Simulation of the Rungis Wholesale Market: lessons on the calibration, validation and usage of a Cognitive Agent-based Simulation

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***Abstract*—We present some methodological lessons and thoughts inferred from a research we are making on a simulation of the Rungis Wholesale Market (in France) using cognitive agents. The implication of using cognitive agents with an objective of realism at the individual level question some of the classical methodological assertions about simulations. Three such lessons are of particular interest: the calibration and validation focus on individuals rather than global values (1); the definition of the simulation model is made independently from the research objectives (2), and without targeting the usual objective of hypothesis simplicity (3).**

I. Introduction

Domains investigated with Multi-Agent simulations (MAS) usually suppose a large number of interacting agents who, at an aggregated level of the simulation, must act in coherence with chosen stylized facts derived from empirical compilation of data. Agent-based Computational Economics (ACE) constitutes a powerful tool to test the impact of clearly delineated variables on outputs at an aggregated level, without going through complicated—if not insoluble—calculus [1]. However, this approach is problematic when applied to the study of individual activities, when the system involves few agents that interact many times, in a complex manner, and when these interactions have a strong impact on the dynamics of the system. Our case, the Fruits and Vegetables wholesale market of the Rungis Food Market, constitutes a good example of such a system. Indeed, understanding its dynamics requires the consideration of official quotations, the pre-negotiated prices, the perishable nature of the goods, the different types of buyer-seller relations, among others. To investigate such a system, one may choose to focus on a fragment of the issue with a minimum number of variables related to a defined objective. This method is at the heart of traditional ACE. This paper proposes a different approach: modeling the domain in a realistic way with complex/cognitive agents and without any limitation in the number of rules and parameters. This choice enables to build a virtual environment in which one can conduct various experiments. The choice of cognitive agents and individual realism implies a very different methodology compared to simulations of global behaviors. In particular, the number of variables to be defined and calibrated is higher, one has to consider individual realism during the validation phase, and the results interpretation phase, involving many variables and parameters, may be challenging sometimes. The modelling process itself is also different: with ACE, one defines a simulation model considering one objective, and another objective would require another simulation model. Simplest model definition is very effective to deal with economic issues—it is in fact inherited from economical/physical theory—but, when one has to handle strategic/sociological questions, it can be interesting to inspire from strategic/organisational theory methodology, where specific context does matter. Applied to the MAS world, that gives a simulation model corresponding to one environment and as rich as possible. With a single model, it is possible to carry on several experimental studies concerning several research questions. Simplicity is not an objective, realism is. Thus, the KISS (Keep It Simple, Stupid!) principle is no longer the core motto here.

Our goal in this paper is to present a simulation of the Rungis wholesale market as an illustration of methodological issues related to Cognitive Agent Based Simulation. After a short overview of the state of the art (section II) and our application (section III), we will describe the calibration, validation and usage methodology in section IV and conclude.

II. State of the Art

A variety of social and economic problems have been investigated using multi-agent systems (MAS) [1]. MAS have demonstrated their ability to represent (cognitive) agents and constrained interaction rules, and provide insightful pictures of the dynamics of the system. Several frameworks are available, such as RePast[2] and ModulEco[3] (see a review in [4]). Perishable goods wholesale markets, specifically the Marseille Fish Market [5], [6] and Fruit&Vegetable Market [7] have been studied with an ACE perspective and reactive multi-agent based simulations.

Calibration and validation has always been a serious issue for MABS. Few general methodologies have been proposed, due to the huge variety of simulation types. [8] has identified three different approaches for simulation calibration and validation: The indirect calibration approach, The Werker-Bremer approach and The History-Friendly approach. [9] adds a fourth approach, corresponding to the Companion approach [10]. In this model, there is a continuous interaction between the model and the reality/expert that leads to progressively improve the model.

III. Domain description and model

Domain description The Rungis Market locates near Paris and is the biggest professionnal market for fresh products in the world. It gathers more than 800 small or medium sized firms that sell fresh products like fruits, vegetables, fishery goods or meat, and buyers like retailers or restaurateurs. The market is strictly controlled by market authorities and governmental bodies. Transactions happen by private mutual agreements between the buyer and the seller: there is no posted price by the sellers, no electronic quotation or auction mechanism. Governmental bodies publish a daily quotation list by product, based on the informal information they can gather on the market.

Environment model The market is open for a limited amount of time. Products exist in different qualities—quality is modeled with a continuous variable, agents can only perceive a limited (and variable) number of quality ranges.

Agents. Three main types of agents interact on the market: **sellers** (who buy bags of homogeneous products from producers and sell them in smaller bags to buyers); **buyers** (who buy from sellers and sell to final consumers); **official** administrative agent (who gathers information and gives the official quotation of day n-1 for each product and for three quality ranges before the market opens on day n). Each agent uses parameters and behavior rules defined after empirical observations. For example, the probability to change the price or to quit a negotiation for each agent depends on several empirically defined parameters, like their mutual knowledge, the age of the product, the time spent on the market or the number of competitors.

We distinguish between four buyer behaviours: **Restaurateurs**: Each one has a fixed need for his restaurant. For each product, he negotiates a fixed price with a single seller. A new agreement can be contracted with another seller if a better proposition is made; **Barbes** and **Neuilly**[1] are retailers. Each one has a list of product and a minimum quality level (high for Neuilly, low for Barbes), and wants a minimum profit rate. They have a small number of preferred sellers for each product with whom they negotiate everyday. **TimeFree**, also retailers, seek good opportunities on the market.

Negotiation. Coherently with market observations, negotiations are composed of series of propositions made successively by each actor. Negotiations stop when both sides agree on the price or when one agent decides to quit the negotiation (and leaves or negotiates another product).

[1]Neuilly and Barbes refer to two Parisian districts, the former very healthy and the latter rather poor

Our simulation is based on the BitBang Framework [11] (see Fig. 2). The simulation results we present concern a market with 3 types of products, 20 sellers (1 pavilion) and 50 buyers (20 Barbes, 13 Neuilly, 13 Restorateurs and 4 TimeFree, following the proportion observed empirically). Each run is done over 30 market days of 5 hours each.

IV. Methodological issues

Objective: global AND individual realism. Our goal is to model an environment (the Rungis Market) with both a global and individual realism (whereas classic ACE methodology supposes only global realism). A question arises, of course, about what a "realistic" model is and about the limits to realism. A model obviously cannot reproduce reality, but only mimic it. However, the fact that we focus on individual results affects our methodology.

1 model = 1 environment. Classical development steps remain unchanged: definition and calibration, validation and usage. But their interactions are different. In ACE models, one model is defined for one problem, the usage is usually known at the beginning of the definition phase and the hypotheses are chosen accordingly. Here, the first goal is to calibrate and validate a model which must be as realistic as possible, in order to be able to use it for different experiments in a later phase. The calibration/validation can be made independently from the future - and possibly unknown - usages.

A. *Definition and calibration*

Ethnographic approach: The first step concerns the definition and calibration of the model. Due to the objective of individual realism, it is necessary that an expert helps to define and improve the model. And as we do not want a goal-driven type of model, the best way to keep an open mind and make the model as realistic as possible is to use an ethnographic approach: one of the researchers goes on the field, observes and interviews the actors with a minimum guidance. Once this is done, the "domain expert" knowledge is transcribed in an intermediate document between the raw material (fieldnotes and interviews) and the program. This intermediate document must be understandable both by the domain expert and the computer scientist. In our case, in the first phase of the research, one of the authors spent ten days (i.e. ten nights) on the market, and gathered data on the real day-to-day interactions between buyers and sellers, through interviews and observations. More than 100 pages of fieldnotes constitute the output of this ethnographic phase. Then, the observation report was transcribed into a frame for a multi-agents system model, with a first set of rules and parameters calibrations, most of them defined as probalistic laws. Seller agents, for example, were defined through 18 negociation/behavior rules and 7 possible states, 5 algorithms computing the prices and probabilities to change price/product, 25 parameters and 20 variables. These descriptions were checked and discussed in a third phase, involving numerous rounds of model rewriting.

Empirical data: Even if the expert is the main source of information, empirical data still constitutes the most reliable source for calibration. This type of source, however, generally presents aggregated facts and figures and rarely goes into the study of behavioral parameters. For our simulation, official data from the Ministry of Agriculture was used to calibrate the total margin of the (wholesale market) sellers and buyers, relative to the producer price.

Normalization: Normalization can be useful mostly for result clarity reasons. In our case, when absolute value had no impact on behaviors, we chose to normalize all related values. For example, we set the average producer price (for the worse quality) at 10 units for every product, and the needed quantity has been set at 10 units per product for every buyer. Indeed, here, absolute values had no impact on the behaviors, all reasonings being on margins.

Auto-calibration: Finding the right equilibrium values so that the systems evolves in a coherent way has always been a problem in MABS. A very efficient solution, when possible, is to let the system calibrate itself. If one simulates a market, why not let the market law do its "job", i.e. encourage the weakest actors to quit the market and equilibrate by itself? This means one has less parameters to calibrate manually, but it also implies one looses the control of these parameters. For this reason, we chose a more balanced approach, applying the law of Supply and Demand and computing the quantity the sellers buy from the producer, such that on average $Supply = MT \times \ Demand$, MT measuring the Market Tension.

B. Validation

1) Individual behavior analysis: The validation objective of our simulation is close to the "historical" approach [8]: the objective is that our model matches the reality of a specific application (the Rungis Market as it was observed by the expert). The goal is to have a realistic virtual environment and realistic agents, and to conduct experiments. For these reasons, validation focuses on individual behavior as much as—if not more than—on aggregated and global values. In our case, the main validation and improvement method is the critical analysis of individual logs. Considering a specific agent on a given day (chosen at random or because some aggregated values seemed abnormal), the expert analyzes all its movements on the market and its negotiations to evaluate their realism. An interesting point about this kind of simulation is that when the expert detects some anomalies, there is no problem with adding complexity to the model by adding some new rules: **To add new rules is a good thing** (or at least not a bad thing).

2) Aggregated values observations: Aggregated values can be used at different levels to validate the simulations: **Individual Agent Level**: even if individual logs and 3D behavior observation constitute the main validation tools, some aggregated values (for example, the Time on the market for a specific Neuilly buyer, the Quantity he bought and his Margin for each of the 50 days of a simulation run) can be used as complement; **Agent Group Level**: One can compute global values both on a single or on several runs to observe group behaviors; **Simulation Level**: Global indicators give a useful overview of the system dynamics. For example, for average prices represented Fig. 3, the division of the surplus between buyers and sellers is coherent with the real one (obtained via the Ministry of Agriculture reports).

C. Usage

1) Objective types: Once the simulation environment is defined, there are many possible usages for a single simulation. **i) Positive objectives**. One can use simulations results analysis to explain and describe market dynamics. For example, testing the robustness of agent strategies with regard to different market conditions can help explain the behavior of the actors on the real market; **ii) Normative objectives**. Different strategies or market configurations can be tested with a final objective of improving the situation: for example, one may test different tactics of pricing diffusion by the Market officials, or different strategies for specific buyers objectives. **iii) Emergence study**. The high number of variables and the minimum-guidance policy when designing the simulation makes it well adapted to the study of emergent phenomena or behaviors. By using an adapted Data Mining tool, one may identify unexpected regularities in the simulation, which may lead to explore new phenomena. **iv) Presentation/Teaching**. The Market and agent behavior complexity makes the simulation an appropriate tool to present and explain market mechanisms.

2) Experimental protocol: When mixing this kind of simulation and an experimental design, the concerns of reproductibleness and hypothesis simplicity come back into the agenda. Indeed, here, an experimental design requires to build precise and simple hypotheses, to control conditions *within* the virtual simulation environment and to create the conditions for reproductibleness of the experiment. For example, in a recent work, we asked the question of what is the best buyer relationship strategy according to the supply/demand level of uncertainty. Five new agents were defined with generic strategies and placed successively in four experimental set of conditions. These five new agents "lived" with the 50 others used for the validation. The results show, firstly, that pure loyalty is on average less profitable than mixed strategies of both cooperation with a few suppliers and simultaneously bringing competitive pressure among them; secondly, that the best strategies in terms of profitability may be the worst in terms of regularity of supply, depending on market uncertainty (see [12] for more details).

V. Conclusion

In this paper, we have presented some methodological lessons learned when working on a simulation of the Rungis wholesale market using cognitive agents. This work is original in the sense that it is designed to obtain realistic behaviors at an individual level. The methodology presents at least three specificities. Firstly, the calibration and validation phases involve many interactions between an expert and the computer scientist, with a progressive construction and refinement of the model independently from the research questions or objectives. Here, simplicity is not desirable and adding rules and complexity to the model is not considered a bad thing. Secondly, validation focuses on individual rather than aggregated values, with an objective of realism at the individual level. Thirdly, once the model is achieved, traditional experimental protocol with simple hypothesis definition and testing may be implemented as an exploitation of the simulation. Beside these methodological considerations, some epistemological lessons may also be put forward. Firstly, the elaboration of such a simulation follows a non-linear process which is closer to "bricolage" than design, in the sense given by Claude Levi-Strauss[13]. A "bricolage" is strongly contingent to a specific context and a specific "bricoleur" and is not constrained by "ways of doings" or "norms": the only considered parameter is efficiency, in terms of solving the issue at stake with the existing tools. Secondly, behind the method, there is the idea that context specificities do matter. The objective is more to understand the way human behaviors and social interactions happen in a specific market rather than to understand the way they generally happen on markets. The method enables to design quasi n-vivo experiments - as opposed to n-vitro - due to its capacity to keep the richness and complexity of the setting. This explains why it is certainly more appropriate for organization studies and strategic management issues than for micro-economic investigations.

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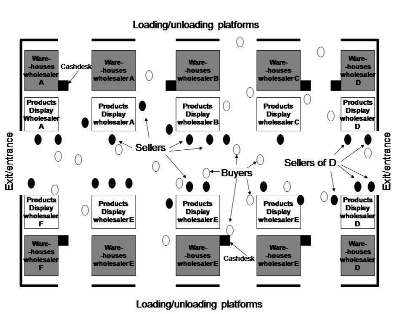

Figure 1. Rungis Pavilion description

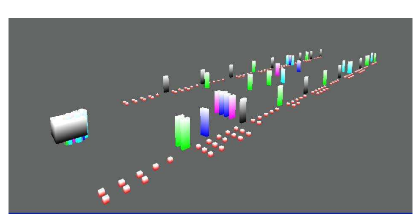

Figure 2. Simulation framework

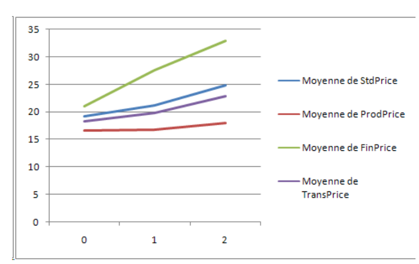

Figure 3. For three quality range, average final consumer price, standard price (price publicly given by the sellers before negotiation), transaction price and producer price