Proceedings of the 2012 Winter Simulation Conference
C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A.M. Uhrmacher, eds

EVALUATION OF PARADIGMS FOR MODELING SUPPLY CHAINS AS COMPLEX SOCIO-TECHNICAL SYSTEMS

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ABSTRACT

Each simulation paradigm is characterized by a set of core assumptions and some underlying concepts to describe the world. These assumptions, in fact, constrain the development of a conceptual model for the system of study. Consequently, the choice of appropriate simulation paradigm is an important step in the model development process. In this paper, selection of a simulation approach for supply chain modeling is discussed. For this purpose, the supply chain is described from perspective of two well-established system theories. Firstly, supply chains are defined as socio-technical systems. Afterwards, they are described from complex adaptive systems perspective. This study gives a set of features for supply chains as complex socio-technical systems which is subsequently used to compare three simulation paradigms for supply chain modeling – namely, system dynamics, discrete-even simulation and agent-based simulation.

1 INTRODUCTION

Supply chain is an integrated system of companies involved in the upstream and downstream flows of products, services, finances, and information from primary sources to the final customer (Mentzer et al. 2001; Min and Zhou 2002). Despite the term, most of supply chains are not linked in a linear and sequential way. For instance, a manufacturer might have direct contact with some of retailers or even final customers. Moreover, more than one actor might be involved in each stage of a supply chain; for example, a manufacturer may receive the raw material from suppliers in different locations and produce many types of products and send them to different distributers. Making decisions in such a complex network of entities can be very challenging and calls for appropriate models and simulation studies.

The starting point in any simulation design is to identify the system of study and define the problems based on the real world (Robinson 2004). From the understanding of the system and problem situation the *conceptual model* can be derived. To develop a conceptual model, various assumptions and simplifications are normally introduced. Part of these assumptions and simplifications are imposed by the choice of simulation paradigm. In fact, each simulation paradigm is characterized by a set of core – or fundamental - assumptions and some underlying concepts (Lorenz and Jost 2006) or, as Meadows and Robinson (1985, p. 17) explain, “every modeling discipline depends on unique underlying assumptions; that is, each modeling method is itself based on a model of how modeling should be done”. For example, when a modeler selects System Dynamics as simulation paradigm, he explicitly assumes that “the world is made up of rates, levels and feedback loops” (Meadows 1989). The existence of these assumptions in each simulation paradigm implies that selection of a modeling paradigm is also part of conceptualization process in each simulation study.

In this paper, the choice of simulation paradigm for supply chain modeling is discussed. Firstly, a supply chain is described from perspective of socio-technical systems theory and complex adaptive systems theory in Sections 2 and 3. After an overview on three simulation paradigms, these paradigms are

978-1-4673-4781-5/12/$31.00 ©2012 IEEE

compared based on described features for a complex supply chain in Section 5. Finally, Section 6 gives some concluding remarks and a general discussion on choice of other modeling approach.

2 SUPPLY CHAINS AS SOCIO-TECHNICAL SYSTEMS

Socio-technical systems are "systems that involve both complex physical-technical systems and networks of interdependent actors" (de Bruijn and Herder 2007). The key contribution of the socio-technical theory is that the system behavior can be analyzed (and improved) only by considering both social and technical subsystems and the interdependencies between them (Otten et al. 2006). In other words, the structure and behavior of both social and technical sub-systems give rise to the overall behavior of a socio-technical system. Modern supply chains can be typically viewed as socio-technical systems. From one hand, the supply chain is a network of technical elements (e.g., manufacturing facilities, warehouses, etc.) which are physically inter-connected: the material flows by tracks or ships from suppliers to manufacturers; components and semi-finished parts are produced in the manufacturing centers and finished goods are assembled at different assembly plants; the final product is then shipped to Central Distribution Centers (CDC) and Regional Distribution Centers (RDC) and finally to retailers and final consumers in different locations (Figure 1). Each of the physical nodes and links in this extended network may itself comprise several other physical subsystems. For example, manufacturing plants contain production lines, storage facilities and material handling equipment, while the transportation link between assembly plants and distribution centers may include large scale vessels, cargo terminals and material handling equipment in ports, train or road infrastructures. On the other hand, in a supply chain, suppliers, manufacturers, retailers and customers form a social network with many formal and informal interactions. The most formal interaction among actors is through contracts specifying the commitments and terms of transactions between different parties. In addition, information flows among actors influence the decision making process for operation and the development of physical entities. For example, sharing Point-of-Sale (POS) information between retailers and manufacturers can influence the production planning in manufacturing plants and also reduce the risk of stock-outs and improve on-shelf availability in the retailer shops (Zhao et al. 2002). Different types of interactions in the chain might also directly or indirectly depend on each other. For instance, sharing information between supply chain parties can be influenced by formal interaction (e.g., the terms of contract) or informal social factors (e.g., the trusts between parties) in the chain. The decision in the social network, also, is influenced and constrained by characteristics of physical components. For instance, the rate of producing different products in a manufacturing plant is not only determined by customers' orders and contract setting (e.g., the requested product by customer or the time of order delivery) but also controlled by the characteristics of production facilities (e.g., production capacity or the cost/speed of switching from one product to another on a production line). Consequently, the overall performance of a supply chain is the output of behavior of both social and physical networks and the interactions and interdependencies among these networks.

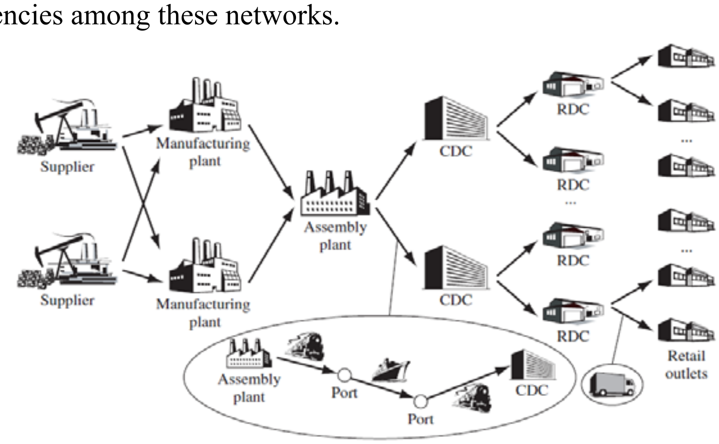

Figure 1- A physical representation of a supply chain (Ghiani et al. 2004)

Based on all these aspects, an appropriate model for supply chain must necessarily describe the social and physical aspects of the supply chain and allows alterations in both networks.

3 SUPPLY CHAINS AS COMPLEX ADAPTIVE SYSTEMS

A complex adaptive system is a system that emerges over time into a coherent form, and adapts and organizes itself without any singular entity deliberately managing or controlling it (Holland 1996). To characterize a complex adaptive system, several common features have been discussed in the literature. All these features can be generally classified into "Micro-level" and "Macro-level" characteristics. Micro-level characteristics are about the building blocks of the system - which are commonly called "Agents" (Holland 1996) - and describe the internal structure of a complex system. The macro-level properties, on the other hand, describe how a complex system looks like if we observe (and study) it at the system level. In following sub-sections, some of generally-accepted characteristics of a complex system in each of these two levels are described. As will be also discussed, a supply chain has most of these features and accordingly, it needs to be treated as a complex adaptive system in the modeling and simulation studies.

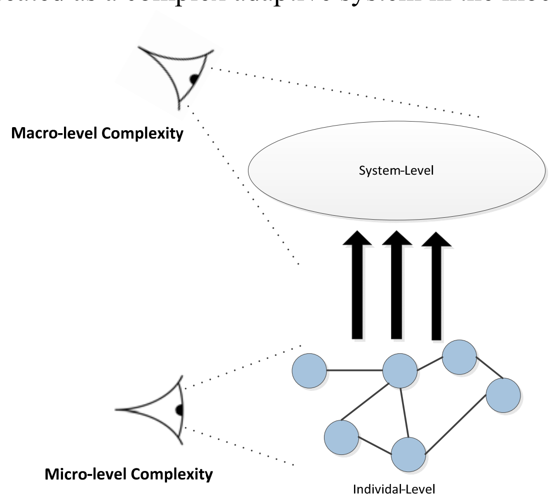

Figure 2- Micro-Level vs. Macro-Level Complexity

3.1 Micro-level Properties of Complex Adaptive Systems

The micro-level features describe the structure of a complex adaptive system and properties of its constituting components. Consequently, the terms "structural complexity" (Senge 1990; Daft 2004) or "micro-structure" of complex system (Yolles 2006) can be also used to refer to these properties.

Numerousness and heterogeneity:
Numerousness is one of overall-accepted attributes of complex systems (Simon 1962); a complex system consists of many elements. In addition, these elements normally differ in their characteristics. This property is frequently called "Diversity" (Page 2011), "Heterogeneity" (Miller and Page 2007) or "Differentiation" (Foster and Hölzl 2004). For instance, a supply chain comprises many different actors (suppliers, customers, etc.) with different needs, objectives and decision making behaviors. They are located in different geographic locations (with unique cultures and local business environment), possess different types of technologies and ask for specific types of products. Therefore, numerousness and diversity can be seen in both physical and social sub-systems of a chain. The number of products (and their differentiation), the number of production lines (with different level of flexibility to produce different range of products) and number of parts which are needed in producing the final products are examples of deriving factors for supply chain complexity at the physical level. The greater number of suppliers in the upstream of supply

chain with diverse characteristics (e.g., delivery performance) and more customers with different preferences in terms of product features and order delivery expectations are examples of social-level issues that increase the supply chain complexity (Choi and Krause 2006; Bozarth et al. 2009).

Local Interactions:
Another key feature of complex systems is local interactions and interdependencies of the system elements (Bar-Yam 2003). Like system components themselves, the interactions can be seen in both the social and physical levels of the system. For instance, in the physical level, the technical entities of a supply chain are connected through material and energy flows. In the social level, however, interactions are usually in the form of contacts and information flows among different actors.

The other key point is that interactions in complex systems are local (Lane 2002); two components in the system (in social or physical level) are either connected to each other or not. Therefore, each component in a complex system is connected only to a small number of other components and assuming an average value for sub-systems' interactions is not acceptable (Finnigan 2005). For instance, in analyzing the cooperation among actors, the results with local interactions will differ from the results for well-mixed populations where everyone can potentially contact everyone (Helbing et al. 2011).

The other important issue about interactions in complex systems is that – as the system components are numerous and heterogeneous - the interaction between two components can also be in numerous and heterogeneous ways. For example, a manufacturer may have different contracts for different materials with different terms of delivery with one specific supplier (i.e., multiple social connections). For shipping the raw material from supplier to his plants, the manufacturer may also consider different routes and modes of transportation (i.e., multiple physical connections). The multiple interactions among two actors in a chain are also usually interdependent. For instance, the material flow from supplier storage facilities to the manufacturing plants is dependent on the flow of information between these two actors.

Nestedness:
Another characteristic of complex systems is that the internal organization of system displays some sort of nestedness associated with some type of hierarchical organization (Allen and Starr 1982). In other words, complex systems are built up from other complex systems and we can call them "systems of systems" (Eisner, 2005). For example, as in a supply network, suppliers, manufacturers, retailers and customers from a complex adaptive system, each of these actors (e.g., the manufacturer) has also several production plants in different locations and each of these plants has some internal departments that are responsible for some internal activities. The interaction and behavior of internal departments determine the behavior of each plant; the collective behavior of plants give rise to the behavior of each company in the network; and the interaction among different companies and their individual behavior define the behavior of a supply network as a whole.

Adaptiveness:
Adaptiveness refers to the ability of components of a complex system to change their behavior as a result of interactions with the other components and the environment (Kauffman and MacReady 1995). For example, customers in a supply chain change their opinion and perception about the manufacturer after each transaction. The manufacturer also adapts its policies (e.g., raw material ordering policy) based on the history of interactions with other actors (e.g., the history of order delivery from a specific suppliers). The interaction with the environment can also adaptively influence the behavior of actors (Surana et al. 2005). To give some examples, suppliers define the acceptable range for raw material price according to the average market price for a specific product or new international or national regulations to ban some materials in specific products may force a company to redesign its whole supply chain.

3.2 Macro-level Properties of Complex Adaptive Systems

In addition to micro-level complexity, a complex adaptive system needs to be analyzed at the macro-level from outsider point of view. Looking at a system in this level, a complex system shows "emergence", "self-organization", path dependency and co-evolution. Emergence and self-organization are "scale-related" features of system as they describe the relation between micro-structure of system and system-level behavior. (Co-)evolution and path dependency are, however, "time-related" features and describe the changes in the structure and state of system over time.

Emergence:
The "system-level" behavior in a complex system emerges from the behavior of individual components (both social and physical) and their interactions (Holland 1999). The delivery performance of a supply chain – e.g., the customer order cycle time - and the robustness of a supply chain to cope with abnormal events are examples of emergent properties. None of these properties can be assigned to one specific individual entity but they are result of micro-structure of system and all individual behaviors.

Self-organization:
The emergence is a property of every system; in every system the system-level properties are the result of sub-system behavior and their interactions. But what is specific about a complex adaptive system is that the emergent behavior arises without any external influence but it is the result of interactions of local autonomous decision makers (Finnigan 2005). This property is called self-organization (Kauffman 1993), self-governance (Berkes 2006) or distributed decision making (Schneeweiss 2003). Therefore, complicated artifacts like cars also have emergent features in the sense that the overall functioning of a car is the output of interactions among different parts of the car. However, contrary to a car in which the properties are pre-designed and imposed by external designer, in a complex system like a supply chain, there is no external controller or planner and the overall system behavior emerges from interaction of local autonomous and heterogeneous actors.

Co-evolution:
The components of a complex adaptive system change over time. The social entities learn and adapt to the changing environment and action of other actors. Likewise, the physical components might be changed with time; new production lines may be installed at some of the production plants, new products might be designed to fulfill new needs of final customers and new transportation modes and routes are being selected by manufacturer or suppliers. As a result of all these changes, the system structure and content change and evolve over time making the supply chain a dynamic system (Choi et al. 2001).

The changes in the system, however, are co-evolutionary in two perspectives. Firstly, the constituents of a complex (socio-technical) system are evolving together in a complimentary way (Mittleton-Kelly 2003). Changes in one component in the system, alters the context for all other entities. For instance, a supplier's switch to a new production technology (e.g., with faster production rate) would influence all entities in the downstream of supply chain. Similarly, if a manufacturer likes to introduce a new product, he might need suppliers to adapt their technologies to provide some specific parts for new product. Therefore, all entities within a complex system mutually co-evolve.

Moreover, the structural changes in a complex system cause the co-evolution of system and environment (Choi et al. 2001). As an example, when a buying firm switches to a new supplier for a specific material, this action in turn creates a whole new set of second- and third-tier suppliers who will now deliver parts to this new supplier. Moreover, changing the supplier puts supply chain in a new business environment with new cultural, economical, social and regulatory issues.

Path dependency:
Path-dependency means that current and future states and decisions in a complex system depend on the path of previous states, actions, or decisions, rather than simply on current conditions of the system (Choi

et al. 2001; Page 2006). Path-dependency is also reflected in the decision-making of each of the actors at the micro-level of system as past decisions made by that actor (and other actors in the system) constrain the current options (Choi et al. 2001). For example, in a supply chain, the decision to install a specific physical setting influences all operational decisions and possible states of the system in future. A flexible multi-product production line gives the opportunity to better adapt to demand volatility and changes in customer taste. Another example in a supply chain is order acceptance process; the decision for accepting a new order from a customer highly depends on the previously-accepted orders waiting for the processing in the production plants.

4 OVERVIEW OF SIMULATION PARADIGMS FOR COMPLEX SOCIO-TECHNICAL SYSTEMS

Three main paradigms have been frequently discussed for simulation of complex socio-technical systems: System Dynamics (SD), Discrete-Event Simulation (DES) and Agent-Based Modeling (ABM). Each of these paradigms comes along with a set of (implicit or explicit) assumptions regarding the key aspects of the world as discussed further below.

4.1 System Dynamics (SD)

System dynamics is a field of study that Jay Forrester developed at the Massachusetts Institute of Technology (MIT) in the 1950s. Forrester called this new field “Industrial Dynamics” and defined it as: “the study of information feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise” (Forrester 1961, p. 13). To capture the complexity of a system, Forrester suggested the “feedback loop” concept and discussed that a “complex system has a multiplicity of interacting feedback loops” (Forrester 1969, p. 9). Therefore from Forrester’s perspective, the feedback loop is regarded as the basic building block of a complex system and the existence of multiple feedback loops is the driver of complex dynamic behavior in a system (Richardson 1991). Intuitively, a feedback loop exists when information resulting from one action travels through a system and eventually returns in some form to its point of origin, potentially influencing future action (Sterman 2000).

All feedback loops identified for a system form the Causal Loop Diagram (or also called the Influence Diagram (Coyle 1996)). Causal loop diagrams aid in visualizing a system’s structure and behavior and analyzing the system qualitatively. However the overall net effect of all the feedback loops in a very complex system cannot be determined merely by inspecting the causal loop diagram. The same system element may belong to several feedback loops, some negative and some positive, and it may not be instantly obvious which loop dominates and drives system behavior (Heath et al. 2011). To determine this, a detailed quantitative analysis of system behavior is necessary. For this purpose, a causal loop diagram needs to be transformed to a stock-flow diagram (Forrester 1968) which consists of two fundamental types of variables: Stocks (or levels) and Flows (or Rates). Stocks are the accumulations of rates of flow, which themselves are the output of the decision rules. The process of accumulation is mathematically expressed by integrating the net difference between inflow and outflow over time (Forrester 1968). Therefore, the state of a system at any specific point in time is solely described by the level variables. This explicitly means that the system dynamics paradigm models the systemic problems at an aggregate level over time. Moreover, system dynamics models are typically formulated in continuous time and assume continuous variables, though most simulators discretize the time to solve the set of differential equations describing the system behavior (Sterman 2000).

In summary, system dynamics is a feedback-based simulation paradigm. The feedback concept is at the heart of system dynamics and diagrams of information feedback loops and circular causality are tools for conceptualizing the structure of complex systems (Forrester 1961; Richardson 1991).

4.2 Discrete Event Simulation (DES)

The modeling paradigm that suggests approximating the real-world systems and processes with distinct events is called Discrete Event Simulation (Altiok and Melamed 2007). In this simulation paradigm, system possesses at any point in time a state whose change over time is triggered by discrete events. The model evolution is governed by a clock and a chronologically ordered event list. The simulation run starts by placing an initial event in the event list, proceeds as an infinite loop that executes the current most imminent event (the one at the head of the event list), and ends when an event stops or the list becomes empty. In addition to this formalization for DES –which is usually termed "Event-Scheduling (ES)" (Cassandras and Lafortune 1999) or "Event-Oriented Modeling" (Silver et al. 2010) - a number of other methods and formalizations for carrying out discrete-event simulation have been discussed in the literature (Pidd 1998). Two important formalizations are "Activity Scanning (AS)" and "Process-Interaction (PI)". These different formalisms are usually called different "worldviews" (Altiok and Melamed 2007) or different "simulation strategies" (Martinez, and Ioannou 1999) in DES literature. In activity-scanning approach, the model focuses on activities and their preconditions. For instance in Petri-Nets approach - which is classified as an activity scanning method-the model consists of two types of nodes, "transition" and "place", and a "transition" will fire if there is enough "tokens" at each of its input "places" (Miller et al. 2004). The Process-Interaction (PI) approach focuses on processes which describe the life cycle of one entity in the system (Banks et al. 2010). PI assumes that entities in the system will progress through a set of steps and each step requires one or more resources and takes a certain (usually stochastic) amount of time (Silver et al. 2010). The process view is the most-commonly-used formalism for DES and most of commercial DES software such as GPSS, SIMAN, SIMSCRIPT and SLAM are based on this approach. Because of Popularity of this method, the DES is also sometimes termed "process-centric" simulation paradigm (Salamon 2011).

Besides these three classical worldviews, there are other popular modeling approaches which are usually classified as DES. State-Transition models (e.g., Markov Chains) whose focus is on identifying the system states, determining which of the states are linked and describing the transitions, is one example (Miller et al. 2004).

As can be seen, despite SD has a more-commonly-accepted conceptualization for a system, the DES has many different forms to conceptualize a system. However, in all these approaches, the entities that describe the structure of system (events, activities and processes) are passive 'objects' (Siebers et al. 2010); they are pre-defined by modeler. The main strength of DES, however, is its capability to model distinctive entities with heterogeneous characteristics.

4.3 Agent-based Modeling (ABM)

Agent-based modeling is a type of modeling in which the focus is on representing the individuals in the system – which are termed "Agents" - (such as people or companies) and their interaction with each other and their environment (North and Macal 2007).The global (system-level) behavior then emerges as a result of interactions of agents and their individual behaviors.

To describe an "Agent" –as core element of ABM- a wide range of properties have been discussed in the literature. There is a general consensus that the agent needs to be autonomous but there is little agreement beyond this because the potential properties may vary in their importance for different domains and different applications (Wooldridge 2002). The following characteristics are, however, among the features which are usually mentioned for an agent in agent-based modeling (Wooldridge and Jennings 1995; North and Macal 2007):

- **Autonomy**: agents have a certain level of autonomy; they can take decisions without a central controller. To achieve this, they have a set of rules that determines their behavior.
- **Reactivity**: agents are capable to perceive the changes in the environment and other agents and then respond to those changes with their own actions whenever necessary.

- **Pro-activeness**: agents have proactive ability; they do not just act in response to changes that have occurred in their surroundings but they have their own goals.
- **Social ability**: agents have social ability to interact and communicate with each other.
- **Adaptivity**: agents may have memory to learn and adapt their behaviors based on experience.

Developing an agent-based model typically starts by defining the internal states (or attributes) and behavioral rules of different types of agents (North and Macal 2007). The behavioral rules describe, e.g., how an agent changes state or selects an action to do, how agents interact with each other and how agents interact with the environment. The agents - states and behavior- and the environment are next structured in a simulation program. ABM programming can be done in any language, but "Object-Oriented Programming" is the most-recommended programming paradigm because of similarities between two concepts of "object" and "agent" (Gilbert and Terna 2000).

Comparing with two other paradigms, ABM is a relatively new. However, some specific features of ABM make it a popular paradigm for modeling complex systems in different domains in last two decade. First, it is easy to model heterogeneous agents in an agent-based model. The heterogeneity can be both in behavioral (decision-making) rules of agents and their attributes (Gilbert 2007). Second, learning mechanisms and adaptive behavior can be easily represented in an agent-based model. This is especially important in the domains in which an explicit representation of human decision making is necessary to model the system behavior. Examples include economics, crowd simulation and traffic management (Helbing 2001). The other particular feature of ABM is the ability to model the spatial aspects. In some cases, like ecological problems, land use modeling or urban systems planning (Crooks et al. 2008), an explicit spatial representation may be required for the analysis. Finally, an agent-based model can be easily extended or used for other purposes. For instance, it is easy to add more agents to a previously-developed model or change the level of details by "tuning the complexity" of agents, e.g., in terms of degree of rationality and rules of interactions (Bonabeau 2002b). This is especially useful when the appropriate level of description or complexity is not known ahead of time and finding it requires some tinkering. Moreover, it gives the opportunity to develop agent-based models in an iterative process in which the modeler may start out with an idealized and general model and make the underlying structure of model more complicated by iteratively adding details (Epstein 2006).

5 COMPARISON OF SIMULATION PARADIGMS FOR SUPPLY CHAIN SIMULATION

Three main paradigms for modeling complex systems consider different building blocks for describing the system structure/behavior and have some key assumptions about the world. A summary of main characteristics of these approaches is presented in Table 1. Moreover, these paradigms have different capabilities to capture the micro- and macro-level features of a supply chain as a complex socio-technical system.

5.1 Capturing Micro-level Complexity

ABS, DES and SD modeling paradigms take fundamentally different perspectives when modeling the micro-level complexity of supply chains. SD basically belongs to a class of modeling approaches which are usually labeled "top-down modeling", i.e., focusing on system observables and modeling the system components with aggregated state variables (Heath et al. 2011). In contrast, DES and ABM have a "bottom-up" perspective in modeling; they start with a detailed representation of individual parts of the system and their interactions.

The top-down approach and high aggregation level in SD could be problematic for modeling complex system. Firstly, SD is unable to model the ***heterogeneity*** and numerousness in a complex system. The discrete entities which compose a complex supply chain (people, firms, products, etc.) are modeled homogenously and represented by their quantities (described as system's observables) in SD models (Rahmandad and Sterman 2008). To put it another way, instead of working with distinctive entities with different characteristics, SD works with an "average individual" which represent a population of entities (Scholl, 2001). Similarly, SD has an aggregate view of the interactions in a complex system and assumes perfect mixing within compartments of a system where everybody is connected to everybody else (Rahmandad and Sterman 2008). Assuming uniform distribution for the interactions between actors in the system is a challenging issue because –as mentioned before- the interactions in a complex system are local and we cannot define an average value to represent them in a model (Finnigan 2005).

Table 1- Summary of main characteristics of three simulation paradigms

System Dynamics (SD)	Discrete-event Simulation (DES)	Agent-based Simulation
System-oriented; focus is on modeling the system observables	Process-oriented; focus is on modeling the system in detail	Individual-oriented; focus is on modeling the entities and interactions between them
Homogenized entities; all entities are assumed have similar features; working with average values	Heterogeneous entities	Heterogeneous entities
No representation of micro-level entities	Micro-level entities are passive 'objects' (with no intelligence or decision making capability) that move through a system in a pre-specified process	Micro-level entities are active entities (agent) that can make sense the environment, interact with others and make autonomous decisions
Driver for dynamic behavior of system is "feedback loops".	Driver for dynamic behavior of system is "event occurrence".	Driver for dynamic behavior of system is "agents' decisions & interactions".
Mathematical formalization of system is in "Stock and Flow"	Mathematical formalization of system is with "Event, Activity and Process".	Mathematical formalization of system is by "Agent and Environment"
handling of time is continuous (and discrete)	handling of time is discrete	handling of time is discrete
Experimentation by changing the system structure	Experimentation by changing the process structure	Experimentation by changing the agent rules (internal/interaction rules) and system structure
System structure is fixed	The process is fixed	The system structure is not fixed

Although there is general agreement among scholars that the aggregate philosophy in SD limits modeling the basic micro-level features of a complex system, there is still much debate on the importance of these features on the dynamic behavior of system and also on which specific issues can/cannot be captured by a SD model. In an effort to evaluate the impact of aggregation assumptions, Rahmandad and Sterman (2008) developed agent-based and SD models for a case of contagious disease epidemic in a classic SEIR model. Experimenting with different network topologies- including fully connected, random, scale-free and lattice networks – they concluded that the effect of network representation on the results was small except for lattice networks. They also evaluated the impact of heterogeneity and claimed that in their case the effect of heterogeneity assumption on the results was small and negligible. However, they also believed that "AB models enable analysts to examine questions not easily modeled in the DE [Differential Equation] paradigm, e.g., creating and removing nodes and links to simulate random failures or targeted attacks" (Rahmandad and Sterman 2008, p. 1012).

In another study, Demirel (2007) compared two models of SD and ABM for a case of a three-level supply chain consisting of retailers, wholesalers, and manufacturers. Many different issues including different ordering policies, shadow ordering, dynamic pricing and the impact of supplier prices and loyalty in supplier selection are modeled and analyzed with both models. Based on the analysis of two models, Demirel (2007) made some general conclusions regarding the comparison of aggregated (SD) and disaggregated (ABM) approaches. Some factors are shown to be difficult or impossible to define with a system dynamics model at an aggregate level. For instance, when the interactions between agents are impacted by discrete factors – e.g., considering the price in the selection of supplier- a SD model cannot capture this detail dynamics as there is no distinction among individual agents and individual entities in the model. Consequently, there may be factors which significantly affect the supply chain behavior, but the dynamics generated by these factors cannot be captured by the SD model at an aggregate level. In addition, Demirel (2007) showed that assuming the heterogeneity among the agents can result to a different dynamic behavior for the system which cannot be captured in a SD model.

In addition to numerousness, heterogeneity and interconnectedness, the aggregated view in in SD makes it difficult to model the ***nestedness*** and multi-level characteristics of complex supply chains (Mussa 2009). There are, however, several efforts in the literature to model the nestedness of complex system; one of them is the work of Mussa (2009) in which a SD model for a chemical enterprise with multiple levels of decision making is presented. In this case, the enterprise consists of several plants and each of plants has some departments. The behavior of each department is described with a stock-flow diagram. The behaviors of departments give rise to the behavior at the plant-level and plants together form the behavior at the enterprise-level.

Probably the main strength of SD is in modeling the ***adaptiveness*** in a complex system as feedback loops are the key driver of dynamic behavior in a SD model (Sterman 2000). This, however, can be challenged as in a complex system the individual agents learn or adapt (Holland 1999). In other words, the learning and adaptiveness for a complex system happen at the individual-level and not at the system-level.

All in all, the general conclusion is that SD is not capable –in nature- to capture most of micro-level features of a complex adaptive system and this would influence the validity of results of SD for modeling supply chains. On contrary, the DES and the ABM have the capability to model micro-level of system in details. There are, however, basic differences between these two paradigms. Firstly, in DES the events are the atomic part of the model and the occurrence of events is triggered by previous events or timing rules. In ABM, this atomic part is agent and all events and activities are triggered by decisions of agents (actors) in the system (Heath et al. 2011). This difference in the micro-level components of two approaches is described in Siebers et al. (2010) as "Passive vs. Active". In event-driven simulation, the contents of the model are "Passive" objects, on which in some sequence some set of operations is performed. In ABM, the entities themselves can take on the initiative to do something; they are "Active" entities. This explicitly indicates that modeling the social-level behavior in a socio-technical complex is not straightforward in a DES model. The knowledge sharing and change of opinion among different actors in the system about each other are examples of challenging aspects to capture with a DES model. This is especially an issue as the social interaction in a supply chain is a main driver of dynamic behavior of the system. Customers might share their experience with a manufacturer or a specific brand and this share of information may impact the attitude of other customers for transaction with that manufacturer or towards that brand. Moreover, the adaptiveness of actors is not usually modeled in a DES model as entities in the system are considered as passive. Modeling these aspects is solely possible in an ABM.

Altogether, DES is an appropriate paradigm for modeling the details of physical components of a complex system; however, it is not in nature considering the social entities and the social-level complexity in the supply chains.

5.2 Capturing Macro-level Complexity

Similar to micro-level complexity, the three modeling paradigms -i.e. SD, DES and ABS – are distinct in the way that they capture the macro-level complexity of supply chains.

The ***emergence*** in complex system can be addressed in every simulation approach; in all cases the simulation outputs are emerging from model entities and their interaction. The capability of SD to produce the emergent properties in a complex system, however, has been challenged by several authors. In their book – Simulation for Social Scientist - Gilbert and Troitzsch (1999) argue that as the emergent properties are the "system properties" resulting from "individual-level" behavior and interactions, "A technique capable of modeling two or more levels is required to investigate emergent phenomena" (Gilbert and Troitzsch 1999, p. 12). In other words, the necessary condition for emergent properties in a system is existence of hierarchy of system levels. Since SD models the behavior of system in an aggregate level, Gilbert and Troitzsch (1999) explicitly deny its ability to display the emergence in a complex system. With similar reasoning, Bonabeau (2002a) claimed that the only way to analyze and understand emergent phenomena is to model them from the bottom up.

Similar to SD, some authors also criticized modeling the emergence in DES. They argued that in DES, the "macro behavior is modeled" by programmer and it is not emerging in the system level (Siebers et al. 2010). This is in contrast with ABM in which "macro behavior is ***not*** modeled; it emerges from the micro decisions of the individual agents" (Siebers et al. 2010, p. 207). The programmer only models the behavior of individuals in the ABM and the system behavior emerges collectively from the interactions of individuals (Garcia 2005).

Despite these arguments, the main drawback of SD and DES in modeling macro-level behavior is not in capturing the emergence but it is about the ***self-organization*** characteristics of complex systems. The decentralized decision making is not (adequately) modeled in none of these two simulation paradigms. As mentioned before, SD is not an individual-based modeling in nature. Likewise, DES models ignore the self-organization in the system as system-level rules govern the movement and behavior of entities and these entities do not have any intelligence or decision making capability within them (Siebers et al. 2010). This is, however, basically different in ABM in which agents – as autonomous decision makers- have rules and can alter the way of interactions with other agents and environment (Heath et al. 2011).

Both SD and DES have also difficulty to capture the ***evolution*** of complex adaptive systems; because in both paradigms, the system structure is assumed fixed. In a System Dynamics model, the structure – in form of causal diagrams and stock-level diagrams- has to be defined before starting the simulation (Schieritz and Grobler 2003). This structure of system is constant and cannot be modified throughout the course of the simulation (Schieritz and Milling 2003). Similarly, in DES, the process must be well-defined beforehand (Siebers et al. 2010). On the contrary, for an agent-based model the underlying processes are not fixed; but, based on its decision making rules and the interactions with other agents and with environment, each agent may select a different course of actions and follow a different process. Consequently, the network structure is modified dynamically.

About ***path-dependency***, comparing three simulation approaches needs to explicitly differentiate between two main issues. As previously mentioned, path-dependency means that the *current* and *future* states of a complex system depend on the path of previous states and decisions (Page 2006). This firstly implies that a small change in the initial condition or the early stages is exacerbated over the course of time and result in a basically-different present state for the system (Choi et al. 2001). This aspect of path-dependency can be captured by all three simulation paradigms: in every model, any event which alters one of previous states of the system can be a critical determinant of the current state of system and any change in the path of events would result in a different configuration for the system (Sterman and Wittenberg 1999). The path-dependency in a complex system, however, has an additional implication which is in transition from current state to the next state of the system, the path of events and states –and not solely the current state of system- are influential and must be taken into account (Schieritz and Milling 2003). With this aspect of path-dependency, there is a basic difference between ABM and two other paradigms. Actually, future behavior of system in a SD or DES model only depends on the current state of system. For example, in a SD model, state of system at time "t" is calculated based on the state variables at previous time and the "Net Rate" at time "t" (i.e., $S_t = f(S_{t-1}, R_t)$ or in the simplest form $S_t=S_{t-\Delta t} + R_t*\Delta t$) and no explicit dependence on the past states is usually reflected in the model. In an agent-based model, however, individual agents can possess the internal memory of past events (e.g., the history of interactions with other agents) which impacts every future decisions of that agent and consequently, the next state of the system (Schieritz and Milling 2003).

6 DISCUSSION AND CONCLUDING REMARKS

Based on the discussion of section 5, Table 2 summarizes how alternative simulation paradigms are fitting with different characteristics of supply chains. As can be seen, ABM is the sole modeling approach which can capture the properties of supply chains as complex socio-technical systems. The underlying assumptions in SD and DES, however, make it hard – if not impossible- to model some of main aspects and consequently, constrain developing a conceptual model for the system. Of course, the need for a model to grasp all key system features is also dependent on the specific problem and the necessary interventions. For instance, with a system dynamic model, it is possible to model the impact of variations in market demand on the manufacturing performance (e.g., in Beer Game (Sterman 2000)); but, the intervention to steer customers and change the demand pattern needs to include the individual customers' decision making in the conceptual model - which is not straightforward in SD. Likewise, DES might be very well-suited if the focus lies on the logistics of the order fulfillment and delivery. However, modeling the information exchange between customers about a brand or a particular company is impossible with the fundamental concepts and standard procedure of discrete modeling. Of course, some efforts have been done to develop DES models in which the entities are the center of focus and exhibit active behavior (Siebers et al. 2010). Regardless of how successful those efforts have been, it can be argued that if someone accepts the need to include active entities in the model for a specific system, then he is not thinking in DES paradigm anymore; he is closer to ABM conceptual thinking. Therefore, it is more straightforward to use ABM tools and simulation software for modeling that system. In other words, the differences between paradigms are basically in system conceptualization and not in the implementation of a conceptual model.

Table 2- Comparison of different simulation paradigms for supply chain disruption modeling

		System Dynamics (SD)	**Discrete-event Simulation (DES)**	**Agent-based Simulation**
micro-level complexity	Numerousness and heterogeneity	No distinctive entities; working with average system observables (homogenous entities)	distinctive and heterogeneous entities in the technical level	distinctive and heterogeneous entities in both technical and social level
	Local Interactions	Average value for interactions	Interactions in technical level	Interactions in both social and technical level
	Nestedness	Hard to present	Not usually presented	Straightforward to present
	Adaptiveness	No adptiveness at individual level	No adptiveness at individual level	Adaptiveness as agent property
macro-level complexity	Emergence	Debatable because of lack of modeling more than one system level	Debatable because of pre-designed system properties	Capable to capture because of modeling system in two distinctive levels
	Self-organization	Hard to capture due to lack of modeling the individual decision making	Hard to capture due to lack of modeling the individual decision making	Capable to capture because of modeling autonomous agents
	Co-evolution	Hard to capture because system structure is fixed	Hard to capture because processes are fixed	Capable to capture because network structure is modified by agents interactions
	Path dependency	Debatable because of no explicit consideration of history to determine future state	Debatable because of no explicit consideration of history to determine future state	Capable to capture because current and future state can be explicitly defined based on system history

Despite comprehensive study of supply chain features and simulation paradigm characteristics in this paper, it is noteworthy to mention that it might not be necessary to capture all complexity dimensions of a supply chain in every modeling effort; however, when we choose a simulation paradigm or when we make some simple assumptions to reduce the complexity of a system in the model development process, we must be fully aware of complexity dimensions that are influenced by decisions we make. As a final point, it must be emphasized that although the focus of this paper was on the choice paradigm for supply chain modeling, the arguments that are summarized in Table 2 can be generalized for modeling any complex socio-technical system.

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