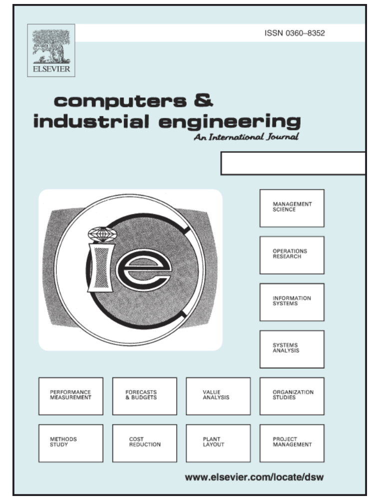

An introductory guide for hybrid simulation modelers on the primary simulation methods in industrial engineering identified through a systematic review of the literature

Anna Paula Galvão Scheidegger, Tábata Fernandes Pereira, Mona Liza Moura de Oliveira, Amarnath Banerjee, José Arnaldo Barra Montevechi

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An introductory guide for hybrid simulation modelers on the primary simulation methods in industrial engineering identified through a systematic review of the literature

Anna Paula Galvão Scheidegger*
Industrial and Systems Engineering Department, Texas A&M University, 3131 TAMU, College Station, TX 77843, USA
apscheidegger@tamu.edu

Tábata Fernandes Pereira
Campus in Itabira, Federal University of Itajubá, R. Irmã Ivone Drumond, 200 - Distrito Industrial II, Itabira, MG, 35903-087, BRAZIL
tabatafp@unifei.edu.br

Mona Liza Moura de Oliveira
Management and Industrial Engineering Department, Federal University of Itajubá, Av. BPS, 1303, Pinheirinho, Itajubá, MG, 37500-000, BRAZIL
monaoli@yahoo.com.br

Amarnath Banerjee
Industrial and Systems Engineering Department, Texas A&M University, 3131 TAMU, College Station, TX 77843, USA
banerjee@tamu.edu

José Arnaldo Barra Montevechi
Management and Industrial Engineering Department, Federal University of Itajubá, Av. BPS, 1303, Pinheirinho, Itajubá, MG, 37500-000, BRAZIL
montevechi@unifei.edu.br

*Corresponding author.
E-mail address: apscheidegger@tamu.edu
Full postal address: 3131 TAMU, College Station, TX 77843-3131, Office 2017

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Abstract

Modeling and simulation are a powerful and effective problem-solving methodology to study how complex real-world systems behave over time. In the literature, many authors have indicated that discrete event simulation, agent-based simulation, and system dynamics are the primary and most important simulation techniques to aid industrial engineers in making decisions. Given this context, this paper is expected to be an introductory guide, especially for novice simulation modelers willing to work with hybrid simulation, by providing knowledge and insight about the primary simulation methods in industrial engineering. This paper is expected to support the decision about which simulation technique best suits the system being studied. For that, a systematic literature review was conducted based on pre-defined search criteria. After applying the filters and including some relevant papers published in the field, a total of 145 papers were selected. Some of the analysis performed in this study include, for each simulation method, the number of publications over the years and a list of the top 10 sources, countries, and authors according to the number of publications. Besides that, a brief history is provided and the definition of the three primary techniques is discussed, as well as the main characteristics of each technique, such as modeling steps, elements, conceptual modeling tools used, software, inputs and outputs, programming languages, advantages, disadvantages, and application areas. Simulation modelers can use this paper as a quick reference to the primary simulation techniques in order to identify the best tool for a specific simulation project in the field of industrial engineering and related areas.

Keywords

Simulation; Discrete event simulation; Agent-based simulation; System dynamics.

1. Introduction and background

The modeling and simulation (M&S) field includes the methods, tools, and techniques used to represent, experiment, and study complex systems. The M&S tools and techniques have advanced in the past decades and have been increasingly applied in more challenging areas (Tuncer Ören, 2010).

Models are simplified abstractions to represent a system for some specific goal and are used to test theories and to explore their implications and contradictions (Balci, 2001, 2003). Simulation is one particular approach to study models or to experiment with a model based on numerous goals (Balci, 2003; White & Ingalls, 2015). Simulation models are computer representations of how the real world system operates at some level of aggregation. Modeling and simulation are frequently more useful to promote knowledge and valuable understanding about the system and the problem structure than to provide accurate predictions and exact answers (Eldabi et al., 1999; Winz et al., 2009). The definition of modeling and simulation can be found in Maria (1997); White and Ingalls (2009, 2015, 2016).

Simulation is frequently the most time-effective and cost-effective, and every so often the only means of detecting causal effects, stipulating critical parameter estimates and clarifying how processes develop over time (Garson, 2009). Simulation allows people to analyze systems optimization prior to implementation. In general, simulation is a more suitable methodology to investigate complex problems, especially when the problem cannot be formulated in mathematical terms (Barton et al., 2013; Huanhuan et al., 2013). Simulation modeling technique is (a) a widely used art, (b) a key approach to characterize complex process configurations and constraints, and (c) used to study how the system behaves under uncertainty and different scenarios (Jeon & Kim, 2016; Kaur & Mittal, 2014).

According to Goldsman (2007), simulation is the most useful tool in the industrial engineering, operations research, and management science fields. Although originally simulation was mainly used by industrial engineers, recently the tool has been applied in a large set of domains, ranging from biology and ecology to psychology and anthropology; from economics and education to public administration, policy design, engineering and medicine; from urban planning to military planning; and several other areas (Figueredo & Aickelin, 2011; Tuncer Ören, 2005a; Scholl, 2001). Tuncer Ören (2005a, 2007, 2009, 2011) provided a great discussion on the different meanings the term simulation can have, in its areas of domain, its different contributions, its challenges, and its different goals as a tool for training, decision support, understanding, learning, and entertainment. Different stakeholders may use simulation for different purposes (Tüncer Ören, 2005b).

Many modeling and simulation methods exist and a list of several of the methods can be found in Diallo et al. (2015). Some of these methods are predominantly used in a specific domain, as is the case of Monte Carlo simulation in the field of finance and economics or computational fluid dynamics (CFD) in the field of aerospace engineering. Besides, some methods, such as Monte Carlo simulation and discrete event simulation, are applied to modeling systems and processes, while other methods, such as CFD and finite element analysis (FEA), are applied to modeling products and prototypes. With respect to simulation methods applied to modeling systems and processes, despite the wide range of simulation applications, there are currently three methods that can be considered important and suitable for widespread applications in industrial engineering and related areas (Carley, 2009; Goh & Ali, 2016; Jahangirian et al., 2010; Weidmann et al., 2015). They are: system dynamics (SD), discrete event simulation (DES) and agent-based simulation (ABS). SD and DES are more traditional approaches, whereas ABS is relatively new. SD is usually used at high abstraction levels, whereas ABS can be used across all levels and DES better deals with low to middle abstraction levels. According to Brailsford et al. (2017), for many years DES and Monte Carlo simulation were the only methods that researchers and practitioners would think when discussing simulation. The authors highlighted that for many years the Journal of Simulation and the Winter Simulation Conference focused mainly in DES, but this has completely changed. Now, both the journal and the conference welcomes not only papers related to DES, but also papers related to ABS and SD (Brailsford et al., 2017).

For novice modelers, a quick and general introduction to simulation can be found in papers of the Winter Simulation Conference, entitled “Introduction to Simulation” and/or “Introduction to Modeling and Simulation”. Banks (1999, 2000) discussed the basic concepts and definitions of simulation, as well as the advantages and disadvantages of the technique. He also provided a simple example of a simulation done by hand. Ingalls (2001, 2002, 2008, 2011, 2013) also talked about the basic concepts related to simulation, but he also discussed the main steps of a simulation project and he walked the readers through a detailed example about how discrete-event simulation works. The example is applied to a drive-through window process at a fast food restaurant. Similarly, White and Ingalls (2009, 2015, 2016) walked the readers through a detailed call center simulation example. In addition to the basic definitions, the advantages, and the disadvantages of the simulation technique, Carson (2003, 2005) provided the readers with the main steps of a simulation project and with information about when one should use simulation. Although more than ten years have elapsed since Carson’s papers and, consequently, the problems tackled by simulation have changed, the definition of when to use simulation still prevails. Goldsman (2007) also gave an introductory simulation tutorial, but in his paper, he focused on the statistical aspects of a simulation project, such as random numbers generation, input analysis, output analysis, and comparison of systems. For an introduction to specifically input modeling, it is suggested to check the paper by Biller and Gunes (2010), who discussed three cases when standard input models may not represent the available data adequately. The previous introductory tutorials are easy to understand. However, it is important noting that the tutorials are mainly focused on discrete-event simulation. For a tutorial on agent-based modeling and simulation, one can check Macal and North (2005, 2006, 2007, 2010, 2011, 2013, 2014); Weimer et al. (2016), who provided information about when to use agent-based modeling and simulation, the current applications of this method, some examples, general definitions, and the structure of this method. For a simple tutorial on system dynamics, one can check Brailsford (2008); Kunc (2016). However, the first provided the main tools and data requirements, with an application focused in healthcare, and the second provided general definitions, with an application focused on system dynamics as a behavioral method. Kunc (2017) also gave an overview of system dynamics, but he focused on discussing how SD can be used as a soft and also a hard method for modeling.

SD is a top-down approach grounded in differential equations systems and feedback loops. The SD model is made up of cause and effect loops, stocks, flows, and auxiliary variables that are inter-connected (Sterman, 2000). Unlike SD models that advance time continuously, pure DES models advance time from one event to another in discrete time steps, while the transition between states in ABS models can be implemented in either fixed or variable time steps. These two ways of implementation in ABS models are called synchronous and asynchronous, respectively. In the synchronous case, the decision is made every time step. In the asynchronous case, the time delay is recalculated every time an agent enters a new state, which may reduce the computational power needs.

Usually, DES models take a process view of the world, i.e., the system is considered as a list of events to be processed or a flow chart and the entities and mobile resources flow through the processes (Goh & Ali, 2016). By default, entities and resources are not able to interact with each other and they do not display adaptive behaviors. ABS is a bottom-up approach focused on the design of heterogeneous individual agents, the adaptive decisions and actions they perform, the rules that they follow and the emergent behavior that arises from their interactions (Borshchev, 2013; Dubiel & Tsimhoni, 2005).

Different problems and contexts may demand different simulation methods depending on the research goals, available data, and the nature of the system being modeled (Borshchev, 2013; Lättilä et al., 2010). Even though it is possible to model most real-life systems using one of the aforementioned simulation techniques, the increasing level of complexity often requires substantial improvisation in the selected approach (Swinerd & McNaught, 2012). Therefore, it may be advantageous to integrate two or more simulation methods in order to develop simpler, more natural and more efficient models. The combination of two or more simulation approaches leads to what is called hybrid (or multi-method) simulation model. According to Eldabi et al. (2016), hybrid simulation can provide a better understanding of complex systems because researchers can investigate the problem from different dimensions and perspectives. Hybrid simulation is also important because, as highlighted by Zeigler and Ören (1986), the simulation project usually has multiple objectives, multiple levels of aggregation, and multiple levels of behavior and structure, which can only be adequately represented by combining different simulation methods together. Some examples of the possible use of multi-method can be found in Borshchev (2013) and Eldabi et al. (2016), such as: using system dynamics inside an agent; using agents as entities of a DES model; using process flow inside an agent; among others.

Table 1 shows a brief comparison of the number of papers published for each primary modeling and simulation technique individually and combined, as well as the papers describing hybrid or multi-method modeling and simulation in general. In this table, it is also possible to check when the first paper on each topic was published. We decided to include the word 'modeling' in the keywords for two reasons: first, simulation is often referred as computer modeling, and second, conceptual modeling is usually the first step in a simulation project and, hence, modeling and simulation are frequently used together. We recognize that Table 1 might contain papers not directly related to SD, DES, and ABS, but we believe it gives a good idea about the beginning of the methods and the researchers' interest on them.

The previous discussion leads to two fundamental questions: (1) when should one use SD, DES, ABS or a combination of these methods?, and (2) what methods are most appropriate to be used together? Although they look like simple questions (or at least they should be), these decision choices seem to be frequently made based on an unknown or implicit user preference (Koelling & Schwandt, 2005). Each method has its strengths and weaknesses (Rahmandad & Sterman, 2008). Therefore, every modeler and researcher willing to work with hybrid simulation must be able to effectively choose among those methods, based on the project purpose, the data availability and the characteristics of the system of interest. Also, in order to choose the correct methods, it is important to know the characteristics, advantages, and limitations of each method.

Table 1

Number of papers published and the first year of publication on the main simulation techniques.

Keywords[a]	Total number of papers	First year of publication
("System Dynamic* modeling" OR "System* Dynamic* simulation")	1099	1970
("Discrete event modeling" OR "Discrete event simulation")	7210	1974
("Agent-based modeling" OR "Agent-based simulation")	2370	1997
(("System* dynamic*") AND ("Discrete event") AND ("Simulation" OR "Modeling"))	184	1977
(("System* dynamic*") AND ("Agent-based") AND ("Simulation" OR "Modeling"))	146	2001
(("Discrete event") AND ("Agent-based") AND ("Simulation" OR "Modeling"))	150	1997
(("System* dynamic*") AND ("Discrete event") AND ("Agent-based") AND ("Simulation" OR "Modeling"))	20	2003
("Hybrid simulation" OR "Multimethod simulation" OR "Multimethod modeling" OR "Hybrid modeling")	2048	1964

[a] **Search criteria**
Database: Scopus
Date of search: first half of June/2016
Search fields: Topic (Title, abstract and keyword)
Language: English
Subject: Engineering, Decisions Sciences, and Business, Management and Accounting
Type of document: Article, Article in Press, Conference Paper, Conference Review and Review

This work is an attempt to provide simulation researchers and practitioners with an easy, quick and practical way of gaining knowledge and information about the three primary simulation methods in industrial engineering and, hence, a means to support the decision making of what is(are) the most suitable simulation method(s) to be used in a specific simulation project. Therefore, the main objective of this paper is to offer an introductory guide on discrete event simulation, agent-based simulation, and system dynamics. We hope that the findings of our analysis will be beneficial to the community of simulation academics and practitioners within various sectors and industries. This paper is also a partial response to the future work proposed by Jahangirian et al. (2010), who suggested researchers to perform a comparison of various simulation techniques.

To the best of our knowledge, there is not yet any paper published providing a general overview and comparison of all three primary simulation techniques in industrial engineering. The works that we have found so far usually fall in one of the following five groups: (1) a specific review on the three primary simulation methods in a particular field without application; (2) a general review that encompasses only one or two of the three primary simulation methods; (3) a specific review on only two of the three methods in a particular domain; (4) an application of two or three of the methods combined; or, (5) a review of simulation studies in a specific field, without discussing the simulation methods in detail.

As examples of work in group 1, we cite: Jahangirian et al. (2010), where the simulation methods applied in manufacturing and business were reviewed; Jeon and Kim (2016) who have performed a survey of simulation techniques used in production planning and control; and, Dessouky and Roberts (1997) who reviewed the main combined simulation languages being used at that time, but did not classify the languages into the three primary methods addressed in this paper.

In group 2, we found: Huanhuan et al. (2013), where they proposed a framework for integrating discrete event simulation with agent-based modeling; Lättilä et al. (2010), who have provided a comparison among ABS and SD, and discussed five different situations where it would be useful to combine these methods; and, Rahmandad and Sterman (2008) who provided a discussion on when to use ABS and when to use SD.

In group 3, there are: Tako and Robinson (2012), where they have reviewed the application of DES and SD in logistics and supply chain; El-Gafy and Abdelhamid (2008) who have contrasted the use of DES and SD as tools for lean construction work; Garson (2009) who has reviewed the current developments in social science using ABS, SD, network and spatial models; Kleijnen (2005) who has reviewed different simulation methods applied in supply chain management, including DES and SD; and, Ashworth and Carley (2007) who conducted a review on ABS and SD addressing organizational theory and modeling.

In group 4 we have: ElBanhawy et al. (2013), who have integrated ABS and DES to simulate electrical vehicles population in metropolitan areas; Rabelo et al. (2007) who have proposed an approach that integrates SD and DES to model the service and manufacturing activities of the global supply chain of a construction corporation; Goh and Ali (2016) who proposed a hybrid simulation framework consisting of ABS, DES and SD, to facilitate integration of safety management considerations into construction planning; Lee et al. (2002) who proposed a combined discrete-continuous architecture for simulating supply chain; and, Wang et al. (2014) who proposed a new integrated lifecycle assessment approach using ABS, SD and DES.

Finally, in group 5 we have: Aboueljinane et al. (2013), who discussed the decisions, the performance measures, the input data used, and the dispatching rules applied in simulation studies in the field of emergency medical service; Gul and Guneri (2015), who discussed the goals, the performance measures, the data gathering method used, and the software used in simulation studies in the field of emergency department during normal and disaster conditions; and, Alrabghi and Tiwari (2015), who discussed the decision variables, the optimization method, the simulation and optimization software used, and the maintenance strategy applied in simulation studies in the field of maintenance systems. Gul and Guneri (2015) mentioned the simulation method being used in the studies as well: about 95% of the studies used DES or DES in combination with another method and the remaining 5% used ABS or ABS in combination with other method. Similarly, Alrabghi and Tiwari (2015) also aimed to discuss the simulation method used in the studies. However, 68% of the studies used DES and 19% did not disclose the method used, which gave only 14% of the studies selected using a different method.

This paper is divided into five sections. In section 1, we provided a brief background of the area and the context that led to this work. The second section describes the methodology adopted for the systematic literature review. Next, we provide a summary of the results of the literature search. The fourth section provides a discussion of the characteristics of each method and a comparison among them. Finally, concluding remarks and further research in the simulation field are presented.

2. Material and methods: Systematic literature review methodology

The systematic review was carried out using the Scopus® citation database. This choice was justified as Scopus® is one of the largest and main multidisciplinary databases, including approximately 15,000 peer-reviewed journals (Franceschini et al., 2014; Jahangirian et al., 2010). The search was performed in the first half of June 2016. The method adopted during the review is depicted in Fig. 1.

The readers should be aware of three important notes. First, this paper was not meant to be a full bibliographical survey on simulation methods. Instead, the goal was to provide simulation modelers with an introductory guide about the three main simulation methods in industrial engineering and related fields. Second, only the DES, SD and ABS methods are being discussed in detail in this paper. There are other simulation methods available, such as Monte Carlo simulation, distributed and parallel simulation, game-theory simulation, neural network simulation, CFD, FEA, and so on. The choice of the three methods was based on the importance in the field of industrial engineering and wide range of applications, as mentioned in section 1. Third, due to the large number of available databases and publications in the field, performing the search in different databases and analyzing all the results would be impractical in a timely manner. Therefore, the authors chose the database based on its size and relevance to the field, as discussed above, and the authors selected the publications to be included in this paper based on a pre-defined selection criterion, as discussed below. Despite the considerable number of papers included in this guide, it is possible that some important papers may have been missed. To minimize this drawback, a list of some important resources is provided to the readers at the end of this paper. After years of work in the field of discrete-event simulation, the authors of this paper have recently started working with other simulation techniques. While performing different literature search in the area, the authors noticed that there was a lack of review in the literature with respect to some simulation approaches, such as agent-based, system dynamics, or a combination of approaches.

An initial search was performed in the Scopus® database to define the most appropriate keywords to address the research objective. Next, a second search based on the defined search criteria was performed. Given that our aim was to compare the three most used and important simulation methods in industrial engineering, other simulation approaches such as Monte Carlo simulation was not included in the final search.

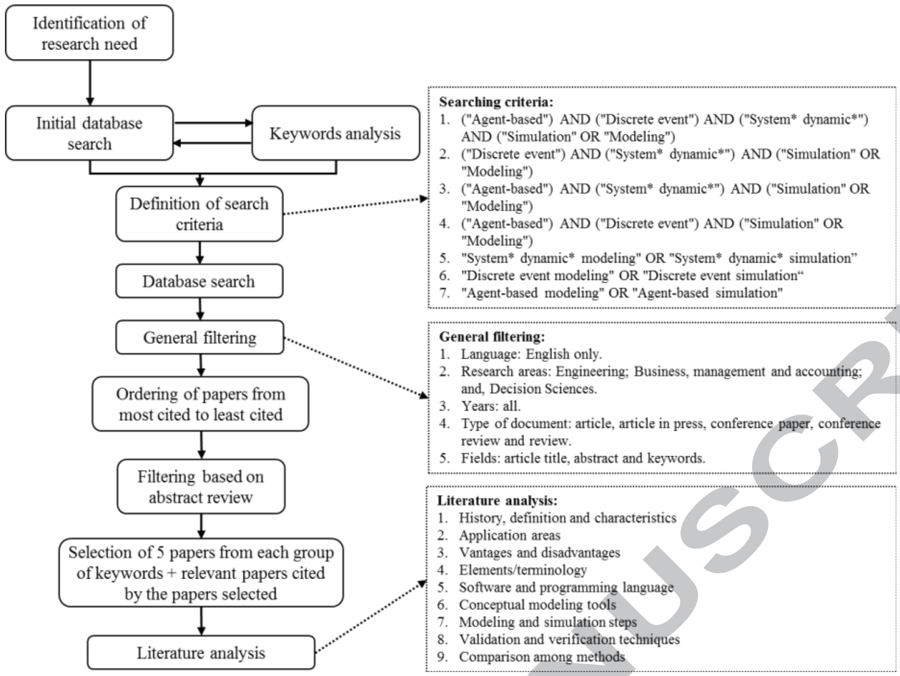

Fig. 1. The literature review methodology.

Some general filters were applied in an attempt to improve the search results for the target audience of this paper. These filters can be seen in Fig. 1 and include: (i) inclusion of papers written in English only, (ii) inclusion of research areas related to Engineering, Business and Decision Sciences only, and (iii) inclusion of articles published in peer-reviewed journals, conferences or reviews. The authors ordered the papers from the most cited to the least cited, as a possible criterion of the quality and importance of a publication (Ahlgren & Waltman, 2014). Then, a screening process of the abstracts was performed. A total of 489 abstracts were read by the authors. Due to time constraints, the 15 most relevant papers according to the objective of this study from each of the 7 keyword groups were selected. This means that papers who discussed only the application, but not any characteristics of the method were not selected. As a result, a total of 105 papers were selected. Then, the full-text screening process was started in order to capture the intended information. While performing the literature analysis, the most relevant works cited in the papers were also identified by the authors. Additionally, some papers suggested by colleagues and reviewers as relevant to the field were also included, as well as some interesting books and papers known to the authors. Thus, an additional 30 papers were selected to be part of this literature review. So, a total of 145 papers formed the basis for this literature review, as can be seen in the References section. The list of the original 105 papers selected through the systematic review can be obtained by contacting the corresponding author.

3. Results

In this section we present a summary of the results of the bibliometric analysis performed.

From Fig. 2, we observe that discrete event simulation and system dynamics publications arose in the same period (in the mid-1970's), while agent-based simulation is a more recent topic that started to arouse interest of academics in the mid-to-late 1990's.

We notice that although DES and SD have appeared in the same period, DES is a much more popular topic with a higher number of publications through all these years. In spite of being a more recent topic, we can also perceive that ABS is already more popular than SD.

Due to the sharp increase in interest in ABS, it can be projected that within the next 10 years ABS will be a method as popular as DES. The accentuated growth of ABS may also explain the decrease in the number of DES and SD publications from 2014 to 2015, by showing that academics are currently placing more effort on ABS studies.

Fig. 3 shows the top 10 countries according to the number of papers published, per simulation method. According to this chart, the United States, followed by China, are the countries that have the highest number of publications in all three methods. SD is the method where the difference in the number of publications is smaller, but even in this case, the publications from the United States are almost twice as many as from China.

It is also interesting to note that countries such as the United Kingdom, Germany, Canada and Netherlands, appear in the top 10 in all three methods; while France, Italy, Australia and Japan appear in two of the three methods and other countries, like India and South Korea, appear in only one method.

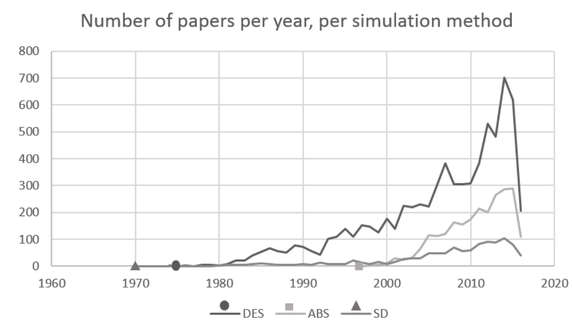

Fig. 2. Number of papers per year, per simulation method.

Top 10 countries according to the number of papers, per simulation method

Country	DES	Country	ABS	Country	SD
United States	2431	United States	792	United States	207
China	545	China	227	China	119
Canada	434	United Kingdom	192	United Kingdom	72
France	434	Germany	165	Netherlands	33
Germany	419	Netherlands	128	Australia	29
United Kingdom	405	Japan	125	Canada	27
Italy	371	Canada	94	Germany	25
Netherlands	210	Australia	87	India	25
Japan	176	France	83	Iran	19
South Korea	151	Italy	79	Finland	18

Fig. 3. Top 10 countries according to the number of papers, per simulation method.

From Fig. 4, we observe that there is not a researcher that shows up as a top 10 publisher in all three methods. In fact, there is no author in common in any of the areas, which indicates that the top 10 authors are very specialized and may not devote themselves to hybrid studies. Moreover, we also note that the top 10 authors in DES published around three times the number of papers produced by the top 10 ABS authors, who in turn published around two times the number of papers produced by the top 10 SD authors.

Top 10 authors according to the number of papers, per simulation method

Country	DES	Country	ABS	Country	SD
Fanti, M.P.	37	Terano, T.	13	Hilmola, O.P.	9
Lin, F.	37	Frayret, J.M.	10	Simonovic, S.P.	7
Lafortune, S.	36	Son, Y.J.	10	Howick, S.	6
Takai, S.	35	Dijkema, G.P.J.	9	Andersen, D.F.	5
Kumar, R.	34	Gilbert, N.	9	Munitić, A.	7
Martinez, J.C.	34	Pavón, J.	9	Rabelo, L.	5
De Schutter, B.	32	Blom, H.A.P.	8	Slootweg, J.G.	5
Zeigler, B.P.	28	Bunn, D.W.	8	An, L.	4
Giua, A.	27	Lukszo, Z.	8	Bianchi, C.	4
Renna, P.	27	Mizuta, H.	8	Blumberga, A.	4

Fig. 4. Top 10 countries according to the number of papers, per simulation method.

Fig. 5 presents the top 10 sources according to the number of papers published, per simulation method. As we can see, the Winter Simulation Conference (WSC) is the main conference of the field, showing up as a top 10 source in all three methods and being in the first position in the number of DES papers. We also note a common problem of scientific databases for bibliometric studies that differentiate two sources (or authors, for example), if the names are written in a different way. This can be observed in the WSC for the DES method.

On the other hand, journals that are very relevant to the area, such as Simulation and European Journal of Operational Research, do not appear as a top 10 journal for all methods. The journal Simulation appears only for the DES papers, while the European Journal of Operational Research appears for both DES and SD papers, but not for ABS. Another journal that also appears as a top 10 in DES and SD papers is the International Journal of Production Research.

It is also worth noting that the first position of the top 10 sources in SD papers is a specialized journal, entitled System Dynamics Review. The WSC is the only conference that appears in the top 10 sources for SD method, while at least one more conference, besides WSC, appears for DES and ABS methods.

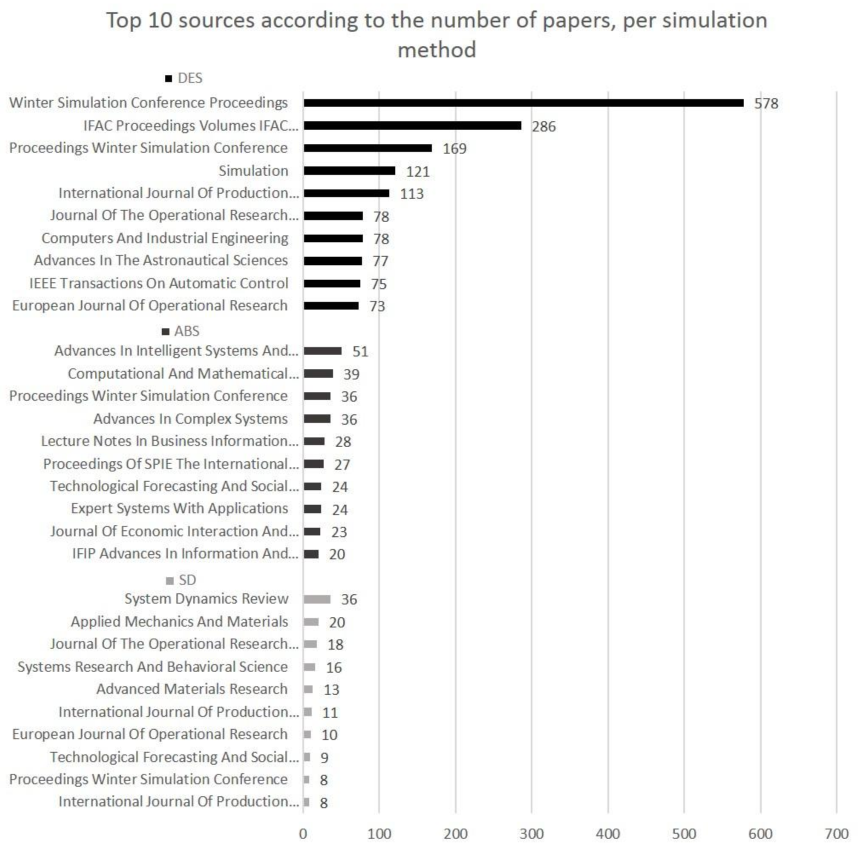

Fig. 5. Top 10 sources according to the number of papers, per simulation method.

Fig. 6 shows the top 10 subjects according to the number of papers, per simulation method. As expected, Engineering occupies the first position in all three methods, followed by Computer Science in second or third position. We notice that most of the subjects are common to all methods, with very few subjects appearing in only one or two methods. Examples include Earth and Planetary Sciences using DES method and Energy using ABS and SD methods.

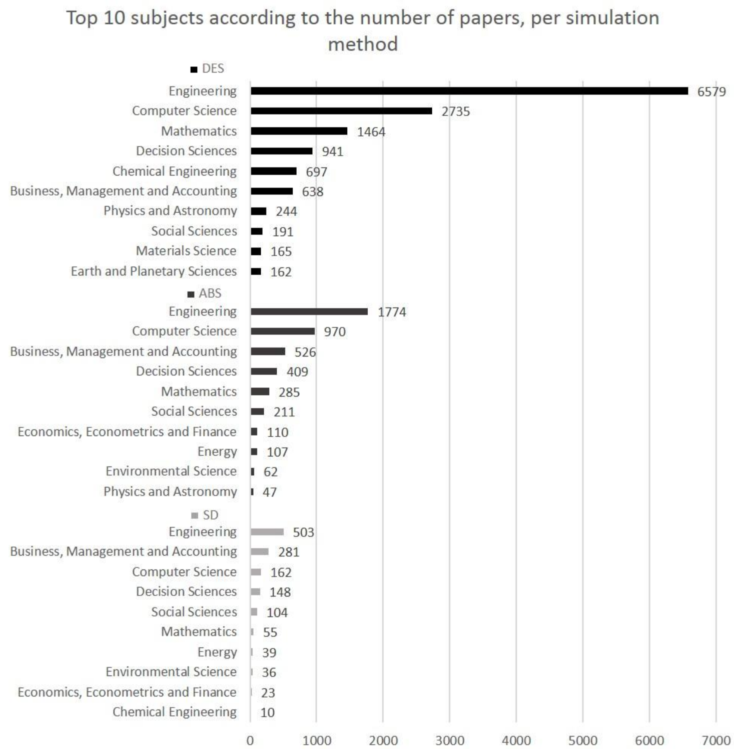

Fig. 6. Top 10 subjects according to the number of papers, per simulation method.

4. Discussion

4.1. Some papers dedicated to simulation history

In 2017, the Winter Simulation Conference, one of the main conferences in the field of simulation, celebrated 50 years of history. As a result, many papers discussing the history of simulation, as well as the history of the conference were published in the 2017 WSC edition.

For a detailed history of the WSC, one can read Alexopoulos et al. (2017); Barton, Joines, et al. (2017); R. G. Sargent (2017a); R. G. Sargent and Roth (2017); Schriber et al. (2017). Schriber et al. (2017) discussed the origins of the conference from 1967 to 1974 and the different names originally adopted. R. G. Sargent and Roth (2017) discussed the period of 1975 to 1982, which included the collapse of the conference in 1975 and the changes made to ensure the continuity of the conference from 1976 onwards. R. G. Sargent (2017a) gave an overview about the WSC from 1983 to 1992, its attendance, the number of papers published, and the keynote speakers and topics. It was during this period that the Ph.D. colloquium was initiated at the conference. Barton, Joines, et al. (2017) discussed the developments during the period of 1993 and 2007 when a lot of progress was made in terms of tracks, the conference website, the proceedings, and attendance. Finally, Alexopoulos et al. (2017) discussed the last ten years of the conference and the recent developments.

Roberts and Pegden (2017) provided a discussion on the 60 years of simulation and how the world-views changed from event to activities, to process, to object-oriented. The authors also briefly discussed the system dynamics and agent-based simulation methods, their origins, and the software available for each of the methods. R. G. Sargent (2017b) discussed the evolution of discrete event simulation from 1961 to 2017. The author described his first contact with simulation and how the field developed with respect to technology, software, books, journals, and professional societies, to gain the scientific respect in the 1990's.

For software history, one should read Nance and Overstreet (2017), who provided a list of software dedicated to simulation and their number of years in the market. The authors also discussed the language and environments used in the software, as well as the method supported. Alexopoulos and Kelton (2017); Cheng (2017) discussed the history of output analysis and input modeling, respectively. Barton, Nakayama, et al. (2017) presented the history of simulation experiments designs, variance reduction techniques, and rare event simulation, with focus on the early years. For a list and discussion on two seminal papers about simulation and other eight award-winning papers on different topics of the simulation field one can read Nelson (2004).

4.2. Discrete event modeling and simulation

History:

Discrete event simulation emerged between the decades of 1950 and 1960 around the same time as system dynamics (as previously indicated in the bibliometric analysis). It was initially applied in the Operations Research and Industrial Engineering areas and subsequently applied to other areas (Hollocks, 2006; Karnon et al., 2012). Goldsman et al. (2010) provided a history of DES in terms of important people, places, and events that contributed to the progress of the method.

The first discrete event simulation models were developed using low-level programming languages (Jenkins & Rice, 2009). Software packages focusing on DES were developed subsequently (Pidd, 2004). The first software implementation of discrete event simulation was introduced in 1961 by the International Business Machines Corporation (IBM) engineer Geoffrey Gordons, named General Purpose Simulation System (GPSS) or originally Gordon's Programmable Simulation System (Borshchev, 2013; Ross et al., 2014).

However, until 1990-2000, simulation was a very expensive and specialized tool, used mainly by large companies (Kelton et al., 2015). Discrete event simulation followed the evolution of computer development (Robinson, 2005). DES has begun to mature in the early 1990's, along with the emergence of graphical user interfaces in simulation software and facilitated by the introduction of personal computers (Banks et al., 2013). Besides that, other improvements in the method, such as animation tool, ease of use and integration with other software packages, led simulation to become a standard tool in many companies, including small ones (Kelton et al., 2015). In the past 15 years, the most important developments in DES have included: interactive visual modeling, distributed simulation, integration with other software, optimization, virtual reality, simulation applied to service sectors and the use of the World Wide Web (Robinson, 2005). DES still expanded accompanying the evolution of software technology and making the models more accessible to decision makers (Harrell et al., 2004). Nowadays, DES is supported by a larger number of software tools, including modern versions of GPSS (Borshchev, 2013).

Definition:

Discrete event simulation is by far the most common simulation method applied to manufacturing systems (Rabelo et al., 2005), but it also covers technical and service applications (Weidmann et al., 2015). It has been increasingly employed to aid decision-making (Pereira et al., 2015) and it is a method concerned with the modeling of systems that can be represented by a series of discrete events with passive entities flowing through it. The entities have a number of attributes and can be connected to resources, so they can be processed during an event if the necessary resources are available (El-Gafy & Abdelhamid, 2008; Greasley, 2009; Weidmann et al., 2015). The simulation typically maintains data structures of state variables, an event queue of forthcoming timestamped events, and a global clock that indicates the progress of the simulation. The simulation advances by processing the next event in the event list. When an event is processed, the value of one or more state variables may change and new events may be added to the event list (Hybinette et al., 2006). The simulation analyst is responsible for discerning among the state variables the ones that reproduce the system behavior, the events that alter those state variables, and the proper logic to represent this process (Rabelo et al., 2005).

Despite being a static representation, the DES inputs can be randomized to examine the impacts of different changes in the system (Ross et al., 2014). DES is usually represented by flowcharts, which makes it at the same time a straightforward and valuable performance analysis tool to pinpoint process bottlenecks and to collect performance measurements of either an existing or new system (Ross et al., 2014). In order to allow for performance analysis, a DES model calls for detailed and precise information on how the system worked previously or educated approximations on the future system's characteristics (El-Gafy & Abdelhamid, 2008).

Table 2 presents a summary of the main DES characteristics.

Table 2
Summary of DES characteristics.

Main concept	The system is frequently modeled as a process, that is, a sequence of operations performed across entities and resources (Borshchev, 2013; Greasley, 2009; Macal & North, 2005; Rabelo et al., 2007).
Goal	To replicate the system's structure to investigate its results under a different number of situations (Greasley, 2009).
Application areas	Due to the diversity of applications, it is difficult to list all the areas in which DES has been applied. Some examples are: manufacturing systems (e.g. production planning, routing, and scheduling), project management, logistics, supply chain, distribution network, transport and traffic systems, construction, inventory management, healthcare sector, military applications, queueing systems (e.g. bank teller), computer systems (e.g. multiple tasks served by a central processing unit (CPU)), communication systems (e.g. message transfer via multiple servers) and in several other service areas (e.g. government offices, hotels, restaurants and educational institutions). Source: Banks et al. (2013); Borshchev and Filippov (2004); Hillier and Lieberman (2010); Rabelo et al. (2005).
Modeling requirements	Not found
Modeling steps	A comparison of eight main DES modeling phase-structure is provided in Montevechi et al. (2015). According to this comparison, DES usually encompasses three big phases: conception, implementation, and analysis. The conceptual phase unfolds in 8 smaller steps: (i) real system definition, (ii) problem formulation, (iii) requirements specification, (iv) building the conceptual model, (v) conceptual model validation, (vi) architectures and design specifications, (vii) data documentation, and, (viii) collection and modeling of input data. The implementation phase consists of 4 smaller steps: (i) building computer sub-models, (ii) building the computer model, (iii) computer model verification, and (iv) computer model validation. The analysis phase is divided into 6 steps: (i) design, conduct, and analysis of experiments, (ii) data analysis or interpretation, (iii) data documentation up to date, (iv) conclusions and recommendations, (v) presentation of results, and (vi) implementation in the real system.
Model clock	Discrete-time: the model advances chronologically based on the sequence of events in the event list. First, an initial event is placed in the event list. Then, the simulation run starts by executing this event and by proceeding as an infinite loop that is advanced only when an event occurs (i.e., executes the current most imminent event). The simulation run ends whenever

	there is no other event to be executed in the event list or whenever a specific event forces the end (Behdani, 2012; Borshchev, 2013).
Abstraction level	Low-level abstraction: each object in the system is individually represented by an entity or resource (Borshchev, 2013).
Object behavior	Passive: the entities have no behavior of their own, they just carry their data. Source: Borshchev (2013); Borshchev and Filippov (2004).
Main elements or components	1. Source blocks: generate entities and inject them into the process. 2. Entities: represent clients, patients, documents, parts, products, pallets, vehicles, and projects, i.e., everything that is waiting for a service or to be processed. 3. Resources: represent staff, doctors, operators, workers, servers, vehicles, and equipment, i.e. everything that is used to provide a service, transport or process some entity. 4. Queues: represent entities that are waiting for a service or to be processed. 5. Sink blocks: remove entities from the model. Source: Borshchev (2013); Borshchev and Filippov (2004); Greasley (2009).
Main inputs	1. Service time or delays: the deterministic or stochastic time spent to provide a service or to process some entity. 2. Inter-arrival time: the time interval between entities arrivals. 3. Number of entities per arrival. 4. Operations: process branches, splitting, combining, seizing or releasing resources. 5. Attributes: characteristics of each entity or resource, such as cost, size, age, product type, working shift, etc. 6. Timer: a clock that fires an operation. Source: Borshchev (2013); Borshchev and Filippov (2004); Greasley (2009).
Main outputs	1. Utilization of resources. 2. Time spent in the system. 3. Waiting times. 3. Queue lengths. 5. System throughput. 6. Bottlenecks. 7. Costs (processing cost, idle cost, among others). Source: Borshchev (2013).
Conceptual modeling tools	Business Process Modeling (BPM), Activity Cycle Diagram (ACD), process flow diagram, component list, flowcharts, control flow graph, IDEF-SIM, Soft System Methodology (SSM) applied to DES, and Discrete Event Systems Specification (DEVS). Source: Borshchev (2013); Chwif et al. (2006); Cota et al. (1994); El-Gafy and Abdelhamid (2008); Kotiadis and Robinson (2008); Montevechi et al. (2010); Pereira et al. (2015); Robinson (2017); Ross et al. (2014); Ryan and Heavey (2006); Zeigler (2003); Zeigler et al. (2000). Robinson (2017) provided a tutorial on conceptual modeling for discrete-event simulation.
Simulation software	Various free and commercial software are available and they have powerful graphical and animation facilities to clarify behavior or results. The list provided in this table is by no means complete; but it is intended to give the readers a quick access to some options available. Some of them are: Simio®, ProModel®, Arena®, AnyLogic®, FlexSim®, SimEvents®, Simul8®, ExtendSim®, SimProcess®, AutoMod®, Enterprise Dynamics®, JaamSim®, EZStrobe®, Simscript®, SimPy, and NS-3. From the previous list, the first 12 software offer drag and drop interface to the users as well as graphical animation, while the last 4 software work mainly with command line structure. Source: Borshchev and Filippov (2004); Dubiel and Tsimhoni (2005); El-Gafy and Abdelhamid (2008); Swain (2017); Weidmann et al. (2015).
Programming language	There is no agreement on language for specifying discrete event models and compatibility is not planned by software developers yet. However, few examples of specialized languages can be cited, such as Stroboscope, GPSS, GASP, Simscript, and Simula.

	Source: Borshchev (2013); El-Gafy and Abdelhamid (2008); Ho and Cassandras (1983).
Validation and verification procedures	R. G. Sargent (2011) offers a verification and validation list that includes: animation, comparison to other models, degenerate tests, event validity, extreme condition tests, face validity, historical data validation, historical methods, internal validity, multistage validation, operational graphics, parameter variability - sensitivity analysis, predictive validation, traces, and Turing tests.
Advantages	Among the advantages of DES, we can cite: 1. Unlike artificial intelligence and mathematical optimization, it does not demand many simplifying assumptions. 2. It is a flexible tool with a wide range of applications. 3. It can describe the most complex systems, at different level of details while including stochastic elements that cannot be easily described by other analytical models. 4. It allows analysts to track the status of individual entities and resources. 5. Since the model advances in discrete time steps, the time elapsed between two events is ignored, which makes DES models be quick. 6. It is capable to model distinctive entities with heterogeneous characteristics. 7. It is preferred, compared to ABS and SD, when the system contains a high degree of uncertainty or many stochastic processes. 8. It can replicate the real system by collecting data on process flows, process times and demand patterns and, therefore, it provides a useful estimation of real system performance under different scenarios. 9. It is able to model queuing behavior, which is an important feature when examining the service level performance of a business system. Source: Behdani (2012); Hybinette et al. (2006); Macal and North (2005); Rabelo et al. (2005); Wakeland et al. (2004).
Disadvantages	Among the disadvantages of DES, we can cite: 1. Representing or mimicking social behavior in DES models is complicated and demanding. 2. It is not an appropriate approach for modeling movements and decision making. Routing logic must be implemented in the DES servers, as entities or resources cannot actively make decisions. 3. Since DES model proceeds in discrete time steps, representing entities' real-time decision is very challenging. 4. It is not the best approach for modeling more complex integrated systems, being more suitable for strategic and operational investigations, where the dynamicity of the system is limited and few options are presented, but detailed examination is essential. 5. It requires some statistical background to make sense of the resultant estimates and to recognize the differences between causality and correlation among the variables and the output measures. When modeling large-scale systems, this task may not be straightforward. 6. It does not take into account stability estimates in the neighborhood of the decision variables. Therefore, the results of the model must be carefully evaluated in systems where small changes in the decision variables can lead to unexpected large changes in the results. 7. It requires data availability and accuracy. Consequently, it may not be applicable to investigate many business level decisions of companies, where data is not available or accurate. 8. It is not suitable to simulate continuous dynamic behavior. 9. It is not capable to adapt its structure at runtime, which makes it useful only when the governing rules in the flowchart blocks are known in advance. Source: Behdani (2012); Borshchev and Filippov (2004); Dubiel and Tsimhoni (2005); Kim and Kim (2010); Rabelo et al. (2007); Rabelo et al. (2005).
Classification / types of models	Not found

4.3. Agent-based modeling and simulation:

History:

ABS is a relatively new and novel simulation technique that has been continuing to grow in popularity. ABS continues to grow quickly in terms of problem applications as well as in different domains (Kasaie & Kelton, 2015). It is a more recent modeling and simulation method than System Dynamics and Discrete Event Simulation. The method is also known as individual-based simulation models (IBMs) and it has its roots in computer science, and more specifically, in object-oriented modeling (Borshchev, 2013).

The use of ABS for research and management has been growing rapidly in a number of areas. The remarkable growth of ABS publications started around 1990 due to the capability of this simulation approach to easily and efficiently represent problems that other conventional approaches could not address (Railsback et al., 2006; Wu et al., 2010). However, it was only in the early 2000s that ABS arrived as the third powerful modeling paradigm (Borshchev, 2013). As we saw in Section 3, our bibliometric analysis is in line with this statement. The first publications in ABS appeared in 1997, but it was only in the early 2000s that we observed a growth in the number of papers.

The growth in the use of the method was also a result of the availability and access to a high number of and the quality of software platforms that made it feasible to build and use agent-based simulation applications (Luke et al., 2005; Railsback et al., 2006). ABS models are computationally more demanding compared to SD and DES (Borshchev, 2013). The interest and advances in the ABS method coincided with the advances in modeling technology, namely, object-oriented modeling, Unified Modeling Language (UML) and statecharts, coupled with the rapid growth in the availability of CPU power, memory, and distributed computing. However, at the same time, ABS progress was still hindered by computational power and software availability. Researchers in many fields, such as biology, ecology, economics, political science, and sociology, do not possess sufficient training in software skills related to developing and using comprehensive ABS models, which limits the current usage level of ABS (Railsback et al., 2006).

Despite the current general accepted usefulness of ABS to represent human behavior, the method has still some ways to go to become one of the mainstream simulation methods in Operations Research and Management Science (Siebers & Onggo, 2014). On the other hand, the method is already flourishing in other areas, such as Economics, Biology, and Social Science, where complex ABS models have been developed to capture detailed behaviors from problems in those areas. In general, the use of ABS was steadily increasing in all disciplines (Devillers et al., 2010). Although many studies have been conducted, the development of practical and empirical agent-based models is still overlooked (Kim & Kim, 2010).

Since 2000 several conferences dedicated to ABS have been hosted and several distinguished conferences have opened tracks concentrating specifically on this simulation approach (Dubiel & Tsimhoni, 2005).

Definition:

Agent-based Simulation is a very efficacious modeling and simulation technique that allows the representation of very complex and dynamic systems composed of autonomous, heterogeneous and possibly intelligent entities that interact to attain some goal (Bandini et al., 2009; Dubiel & Tsimhoni, 2005; Kim & Kim, 2010; Macal & North, 2005; Tuncer Ören & Yilmaz, 2012; Wu et al., 2010). ABS is a useful tool for representing knowledge and information processing, such as reasoning, planning, and deciding (Yilmaz & Ören, 2007). The entities are represented as individuals, referred to as agents. These entities interact with each other and with their environment according to rules, resulting in an emergent system behavior as time and space evolve (Higgins et al., 2010; Kasaie & Kelton, 2015; Swinerd &

McNaught, 2012). The environment is part of the system occupied by one or more agents (Logan & Theodoropoulos, 2001).

The behavior of the agents at discrete points in time can be represented through statecharts diagram. This behavior can be both reactive when an agent responds to an event, or proactive when an agent pursues a goal or actively makes a decision (Ross et al., 2014). The agent's state changes over time and during the transition from one state to another an action may be performed, dictated by some decision or behavioral rule (Esmaeili et al., 2010; Siebers & Onggo, 2014).

In many cases, the internal dynamics of the agent can be captured using system dynamics or discrete event approach. Likewise, the dynamics of the environment where the agents live are often modeled using traditional simulation methods. In these cases, a flow diagram or a process flowchart can be placed inside an agent and that is why many agent-based models are, in fact, multi-method (or hybrid) models (Borshchev, 2013).

ABS is uniquely characterized by the decentralized representation of the system through agents and their environment(s) (Kasaie & Kelton, 2015). The decentralized bottom-up approach enables the modeler to describe a system from the perspective of its constituent units (agents) even when the modeler may not know how the system behaves as a whole and what are the key variables and dependencies between them, as long as he/she has some insight into how the objects behave individually (Borshchev, 2013). The multi-level nature of ABS models enables explicit definition of various interventions at the individual level, as well as at the population level, providing a powerful experimental platform to study the system's behavior.

Applications of ABS range from small, sophisticated and detailed academic models to large-scale decision support systems, involving studies from modeling agent behavior in the stock market and supply chains, to predicting the spread of epidemics and the threat of bio-warfare, from modeling consumer behavior to understanding the fall of ancient civilizations, from military applications to web-based agent behavior (Ghasem-Aghaee & Ören, 2007; Macal & North, 2005).

Table 3 presents a summary of the main ABS characteristics.

Table 3
Summary of ABS characteristics.

Main concept	Behavioral patterns are replicated by representing individual actors that interact with each other in a dynamic adaptive system and by manipulating them in order to study how micro-level behavior of individuals can result in a macro-level group behavior. Source: Garcia (2005); Huanhuan et al. (2013).
Goal	To investigate how entities or agents interact with each other to achieve specific goals and to analyze the individuals' and the system's emergent behavior. Source: Garcia (2005); Huanhuan et al. (2013).
Application areas	ABS is commonly used in social and biological sciences, economics and engineering. Studies include: pedestrian movements, comprising destination choice, route choice model, and collision avoidance; evacuation and disaster scenarios; population dynamics; human social interaction; diffusion of innovations; organizational strategy; knowledge and information flows; animal behavior; predator prey models; ecosystems, urban systems; traffic-flow systems; land use; politics; homeland security; computer network security; civil violence; cooperation and communication within supply chain; cultural issues; disease spread; electronic commerce; energy; environmental chemistry and toxicology; bio molecular models; behavioral and evolutionary game theory; housing market dynamics; consumer market analysis; advertisement effectiveness; military planning; battlefield models; and, healthcare interactions. Source: Antonini et al. (2006); Bobashev et al. (2007); Borshchev and Filippov (2004);

	Bouanan et al. (2016); Brailsford and Schmidt (2003); Devillers et al. (2010); Dubiel and Tsimhoni (2005); Esmaeili et al. (2010); Garcia (2005); Huanhuan et al. (2013); Hybinette et al. (2006); Kasaie and Kelton (2015); Lättilä et al. (2010); Luke et al. (2005); Tuncer Ören and Yilmaz (2009); Siebers and Onggo (2014); Wakeland et al. (2004).
Modeling requirements	ABS modeling entails knowledge about the individuals' behaviors and expressing them in terms of rules that dictate how the individuals act and interact with/within the environment. These behavioral interactions are usually better described by "what-if" scenarios depicted in the form of statecharts than analytically (Garcia, 2005).
Modeling steps	Similar to DES, there are different steps proposed by different authors. So, here, we provide an ordered summary of the steps found in the literature. They are: (i) define the research question; (ii) abstraction of the real system to a specific expertise domain through knowledge gathering; (iii) the process of "agentification", i.e. theory operationalization through conceptual mapping technique; (iv) conceptual model validation; (v) specification, that includes agent specification, environmental specification, rules establishment, measurement/ data recording specification, scenarios/ experiments specification, and run-time specification; (vi) implementation that involves building the computational model; (vii) verification and validation of the computational model; and, (viii) modification, if needed; (ix) experimentation where different scenarios are executed; and (x) analysis of the results by the simulation expert in conjunction with the domain expert (case-study partners or decision-makers). Source: Figueredo and Aickelin (2011); Garcia (2005); Long and Zhang (2014); Siebers and Onggo (2014). The various specifications do not need to be followed in sequential order, as it is sometimes required to return to some of them for further refinement as the model is developed (Garcia, 2005).
Model clock	Most ABS models work in discrete time. However, as previously mentioned, it is often common to represent an agent internal dynamics or a dynamic environment by differential equations. In this case, ABS will also work in continuous time. Source: Antonini et al. (2006); Borshchev (2013).
Abstraction level	ABS does not assume a particular abstraction level (Borshchev, 2013). According to the goal of the study, ABS models can assume a more detailed level or a more aggregate level. However, defining the scope and boundary of the model and the inclusion or exclusion of a specific level of detail is a very difficult task (Kasaie & Kelton, 2015).
Object behavior	The agent can be: (i) proactive, by proactively making decisions and controlling its future and actions in order to attain specific goals; (ii) reactive, by observing its environment and responding to changes that happen on it; and (iii) passive, which does not present any behavior on its own. However, there are some academic disagreements on the characteristics of an agent, especially with respect to its passiveness. Source: Borshchev (2013); Lättilä et al. (2010).
Main elements or components	1. Agents: they are the units of analysis, the individuals that interact with each other or with their environment and populate the simulation environment. They can be: firms, research labs, markets, people, insects and other organisms. There is a lot of discussion on what properties an object must have to be considered as an agent (Lättilä et al., 2010). However, as proposed by Borshchev (2013), there is a belief that even a passive object can be considered as an agent depending on the goal of the simulation study. 2. States: they may represent any individual characteristics that change according to some rules or time (e.g. age, mood, interest, etc.) and they define the individuals' actions and reactions. 3. Environment: the boundaries within which the agents will interact. The boundaries are usually spatial but can also be temporal. Source: Garcia (2005); Logan and Theodoropoulos (2001); Luke et al. (2005).
Main inputs	1. Number of individuals or population size.

	2. Connections: the links between individuals (e.g. mom to son, neighbors, etc.). They can be spatial, temporal, relationship or any other type of connection. 3. Agent rules of behavior and environment rules: agent movement, agent interactions and state transitions are defined by the behavior rules of the agents and by the environment rules (e.g. places may not accept children, places that open only after some time of the day, etc.). 4. Parameters, such as contact rate, probability of infection, etc. 5. Time, space and communication information of agents. Source: Borshchev (2013); Garcia (2005); Luke et al. (2005).
Main outputs	1. Time of occurrence of an event or state. 2. Frequency of occurrence of an event or state. 3. Number of individuals in a specific state at the end of the simulation. 4. Cost of a specific control alternative. 5. Number of individuals that moved outside or inside the environment. Source: Borshchev (2013).
Conceptual modeling tools	Unified Modeling Language (UML), including class diagrams, instance diagrams, especially statechart diagrams, Agent-Object-Relationship (AOR) diagrams, Cognitive Mapping, and Business Process Modeling (BPM). Source: Borshchev (2013); Esmaeili et al. (2010); Garcia (2005); Kim and Kim (2010); Siebers and Onggo (2014); Wagner and Tulba (2003).
Simulation software	Currently, there are several software products available for modeling ABS (Garcia, 2005). However, some of them require a lot of coding while others are more graphical tools with limited capabilities. In essence, the number of professional ABS software is still limited when compared to the number of DES software products. Some examples of available ABS software are: NetLogo®, Ascape®, RePast®, Objective-C Swarm®, Java Swarm®, MASON® (Java), AnyLogic®, StarLogo®, EXODUS packages, AutoMod®, SIMCON, SIGMA, ExtendSim®, and Vensim®. Source: Borshchev (2013); Borshchev and Filippov (2004); Dubiel and Tsimhoni (2005); Garcia (2005); Kim and Kim (2010); Luke et al. (2005); Macal and North (2007); Railsback et al. (2006); Wakeland et al. (2004); Wu et al. (2010). Some of these software, such as AutoMod® and Vensim®, were initially developed for DES or SD, but they can also be used to build ABS models. Furthermore, some packages are very specialized and intended to yield only a particular type of model (Dubiel & Tsimhoni, 2005).
Programming language	There are no standard languages for ABS (Borshchev, 2013). However, the most commonly used languages are: Java and Jade, followed by C++, Common Lisp, Python, and Smalltalk. Since many ABS software are written in Java, a relatively slow language, sometimes they can be more time-consuming than DES software. Source: Borshchev and Filippov (2004); Devillers et al. (2010); Gianni (2008); Long and Zhang (2014); Macal and North (2007).
Validation and verification procedures	- Subjective validation of the model results compared to the expected results of the real system. - Verification of the model through animation observation: visually check whether the agents' decisions and movements properly represent the reality. Source: Dubiel and Tsimhoni (2005).
Advantages	1. ABS can be easily and flexibly applied to model complex systems where different components interact among themselves, such as systems comprising human behaviors. 2. It is a great method to investigate adaptive systems and how they evolve over time. 3. Unlike most traditional models, ABS is a powerful tool to understand the effects of unexpected events, such as accidents and breakdowns. 4. ABS allows investigation of emergent phenomena. 5. ABS is a valuable tool to investigate non-linear behavior, e.g., when learning occurs. Therefore, ABS can be effortlessly used to represent systems where individuals exhibit non-Markovian or path-dependent or temporal correlated behavior.

	6. ABS is extremely useful to model social networks and it allows for easily differentiating between temporal and physical spaces. 7. Depending on the model objective, ABS can be easier to implement than other analytic models. As such, ABS is better applied to model systems described by “what-if” scenarios, than those described by rate equations. 8. It does not require a deep understanding of differential equations, statistics, or integrals. 9. It allows for modeling systems where there is only information available about how individuals behave, but there is no knowledge about aggregate behavior and global interdependencies. 10. It can guide decision-makers’ instinct by allowing them to virtually analyze interaction among agents and emergent behavior, thus, improving decision-making. 11. ABS can incorporate genetic algorithms, neural networks, and other machine learning techniques. 12. Unlike other modeling approaches, ABS allows for entering randomness into the appropriate decision level of the model, as opposed to inserting noise at arbitrary levels. 13. In general, it is simple to maintain and adapt ABS models, as changes can usually be made at local levels, instead of global levels. Source: Behdani (2012); Bonabeau (2002); Borshchev and Filippov (2004); Devillers et al. (2010); Dubiel and Tsimhoni (2005); Garcia (2005); Kasaie and Kelton (2015); Lättilä et al. (2010); Siebers and Onggo (2014); Wakeland et al. (2004); Wu et al. (2010).
Disadvantages	1. Agents are usually influenced by their social context or by what others around them do, but these interactions are not always easily modeled to imitate reality. ABS usually encompasses modeling of soft factors, such as subjective decisions and psychological factors, which are hard to quantify and estimate. 2. The results of ABS should be mainly understood at the qualitative level, that is, ABS should be more used to understand how emergent behavior arises than to try to predict them. However, with improvements in calibration tools (such as the Calibration Experiment available in AnyLogic®) prediction may be more successful. 3. ABS looks at a system not only at the aggregate level but also at the individual level and simulating the behavior of individual agents can be computationally intensive and time-consuming. Even with technological developments, ABS may still require a lot of time to model large systems. So, speed versus software functionality is still a tradeoff. 4. There is still a few professional user-friendly software. So, to apply ABS one may still have to possess computer-programming knowledge and expertise. 5. It requires different types of information, such as social contacts, and, economic and geographical data, which are usually not available in real-world applications or, at least, are not accurate. This may require specialized calibration techniques. 6. Sometimes, it is necessary to use modelers’ personal assumptions and mechanisms for specifying agents’ behavior and interactions without explicit validation. 7. Understanding the resultant behavior of multiple agents can be very difficult. Therefore, verification and validation of the model is a complex task and it requires a meticulous approach. 8. Parameter changes in ABS models can lead to further complications due to non-linearity, giving rise to chaotic results. Again, validation of this type of behavior is troublesome. 9. Modeling mistakes can occur due to the vague definition of errors in ABS applications. 10. For modeling routine and deterministic processes, ABS may require more effort than other methods. 11. Finally, more a limitation on the ABS field than a disadvantage of the method itself are: (a) the elaboration of a common curriculum or a standard modeling protocol for developing, analyzing and teaching ABS models is still in its early stage; (b) there is a gap between traditional simulation principles, mostly developed for DES, and existing ABS practice, which often leads to a lack of justification for choosing ABS models over simpler modeling

	paradigms; and, (c) a predisposition of ABS modelers to develop in depth models despite the compromise between transparency of results, difficulty of analysis and computational power required. Source: Bobashev et al. (2007); Bonabeau (2002); Devillers et al. (2010); Garcia (2005); Higgins et al. (2010); Kasaie and Kelton (2015); Ross et al. (2014).
Classification / types of models	Not found

4.4. System dynamics modeling and simulation:

History:

System dynamics (SD) is a popular simulation paradigm and its principles are extensively established and recognized by simulation practitioners and researchers (Lättilä et al., 2010). SD is recognized as a system thinking methodology (Rabelo et al., 2005). At first, system dynamics was mainly identified as a computer simulation approach (Wolstenholme, 1999).

The origin of system dynamics can be traced back to 1956 and the work of Forrester at the Massachusetts Institute of Technology (Ahmad & Simonovic, 2000). SD has a long history and evolution, which can be found in detail in several papers (Angerhofer & Angelides, 2000; Baines & Harrison, 1999; Behdani, 2012; Lättilä et al., 2010; Swinerd & McNaught, 2012; Winz et al., 2009).

Forrester (1958) introduced his ideas in Industrial Dynamics, and launched his thoughts as a 'major breakthrough for decision makers'. Applications of the method spread into the social sciences area, and as a consequence, Forrester re-named the technique 'System Dynamics'. He considered SD to reflect a universal applicability to any situation that could be modeled as a 'system' that combines people and/or machines. In fact, Forrester (1969) viewed SD as an approach to corporate policy design and to understand and solve top management problems. SD is not a data-dependent technique and is very suitable for qualitative and continuous parameters in management decisions (Winz et al., 2009).

Numerous simulation studies have been developed using system dynamics and the increase in complexity and uncertainty has promoted an increase in the use of flexible simulation tools that SD provides (Winz et al., 2009). Since the early conception by Forrester, the SD field has greatly advanced and its application has been expanded to several areas (Angerhofer & Angelides, 2000; Baines & Harrison, 1999).

Definition:

System dynamics is a methodology for analyzing and solving complex problems with a focus on policy analysis and design. As any simulation methodology, SD lets us investigate how the system behaves and how the system responds to different situations over time (Angerhofer & Angelides, 2000; Behdani, 2012; Swinerd & McNaught, 2012; Wang et al., 2014; Winz et al., 2009). SD is used to model and simulate a system from a higher system-level viewpoint (Angerhofer & Angelides, 2000), describing human systems in terms of feedback and delays. It is useful for identifying the important variables and causal linkages in a system, and for structuring many aspects of model development (Macal & North, 2005).

SD is characterized by stocks, representing the items moving in the system (e.g., knowledge, people, or money), and flows, representing the interconnections between the stocks. In addition, the causal diagram depicting the stocks and flows also shows the causal variables that influence the flows and any delays associated with those variables. The power of this paradigm is in its ability to abstract from the effect of a single entity and focus on the aggregate effect. Thus, the effect of different strategies and configurations of the system can be investigated (Rabelo et al., 2005; Ross et al., 2014; Swinerd & McNaught, 2012; Wang et al., 2014).

The central concept is that all the objects in a system interact through causal relationships. These relationships come about through feedback loops, where a change in one variable affects other variables over time; these variables, in turn, affect the original variable, and so on. More specifically, SD acknowledges that the dynamic behavior of the system arises from the feedback and cause-and-effect loops, and as such, SD takes a systems thinking view to represent the system (Rabelo et al., 2005).

The creation of a dynamic model of a system requires the identification of the causal relationships that form the system's feedback loops (Forrester, 1961). Feedback loops can be either positive or negative based on the direction of influence a parameter has on another. A positive loop is a series of causal relationships that reinforces behavior towards a particular goal in the system. In contrast to a self-reinforcing positive loop, a negative loop is a sequence of interactions that causes the system to behave contrary to a specific goal. A causal loop diagram consists of a set of interconnected feedback loops represented by system variables interconnected by arrows. Whether the causal interaction between the system variables is positive or negative can be determined by the form of the arrows (Rabelo et al., 2005; Swinerd & McNaught, 2012).

SD model is based on ordinary differential equations and their numerical solution over time. First the differential equations that govern the system are specified, then the values of the parameters are approximated or collected from real data, and, finally, the time trajectories of the interesting factors are estimated and presented (Wakeland et al., 2004). Once dynamical systems modeling has identified specific frontiers of criticality, specific scenarios can be simulated to understand potential responses of the value chain to (i) drive the system to a new state of equilibrium, or to (ii) permit the system continued function within bounds of normality. These applications are particularly valuable when someone wants to investigate or propose improvements to value chain resiliency (Higgins et al., 2010).

Table 4 presents a summary of the main SD characteristics.

Table 4

Summary of SD characteristics.

Main concept	SD maps a problem onto a generic feedback structure that can help understanding of the underlying causes of the system's behavior (Angerhofer & Angelides, 2000).
Goal	To improve the system understanding with the development of a tool to analyze the causal relationships, to examine different actions and strategies, and to experiment different concepts (Winz et al., 2009).
Application areas	Some examples of the diversity of SD applications are: mathematics, physics, engineering, servomechanisms (e.g. control systems view), cybernetics (e.g. organizational/human systems structuring for problem solving), manufacturing, agriculture, resources modeling at a global level, supply chain (e.g. inventory decision and policy development, time compression, demand amplification, supply chain reengineering, supply chain design and integration, international supply chain management, stock management, participative business modeling, transportation policy), system monitoring, healthcare (e.g. epidemiology), decision-making (e.g. business decision modeling), corporate planning and policy design, economic behavior, public management and policy (e.g. water management, reservoir operations for flood management), biological and medical modeling, energy and the environment, theory development in the natural and social sciences, complex non-linear dynamics, software engineering, economics, ecology, innovation diffusions, work force management, software development, competition, markets. Source: Ahmad and Simonovic (2000); Angerhofer and Angelides (2000); Baines and Harrison (1999); Behdani (2012); Borshchev and Filippov (2004); Brailsford et al. (2012);

	Dangerfield (2016); El-Gafy and Abdelhamid (2008); Figueredo and Aickelin (2011); Higgins et al. (2010); Hybinette et al. (2006); Jeon and Kim (2016); Lättilä et al. (2010); Rabelo et al. (2005); Winz et al. (2009); Wu et al. (2010).
Modeling requirements	SD modeling requires specific knowledge by modelers because engine includes numerical solver for differential, algebraic, and mixed equations.
Modeling steps	Based on the literature we could identify the main steps for a system dynamics model development. These steps are: (i) to define the purpose (goal) of the system, (ii) to specify the system boundaries, (iii) to identify key variables of the system, (iv) to describe behavior of the key variables, (v) to identify stocks and flows in the system, (vi) to map system structure into modeling tool or system conceptualization (initial model), (vii) data collection, quantification, and development of simulation model (model parameterization), (viii) to run the model, (ix) model testing through various experiments, (x) implementation of findings, (xi) to disseminate the results and insights. Source: Ahmad and Simonovic (2000); Angerhofer and Angelides (2000); Brailsford and Schmidt (2003); Haghani et al. (2003); Wolstenholme (1999).
Model clock	Handling of time is continuous in most cases. Delays are usually represented by exponential distribution, and deterministic delays are special cases. Source: Behdani (2012); Jeon and Kim (2016).
Abstraction level	High abstraction level and it is positioned as a strategic modeling methodology. Source: Borshchev (2013).
Object behavior	Usually, the average aggregate behavior is considered, that is, agents are considered to be homogeneous and possess similar characteristics. Source: Behdani (2012).
Main elements or components	1. Stocks: represent anything that accumulates or drains. 2. Inflows: represent activities that fill stocks. 3. Outflows: represent activities that drain stocks. 4. Links or connectors: represent the interactions between variables and convey information between one component to another. Arrows are usually used as symbols in the software to characterize the connectors and the direction of the arrows designates the causal relationship. 5. Converters: transform input into output. 6. Time delay functions: provide delays between the measuring and acting in that measurement. 7. Shadow: it is simply a copy of a variable or parameter used in different causal loops. Source: Ahmad and Simonovic (2000); Lättilä et al. (2010); Ross et al. (2014); Wolstenholme (1999).
Main inputs	1. Operations. 2. Connections between the operations. 3. Auxiliary variables: they serve as inputs to the feedback loop structures. 4. Variables and parameters: characteristics of the stocks and flows (inflow and outflow). 5. Timer: a clock that fires an operation. 6. Loop types: designate the causal relationship or feedback type, whether it is negative or positive. Source: Borshchev (2013).
Main outputs	1. Utilization of resources. 2. Time spent in the system. 3. Waiting times. 4. Variable analysis. 5. System throughput. Source: Borshchev (2013).
Conceptual modeling tools	Stock-and-flow Diagram, Causal Loop Diagram, Flowchart, Hexagons, Archetypal Structure, Influence Diagram. Source: Ahmad and Simonovic (2000); Behdani (2012); Dangerfield (2016); El-Gafy and

	Abdelhamid (2008); Greasley (2009); Haghani et al. (2003); Ho and Cassandras (1983); Koelling and Schwandt (2005); Rabelo et al. (2007); Rabelo et al. (2005); Winz et al. (2009); Wolstenholme (1999); Wu et al. (2010).
Simulation software	STELLA®, Vensim® PLE, Powersim, and AnyLogic®. Source: Ahmad and Simonovic (2000); Baines and Harrison (1999); Borshchev and Filippov (2004); Lättilä et al. (2010); Wakeland et al. (2004); Wu et al. (2010).
Programming language	Java and Dynamo. Source: Borshchev and Filippov (2004); Haghani et al. (2003).
Validation and verification procedures	Face validation and three classes of tests are suggested: structure tests, behavior tests, and policy implication tests. Structure tests are used to evaluate how accurate the model structure matches the real world structure. Behavior tests are used to evaluate whether the model results adequately represent the behavior of the real world. Policy implication tests are used to investigate if the model consistently predicts how the system reacts to policies changes. Source: El-Gafy and Abdelhamid (2008); Winz et al. (2009).
Advantages	1. It allows for investigating the aggregate effects, instead of focusing on single entities. 2. It enables experimenting the effects of different interventions on the system, focusing on policies and system structure. 3. It is usually easily understood due to its continuous characteristics and, as such, it can efficiently represent problems of manufacturing systems. 4. It explains the underlying behavior by giving an understanding of the system structure. 5. It is able to keep track of cause-effect relations between the system elements and to capture the impact of situations where an element causes changes in other components of the system. 6. It is able to account for feedback loops, time delays, and non-linearity. 7. It provides a holistic view of the system by integrating many components and subsystems. 8. It provides a dynamic picture of the cause-effect interactions among the components of the system. 9. It usually does not require a large amount of data. 10. It offers an easy way to build a simulation model, it requires reduced execution time by facilitating rapid prototyping, and it reduces programming effort. 11. It provides more transparency in dealing with real-world complications. 12. It promotes the integration between hard and soft system components, that is, it takes advantage of computers and their processing and data manipulation capabilities, as well as of people and their creative thinking skills. As consequence, it allows a more in-depth and meticulous analysis. 13. It is user-friendly and it usually allows for modeling quickly and successfully. 14. Whenever needed, it is usually simple to make changes in the model with respect to the type of data and its structure. Modeling is very intuitive and interactive. 15. It can be used in a large number of applications, being very flexible (multi-disciplinary projects, cross-scalar, modular object-oriented models). 16. It facilitates the performance of sensitivity analysis and the testing of assumptions. 17. It allows modeling and simulating management decisions and strategies in long-term, complex and uncertain settings. 18. It facilitates the participation of all stakeholders, it builds consensus among them and it improves the understanding of the system. Source: Ahmad and Simonovic (2000); Dangerfield (2016); El-Gafy and Abdelhamid (2008); Greasley (2009); Higgins et al. (2010); Jeon and Kim (2016); Koelling and Schwandt (2005); Rabelo et al. (2007); Rabelo et al. (2005); Ross et al. (2014); Tako and Robinson (2012); Winz et al. (2009); Wolstenholme (1999); Wu et al. (2010).
Disadvantages	1. Modeling low-level and detailed systems is not simple because SD uses aggregate items and high-level components. 2. Since it uses a considerable amount of differential equations, the user must have an

	understanding of underlying mathematics. 3. Gathering the right team is important to achieve good modeling results and it requires considerable skill. 4. It has been proven not effective in modeling operational decisions in manufacturing settings. 5. It is incapable of modeling heterogeneous entities in complex systems. 6. The causal loop, although useful, does not bring deep understanding about all feedback loops in a complex system. 7. It is usually not the preferred method by managers, due to the frequent use of mathematical equations. 8. Although it requires a little amount of data, models are frequently not valuable due to lack of data. 9. It is hard to produce sophisticated, but simple models at an appropriate level of aggregation in time and space while maintaining its usefulness. 10. It does not give exact results as solutions, due to the intrinsic uncertainties. 11. The recommendations may be deeply influenced by subjectivity. 12. The quality of the results may be impaired by inappropriate problem boundary and goals definition. 13. The models are sometimes centered on non-verified mental models. 14. Sometimes the model is built independently by simulation experts and may seem complicated to stakeholders and managers. Source: Baines and Harrison (1999); Behdani (2012); Borshchev (2013); Jeon and Kim (2016); Rabelo et al. (2005); Ross et al. (2014); Winz et al. (2009); Wolstenholme (1999).
Classification / types of models	System dynamics can be divided into 3 types depending on the flow of dynamic behaviors over time: exogenous dynamics, endogenous dynamics, and mixed system dynamics. Source: Haghani et al. (2003) Other classifications divide SD models into: qualitative/conceptual and quantitative/numerical. Qualitative modeling increases the conceptual understanding of the system through the use of causal loop diagrams, while quantitative modeling provides an investigation and visualization tool to simulate the results of different interventions through the use of stock-and-flow models. Quantitative modeling requires explicitly stating the assumptions adopted in modeling the system and identifying possible issues due to uncertainties about the system structure and due to lack of data. Source: Winz et al. (2009).

4.5. Comparison of the three methods

Table 5 was created based on the previous discussion. It summarizes the main characteristics and differences among the three simulation methods and it aims to facilitate the comparison among those techniques.

Table 5

Comparison of the three main simulation methods.

	DES	ABS	SD
Key concept	The simulation system changes only at discrete points in time, according to an event list.	The simulation system changes the action or interactions of agents mainly at discrete points in time. It can also occur continuously.	The simulation system changes continuously, in countless points in time: smooth and steady changes.
Orientation	Process-oriented: the focus is on modeling the system in	Individual-oriented: the focus is on modeling the	System-oriented: the focus is on modeling the system

	detail.	entities and interactions between them.	observables.
Model	Discrete event model: to represent process flow chart. a. Entities: objects that move through the system. b. Event: the process that causes one or more state variables to be modified and through which the entities pass. c. Resource: required objects to trigger events.	1. Low-level model: discrete time-based agent interaction, decision-making. 2. High-level model: multi-agents' network. a. Autonomous agents: self-directed objects. b. Rules: that agents follow to achieve their objectives.	1. Open loop model: feedback loop. 2. Stock and flows model. a. Stocks: basic stores of objects (= quantities). b. Flows: the movement of objects between stocks in the system (= time period). c. Delays: delays between the measuring and then acting on that measurement.
Modeling methodology	Operational-tactical-level modeling. Physical process: each object in the system is represented by an entity or a resource unit. Entities are passive: they do not exhibit behavior; they just carry data. Time delays: stochastic delay or deterministic delay.	Statechart inside agents modeling. It is usually a multi-method modeling, where SD and DES can be used inside the agents to represent an individual decision making or process. Agents are usually active and exhibit behavior. Time delays: stochastic delay or deterministic delay.	Strategic-level modeling. Stocks: products, items, jobs. Flows: purchase decision trends or patterns. Time delays: the delay parameter usually uses an exponential distribution and deterministic delays are special constructs.
Building blocks	Event diagram, process flowchart diagrams.	Individual agents and their decisions, statechart diagrams.	Equations, feedback-loops, stock and flow diagrams.
System structure	Fixed.	Flexible.	Fixed.
Structure type	Mainly homogenized, but sometimes heterogeneous entities.	Heterogeneous entities.	Homogenized entities, all entities are assumed to have similar features.
Application Type	Problem-solving.	Exploring.	Problem-solving.
Handling of time	The system being modeled can be continuous or discrete, but the model only considers the state changes at discrete time.	Mainly discrete, but can also be continuous.	Continuous.
Mathematical formalization of the system	Event, activity, and process.	Agent and environment.	Stock and flow.
Experimentation	By changing the processes structure.	By changing the agents' rules (internal/interaction rules).	By changing the system structure.
Conceptual modeling technique	Business Process Modeling (BPM), Activity Cycle Diagram (ACD), flowcharts, IDEF-SIM, Soft System Methodology (SSM) applied to DES, and Discrete Event Systems Specification (DEVS).	Unified Modeling Language (UML), including class diagrams and instance diagrams, but especially statechart diagrams, Agent-Object-Relationship (AOR) diagrams, Cognitive Mapping, and Business	Stock-and-flow diagram, Causal Loop Diagram, Flowchart, Hexagons, Archetypal Structure, Influence Diagram.

		Process Modeling (BPM).	
Software tools	Simio®, ProModel®, Arena®, Anylogic®, FlexSim®, SimEvents®, Simul8®, ExtendSim®, SimProcess®, AutoMod®, Enterprise Dynamics®, JaamSim®, EZStrobe®, Simscript®, SimPy, and NS-3	NetLogo®, Ascape®, RePast®, Objective-C Swarm®, Java Swarm®, MASON® (Java), AnyLogic®, StarLogo®, EXODUS packages, AutoMod®, SIMCON, SIGMA, ExtendSim®, and, Vensim®.	iThink/Stella®, Vensim® PLE, Powersim, and Anylogic®.
Application areas	Manufacturing systems (e.g. production planning, routing, and scheduling), project management, logistics, supply chain, distribution network, transport and traffic systems, construction, inventory management, healthcare sector, military applications, queueing systems (e.g. bank teller), computer systems (e.g. multiple tasks served by CPU), communication systems (e.g. message transfer via multiple servers) and in several other service areas (e.g. government offices, hotels, restaurants and educational institutions).	Pedestrian movements; evacuation and disaster scenarios; population dynamics; human social interaction; diffusion of innovations; organizational strategy; knowledge and information flows; animal behavior; predator prey models; urban systems; traffic-flow systems; land use; politics; homeland security; computer network security; civil violence; cooperation and communication within supply chain; cultural issues; disease spread; environmental chemistry and toxicology; bio molecular models; behavioral and evolutionary game theory; housing market dynamics; consumer market analysis; advertisement effectiveness; military planning; battlefield models; and, healthcare interactions.	Mathematics, physics, engineering, software engineering, servomechanisms (control systems view), ecology, cybernetics (organizational/human systems structuring for problem solving), manufacturing, agriculture, modeling resources, supply chain, monitoring system, healthcare (e.g. epidemiology), corporate planning and policy design, public management and policy (e.g. water management, reservoir operations for flood management), biological and medical modeling, energy and the environment, theory development in the natural and social sciences, complex non-linear dynamics.

Source: Ahmad and Simonovic (2000); Angerhofer and Angelides (2000); Antonini et al. (2006); Baines and Harrison (1999); Banks et al. (2013); Behdani (2012); Bobashev et al. (2007); Borshchev (2013); Borshchev and Filippov (2004); Bouanan et al. (2016); Brailsford et al. (2012); Brailsford and Schmidt (2003); Chwif et al. (2006); Dangerfield (2016); Devillers et al. (2010); Dubiel and Tsimhoni (2005); El-Gafy and Abdelhamid (2008); Esmaeili et al. (2010); Figueredo and Aickelin (2011); Garcia (2005); Goh and Ali (2016); Greasley (2009); Haghani et al. (2003); Higgins et al. (2010); Hillier and Lieberman (2010); Ho and Cassandras (1983); Huanhuan et al. (2013); Hybinette et al. (2006); Jeon and Kim (2016); Kasaie and Kelton (2015); Kim and Kim (2010); Koelling and Schwandt (2005); Lättilä et al. (2010); Luke et al. (2005); Montevechi et al. (2010); Pereira et al. (2015); Rabelo et al. (2007); Rabelo et al. (2005); Railsback et al. (2006); Ross et al. (2014); Ryan and Heavey (2006); Siebers and Onggo (2014); Swain (2017); Wagner and Tulba (2003); Wakeland et al. (2004); Wang et al. (2014); Weidmann et al. (2015); Winz et al. (2009); Wolstenholme (1999); Wu et al. (2010); Zeigler et al. (2000).

By conducting this study, it was possible to understand that each method serves a particular range of abstraction levels. Discrete event modeling with the underlying process-centric approach supports medium and medium-low levels of abstraction. Agent-based models can vary from very detailed level, where agents represent physical objects, to highly abstract level, where agents are competing companies or governments. System dynamics operates at high abstraction level and is mostly used for strategic modeling (Borshchev, 2013).

It is worth highlighting some interesting points of the comparison presented in Table 5. Each simulation method also has a specific orientation. DES method focuses on modeling the system in detail (process-oriented), works at discrete times, and has specific elements such as source blocks, entities, resources, queues, and sink blocks. ABS method focuses on modeling the entities and interactions between them (individual-oriented), it handles continuous or discrete times, and it includes elements such as agents, states, and environment. SD method focuses on modeling the system observables (system-oriented), it deals with continuous time, and it comprises of elements such as source, inflow/outflow, sink, stocks, flows, connectors, converters, and delays.

With respect to the conceptual modeling tools used, it is an interesting fact that in each simulation method specific tools are adopted to develop the conceptual model. Only one conceptual modeling technique was found to be used in two simulation methods: Business Process Modeling (BPM), which is used in applications of DES and ABS. The same happens when analyzing the software tools used in each simulation method. AnyLogic® is the only one found that works across all three simulation methods. AutoMod® was found in applications of DES and ABS, but not SD. Vensim® was used in studies of ABS and SD, but not in DES studies.

One very important point to be considered by simulation modelers is the modeling steps. With this study, it was possible to identify the most common sequence of steps for each of the simulation methods. Basically, all three methods follow the same general idea, however, the distinguishing feature is the level of detail that is applied by modelers in each step. Three main phases were identified: conception, implementation, and analysis. In the conceptual phase, the modelers define the problem, the project goal, the research question, the specification, and all the system and problem boundaries. From there, they build the conceptual model, using a chosen conceptual modeling tool. Next, they conduct the validation of the conceptual model and document all the information. Finally, still in the conceptual phase, they collect the data needed to build the computational model. In the implementation phase, the computational model is developed based on the validated conceptual model. Then, the modelers need to verify and validate the computational model in order to obtain the necessary inferences. From this point, the modelers can plan the execution of experiments. Whenever needed, the modelers may go back to the conceptual phase to review the conceptual model. However, if the conceptual phase is carefully executed, the need for review should be very low. Finally, in the analysis phase, modelers run the computational model and perform the analysis. Reports from the results of the simulation study are elaborated and shared with stakeholders. These reports are evaluated and, then, the stakeholders can decide whether the recommendations from the simulation study will be implemented in the real system or not. The implementation in the real system is not part of the simulation study. However, a new simulation project may be needed to evaluate the new changes implemented in the system.

Ultimately, an analysis of the application areas was performed. As shown in Table 5, there are several types of applications in which the three simulation methods are used. There are some similar areas, such as manufacturing systems, healthcare sector, transport and traffic systems, market analysis, supply chain, military applications and planning, and some services areas. However, it is important to note that even though these different simulation methods may be used in the same application area, the focus of the analysis and the level of details are usually different, as explained earlier. On the other hand, some applications are specific to a single simulation method. For example, human social interaction, evacuation and disaster scenarios, pedestrian movements, etc. are often specific applications found only in ABS studies. Project management is usually a specific application of DES, while mathematics, physics, and agriculture are applications found predominantly in SD studies.

4.6. Other resources available

As previously discussed, although a systematic review was conducted in this manuscript, the main goal was to provide simulation modelers with an introductory guide, instead of a complete systematic review or bibliographic survey on simulation methods. The downside of this guide is that some important papers may not have been included. To alleviate this problem, Table 6 provides a list of other important resources available to simulation modelers, as well as some important contributors to this research domain. Along similar lines, this list is by no means complete; rather it is intended to give the readers a quick access to other available resources. Another list of conferences, journals, and research centers in the field of simulation can be found in Diallo et al. (2015).

Table 6

Other important resources available to the readers and some important contributors to the field

Some conferences or group meetings	Some books in the field	Some important contributors to the field
- Winter Simulation Conference (WSC) - Summer Simulation Multi-Conference (SummerSim) - Spring Simulation Multi-Conference - AnyLogic Conference - Simio User-Group Meeting - Institute of Industrial and Systems Engineers Conference (IISE Annual Conference & Expo) - INFORMS Annual Meeting **Some simulation journals** - Simulation Modeling Practice and Theory (Elsevier): https://www.journals.elsevier.com/simulation-modeling-practice-and-theory - Journal of Simulation (Palgrave McMillan): https://www.palgrave.com/gp/journal/41273 - Journal of Simulation (Taylor & Francis): https://www.tandfonline.com/loi/tjsm20 - Simulation (SAGE): http://journals.sagepub.com/home/sim - European Journal of Operational Research (Elsevier): https://www.journals.elsevier.com/european-journal-of-operational-research/ - Computers & Industrial Engineering (Elsevier): https://www.journals.elsevier.com/compute	- Handbook of Simulation: Principles, Methodology, Advances, Applications, and Practice (Banks, J.) - Simulation Modeling and Analysis (Law, A. M.) - Design and Analysis of Simulation Experiments (Kleijnen, J.P.C.) - Stochastic Modeling: Analysis and Simulation (Nelson, B.L.) - Conceptual Modeling for Discrete-Event Simulation (edited by Robinson, S., Brooks, R., Kotiadis, K., and van der Zee, D.) - Principles of Modeling and Simulation: A Multidisciplinary Approach (edited by Sokolowski, J.A., and Banks, C.M.) - Theory of Modeling and Simulation (Zeigler, B.P., Praehofer, H., and Kim, T.G.) - Guide to Modeling and Simulation of Systems of Systems (Zeigler, B.P., and Sarjoughian, H.S.) - Simulation and Model-Based Methodologies: An Integrative View (edited by Ören, T.I., Zeigler, B.P., and Elzas, M.S.) - Agent-Directed Simulation and Systems Engineering (edited by Yilmaz, L., and Ören, T.) - Discrete Optimization via Simulation (Hong, L.J., and Nelson, B.L.)	- Averill M. Law - Barry L. Nelson - Bernard P. Zeigler - Charles M. Macal - David M. Goldsman - Gabriel Wainer - Jack P. C. Kleijnen - Jeffrey Smith - Jerry Banks - Jie Xu - K. Preston White - L. Jeff Hong - Levent Yilmaz - Luis Rabelo - Michael J. North - Parastu Kasaie - Richard E. Nance - Ricki G, Ingalls - Robert G. Sargent - Russel R. Barton - Sally Brailsford

rs-and-industrial-engineering - International Journal of Simulation and Process Modeling (InderScience): http://www.inderscience.com/jhome.php?jcode=IJSPM - Computers & Operations Research (Elsevier): https://www.journals.elsevier.com/computers-and-operations-research - Computers & Mathematics with Applications (Elsevier): https://www.journals.elsevier.com/computers-and-mathematics-with-applications/ - International Journal of Simulation Modeling (DAAAM Int.): http://www.ijsimm.com/ - Simulation in Healthcare (Wolters Kluwer): https://journals.lww.com/simulationinhealthcare/pages/default.aspx	- Simulation with Arena (Kelton, W.D., Sadowski, R.P., and Zupick, N.B.) - Simulation Modeling with SIMIO: a Workbook (Joines, J.A., and Roberts, S.D.) - The Big Book of Simulation Modeling: Multimethod Modeling with Anylogic 6 (Borshchev, A.) - Introduction to System Dynamics and Vensim Software (Sapiri, H., Zulkepli, J., Ahmad, N., Abidin, N.Z., and Hawari, N.N.) - Agent-Based and Individual-Based Modeling: A Practical Introduction (Railsback, S.F.) - Monte-Carlo Simulation-Based Statistical Modeling (Chen, D., and Chen, J.D) - Explorations in Monte Carlo Methods (Shonkwiler, R.W., and Mendivil, F.)	- Scott E. Page - Stewart Robinson - Thomas J. Schriber - Tuncer Ören

5. Conclusions

In this paper, we provided a review of the literature published on the three primary simulation techniques in industrial engineering and related areas: discrete event, agent-based, and system dynamics. The methodology adopted to perform the review was presented in section 2, as along with the database and the search criteria adopted.

We first showed that SD and DES have more than 40 years of history, while ABS is a more recent technique with circa 20 years. Studies applying two of the main techniques in conjunction appeared relatively in the same period that the techniques were developed, with the longest period between the first technique publication and the first hybrid publication using the same technique being seven years, relative to the combination of SD and DES. Although studies with the three techniques together appeared about six years after the first publication of ABS, the number of publications on all three methods together is still very small (only 20 papers explicitly cite the three methods together in the Scopus® database).

Next, we discussed the first results of our review, which encompassed the history of the number of papers published on each technique separately and a list of the top-10 countries, authors, sources, and subjects publishing about the techniques. The most popular technique, with respect to the number of papers, is undoubtedly DES, followed by ABS with less than 50% the number of papers when compared to DES. The United States is unquestioningly the country that develops and publishes more research in all three simulation techniques, followed distantly by China. Analyzing the top-10 authors, we noted that there is no single author with a large number of publications in more than one technique. This reinforces what we observed earlier, that there is still a large opportunity for exploration of multimethod studies using SD, DES, and ABS at the same time. It seems that multimethod works have been developed more by industry and practitioners, than by researchers, which was also indicated by Borshchev (2013).

Subsequently, the history, definition and main characteristics of each technique were discussed separately and in detail. Finally, in the last part, a comparison of the three techniques was provided.

The relevance of this work lies in that, to the best of our knowledge, there is not any paper published providing a general overview and comparison of all three primary simulation techniques. So, this work can be seen as an easier, more complete and accessible means for academics and practitioners to learn about and compare the primary simulation techniques.

As expected contributions of this work to the field, we can cite: (i) to support the decision making about the method that is more suitable for different simulation projects and contexts; (ii) to encourage researchers and practitioners of a specific simulation method to consider and start applying other simulation techniques when they are more appropriate; (iii) to encourage the use of a multimethod approach; (iv) to provide an overview on simulation for novice simulation modelers; and, (v) to launch the development of a simulation knowledge database by documenting the main characteristics of each simulation technique. Finally, we expect this paper to be used as a guide in simulation projects and to improve the quality of simulation projects by a better selection of the simulation method.

As future work, we propose to perform a deeper systematic review that includes more papers and to gather other important characteristics of simulation techniques, besides the ones discussed here. As mentioned before, our intention is to develop an extensive knowledge database on simulation, so we greatly welcome any suggestions of characteristics and important facts for each simulation technique individually or for comparison purposes.

Declaration of interest

Declarations of interest: none

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References

Aboueljinane, L., Sahin, E. & Jemai, Z. (2013). A review on simulation models applied to emergency medical service operations. Computers & Industrial Engineering, 66(4), 734-750.

Ahlgren, P. & Waltman, L. (2014). The correlation between citation-based and expert-based assessments of publication channels: SNIP and SJR vs. Norwegian quality assessments. Journal of Informetrics, 8(4), 985-996.

Ahmad, S. & Simonovic, S.P. (2000). System dynamics modeling of reservoir operations for flood management. Journal of Computing in Civil Engineering, 14(3), 190-198.

Alexopoulos, C., Joines, J.A. & Kuhl, M.E. (2017). History of the Winter Simulation Conference: modern period (2008-2017). In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 100-114): IEEE.

Alexopoulos, C. & Kelton, W.D. (2017). A concise history of simulation output analysis. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 115-130): IEEE.

Alrabghi, A. & Tiwari, A. (2015). State of the art in simulation-based optimisation for maintenance systems. Computers & Industrial Engineering, 82, 167-182.

Angerhofer, B.J. & Angelides, M.C. (2000). System dynamics modelling in supply chain management: research review. In: Simulation conference, 2000. proceedings. winter (Vol. 1, pp. 342-351): IEEE.

Antonini, G., Bierlaire, M. & Weber, M. (2006). Discrete choice models of pedestrian walking behavior. Transportation Research Part B: Methodological, 40(8), 667-687.

Ashworth, M.J. & Carley, K.M. (2007). Can tools help unify organization theory? Perspectives on the state of computational modeling. Computational and Mathematical Organization Theory, 13(1), 89-111.

Baines, T. & Harrison, D. (1999). An opportunity for system dynamics in manufacturing system modelling. Production Planning & Control, 10(6), 542-552.

Balci, O. (2001). A methodology for certification of modeling and simulation applications. ACM Transactions on Modeling and Computer Simulation (TOMACS), 11(4), 352-377.

Balci, O. (2003). Verification, validation, and certification of modeling and simulation applications: verification, validation, and certification of modeling and simulation applications. In: Proceedings of the 35th conference on Winter simulation: driving innovation (pp. 150-158): Winter Simulation Conference.

Bandini, S., Manzoni, S. & Vizzari, G. (2009). Agent based modeling and simulation: an informatics perspective. Journal of Artificial Societies and Social Simulation, 12(4), 4.

Banks, J. (1999). Introduction to simulation. In: P.A. Farrington, H.B. Nembhard, D.T. Sturrock & G.W. Evans, Proceedings of the 1999 Winter Simulation Conference (Vol. 1, pp. 7-13): IEEE.

Banks, J. (2000). Introduction to simulation. In: Simulation Conference, 2000. Proceedings. Winter (Vol. 1, pp. 9-16): IEEE.

Banks, J., Carson, J.S., Nelson, B.L. & Nicol, D.M. (2013). Discrete-event system simulation: Pearson new international edition: Pearson Higher Ed.

Barton, R.R., Joines, J.A. & Morrice, D.J. (2017). History of the Winter Simulation Conference: period of growth, consolidation, and innovation (1993-2007). In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 87-99): IEEE.

Barton, R.R., Nakayama, M.K. & Schruben, L. (2017). History of improving statistical efficiency. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 158-180): IEEE.

Barton, R.R., Nelson, B.L. & Xie, W. (2013). Quantifying input uncertainty via simulation confidence intervals. INFORMS Journal on Computing, 26(1), 74-87.

Behdani, B. (2012). Evaluation of paradigms for modeling supply chains as complex socio-technical systems. In: Simulation Conference (WSC), Proceedings of the 2012 Winter (pp. 1-15): IEEE.

Biller, B. & Gunes, C. (2010). Introduction to Simulation Input Modeling. Proceedings of the 2010 Winter Simulation Conference, 49-58.

Bobashev, G.V., Goedecke, D.M., Yu, F. & Epstein, J.M. (2007). A hybrid epidemic model: combining the advantages of agent-based and equation-based approaches. In: Simulation Conference, 2007 Winter (pp. 1532-1537): IEEE.

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.

Borshchev, A. (2013). The big book of simulation modeling: multimethod modeling with AnyLogic 6: AnyLogic North America.

Borshchev, A. & Filippov, A. (2004). From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. In: Proceedings of the 22nd international conference of the system dynamics society (Vol. 22): Citeseer.

Bouanan, Y., Zacharewicz, G. & Vallespir, B. (2016). DEVS modelling and simulation of human social interaction and influence. Engineering Applications of Artificial Intelligence, 50, 83-92.

Brailsford, S. (2008). System dynamics: what's in it for healthcare simulation modelers. In: Proceedings of the 40th Conference on winter simulation (pp. 1478-1483): Winter Simulation Conference.

Brailsford, S., Carter, M.W. & Jacobson, S.H. (2017). Five decades of healthcare simulation. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 365-384): IEEE.

Brailsford, S., Evandrou, M., Luff, R., Shaw, R., Viana, J., Vlachantoni, A. & Willis, R.M. (2012). Using system dynamics to model the social care system: simulation modeling as the catalyst in linking demography to care delivery. In: Simulation Conference (WSC), Proceedings of the 2012 Winter (pp. 1-12): IEEE.

Brailsford, S. & Schmidt, B. (2003). Towards incorporating human behaviour in models of health care systems: An approach using discrete event simulation. European Journal of Operational Research, 150(1), 19-31.

Carley, K.M. (2009). Computational modeling for reasoning about the social behavior of humans. Computational and Mathematical Organization Theory, 15(1), 47-59.

Carson, J.S. (2003). Introduction to modeling and simulation. Proceedings of the 2003 Winter Simulation Conference, Vols 1 and 2, 7-13.

Carson, J.S. (2005). Introduction to modeling and simulation. Proceedings of the 2005 Winter Simulation Conference, Vols 1-4, 16-23.

Cheng, R. (2017). History of input modeling. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 181-201): IEEE.

Chwif, L., Paul, R.J. & Barretto, M.R.P. (2006). Discrete event simulation model reduction: A causal approach. Simulation Modelling Practice and Theory, 14(7), 930-944.

Cota, B.A., Fritz, D.G. & Sargent, R.G. (1994). Control flow graphs as a representation language. In: Proceedings of the 26th conference on Winter simulation (pp. 555-559): Society for Computer Simulation International.

Dangerfield, B. (2016). System dynamics applications to European healthcare issues. In: Operational Research for Emergency Planning in Healthcare: Volume 2 (pp. 296-315): Springer.

Dessouky, Y. & Roberts, C.A. (1997). A review and classification of combined simulation. Computers & Industrial Engineering, 32(2), 251-264.

Devillers, J., Devillers, H., Decourtye, A. & Aupinel, P. (2010). Internet resources for agent-based modelling. SAR and QSAR in Environmental Research, 21(3-4), 337-350.

Diallo, S.Y., Gore, R.J., Padilla, J.J. & Lynch, C.J. (2015). An overview of modeling and simulation using content analysis. Scientometrics, 103(3), 977-1002.

Dubiel, B. & Tsimhoni, O. (2005). Integrating agent based modeling into a discrete event simulation. In: Proceedings of the 37th conference on Winter simulation (pp. 1029-1037): Winter Simulation Conference.

El-Gafy, M. & Abdelhamid, T. (2008). Using system dynamics modeling as a lean construction work structuring tool. Proceedings IGLC-16.

ElBanhawy, E.Y., Dalton, R. & Nassar, K. (2013). Integrating space-syntax and discrete-event simulation for e-mobility analysis. In: AEI 2013: Building Solutions for Architectural Engineering (pp. 934-945).

Eldabi, T., Balaban, M., Brailsford, S., Mustafee, N., Nance, R.E., Onggo, B.S. & Sargent, R.G. (2016). Hybrid simulation: Historical lessons, present challenges and futures. In: Winter Simulation Conference (WSC), 2016 (pp. 1388-1403): IEEE.

Eldabi, T., Paul, R.J. & Taylor, S.J.E. (1999). Computer simulation in healthcare decision making. Computers & Industrial Engineering, 37(1), 235-238.

Esmaeili, M., Vancheri, A. & Giordano, P. (2010). Mathematical and computational modeling of housing market dynamics. In: Systems Conference, 2010 4th Annual IEEE (pp. 29-34): IEEE.

Figueredo, G.P. & Aickelin, U. (2011). Comparing system dynamics and agent-based simulation for tumour growth and its interactions with effector cells. In: Proceedings of the 2011 Summer Computer Simulation Conference (pp. 52-59): Society for Modeling & Simulation International.

Forrester, J.W. (1958). Industrial dynamics: a major breakthrough for decision makers. Harvard business review, 36(4), 37-66.

Forrester, J.W. (1961). Industrial dynamics. Portland: Productivity Press.

Forrester, J.W. (1969). Urban dynamics. Portland: Productivity Press.

Franceschini, F., Maisano, D. & Mastrogiacomo, L. (2014). Scientific journal publishers and omitted citations in bibliometric databases: Any relationship? Journal of Informetrics, 8(3), 751-765.

Garcia, R. (2005). Uses of agent-based modeling in innovation/new product development research. Journal of Product Innovation Management, 22(5), 380-398.

Garson, G.D. (2009). Computerized simulation in the social sciences: a survey and evaluation. Simulation & Gaming, 40(2), 267-279.

Ghasem-Aghaee, N. & Ören, T. (2007). Cognitive complexity and dynamic personality in agent simulation. Computers in Human Behavior, 23(6), 2983-2997.

Gianni, D. (2008). Bringing discrete event simulation concepts into multi-agent systems. In: Computer Modeling and Simulation, 2008. UKSIM 2008. Tenth International Conference on (pp. 186-191): IEEE.

Goh, Y.M. & Ali, M.J.A. (2016). A hybrid simulation approach for integrating safety behavior into construction planning: An earthmoving case study. Accident Analysis & Prevention, 93, 310-318.

Goldsman, D. (2007). Introduction to simulation. Proceedings of the 2007 Winter Simulation Conference, Vols 1-5, 14-25.

Goldsman, D., Nance, R.E. & Wilson, J.R. (2010). A brief history of simulation revisited. In: Proceedings of the winter simulation conference (pp. 567-574): Winter Simulation Conference.

Greasley, A. (2009). A comparison of system dynamics and discrete event simulation. In: Proceedings of the 2009 Summer Computer Simulation Conference (pp. 83-87): Society for Modeling & Simulation International.

Gul, M. & Guneri, A.F. (2015). A comprehensive review of emergency department simulation applications for normal and disaster conditions. Computers & Industrial Engineering, 83, 327-344.

Haghani, A., Lee, S.Y. & Byun, J.H. (2003). A system dynamics approach to land use/transportation system performance modeling part I: methodology. Journal of advanced transportation, 37(1), 1-41.

Harrell, C.R., Ghosh, B.K. & Bowden, R. (2004). Simulation using Promodel (2th ed.). New York: McGraw-Hill.

Higgins, A., Miller, C., Archer, A., Ton, T., Fletcher, C. & McAllister, R. (2010). Challenges of operations research practice in agricultural value chains. Journal of the Operational Research Society, 61(6), 964-973.

Hillier, F.S. & Lieberman, G.J. (2010). Introduction to operations research (9th ed.). New York: McGraw-Hill.

Ho, Y.-C. & Cassandras, C. (1983). A new approach to the analysis of discrete event dynamic systems. Automatica, 19(2), 149-167.

Hollocks, B. (2006). Forty years of discrete-event simulation—a personal reflection. Journal of the Operational Research Society, 57(12), 1383-1399.

Huanhuan, W., Yuelin, Z. & Meilin, Z. (2013). A framework for integrating discrete event simulation with agent-based modeling. In: Information Management, Innovation Management and Industrial Engineering (ICIII), 2013 6th International Conference on (Vol. 3, pp. 176-180): IEEE.

Hybinette, M., Kraemer, E., Xiong, Y., Matthews, G. & Ahmed, J. (2006). SASSY: a design for a scalable agent-based simulation system using a distributed discrete event infrastructure. In: Simulation Conference, 2006. WSC 06. Proceedings of the Winter (pp. 926-933): IEEE.

Ingalls, R.G. (2001). Introduction to simulation. Wsc'01: Proceedings of the 2001 Winter Simulation Conference, Vols 1 and 2, 7-16.

Ingalls, R.G. (2002). Introduction to simulation. Proceedings of the 2002 Winter Simulation Conference, Vols 1 and 2, 7-16.

Ingalls, R.G. (2008). Introduction to Simulation. 2008 Winter Simulation Conference, Vols 1-5, 17-26.

Ingalls, R.G. (2011). Introduction to Simulation. Proceedings of the 2011 Winter Simulation Conference (Wsc), 1374-1388.

Ingalls, R.G. (2013). Introduction to Simulation. 2013 Winter Simulation Conference (Wsc), 291-305.

Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L.K. & Young, T. (2010). Simulation in manufacturing and business: A review. European Journal of Operational Research, 203(1), 1-13.

Jenkins, C.M. & Rice, S.V. (2009). Resource modeling in discrete: event simulation environments: a fifty-year perspective. In: Winter Simulation Conference (pp. 755-766): Winter Simulation Conference.

Jeon, S.M. & Kim, G. (2016). A survey of simulation modeling techniques in production planning and control (PPC). Production Planning & Control, 27(5), 360-377.

Karnon, J., Stahl, J., Brennan, A., Caro, J.J., Mar, J. & Möller, J. (2012). Modeling using discrete event simulation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-4. Value in Health, 15(6), 821-827.

Kasaie, P. & Kelton, W.D. (2015). Guidelines for design and analysis in agent-based simulation studies. In: Winter Simulation Conference (WSC), 2015 (pp. 183-193): IEEE.

Kaur, A. & Mittal, M. (2014). A Comprehensive Review on Performance of AODV and DSDV Protocol using Manhattan Grid Mobility Model. International Journal of Research in Engineering and Technology, 3, 496-505.

Kelton, W.D., Sadowski, R.P. & Zupick, N.B. (2015). Simulation with Arena (6th ed.). New York: McGraw-Hill.

Kim, K. & Kim, K.J. (2010). Multi-agent-based simulation system for construction operations with congested flows. Automation in Construction, 19(7), 867-874.

Kleijnen, J.P. (2005). Supply chain simulation tools and techniques: a survey. International Journal of Simulation and Process Modelling, 1(1-2), 82-89.

Koelling, P. & Schwandt, M.J. (2005). Health systems: a dynamic system---benefits from system dynamics. In: Proceedings of the 37th conference on Winter simulation (pp. 1321-1327): Winter Simulation Conference.

Kotiadis, K. & Robinson, S. (2008). Conceptual modelling: knowledge acquisition and model abstraction. In: Proceedings of the 40th Conference on Winter Simulation (pp. 951-958): Winter Simulation Conference.

Kunc, M. (2016). System Dynamics: A Behavioral Modeling Method. 2016 Winter Simulation Conference (Wsc), 53-64.

Kunc, M. (2017). System dynamics: a soft and hard approach to modelling. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 597-606): IEEE.

Lättilä, L., Hilletofth, P. & Lin, B. (2010). Hybrid simulation models–when, why, how? Expert Systems with Applications, 37(12), 7969-7975.

Lee, Y.H., Cho, M.K., Kim, S.J. & Kim, Y.B. (2002). Supply chain simulation with discrete–continuous combined modeling. Computers & Industrial Engineering, 43(1), 375-392.

Logan, B. & Theodoropoulos, G. (2001). The distributed simulation of multiagent systems. Proceedings of the IEEE, 89(2), 174-185.

Long, Q. & Zhang, W. (2014). An integrated framework for agent based inventory–production–transportation modeling and distributed simulation of supply chains. Information Sciences, 277, 567-581.

Luke, S., Cioffi-Revilla, C., Panait, L., Sullivan, K. & Balan, G. (2005). Mason: A multiagent simulation environment. Simulation, 81(7), 517-527.

Macal, C.M. & North, M.J. (2005). Tutorial on agent-based modeling and simulation. In: Simulation conference, 2005 proceedings of the winter (pp. 14 pp.): IEEE.

Macal, C.M. & North, M.J. (2006). Tutorial on agent-based modeling and simulation part 2: How to model with agents. Proceedings of the 2006 Winter Simulation Conference, Vols 1-5, 73-83.

Macal, C.M. & North, M.J. (2007). Agent-based modeling and simulation: Desktop ABMS. In: Simulation Conference, 2007 Winter (pp. 95-106): IEEE.

Macal, C.M. & North, M.J. (2010). Tutorial on agent-based modelling and simulation. Journal of Simulation, 4(3), 151-162.

Macal, C.M. & North, M.J. (2011). Introductory Tutorial: Agent-Based Modeling and Simulation. Proceedings of the 2011 Winter Simulation Conference (Wsc), 1451-1464.

Macal, C.M. & North, M.J. (2013). Introductory Tutorial: Agent-Based Modeling and Simulation. 2013 Winter Simulation Conference (Wsc), 362-376.

Macal, C.M. & North, M.J. (2014). Introductory Tutorial: Agent-Based Modeling and Simulation. Proceedings of the 2014 Winter Simulation Conference (Wsc), 6-20.

Maria, A. (1997). Introduction to modeling and simulation. Proceedings of the 1997 Winter Simulation Conference, 7-13.

Montevechi, J.A.B., Leal, F., de Pinho, A.F., da Silva Costa, R.F., de Oliveira, M.L.M. & da Silva, A.L.F. (2010). Conceptual modeling in simulation projects by mean adapted IDEF: an application in a Brazilian tech company. In: Simulation Conference (WSC), Proceedings of the 2010 Winter (pp. 1624-1635): IEEE.

Montevechi, J.A.B., Pereira, T.F., da Silva, C.E., Miranda, R.d.C. & Scheidegger, A.P.G. (2015). Identification of the main methods used in simulation projects. In: Winter Simulation Conference (WSC), 2015 (pp. 3469-3480): IEEE.

Nance, R.E. & Overstreet, C.M. (2017). History of computer simulation software: an initial perspective. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 243-261): IEEE.

Nelson, B.L. (2004). 50th anniversary article: stochastic simulation research in management science. Management Science, 50(7), 855-868.

Ören, T. (2005a). Maturing phase of the modeling and simulation discipline.

Ören, T. (2005b). Toward the body of knowledge of modeling and simulation. In: Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC) (pp. 1-19).

Ören, T. (2007). The importance of a comprehensive and integrative view of modeling and simulation. In: Proceedings of the 2007 Summer Computer Simulation Conference (pp. 996-1006): Society for Computer Simulation International.

Ören, T. (2009). Uses of simulation. Principles of Modeling and Simulation: A Multidisciplinary Approach, 153-179.
Ören, T. (2010). Simulation and reality: The big picture. International Journal of Modeling, Simulation, and Scientific Computing, 1(01), 1-25.
Ören, T. (2011). A Basis for a Modeling and Simulation Body of Knowledge Index: Professionalism, Stakeholders, Big Picture, and Other BoKs. SCS M&S Magazine, 2(1), 40-48.
Ören, T. & Yilmaz, L. (2009). On the synergy of simulation and agents: an innovation paradigm perspective. International J. of Intelligent Control and Systems, 14(1), 4-19.
Ören, T. & Yilmaz, L. (2012). Synergies of simulation, agents, and systems engineering. Expert Systems with Applications, 39(1), 81-88.
Pereira, T.F., Montevechi, J.A.B., Miranda, R.d.C. & Friend, J.D. (2015). Integrating soft systems methodology to aid simulation conceptual modeling. International Transactions in Operational Research, 22(2), 265-285.
Pidd, M. (2004). Computer simulation in management science (5th ed.). New York: Wiley.
Rabelo, L., Eskandari, H., Shaalan, T. & Helal, M. (2007). Value chain analysis using hybrid simulation and AHP. International Journal of Production Economics, 105(2), 536-547.
Rabelo, L., Helal, M., Jones, A. & Min, H.-S. (2005). Enterprise simulation: a hybrid system approach. International Journal of Computer Integrated Manufacturing, 18(6), 498-508.
Rahmandad, H. & Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. Management Science, 54(5), 998-1014.
Railsback, S.F., Lytinen, S.L. & Jackson, S.K. (2006). Agent-based simulation platforms: Review and development recommendations. Simulation, 82(9), 609-623.
Roberts, S.D. & Pegden, D. (2017). The history of simulation modeling. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 308-323): IEEE.
Robinson, S. (2005). Discrete-event simulation: from the pioneers to the present, what next? Journal of the Operational Research Society, 56(6), 619-629.
Robinson, S. (2017). A tutorial on simulation conceptual modeling. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 565-579): IEEE.
Ross, W., Ulieru, M. & Gorod, A. (2014). A multi-paradigm modelling & simulation approach for system of systems engineering: A case study. In: System of Systems Engineering (SOSE), 2014 9th International Conference on (pp. 183-188): IEEE.
Ryan, J. & Heavey, C. (2006). Process modeling for simulation. Computers in industry, 57(5), 437-450.
Sargent, R.G. (2011). Verification and validation of simulation models. In: S. Jain, R.R. Creasey, J. Himmelspach, K.P. White & M. Fu, Proceedings of the 2011 Winter Simulation Conference (Vol. 1, pp. 183-198): IEEE.
Sargent, R.G. (2017a). History of the Winter Simulation Conference: coming-of-age period (1983-1992). In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 82-86): IEEE.
Sargent, R.G. (2017b). A perspective on fifty-five years of the evolution of scientific respect for simulation. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 3-15): IEEE.
Sargent, R.G. & Roth, P.F. (2017). History of the Winter Simulation Conference: Renassaince period (1975-1982). In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 50-59): IEEE.

Scholl, H.J. (2001). Agent-based and system dynamics modeling: a call for cross study and joint research. In: System Sciences, 2001. Proceedings of the 34th Annual Hawaii International Conference on (pp. 8 pp.): IEEE.

Schriber, T.J., Reitman, J., Ockene, A. & Hixson, H.G. (2017). History of the Winter Simulation Conference: origins and early years (1967-1974). In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer & E. Page, Proceedings of the 2017 Winter Simulation Conference (Vol. 1, pp. 40-49): IEEE.

Siebers, P.-O. & Onggo, S. (2014). Graphical representation of agent-based models in operational research and management science using UML.

Sterman, J.D. (2000). Business dynamics: systems thinking and modeling for a complex world.

Swain, J.J. (2017). Simulation software survey. In: INFORMS OR/MS Today (pp. 1-9): INFORMS.

Swinerd, C. & McNaught, K.R. (2012). Design classes for hybrid simulations involving agent-based and system dynamics models. Simulation Modelling Practice and Theory, 25, 118-133.

Tako, A.A. & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. Decision support systems, 52(4), 802-815.

Wagner, G. & Tulba, F. (2003). Agent-oriented modeling and agent-based simulation. In: International Conference on Conceptual Modeling (pp. 205-216): Springer.

Wakeland, W.W., Gallaher, E.J., Macovsky, L.M. & Aktipis, C.A. (2004). A comparison of system dynamics and agent-based simulation applied to the study of cellular receptor dynamics. In: System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference on (pp. 10 pp.): IEEE.

Wang, B., Brême, S. & Moon, Y.B. (2014). Hybrid modeling and simulation for complementing Lifecycle Assessment. Computers & Industrial Engineering, 69, 77-88.

Weidmann, D., Maisenbacher, S., Kasperek, D. & Maurer, M. (2015). Product-Service System development with Discrete Event Simulation modeling dynamic behavior in Product-Service Systems. In: Systems Conference (SysCon), 2015 9th Annual IEEE International (pp. 133-138): IEEE.

Weimer, C.W., Miller, J.O. & Hill, R.R. (2016). Agent-Based Modeling: An Introduction and Primer. 2016 Winter Simulation Conference (Wsc), 65-79.

White, K.P. & Ingalls, R.G. (2009). Introduction to Simulation. Proceedings of the 2009 Winter Simulation Conference (Wsc 2009), Vol 1-4, 12-+.

White, K.P. & Ingalls, R.G. (2015). Introduction to Simulation. 2015 Winter Simulation Conference (Wsc), 1741-1755.

White, K.P. & Ingalls, R.G. (2016). The Basics of Simulation. 2016 Winter Simulation Conference (Wsc), 38-52.

Winz, I., Brierley, G. & Trowsdale, S. (2009). The use of system dynamics simulation in water resources management. Water resources management, 23(7), 1301-1323.

Wolstenholme, E.F. (1999). Qualitative vs quantitative modelling: the evolving balance. Journal of the Operational Research Society, 50(4), 422-428.

Wu, D.D., Kefan, X., Hua, L., Shi, Z. & Olson, D.L. (2010). Modeling technological innovation risks of an entrepreneurial team using system dynamics: An agent-based perspective. Technological Forecasting and Social Change, 77(6), 857-869.

Yilmaz, L. & Ören, T. (2007). Agent-directed simulation systems engineering. In: Proceedings of the 2007 Summer Computer Simulation Conference (pp. 897-904): Society for Computer Simulation International.

Zeigler, B.P. (2003). DEVS today: Recent advances in discrete event-based information technology. In: Modeling, Analysis and Simulation of Computer Telecommunications Systems, 2003. MASCOTS 2003. 11th IEEE/ACM International Symposium on (pp. 148-161): IEEE.

Zeigler, B.P. & Ören, T. (1986). Multifaceted, multiparadigm modeling perspectives: tools for the 90's. In: Proceedings of the 18th conference on Winter simulation (pp. 708-712): ACM.
Zeigler, B.P., Praehofer, H. & Kim, T.G. (2000). Theory of modeling and simulation: integrating discrete event and continuous complex dynamic systems: Academic press.

Highlights

- It contains a bibliometric analysis on the three primary simulation methods
- Details such as history, definition, and main aspects of three methods are provided
- Agent-based, discrete event, and system dynamics simulation are compared
- The work can be used as a quick reference by novice and expert hybrid simulation modelers
- Modelers must know the methods to select the one that best suits the project goal

Graphical abstract