and AB, in order to explore how their integration can yield insights that cannot be generated with only one methodology alone. This section draws from a review of recent studies that combine both paradigms. Section 4 presents how both methods have been integrated during the last decade, and explores expected developments in this field. Lastly, Section 5 concludes by answering the research question and delineating opportunities for future research.

2 Single Paradigms: System Dynamics and Agent-based

Prior to the 2010s, the SD and AB paradigms developed as separate schools of modeling and simulation (Pruyt, 2015), in spite of both paradigms being used for the analysis of complex dynamic systems (Phelan, 1999). This Section presents an overview of the fundamental theories behind each paradigm and of the building blocks and characteristics of their corresponding models.

2.1 System Dynamics (SD) Models

More than 50 years ago, Forrester (1958) founded SD around two notions from systems theory (Phelan, 1999): first, aggregated-level variables affect each other through feedback loops; second, system's structure drives system's behavior. These notions challenge the predominant rather simplistic cause-and-effect thinking of traditional science, decoded into independent and dependent variables. Instead, systems theory explains the behavior of complex dynamic systems endogenously: it identifies feedback effects that are often hidden because they are delayed at large time scales. Consequently, systems dynamics modelling targets the underlying causes of problems instead of only treating their symptoms (Forrester, 1958; Sterman, 2000).

In practice, the building blocks in specifying an SD model are stocks, flows and auxiliary variables (Forrester, 1958; Sterman, 2000). Stocks represent the accumulation of material and information, caused by the action of inflows and outflows. While stocks are mathematically described by integral equations, flows are described by differential equations (Macal, 2010; Parunak et al., 1998) . The solution of these sets of equations describes the aggregated state of the system. This state changes continuously over time and depends on the previous state of the system. These sets of equations are solved through numerical integration at discrete time steps (Forrester, 1958; Meadows, 2009; Sterman, 2000).

2.2 Agent-based (AB) Models

The theory of complex adaptive systems (CAS) states that systems do not have central control and do not have a fixed structure. Based on this theory, the AB paradigm models the structure of a system as the result of decentralized decisions of individual entities or agents over time (Macal, 2010; Macal and North, 2006). Therefore, instead of assuming a given system structure, agents' decisions shape and change the state and structure of the system. In turn, agents react to the dynamic changes in the system, which can potentially alter their decision rules.

It follows that the main building blocks of AB are autonomous agents, their decision rules and actions, and the environment in which they interact (Bonabeau, 2002; Epstein and Axtell, 1996; Phelan, 1999). Although agents' decision rules usually govern agents' behavior to achieve individual benefits (Macal and North, 2006), collective intelligence may also emerge when agents coordinate their decisions to achieve common goals (Phelan, 1999). Therefore, analyzing solely the internal mechanism of agents does not explain the macro level observations (Epstein, 2006). Moreover, agents' decision making is typically based on limited observed knowledge (their view on the world) rather than on complete knowledge of the entire state of the system (Jennings et al., 1998).

3 Potential benefits of integrating System Dynamics and Agent-based

The contrasts between SD and AB, including scope, the focus on system behavior or on emergent behavior, aggregation level and the current capacity to study heterogeneity and spatial variability, make the application of each paradigm more suited to different situations (Macal, 2010; Scholl, 2001; Teose et al., 2011; Wakeland et al., 2004). Nevertheless, knowledge about the differences between SD and AB does not necessarily result in an appropriate choice of paradigm: one paradigm alone cannot always provide enough insights to analyze the complex system of interest (Lättilä et al., 2010; Macal, 2010; Rahmandad, 2004; Scholl, 2001; Shafiei et al., 2013a).

In this Section, five characteristics in which SD and AB differ fundamentally are explained first. Second, the potential benefits of combining both paradigms are clarified.

3.1 Contrasting SD and AB - five fundamental differences

The applicability, strengths and weak points of SD and AB paradigms have been compared by designing independent models of the same system and contrasting their outcomes. Recent contributions include, but are not limited to Figueredo and Aickelin (2011), Macal, (2010), Milling and Schieritz (2003), Parunak et al. (1998), Rahmandad and Sterman (2008), Schryver et al. (2015). For this article, a number of such comparisons were reviewed and five fundamental characteristics in which SD and AB differ were identified. These aspects include the paradigms' capacity to model continuous aggregated and discrete disaggregated system states; physical space, topographies, and network structures; stochastic & deterministic phenomena; learning and adaption; and ease of model building and interpretation. The paragraphs below elaborate on each of these aspects.

3.1.1 System states: continuous aggregated vs. discrete disaggregated

SD and AB paradigms differ in the level of aggregation and their handling of time. On the one hand, SD excels at representing continuous aggregated systems. This paradigm can account for a wide range of feedback effects, at the cost of reducing real world diversity to aggregated average values by assuming homogeneity and perfect mixing within stocks and flows (Parunak et al., 1998; Rahmandad and Sterman, 2008; Sterman, 2000). However, While SD excels at modeling continuous processes, it has difficulties in coping with discrete events (Parunak et al., 1998). Therefore, AB is more appropriate to model discontinuous system properties (Bonabeau, 2002).

In contrast to SD, the AB paradigm inherently includes heterogeneity between agents. To account for the diversity of agents in the real world, agents act according to properties and decision rules that can be derived from distribution functions (Bonabeau, 2002; Epstein, 2006; Macal, 2010). By accounting for the diversity within and between agents, AB is suitable to study problems where the distribution of resources, costs or benefits is the focus of interest (Bonabeau, 2002; Osgood, 2007).

Empirical research has emphasized a tension between the level of analysis and the scope of the system under study when using SD or AB alone (Alam Napitupulu, 2014; Cherif and Davidsson, 2010; Figueredo et al., 2015; Silva et al., 2011; Thompson and Reimann, 2010). While SD can study large systems by handling highly aggregated data, AB typically studies heterogeneous systems with relatively limited scope.

In practice, choosing a paradigm to describe a system at an appropriate level of analysis is not straight forward. In reality, this aspect is observer dependent: the same system can be described with both discrete and continuous representations. Rahmandad & Sterman (2008) demonstrate that the outcomes of equivalent SD and AB models are alike under many conditions. Other authors have come to the same conclusion by comparing single SD and AB models in the fields of health sciences (Ahmed et al., 2013; Figueredo et al., 2015; Figueredo and Aickelin, 2011b), economy (Alam Napitupulu, 2014), transportation (Silva et al., 2011), software development (Cherif and Davidsson, 2010), land use (Haase and Schwarz, 2009) and education (Thompson and Reimann, 2010).

3.1.2 Stochastic & deterministic phenomena

SD and AB can both model deterministic systems: systems which do not contain randomness and thus yield the same result from a given initial state (Brock, 1986). However, in AB models, decision rules, actions and properties are normally derived from distribution functions, and are therefore probabilistic (Bonabeau, 2002).

Due to its stochastic character, the AB paradigm can naturally account for outlier values that would not be shown in an aggregated system representation. Outlier values represent random events, such as Black Swans, that are unlikely but can alter the system radically. Therefore, when assumptions of homogeneity and perfect mixing can be made for a particular study, SD and AB can produce outcomes that are not statistically different (Ahmed et al., 2013; Rahmandad and Sterman, 2008). However, when heterogeneous clustered agent networks are central for answering the problem, AB is usually a more appropriate paradigm to study the problem (Rahmandad and Sterman, 2008).

However, there is a trade-off between the stochasticity of an AB model and its computational requirement (Osgood, 2007; Rahmandad and Sterman, 2008). A conflict in goals arises between the richness of feedback structure captured endogenously, the number of agents and their complexity of interaction, and the exhaustiveness of the sensitivity analysis (Rahmandad & Sterman, 2008). As a result, AB can be discarded as the preferred method in modeling and simulation studies due to its high computational resource demands (Ahmed, Greensmith, & Aickelin, 2013; Figueredo & Aickelin, 2011; Figueredo et al., 2011; Figueredo et al., 2015; Silva, Coelho, Novaes, & Lima Jr, 2011).

3.1.3 Physical space, topographies, & network structures

Inherently, SD was not designed to cope with spatial diffusion and propagation processes, but to model the aggregate properties of such systems and so provide strategic insight into their behaviour. When the number of entities is small and when the entities are highly dispersed or clustered, this can be problematic (Rahmandad & Sterman, 2008). Emerging paradigms, such as spatial system dynamics (SSD), are trying to overcome this limitation (Ahmad and Simonovic, 2004; Neuwirth and Peck, 2013). SSD is based on coupling SD with geographic information systems (GIS) to provide feedback effects across physical space (Ahmad and Simonovic, 2004).

In contrast, AB has the capability to distinguish physical space, topographies, and other network structures (Bonabeau, 2002; Parunak et al., 1998; Rahmandad & Sterman, 2008). The former allows the explicit study of the dynamics across landscapes or networks (Osgood, 2007). Hence, AB models have proven attractive for classes of modelling problems where topographies (particularly irregular and clustered) are crucial with respect to understanding the problem and the assessment of policies. Furthermore, the characteristics of mobile agents in a network, able to alter system structure, can be utilized to account generally for evolving systems in which relations disintegrate and are created dynamically over time (Scholl, 2001). This property and the possibility to construct goal-oriented agents makes AB models ideally suited to model many social systems and implement concepts from social and behavioral science such as bounded rationality (Edmonds, 1999; Manson, 2006; March and Simon, 1958).

3.1.4 Learning & adaption processes

Experience based learning effects and adaptation processes such as the "eroding quality standards" archetype are frequently modelled in SD.. Nevertheless, explicit individual learning and adoption processes are a focus within AB models (Bonabeau, 2002). For this, machine learning algorithms are used to design agents that have the ability to modify their own decision rules (Parunak et al., 1998; Phelan, 1999; Scholl, 2001; Stone and Veloso, 2000).

3.1.5 Ease of model building and interpretation

As the previous examples demonstrate, AB model have numerous virtues in specific contexts. However, these virtues often come at the cost of more time consuming modeling simulation and interpretation processes (Osgood, 2007). Indeed, the interpretation of AB model outputs at aggregate level is still in its infancy. Whereas the formulation of an SD model makes use of system level observables to identify the feedback loops that govern the system's behavior (Rahmandad & Sterman, 2008), the construction of an AB model requires not only knowledge of the system at an aggregated level, but also in-depth insights on decision processes of agents and their behavior (Macal, 2010; Macal & North, 2006). Moreover, AB models require knowledge on the disaggregated distributions of agent properties for parametrization (Macal, 2010; Macal & North, 2006).

Next, as described in the paragraphs devoted to stochastic and deterministic phenomena, AB models have considerably longer simulation times than their SD counterparts.

Additionally, the interpretation of simulation results is typically easier for SD models than for AB models, because the underlying dynamics of these models are transparent and the toolbox for analyzing and understanding simulation results is already well developed. This availability of methods facilitates the rapid development of small models to explore the driving dynamics of current 'hot' issues (Pruyt, 2013; Pruyt et al., 2009).

Finally, SDs popularity has been facilitated by the availability of several drag-and-drop software tools for constructing and analyzing models, including Vensim® (www.vensim.com), Stella® (www.stella.com) and PowerSim® (www.powersim.com) (Borshchev and Filippov, 2004). Until recently, one of the obstacles for wider adoption of AB had been the limited availability of easy to use tools that do not require programming skills (Parunak et al., 1998; Wilensky, 1999). However, the emergence of software such as AnyLogic® ("Multimethod Simulation Software and Solutions," n.d.) and NOVA® (Salter, 2013) may facilitate faster adoption.

3.2 Potential benefits of combining SD and AB

Despite fundamental differences, both modelling approaches are effective in describing and simulating complex dynamic systems. AB has received increasing attention because it holds promise of significant benefits compared with other modeling paradigms, including SD (Bonabeau, 2002; Epstein, 2006; Jennings et al., 1998; Macal and North, 2006). Nevertheless, there is no simple dividing line indicating when which modelling approach will provide superior results. Instead, the choice of paradigm depends on the problem and the purpose of the modelling exercise and should take into account the paradigms' capabilities, limitations and tradeoffs (Figueredo and Aickelin, 2011b; Parunak et al., 1998).

By combining SD and AB, some components can be modelled discretely and in a disaggregated fashion when this is needed, while other components can be modelled continuously and in an aggregated fashion, based on the different system characteristics and the specific model purpose (Osgood, 2007). In this way, a hybrid SD-AB model facilitates the definition of appropriate levels of aggregation for each component of the system. Furthermore, for many modelling problems, a combination of SD and AB can reduce computation times, provide the strategic overview characteristic of SD, while still capturing relevant elements of the individual heterogeneity and stochasticity of entities and processes.

Another potential advantage of combining SD and AB is that this can be seen as a way to enhance the capability of SD models to cope with spatially explicit problems. The resulting models permit arranging agents in a spatial or network structure, while integrating important properties of SD, such as continuity and non-linear multi-loop feedback. This approach can be refined when the individuals are mobile and consequently the spatial dimension becomes dynamic. Besides this, it is possible to use multiple SD sub-models to create different properties across a spatial grid. As a result, individuals interact with a different SD sub-models depending on their position (Vincenot et al., 2011). Agents can plausibly even interact with more than one SD sub-model at a time.

4 Recent efforts to integrate SD and AB

While no unified definition exists for hybrid SD-AB models, countless architectures are possible for coupling or matching SD and AB. This section discusses first, how AB features have been incorporated through emulation into the field of SD. Then, it presents three classifications of possible architectures for hybrid SD-AB models. Finally, it summarizes recent efforts and breakthroughs in the design of hybrid SD-AB models, and sketches the state-of-the-art of SD and AB integration. The focus lies on work conducted within the last decade and particularly in the last five years.

4.1 Emulation of AB features within the SD field

In the field of SD, some authors have made attempts to emulate the capabilities of AB without changing the overall SD paradigm. Pasaoglu et al. (2016), Powell and Coyle (2005) and Wu, Kefan, Hua, Shi, and Olson (2010), for instance, integrated an AB perspective in the construction of an SD model. Teose et al. (2011) embedded SD notions into AB models using Gillespie's *τ-leap algorithm*, an equation that connects the paradigms by interpreting rates of flow into movement of agents.

While paradigm emulation has contributed to expanding the applications of SD during the last few years, it is the appropriate combination of the two approaches that has become the most promising research line (C Swinerd & McNaught, 2014). Integrating SD and AB makes it possible to avoid their individual pitfalls and, hence, to exploit the full potential of their complementary characteristics, so as to provide a more complete representation of complex dynamic systems (Scholl, 2001; Stemate et al., 2007).

4.2 Hybrid SD-AB architectures

Swinerd and McNaught (2012), Kirandeep et al. (2013) and Vincenot et al. (2011) proposed different architectures for hybrid SD-AB models.

Based on Shanthikumar and Sargent (1983), Swinerd and McNaught (2012) presented three classes that vary depending on how the model's modules, either SD or AB single paradigm meta-models, interact to produce the model's outcome. In the first class, the sequential class, the outcome of each module forms the input for the next module; the outcome of the final module represents the model's outcome. The second class, the interfaced class, includes non-sequential combinations of modules that do not influence each other but combine their independent outcomes to produce the model outcome. Lastly, in the integrated class, modules and even model outcomes provide feedback to one another.

The second classification, developed by Kirandeep et al. (2013), presents two classes that are analogous to the aforementioned sequential and integrated ones.

Vincenot et al. (2011), in turn, identified four reference cases or typical SD-AB structures. Case 1 refers to AB agents interacting within their environment, an SD module. Emergent properties from the AB module can dynamically parameterize the SD module. Case 2 refers to AB agents containing SD modules that determine their dynamic decision rules and spatial structures. In Case 3, individuals interact with an environment made of more than one SD module. Unlike Case 1, Case 3 is spatially explicit and the SD module with which an agent interacts depends on the agent's position and the SD module's area of influence. Finally, Case 4 refers to SD-ABM model swapping. This case reduces computation time by allowing only modules of the same paradigm to run at any given time. During the run, threshold values or events cause the change from modules of one paradigm to modules from the other one.

However, the architectures of Swinerd and McNaught (2012), Kirandeep et al.'s (2013), and Vincenot et al. (2011) are non-exhaustive in nature. While Chris Swinerd and McNaught (2012)'s interfaced class implies that modules in a hybrid model do not necessarily have to be connected during the simulation, all the reference cases by Vincenot, Giannino, Rietkerk, Moriya, and Mazzoleni (2010) consider interaction between the modules during the simulation. In practice, the architecture of hybrid SD-AB models is usually based on the specific needs of the problem under study. Examples are provided in the following sub-section.

4.3 Recent hybrid SD-AB models and modeling environments

Hybrid SD-AB models have proven useful in studying diffusion processes of technological innovation. In their independent studies, Swinerd and McNaught (2014) and Shafiei et al. (2013) embedded individual agents in an SD environment. In Swinerd and McNaught's model, an SD module is embedded in each agent to dynamically parameterize its properties. Similarly, Swinerd and McNaught (2015) simulated the international diffusion of consumer technology by modeling nations as agents, with internal decision processes consisting of SD models, and global diffusion processes with an equation-based rate model.

Hybrid SD-AB models have also been developed in other fields. Jo et al. (2015) designed a dynamic alternative to cost benefit analysis for infrastructure projects. This work integrates AB and SD modules by enabling dynamic feedback from the SD states to the AB environment, and from the AB environment to the SD rates of change. Tran (2016) developed a multi-paradigm framework to analyze techno-behavioral dynamics in networks, and to assess the impact of technology on society. This framework integrates the notions of system dynamics to explore the most aggregated and macro layers of the system, and notions from agent-based to study network structures and individual behavior. Lewe et al. (2014) studied intercity transportation by integrating SD and AB modules to represent macro-level, and micro-level variables, respectively. Kolominsky-Rabas et al. (2015) developed the framework ProHTA, a hybrid SD-AB tool the aim of which is to the assessment of innovative health technologies prior to their launch.

Other examples explicitly include discrete event simulation models, in addition to the SD and AB components. For instance, a study of the elements of a hybrid simulation model for blood supply chains (Onggo, 2015); a feasibility assessment of hybrid approaches in the context of complex healthcare operation management (Viana, 2014); an analysis of real workforce choices (Flynn et al., 2014); a hybrid approach to integrate safety behaviour into construction planning, by Goh and Askar Ali (n.d., in press) and the study of reusability in hybrid simulation by Djanatliev et al. (2014), to mention but a few.

The availability of modelling environments that can handle multiple paradigms, including SD, AB and discrete events has also increased. For instance, Salter (2013) reports on NOVA®, a modeling and simulation platform that supports the integration of both paradigms. Moreover, this work envisions the integration of Geographic Information Systems (GIS) within the platform. Other platforms include Anylogic® ("Multimethod Simulation Software and Solutions," n.d.), which supports modeling and simulation with SD, AB, discrete events and incorporates certain GIS features, as well as NetLogo (Wilensky, 1999), a free and open source modeling environment with similar capabilities.

4.4 Exploring the next generation of hybrid paradigms

As explained in the previous Sections, integrating the SD and AB paradigms is a promising approach to overcome the limitations of each single paradigm. However, the integration of SD and AB is only a piece in a bigger puzzle (Pruyt, 2015). Recent innovations suggest that, in the future, mainstream research frameworks and methods to model complex dynamic systems will reach beyond the boundaries of SD, AB, and even beyond the reach of hybrid SD-AB paradigms.

Currently, the adoption and diffusion of methods and techniques from other disciplines, such as data analytics and machine learning, are turning modeling and simulation into an interdisciplinary field (Pruyt, 2015). This process of blending tools and methods across disciplines, which has just started, is enabling the emergence of a new generation of computational models with radically expanded capabilities that promise to deliver significant breakthroughs.

For several reasons, the development of this new generation of computational models is likely to occur using high-level programming language, such as Python, R Project and Java, instead of commercial and closed source modeling environments (Pérez, Granger, & Hunter, 2011). First, many scientific disciplines use these languages for scientific computing and quantitative data analysis. The open source environment fosters transparency and reproducibility of research, while these languages facilitate the balance between full flexibility of general-purpose programming languages and ease of use. In addition their object-orientation supports the implementation of multi-model approaches.

Examples of the methodological innovations that will lead to the new generation of models include Exploratory Model Analysis (EMA) (Kwakkel and Pruyt, 2015, 2013) and data analytics using tools such as PySD (Houghton, and Siegel, 2015).

5 Conclusion

This literature review seeks to update the work of Scholl (2001) and Macal (2010) by providing an overview of attempts to integrate SD and AB over the preceding decade, with a particular focus on the last five years. The review described the building blocks of both paradigms and contrasted their capabilities to explore how their integration can yield insights that cannot be generated with one methodology alone. Five fundamental characteristics in which SD and AB differ were identified. These characteristics are the paradigms' capacity to model continuous aggregated and discrete disaggregated system states; physical space, topographies, and network structures; stochastic & deterministic phenomena; learning and adaption; and ease of model building and interpretation.

This article also provided an overview of recent work on the integration of SD and AB paradigms, and the development of multi-paradigm and multidisciplinary modeling and simulation frameworks. However, he unique contribution of this paper is the conclusion that while paradigm emulation has contributed to expanding the applications of SD, the dynamic combination of the two approaches is the most promising research line. Integrating SD and AB, as well as tools and methods from other disciplines, makes it possible to avoid their individual pitfalls and, hence, to exploit the full potential of their complementary characteristics, to provide more complete representations of complex dynamic systems.

Ultimately, the widespread adoption of hybrid SD-AB models will depend on the development of tools that are able to effectively integrate different modelling paradigms. Therefore, an area of research that should be encouraged is the development and refinement of free and open source hybrid modelling tools that they are easy to use and in which models can be documented.

Furthermore, this review concludes that although SD and AB are only a piece in the bigger puzzle of innovative modeling and simulation environments, their integration into hybrid models plays an important role in these exciting times. Breakthroughs in the integration of SD and AB can yield insights in how to build and use smarter modeling tools to support decision-making.

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