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UNDERSTANDING COMPLEXITY IN ECONOMIC SYSTEMS WITH AGENT BASED MODELING

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***Abstract*-The science of complexity contains a plethora of models and ideas through which we can interpret and understand the world around us. Thus, we keep an eye on reality throughout, touching on the practical benefits of gaining an understanding of complex systems. Agent based modeling is a methodology that has been driving a lot of research in complex systems. In this work, we present how agent-based models enable us to explore and understand complexity in economic systems.**

Keywords -Understanding Complexity; Emergence; self-organization; Agent based modeling; multi-agent simulation; Agent-based Tool; Economic systems;Complexity economics.

I. INTRODUCTION

Although definitions of complexity vary greatly and are still a field of mines terminology, the scientific community agrees that the characteristics of complex systems are: a large number of autonomous entities, sensitivity and criticality to initial conditions, different organization levels, dynamic structures, emergent and self- organization properties [1].
Complexity exists in diver's fields: Economies, political systems, social networks, ecologies, and even our brains can be thought of as complex;
Understanding complex systems is done by their modeling. To do so, the approach of Agent based modeling (ABM) appears to be the best answer to the needs of the complexity theory [2].
In this paper, we present complex system, emergence and self-organization, and we expose the benefit of using agent-based modeling approaches, to modeling and simulating complex systems and we illustrate how they allow us to understand complexity in economic systems with are considered as complex systems.

II. COMPLEX SYSTEM, EMERGENCE AND SELF-ORGANIZATION

A system will be complex if the whole transcends the parts. Complex systems consist of diverse entities or agents that interact both in space (real or virtual) and in time who are connected behaviors and actions are interdependent and who adapt [3]. For example when we see that economic systems are complex because they have diverse producers, firms are connected to suppliers in a supply network and interdependent between them, also they're adapting to a changing environment.

Complex systems produce bottom up emergent phenomena, where what occurs on the macro level differs in kind, from what we see in the parts, Emergence takes many forms, including self-organization. This occurs when we get some sort of spatial pattern or structure: flocking of birds, schooling of fish, or in physics, crystal structure are what we call self-organization phenomena.
Complex systems product unbelievable novelty, all these interacting diverse things can produce all sorts of new, exciting things [3].

III. MODELING AND SIMULATION OF COMPLEX SYSTEMS

Epstein defined modeling, as the development of a *simplified* representation of *something*. Epstein also clarified misconceptions about modeling and simulation giving a list of different reasons for modeling [4].

A model of a system is a simplified mathematical representation of this system, which should be as simple as possible but, however, being able to capture the key elements of the system allowing to eliciting highly relevant questions [5]. Simulation model is a set of instructions, rules, equations or constraints for generating input and output behavior [6].

While it is easy to make models of some aspects of a Complex system, it is quite difficult to model it entire and its emergence [7]. Previously, a number of aspects of the Complex System have traditionally been modeled using simplification of complex components of aggregates [5], for example, by using differential equations, system dynamics or Monte Carlo simulations. Mathematical models rely on the identification of the key system components, often representing them in a discrete manner. This limits mathematical models because emergence present in complex systems arises as a consequence of local interactions, and cannot be previously identified as a key system component [8]. Mathematical models are analogues, but cannot provide significant insight into the continuous internal process of a complex system [9]. Moreover, they only take into consideration the global point of view, usually not explaining

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the reasons locally leading to the global behavior of the modeled system [10].

However, more recently, we can see by examining the literature that Complex System researchers often prefer to use agent-based (or individual) modeling approaches, to modeling and simulating complex systems [Schelling 1971 [11]; Ray et al 1991 [12]; Palmer et al, 1994 [13]; Epstein and Axtell 1996 [14]; Berry et al, 2002 [15]; Macy and Willer 2002 [16]; Grimm and Railsback 2005 [17]; Gilbert 2007 [18]; Page et al, 2008 [19] ; Niazi and Hussain [7].

IV. AGENT BASED MODELING

According to Ferber [21], Wooldridge & Jennings[28], Weiss [29] and Russell & Norvig [30], Agent based models consist of entities of various types endowed with limited memory and cognitive ability and they are embedded in some sort of network, and the behavior of these agents are interdependent .A key assumption will be that the agents follow rules. Nowadays, the rules are written in computer code, and the behavior of the models can be watched on a computer screen. The rules that agents follow can be simple and fixed, or they can be sophisticated and adaptive.

In Agent based models, the agents take discrete actions, they decide to move locations, switch from being cooperative to defecting, or change whether to join or exit a particular activity. Because that, the rules they follow are threshold-based [3]. "Threshold-based" means that the agent's behavior remains the same unless some threshold is met. Once that threshold is passed, the agent change its behavior. These threshold effects can produce either positive or negative feedback.

All complex models can be constructed as agent-based models, the goals are to make predictions that can be empirically falsified, to explore and to run counterfactuals.

V. MULTI-AGENT SIMULATION PRINCIPLE

The multi-agent modeling and multi-agent simulation allows studying and understanding complex systems. It represents complexity of a phenomenon through the interaction of all its agents [21].

According to Drogoul [22], the Principe of multi-agent simulation can be shown in Figure 1. The real phenomenon is decomposed into a set of elements that act or interact. Each of these elements is modeled by an agent, and the general model is the result of interactions between agents.

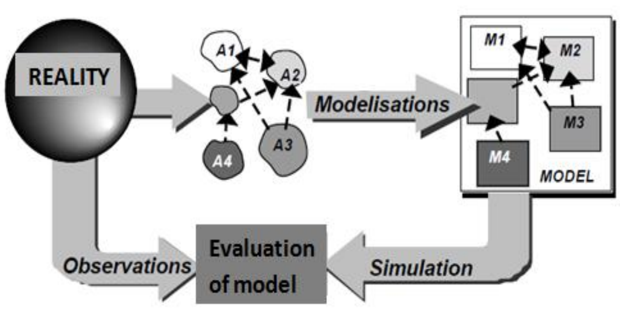

Fig. 1Multi-Agent Simulation principle according to Drogoul [22]

The multi-agent simulation provides solutions to the limitations of the mathematical approach [25]. It allows to:

- Represent the inter-temporal phenomena in economics;
- Represent, through the MASs, heterogeneous behavior;
- Ignore the assumption loopback model and represent for example changes without a constraint demand or budget;
- Represent a continuously evolving system and consequently avoids the account equilibrium;
- Consider the consequences of strategic choices on the properties of resources committed by the agent in the competitive process (integration of changes and innovations).

In multi-agent approach other properties, can be given to an agent but they are difficult or impossible to have its in mathematics equation, they are listed below [26]:

- Birth, death, and reproduction
- Individual needs of resources (i.e.to eat and drink)
- Competition and fighting ability
- Tool making ability (i.e. the possibility to grow food, hunt etc.)
- Perception
- Curiosity, exploration behavior, ability for innovation
- Emotions
- Memory and future expectations
- Mobility and carrying capacity
- Communication
- Learning and teaching ability
- The possibility of trading and exchange
- The tendency to have relationships with other agents (i.e. family or friendship ties etc.).

The multi-agent simulation preserves also the heterogeneity of the system to be simulated, as it represents multiple levels of granularity in heterogeneous systems [21].

VI. ECONOMIC SYSTEM AS A COMPLEX SYSTEM

According to Arthur [2]: "*Complexity economics holds that the economy is not necessarily in equilibrium, that computation as well as mathematics is useful in economics, that increasing as well as diminishing returns may be present in an economic situation, and that the economy is not something given and existing but forms from a constantly developing set of institutions, arrangements, and technological innovations*".

According to Tesfatsion [20] Economy is a complex system,and complexity in economic systems it is due to:

• Large number of economic agents involved in local interactions, which are distributed;
• Information in the two directions between the microstructure and macroeconomic patterns induced by the interactions of agents;
• Uncertain invasive behavior;
• Potential existence of multiple equilibriums;
• Critical Role of institutional arrangements.

VII. UNDERSTANDING COMPLEXITY IN ECONOMIC SYSTEMS WITH AGENT BASED MODELING

To understand the complexity in economic systems, we must model it's, and as we have seen, multi-agent systems are an effective tool for modeling complex systems. Multi-agent systems allow to model economic systems by building their global structures based on agents that interact with each other; for each agent its micro states are defined (e.g. microeconomic states: firm's output, consumption levels, etc.) and also its micro parameter (e.g. endowments, firms' factors productivity, workers' reservation wages, consumption elasticities, etc). Through these interactions between agents, a macro behavior emerges. Macro level represents the whole system with new properties that are not found in any of the individual components, and this emergence represents the root cause of the complexity in these systems.

We can describe agent based modeling structure with eight elements, which are presented as following [27]:

1. Time: We typically model a system evolving in discrete time steps, i.e. $t = 1, 2, \ldots$
2. Agents (or Actors): The system is populated by a set of agents $I_t = \{1, 2, \ldots, N_t\}$. In many examples, but not necessarily, a constant population size is assumed ($N_t = N$).
3. Micro States (or Actions): Each agent $i \in I_t$ is characterized by a vector of L microeconomic states (or micro-variables) $x_{i,t} = (x^1_{i,t}, \ldots, x^L_{i,t})$. These variables are fast ones, which can be endogenously modified by agents' decisions (e.g. firm's output, consumption levels, etc.)
4. Micro-Parameters: Each agent $i \in I_t$ is also characterized by a vector of H micro-economic parameters $\theta i = (\theta^1_i, \ldots, \theta^H_i)$. Micro-parameters are slow-variables, i.e. quantities that cannot be endogenously modified by the agents within the time-scale of the dynamic process. Therefore, θ_i typically contains information about behavioural and technological characteristics of agent i (e.g. endowments, firms' factors productivity, workers' reservation wages, consumption elasticities, etc.
5. Macro-Parameters: The system as a whole is instead characterized by a vector of M time-independent macro-parameters $\underline{\Theta} = (\Theta_1, \ldots, \Theta_M)$ governing the overall technological and institutional setup. Once again, $\underline{\Theta}$ are slow-variables and cannot be modified by the agents. Examples of $\underline{\Theta}$ parameters are the level of opportunities in a technological environment, the strength of unions in wage-bargaining, etc..
6. Interaction Structures: At each t, the way in which information is channeled among agents is governed by a (directed and possibly weighted) graph G_t containing all directed links ij_t currently in place (i.e. open) from agent i to agent j. The existence of a directed link ij_t means that agent i, when updates his micro-variables $x_{i,t}$, is affected by the choices made in the past by agent j (i.e. past j's micro variables)
7. Micro Decision Rules : Each agent is endowed with a set of decision rules $R_{i,t} = \{R_{i,t}(\bullet \mid \bullet), b = 1, \ldots, B\}$, mapping observable variables (e.g. past micro variables of relevant agents, micro and macro parameters, etc.) into next-period micro-variables $x_{i,t+1}$. Examples of such decision rules are: production functions, innovation rules, consumers' demand, etc..
8. Aggregate variables: By aggregation (e.g. average, sum, etc.) of micro-variables, one K obtains a vector of K macro-variables $X_t = (X^1_t, \ldots, X^K_t)$ which contain all macro information relevant to the analysis of the system.

Thanks to this structure based agents; we can understand and analyze the results and the output of the economic system running from micro to the macro (witch present the emergence phenomena, the root cause of the complexity)by implementing a process which it depicted in Figure 2

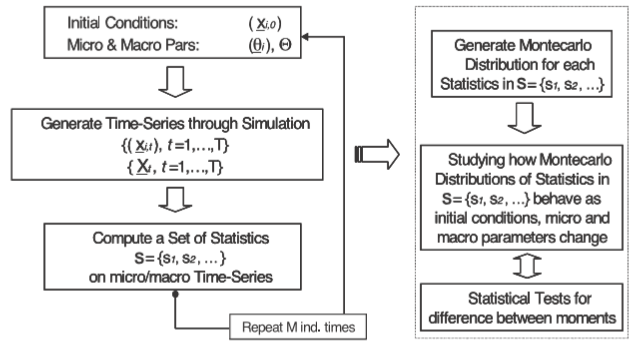

Figure 2: A schematic procedure for understanding the output of Economics Agent-Based Models [27]

VIII. AGENT-BASED TOOL FOR MODELING AND SIMULATING COMPLEX SYSTEMS: NETLOGO

NetLogo has been developed from grounds up for complex systems research. Historically, NetLogo has been used for modeling and simulation of complex systems including multi-agent systems, social simulations, biological systems etc., on account of its ability to model problems based on human abstractions rather than purely technical aspects [7].

NetLogo is used to build an endless variety of simulations. Members of user community have turned turtles into molecules, wolves, buyers, sellers, bees, tribespeople, birds, worms, voters, passengers, metals, bacteria, cars, robots, neutrons, magnets, planets, shepherds, lovers, ants, muscles, networkers, and more. Patches have been made into trees, walls, terrain, waterways, housing, plant cells, cancer cells, farmland, sky, desks, fur, sand, you name it. Turtles and patches can be used to visualize and study mathematical abstractions, too, or to make art and play games. Themes addressed include cellular automata, genetic algorithms, positive and negative feedback, evolution and genetic drift, population dynamics, path-finding and optimization, networks, markets, chaos, self-organization, artificial societies and artificial life. The models all share our core themes of complex systems and emergence [24].

It is particularly well suited for modeling complex systems evolving over time. Modelers can give instructions to hundreds or thousands of independent "agents" all operating concurrently, in order to explore connections between micro-level behaviors of individuals and macro-level patterns that emerge from their interactions [23].

IX. CONCLUSION

Complex systems are inherently interesting, producers of amazing novelty, and not clean and simple, which makes them a lively playground for the mind. Complex systems are where the action is. The fundamental challenges of our time are all complex.

In this paper, we have seen that Agent-based models (ABM) can provide empirical with understanding of macroscopic features nature without top-down control. In addition, ABM can provide normative investigation, testing the qualities of different designs, looking for one that gives desirable system performance. ABM can provide heuristic investigation of market phenomena, understanding of economic system behaviors under alternatively initial conditions. ABM sheds some new light on causal mechanisms in social systems.

We have also shown that mathematical approaches are limited to understanding complex systems and the agent based modeling approach is the most optimal concept that can model and simulate the interaction between different agents and explain phenomena and mechanisms associated with complex systems include emergence.

We have illustrate how multi-agent systems allow us to understand the complexity in economic systems by building their Economic agent based modeling structure which allow us to analyze the results and the output of the economic system running from micro to the macro (witch present the emergence phenomena, the root cause of the complexity).

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