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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 a simple guide to select the appropriate method for modelling a Complex System.

1 INTRODUCTION

Simulation consists of mimicking the operation of a real system in order to understand and/or predict its functioning in different situations. It requires modelling the system and developing a simulator that implements that model (Obaidat and Papadimitriou, 2003). 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, non-deterministic and unpredictable behaviours (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. Then, we propose a simple guide for selecting the method that fits the CS to model: we start by presenting two approaches used for modelling and simulating CSs; the analytical and the systemic approach. For each one, we explain its methods and limits. We compare the mentioned approaches and methods, and then we explain our guide. Finally, we conclude by in Section 4.

2 COMPLEX SYSTEMS

The concept of holism considers the system as a whole in order to study its behaviour (Nicolet, 2010). The concept “the whole is greater than the sum of its parts”, stated by the famous 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, often called agents, are “active, persistent (software) components that perceive, reason, act, and communicate” (Huhns and Singh, 1998).

Compared to other large-scale systems, 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 with each other through a network of feedback loops (Lam, 1998).

2.1 Behavioural Characteristics

Despite the large spectrum of CSs, they share a number of behaviours. These behaviours can be seen

as properties or phenomena that are intrinsic to the system. Therefore, a system can be labelled as complex if it expresses some of the following behaviours. We stress that a CS does not necessarily exhibit all the following behaviours, rather a subset:

- **Emergence:** is the unexpected production of new units, structures, properties, behaviours or patterns that have unpredicted aspects, e.g. the V-shape of a flying flock of birds. Such production was not programmed, nor embedded (not even partly) in the agents beforehand. It rather results from the continuous interaction of a large number of entities and occurs without any central controller. It exists within the system independently of the observer's point of view. In fact, the emergent phenomenon is stable at the macro-level of the system. And in order to explain an emerging property, the observer must inspect not only the components of the system, but also the micro behaviours of the agents. Besides that, emergence can be detected and interpreted by the system entities, referred to as 'strong emergence', or by an external observer, in which case we have 'weak emergence' (Elsner et al., 2015; Lichtenstein, 2014; Nicolet, 2010; Johnson, 2007).
- **Multi-level structure:** CSs enclose a relationship between the macro level and the micro level, i.e. the elements of the system. This results from the emergence that can only be detected at levels higher than the agents. Indeed, in CSs, micro movements lead to emergence at the macro level. Thus, emergence involves and links between different levels of a CS. In addition, CSs can have multiple spatial and temporal scales through a global hierarchy and intra-entity hierarchy, e.g. a society is composed of humans, themselves composed of cells (Elsner et al., 2015; Lichtenstein, 2014; Mittal, 2013; Nicolet, 2010).
- **Distributed decision-making:** In a CS, the highest level of the hierarchy doesn't manage and guide the system. Instead, all actors contribute to its development and functioning through micro movements. Besides, since interactions and most information are local, there is very little central organization. Thus, the decision-making mechanism is distributed among the agents. These latter are therefore autonomous and spontaneous (Nicolet, 2010; Wolf and Holvoet, 2005).
- **Dynamism and complicated interactions:** A CS can be in incremental growth since new entities can dynamically be created (Mittal, 2013). These entities are constantly evolving, and the interactions between them and the environment are complex with mechanisms of flow diffusion and

propagation. Therefore, it may prove to be difficult to understand the complicated, and sometimes simultaneous set of interactions occurring within the system.

- **Feedback loops:** This phenomenon occurs when an agent receives stimuli influenced by stimuli that he issued. The CS contains a large number of interactions that lead to circular causalities. The system's complexity renders it difficult to identify and understand all the loops occurring in the system; unseen causalities can cause discomfort to modelling CSs, but they still need to be admitted and recognized as part of the system's functioning (Lichtenstein, 2014). The circular causalities render it difficult to explain the cause of an observed situation. Breaking the loop will definitely lead to a false or incomplete comprehension of the system. It is therefore necessary to consider the totality of a loop in order to understand its functioning. Feedback loops can be either convergent or divergent. Convergent loops have stabilization effects. They attenuate the stimuli and reduce its amplitude, leading eventually to a stable status of the considered phenomenon. On the other hand, divergent loops accentuate the stimuli and amplify its effects, leading to exponential change and development of the phenomenon, e.g. the snowball effect or a spreading fire. The divergence speed can render it quite difficult to control the system. These loops are known to have dramatic effects that lead to either the growth of the system or its destruction. Whereas convergent loops are known to conserve the system's stability (Nicolet, 2010).
- **Adaptability:** The environment can limit the agents' behaviours. Having their behaviour boxed, the agents adapt in order to better achieve their goals. In fact, adaptation can lead to an emerging global phenomenon that can also have a power of adaptability of his own. 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:** In a CS, each agent seeks to satisfy to his own goals that can be personal or shared among agents. 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:** In a CS, the behaviours of the agents can be various, simple, intelligent, ordered, disordered or even chaotic. Much of the CSs, namely communities and living organisms, tend to

express a certain order in their evolution. The order we are referring to here is a non-deliberate behaviour; it emerges as the agents evolve in their environments (Wolf and Holvoet, 2005; Kauffman, 1993). In his book, Kauffman (1993) refers to this phenomenon as “organized complexity” and gives the example of neural systems that mobilize parallel activities or even billions of neurons to assess, classify, and respond to an external or internal stimulus. Kauffman also states that “contrary to our deepest intuitions, massively disordered systems can spontaneously crystallize a very high degree of order”, which means that order can emerge from high disorder.

2.2 The Main Complex System Theories

“Complexity theory is an emerging approach or framework. It 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 a set of real life 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 more resilient to disturbances. The adaptive character emerges from their will to survive by making efforts to meet their local objectives, which leads to conflict and competition (Mittal, 2013; Thiétart, 2000). Besides that, CASs are able to reach a state of equilibrium between simple order and chaos, it’s a “poised state” that simultaneously optimizes the entities’ evolution and the tasks’ complexity (Kauffman, 1993). Among other famous examples of CASs, we cite the stigmergic ant colonies (Grassé, 1959) and Darwin’s evolution theory (Darwin, 1977).
- **Self-organization theory:** In a self-organization, 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. This order was not preconceived within the agents, it’s the adaptation of the spontaneous agents that leads to maintaining it. A self-organizing system maintains its order while the agents adapt and cope with the changes, making them quite robust to environmental disturbances. In this context, Kauffman (1993) introduces the concept of dynamical attractors, which are parts of the system or specific parameters that steer and box the behaviour of the

system. These dynamical attractors limit the behaviour of the system in a limited space of possible states. The author considers this concept to be the main cause of the appearance of self-organization.

A self-organizing system 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). Self-organization can be found in the study of patterns such as landscapes (Bolliger et al., 2003).

- **Stigmergic systems:** Stigmergy can be defined as “a series of behaviours driven by repeated stimulus–response cycles” (Lewis, 2013). It happens when a particular organizational structure emerges in an environment through indirect communication. This phenomenon was observed in ant colonies by Grassé (1959) who was interested in understanding the non-centralized coordination mechanisms capable of creating sophisticated messaging systems leading to the emergence of global structures, e.g. architectural structure. According to Grassé, 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). Stigmergic systems can uphold complex adaptive behaviours; They are often considered as a special case of CASs (Mittal, 2013) or self-organizing systems (Lewis, 2013).
- **Coevolution theory:** Coevolution is “the process of reciprocal adaptation and counter-adaptation between ecologically interacting species” (Brockhurst and Koskella, 2013). Indeed, coevolution happens when two systems are about to change, with feedbacks between the different components. Each system, during its own development, influences the evolution of the other. Norgaard (1994) believes that the main characteristics of coevolution are variation, selection, and generation of new variation. It is the latter that makes the difference between evolution theory (Darwin, 1977) and coevolution theory. Along the line of CASs and self-organizing systems, coevolutionary systems are based on the dynamism and adaptability of its agents, as well as order. Entities rely on their vision and local capacities, and they evolve towards a more balanced system by being attracted to dynamical attractors (Kauffman, 1993). However, unlike in CASs and self-organization theory, in coevolution, an agent’s adaptive mechanism changes his state

while taking into account the simultaneous changes of other agents. Besides that, these entities are probably not trying to optimize anything whatsoever. Their behaviour is therefore not necessarily limited by reaching the dynamical attractors (Kauffman, 1993). As an example, we cite the coevolution of plants and viruses (Fraile and García-Arenal, 2010).

- **Chaos theory (the butterfly effect):** 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 order systems, i.e. capable of exhibiting emerging order, chaotic systems have random and hazardous dynamics (Kauffman, 1993). The phenomenon of the butterfly's flutter effect stated by Lorenz (1963) is one of the most known chaotic systems in the literature.

- **Critical self-organization (catastrophic complexity):** Critical self-organization follows the law according to which the size of an event is inversely proportional to its frequency. Therefore, it consists of studying the abrupt system transition

from one state to another. In fact, the system starts to evolve steadily until it gets to the point where a small event causes repercussions on the entire system. This abrupt transition makes the system move from a state where the effect of the entities' dynamics is local to a state where the effect is global (Thiéart, 2000). Catastrophic complexity is illustrated in several models, such as the sand pile model with few large avalanches and lots of small ones (Christensen et al., 1991) and the study of stock market dynamics (Bartolozzi et al., 2005).

2.3 A Comparison Between Complex System Theories

Identifying the theory that corresponds to one's CS model is very important. It facilitates the analysis and comprehension of the CSs' dynamics and behaviours. The synthesis of our readings on CSs allows us to establish a summary of the main behavioural characteristics of different CS theories. Thus, Table 1 facilitates the understanding of the depicted CS theories and helps compare them.

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

Behavioural characteristics	Complex System theories				
	Complex Adaptive Systems	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	Adaptability 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					

3 SIMULATING COMPLEX SYSTEMS

In general, the simulation is the imitation over time of the operation of a real world system or process. It is to create a virtual laboratory that is as similar as possible (from the designer's point of view) to the original system.

"Simulation is safer, more feasible and flexible, and possibly much less costly in practice" (Chen et al., 2012). Indeed, 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. Simulation can be summarized in designing a modelling that allows the study of the system's behaviour during its evolution over time. It gives a precise description in a given experimental context using a symbolic or theoretical language. The modelling is followed by the development of a simulator, which is a computational tool that implements the designed modelling and generates the desired behaviour. It can be considered as a measure of the modelling rather than the real system (Chen et al., 2012; Obaidat and Papadimitriou, 2003).

We identify and compare the approaches used in modelling CSs. In fact, some researchers, e.g. (Müller, 2013; Le Moigne, 2003), suggest that there are three main approaches for modelling CSs, namely, the analytical approach, the systemic approach and the constructivist approach. Others, e.g. (Laperriere, 2004), argue that the constructivist approach is a sub category of the systemic approach. However, both parties agree that the constructivist approach stems from the systemic approach.

We believe the fundamental reason for this difference is that the second classification relies on a methodological definition of constructivism that, according to Avenier (2011), deals with "the methodology or the sociology of knowledge" and does not claim any particular "constructivist epistemological legitimacy". On the other side, the first classification deals with constructivism as an epistemology containing other dimensions in addition to the methodological one: thegnoseological dimension (knowledge formation) and the ethical dimension (knowledge validity) (Nelissen, 1999). In our case, we are interested in constructivism as a method of CS modelling. Therefore, we choose the second classification, without refuting the first one.

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 elements' behaviours. And these pre-programmed details are the ones that guide the study and its understanding (Krichewsky, 2008). This approach works by breaking down the entire system into a set of sub-systems. Then it focuses on each part separately in order to understand or model it. In the end, the addition of these model parts 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 and still reflects the state of each individual, e.g. (Thomas et al., 2014). However, it is of limited use if the heterogeneity of the environment and the heterogeneity of the characteristics/behaviours of entities are too high to be reasonably described with variables (Breckling, 2002).
- **Stochastic processes:** In the study of some CSs, hazard can be very important in determining the outcome of the system. The difficulty of modelling what Lam (1998) refers to as "the interplay of chance and necessity" 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 rely on random calculations. They are widely used to represent hazardous dynamics, e.g. the modelling of stochastic description of human feelings (Carbonaro and Giordano, 2005).

For instance, genetic algorithms are one of the best known stochastic methods. They represent a research technique mimicking natural selection in which some individuals are eliminated and others are held to generate other individuals. Another stochastic method is the Monte Carlo simulation. This method aims to empirically explain a statistic's sampling distribution. In this subject, Mooney (1997) states: "The principle behind Monte Carlo simulation is that the behaviour of a statistic in random samples can be assessed by the empirical process of actually drawing lots of random samples and observing this behaviour".

Thus, this method artificially generates the data that it uses and studies. Then it applies the studied procedure and investigates the behaviour expressed by these samples. The generated data resemble the real population in relevant ways (Chen et al., 2008; Lam, 1998; Mooney, 1997).

Limits of the analytical methods in modelling CSs: Differential equations and stochastic processes can be combined. Different 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 different behaviours of CSs; their deterministic aspect does not accurately represent the nonlinearity, non-determinism and unpredictability of CSs. In fact, these systems describe relationships as global parameters, and do not explicitly account for the fact that these relationships result from the interlocking behaviours of individuals. By consequence, analytical methods reduce the overall system into a set of parts, causing a loss of relationships and properties that could emerge from their coexistence. These methods are useful in modelling systems that have deterministic dynamics, predictable behaviours and centralized decision-making. As for the case of CSs, they can lead to ignoring and simplifying complex properties that could be important in CSs (Krichewsky, 2008; Thiétart, 2000; Parunak et al., 1998).

3.2 The Systemic Approach

This approach (also known as the global 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. This approach is based on the principle of interaction between the elements, and it can represent a large number of nonlinear interactions. The elements' behaviour is guided by objectives and not by details, which promotes complex behaviours, namely, emergence (Müller, 2013).

The systemic modelling goes both directions: top-down and bottom-up. The first way considers the system as a whole. It uses its macroscopic behaviour as variables to model the dynamics in the macroscopic scale, and it is often based on experimental observations. Top-down systemic modelling is known to be easy to understand and relatively simple. However, it does not explain the general behaviour of the system and cannot correctly

reveal the mechanisms responsible in case of emergence. On the other hand, the bottom-up modelling simulates the individual components and their interactions and then investigates the system's behaviour. It is suitable for studying emergence in systems with complex interacting components. Yet in some cases, the disadvantage could be that the model is too complex and difficult to grasp (Qu et al., 2011).

The systemic models can be categorized as traditional models or constructivist models.

3.2.1 Traditional Systemic Models

There are several traditional systemic models, such as:

- **Rule based systems:** they are based on an inference engine that uses uniform rules (like conditional rules) given by experts. They are usually easy to understand, to implement and to maintain because they gather knowledge in a uniform manner. Usually, these models 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. Neural networks are basically uninformative and considered black box models. Methods have been developed involving sensitivity analyses to understand why an artificial neural network is providing the responses it is (Chen et al., 2008; McCulloch and Pitts, 1943).

3.2.2 Constructivist models

Deriving from the systemic approach, 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, e.g. modification, creation, and destruction (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 models, microsimulation and Cellular Automata:

- **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. Among other examples, we cite the synergistic modelling of dialogues between people (Fusaroli et al., 2013).

- **Microsimulation (or micro analytic simulation):** It is a constructivist mathematical method that expresses the decision-making processes of an individual using probability (Koch, 2015). In other words, an agent behaves and interacts based on stochastic parameters, which reflects, for example, the agent's attitude or preferences. In fact, 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: intra-individual features do not interfere with their decision-making mechanisms. Also, individuals' behaviours can only be homogeneous (Laperriere, 2004).

Besides that, in both synergistic models and microsimulation, individuals are very independent. Thus, 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. In other words, if a macrostructure emerges from the sum of individual actions, it cannot be retroactive back to the individual (Koch, 2015; Laperriere, 2004).

- **Cellular Automaton (CA):** A CA is a spatial model that is discrete in space and time. It offers a simple and flexible way for modelling homogeneous populations residing in a physical environment. It is composed of identical cells in a regular grid. Each cell can either be empty, or it represents an agent. 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).

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, the

system's dynamics might face inaccurate restrictions like in social relations that become 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, which is not consistent with real life. Chen et al. (2008) explain that in order to avoid this problem, some designers choose to model a large CA grid that will dispel border errors. This solution could be effective, but it inflates another inconvenience with CA, that is the fact that all cells are recalculated at every step, i.e. even vacant cells are updated. For example, a CA for simulating people's movement (Sarmady et al., 2011).

3.2.2.2 Multi-Agent Systems (MASs)

A MAS is composed of a set of agents that evolve within a social network and a physical environment. These agents are dynamic and free in their movements, and the spatial dimension is not mandatory. Unlike in CA, the state of an individual depends on more than just its own state and that of its neighbours. Besides that, MAS agents evolve based on a complex set of rules that can differ from one agent to another (Siebers et al., 2010). This allows agents to have heterogeneous behaviours and represent different levels: genes, cells, organs, individuals, groups, organizations, systems, etc. Each agent influences others, changes its state or thoughts, and modifies its environment (Bagdasaryan, 2011; Qu et al., 2011). Besides that, just like in real life, an agent does not necessarily see the entire system, but rather keeps its own perception of things around him (Müller, 2002). This perception is subjective, and can be by consequence incorrect or incomplete.

A MAS can have spatial components that are represented via spatial agents or as part of the system's configuration. Agents can also be part of social structures. They have agency; i.e. the agents behave in a way that satisfies at best their personal goals. Such behaviour can be unconscious and deterministic. In such case, the agents make the same decision when put in the same situation, they are known as reactive agents (Frantz, 2012). On the other hand, the agents can rely on human-like thinking mechanisms to steer their own behaviours; such agents are known as cognitive agents. These latter use a deliberative architecture: they perceive, reason and execute. Their reasoning helps decide which is best (from their point of view) for achieving their goals/desires. In fact, cognitive agents are built on an internal state that can be expressed via beliefs, desires, preferences, intentions, emotions, etc.

The MAS paradigm allows modelling CSs when dynamics are determined by individual activities and inter-agent interactions and not by general laws. The behaviour of the system will emerge and therefore it is not modelled directly (Bagdasaryan, 2011). Besides that, the MAS paradigm is very useful in modelling social systems and simulating social learning mechanisms 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 in MASs, an agent can change his behaviour, yet according to him, behavioural rules in CSs are simple and unchangeable. At the same time, he considers CA suitable for complex modelling because the cells' behaviour is based on a set of simple rules. On the other hand, Hegselmann (1998) argues that "conventional CA have simple mechanisms to determine the state of their cells, but the same principle can be used with more complex mechanisms". From this point of view, CA and MASs can both model complex entities based on both simple and complex behaviours. These divergent views result from the difference in the definition of complexity science itself and has other repercussions, like the fact that Rouquier (2008) rejects stigmergy as a complex behaviour and supports the use of MASs in stigmergic systems. On the other hand, many other researchers – such as Macal and North (2010), Mittal (2013), and Doyle and Marsh (2013) – consider MAS to be positively suited for modelling CSs.

In light of the foregoing, we do not stand by Rouquier. We consider that the system's complexity can be described by entities with a simple set of behavioural rules, but can also result from an intrinsic complex behaviour of these entities. In other words, if a system expresses complex behavioural characteristics and has entities that behave based on complex mechanisms, it can still be considered as a CS. In such a system, the entities are not the bottom of the hierarchy. Deeper levels can be found within each entity, which goes in tandem with the multi-level hierarchy of CSs. Therefore, we support the use of MASs to simulate CSs. As examples of MASs, we cite the simulation of marketing research (Negahban and Yilmaz, 2014) and the simulation of people's movement in a city (Zhu et al., 2013).

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. Also, if the goal is to make predictions, then the model's accuracy is very important (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. behaviours, reasoning mechanisms, conflicts, and resources. In addition, since it is often used for simulating social networks and human behaviours, MASs require significant technical and interdisciplinary competences (Frantz, 2012; Bonabeau, 2002). It should also be noted that some researchers, such as Tissera et al. (2012), believe that the spatial dimension is underestimated in MASs because it is essential in many systems.

3.3 Comparing the Methods Used to Model Complex Systems

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

3.3.1 Analytical Approach vs. Systemic Approach

The analytical and the systemic approaches differ in principle. De Rosnay (1975) upholds that the analytical approach opposes to the systemic approach. He explains that in order to understand the overall behaviour of the system, 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. We compare the two approaches and we mention some of their differences in Table 2.

Lichtenstein (2014) states that an emergent phenomenon cannot be studied using a reductionist paradigm, as it "requires a fundamental shift in the worldview that underlies traditional scientific methodologies. This shift was the origin of the complexity sciences". Indeed, the analytical approach has its limitations especially in capturing the nonlinear or emergent behaviours within the CSs.

Yet we would like to point out that the analytical methods are still very useful in modelling such systems. In fact, in some cases, they can prove to be more suitable as a choice for modelling a given CS, e.g. the modelling for predicting obesity prevalence trends (Thomas et al., 2014). For example, if a system has processes that can be considered as

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

Analytical approach	Systemic approach
Reductionism	Holism
Predictable pattern, deterministic behaviour	Unpredictable behaviour
elements isolated from their environment	Element are not isolated from their environment
Linear, simple interactions	Nonlinear complex interactions
The temporal dimension is considered reversible	The temporal dimension is acknowledged as irreversible
The validation of events takes place by experimental evidence in the context of a theory	The validation of events takes place by comparing the functioning of the model with reality
Focuses on the elements' characteristics	Focuses on the dynamics of relations
Behaviours guided by details	Behaviours guided by goals

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. Such choice should greatly take into account the specific aspect that the designer aims to model and understand, and not all the phenomena that occur within the CS.

Furthermore, despite their dissimilarities, the two approaches can be combined. For instance, we can have a MAS with differential equation dynamics. In this particular case, Parunak et al. (1998) believe that the structure of MASs is more consistent with reality due to its multi-scale modelling and respect to natural boundaries. Thus, combining MASs with differential equations, is better than using only these latter. 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.

3.3.1 Comparing the Constructivist Models

Constructivist models, compared to traditional systemic ones, keep the link between the global behaviour and the local behaviours of the elements. They allow explaining the overall behaviour based

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
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 (limited to adjacent neighbours)	yes
	Intra-individual factors (other than cognitive)	no	yes	yes	yes
	Cognitive factors	no	no	no	yes

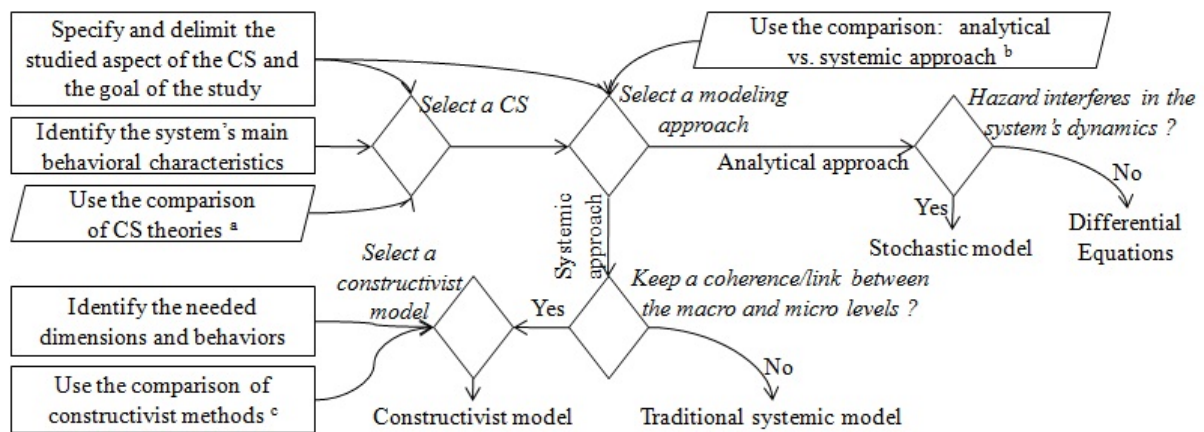


Figure 1: How to choose the appropriate model to simulate a CS in any study field of study. (a): see Table 1, (b): see Table 2, (c): see Table 3.

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 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. 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.

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.

4 CONCLUSIONS

In this article, we presented an overview of modelling CS. We first took a step back, studied the CS theory 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 a simple tool that lists some guidelines to help better understand one's complex context and choose the most adequate model to simulate it.

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.

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 for his needs, and make the final decision after a deeper analysis.

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