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

Philippe Caillou*, Corentin Curchod† and Tiago Baptista‡
*LRI, Universite Paris Sud, France, Email: caillou@lri.fr
†Audencia Nantes School of Management, France, Email: ccurchod@audencia.com
‡CISUC, Department of Informatics Engineering, University of Coimbra, Portugal, Email: baptista@dei.uc.pt

Abstract

In this paper, 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 contradicts 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). Our goal here is to briefly present the simulation and to discuss more in-depth the main methodological lessons learned from this work.

1. Introduction

Multi-Agent simulations (MAS) are increasingly being considered as flexible and versatile modeling frameworks, enabling positive and normative investigations of phenomena out of reach when one uses analytical studies[1], [2]. Investigated domains 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. In other words, in Agent-based Computational Economics (ACE), the global dynamics of the system is supposed to be realistic, but not the individual behavior. 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 supposes to take into consideration the impact of official quotations, the negotiated and individual prices, the perishable nature of the goods and the trust agreements between actors, among others. To investigate such systems, one may chose to focus on a small part of the issue with a minimum number of variables related to the defined objective. This method, which allows an extensive study of the parameters wrt the small number of hypothesis, is at the heart of traditional ACE. One may opt for a very different approach, like modelling 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. In our Rungis market case, we followed this approach, with the objective of studying the interactions between buyers and sellers on the market through a very realistic simulation of individual behaviors and social interactions.

The choice of cognitive agents (proactive agents that use information on the environment to behave in a certain way) 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 modelisation process itself is also different: with ACE, the different phases usually happen in that order: $objective \rightarrow\ hypothesis \rightarrow\ simulation$. In other words, 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, several experimental studies concerning several research questions is possible. 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 2) and our application (section 3), we will describe the calibration, validation and usage methodology in section 4. Then we will discuss the epistemological implications and the limits of this kind of approach in section 5, and conclude.

2. State of the Art

A variety of social and economic problems have been investigated using multi-agent systems (MAS) [1], [2]. 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[3] and ModulEco[4] (see a review in [5]). Perishable goods wholesale markets, specifically the Marseille Fish Market [6], [7] and Fruit&Vegetable Market [8] have been studied with an ACE perspective and reactive multi-agent based simulations.

Calibration and validation have always been a serious issue for MABS. Few general methodologies have been proposed, due to the huge variety of simulation types. [9] has identified three different approaches for simulation calibration and validation: The indirect calibration approach, dealing with a definition of the model from domain knowledge, a validation by stylized fact and a study of parameter regularity; The Werker-Bremer approach, which supposes a definition from empirical data and reduction of parameter spectrum with stylized fact, followed by an analysis of the remaining parameter range by the expert; The History-Friendly approach, with a definition and calibration through empirical data, stylized facts and casual/anecdotic knowledge, a validation by reproducing a single example—for example IBM history in the 60s. [10] adds a fourth approach, corresponding to the Companion approach [11]. In this model, there is a continuous interaction between the model and the reality/expert that leads to progressively improve the model. This approach is well fitted for negotiation and human interaction simulation, when empirical data is very rare and difficult to obtain. Our objective has similarities with the History-Friendly approach in the sense that we seek a maximum of realism for a specific application—the Rungis Market. But this approach is still top-down, in the sense that it seeks the most abstract and minimum set of hypothesis to reproduce some given empirical facts (corresponding to the specific example). Our approach is more bottom-up: we progressively build and add rules to match the observed facts and to reach a satisfactory level of realism for the expert. The continuous model-expert interactions we advocate constitute a noticeable common point with the Companion approach. The main differences with this latter, however, is that it focuses on knowledge acquisition via Role-Playing games—placing actors into the simulation—to acquire implicit domain knowledge, and then uses simulation to validate and test different scenarios. The main objective is the negotiation preferences and process elicitation. Our main goal is different: obtaining the final simulation and using it. In order to be able to model the preferences, we used an alternative ethnographic approach (see section 4.1) so that one of the researcher becomes the expert and is able to explicitely describe the domain.

3. Application

3.1. 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. The quotation list published day N gives average prices collected day N-1 for each type of product and each quality. Since the goods are highly perishable and the time schedule for transactions is limited to 5 hours a day, the market is highly liquid and volatile. Because of the absence of rigid frame for pricing, each buyer is free to adopt a specific strategy with the sellers. Some of them spend a lot of time comparing the different prices and qualities of the goods. Some choose a seller for each good or bunch of goods and maintain long term relations with him. The Fruit&Vegetable submarket is the biggest one, with more than 200 corporate sellers. It is composed of ten pavilions, each of them composed of around 20 displays (see Fig. 2).

3.2. Simulation model

Environment. The market is open for a limited amount of time. Products exist in different qualities —even if 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 three quality range 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 with no specific needs.

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 goes to another seller or negotiates another product).

3.3. Simulation framework

Our simulation is based on the BitBang Framework [12], developed combining concepts from both Artificial Life and Complex Systems. One advantage of this framework is the liberty it allows regarding the type of brain used by the agent. Here, we use a rule-based brain, which fits our model quite well since the objective is to add new rules and complexify the existing ones until the model leads to a realistic simulation and since the behaviors of agents on a market follow rules linked to the necessity to make good deals. Moreover, rules facilitate the understanding of the agents' behavior. A second advantage of this Framework is the 3D world modelings, which allows an intuitive visualisation of the simulation for the expert (see Fig. 1).

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.

4. 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 remains a model, and can only mimic the reality, not perfectly reproduce it. But the fact that we focus on individual results will affect our methodology.

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

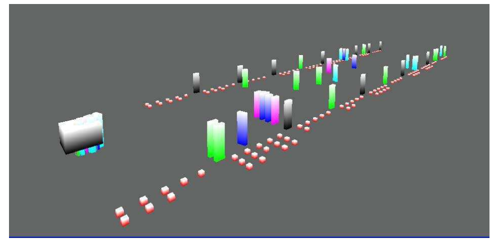

Figure 1. Simulation framework

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 eventually unknown) simulation usages.

4.1. Definition and calibration

4.1.1. Ethnographic approach. The first step concerns the definition and calibration of the model. Because of the objective of individual realism, it is necessary that an expert helps defining and improving 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 realist as possible is to use an ethnographic approach: one of the researchers goes on the field, observes and interviews the actors with a minimum of 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. A few wholesale firms accepted to cooperate and let their doors open for hours of observation of their sellers, and market authorities also kindly accepted to be interviewed. 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 (some of them being multiplied by the number of buyers/products/producers - for example, there exists a random ”Sympathy factor” for each buyer) and 20 variables (here again, some of them multiplied by the number of products/buyers/producer). This descriptions were checked and discussed in a third phase, involving numerous rounds of model rewriting.

4.1.2. Empirical data. Even if the expert is the main source of information, empirical data still constitute 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, relatively to the producer price (final consumer price being almost twice the producer price for fruit and vegetables).

4.1.3. 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. Two reasons, however, may lead us to renounce to such a normalization sometimes. Firstly, if the expert insists that some psychological threshold may exist. For example, to lower the price from 15,00 to 14,99 has more impact on a buyer than to lower it from 14,37 to 14,36. Secondly, when presenting the results to real market actors, if the realism must be increased at a maximum level. Oversimplistic normalization, even if it has no impact on the behaviors, may raise doubts. In both cases, the prices used would be extracted from the official Rungis quotations.

4.1.4. Auto-calibration. Finding the right equilibrium values so that something happens has always been a problem in MABS. A very efficient solution, when it is possible, is to let the system calibrate by itself. If one simulates a market, why not letting the market law do its ”job”, i.e. encourage the weakest actors to quit the market and equilibrate by itself? Using natural selection and evolutionary computation of parameters is one way of dealing with this problem. This means one has less parameters to calibrate manually, but it also implies one looses the control on 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.

Table 1. Log sample: a negotiation between Buyer 38 and Seller 4 about 4 units of Product 2 with minimum quality 0.4

D 22 H 170 Hi Again From 4 To 38
D 22 H 170 BeginNeg 38 To 4
D 22 H 171 HowMuchFor 2 0.4 From 38 To 4
D 22 H 171 Propose 20 From 4 To 38
D 22 H 171 Propose 18.5 4 From 38 To 4
D 22 H 171 Propose 19.86 From 4 To 38
D 22 H 171 Propose 18.5 4 From 38 To 4
D 22 H 172 Propose 19.44 From 4 To 38
D 22 H 172 Propose 18.5 4 From 38 To 4
D 22 H 172 NoWay! From 4 To 38
D 22 H 172 EndNeg 38 To 4

4.2. Validation

4.2.1. Individual behavior analysis. The validation objective of our simulation is close to the “historical” approach of validation [9]: 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 (see a log extract sample in Table 1). 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 markets and its negotiations to evaluate their realism.

To add new rules is a good thing (or at least not a bad thing). 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. For example, it appeared that sellers, very good negotiators, came sometimes 10 times to negociate with the same seller and, each time, succeeded in lowering the price. This was unrealistic, and the probability of the seller to stop a negotiation (Say ”NoWay!”), which depended on the number of proposals, the number of times the buyer changed its price and the age of the product, was modified to add the number of times the buyer came back.

4.2.2. Aggregated value 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 (corresponding to a single run since we consider a specific agent), can be used as complement. For example, Fig. 3 represents 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. This kind of results seems realistic: after a starting period where he has no contact on the market and thus makes low profit and doesn't manage to get everything he needs, the Buyer progressively constitutes a small network of regular sellers which allows him to stabilize his Margin and to ensure a stable procurement of the needed products.

- Agent Group Level: One can compute global values both on an single or on several runs to observe group behaviors. For example, Fig.4 describes the total quantity bought each minute of the simulation (without considering the day), differentiating by buyer type. The result is consistent with empirical facts: Restorateurs are the fastest agents, because they have previously negotiated the prices with chosen sellers (Trust agreements), and thus can buy directly when they arrive on the market. Neuilly agents are faster than Barbes agents to make their purchase, because since they focus on quality, they have a lower tendency to negotiate. TimeFree agents take their time to negotiate and choose the best prices (their purchasing Quantity is lower due to the low number of such agents on the market).
- Simulation Level: Global indicators give an useful overview of the system dynamics. Furthermore, available empirical data usually correspond to global variables. For example, the overall distribution of exchanges during one day (Fig. 4) corresponds to the empirically observed distribution. Another example is the average prices represented Fig. 5. The division of the surplus between buyers and sellers is coherent with the real one (obtained via the Ministry of Agriculture reports). And the 10% difference between standard and transaction prices in the simulation matches the difference noticed by Rungis officials between the official quotation price (deduced from standard prices) and effective transaction prices.

4.3. Usage

4.3.1. Objective types. Once the simulation environment is defined, there exist many possible usages for a single simulation:

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 to explain the behavior of the actors on the real market.

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.

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.

Table 2. Generic Agent Strategies for the experimental protocol

Ag	Description
A	search strategy, high propensity to compare prices, systematic negotiation, no loyalty
B	long term relation with one seller for each good, stable prices negotiated once and for all
C	same as B plus frequent check that other suppliers do not make better offers, capacity to change suppliers if a better offer
D	preferred relation with three sellers for each good, systematic comparison among these three and choice of the best offer
E	same as D plus frequent check that other suppliers do not make better offers, capacity to change suppliers if a better offer

Table 3. Experimental environment conditions

Xp #	Market environment
XP 1	No uncertainty: both supply and demand are stable
XP 2	Variance of demand for each buyer = 30%
XP 3	Variance of supply for each supplier = 30%
XP 4	Combined experiment #2 and #3

Presentation/Teaching. The Market and agent behavior complexity makes the simulation an appropriate tool to present and explain market mechanisms.

4.3.2. Experimental protocol. When mixing this kind of simulation and an experimental design, the concerns of reproductibleness and hypothesis simplicity come back in 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 (Table. 2) and placed successively in four experimental set of conditions (Table 3). These five new agents "lived" with the 50 others used for the validation. For each experimental set of conditions, the experiment lasted 30 days, repeated 10 times. An example of the obtained results concerns the average margin rate (Fig. 7) and quantity (Fig. 6) bought by each of these five new agents. 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 [13] for more details).

4.3.3. Specific tools. Specific tools can be used due to the large number of parameters used in this kind of simulation:

Data Mining Tools. They should be very useful both to describe the result of a simulation (by identifying clusters of behaviors and important variables) and to identify emergent phenomena within the simulation. DM tools adapted to simulation logs analysis are however still an “emergent” field and many improvements are yet to be expected.

Statistical Tools. Statistical tests are very well adapted to validate experiments results. One advantage of MABS is that the number of experiments is potentially infinite. It is thus possible to reproduce an experiment with similar conditions until the obtained result (for example a strategy better than another) is statistically significative. Such a methodology would obviously have been difficult to apply with real actors.

Evolutionary algorithms. They can be used with at least three possible objectives: First to seek better strategies (normative objective) for the agents. Second, to check if existing strategies emerge while applying the algorithm (this would explain why the market actors apply them). Third to help to auto-calibrate the simulation by letting the sellers and buyers population evolve through a natural selection process. The framework used (BitBang Framework), having roots in Artificial Life systems, already provides the capabilities necessary to later pursue these objectives.

5. Discussion

5.1. Epistemological discussion

The lessons we learned from simulating the Rungis market also bring some epistemological thoughts on the table.

5.1.1. Building the model through a ”bricolage” process. The elaboration of the simulation followed a non-linear process. However, one may identify two main steps: the building of the initial algorithm and the refinement through the calibration and validation phases. Designing the initial model supposes long and numerous interactions between the expert and the computer scientist, but this part of the process is nearly linear: precise explanations by the expert on how the market really works constitute the raw material that the computer scientist translates into a simulation model. Refining the initial model certainly constitutes the longest part : it involves a continuous dialogue between the expert and the computer scientist, the former pushing towards revising the model whenever he/she thinks it does not fit the reality. probabilities that were considered plausible during the initial phase may appear unrealistic; rules may prove incomplete and functions ill-defined. Step by step, the global model evolves and comes closer to the reality it is supposed

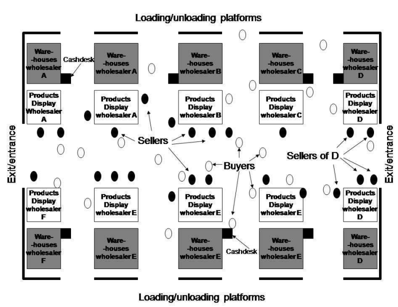

Figure 2. Rungis Pavilion description

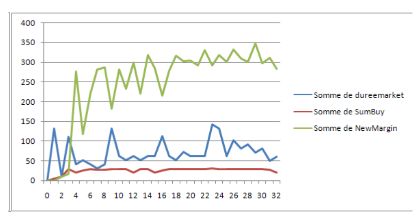

Figure 3. For a Neuilly Buyer, Time on the market, Quantity bought and Margin each day

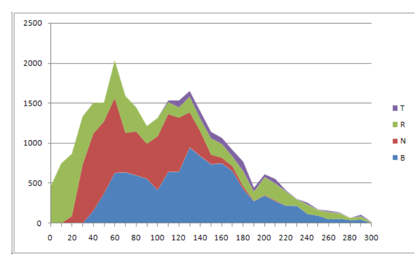

Figure 4. Total Transaction Quantity during one day, by buyer type

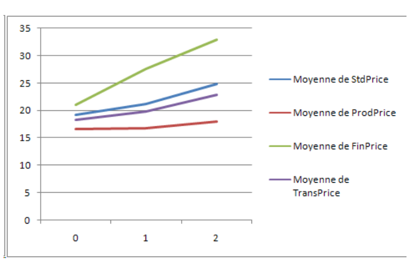

Figure 5. For three quality range, average final consumer price, standard price (price publicly given by the sellers before negotiation), transaction price and producer price

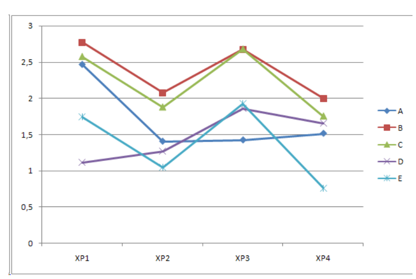

Figure 6. Average Quantity bought (maximum : 3) on the market per day and per strategy for each experiment XP1-4

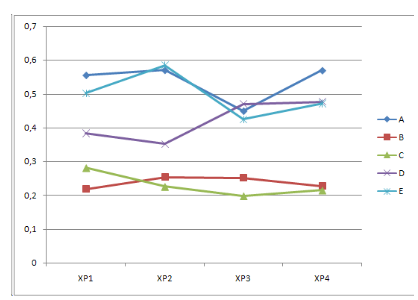

Figure 7. Average margin rate per day and per strategy for each experiment XP1-4

to reproduce. It also becomes more complex: new rules appear and existing rules are refined, through a work closer to ”bricolage” than design, in the sense given by Claude Levi-Strauss [14]. 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. The validation phase of the simulation of the Rungis Wholesale Market is very close to this notion, and leads to a very rich and complex model, made of several stratums of refinements that, in fine, constitute for the expert a realistic simulation of the market.

5.1.2. Designing quasi n-vivo rather than n-vitro experiments. N-vitro experiments suppose to isolate a few parameters the scientist wants to test or to control and to ignore the others. This ”parcimony” rule has been the norm at least since Claude-Bernard [15] call for more experimental works in life science. In the case of the Rungis market, our objective was to put individual behaviors and social interactions at the center of the study. Closer to organizational studies and strategic management fields than to micro-economics, the research aimed at understanding the richness of the case, as it is the norm in qualitative methods for social sciences [16], [17]. Because of the complexity of such cases, it is often assumed that rigorous experiments are both difficult and undesirable. The difficulty comes from the limited power of the scientist to reproduce human and social behaviors in vivo, because they strongly depend on the specific environment they are embedded in. Of course, it is sometimes possible to experiment ”in-vivo” with very convincing results (see for example [18]), or to use students to reproduce in the classroom the setting of ”real-life” interactions [19] but the scientist heavily relies on opportunities offered by the organization or the group under study, has a limited control over the course of events and is confronted to serious biases when using students to make the experiment. Another possibility is to find several similar cases and to compare them by isolating the relevant variables[20]. This quasi-experimental setting is however biased by the fact that two different cases are never exactly the same and that differences in outputs may be explained by other variables than the ones under control. The undesirability comes from the idea that by trying to design an experiment ”the classical way”, the scientist will loose the richness of the cases he or she investigates. This reproach is very common towards statistical studies, which try to replicate the experimental setting when in-vitro experiments are impossible, by using ”representative samples”. The method we propose is slightly different: by creating a model that is sufficiently complex to replicate in a fair manner the complexity of the reality, by being able to change some parameters or to introduce some new actors with different behaviors in the model, the scientist is able to make some experimentations that are impossible to organize in the real world, without losing too much of the complexity of this real world.

5.1.3. Privileging context specificities over general laws. Behind this way of building a complex model and of designing quasi n-vivo experiments, there is the idea that context specificities matter. The objective is more to understand the way human behaviors and social interactions happen in a specific market than to understand the way they generally happen on markets. This idea is common in sociological approaches, where it is assumed that the work of the scientist is to understand micro and contextualized phenomena rather than to propose simple and general laws (see for example [21], [22]). In the organization studies and strategic management fields, some scientists assert that contextualized research may bring rich knowledge and novelty to both the academics and the practitioners [23], [24]. By privileging context specificities over general laws, the method that is presented in this paper is maybe more appropriate when studying social, organizational and managerial phenomena than for more economic-oriented types of research, which target more conceptual frames and simplified models.

5.2. Limitations

5.2.1. A time-consuming method. As said above, the building of the model and the validation-calibration phases are time consuming, because of the dialogue between the expert and the computer scientist, the numerous changes this dialogue implies in the initial model, and the possible chain of reactions that occur when a minor change in a parameter impacts some other parameters in an unexpected manner.

5.2.2. A lack of general results. As discussed above, the objective of such a simulation is not to offer general results. This may be considered as a limitation, since the academic world is more interested by knowing ”how social interactions impact the way markets work” rather than by knowing how they impact ”the way the Rungis wholesale market works”. But this is not a very serious concern, since once a model has been built for one specific market, it is possible to investigate some other carefully chosen markets and build other models. By doing multiple simulations of multiple cases, computer scientists may reach the level of generalizability they aspire, without over-simplifying the real world in their models.

5.2.3. A non-reproducible model. Because of the ”bricolage” process described above, it is difficult for another scientist to reproduce the model. One may even suppose that, with this method, two scientists working simultaneously on simulating the same reality would propose two different models. Is that a problem? No, if both models lead to a plausible simulation of the reality for the expert. More important is the experimental setting. In the simulation of the Rungis wholesale market, this setting is reproducible: another scientist could use the model to carry on the same experiment, and would find the same results.

6. 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. Many different experiments can be conducted with the same model, which gives to this type of simulation an interesting research potential, especially if it is mixed with specific data mining and statistical tools.

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