Fuzzy Worlds and the Quest for Modeling Complex-Adaptive Systems

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Abstract This chapter introduces the concept of fuzzy world as an ontological basis for modeling complex-adaptive systems. The concept is grounded on a phenomenological analysis of these systems over micro and macro scales. Discussion is developed from a recapitulation of some concepts of complexity science and complex systems modeling. Finally, the argument points out that fuzzy worlds find in fuzzy sets and systems theory a natural epistemological and methodological support.

1 Introduction

Complex systems surround our lives, these systems can be found not only across the natural world but also in technical worlds created by humans. Complex systems found in nature are so diverse that to develop a taxonomy for these systems has been a hard task. A very long list of complex systems can be given but surely a lot of pages should be written. There are some complex systems that are cited in literature for pedagogic purposes, for example ant colonies, flocking birds, oceans, cities, the atmosphere, the internet among others. We study about these examples superficially at some point of our basic education and we never hear about others in our lives. Although we are amazed by complex systems, most of the time how they behave remains a mystery for the majority of people.

Complexity science has emerged as a new field of study to tackle the problem of understanding the underlying mechanisms in complex systems, whereas complex systems engineering has been devoted to design and manage these systems. New categories have been identified as these two fields have been interacting, for example socio-technical systems refer to complex systems where both human and technology converge and socio-ecological systems describe the complex interaction of humans

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and ecosystems. In fact the convergence of the three dimensions (social, technological and ecological) has called the attention of a portion of researchers and managers.

Modeling complex systems is an important part of the whole picture and the computational intelligence community has not been indifferent to this challenge. This chapter follows this interest presenting a discussion about developing complex models for complex-adaptive systems (i.e. complex systems where learning and adaptation is possible) from the ontological necessity of capturing complexity at both micro and macroscopic scales. A phenomenological perspective is introduced in which the building block for constructing complex simulation models relies on the idea of *fuzzy worlds*, a concept that takes a different path from the well-known agent-based framework.

The chapter is divided in three sections: a brief summary about complex and complex-adaptive systems, an argument in favor of building complex models that capture some attributes of complex-adaptive systems and finally the presentation of fuzzy worlds and their role in the quest to model these systems.

2 Complex Systems

2.1 The Footprint of Complexity

Nowadays there is not a unique definition for the attribute referred as complexity [26]. In terms of behavior, it is often used as a synonym for irregularity, uncertainty or unexpectedness. On the other hand, when emphasis is given to structure, complexity may refer to the abundance of variables and their relations. The absence of a formal postulate that defines complexity does not restrict the possibility of pointing out some elements that configure the footprint of a complex system [5, 18, 28]:

- *Nonlinearity*: complex systems exhibit the characteristics of non-linear dynamical systems such as sensitivity to initial conditions and non periodic but recurrent behaviors. Some forms of chaos can appear in the evolution of a complex system given by the multiplicity of non fixed interacting elements inside it.
- *Emergence*: unexpected behavior is a nice term that can be used in this context to make reference to an emergent property. In a complex system these behaviors depend on it as a whole and can not be explained by reducing them in terms of the individual parts that configure the system.
- *Self-organization*: a complex system is able to promote an internal organization in ordered and coherent states for a long range. Such states can sustain hierarchical structures that control disorder at local scales.
- *Unpredictability*: predicting the evolution of the dynamics of a complex system can be a hard task, not only because of the dynamics itself but also due to the incapacity of the observer. The measurement act may be a perturbation introduced in the system resulting in a modification of the trajectory the dynamics was following. In addition that modification can go back perturbing the observer, thus a sort of

communication is established between the system and who is observing it [28]. This deep interconnection implies that there would not be an ontological difference between both [16].

2.2 Levels of Analysis

The perception of complexity in a system is subject to the scale in which observations are made. Thus the analysis of complex systems should be performed in terms of a hierarchy of description levels. There is a serious connection between the level of description and the different epistemic perspectives that can guide the analysis process of the observer [27, 40]. A brief summary of such levels and related epistemic approaches is presented as follows:

- *Microscopic*: this is the level of fundamental interactions among the entities that constitute the complex system. Both Newtonian and quantum systems may be described from this level. That description is often characterized by an universality nuance in terms of laws that govern the behavior of such entities. These laws can be understood as minimal algorithms that determine the dynamics of the elements of the system.
  The perspective that guides the analysis in this level of description is grounded on deterministic postulates. The dynamics of the complex systems can be studied in terms of universal principles like the Newton's laws or the Schrödinger's equation, which govern the behavior of the multiple entities inside the system. Deterministic chaos is often found in these cases due to the variability induced by the interaction among the entities.
  Even though this level of analysis seems to be strictly destined to deal with systems governed by laws over their microscopic entities, it has been recognized the possibility of using it for approaching to systems where no complete knowledge of the rules is available, for example social systems [9]. However, the ignorance about rules would motivate to develop an approximation from other levels of analysis.
- *Macroscopic*: a new set of variables can be constructed from the multiplicity of entities found in the microscopic level. This set models the collective properties of such entities. Its dynamics is induced by clusters of microscopic processes. Therefore the number of macroscopic variables is much fewer than the entities that shape the system.
  Equations that describe the behavior of macroscopic observations are presented as a balance between sources and sinks. This behavior often emerges as a nonlinear dynamics which is not reversible in time. On the other hand, dynamics of macroscopic variables can be understood as the smooth expression of all microscopic descriptions.
  Expected variability in macroscopic levels is smaller than in microscopic ones. Thus the macroscopic description is understood as an average of microscopic

irregularities that retains wide scale features. In epistemic terms, the macroscopic representation is an empirical or ad hoc model that should be experimentally verified.

- *Mesoscopic*: an intermediate point between the previous levels can be sketched. Involved variables in this level are an extension of the macroscopic set. Possible descriptions of dynamics must consider the uncertainty associate to the variability of microscopic processes. Evolution in time should be understood in terms of a set of trajectories with finite fluctuations that can be modeled as a footprint around an average dynamics.
  The nature of variables is assumed as random so that the system dynamics is studied in terms of how probability distributions evolve in time, for instance by using the Fokker-Planck equation [27]. The analysis of a complex systems in the mesoscopic level tries to model the uncertainty, which is classically performed by means of probability theory, however other ways are being investigated such as the possibility theory approach [20].

2.3 Complex-Adaptive Systems

From the spectrum of complex systems, those with learning and adaptation abilities are of special interest, particularly when these properties arise in the macroscopic level. These systems have been called as *Complex-adaptive systems* [18] since their internal configuration promotes the emergence of phenomena such as anticipation, collective behavior and evolution.

Human social systems configure an interesting class of complex-adaptive system whose main particularity is to set purposes not only in its interacting elements but also in the whole picture that identifies it [1]. The modeling of human social systems has followed different paths which cover mechanistic, organismic and more recently evolutionary approaches [10]. The main focus of these models are not the entities of the system (i.e. agents) but the rules that they generate and carry [9].

Approaching a social system implies taking advantage of an epistemic evolution to be able to capture the evolution of the dynamics of the system [35]. The multiple transformations that can occur from the adaptation of a social system make the search for its understanding only in terms of its parts too narrow. Thus to assign the category of "system" to a phenomenon demands an a-priori understanding of the context not only from the parts but also from the relations between them, which is the point where the purposes that identify the system can be observed.

Social systems demand an epistemology that recognizes the same definition of system may be dynamic, so that the epistemic background of social systems can be itself complex by integrating several forms of knowledge, for example one of them the approach from engineering [22]. Entities that shape the system can interpret it and disturb its original purposes, thus agents are at the same time parts and designers of the system. One relevant aspect of social agency is its immersion in technology [15], which makes human systems to be treated at same time as social and as technical systems. This particularity produces in socio-technical systems, such as cities, the emergence of very unique properties that other similar complex systems found in nature do not exhibit [7].

Models for complex adaptive systems, in particular socio-technical systems, can be constructed from different epistemic perspectives. These go from the qualitative approaches of social sciences to the quantitative models of physics, crossing by the organismic models of biology [1], the agent-based models of computer science [13] or the rule-based models of the evolutionary economics [29] among others. An interesting aspect of these models has to do with the purpose behind them. Although prediction seems to be the unique purpose of modeling, today a multiplicity of purposes have been recognized which are connected to the intentions, perspectives or interests of the modeler [12].

3 Complex Models for Complex Adaptive Systems

3.1 Types of Complex Systems and Their Modeles

Complexity of a system is a wide concept that can be studied from different perspectives without the availability of a formal definition. The perspective that will be followed is described extensively in [3], which is focused on typifying a complex system according to its structure and the necessary knowledge to model and manage it. According to this framework complex systems can be typified as follows:

- *Type-I* complex systems are those whose dynamics is governed by simple rules but the system exhibits interesting behaviors such as irregular oscillations, chaotic attractors, self-organization and emergent properties. Models for this type of system are usually represented by regression equations, nonlinear differential equations, information flows etc. Some examples of this type are tectonic plates, sand piles and some cellular automata among others, whose dynamics can be explained from the Self-Organized Criticality (SOC) theory [4].
- *Type-II* complex systems are characterized by their diversity of rules, interacting processes and scale-dependent behavior. Models of these systems should capture both the multiplicity of rules as well as the scale transitions. Nowadays several examples are found: mental maps, fuzzy differential equations and hybrid intelligent tools. Spatial phenomena like territory transformation and land use in cities can be explained from this type of complex system.
- *Type-III* complex systems come in the scene when managing several perspectives towards particular common objectives of human agents. These agents interpret in different ways the dynamics of the system. Interpretations may produce consensus that is influenced by the emergent properties of the system in the long term. Several models that deal with this kind of complex behavior have been developed from decision theory.

- *Type-IV* complex systems exhibit macroscopic structures designed by societies to promote self-management. These systems are composed by diverse actors such as national governments, industries, local governments, universities among others. Part of the agents in the system often generate strategies focused in promoting the ultimate goal of controlling the system in several scales

When looking at the previous typification, complex adaptive systems may be included in type 3 or 4, however this observation does not discard that these systems can be studied from the other types of complexity. When approaching a complex adaptive system, models would be structured from the first two types of complexity so that they can be nurtured in the process from latter ones. Note that there is not particular emphasis regarding modeling tools in types III and IV. To develop these tools is currently an open problem.

3.2 Modeling Complex-Adaptive Systems

Constant adaptation in a socio-technical system compromises the controllabilty of its behavior given its unpredictable nature. Thus system dynamics theory can offer helpful insights about the modeling of these systems [34]. Models in this perspective are designed to understand the dynamics of the system rather to cope with its accurate prediction. Diverse epistemic perspectives should be taken into account when conceiving these models, transcending the purely scientific perspective [14].

Modeling complex adaptive systems demands today an understanding exercise that goes beyond the reductionist approach of traditional science. The whole is more than the sum of its parts is a well known premise in this quest and not necessarily the simplest explanations, tested under same conditions, are correct, challenging the Occam's razor [24]. The ultimate goal of modeling a system of this kind is to capture some of its properties in an artificial representation. That movement from reality to the representation depends on the intention of the modeler regarding the model [12, 30].

Modern science has encountered in simulation a valuable tool for dealing with complexity [12]. Simulation models of complex adaptive systems must approach complexity by being also complex. The idea that a reductionist simulation model exhibits the richness of a complex dynamics is indefensible today [33]. Therefore adaptations in a complex system should be transferred to the model, which is only possible as long as it is able of self-organization.

The process of modeling a complex adaptive systems requires a reduction of complexity without omitting essential components. In the end the model is still complex since the real system is so [38]. A minimal simulation model is necessary that preserves key elements of the system. Including additional components would not necessarily give useful knowledge, but surely increases the computational cost of the simulation. Therefore simplest complex models can be used to guide the initial discussions about the system, whereas more detailed models are preserved for a posterior deeper analysis. To capture the entire footprint of complexity of a system in a simulation model with reasonable costs in time, effort and resources is today an open problem [6, 33, 37].

Transferring complexity from the system to the model is critical and invites to think about several questions: Is just one modeler able to transfer a good portion of the complexity from the system to the complex model? Should the transference of complexity be performed by a complex adaptive system composed by modelers and intelligent modeling tools? Which characteristics should this system have? Is it sufficient one complex adaptive system to model another one? Supposing the complexity of a system can be quantified, would not be necessary a more complex system to perform the modeling task? Some of these questions are partially considered in [3, 39].

Designing a complex system is a process guided by learning and evolution. It embodies a metaphor in which modeling agents interact collaboratively in the integration of micro-worlds (i.e. elements of the system) like children constructing a toy from constructions blocks [8]. Thus a complex system can be interpreted as a macro-world shaped by the ensemble of micro-worlds, which are more than being interconnected, they are entangled.

The process of configuring a simulation complex model can be delineated from the previous metaphor. Simulation micro-worlds are configured in order to structure simulation macro-worlds that shape the model of the complex-adaptive system. This is similar to the model building approach of systems dynamics [34], however micro-worlds a key differential element.

In models of complex-adaptive systems, micro-worlds can be configured as networks of agents or rules, however these networks can also be the result of self-organizing agents. Assign a purpose to self-organized networks is somehow fuzzy, but these may represent small associations or territories. Macro-worlds would emerge as the interconnection of smaller worlds reflecting a wider organization supported on interacting associations. As a result, it would be expected that emergent macro-worlds operate in several scales.

The simulation building blocks are based on the presence of cognitive agents [36], which represent human beings. Given their autonomy, plasticity and openness to be, establishing an guiding theory about human behavior is not just around the corner [19]. The way in which humans relate to technology they build is conditioned by their autonomy [2]. In the end, each agent can freely interpret the objects that are part of its world. Therefore, visualizing the consequences of this relationship would exceed any analytical effort.

Although capturing the whole complexity of a human being in a cognitive agent would be unsuccessful, this does not imply that to approach this goal can not be developed from some perspective. Complex system engineering as well as multi-agent systems methodologies can find inspiration regarding this task in different representations of the world, for example in [32] a combination of attachment theory and ant colony algorithms is proposed to study the properties of some human social systems. However, the purely scientific character given to the problem of representation is up to date a difficulty in human systems simulation [11, 36].

4 Fuzzy Worlds

One of the fundamental aspects of agent design focused in human behavior is the problem of interaction. Communication is a key element in the interaction between humans and their organizations [19]. It requires a common ground where humans share interpretations of their world in terms of rules. In the design of a complex model using the building block metaphor, agents in micro-worlds may satisfy the condition of common ground. In a group of agents that share the same environment, each agent can interpret the context in a particular way thus its world acquires a different dimension regarding the other agents. Therefore the agent and the world are one.

The human agent may be represented as an evolving process [31] that relates rules and the surrounding field, instead of a an independent element that interacts with its environment [11]. Thus there is no clear boundary between the agent and its world. Figure 1 presents a comparison between the classical vision of an agent (Cartesian) and an agent which is immerse in the world, called here as the Heideggerian perspective on an agent. In the classical perspective the boundary that separates the agent and its world is well defined, on the other hand the boundary is fuzzy in the Heideggerian perspective [23].

Immerse agents in a micro-world play a variety of roles in different moments, however these roles may be modified by new rules or relations between existent rules. Role changes would develop in a temporal scale, therefore the structure of the world that was consistent with existent roles gives way progressively to a new one. Adaptations in agents promote adaptations in the world. The agent is able of transforming its world, however the world strikes back by also transforming the agent. Thus talking about one necessarily refers to the other (i.e. fuzzy world).

If a modeling approach for complex adaptive systems following this perspective is attractive, emphasis would be given to micro-worlds rather than agents. This imposes a challenge to incorporate the self-interpretation of the human agent as a part of the model. According to [15] self-interpretation is given by the direct interaction with the world without any kind of mediation. Hence the traditional approach of artificial intelligence, where the agent has an internal representation of the knowledge of its desires and intentions expressed as a logic the agent uses to deliberately infer, must

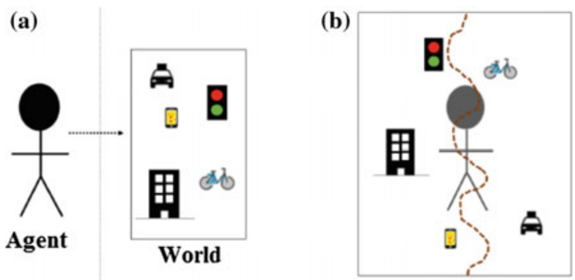

Fig. 1 **a** Classical agent (Cartesian), there is a clear boundary between the agent and the world. **b** Immerse agent in the world (Heidggerian), the boundary between the agent and the world is fuzzy

be reformulated [36]. The simulation micro-world should be able of executing a self-modification according to perturbations induced by itself or other micro-worlds which is entangled with.

Should the conception of building blocks based on fuzzy worlds be developed as a purely scientific task or as a convergence field of different kinds of knowledge? To talk about a complex-adaptive system by itself is already imposing a particular way of looking at reality, since relations between agents are understood as flows of mater, energy or information. Giving this connotation implies to uncover the human dimension as something susceptible of being modeled and computationally represented. A purely scientific perspective to define a fuzzy micro-world would require guiding theories of a "computational human nature" which would be in the opposite direction of the opening to the be.

Although the scientific approach to fuzzy worlds would find a contradiction, the quest for modeling complex adaptive systems from this perspective should be faced in the aim to grasp something about these systems. The uncertainty regarding the comprehension of these systems can not be controlled, however to cope with is a possibility. The paradigm of fuzzy sets or its several ramifications (i.e. interval fuzzy sets, type-2 fuzzy sets, intuitionistic fuzzy sets, etc.) [20, 25] can be used to model the inherent uncertainty of a micro-world. Modeling a fuzzy world in this sense is a design exercise that should find inspiration in both experience and language.

Engineering can think about the modeling of a complex-adaptive systems as a design process that creatively and rigorously connects building blocks [21, 22]. Reality is susceptible to be captured not by fragmentation (i.e. analysis) but by aggregation (i.e. synthesis). This process is performed having in mind the necessity of a minimum representation of the complexity. Hence aggregation should be understood as the confection of an entanglement of fuzzy worlds, where scale should not be a problem since micro and macro worlds are mutually related.

A graphical representation of entangled fuzzy micro-worlds is depicted in Fig. 2. The vision of interaction (between agents) is replaced here by the vision of entan-

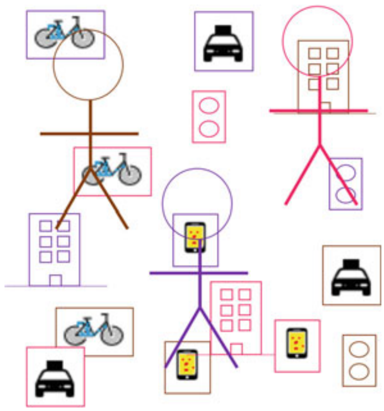

Fig. 2 Entangled fuzzy micro-worlds. Same pieces of reality can be interpreted in different ways. Each color (cyan,purple and brown) represents a particular way of interpretation

glement (of worlds). Entangled fuzzy micro-worlds are enriched by the diversity of interpretations about the human and technical phenomena that converge in the aggregation. Note the notion of complexity is extended here since the premise that the whole is more than the sum of its parts is debatable in the sense that the parts are not simple. Complex macro-worlds can emerge from the entanglement of fuzzy micro-worlds which is also complex. Hence this perspective of modeling is revealing that complexity would be scale-free attribute in complex-adaptive systems.

The building block as the entanglement of fuzzy micro-worlds embodies a paradox since it is an element which is at same time a complex phenomenon. It can be the size of a micro-world or several micro-worlds. The building block contains agents that interpret their own worlds, but also worlds that modify the agents. The same argument can be extrapolated to the construction of a macro-world from micro-worlds: the macro-world is shaped by micro-worlds but these are modified in the construction process. Figure 3 depicts the entangling process of macro-worlds W_A and W_B that are composed of several fuzzy micro-worlds (micro-worlds that share common attributes are represented by the same color). Notice the final entanglement produces a new fuzzy micro-world. This is possible since macro phenomena (i.e. structures, organizations, etc.) can introduce new rules or interpretations in the context of an existent micro-world.

The mental exercise around this entangling process evokes the phenomenology of the worldliness of the world [11, 17], paraphrasing: If a common structure for the sub-worlds of a world is discovered then the structure of the world has been found. If there is one common structure of the sub-worlds, this same structure should be

Fig. 3 The entangling process of macro-worlds W_A and W_B. Micro-worlds that share common characteristics are depicted with a particular color (orange,gray and black). In the end, the entanglement of macro-worlds produces a new micro-world (blue)

discovered in the world that contains these sub-worlds. This consideration allows to think about the structure of the world as self-similar no matter the scale.

One of the purposes of phenomenological analysis is to discover the structure of the world. Interpretation is in the heart of this analysis which is grounded on natural languages. If the paradigm of computing with words [24] is used to interpret the dynamics of sub-worlds in a complex-adaptive system, the model can be understood as a linguistic phenomenology of the system. In this context fuzzy worlds can be modeled by means of the perceptions and their relations given by one or several observers. Thus fuzzy sets and systems would be the natural representation mechanisms for fuzzy worlds.

A graphical view of two linguistic phenomenologies is depicted n Fig. 4. A macro world is considered where the word "high" is being interpreted from the analysis of a linguistic variable in the fuzzy worlds. Phenomenology represented in Fig. 4a makes use of a type-1 fuzzy set [20] to model the word. The set has been used to produce a heat map over the macro-world given some numerical observations surveyed from the worlds. The observer interprets the current state of the system is a kind of isotropic dissipation from the center to the corners. Another phenomenology is presented in Fig. 4b where the same word "high" is represented as an interval type-2 fuzzy set [25]. In this case linguistic phenomenology represents the interpretation of two observers about the system. Both agree that an isotropic dissipation is happening in the current state of the system, however one of them perceives a faster dissipation dynamics.

The fuzzy world concept can be considered as an ontological basis for modeling complex-adaptive systems grounded on phenomenological analysis. It finds in fuzzy set theory and fuzzy logic a natural epistemological and methodological tool to support the process of modeling. Although the fuzzy systems perspective has been used in the past to deal with complex systems, the ontological perspective introduced

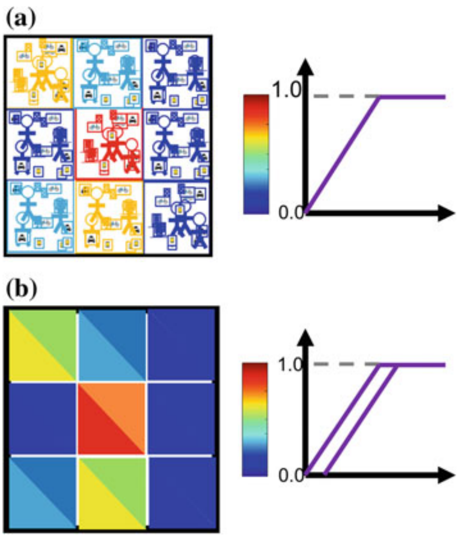

Fig. 4 Linguistic phenomenology of a macro-world: **a** Captured by a type-1 fuzzy perception, **b** captured by an interval type-2 fuzzy perception

by fuzzy worlds points out a different path regarding the classical approach of agent-based modeling. Formalization of fuzzy worlds and its application to complex system engineering should be a matter of near-future discussions.

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