Simulating Complex Systems

Complex System Theories, Their Behavioural Characteristics and Their Simulation

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Abstract: Complexity science offers many theories such as chaos theory and coevolutionary theory. These theories illustrate a large set of real life systems and help decipher their nonlinear and unpredictable behaviours. Categorizing an observed Complex System among these theories depends on the aspect that we intend to study, and it can help better understand the phenomena that occur within the system. This article aims to give an overview on Complex Systems and their modelling. Therefore, we compare these theories based on their main behavioural characteristics, e.g. emergence, adaptability, and dynamism. Then we compare the methods used in the literature to model and simulate Complex Systems, and we propose and discuss simple guidelines to help understand one's Complex System and choose the most adequate model to simulate it.

1 INTRODUCTION

Simulation consists of mimicking the operation of a real system in order to understand its behaviour. The more complicated a system, the more difficult it is to simulate. And such is the case of Complex Systems (CSs) that contain a large number of elements with nonlinear behaviours (Obaidat and Papadimitriou, 2003; Lam, 1998). This study presents an overview of the CS theories and compares the methods used to model them. Also, we propose a simple guide that helps in choosing the appropriate model to describe a CS in any domain.

The paper is structured as follows. In Section 2, we explain the main behavioural characteristics in a CS and we compare its main theories. In Section 3, we compare the approaches and methods used for modelling CSs. Then, we propose a simple guide for selecting the method that fits the CS to model. Finally, we conclude in Section 4.

2 COMPLEX SYSTEMS

The concept of holism considers the system as a whole in order to study its behaviour. The concept "the whole is greater than the sum of its parts", stated by the Chinese philosopher Confucius, is the heart of the definition of complexity science that refers to the study of CSs. A CS is a set of a large number of interconnected elements that interact with each other and with the environment in a nonlinear way. These elements, called agents, are "active, persistent components that perceive, reason, act, and communicate" (Huhns and Singh, 1998). The behaviour within CSs is nonlinear, non-deterministic and unpredictable. In fact, a CS is guided by a decentralized complex decision-making process, and the complexity is generated by the cooperation of many entities that use their own local rules in order to evolve and interact through a network of feedback loops (Lam, 1998; Nicolet, 2010).

2.1 Behavioural Characteristics

A system can be labelled as complex if it expresses a subset of the following behaviours:

- **Emergence:** is the unexpected production of new structures, behaviours or patterns, e.g. the V-shape of a flying flock of birds. Such production was not programmed beforehand. It rather results from the continuous interactions. It can be detected and interpreted by the entities (strong emergence), or by an external observer (weak emergence) (Elsner et al., 2015; Lichtenstein, 2014).
- **Multi-level Structure:** CSs enclose a relationship between the macro level and the micro

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levels. This results from the emergence that can only be detected at levels higher than the agents. In addition, CSs can have multiple spatial and temporal scales (Elsner et al., 2015; Lichtenstein, 2014; Mittal, 2013; Nicolet, 2010).

- **Distributed Decision-making:** In a CS, the highest level of the hierarchy does not manage and guide the system. Instead, all actors contribute through their micro movements. Besides, there is very little central organization. Thus, the decision-making mechanism is distributed among the agents (Nicolet, 2010; Wolf and Holvoet, 2005).
- **Dynamism and Complicated Interactions:** A CS can be in incremental growth since new entities can dynamically be created. The interactions between these entities and the environment are complex with mechanisms of flow diffusion and propagation (Mittal, 2013).
- **Feedback Loops:** They occur when an agent receives stimuli influenced by stimuli that he issued, and they lead to circular causalities that complicate the understanding of the system. They can be convergent or divergent. Convergent loops attenuate the stimuli and stabilize the system. On the other hand, divergent loops accentuate the stimuli and amplify its effects, leading to exponential change, e.g. the snowball effect or a spreading fire (Lichtenstein, 2014; Nicolet, 2010).
- **Adaptability:** The environment can limit the agents' behaviours, making them adapt to better achieve their goals. This characteristic shows that the agents exhibit robustness faced to the perturbations that occur within their environment (Johnson, 2007; Wolf and Holvoet, 2005).
- **Competitiveness and Conflict:** Each agent seeks to satisfy his goals, common or personal. Thus, agents can be collaborating to reach common goals, in competition, i.e. expressing a will to live, or in conflict, e.g. over the use of resources (Mittal, 2013; Rouquier, 2008).
- **Order:** Agents can be simple, intelligent, ordered, disordered or chaotic. This order is non-deliberate; it emerges as the agents evolve in their environments (Wolf and Holvoet, 2005).

2.2 Complex System Theories

"Complexity theory is a set of theoretical and conceptual tools, not a single theory to be adopted holistically" (Walby, 2007). Indeed, each theory stemming from complexity science illustrates real systems that share some behavioural characteristics.

The main CS theories in the literature are:

- **Complex Adaptive Systems (CASs):** In a CAS, agents have the ability to acclimatize to changing environments, making them resilient to disturbances. The adaptive character emerges from their will to survive (Mittal, 2013; Thiétart, 2000), e.g. the ant colonies (Grassé, 1959) and Darwin's evolution theory (Darwin, 1977).
- **Self-organization Theory:** The system is initially in a state of partial or total disorder. A continuous increase of order allows it to evolve to a state of order that emerges at a higher level. Such system maintains its order while the agents adapt and cope with the changes. It is also constantly dynamic and responds well to sudden or frequent changes. For that, it needs to be in a state far from equilibrium to maintain the order and structure of the system (Thiétart, 2000), e.g. the study of patterns such as landscapes (Bolliger et al., 2003).
- **Stigmergic Systems:** Stigmergy is "a series of repeated stimulus–response cycles" (Lewis, 2013). It causes a structure to emerge through indirect communication. The stigmergic complexity stems from the fact that people interact through the changes they make in their neighbourhood, which impacts the others who respond to these changes in turn (Doyle and Marsh, 2013; Grassé, 1959), e.g. the dynamics of ant colonies (Grassé, 1959). It is often considered as a special case of CASs or self-organization.
- **Coevolution Theory:** Coevolution is "the process of reciprocal adaptation and counter-adaptation between ecologically interacting species" (Brockhurst and Koskella, 2013). It happens when two systems are about to change, with feedbacks between the components that influence them, e.g. the coevolution of plants and viruses (Fraile and García-Arenal, 2010).
- **Chaos Theory:** In chaotic systems, small changes can lead to very different behaviours, which make the system exponentially unstable and unpredictable in the medium and long terms. Unlike systems capable of emerging order, chaotic systems have hazardous dynamics (Elsner et al., 2015), e.g. the butterfly effect (Lorenz, 1963).
- **Critical Self-organization:** happens when the size of an event is inversely proportional to its frequency, leading to abrupt system transitions. In fact, the system starts to evolve steadily until it gets to the point where small events have repercussions on the macro level (Thiétart, 2000), e.g. the sand pile model (Christensen et al., 1991).

Table 1: Comparing the main Complex System theories based on their common behavioural characteristics.

Behavioural characteristics	Complex System theories				
	CAS	Self-organization	Coevolution	Theory of chaos	Catastrophic complexity
Emergence	key	key	key	key	key
Multi-level structure	yes	yes	yes	yes	yes
Distributed decision	yes	yes	yes	yes	yes
Dynamism and complicated interactions	yes	key	yes	key (random flow propagation)	key (micro forces have global effects)
Feedback loops	yes	yes	key	in some cases	yes
Adaptability	key	key	key	in some cases	in some cases
Order	yes	key (increase in order)	yes	no (increase in disorder)	key
Competitiveness	in some cases	in some cases	in some cases	in some cases	in some cases
Other	The system is in a poised state between simple order and chaos	The system is far from equilibrium and changes frequently	Considers other agents' simultaneous changes	Exponential instability, unpredictability and hazard	Abrupt transitions and the event's size is inversely proportional to its frequency
	Agents are quite resilient to disturbances				

key: important behaviour, yes: expressed behaviour, no: behaviour not expressed, in some cases: the Complex Systems of this theory may express this behaviour

2.3 A Comparison between Complex System Theories

The synthesis of our readings on CSs allows us to establish a summary of the main behavioural characteristics of different CS theories in Table 1.

3 SIMULATING COMPLEX SYSTEMS

Simulation is the imitation over time of the operation of a real world system or process. It allows the conduct of virtual experiments where different scenarios can be tested and predictions could be made for better decision-making. Moreover, it obviates the temporal dimension by allowing the simulation of long periods in a matter of seconds. And it helps avoid the costs and effects of these tests on reality. The literature proposes two main approaches for modelling CSs: the analytical and the systemic approach (Müller, 2013; Chen et al., 2012).

3.1 The Analytical Approach

This approach is often used for modelling simple deterministic systems. It requires a prior and (assumed) complete understanding of the domain because it needs detailed programming of the behaviours (Krichewsky, 2008). It works by breaking down the system into sub-systems. The addition of the modelling of each part is considered to be the overall system model. It is therefore based on the principle of isolating the system's elements, and allows the modelling of a small number of linear interactions. This approach includes:

- **Differential Equations:** This method is well suited to describe homogeneous populations in homogeneous environments when continuous variables are appropriate to represent the whole population as well as the state of each individual. However, it is of limited use if the heterogeneity of the entities is too high to be reasonably described with variables (Breckling, 2002), e.g. equation based modelling of obesity (Thomas et al., 2014).
- **Stochastic Processes:** In the study of some CSs, hazard can be important in determining the outcome of the system. The difficulty of modelling the "interplay of chance and necessity" (Lam, 1998) can be caused by the lack of data in the studied field, the inability to recreate the events, and the absence of a realistic mathematical model representing these CSs. Stochastic systems are widely used to represent hazardous dynamics, e.g. the stochastic description of human feelings (Carbonaro and Giordano, 2005).

Limits of the analytical methods in modelling CSs: Differential equations and stochastic processes can be combined, and other techniques of Artificial Intelligence can also be used at different levels, such as Fuzzy Logics for representing vague and imprecise knowledge, Multimodal Logics for representing symbolic data, and neural networks for optimizing complex tasks. However, these methods fail to model the nonlinearity and unpredictability of CSs. In fact, they describe relationships as global parameters, and do not explicitly account for the fact that these relationships result from the interlocking behaviours of individuals. Thus, analytical methods reduce the overall system into a set of parts, causing a loss of relationships that could emerge from their coexistence. They are useful in modelling systems that have deterministic dynamics, predictable behaviours and centralized decision-making (Krichewsky, 2008; Thiétart, 2000).

3.2 The Systemic Approach

This approach overcomes the limits of the analytical one. It considers the system as a whole and focuses on the dynamic relationships between its components, rather than the characteristics of each component considered separately. The elements' behaviour is guided by objectives, which promotes complex behaviours, namely, emergence (Müller, 2013). The systemic models can be categorized as traditional models or constructivist models.

3.2.1 Traditional Systemic Models

Examples of traditional systemic models:

- **Rule based Systems:** they are based on an inference engine that uses uniform rules given by experts. They are used when: the interacting variables are not numerous, the system processes are understood and the knowledge expressed by the experts is considered complete (Chen et al., 2008). Despite its limitations, this method has been used for CSs, for example, rule-based simulation of biochemical systems (Harris et al., 2009).
- **Artificial Neural Networks:** they imitate the way human brains work. They are composed of a set of interconnected nodes, and use nonlinear calculations that fit complex and multivariable data (Chen et al., 2008).

3.2.2 Constructivist Models

Constructivist models keep the link between the overall system behaviour and the behaviour of local elements. They are used to represent different level entities, e.g. molecule, cell, person, and group, and the interactions between them (Müller, 2013). They can be classified into two main categories: Individual-Based Models and Multi-Agent Systems.

3.2.2.1 Individual-based Models (IBMs)

The most known IBMs are:

- **Synergistic Modelling:** It is based on a stochastic description of the individual decision-making processes. The link between the individual level and the macrostructure level is modelled with continuous differential equations that express the probability of a given configuration, e.g. modelling dialogues between people (Fusaroli et al., 2013).
- **Microsimulation:** It expresses the decision-making processes of an individual using probability (Koch, 2015). An agent behaves and interacts based on stochastic parameters, and each decision takes into account the choice made by the individual at an earlier time. This mechanism allows individuals to have different behaviours.

Limits of synergistic models and microsimulation: Individual decisions in synergistic models are explained by macroscopic factors and not intra-individual features. Also, the behaviours can only be homogeneous. Besides that, in both synergistic models and microsimulation, individuals are very independent; decisions are not influenced by social nor spatial factors. In these models, space is not taken into account, unless modelled as a global parameter. In addition, these models do not consider interactions between individuals and their environment nor the spatial influence of their actions. Thus, if a macrostructure emerges from the sum of individual actions, it cannot be retroactive back to the individuals (Koch, 2015; Laperriere, 2004).

- **Cellular Automaton (CA):** A CA is a spatial model that is discrete in space and time. It models homogeneous populations residing in a physical environment. It is composed of identical cells in a regular grid. All cells are updated every unit of time, and their states are determined by the same set of rules. A state depends only on the cell's current state and its immediate neighbours' states. Complex dynamics and emerging properties can result from this monotonous and simple update (Qu et al., 2011; Kari, 2005), e.g. simulating people's movement (Sarmady et al., 2011).

Limits of CA: A CA automatically provides a spatial dimension. Yet it treats the distances between adjacent agents as uniform, and private relations between distant cells are not allowed. Thus, social relations are limited to spatial proximity. A CA also has a problem with border conditions. In fact, since a cell's state depends on its neighbours, the borders may face some miscalculations. In order to avoid this problem, we can model a large CA grid that will dispel border errors. But this solution reduces the performances because all cells are recalculated at every step, even the vacant ones (Chen et al., 2008).

3.2.2.2 Multi-Agent Systems (MASs)

A MAS is composed of agents that evolve within a social network and a physical environment. These agents are heterogeneous, dynamic and independent (Siebers et al., 2010). They can represent different levels: genes, cells, organs, individuals, and organizations. Each agent influences others, changes its state or thoughts, and modifies its environment. A MAS can have spatial components that are represented via spatial agents or as part of the system's configuration. Agents can also have agency; they behave in a way that satisfies at best their personal goals. Such behaviour can be unconscious and deterministic. In such case, the agents are reactive. It can also rely on human-like thinking mechanisms; such agents are cognitive. These latter perceive, reason and execute. Their internal state can be expressed via beliefs, desires, preferences, intentions, emotions, etc. (Bagdasaryan, 2011; Qu et al., 2011; Frantz, 2012).

The MAS paradigm is very useful in modelling social systems, because it can take into account the human behaviour, the complex reasoning, and the psychological factors (Chen et al., 2008). As for classifying MASs, Rouquier (2008) claims that they are not part of CS models. Among other reasons, he states the fact that an agent can change his behaviour, yet according to him, behavioural rules in CSs are simple and unchangeable. On the other hand, many other researchers (Mittal, 2013; Doyle and Marsh, 2013) consider MAS to be positively suited for modelling CSs. We stand by the latter opinion, and we consider that the system's complexity can be described by simple entities, but can also result from an intrinsic complex behaviour, which goes in tandem with the multi-level hierarchy of CSs. E.g. the MAS of marketing research (Negahban and Yilmaz, 2014).

Limits of MASs: MASs help cut off some limits of IBMs. Nevertheless, while modelling a MAS, the designer needs to find a balance between modelling all identified factors and keeping it simple. Indeed, simplifying might result in eliminating some micro-factors that may cause emergence later on. So the objective is to keep the model understandable and to limit the unnecessary complexity without harming emerging effects (Bonabeau, 2002; Axelrod, 1997).

Besides that, MASs generally require a lot of modelling time and computing resources because they need a deep understanding of all actors in the system, e.g. reasoning mechanisms, conflicts, and resources. In addition, since it is often used for simulating social and human behaviours, MASs require significant technical and interdisciplinary competences (Frantz, 2012; Bonabeau, 2002).

3.3 Comparing the Methods Used to Model Complex Systems

In this section, we draw a comparison between the analytical and the systemic approaches. Then we compare the different constructivist methods.

3.3.1 Analytical Vs. Systemic

The analytical and the systemic approaches differ in principle, see Table 2. The first one only takes into account the elements' state and behaviour, while the second focuses more on the interactions between the elements and with the environment (de Rosnay, 1975). An emergent phenomenon cannot be studied using a reductionist paradigm as the latter has its limitations especially in capturing the nonlinear behaviours (Lichtenstein, 2014). Nevertheless, it is still very useful in modelling CSs. In fact, in some cases, it can prove to be more suitable as a choice for describing a given CS. For example, if a system has processes that can be considered as reversible, its dynamics are linear and it contains quite simple interactions, then a deterministic analytical approach is appealing and probably more representative of the studied aspect of the system, e.g. the modelling for predicting obesity prevalence trends (Thomas et al., 2014). Such choice should greatly take into account the specific aspect that the designer aims to understand, and not all the phenomena that occur within the CS.

Table 2: Analytical approach vs. systemic approach (Nicolet, 2010; de Rosnay, 1975).

Analytical approach	Systemic approach
Reductionism	Holism
Predictable, deterministic	Unpredictable behaviour
Elements isolated from their environment	Element are not isolated from their environment
Linear, simple interactions	Nonlinear complex interactions
Focuses on the elements' characteristics	Focuses on the dynamics of relations
Guided by details	Guided by goals
The temporal dimension is considered reversible	The temporal dimension is acknowledged as irreversible
Validation: experimental evidence based on a theory	Validation: comparison with reality

Furthermore, the two approaches can be combined. For instance, we can have a MAS with stochastic dynamics, e.g. the MAS for studying diseases (Snijders et al., 2010). The choice of a combined model depends on the modelled processes and the researcher's preferences (Bagdasaryan, 2011). In the following paragraph, we go further by comparing systemic constructivist models.

3.3.2 Comparing the Constructivist Models

Constructivist models keep a link between the global behaviour and the local behaviours of the elements. They allow explaining the overall behaviour based on individual behaviours, and they are very appropriate for modelling social and ecosystems (Müller, 2013). In Table 3, we compare the constructivist models. This comparison is based on a non-exhaustive set of dimensions, system behavioural characteristics, and agent behaviours.

3.4 How to Select a Method for Modelling a Complex System?

We believe the method that models a CS should be carefully chosen on a case-by-case basis. This choice is important and has great influence on the outcome of the model. In fact, it mainly depends on the system's characteristics, the available resources, the designer's abilities, and our understanding of the system's dynamics. In this section, we propose a simple guide to help designers understand their CS's main behavioural characteristics, in order to choose the appropriate model for it. This guide, see Figure 1, can be applied in any field of study since all the steps are independent of the application context.

The designer first selects a CS theory that best describes the CS to model. For that, he/she relies on their knowledge of the system, their study goal, and the comparison in Table 1. Then, the user chooses the approach to follow based on the goal of the study and the comparison depicted in Table 2. If the chosen approach is analytical, the need to model hazard within the system allows the designer to pick either stochastic processes or differential equations.

Table 3: Comparing the systemic constructivist models.

Models		Synergistic modelling	Microsimulation	Cellular Automata	Multi-Agent Systems
Dimensions					
Spatial dimension		no (modelled as a global parameter)	no (modelled as a global parameter)	yes (mandatory)	yes
Social dimension		no	no	yes (adjacent neighbours)	yes
Cognitive dimension		no	no	no	yes
Difficulty of designing the system (e.g. resources, time, and call for interdisciplinary skills)		medium	medium	medium	difficult
System behavioural characteristics					
Emergence		yes	yes	yes	yes
Feedback loops	Local (agent ↔ agent)	yes	yes	yes	yes
	Global (global emergence → agent)	no	no	yes	yes
Open system		yes	yes	no (errors at the borders)	yes
Agent's behaviour					
Autonomy regarding the environment		yes	yes	no	yes
Interaction between individuals and their environment		no	no	yes	yes
Heterogeneous agents		no	yes	no	yes
Dynamic inter-agent relations		no	no	no	yes
Interaction between distant agents		no	no	no	yes
Factors involved in agents' decision-making	Spatial factors	no	no	yes	yes
	Social factors	no	no	yes (adjacent neighbours)	yes
	Intra-individual factors (other than cognitive)	no	yes	yes	yes
	Cognitive factors	no	no	no	yes

If the approach is systemic, the user decides if it is necessary to keep a link between the macro and micro levels of his/her model; this is important in case we want to model emergent phenomena because, as we said earlier, emergence can be detected on levels higher than the agents themselves, but it is caused by the agents' micro dynamics.

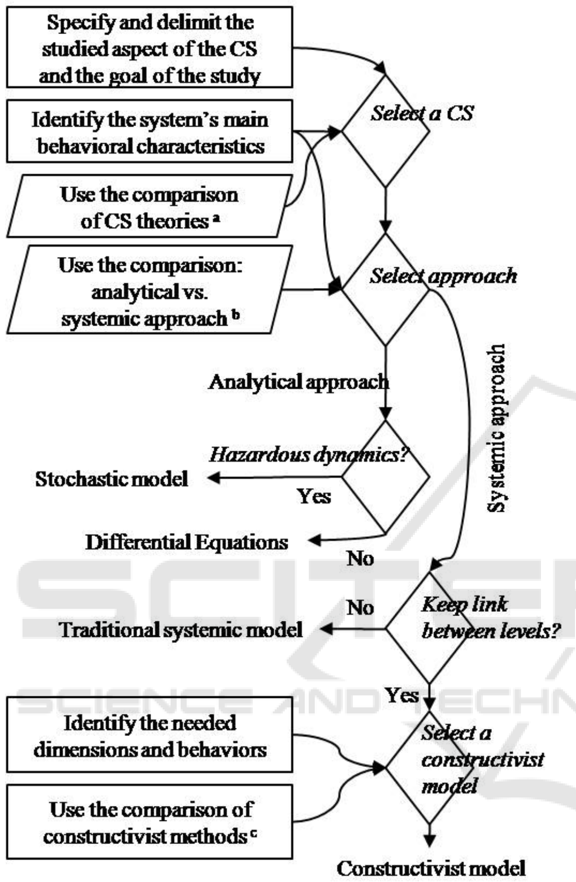

Figure 1: How to choose a method to simulate a CS in any field of study. (a) Table 1, (b) Table 2, (c) Table 3.

Therefore, a link between the micro and macro levels is crucial for modelling emergence. If no such phenomena need to be modelled, the designer should opt for one of the traditional systemic models. Otherwise, he/she should choose between the constructivist models.

In fact, the proposed guide facilitates the task of designing CSs. Nevertheless, it does not take into consideration combining several models, e.g. constructivist/traditional systemic, constructivist /analytical, traditional systemic/analytical, and constructivist/constructivist. Thus, it should be extended to allow more flexible choices, and also propose the supporting tools for each choice.

We would also like to point out that identifying the CS theory to adopt could be quite difficult. In fact, more than one theory may seem appropriate because they share some behavioural characteristics e.g. CAS and self-organizing systems, or evolution and coevolution theories. In such cases, one should limit the suitable theories, and make the final decision after a deeper needs analysis of the studied aspects of the CS. In some cases, both the analytical and the systemic approaches can be suitable candidates. For instance, in the study of obesity, the literature proposes equation based models (Thomas et al., 2014) and MASs (Aziza et al., 2014). Besides that, a further study should be made in order to apply this guide on different contexts of different domains.

4 CONCLUSIONS

In this article, we presented an overview of modelling CS. We first took a step back, studied the main behavioral characteristics in complexity science, and compared its main theories, namely, CAS, chaos theory, and coevolution theory. We described and compared the different approaches and models used for simulating CSs. Then, we proposed and discussed a simple tool that lists some guidelines to help understand one's complex context and choose the most adequate model to simulate it.

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