ABSS Methodology for Testing Complexity-Levels: Case of Elementary Forms of Sociality [1]

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Abstract. In this paper, we studied the problem of trade-off between including theoretically required elements against excluding irrelevant levels of complexity, one difficult dilemma that ABSS practitioners must cope with because today social scientists still finds hard to code even the most simple artificial societies while they need to consider all kind of social complexity. We argued that there exists heterogeneity between ABSS communities, and we characterise in general terms the ordered set of preferences of the two main variants. Therefore, with a commitment to the academic variant, we make some remarks about the acceptability of a social simulation among the social sciences scholars. Finally, we present 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 an example that considers Fiske's theory about elementary forms of sociality in a *quasi-experimental* way.

1. ABSS as a crosspoint between MAS and Social Modeling: Growing Interest and a Dilemma.

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 bias in any MAS. Conversely, earlier developments of social theory or social philosophy try to make some kind of formalization or modeling, not just empirically descriptive but "building ideal societies" in order to explore its consequences or to make experimental "control comparisons" with the real ones. Part of the works of Plato, Moro, Campanella, Bacon, Fourrier and other classic utopian social thinkers could loosely illustrate it, but the socio-economic developments around the formalization tradition and the analytical soci-

1 *This is an extended version of the paper to be published as "Acceptability and Complexity: Social Scientist Dilemma, and a ABSS Methodology case example", in INTELIGENCIA ARTIFICIAL (2009), forthcoming.*

ology can better illustrate this idea [3] [4]. There are multi-agent systems, with a social flavor, and there are social theory, with a formalization flavor. Then, agent-based social simulation (ABSS) can be seen as a clear connector or bridge between at least two disciplinary boundaries: those corresponding to some of the social scientists' community and some of the computer engineering's community.

The list of social processes and phenomena subject to research by mean of formalized methods, modeling and experimental computer simulating is large and is increasing -as the JASSS index can show [5]-. Some recent books about general sociological theory incorporate results of 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 sciences research.

Our argument is that we cope with a "Social Scientist Dilemma": without a strong programming competence the social scientist finds hard to build even the most simple artificial society, but 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 balance the amount of complexity that she/he wants to implement into the model against the programming learning-curve effort needed for that level of complexity.

2. Theoretical Vs. Empirical Quality and the two Communities.

Research is not an individual issue, but an institutional social practice, so the "Satisfacing 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 mentioned dilemma.[2]

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 research. A satisfacing 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 most 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 four ideal types as show 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)

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

A plausible conjecture about the order or preferences among ABM practitioners is that there is a significant degree of heterogeneity between different communities. So, at least two variants could exist: an *academic/research* variant (ex>vn>bb>in) and an *engineering/professional* variant (ex>bb>vn>in). For instance, in regard to computational economy, López 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 the general hypothesis about the heterogeneity in the arrangement of preferences, as well as to establish the specific characterization, for different communities of ABM practitioners. With no need to formalizing here this argument -by means of Game Theory- it can be said 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 computer simulation. It is necessary to choose a variant in order to face the problem of social systems complexity. From an understanding perspective, 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[3], is preferable to assure high levels of theoretical quality (ex, vn).

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 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 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 [10]: 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 and other well-know epistemological proposals. [6] [12]

3 This is a widespread psycho-social perspective, illustrated by the weberian claim for *verstehen*, that have been recognized as close to the ABSS methodology [10] [11].

3. Levels of Social Complexity: Necessary in an ABSS?

So, ¿what will be the best approaching 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 in ABSS and there is relevant work about the validation problems [11]. As for the first issue, if social scientists community considers "complexity" as a key issue then the first step is to inquire into the sources or complexity that relates with ABSS. It is not just the heterogeneity of the human behavior considered as 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.

At least five levels of complexity[4] can be recognized in any ABSS of a complex social system [5]:

- 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 images/maps" about other's behavior 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] [12], or some kind of sociability contexts such as Relational Models [13].
- 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 loopback systems, with effect processes from the macro-social into the most basic levels by means of "cognitive *reconfiguration*" and "experience *learning*", or "second-level emergence" [11].

Each of these levels affects the "upper" one, except for the last loopback, specially linked to 1-level and 2-level [6]. The 0-level does not 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-

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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 [14].

5 It can be considered, according with the personal dimension of the "Social Scientist Dilemma" but out of the proposed incrementalist schema, an additional 0-level that becomes from the technique complexity of computer simulation itself, and from computational limitations.

6 The difference between second-order emergence in Nigel Gilbert's view and immergence or sociocognitive emergence in Rosaria Conte's view is related to this loopback link.

specific. The 4-level and 5-level complexity is shared with any material multi-particles 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 specific, for instance, the social labeling learning.

4. An Example of Complexity Level Checking Methodology: The 4 basic social bounds (3-level)

While social simulations are just simplified models of object social systems -or parts of social systems-, is not necessary to include every complexity level 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 on 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.

Regardless of this general theoretical-including criterion, there are a number of theoretical models that have been not yet included into any computer simulation, so that they are not validated. A simple methodology to validate or dismiss hypothesis about the relevance of a certain complexity n-level -or about some element or mechanism- is to check the outcomes from a simulation that includes it against an identical simulation except for the lack of it. Then, if data analysis supports the null hypothesis of no significance differences between outcomes we can conclude that the n-level (or element or mechanism) is irrelevant. In ABSS, due to the 0-level complexity, it is no acceptable to include any irrelevant element, because of the risk of decreasing computational performance. Following this methodology, after the implementation of an additional feature into a base 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"* (Fiske, 2005). There are many ways to solve each interaction context, but the Relational Models Theory (RMT) posits that *"human relationships and social systems are culture-specific implementations of just four elementary rela-*

tional models in various combinations" [17][18][19]. Concerning interchange of goods, services or information[7], 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.
- *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" [20]- is a good candidate to be considered one of the essential pieces of social theoretical development to be included in an ABSS builder. But, this simple idea 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 will be of maximum interest.

An existing simulation model can be chose to check against it the "addition" of this level of complexity -as control model-. The requirement for the basic model is that the agents should have some cognitive capabilities to percept the environment, some social mapping capabilities, can perform actions that affect the environment and other agents, and can reconfigure (learning) his own cognitive model as a loopback 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 exist some kind of performance indicator to be tested against alternative simulation models.

5. Shopping Agents Revisited: Preliminary approach using Netlogo.

A slightly modified version of the very well-know "Shopping Agents" Netlogo model[8] from Gilbert & Troitzsch [21] should be useful as a base model. In this model there are 10 shopping agents and 12 shop-objects scattered over a torus-topology 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 go to all the shops that sell the product in the shopping-list until this list becomes empty. Each time turn

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

8 Original code at <http://cress.soc.surrey.ac.uk/s4ss/code/NetLogo/shopping-agents.nlogo>. Remove the " ; " to run the full version model.

(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 another agent in the same patch. The movement of each shopper are a function of their "state of mind", that is, the shopping-list (as motivational goals) and the 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. 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"* ([21]: 182).

In the interaction complexity 3-level, the agents of this basic model acts 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 a same location, each one always shares all the shops information to each other by means of an unconditional full information sharing procedure. In the interaction complexity 2-level, the agents of the basic model have no record about the other agents, even after a sharing information interaction with a partner so, even if they have an environmental memory of shop locations, they lack of any kind of social mapping or image.

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. First, the proper operation of RM implies a number of new agent attributes to be modeled. 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 respective relational model. A chain of digits can be assigned to each shopping agent as external observable features. This could be understood as the agents "chromosome" [22][21], and in a later extended version of the model can be used in the offspring recombination process to study some evolutionary properties. In a straightforward approach, a random number in the 1-10000 range will be sufficient.

Second, the proper operation of 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 interaction record and could be used in a later extended version of the model into a more complex "social labeling" 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 tree kinds of knowledge necessary for the agents to be able to operate RM with social competency. These are the cultural features that children, immigrants and sociologists/anthropologists must learn to "enter" into any social community:

- 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).
- 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.
- Competence to correctly operate each RM, as rules or criteria to make a decision about the exact amount of cooperation to give.

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 conditions of CS model against the basic model. Next versions will add other relational models with the same methodology. The final version 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. This meta-rules are strongly environmental or context-dependent and can be considered as a model of "cultural traits".

The requirements for the CS model to be checked are: 1) the possibility of set-up the model with a different number of groups, and with a different proportion of agents of 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) the 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 a narrow version of "labeling", where simple procedural rules affect the agent action at every partner meet without memory, or a complex version of two phase "labeling" procedure that rules the updating of a social mapping or memory: a) "substantive labeling" at first meet based on *preos* rules (following Fiske [13]: 281), and "procedural labeling" after experience based on interaction outcomes evaluation [23][24].

The general requirements for the AR model are the same than 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 [25] [26], that could be solved in a twofold manner: 1) to assume a centralized hierarchy ranking, with no error possibility -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-.

Finally, the requirements for the EM and MP models are not yet completely established up to the present, but preliminary analysis give some clues and the suitable models are under active development. The following sections will show some early results, after a brief description of the quasi-experimental setups.[9]

6. Some quasi-experimental results about checking Fiske RM.[10]

Experiment #1: "Leave the market Vs. Keep chatting" - Global performance.

The proposed methodology prescribe 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 shows the distribution of outcomes for the "leave market" variant, and Figure 2 shows the basic model outcomes (for 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 [11].

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 the 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 one, and "information-transfer" (IT) means the basic "talk" process between agents that brings to transfer information about the shops location to other agent in a meeting.

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 [12]. Although the global performances are quite similar, there are a salient qualitative differences in the interaction patterns along the simulation time. 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 Fig-

9 A more in-detail description of each experiments can be found in other papers associated with the SICOSSYS-F project. <http://www.uab.cat/ssasa>

10 The following reference Figures and Tables can be found in Annex of this paper.

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

12 All models have spanish legends. Translation: *"Encuentros"* (grey-middle line) means Meetings, *"Reconocimientos"* (orange-bottom line) means Recognitions and *"Intercambios"* (green-upper line) means Information-transfer.

ure 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 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 shops locations, whenever they meet any other agent. Prior to testing the performance of another behavioural models (i.e., CS vs. AR), 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 other 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 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.

Experiment #5: "AR Vs. CS Model, and number of groups" - Global performance.

After developing 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 (Table 3). The overall performance or 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. 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.

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.

7. Conclusions and further work

In this presentation, we studied the problem of trade-off between including theoretically required elements against excluding irrelevant levels of complexity, a dilemma that any ABSS practitioner must cope with. It is been argued that there exists heterogeneity between ABSS communities, and this has been characterized, in general terms, by the ordered set of preferences of the two main variants. Therefore, following the academic variant, we make some remarks about the acceptability of a certain social simulation among the social sciences community. A first result is 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 generate the artificial societies under consideration (0-level).

Concerning these two requirements, here we have presented, by means of a case exemplification, 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. Our 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 dismiss 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 mistaken for standard ABSS sensitivity analysis, but there is a clear difference: in sensitivity analysis the set-up space been explored corresponds to a single model, but in the checking methodology the contrast explored refers to a pair of models -the control and objective-.

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, and 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. The microlevel data generated by a ABSS adds the opportunity to use some qualitative analysis tools that can bring “fine grain” understanding of some microfundamental mechanisms operating in the case-study been considered.

Up to now we have been developing the CS and AR variants of the basic model, 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, 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.

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ANNEX. Figures and Tables

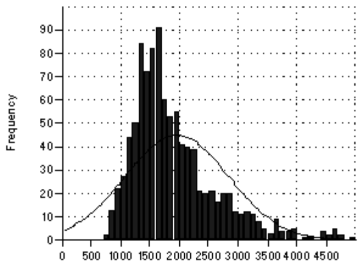


Fig. 1. Agents "left the market"

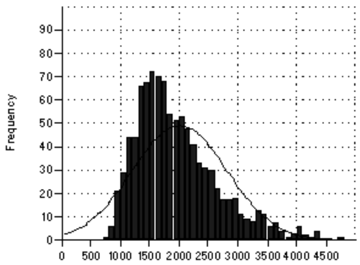


Fig. 2. Agents "stay in the market"

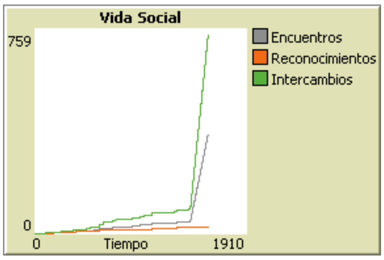


Fig. 3. Agents "keep chatting"

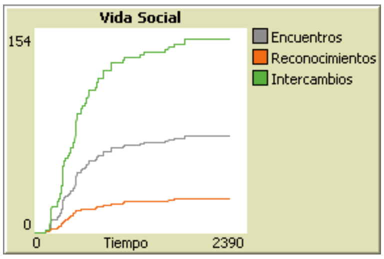
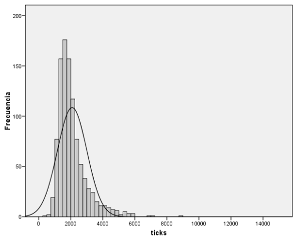
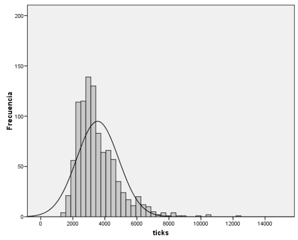


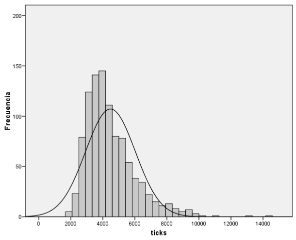
Fig. 4. Agents "leave the market"



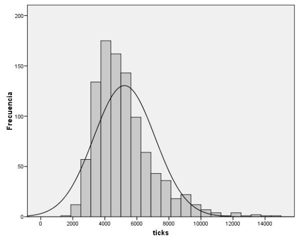
CS g=1. *Mean 2081.9*



CS g=2. *Mean 3548.5*

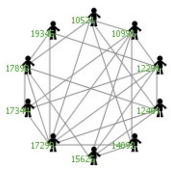


CS g=3. *Mean 4473.3*

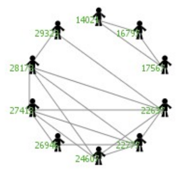


CS g=4. *Mean 5219.8*

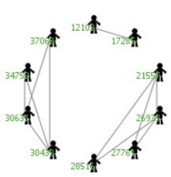
Fig. 5. Final shopping time distribution, by number of groups (CS Model).



CS g=1



CS g=2



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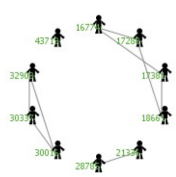


CS g=4

Fig. 6. Typical final shopping time IT networks,

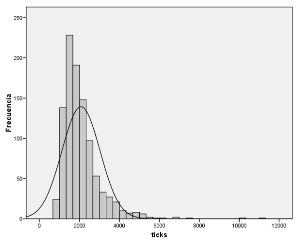
by number of groups included in the simulation (CS Model).

Table 2. Means of "ticks to finish shopping",
in CS models with different number of groups.

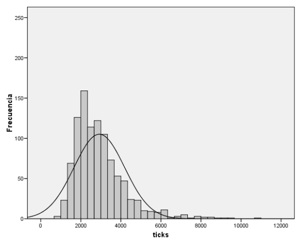
Grups		Group-1	Group-2	Group-3	Group-4
1	N	(1000)			
	Mean	1050,97			
	Std. Dev.	266,12			
2	N	(1000)	(1000)		
	Mean	1824,39	8486,8		
	Std. Dev.	753,47	2568,4		
3	N	(1000)	(1000)	(1000)	
	Mean	2390,45	2441,3	2513,1	
	Std. Dev.	1151,24	1480,7	1668,1	
4	N	(1000)	(1000)	(1000)	(1000)
	Mean	2533,14	2849,3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

Table 3. T-test checking CS vs. AR

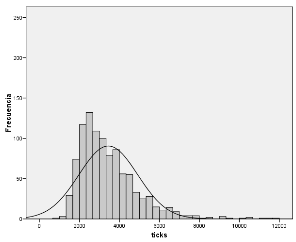
g	CS ticks	AR ticks	t-value	P(t)
1	2081.9	2072.4	0.23	0.82
2	3548.5	2922.7	10.52	0.00
3	4473.3	3443.7	15.05	0.00
4	5219.8	3721.2	19.91	0.00



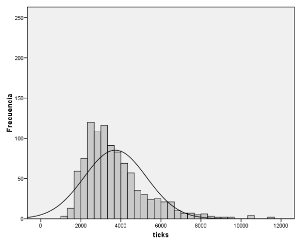
AR g=1. *Mean 2072.4*



AR g=2. *Mean 2922.7*

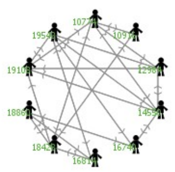


AR g=3. *Mean 3443.7*

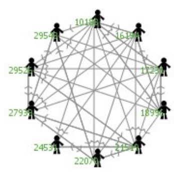


AR g=4. *Mean 3721.2*

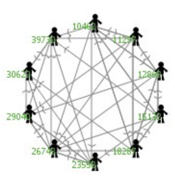
Fig. 7. Final shopping time distribution,
by number of groups (AR Model).



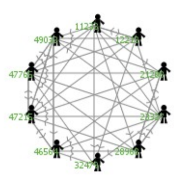
AR g=1



AR g=2



AR g=3



AR g=4

Fig. 8. Typical final shopping time IT networks,

by number of groups included in the simulation (AR Model).

Table 4. 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

...