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A REVIEW OF APPROACHES AND TOOLS FOR COLLABORATIVE NETWORKS SIMULATION

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ABSTRACT

Collaborative networks (CN) are characterised by being complex systems, highlighting the need of considering simulation approaches to support the resolution of CN models. Simulation approaches are seen as a supporting tool to analyse the formal model of a supply network. Three relevant simulation approaches are identified for its application in the context of CN models: Discrete Events Simulation, System Dynamics and Agent Based Simulation. Each simulation approach is briefly described and compared with each other, according to a group of relevant features, with the main aim of aiding the modellers in the task of selecting the most appropriate simulation approach to address the modelling process in the context of CN. Besides, a group of commercial and academic tools are listed for each simulation approach.

Keywords: simulation approach, collaborative networks, discrete event, system dynamics, agent-based simulation

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1. INTRODUCTION

The study of complex systems has its origin in the study of *Systems Theory*. The number of applications of systems theory to organizations is very wide, and a high variety of system models have been developed. The first models were proposed by Barnard 1938, and were based on the notion of "balance". These models evolved towards the *Sociological Systems Theory*, defined by Selznick 1948, which introduced the analogy between the organisms and organizations. Subsequently, the *General Systems Theory* was presented, whose roots were found in the biology study area Bertalanffy 1950, which considered that the organisms are complex systems with rigorous operation of open systems. Bertalanffy 1968 as a biologist defined the systems as a set of interactive elements, and considered them as complex systems (i.e. multicellular organisms, ant colonies, ecosystems, economies, societies, enterprises, supply networks...) those characterized by having a structure composed of several levels. Afterwards, the *Contingency Theory* Kast and Rosenzweig 1981 and the *Theory of Socio-technical Systems* Trist and Bamforth 1951 appeared. The *Contingency Theory* studies the organizations as sets of interdependent subsystems, each one carrying out its own functions to perform within the context of the organization. Due to the importance of the survival of any organization, each subsystem must be viable and effective and must be consistent with each other and with the environment into which it is embedded.

Complex systems are characterised by (i) its decentralized nature, in which the system behaviour arises from the self-organization of its components without these being controlled by any extrinsic entity to the system, (ii) the presence of loops of causality and nonlinear feedback, and (iii) the fact that it contains several self-contained units that can interact, evolve and adapt their behaviour to changes in the environment Vicsek 2002. Collaborative networks (CN) consist of a wide range of decentralised and heterogeneous entities each one carrying out different processes and activities to provide goods or services to final customers Camarinha-Matos and Afsarmanesh 2008. Furthermore, each organisation defines its own objectives and formulates its own strategies. This heterogeneity makes CN complex systems, involving that in most cases it would be very difficult to adequately model and solve them mathematically Izquierdo *et al.,* 2008). Consequently, CN require the use of ad-hoc methodologies, models and tools to tackle problems and succeed in identifying proper and optimal solutions Castilla and Longo 2010. It is at this point where simulation approaches come into play.

In the light of this, this paper is organized as follows: Section 2 highlights the importance of relying on simulation approaches to solve complex systems. Three simulation approaches are described focusing on its application in CN: Discrete Event Simulation (DES), System Dynamics (SD) and Agent Based Simulation (ABS). These approaches are jointly compared in Section 3. In Section 4 an overview of the tools identified in each simulation approach is presented. Finally, the conclusions derived from the review are proposed in Section 5.

2. COLLABORATIVE NETWORKS SIMULATION APPROACHES

Concerning the *supply network* application area, simulation deals with (i) managing the complexity associated (as supply networks are considered complex systems), (ii) supporting the decision making process, and (iii) assessing the key factors (relevant performance measures) for the supply network, such as profits, customers' service or competitiveness. The construction of "WHAT-IF" scenarios, in supply network simulation approaches, will allow decision makers to obtain optimised solutions with less costs and time. Some examples can be found in terms of developing strategic plans based on market trends, company goals and competitors' strategies; creating adaptive operational management strategies that respond to internal and external dynamics such as demand fluctuations, change of suppliers, competitors' activities; or generating holistic plans considering strategic planning, marketing, and HR issues.

According to Shannon (1975), the construction of simulation-based models for supply networks are useful when:

- The supply network model to be simulated cannot be formulated in a mathematical notation.
- The supply network model can be mathematically formulated but there is no resolution method to solve the model.
- The supply network model can be expressed in a mathematical notation and there exist methods for its resolution, but these are costly, tedious and time consuming.
- The objective is to build experiments for comparing different scenarios of the supply network, and these experiments cannot be carried out in a real supply network.

Considering the literature reviewed, three are the main simulation approaches identified for its application in supply networks (Figure 1): Discrete Event Simulation (DES), System Dynamics (SD), and Agent Based Simulation (ABS). SD allows to model continuous process while DE and ABS are more used to model in discrete time. The level of abstraction is the other feature that differs from one simulation approach to another. Whereas SD allows representing models with

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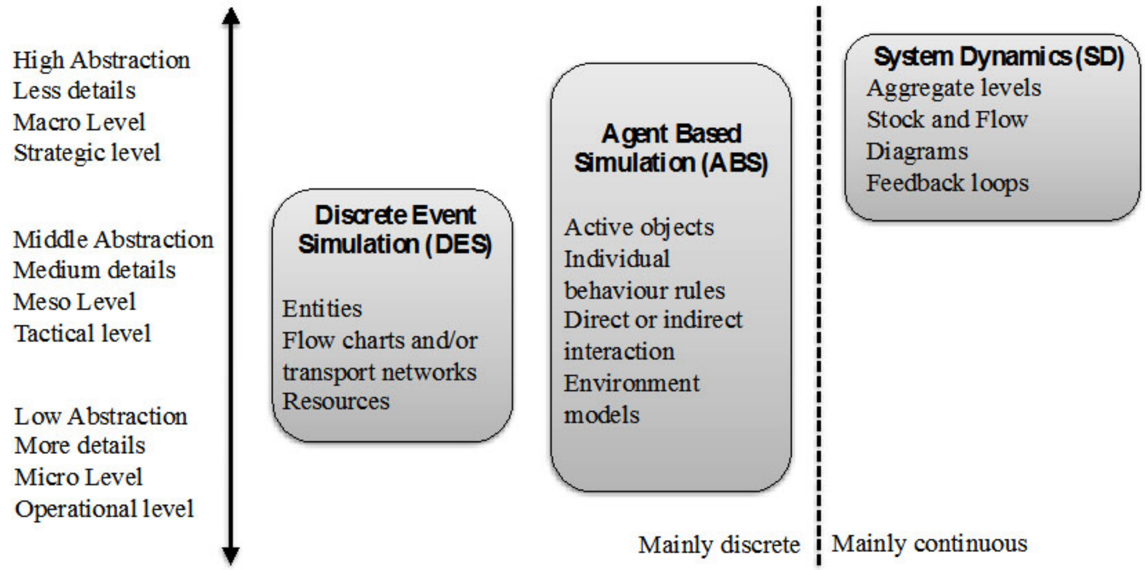

Figure 1. Simulation Approaches
Source: Adapted from Borshchev *et* Filippov (2004)

higher levels of abstraction and causal dependencies, ABS and DES considers higher levels of detail in the representation of individual entities/agents Tako *et* Robinson (2012). Figure 1 provides a graphical comparison of the three simulation approaches, which are analysed in this chapter with the main aim of dealing with supply network simulation-based models.

In the next subsections a brief definition is given for each simulation approach, previously identified.

2.1. Discrete Events Simulation

DES simulation approach has its origin in the evolution of the General Purpose Simulation System (GPSS) (originally *Gordon's Programmable Simulation System*) proposed by Gordon (1961). DES simulation approach considers individual entities , each one with specific attributes, which determine their behaviour along the simulation process Tako *et* Robinson (2012). DES is based on the concept of entities (seen as passive objects representing people, machines, messages, tasks, etc.), resources and block flow charts, through which the entities pass and stay in queues, are delayed or are processed Borshchev *et* Filippov (2004). This means that entities enter the system, visit some of the states and move between different states as time passes, after that the entities leave the system Siebers *et al.,* 2010. DES plays a significant role in modelling supply networks, especially at the tactical level. As DES does not represent systems from an aggregate perspective, it is not appropriate for strategic modelling. Works worth to mention in the context of supply networks are those developed by Lee *et al.,* (2002) and Kleijnen *et* Wan (2007).

One characteristic of DES is that it includes stochastic elements through the use of statistical distributions, when randomness is generated, Kleijnen, 2005. DES state changes occur at irregular discrete points of time, such as network of queues.

The drawbacks associated to DES simulation paradigm in the context of supply networks are the (i) lack of representation of continuous processes, and (ii) the higher complexity obtained due to DES represent high detailed models Lee *et al.,* 2002.

During the seventies DES was solely used in the research field. It was changed in the nineties when software applications were developed for simulating the complex queuing theory and resource allocation problems. The acceptance of DES as a management tool was triggered by the development of well know software tools, such as Kelton, Sadowski, *et* Sturrock (2003).

2.2. System Dynamics

Forrester is considered the precursor of System Dynamics (SD), which has its starting point in the Industrial Dynamics Forrester (1961). The Industrial Dynamics has its origins in a study carried out in a company of electronic components, *Sprague Electric*, as a new approach to address industrial problems. The main trouble found in this company was the appearance of oscillations in the order process. These oscillations were considered unusual due to the nature of the market in which *Sprague Electric* was embedded. That is, a market consisting of a few strong customers, from which it would expect that the orders' flow would be

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maintained regular. Unlike, in the mid 50's, it was observed that the orders generated were characterised by suffering oscillations.

According to this, Forrester, who was teaching at the newly formed *M.I.T. Sloan School of Management*, started to study this phenomenon. In the study, Forrester identified as key issue, in the operation of process, the feedback presented in the information structures. This finding involved an intelligent application of the theory of feedback systems; allowing representing the elements of the system, and their relations, by identifying the feedbacks to justify the appearance of oscillations. This representation enabled to identify and take the necessary measures to correct the existent oscillations in *Sprague Electric*. In the late fifties, and from the results of the performed work, Forrester formalized his ideas and methodology, resulting in the Industrial Dynamics methodology. Industrial Dynamics included structural aspects such as feedback control, and represented a new approach to address industrial problems, based on the analysis of the internal structure of the systems rather than the impact of exogenous factors affecting it.

Once the Industrial Dynamics method reached an acceptable level of maturity, the same concept was extended to social systems. Urban Dynamics was created in Forrester, (1969) as a result from his collaboration with John Collins, the former mayor of Boston and visiting professor of Urban Affairs at Massachusetts Institute of Technology (M.I.T.).

In 1970, Forrester was invited by the *Club of Rome* to apply his methodology in the study of the world, considering it as a dynamic system. The result was the *Model of the World* Forrester (1971). The application of industrial dynamics at urban and worldwide context triggered to rename the Industrial Dynamics methodology into a broader term, currently known as System Dynamics Forrester (1968).

The SD is based on the feedback control theory, decision-making processes, experimental approaches and computational developments Campuzano *et* Mula, (2011). Forrester developed the SD method as a set of tools and an approach to simulate complex systems, such as the supply network. Through SD it was possible to understand the structure of a system and identify how the intrinsic control policies operate. The supporting tools associated to SD enabled to improve the system assessment by simulating its behaviour.

Since its appearance, SD has been widely studied and disseminated in multiple research areas. Its application in case studies can be seen in areas such as defence Cooper, (1980)social sciences Richardson (1991), medical science Homer (1987), ecology Sterman, Richardson, *et* Davidsen, (1998), ecosystem Wang *et* Eltahir (2000), natural resources management, project management Lyneis *et* Ford (2007), social Lane *et* Husemann, 2008, socioeconomic systems and transportation Liu, Triantis, *et* Sarangi, 2010, civil construction Lee *et* Peña-Mora (2007), strategy management Weil (2007) Gary, Kunc, *et* Morecroft, 2009, management Roberts (1978), knowledge sharing Luna-Reyes *et al.,* 2008, resource allocation Lee, Ford, *et* Joglekar, 2007, disruptions (Williams, Ackermann, *et* Eden, 2003 or supply networks Ashayeri, Keij, *et* Bröker (1998) Campuzano, Mula, *et* Peidro (2010).

SD allows building (i) models based on previous situations faced by decision makers in the supply network, by considering their experience; (ii) dynamic models appearing on reality that are able to self-regulate their activities through feedback loops, applying the feedback systems theory; (iii) models using the computer as a supporting tool, allowing to compute models through simulating different scenarios in a short time and at low cost.

SD dissemination is done through the publication of papers in journals such as *System Dynamics Review* and other journals in management, operations research and social sciences. Besides, different groups worldwide, employing system dynamics, are also spreading the SD method, one referent group is the System Dynamics Group at MIT.

2.3. Agent Based Simulation

ABS approach was developed in the nineties as a novel tool to deal with problems that were not completely satisfactorily solved through using DES and SD. For example, in the operation research area, high complex management process and global and dynamic environments, in which enterprises are embedded, makes that traditional simulation approaches, such as DE, present limitations as a supporting tool to model and simulate complex systems North *et* Macal (2007). It is, therefore, recognised the high potential application linked to ABS for modelling and simulating complex systems Siebers *et al.,* 2010performing a new step in the progress of simulation methods, and in the enhancement of simulation applications.

According to Siebers *et al.,* (2010) ABS approach is used in the process of designing an agent-based model of a real system. ABS allows carrying out experiments with the agent-based model for the purpose of understanding the behaviour of the system and/or evaluating various strategies for the operation of the system being modelled. ABS allows representing complex systems through the use of a collection of agents that are programmed according to a set of behaviour rules and objectives, which enables them to have control over themselves and make their own decisions.

In agent-based models, the basic components of the real system are explicitly and individually represented in the model Edmonds (2002) . ABS systems are characterized by comprising multiple autonomous, heterogeneous and

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independent agents, each one with their own objectives, and are generally capable to interact with each other and with their environment. Therefore, interactions established between the individual agents and the environment are also modelled. Each agent has the capacity to evolve over the time and adapt to new environmental conditions or objectives. One of the fundamental points of agent-based simulation is the concept of emergence. The agents' behaviour is modelled at the individual level, and the global behaviour emerges as a result of the interactions with many individuals, each one following its own behaviours and rules. Neither the expert nor the modeller imposes conditions on the overall behaviour of the system directly, due to it emerges as a result of the conditions imposed on the basic system components and their interactions. That is why ABS modelling is also called bottom-up modelling, corresponding to the macroscopic patterns that emerge from the decentralised interactions of simpler individual components Holland (1998). This bottom-up approach allows capturing the complexity and dynamicity of the modelled system. In ABS interactions between the basic components of the system are studied, therefore the system can be modelled even in the absence of the knowledge about the global interdependencies Izquierdo *et al., 2008))*.

ABS approach is a powerful technique for modelling complex systems, such as social systems Gilbert (2007), health Brailsford *et al.,* 1992 traffic and transportation, financial markets, energy usage North *et* Macal, 2007 or supply networks Hernández *et al.,* 2009. Generally, ABS allows analysing the behaviours of real systems that consist of autonomous entities.

It is well known that depending on the type of modelled problem and its characteristics, the simulation approaches used to model and solve them will differ. In some situations, ABS will fit better the modelling requirements due to its flexibility and robustness; nevertheless for some other approaches DES and SD will be useful. In accordance to Siebers *et al.,* 2010 ABS are recommended when:

- The problem to be modelled has a natural representation as agents
- The goal is to model the behaviours of individuals in a diverse population
- Agents are related each other (social networks)
- Individual agents have associated movements in the space
- Agents to be modelled in the population have to learn or adapt
- Agents anticipate other agents' reactions when making decisions
- Represent collaborative behaviours
- The past is not used as a predictor of the future
- It is important to extend models in the future
- The emergence feature is a key issue in the problem modelled

3. SIMULATION APPROACHES COMPARISON

In order to select one or another simulation approach for modelling complex systems (supply networks), the literature brings some works making pairwise comparisons. The characteristics of DES approaches are mostly compared with the SD ones Maidstone (2012) Tako *et* Robinson (2012). Some authors focus on contrasting the usability and application between SD and ABS Borshchev *and* Filippov (2004), Izquierdo *et al.,* 2008, Macal (2010), Maidstone (2012). While others analyse DES paradigm versus ABS approaches Borshchev *et* Filippov (2004) Siebers *et al.,* 2010 Maidstone (2012). The work presented in Sumari *et al.,(*2013) proposes a initial work comparing the three simulation approaches DES, SD and ABS but by only considering the disadvantages, the advantages and the tools (focusing in Promodel, Vensim, and AnyLogic) that can be used in each simulation method. In this area a more comprehensive research is needed to jointly compare the three simulation approaches by considering more features such as the appropriate usage, the decision making level in which there can be applied, the degree of centralisation the level of abstraction, the complexity, components used, the entities behaviour, the modelling approach, the mathematical approximation, the evolution over the time, the data requirement, the validation requirements and the application into the SC context .

In the light of this, Table 1 intends to give an overall comparison of the same features for the three simulation approaches, DES, SD and ABS. Derived from the comparative work it can be concluded that the differences among the compared approaches are sometimes not so clear-cut. In this regard, Macal (2010) states that most of the models build in SD have an equivalent formulation in ABS approaches.

As a general recommendation, the choice of one or the other simulation approach depends on the perspective from which the modeller views the problem and the features that characterises the system, which, in fact, define the requirements of the modelled complex system. Besides, the modellers' familiarity with the software used must be considered in the selection of the simulation approach.

The research carried out to build the comparison work has allowed identifying how common is to combine different simulation approaches in order to model more accurately an only complex system. This definition corresponds to the term multi-method approach of simulation that according to Balaban *et* Hester (2013)resolution, and fidelity consist of

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Table 1 Simulation approaches comparison: DES vs. SD vs. ABS

	Discrete Event Simulation	System Dynamics	Agent Based Simulation
Appropriate usage	Convenient when the evolution of the entities state depends on the occurrence of asynchronous discrete events over the time. Its use is recommended in more detailed models. Mainly used to study the detailed operations of a supply network under uncertainty, and to evaluate the expected performance measures with a high level of accuracy. Useful in problems in which the processes can be well defined with queuing simulations. It focuses on the individual behaviour of entities	Convenient when the modeller has a previous knowledge of the complex system to be modelled and the objectives to achieve with the modelling process. Appropriate when taking a 'distant' perspective, where events and decisions are seen in the form of patterns of behaviour and system structures. It is recommended as a better choice in the high stages of decision making when less detailed models or results are required. It is mostly used for supply network analysis and policy formulation. It focuses more on flows around networks than on the individual behaviour of entities. Allows predicting the behaviour of the system just by looking at the structure	ABS simulation performs the abstractions directly on the basic components of the system. If the abstraction of the emergence process cannot be carried out in a scientifically valid way, given the modelling objectives, then it is more appropriate to explicitly model the emergence process by ABS simulation approach to study the model in detail. Allows modelling populations of diverse individuals (i.e human behaviour models) that have a variety of behaviours and interactions. It focuses more the individual behaviour of entities
Decision Making Level	Modelling problems at an operational level	Modelling problems at a strategic level to deal strategic issues and policy analysis	Modelling problems at operational and tactical level. Strategic levels of operation are less used
Degree of centralisation	Centralised. There is one thread of control. Entities are described as passive objects and the rules that drive the system are concentrated in the flowchart blocks	Centralised. Useful to model systems consisting of homogeneous entities, dominated by general laws, uniform in time and space (as the physical laws). SD is mostly used in entities that can be modelled correctly in a centralized way	Decentralised. Each agent has its own thread of control. The process is described from the entity's viewpoint, thus decentralize (some of) the rules. Therefore it is useful in more complex systems, characterised by high degrees of localization and heterogeneity of its individual components, and dominated by local information exchange processes with asymmetric and decentralized information (like most social systems)
Level of Abstraction	Low. Tends to look at the smaller detail of a system (microscopic)	High. The abstraction is done at the system level. System variables (usually aggregated) and causal relationships that link them are represented. Tends to take a more overall perspective and considers a holistic approach of systems, integrating many subsystems (macroscopic)	Low. The abstraction of the system basic components is individually done on each basic component, not the whole system (mesoscopic)
Complexity of the systems modelled	Low level of abstraction makes the process of modelling more detailed and therefore more complex	Higher degrees of abstraction lead to lower complexity models, facilitating its implementation, analysis and interpretation	The low level of abstraction makes the constructed model to be scientifically more rigorous but considerably more complex
Definition of basic components and observable variables of the system	The model focuses on observable variables	Most of the models focus on observable variables of the aggregate system. Aggregate variables of the system are defined: flow, stock and auxiliary variables	The definition of the agents' behaviour is not necessarily determined by aggregate variables of the system, but can be based only on local information

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	Discrete Event Simulation	System Dynamics	Agent Based Simulation
Entities behaviour to take decisions	Passive. The behaviour of the entities in the model is determined by the system. Passive entities implies that something is done to the entities while they move trough the system; intelligence (i.e., decision making) is modelled as part of the system	Passive. Individual entities are not specifically modelled, but instead, they are represented as a continuous quantity in stock. Feedback loops are used to represent the effects of policy decisions. A dynamic view of the cause and effect relationships is represented along the system elements	Active. Internal to the entities. Active entities, or agents, can take themselves the initiative to perform the decision-making. Specific attributes are assigned to each agent, which determine what happens to them throughout the simulation. Decisions emerge from the micro decisions of the individual agents. Autonomous (self-directed) agents follow a series of predefined rules to achieve their objectives whilst interacting with each other, as well as with the environment. Therefore, intelligence is represented in each individual agent (objects, enterprises, people)
Modelling approach	Process oriented. Top-down modelling approach focused on modelling the system in detail	Process oriented. Top-down modelling approach focused on modelling the system from a global perspective and high level of abstraction	Individual based. Bottom-up modelling approach focused on modelling the entities and interactions between them
Mathematical approximation	Generally stochastic in nature, where randomness is generated through the use of statistical distributions. Being stochastic in nature, it provides different results on different runs. Can use input distributions to model random behaviour	Generally deterministic and variables usually represent average values. Being deterministic in nature, it provides the same results run after run, so only needs to be run once	Generally stochastic feature. Can use input distributions to model random behaviour
Evolution over the time	The system is modelled as a network of queues and activities where state changes occur at discrete points of time. State changes occur at irregular discrete time steps	The system is represented as a set of stocks and flows where the state changes occur continuously over time. State changes are continuous, approximated by small discrete steps of equal length	The system is modelled considering that state changes occur at discrete points of time. State changes occur in a defined steps of discrete time
Data Requirements	Requires gathering more detailed data. Input distributions are often based on collecting/measuring (objective) data	Minimal data requirements to build a model. Input distributions are often based on theories or subjective data	Requires gathering more detailed data to model the agents' behaviour. Input distributions are often based on theories or subjective data
Validation	Established rules for validation	Established rules for validation	Validation rules cannot be directly transferred
Applications in SC context	Supply network structure Replenishment control policies Supply network optimisation Distribution and transportation planning SC integration Information sharing Inventory planning management Planning and forecasting demand Production planning and scheduling	Logistics Inventory planning Market evolution Bullwhip effect Disruptions SC integration Information sharing Inventory planning management Planning and forecasting demand Production planning and scheduling	Production planning and scheduling Information flow Risk management SC coordination Inventory, Production, Transportation Bullwhip effect SC configurations

Source: The authors own.

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a combination of at least two different simulation approaches representing and modelling a unique system. The types of combinations are about:

- Combination of SD and ABS. Development of models in which a group of agents individually and explicitly represented interact in an environment in which certain variables evolve following a dynamic approach. The combination of both simulation approaches, SD and ABS will allow to enhance the ABS model, capturing more sophisticated dynamics Borshchev *et* Filippov (2004).
- Combination of SD and DES. In the context of representing the system of an integrated enterprise DES can be used to model local production planning or sequencing activities while SD can capture the long term effects caused by the disruptions or delays in production planning Rabelo *et al.,* 2005
- Combination of DES and ABS. The process flow is modelled from a DES perspective and autonomous active entities in ABS approach (replacing passive entities modelled in DE), with the main aim of displaying proactive behaviours Siebers *et al.,* 2010.

4. SIMULATION TOOLS

This section gives a brief overview of the tools, and its characteristics, identified in each simulation approach (Table 2). In Table 3, a list of tools – alphabetically ordered – is depicted for each simulation approach.

Most of the tools are characterised its specific use in a particular simulation approach. Nevertheless, AnyLogic (AnyLogic, 2015) commercial tool is characterised by offering a multi-method approach in which the three simulation paradigms can be represented in the same visual environment. It allows modelling different parts of an only model with different simulation approaches. The main disadvantage that modellers have to overcome using AnyLogic is related to their familiarity to work in Java environments.

Table 2. Comparison of tools characteristics of the studied simulation approaches

	Discrete Event Simulation	System Dynamics	Agent Based Simulation
Tools Availability and Software	High software maturity. The scientific community has experience on the software. Increasing computer power and evolving user interfaces led the DES software to progressively move towards ‘drag and drop’. Languages, such as the Simul8, emerged to make the DES accessible and cost effective for all business sizes. Management tools are really applied	High software maturity. The process of designing a SD model is simpler, partly because formal models are usually less complex, and partly due to the availability of software tools at very high level. The ease of construction and analysis of system dynamics models using “drag and drop” tools has been one of the main reasons for its popularity in the scientific community	Low software maturity. The scientific community is less familiar with software. Tools use object-oriented programming languages (i.e. Java, C ++) allowing extensibility to model more agents and behaviours. Software is more focused to academic. Software is too technical for mass adoption and difficult to integrate into teaching

Source: The authors own.

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Table 3. Simulation Approaches Tools

Discrete Event Simulation	System Dynamics	Agent Based Simulation			
adevs	Analytica	A3 / AAA (Agent	ECJ	MaDKit (Multi Agent	SeSAm (Shell
AnyLogic	**AnyLogic**	Anytime Anywhere)	FAMOJA(Framework	Development Kit)	for Simulated
Arena	ASCEND	ABLE (Agent Building	for Agent-based	MAGSY	Agent Systems)
CPN Tools	Consideo	and Learning	MOdelling with	MAML (Multi-Agent Modeling	(fully integrated
DESMO-J	DYNAMO	Environment)	JAva)	Language)	graphical
Enterprise	Dynaplan Smia	Altreva Adaptive	Framsticks	MASON	simulation
Dynamics	Forio	Modeler	FLAME	MASS (Multi-Agent Simulation	environment)
ExtendSim	Simulations	ADK (TryllianAgent	FLAME GPU	Suit)	Jade's sim++
Facsimile	Insight Maker	Development Kit)	FLUXY	MAS-SOC (Multi-Agent	JIAC
Flexim	JDynSim	AgentBuilder	GAMA	Simulations for the SOCial	SimPlusPlus
Galatea	MapleSim	AgentSheets	GPU Agents	Sciences)	SimAgent (alsosim
GoldSim	Mapsim	**AnyLogic**	GROWlab	MIMOSE (Micro-und	agent)
Lanner L-SIM	Minsky	AOR Simulation	iGen	Multilevel Modelling	SimBioSys
Server	NetLogo	AgentService	ICARO-T	Software)	SimPack
MASON	OptiSim	Ascape	Insight Maker	Moduleco	Spatial Modeling
MS4 Modeling	Powersim Studio	Behaviour	JABM	MOOSE(Multimodeling	Environment(SME)
Environemnt	Pyndamics	Composer (Rich	JADE	Object-Oriented Simulation	Soar
NetSim	RecurDyn	Internet Application	JAMEL (Java	Environment)	StarLogo
PlantSimulation	Simantics	building on NetLogo)	Agent-based	NetLogo	MacStarLogo
PowerDEVS	System	Brahms	MacroEconomic	OBEUS (Object Based	OpenStarLogo
ProModel	Dynamics	Breve	Laboratory)	Environment for Urban	StarLogoT
Ptolemy II	Simile	Boris	Janus	Simulation)	StarLogo TNG
Renque	Simulink	Construct	JAS	Omonia(previouslyQuicksilver)	Sugarscape
Sim Events	Sphinx SD Tools	Cormas(Common-	JASA (Java Auction	oRIS	Swarm
SIM.JS	Stella, iThink	pool Resources	Simulator API)	PS-I (Political Science-Identity)	TerraME
Simcad Pro	Sysdea	and Multi-Agent	Jason	Repast	VisualBots
SimPy	SystemDynamics	Systems)	(Jason:Interpreter	SDML (Strictly Declarative	VSEit
SIMUL8	TRUE (Temporal	Cougaar	for extension of	Modeling Language)	Xholon
SystemC	Reasoning	CybelePro	AgentSpeak)	SEAS (System Effectiveness	ZEUS
Tortuga	Universal	DALI	JCA-Sim	Analysis Simulation)	
Vanguard	Elaboration)	DeX	jES (Java Enterprise		
Witness	Vensim	DigiHive	Simulator)		
	VisSim	D-OMAR(Distributed	jEcho		
		Operator Model	JESS		
		Architecture)	LSD (Laboratory		
		ECHO	for Simulation		
			Development)		

Source: The authors own.

5. CONCLUSIONS

The aim of this paper is to discuss the use of different simulation approaches to support the modelling and resolution process of complex systems, such as the CN. Three simulation approaches are considered as relevant to the scope of our purpose: DES, SD and ABS each one with its advantages and disadvantages for modelling the CN. It has been considered that depending on the characteristics of problem/process to be modelled and the availability of the tools in which the simulation approach is supported, one approach or another will be selected. Moreover, the modellers' familiarity with the used software must be considered.

To sum up, DES is recommended to be used for the study of supply network process characterised by being under uncertainty conditions, or collaborative process that can be modelled with queuing simulations, in which the state of the model elements evolves according to discrete events behaviour. SD can be usefully applied in complex systems in which models are represented with less detail in order to predict the behaviour, given certain initial conditions. In SD the processes can be represented from a continuous perspective. Finally, ABS has its application in systems in which the elements that take part are sufficient autonomous to perform themselves the decision-making process.

Focusing on the available tools, AnyLogic (AnyLogic 2015) simulation software must be highlighted due to the multidisciplinary offered enabling to use the same tool to simulate in the three simulation approaches.

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