



## Acceptability and Complexity: Social Scientist Dilemma, and a ABSS Methodology case example\*

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**Abstract** This paper considers the problem of trade-off between including theoretically required elements against excluding irrelevant levels of complexity, one difficult dilemma that all ABSS practitioners must cope with. Social scientists find hard to code even the most simple artificial societies, while they are expected to consider all kind of social complexity. It is argued that there exists heterogeneity between ABSS communities and it is presented a general characterisation based on the ordered set of preferences for two main variants. Therefore, with a commitment to the “academic variant”, some remarks are made about the acceptability of social simulation methodology among the social sciences scholars. Finally, it is presented a methodology to check the relevance of different levels of complexity, as candidates to be included into any ABSS -or as the core of a generic simulation builder-. This is made by means of some Netlogo simulation examples based on Fiske's theory about the sociality elementary forms, in a *quasi-experimental* way.

**Keywords:** Simulation, Artificial Societies, Scientific Communities, Sociology, Consumption, Netlogo.

**Palabras clave:** Simulación, sociedades artificiales, comunidades científicas, Sociología, consumo, Netlogo.

### Introduction

Agent-Based Social Simulation (ABSS) has become a crosspoint between two scientific communities: the AI community -via MAS development- and the Social Modelling community. As states Robert Axelrod [1], “*agent-based modeling is not only a valuable technique for exploring models that are not mathematically tractable; it is also a wonderful way to study problems that bridge disciplinary boundaries*”. Some earlier developments of multi-agent systems as an emerging software paradigm in the domain of artificial intelligence are closely related with Marvin Minsky ideas about the “*mind as society*” [2], so that it is easy to find a kind of “social flavour” in any MAS. Conversely, even the earlier developments of social theory or philosophy try to make some kind of modelling, not just empirically descriptive but “building ideal societies” in order to explore its consequences or to make experimental “control comparisons” with the actual ones. Extensive parts from the work of Plato, Moro, Campanella, Bacon, Fourier and other classic Utopian Social Thinkers could loosely illustrate it; but the current socio-economic developments related to the formalization tradition, and to the recent so called “analytical sociology”, can better illustrate this idea [3] [4]. So there are multi-agent systems, with such a social flavour, and there are many social theory, with such a formalization flavour. Then, ABSS can be seen as a clear connector -or bridge- between at least two disciplinary boundaries: those corresponding to part of the social scientists' community, and part of the computer engineering's community.

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The list of social processes and phenomena subject to research by mean of formalization methods, modelling and experimental computer simulating nowadays is large and is increasing -as the JASSS index can show [5]-. In addition, some recent books about general sociological theory incorporate some results from ABSS research [6]. But, in spite of the “clear bridge” and the growing interest, actually it can be said that the ABSS -or other kind of simulation- approaches are far from belong to the mainstream of social science research.

Our argument is that here we cope with the Social Scientist Dilemma: without a strong programming competence the social scientist finds hard to build even the most simple artificial society, but simultaneously the social scientist is forced to necessarily consider the high complexity of any social system. To solve this dilemma, for each research project, an ABSS researcher have to trade-off the amount of complexity that she/he wants to implement into the model (KIDS approach) against the programming learning-curve effort needed for that level of complexity (KISS approach).

### Theoretical Vs. Empirical Quality: Two Communities

Research is not an individual issue, but an institutional social practice, so the “satisficing<sup>1</sup> trade-off” criteria for the evaluation of a social simulation model are a matter of social scientists Community. Although there exist some efforts to establish quality standards for ABSS research and results dissemination [7] [8] there are still no clear, distinct and common guidelines available. This is a relevant issue, because the scientific acceptability of an ABSS research depends on the aforementioned dilemma.<sup>2</sup>

The question about the meaning of *satisficing trade-off* for social scientists leads to the problem of setting common criteria to evaluate the quality of any social research. A *satisficing* simulation research in any domain can 1) provide excellent quality in the simulated output data, fitting with actual empirical information (“*empirical quality*”, EQ), and can 2) be highly coherent with the set of theoretical mostly accepted and updated knowledge for the specific domain -both in the “fine grain” description of the model, in the rules governing the system evolution throughout the time, and in the initial adjustments of the simulation- (“*theoretical quality*”, TQ). These two cross dimensions provide a typology as shows Table 1.

Table 1: Empirical Quality Vs. Theoretical Quality.

	High TQ	Low TQ
High EQ	Excellence (ex)	Black Box (bb)
Low EQ	Validation needed (vn)	Insufficiency (in)

A plausible conjecture about the order or preferences among ABM practitioners is that there exists a significant degree of heterogeneity between different scientific or scholar communities. So, at least two extreme variants could exist: an *academic/research variant* (ex>vn>bb>in) and an *engineering/professional variant* (ex>bb>vn>in). As an example, in regard to computational economy, López Paredes has enunciated this distinction as follows: “*From an engineering approach it is pursued to generate ideal entities that could act in actual markets. From a social sciences approach it is intended to replicate the most realistic agents attainable taking part in artificial markets, in order to understand how the transactions among actual individuals get organized*”. [9]

There is no systematic research developed until now to confirm this general hypothesis about the heterogeneity in the arrangement of preferences, as well as to establish the specific characterization, for different communities of ABM practitioners. Without explicit formalization of this argument here -by means of Game Theory, for instance- it can be conjectured that the actual existence of the aforementioned heterogeneity between communities can be one of the motives for some problems that have an effect on multidisciplinary collaborations in the domain of applied simulation, that is to say, between academic specialists in social sciences and engineering specialists in

1 The term *satisficing* is here used as proposed by H. Simon: as a unification of “satisfy” and “suffice” [10].

2 Axelrod illustrate his own difficulties to publish [1] (#6 “ABM can be hard sell”).

computer simulation. It is necessary to choose a variant in order to face the problem of social systems complexity. From a so call “generative understanding” approach [11] -so that the analysis of social processes and systems attempt to produce an organized and coherent set of theoretical assumptions about the mechanisms that generate the observational data outputs<sup>3</sup> – it is preferable to assure high levels of theoretical quality (ex, vn).

So, the choose of this variant imply that any option lowering the theoretical quality, in order to assure empirical data fitting, must be rejected as a mere *second-best*: for instance, any knowledge approaching by means of automatic building of neural networks. In other words, it can not be considered satisficing those explanatory models and simulations that generate datasets with a high adjustment with empirical observations, BUT lacking of “fine grain descriptions” about the system elements and relationships as for the actual state of theoretical corpus of social knowledge. Of course, in any model a “fine grain description” is nothing but a formal representation of the object system, and therefore, more or less, a simplification. But, simplification does not necessarily means “black boxes”. Moss & Edmonds point up to a pair of AMSS properties that should attract the interest of sociologists [12]: 1) they capture features of actual social order, producing data with empirical relevance, but also 2) they naturally draw upon and cohere with “detailed” core strands of sociological literature. The same idea can be traced in Epstein’s research programme on generative social science [13] and other well-know epistemological proposals. [6] [14]

### Levels of Social Complexity: Are they all necessary in any ABSS?

So, ¿which will be considered the best approach to complexity in the social domain by means of ABSS? In accordance with the preceding arguments, the answer must be: *including into the simulation model all the relevant elements in line with the most updated theoretical knowledge, even 1) if it must be shaped as plain simplifications, and 2) if it will not produce accurate datasets fitting with empirical observation*. This second issue is a main research field for itself and there are relevant work about the validation problems of ABSS [14]. As for the first one, if social scientists Community considers “complexity” as a key issue, then the first step is to inquire into the sources or complexity in the kind of social systems that concerns ABSS. It is not just the heterogeneity of the human behaviour considered as a result, but especially the heterogeneity of 1) the basic elements that generate such results, and 2) the diversity of levels in which such basic elements interact. An explanation about complexity of a system is not to be necessarily a complex explanation, but a simple account of many elemental particles/agents interacting at the same level of complexity and through different levels -generating emergent properties-, by means of simple mechanisms through a extensive domain of time and space [11].

At least five levels of complexity<sup>4</sup> can be recognized in any ABSS of a complex social system<sup>5</sup>:

**1-level:** The basic complexity of the cognitive subsystem of each social agent, which implies a -more or less-complex cognitive model of environment perception and (re)action.

**2-level:** The added complexity of social agents with operating and evolving “*social maps / images*”, that is internal representations about the Other’s behaviour expectations (i.e., trust, social norms, institutional order...).

**3-level:** The added complexity that becomes from the heterogeneity of multi-agent interaction contexts, both considering some kind of typical situations such as Game Theory formalizations [4] [15], or some kind of sociability contexts such as Relational Models theory [16] (*vide supra*).

**4-level:** The added complexity of multiple individual actions aggregation, which dynamically generate patterns of macro-social outcomes, commonly know as “*first order emergence*”.

**5-level:** The added complexity of system feedback, with effects from the macro-social outcomes into the most basic levels by means of agents cognitive reconfiguration, learning by experience, or “*second-level emergence*” [13].

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3 This is a widespread psycho-social perspective, illustrated by the weberian claim for *verstehen*, that have been recognized by a number of authors as close to the ABSS methodology [12] [14].

4 This hierarchy of levels refers to a simulated or artificial society, and does not intend to match with other “level of social systems complexity” outlines, like the proposal of Fliedner [17].

5 According with the personal dimension of the “social scientist dilemma”, but certainly out of the proposed incrementalist schema, it can be considered also an **additional** 0-level, that becomes from the technical complexity of computer simulation itself (step learning curve) and from some computational limitations.

Each of these levels affects the  $n+1$  level, except for the last one that links to 1-level and 2-level<sup>6</sup>. The 0-level does not just apply to actual social systems, but to any computed simulated society. In the 1-level the complexity is shared with any other ecological system; the 2-level and 3-level can be considered human -or DAI- specific. The 4-level of complexity is shared with any material multi-particles causal system. Although most of the complexity levels can be found in non-social systems, some of the mechanisms that rule the evolution of social systems over time are human -or high developed primate- specific, for instance, the social labelling learning process.

### **An Example of Complexity Level Checking Methodology: The case of basic social bounds (3-level).**

While social simulations are just simplified running models of selected parts of object social systems, it is not necessary to include every complexity level in the implementation. Rather, the specification in detail of every level of social systems complexity into a ABSS could result in a computational trap (0-level). Of course, every simulation is build upon the basis of a particular research problem, and that is the reason why it is not needed to include every level. But, if the case is about establishing the *minimum* complexity level for a *generic* simulation builder or generator, then the criteria should be to include all relevant levels of complexity that assure the wide community acceptance on the basis of the most updated theoretical foundations into the social domain.<sup>7</sup>

Regardless of this general theoretical-including criterion, there are still a number of theoretical models, mechanisms and explanatory proposals in Social Sciences that have been not yet included into any computer simulation. A simple methodology to validate or dismiss the hypothesis about the relevance of a certain complexity  $n$ -level -or about certain element, or mechanism- is: to check the outcomes from a simulation that includes it (observation) against an identical simulation except for the lack of it (control). If data analysis supports the null hypothesis of not statistically significant differences between outcomes we can conclude that the particular  $n$ -level -or element, or mechanism- been tested is probably irrelevant. In ABSS, due to the 0-level complexity, it is no acceptable to include such irrelevant elements, because of the risk of decreasing computational performance. Following this methodology, after the implementation of an additional feature into a control simulation model, the further the variant simulation outcomes deviate from the base simulation outcomes, the greater the doubt cast upon its validity as a relevant element.

As a plain example of this methodology, hereafter are presented some guidelines for checking a theoretical model "located" into the 3-level of complexity, that is, the social complexity that becomes from the fact that social agents interacts with each other in a different way. For instance, in terms of coordinate an action, a group "*can seek a consensus of the group as a whole, the chief can decide (and delegate minor aspects of the decision), people can vote, or they can use a market mechanism based on utility or prices*" [16]. There are many ways to solve each interaction context, and the "Relational Models Theory" (RMT), developed by Alan P. Fiske, posits that "*human relationships and social systems are culture-specific implementations of just four elementary relational models in various combinations*" [18] [19] [20]. Concerning interchange of goods, services or information<sup>8</sup>, this four RM can be characterized as follows:

- *Communal Sharing (CS)*: An equivalence relation, so that agents in each group are the same in respect to resources, so they share each other but not with outsiders.
- *Authority Ranking (AR)*: A linear hierarchy in which agents are asymmetrically differentiated, so that the "upper" agent can take resources from the "lower" one, but not the opposite way.

6 The discussion and the difference between *second-order emergence* (after Nigel Gilbert) and *immergence* or *sociocognitive emergence* (after Rosaria Conte) is related to this feedback link [21] [14].

7 The case under description is related to the SiCoSSys project. The aim is a further development of the INGENIAS methodology and tools to promote its adequacy for acceptable social simulation modelling <<http://grasia.fdi.ucm.es/>>.

8 The RM theory can apply to a wider domain of issues that *interchange*, for instance, the organization of joint tasks, the framework of moral judgements, the social meaning of any institution, even the production of cognitive mental states (social believes) and the production of motivational elements (emotions, desires).

- *Equality Matching (EM)*: The agents keep track of the additive differences regarding the interaction partner resources, with an even balance as the reference point.
- *Market Price (MP)*: A relation based on a socially meaningful proportionality, so that the interchange will be ruled by a consensus ratio (monetary unit, utility, efficiency, effort, merit, or anything else).

This idea of a small and clearly specified set of relational models -or “*schemata*” [22]- is a good candidate to be considered one of the essential pieces of social theoretical development to be included in any ABSS model, or into the menu-list of any ABSS generic builder tool. But, whereas this will make simulation more difficult with regard to the 0-level, this is a “satisficing trade-off dilemma” situation, as it has been described previously, and a validation or dismiss checking procedure will be of maximum interest.

An existing simulation model can be chose to check against it the “addition” of this level of complexity, therefore playing a control role. The requirement for the control model is that the agents should have 1) some cognitive capabilities to percept the environment, 2) some social mapping capabilities, 3) can perform actions that affect the environment and other agents, and 4) can reconfigure his own cognitive model -learning- as a feedback effect of the system macro-states. That is to say, the basic model performs in such a way that considers the 1, 2, 4 and 5 complexity levels. An additional requirement is that there exists some kind of *performance indicator* to be tested against alternative simulation models.

### Shopping Agents Revisited: A Preliminary Approach using Netlogo.

A slightly modified version of the very well-know “shopping agents” Netlogo model<sup>9</sup> from Gilbert & Troitzsch [23] should be useful as a base model. In this model there are 10 shopping agents and 12 shop-objects scattered over a toroidal artificial world. Each shop has and endless stock of one product and each shopper have a shopping-list of 10 different products to buy. The shoppers have to walk to all the shops that sell the product in their shopping-list until the list becomes empty. Each time turn (tick) the entire set of shopping agents move around the world, and can buy product if they reach a patch where a shop is located. Shopping agents can build its own database of shop locations (memory) in two ways: they can remember the location of shops where they have been, and they can interchange this information with other shoppers when meet together in the same patch. The movement of each shopper are a function of their *state of mind*, that is to say: their shopping-list (as motivational goals) and their memory (as an environmental knowledge database), so that shoppers move towards the location of shops whose product are part of the shopping-list or move at random if can not reach any goal from the current memory content. The simulation stops when there is no shopper with non-empty shopping-list. The performance indicator of the simulated system is the number of ticks until reaching the stop condition, in Gilbert & Troitzsch words, “*how long it takes them to complete their shopping trips*” ([23]: 182).

In the interaction complexity 3-level, the agents of this basic/control model performs just using the *Communal Sharing (CS)* model, or schema, as there was just one group. In case of a concurrence of a pair of shoppers in the same location, each one always shares all the shop information with each other by means of an unconditional full information dump and sharing procedure. In the interaction complexity 2-level, the agents of the basic model have no record about the other agents, even after a interaction -sharing information- with a partner, so, even if they have an environmental memory of shop locations, they lack of any kind of social mapping or imaging capabilities.

Some modifications must be done in order to introduce the 2-level and 3-level of social complexity by means of Fiske's relational models of sociality. The proper operation of a RM implies a number of new agent attributes to be modelled. First, perception and recognition of other agent's relevant attributes stands on individual external observable features. So there is a requirement to give each agent a new attribute, different from the Netlogo identification built-in variable “who”, that can be perceived by other agents and used to apply the corresponding relational model. A chain of digits can be assigned to each shopping agent as a model for external observable features. This could be loosely understood as the agents “*chromosome*” [24][23], and in later extended versions of the model can be used in the offspring recombination process to study some evolutionary properties of the system. In a straightforward approach, a random number in the 1-10000 range will be sufficient.

Second, the proper operation of a RM implies a number of new procedures to be coded. At least a social recognition procedure must be included, so that agents can build, along any simulation running, a list of other agents that they previously meet. Similar to the previous visited shops list, this social memory keeps track of the

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9 Original code at <<http://cress.soc.surrey.ac.uk/s4ss/code/NetLogo/shopping-agents.nlogo>> (december, 2008). To run the full version model, remove all the ; comment tags.

interaction record and could be used in a later extended version of the model into a more complex “social labelling” procedure that helps agents to make decisions about cooperation with partners. So a new attribute must be included in the shopper’s creation procedure to complete the basic shop-memory with the added social-memory.

Next, there are three kinds of knowledge necessary for the agents to operate RM with social competency. These are the cultural features that children, immigrants or sociologists/anthropologists must learn to “enter” into any social community: 1) Competence to recognize the relevant individual attributes, as group pertinence (Communal Sharing), social rank (Authority Ranking), balance criteria (Equality Matching) and proportionality interchange unit (Market Price), 2) Competence to recognize where each RM operate, into a variety of cultural meaningful interaction contexts, as for instance the workplace, the family at home, the family with outsiders, a queue, an emergency situation, or a casual meeting, and 3) Competence to correctly operate each RM, as rules or criteria to make a decision about the exact amount of cooperation to give in the interchange.

To proceed step by step, version 2.1 will implement the necessary requirements to deal with Communal Sharing model of interaction and then validation checks will be done about different setup/initial conditions of CS model against the basic model. Next versions will add other relational models following the same methodology. The final version will include agents that can perform any four RM and a set of meta-rules to decide which one to apply in each specific dyadic interaction. These meta-rules are strongly environmental or context-dependent and can be considered as a model of “cultural traits” for the artificial shoppers society.

The requirements for the CS model to be checked are: 1) Possibility to set-up the model with a different number of groups, and with a different proportion of agents for each group, 2) The shopping model characterizes a certain social context, so there is no need to open the model to other social contexts, and 3) Basic shopping model does already include the rule of information interchange for CS model, so there is no need to add new procedures but just to establish a kind of group filter that should trigger or refrain the “full information sharing” procedure as a function of the interaction partner recognition. The recognition procedure can use both A) a narrow version of “labelling”, where simple procedural rules affect the agent action at every partner meet without memory, or B) a complex version of two phase labelling procedure that rules the updating of a social mapping or memory: B.1) “substantive labelling” at first meet based on *preos* rules (following Fiske [15]: 281), and B.2) “procedural labelling” after experience based on past interaction outcomes evaluation [25][26], as feedback effect.

The general requirements for the AR model are the same as for CS model, but there it is needed to modify the information interchange procedures to establish a unidirectional transference from the lower-rank agent to the upper-rank one. The triggering of this new cooperation procedure is a function of the interaction partner recognition of *relative* social rank. The use of a social rank recognition procedure can give rise to relevant ontology matching problems [27] [28], that could be solved in a twofold manner: 1) to assume a centralized hierarchy ranking, without error -may be coded into the agents observable “chromosome”, like chevrons-, and 2) to build new procedures for ontology alignment, or even let the agents interact under discordance consideration of the partner's relative rank -what could be a source of conflict and introduce noise in the system performance-.

Finally, the requirements for the EM and MP models are not yet completely established up to the present moment, but preliminary analysis give some clues and the suitable models are under active development. The following sections will show some preliminary results, after a brief description of the *quasi-experimental* setups.<sup>10</sup>

## Some experimental results about checking Fiske RM.<sup>11</sup>

**Experiment #1 - “Leave the market Vs. Keep chatting” - Global performance:** The proposed methodology prescribes to experiment with model features that can generate relevant differences between outputs, so that it can be checked, for instance, the relevance of “leave” the market once the agents complete their shopping against the base model, where agents wait in shops and continue providing their location knowledge to other agents. Figure 1

<sup>10</sup> A more in-detail description of each experiments can be found in other papers associated with the SICOSSYS-F project, that could be found at <<http://www.uab.cat/ssasa>> site, and [29].

<sup>11</sup> All the following reference Figures and Tables can be found in the electronic version Annex of this presentation, at <[http://www.uab.cat/ssasa/materiales/iberagents08\\_annex.zip](http://www.uab.cat/ssasa/materiales/iberagents08_annex.zip)>, or in the extended version [29].

(see *e-annex*, or [29]) shows the distribution of outcomes for the “leave market” variant, and Figure 2 shows the basic model outcomes (1000 runs each model). With a t-value of  $-1.4082$  for a parametric two means test, and a  $p(t) = 0.1592$  ( $>0.05$ ) it can not be said, with a 95% of confidence, that there exists significant differences between the outcomes. So the variant seems to be irrelevant in this context of Communal Sharing relational interaction.<sup>12</sup>

**Experiment #2 - “Leave the market Vs. Keep chatting” - Interaction patterns:** The global performance of a single task could not be the best indicator of aggregate behaviour in a social complex system. ABSS can generate recordings of interaction patterns between agents -e.g., the evolution of “meetings”, “recognitions” and “information-transfer” against time-. In this context, “meeting” means simultaneous concurrence of a pair of agents over the same patch, “recognition” means a first-time meeting between a pair of agents so that each one update its own social-map by recording the distinctive features of the other, and “information-transfer” (IT) means the basic “talk” process between agents that brings to transfer information about shops location to other agent in a meeting context. Figure 3 displays the typical shape of some interaction evolution indicators in a “keep chatting” model, while Figure 4 shows the typical pattern in a “leave market” model<sup>13</sup>. Although the global performances are quite similar, there are a salient qualitative differences in the interaction patterns along the simulation timeline. If shoppers remain in the market after they complete the shopping, they exponentially increase the probability of relevant information transference, as shows the high step curve on Figure 3. If shoppers leave the market, the probability of social information transfer will decrease over time, as shows the S-shaped curve on Figure 4. Even if global performance quantitative indicators can be very useful for testing of alternative models, careful attention must be focused on the qualitative traits of the simulation time evolution outcome data because similar global performance can be achieved by means of a range of very different interaction patterns. Experiment 2 proves how complex social systems (actual or simulated) must be analysed in the “fine grain” of over-time interaction, and how ABSS can be a suitable tool to do it.

**Experiment #3 - “Number of groups affects CS Model” - Global performance:** Up to now, the experiments has been performed on a simulation model that implements a CS Relational Model with one social group: that is to say, all agents should interchange its own complete set of information about locations whenever they meet any other agent. Prior to testing the performance of another behavioural models, experiment 3 can help to explore the effect of the number of “socially relevant groups” into a CS system -a sensibility analysis to validate ABSS-. Group membership is relevant in a CS system because, after a meeting on the same patch, the recognition of other shopping agent as *insider* or *outsider* will trigger (or inhibit) the IT procedure -*bidirectional information-transfer of shops locations*-. Figure 5 shows four distributions of global performance, using the simulated time (ticks) until the *last* shopper buy its *last* product. A replication of 1000 runs for each case provides the presented histograms of frequencies. The upper-left case ( $g=1$ ) is the basic or control model; in the rest of cases there was different number of groups. The distribution of frequencies for the *final time* shows how the increase in the number of groups is related to the increase in time to finish the shopping simulation. That is because of the decreased probability to meet another agent suitable for “information-transfer” in a CS context. With a F-value of  $847$  for a parametric ANOVA test, and a  $p(F) = 0$  ( $<0.05$ ) it can be said, with a 95% of confidence, that there exists significant differences between the four models. So the number of groups, in a social system ruled by the CS behavioural schema, seems to be relevant because of the social network topology that will be implied. But, again, these quantitative global findings must deserve some “fain grain”, or qualitative, attention.

**Experiment #4 - “Number of groups affects CS Model” - Group performance:** Figure 6 shows four *typical final IT-networks* from simulation runs in social systems ruled by CS behaviour. Agents can be distinguished by its external traits, been the first number of each agent *code* (or *chromosome*) the main source to group allocation. The distribution of agents into different group follows a random function. For this particular run, the time each agent spends to complete the shopping ranges from 852 ticks (shopper 17381) to 3962 ticks (shopper 16774). But if we take into account the intragroup means of ticks, that is 2161.3 for group-1 ( $n=4$ ), 3256.5 for group-2 ( $n=2$ ), 2526.7 for group-3 ( $n=3$ ) and 3283 for group-4 (shopper 43719), a sound hypothesis is that, in a context of CS behaviour and many groups, any performance depending on social-sharing information is a direct function of the *number* of members for each group. Large groups performs better than small ones. A replication of 4000 simulation runs, divided in CS models with 1, 2, 3 and 4 groups of approximately equal membership agents (Table 2), can provide some support to the previous hypothesis, although further analysis is needed.

12 This results has to be revised in other variants; in a Market Price context, for instance, it probably becomes relevant.

13 Legends are in Spanish: “Encuentros” (grey-middle line) means Meetings, “Reconocimientos” (orange-bottom line) means Recognitions and “Intercambios” (green-upper line) means Information-transfer.

**Experiment #5 - “AR Vs. CS Model, and number of groups” - Global performance:** After running a new artificial society where agents behaviour is ruled by the Authority Ranking model (AR), Figure 7 shows four distributions of global performance. In the upper-left case ( $g=1$ ) there was only one group: the basic or control model, where AR rule works like CS rule. With a conventional ranks hierarchy used commonly by all agents, the AR rule about transferring information has been implemented as follows: when they meet in the same patch, agents give all its own shops location information to other agents with equal or higher rank. Checked versus the corresponding CS models, the global performance of AR models shows significance differences (e-Annex Table 3). The overall performance of AR is better in each case, and seems to be an opposite function of the number of groups. As regards to the effect of the number of groups over the global performance in AR artificial societies, with a F-value of 295,97 for a parametric ANOVA test, and a  $p(F) = 0$  ( $<0.05$ ) it can be said, with a 95% of confidence, that there exists significant differences between the four models. The distribution of frequencies for the *AR final time* (Figure 7) shows how the increase in the number of groups is related to the increase in time to finish the shopping simulation. This could rise a question: like in CS models, is it because of the decreasing probability to meet another agent suitable for “information-transfer” in a AR context ?.

**Experiment #6 - “Number of groups affects AR Model” - Group performance:** Results for experiment 4 could support the hypothesis that, in a multi-group CS context, large groups performs better than small ones (due to the corresponding high density network). Figure 8 displays four *typical* information-transfer networks, as it arises from simulation runs in social systems ruled by AR behaviour<sup>14</sup>. On the contrary of CS context, in AR ruled artificial societies, the increasing of the number of groups will lead to high density networks (Figure 8: AR  $g=4$  vs. Figure 6: CS  $g=4$ ). This emerging topology could help to understand the global better performance of AR compared with CS, but appropriate understanding of the output data implies to identify the different mechanism effects of “exclusive sharing” (CS) and “lower-rank exploitation” (AR) over the topology emergence. Taking into account the intragroup means of ticks, for a single *typical* run, that is 1827 for group-1 ( $n=3$ ), 2208 for group-2 ( $n=2$ ), 2122.5 for group-3 ( $n=2$ ) and 1221.7 for group-4 ( $n=3$ ), seems to support the hypothesis that group performance is a direct function of the group size, an effect that overcomes the rank position effect.

**Experiment #7 - “Number of groups affects AR vs. CS” - Group performance:** A replication of 4000 simulation runs of AR models with 1, 2, 3 and 4 groups of approximately equal membership agents (Table 4) can provide comparison elements with CS group performance (Table 2). The corresponding t-test for each pair of group performance means shows significance differences between every CS and AR groups (exception  $g=1$ ). So it can support the hypothesis that AR and CS models are different in group performance, not just in global performance. A comparison between Tables 4 and 2 will support the conclusion that the group performance is a direct function of the rank-position ( $G1 < G2 < G3 < G4$ ). Although further analysis is needed to discard the group size effect, it can be said that in a CS context “cooperation” (less groups, or larger group) performs better, and in a AR context more “exploitation” (more groups) performs better.

## Conclusions and further work

This paper sketches a preliminary study of the ABSS practitioner dilemma about trade-off between including theoretically required elements against excluding irrelevant levels of complexity. This prospective brings to the result that ABSS methodology could not be easily accepted by social science community if it fails to fulfil two kind of requirements, been the first *to include as much* social systems complexity and the second one *not to increase* the “technical” level of complexity for generating the artificial societies under consideration (0-level).

Concerning these two requirements, here it is presented a methodology to check the relevance of any theoretical element that could be considered as a candidate to be included into an acceptable social simulation. This approach tries to test the relevance of any model by analysing the outcomes as if they come from experimental data. By generating pairs of simulation models that differs just in the issue under consideration, some theoretical elements could be dismissed from been a necessary part of any social simulation if the data generated by each model supports the null hypothesis of irrelevance. This methodology could be erroneously mistaken to standard ABSS *sensitivity analysis*, but there is a clear difference: in sensitivity analysis the *set-up space* been explored corresponds to a

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14 It has to be noted that social networks are aggregate outputs of social systems (both simulated or not).



single model with varying parameters values, but in the checking methodology the contrast explored refers to a pair of distinct models -the control one and the objective one- with the same set-up parameters.<sup>15</sup>

Experiments 3 and 5 seems to show that the global performance of the shopper's social system is a function of the number of groups ( $g$ ), and some results from experiments 4 and 6 supports the idea that in a context of many groups, the average performance for a group depends on the extension of membership. In the two coordination models here considered, both CS and AR, as  $g$  increases, the global performance decreases, but some groups will perform better: in a CS model the large groups, in the AR model the higher-rank ones.

All this experiments and conclusions aims to exemplify the suitability of the use of ABSS simulation models to test theoretical claims, as a general methodology in the social domain theoretical research. Standard statistical quantitative tools can be combined with a *quasi-experimental* approach (due to the *simulated* nature of the output data) to discard non relevant theoretical proposals. In addition, the microlevel-data generated by a ABSS allows to use qualitative analysis tools that can bring "fine grain" understanding of some micro-fundamental mechanisms operating in the case-study been considered [30].

Up to now, CS and AR variants of the basic model has been implemented, and for further work, it is planned to develop the other two variants of Fiske's theoretical proposal and to continue testing the four model variants of pure relational models against the basic one. Some further modifications are planned to advance into the integration of all four relational models, together with an agent decisional algorithm to choose what model to use into a particular interaction situation ("*socio-cultural context*"), and the corresponding experiments will also be performed.

We aim to validate and improve this methodology so that the study can be extended to other theoretical candidates to be a necessary part of any social simulation. This research programme, in the middle term, could help a wider social community to face up with the Social Scientists Dilemma, and could promote wider access to ABSS methodology and tools.

## Acknowledgements

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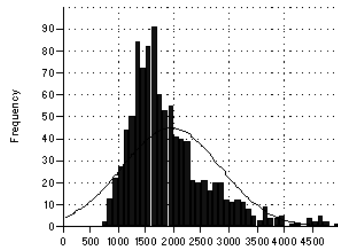
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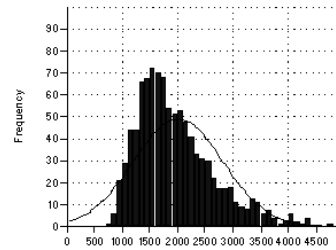
<sup>15</sup> Related with this particular issue, I want to thanks the discussions with participants in the 5<sup>th</sup> ESSA Conference sessions.

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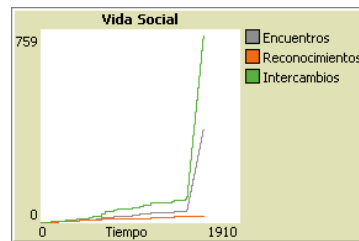
**ANNEX. Figures and Tables**



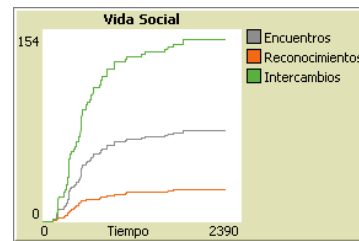
**Fig. 1.** Agents “left the market”



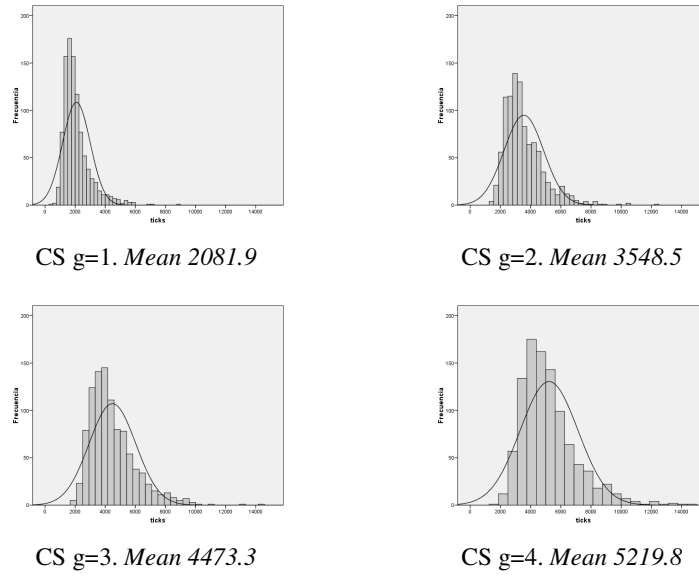
**Fig. 2.** Agents “stay in the market”



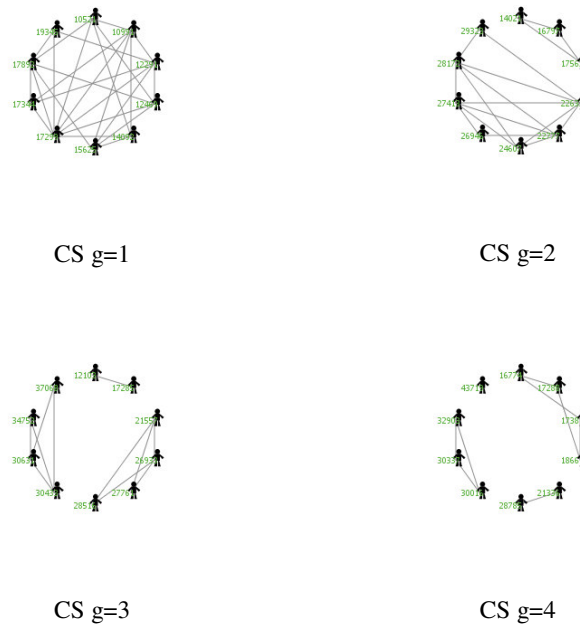
**Fig. 3.** Agents “keep chatting”



**Fig. 4.** Agents “leave the market”



**Fig. 5.** Final shopping time distribution, by number of groups (CS Model).



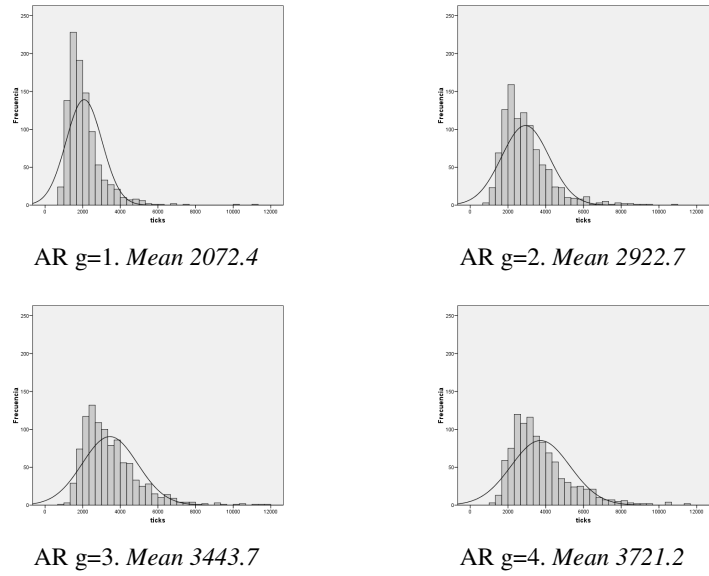
**Fig. 6.** Typical final shopping time IT networks, by number of groups included in the simulation (CS Model).

**Table 1.** Means of “ticks to finish shopping”,  
in CS models with different number of groups.

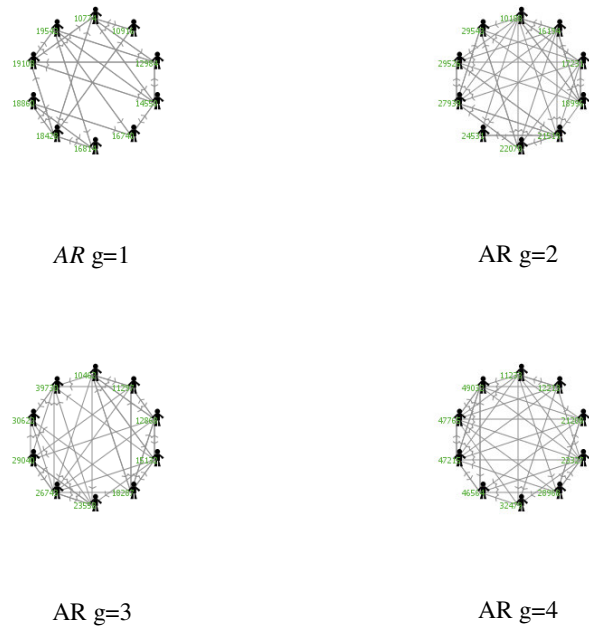
Grups		Group-1	Group-2	Group-3	Group-4
1	N	(1000)			
	Mean	1050,97			
	Std. Dev.	266,12			
2	N	(1000)	(1000)		
	Mean	1824,39	8486,8		
	Std. Dev.	753,47	2568,4		
3	N	(1000)	(1000)	(1000)	
	Mean	2390,45	2441,3	2513,1	
	Std. Dev.	1151,24	1480,7	1668,1	
4	N	(1000)	(1000)	(1000)	(1000)
	Mean	2533,14	2849,3	3166,7	3403,5
	Std. Dev.	1354,17	2019,3	2347,2	2575,4

Table 2. T-test checking CS vs. AR

g	CS ticks	AR ticks	t-value	P(t)
1	2081.9	2072.4	0.23	0.82
2	3548.5	2922.7	10.52	0.00
3	4473.3	3443.7	15.05	0.00
4	5219.8	3721.2	19.91	0.00



**Fig. 7.** Final shopping time distribution, by number of groups (AR Model).



**Fig. 8.** Typical final shopping time IT networks, by number of groups included in the simulation (AR Model).

**Table 3.** Means of “ticks to finish shopping”,  
in AR models with different number of groups.

Grups		Group-1	Group-2	Group-3	Group-4
1	N	(1000)			
	Mean	1051,0			
	Std. Dev.	264,5			
2	N	(1000)	(1000)		
	Mean	1280,2	5316,8		
	Std. Dev.	1628,3	2308,4		
3	N	(1000)	(1000)	(1000)	
	Mean	2333,8	1451,4	1124,1	
	Std. Dev.	1154,6	895,0	836,1	
4	N	(1000)	(1000)	(1000)	(1000)
	Mean	2523,7	1996,1	1662,4	1382,0
	Std. Dev.	1485,5	1778,8	1532,4	1238,1