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Agent-Based Prototyping for Business Management: An Example Based on the Newsvendor Problem

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***Abstract*—Under the current (complex and dynamic) business scene, prototyping has become a key source of competitive advantages. Within these tools for modeling and simulation, agent-based techniques emerge as a powerful approach. This research aims to highlight its potential as a mechanism for supporting the decision-making processes in organizations. The application of agent-based modeling and simulation to this field is illustrated through the Freddie's newsstand exercise. We first model and implement it under an agent-based architecture, and then we carry out several simulation runs to perform a sensitivity analysis and explore the problem. This simple example, based on the newsvendor problem, allows non-experts to understand the rationale behind this notion as well as to find out the advantages derived from it.**

***Index Terms*—Agent-based modeling and simulation, business simulation, business management, decision-making.**

I. Introduction

The business environment substantially evolved over the last two decades as a consequence of globalization. Competition has increased and become more complex, which creates a modern scenario of opportunities and threats for companies. In this context, managers are faced with constant decisions in three different levels: strategic, planning and operational. How they approach the decision-making process can—and does—make the difference.

This research aims to highlight the role of prototypes for supporting the decision making in organizations. *Section II* discusses its interest. More specifically, we focus on agent-based models [1] as powerful mechanisms for business analysis and transformation. Section III describes the main ideas of these models, which are built on a 'bottom-up' approach—they start from the most microscopic units the system consists of. To illustrate this approach, we first model the Freddie's Newsstand exercise [2] and implement it in an agent-based environment. This is described in Section IV. From this point, we perform a sensitivity analysis, which is detailed in Section V to show how this approach can make decisions more robust. Finally, Section VI discusses the potential of ABMS in complex real-world environments.

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II. Prototyping for Business Decision-Making

Just as important engineering decisions are based on detailed plans or scale models that are built on solid scientific theories, key business decisions should be based on strong reasons. However, this is not as usual as it should be. In companies, many decisions at al levels—even those which may have a great financial impact on the firm—are made "just on the basis of personal opinion or a few slides trying to motivate why the idea is sound" [3].

Under this scenario, *business prototyping* proposes a methodology for supporting decision making based on translating the analysis into a fully controllable computer-based environment, where risk-free and cost-free experiments can be performed. This approach to problem solving, which is summarized in Fig. 1, roughly consist of three phases [3]:

1) Reproducing the main essence of a real-world problem in a controllable virtual environment (modeling and implementation).
2) To design new business structures / processes / policies after testing them in the virtual environment (simulation and analysis).
3) To realize the new design in the real world using the prototype as guidance (development),

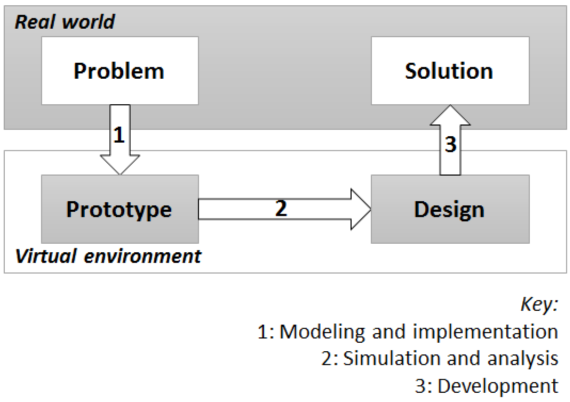

Fig. 1. Business prototyping for business decision-making.

In this sense, business prototyping help managers see the big picture of the organization without losing sight of meaningful details. By means of this approach, they are able to analyze convoluted dynamic problems and to develop solutions, which would be otherwise very difficult [4]. For these reasons, a premium is placed upon *business prototyping* as a key source of competitive advantages. It should be noted that this resource fits perfectly with the well-known VRIO (value / rarity / imitability / organization) framework [5].

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Finally, we must underline validation and verification as two essential stages in the development of a prototype. Fig. 2 expands the process of modeling and implementing the system; see phase 1 in Fig. 1. It highlights an intermediate echelon: the model. Validation refers to checking that the model we have designed is a credible representation (i.e. contains the main essence) of the real system. On the other hand, verification aims to ascertain that the system works properly according to the rationale of the conceptual model. Both are represented in the aforementioned figure. Only if the model has been appropriately validated and verified, practical conclusions can be derived from its analysis.

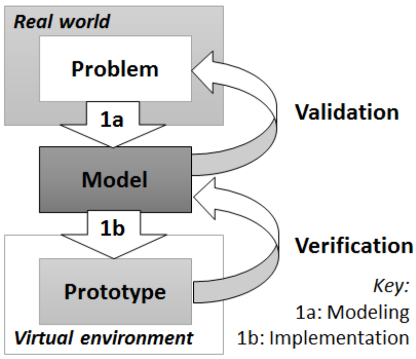

Fig. 2. The role of validation and verification in the prototype development.

III. Fundamentals of Agent-Based Modelling

Agent-based modeling and simulation (ABMS) is a relatively new modeling paradigm, which bases on the usage of "dynamically interacting rule-based entities" [6] called agents. These agents, whose behavior is encoded in algorithms, are autonomous; namely, they can function independently impacting and being impacted by their environment. In addition, they are capable of communicating with each other. Both interactions (on the one hand, among the agents; on the other hand, between the agents and the environment) within a defined context determines the dynamics of the system.

This "bottom-up approach" [6], which is illustrated by Fig. 3, makes ABMS models to be close to the real world. Note that it significantly differs from other methodologies, such as system dynamics or discrete-event simulation, which start with an overall analysis of the system's behavior (a top-down approach). Some authors have gone as to contend that it is "a third way of doing science" [7] in relation to traditional deductive and inductive reasoning.

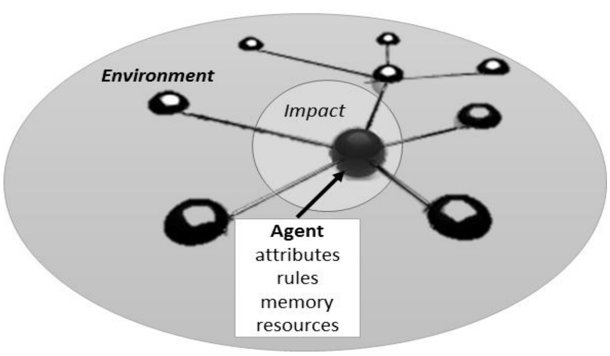

Fig. 3. Overview of the ABMS paradigm.

In this sense, ABMS has far-reaching effects on the way that firms use computers to support decision-making processes [8]. Although its applications are yet emerging, the literature contains a number of works that employ ABMS to support business decisions in different fields, such as supply chain management [9].

In terms of implementing the model, North and Macal [8] distinguish three main approaches to building ABMS systems in terms of the scale of the software employed:

1) Desktop computing for ABMS developing. In this regard, some agent-based prototyping environments that must be highlighted are NetLogo and Repast Symphony. In addition, general computational mathematical software, such as MatLab or Mathematica, can be used to build ABMS systems. It should also be highlighted that some agent-based platforms have been developed, such as Sisco [10] and Scope [11], for easily performing simulation analysis specifically in the business field.
2) Large-scale agent development environments like Repast, Maron, and Anylogic.
3) General programming languages, such as Phyton and C/C++/ C#.

IV. Freddie's Newsstand (1): Modeling and Implementation

Freddie's Newsstand is a business learning exercise set out by Hillier and Lieberman [2] based on the well-known newsvendor problem [12] that investigates optimal order rates in case of uncertain demands for perishable products. This exercise can be expressed by the following formulation:

Early in the morning, Freddie receives the copies ordered of the Financial XYZ, one of the daily newspapers that Freddie sells from *his newsstand. Any copies unsold at the end of the day are returned to the distributor the next morning. Nonetheless, the distributor does give Freddie a small refund for unsold copies to encourage him to order a large number of copies. In this regard, it should be noted that: (1) Freddie pays $1.50 per copy delivered; (2) Freddie sells at $2.50 per copy; and (3) Freddie's refund is $0.50 per unsold copy.*

Freddie has compiled the record of his daily demand. He discovered the demand of the Financial XYZ follows a uniform distribution between 40 and 70. Partially because of the refund (and to avoid lost sales), Freddie has always taken a plentiful supply. However, he has become concerned about paying so much for copies that later are returned unsold, particularly since this has been occurring nearly every day. For this reason, he decides to rethink its ordering rule. He wants to determine the number of copies to receive each day from the distributor to maximize his average daily profit.

Within the modeling process, a p-diagram (parameter diagram, a widely used tool in robust engineering) has been employed to define the scope of this problem, see Fig. 4. Note that the system-in-focus is the newsstand. Horizontally, we represent the main system function: transforming both the customer demand and the selling price into net profit—the higher, the better. Diagonally, we can see the operational function, i.e. what the system does to achieve the main function. In this sense, the newsstand purchases the product to the distributor and sells it to the customer. Vertically, we show the noise factors: the demand variability and the cost of the newspaper paid to the distributor. These uncontrollable factors threaten (decrease) the system function (net profit).

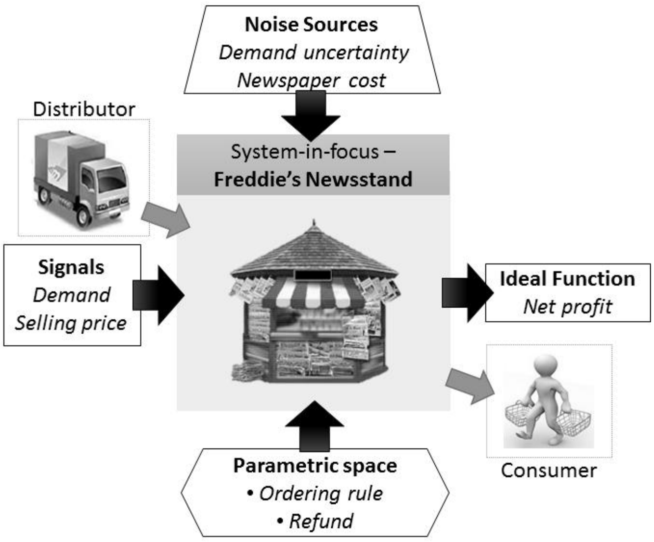

Fig. 4. Scope of the problem described by a p-diagram.

In the bottom of the graph, we represent the parametric space (that is, what Freddie can do to improve the system function). It includes, of course, the ordering rule. Nonetheless, we also may consider that it covers the refund offered by the distributor, in the sense it comes from a negotiation from both nodes of the supply chain. That is, the distributor could be willing to offer a greater refund if Freddie increases his order.

To implement this system, we have used NetLogo 5.0.1. (NetLogo [13] is a programming in continuous development by the Center for Connected Learning and Computer-Based Modeling in the Northwester University that allows the development of agent-based models for simulation and analysis of phenomena of a different type.)

The newsstand (the main agent in the system, which we call *actor*) has been modeled as a mechanism who goes along a cycle of states, see Fig. 5. These are the following:

1) *Purchasing state*, in which the node decides the quantity and orders the newspaper to the distributor.
2) *Demand state*, in which the demand is randomly generated.
3) *Selling state*, in which the customer arrives to the newsvendor and Freddie do the sales when product is available—otherwise, lost sales are generated.
4) *Recording state*, in which the results (sales, lost sales, financial state) are stored.
5) *Idle state*, where the system remains until new action is triggered.

Each complete cycle makes a day. It should be underlined that the action is triggered by *entities*—another breed of agents, which are periodically (one per day) generated by the system. These entities traverse the system during each cycle, carrying and storing the date of what happens in a concrete day. For this reason, entities are stored in a specific area of the system layout. Demand that has been satisfied and demand that has not been satisfied is stored separately (Note: The user of the system can limit the amount of history to be kept for visibility and calculations. That is, oldest entities can be removed in order to prevent reduction of the simulation speed).

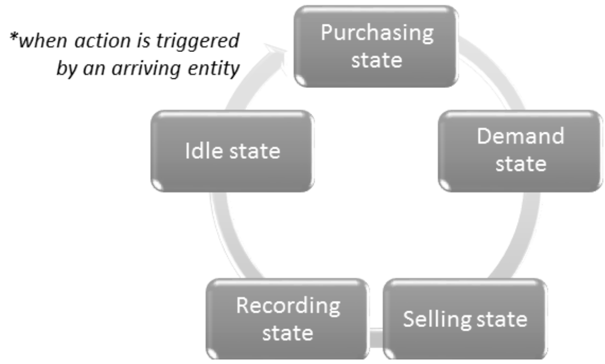

Fig. 5. State transition diagram for the newsvendor.

By way of illustration, Fig. 6 shows the graphical part of the simulation model at a particular time of one of the simulation runs. It shows the purpose of the different areas that make up the agent-based model. The animation frame allows the observer to figure out what is going on in the system.

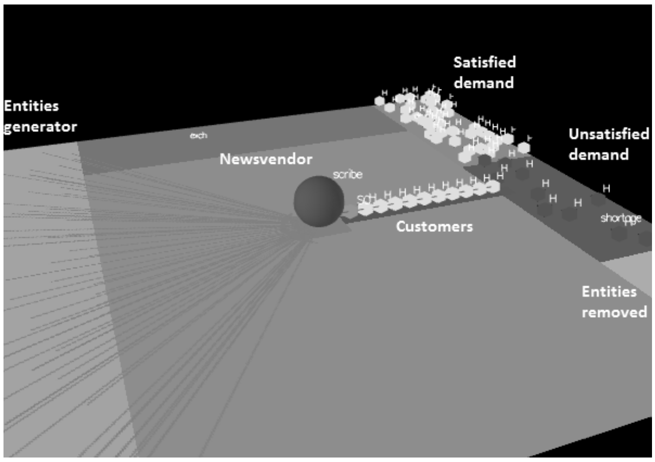

Fig. 6. Screenshot of the animation frame during a simulation run.

Fig. 7 shows the interface window of the ABMS model that we have implemented. (NetLogo provides two additional windows, one for the model documentation and another for the model code). Together with the animation frame, the interface window provides the experimenter with the controls to setup both the controllable and uncontrollable parameters (both prices and the refund), as well as those factors required to run each experiment (duration of the experiment, set-up and go buttons, number of entities to be stored). In addition, the interface window provides information on the key performance metrics. The plots (histograms and run charts) are the balance scorecard for the experimenter, where it is possible to see how the system evolves and how some key metrics distribute. Additional monitors (rectangles with output data) keep showing the position of several key output variables.

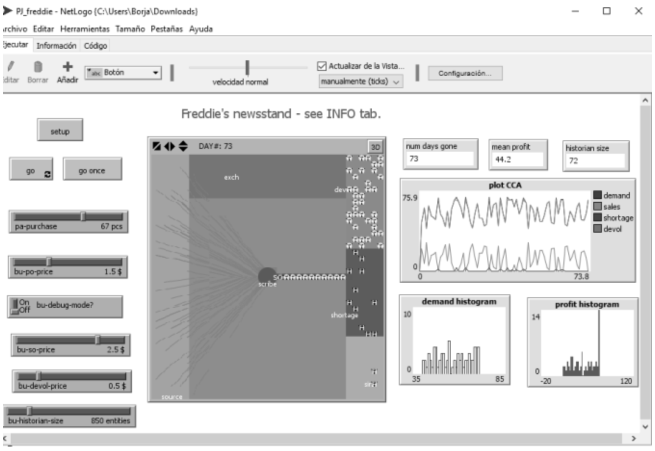

Fig. 7. Screenshot of the interface window during a simulation run.

We now focus on the validation and the verification of the model. In this regard, several techniques have been employed. The use of good practices of software engineering (e.g. clean code, test driven development, failure modal analysis) is highly recommended for early detecting system malfunctions. In addition, the modularity—the functionality of the prototype is separated into independent modules, such that each one is able to function independently—that characterizes ABMS makes easier the verification of the prototype. In this sense, a specific breed of agents (i.e., the so-called "police" [14]) has been used for ensuring the system matches the model. We have also used factory acceptance testing (FAT) [15]. This means to experiment situations whose real outcome is known. For example:

- *Test condition:* Freddie always buys the minimum demand, i.e. 40 copies.
- *Expected system behavior:* sales equal 40 units each period. No copies are returned to the distributor. Lost sales are often generated (except when the demand equals 40 units).
- *Acceptance criteria*: The daily net profit is $40.

V. Freddie's Newsstand (1): Simulation and Analysis

Once the prototype has been developed, Freddie's problem can be studied in a virtual environment. Note that under this powerful approach, we can modify the values not only of the controllable/decision parameters (whose experimentation in the real world could be possible, but it would mean assuming a considerable risk and/or cost, or it would take a long time to derive meaningful conclusions) but also of the uncontrollable/noise parameters (with which we could not experiment in the real world). In this sense, managers can explore in detail the impact of their decisions on the overall system in different scenarios. Hence, decision-making processes become more solid.

Considering the order as the main decision variable, we can easily study the relationship between the expected net profit and the order to the distributor. To do so, we have carried out a sensitivity analysis consisting of running three simulations of 250 days for different values of orders increasing by 2 units within the 40-70 range (i.e., O={40, 42, 44, …, 70}, which covers the range of variation of the customer demand).

The results of the simulations, where the mean net profit is the key performance indicator, are included in Table I. This table also displays the average of the three runs and the 95% confidence interval of the mean. Fig. 8 represents these results. The dashed lines show both limits of the confidence interval for each value of the orders. Note that the confidence interval is relatively narrow, which means that 250 days is a large enough time interval to draw conclusions—the simulation time horizon is an important factor.

TABLE I: Results of the Simulations (Baseline Scenario): Mean Net Profit of the Newsvendor ($)

Order	Run 1	Run 2	Run 3	Average	Conf. int.
40	40	40	40	40	±0
42	41.8	41.7	41.8	41.77	±0.065
44	43.3	43.4	43.3	43.33	±0.065
46	44.6	44.7	44.7	44.67	±0.065
48	45.5	45.7	45.8	45.67	±0.173
50	46.2	45.5	46.7	46.13	±0.682
52	47.6	46.8	46.4	46.93	±0.691
54	47.4	46.9	47.2	47.17	±0.285
56	48.1	47.4	46	47.17	±1.210
58	46.6	46.6	47.7	46.97	±0.719
60	46.6	46.6	45.9	46.37	±0.457
62	45.5	46.7	45.1	45.77	±0.942
64	44.7	45.4	44.7	44.93	±0.457
66	43.8	44.5	44.5	44.27	±0.457
68	41.9	41.1	41.7	41.57	±0.471
70	40.1	38.9	40	39.67	±0.753

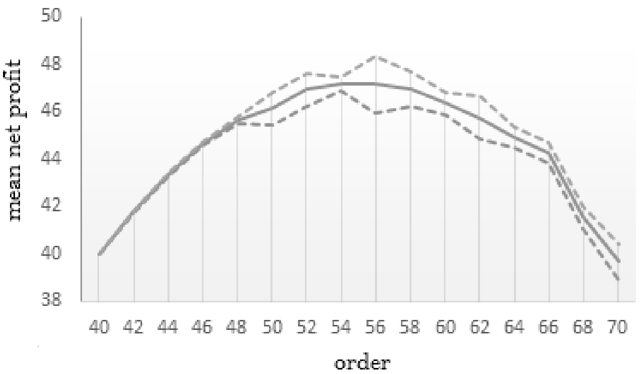

Fig. 8. Relation between the expected net profit and the order (refund=$0.5).

From this perspective, Freddie can notice that he was not making the right decision when he ordered 70 copies per day (starting point). The mean net profit will significantly increase if the daily order is reduced to the range 52-58 (improved situation). For example, he may decide to order 55 copies per day. In this case, the mean net profit is expected to increase by around 20% (approx. from $40 to $48).

However, the reduction of the order will not have a positive impact on the distributor. Under these circumstances, the ABMS system would allow the dyad distributor-newsvendor to explore new scenarios in which both can benefit. For example, we consider the option of modifying the refund. Hence, from the previous *baseline scenario*, we move to a new scenario where the distributor pays $1 per unsold copy in order to encourage that the newsstand increases his orders.

Under this *high-refund scenario*, we have carried out the same analysis. The results are displayed in Table II and Fig. 9.

TABLE II: RESULTS OF THE SIMULATIONS (HIGH-REFUND SCENARIO) MEAN NET PROFIT OF THE NEWSVENDOR ($)

Order	Run 1	Run 2	Run 3	Average	Conf. int.
40	40	40	40	40	±0
42	41.8	41.9	41.9	41.87	±0.065
44	43.6	43.5	43.5	43.53	±0.065
46	44.7	45.1	45.2	45	±0.300
48	46.3	46.4	46.5	46.4	±0.113
50	47.3	47.6	47	47.3	±0.339
52	48.4	48.5	48.2	48.37	±0.173
54	49.2	48.9	49	49.03	±0.173
56	49.7	48.9	49.4	49.33	±0.457
58	50.6	49.3	49.5	49.8	±0.792
60	50	49.2	49.4	49.53	±0.471
62	49.4	50	49.1	49.5	±0.519
64	49.2	49.3	50.5	49.67	±0.819
66	48.8	49.5	49.4	49.23	±0.428
68	48.4	47.3	48.2	47.97	±0.663
70	47.6	46.9	47.8	47.43	±0.535

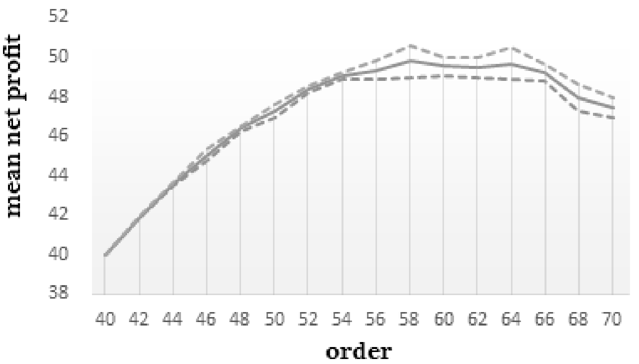

Fig. 9. Relation between the expected net profit and the order (refund=$1).

Fig. 9 provides evidence of how the refund motivates Freddie, who aims to maximize its expected net profit, to increase the number of copies ordered—now the optimal order is in the range 58-66. For instance, let's assume that he orders 62. Noticeably, this high-refund scenario allows the newsvendor to maximize its expected net profit (approx. from $48 to $50 per day). The overall improvement regarding the starting point would increase up to 25%.

Nonetheless, the new scenario will have a double impact on the distributor. On the one hand, the desired effect: sales will increase as Freddie is increasing his order. On the other hand, a counter-effect: his operating costs will grow as a consequence of the increased refund. In this sense, the distributor will have to look for an appropriate balance between both effects. ABMS would allow them to easily integrate the distributor in the simulation model, which represents a major advantage of this approach. The scope of the model would increase from the firm level to the supply chain level.

VI. CONCLUSION: ABMS IN REAL-WORLD SCENARIOS

Business prototyping provides practitioners with a powerful (cost-free, risk-free, fast-testing, high-potential) framework where they can tackle large complex and dynamic organizational business which would be otherwise intractable. This research highlight that this approach to problem solving is a three-step procedure: (1) modeling and implementation; (2) simulation and analysis; and (3) real-world development.

Within the prototyping techniques, agent-based modeling and simulation (ABMS) is an emerging field. These models replicate real-world environments in a natural way: the convoluted system is created from basic units (agents). This makes ABMS especially interesting in the analysis of emergent phenomena—that is, the large-scale behavior of a complex system which does not have any clear explanation in terms of the system's constituent parts but in their interaction.

Another major advantage of this prototyping methodology lie in its modular nature. It may take more time to build simple models than other approached, but modularity makes the effort of making complex systems greatly decreases. For this reason, ABMS systems are highly flexibles: they can be easily integrated in a system with a wider scope and/or they can be simply adapted to additional restrictions and behaviors. In this regard, managers are enabled to handily explore new scenarios.

To illustrate this approach, we have employed the Freddie's newsstand example. We have exhibited how this problem can be modelled and implemented (including validation and verification) in an agent-based environment. From this point, we have showed how the newsvendor can easily explore the baseline scenario and make decisions that increase his net profit, as well as to explore new scenarios. As a venue for future work, we could increase the functionality of the ABMS system by adding new agents, given that scalability is a core property of these models. For example, we may simultaneously consider the newsvendor and the distributor in the system, or we might introduce to the model other products (substitute or complementary) that the newsvendor also sells.

APPENDIX

The model described in this article can be downloaded in http://ccl.northwestern.edu/netlogo/models/community/PJ_freddie and run in free open-source NetLogo.

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Borja Ponte completed his undergraduate studies on Industrial Engineering with expertise in Operations Management at the Polytechnic School of Engineering of the University of Oviedo (Spain) and is currently a PhD candidate and teaching assistant within the same institution. In his dissertation he is trying to combine the fields of Supply Chain and Agent-Based Systems. Part of this research has been carried out at the Cardiff Business School (Cardiff University) under the sponsorship of Professor Stephen Disney. He has participated in two research projects from which he has published seven articles in ISI-indexed journals (three of them in Q1 journals).

Jose Costas is a mathematician (UNED), is expert in system modeling, simulation, and process improvement, and has been certified Six Sigma Master Black Belt. With an extensive experience in process improvement and in the IT field, he has mentored and coached hundreds of projects and more than 30 black belts to their certification. He has been teaching for more than 10 years in master and post-graduation programs disciplines like lean operations, statistical thinking, project management, and discrete-event simulation in the University of Valladolid, the Colegio de Ingenieros de Madrid and the Universidad Católica de Valencia in Spain. In Portugal, he teaches the "Taguchi and Six Sigma Methods" subject in ESCE-IPVC Quality program. He has published more than 50 articles in several journals.