Study of Social Consciousness in Stochastic Agent-Based Simulations: Application to Supply Chains

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ABSTRACT

Empirical game theory allows studying the strategic interactions of agents in simulations. Specifically, traditional game theory describes such interactions by an analytical model, while empirical game theory employs simulations. In this paper, we use empirical game theory to study how the more-or-less selfishness of agents affects their behaviour. To this end, we assume that every agent utility can be split in two parts, a first part representing the direct utility of agents and a second part representing agent social consciousness, i.e., their impact on the rest of the multiagent system. An application to supply chains illustrates this approach. In this application, the collaborative strategy is often used by every company-agent at whatever their same level of social consciousness, which may indicate that every agent is strongly related with one other.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems

General Terms

Economics, Experimentation, Performance

Keywords

Supply Chain, Nash equilibrium, Simulation, Collaboration

1. INTRODUCTION

Walsh and his colleagues [5] have introduced the concept of empirical game theory (GT) by using GT to analyze the behaviour of agents in simulations. In other words, they replaced the analytical model representing strategic interactions in GT by simulation outcomes. Another example of the use of this approach is provided by Wellman and his colleagues [6] who used it to design their agent for the Trading Agent Competition/Supply Chain Management 2003. Our previous work [3] is also such an example of approach suitable for the analysis of interactions in agent-based simulations profitting from GT concepts and applied to supply chains (SC). In our application to SC, we found that the highest level of collaboration was often a Nash equilibrium which incurs the minimum SC cost. We now enhance this previous work in two ways in order to study (Enhan. 1) how the obtained results vary when the utility measuring the achievement of the group goal changes with regard to the individual utility of every agent, and (Enhan. 2) how robust the results are with respect to the stochasticity of some parameters. Our approach is presented in Section 2.

Then, we apply our approach to SC again. In this context, Enhan. 1 is performed by measuring how the SC (i.e., group) goal of delivering products to end-customers is achieved, while the individual goal of every company is to minimize its inventory holding cost. Indeed, companies have to make a trade-off between increasing their inventory level to avoid stock-outs and achieve thus the group goal, and decreasing their inventory level to achieve their individual goal. Finally, the stochastic parameter in Enhan. 2 represents end-customers demand of the two markets buying products to the SC. With Enhan. 2, we check if results depend on the considered instance of a single demand distribution. This application to SC management is described in Section 3.

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2. APPROACH

Concerning Enhan. 1, every agent $i \in I$ in our previous work [3] had a common fixed way to calculate its utility u^i that was based on its direct/individual utility u^i_{dir} and on its impact on other agents u^i_{soc}, so that $u^i = ((1-\epsilon^i)u^i_{\text{dir}} + \epsilon^i u^i_{\text{soc}})/(1-\epsilon^i)$, with $\epsilon^i \in [0;1)$; we divide by $(1-\epsilon^i)$ because u^i_{dir} represents realistic costs in our case study. On the contrary, we always kept $\epsilon^i = 2/3$ for each of the $|I|$ agents ($|I|$ denotes the cardinal of the set of agents I) in our previous paper, while Enhan. 1 consists in relaxing this constraint. More precisely, we now verify that agents still have incentives to use the collaborative strategy when ϵ^i varies, or conversely, if every agent behaviour depends on the value of ϵ^i. Notice that $\epsilon^i \to 1$ implements a fully benevolent agent because u^i_{dir} becomes negligible in comparison with u^i_{soc}. In this paper, we only address the case in which $\epsilon^1 = \epsilon^2 = \ldots = \epsilon$ with $\epsilon \in \{1/6, 2/6, 3/6, 4/6, 5/6\}$, which means that all agents have the same level of selfishness ϵ, but that this common level may be different between two of the considered situations. As a consequence, we do not consider the case in which selfish agents cohabit with benevolent agents (the prisonner's dilemma cannot occur), although the presented approach allows doing so. This assumption simplifies the analysis of the simulation outcomes, and we will try to relax it in future work.

Enhan. 2 deals with taking probability distribution for some stochastic parameters into account in replacement of a fixed sequence of numbers, in order to study stochastic models. This means that we generate an instance of the considered distribution, and then, we apply our approach with this fixed sequence of numbers. This is the same method as in our previous paper, except that we repeat the process with other instances of the considered distribution in order to next use statistical tools. In the case study, the stochastic parameter is end-customer demands D^{lumber} and D^{paper} representing the two markets our SC sells in.

Then, our approach may be described as three successive steps, viz **optParam**, **simAllConfig**, and finally **anaSimOut**: (i) **optParam** first optimizes some parameters for every value of ϵ when every agent i uses the same strategy $s^i \in S$ (the strategy set S is unique to all agents), i.e., optimization is only carried our for the strategy profile $(s^i, s^i, \ldots, s^i)$ in order to save computation time. In the case study, these optimized parameters are the inital inventory levels $\{Inv^i_{\text{init}}\}_{i=1}^{i=|I|}$. (ii) Then, **simAllConfig** simulates the SC for the $|S|^{|I|}$ combinations of s^i among the $|I|$ agents with the $\{Inv^i_{\text{init}}\}_{i=1}^{i=|I|}$ found by **optParam**. (iii) Finally, **simAllConfig** builds games in the normal form with the simulation outcomes generated by **simAllConfig**, and looks for the Nash equilibria of these games. Gambit [2] is the set of software tools used to analyze these games. Depending on $\{\epsilon^i\}_{i=1}^{i=|I|}$, different games can be built based from each output of **simAllConfig**.

3. CASE STUDY: APPLICATION TO SUPPLY CHAIN MANAGEMENT

3.1 Adaptation of the approach

We illustrate this approach in the context of the management of a wood SC. We profit from Enhan. 1 to study if selfish as well as benevolent company-agents should collaborate by sharing information concerning market consumption. This shared information is of importance to companies when they place orders, because this information may be distorted by a phenomenon called the "bullwhip effect" [1] that causes an increase of their inventory level and a decrease in their customer service level, and information sharing is the most often proposed solution to the bullwhip effect [4].

Concerning Enhan. 1, we take u^i_{dir} as company-agent i inventory holding cost, and u^i_{soc} as backorder cost, i.e., as stockout cost. Specifically, backorders correspond to orders that were not fulfilled in the past and that have to be shipped as soon as possible, i.e., there are no lost sales in this simulation model because clients wait for product availability. Since backorders are measured in our specific case as negative inventory levels, the calculation of u^i_{dir} and u^i_{soc} are similar, and thus, their aggregation into u^i represents a cost. Of course, every agent tries to minimize its cost u^i (no money can be earned). We think backorders can be used as a measure for social consciousness u^i_{soc} because agents are *not obliged* to consider them when they make decisions (while they always have to take the inventory holding cost into account in u^i_{dir}), but the *goal of the entire* SC should be to satisfy end-customers and avoid thus these backorders. In other words, the SC has not achieved its goal if products are not available by retailers, which is a problem obvious only to retailers. In order to make the other companies internalize the SC goal, we need to have them take backorders into account.

We profit from Enhan. 2 to consider a stochastic market consumption pattern. More precisely, we assume that market demand is a uniform distribution M of integer numbers spread over $\{11, 12, \ldots, 17\}$, and we carry out our experiments with $|M| = 10$ particular instances m_A to m_J of M over the fifty weeks of a simulation run. For instance, m_A corresponds to the two series of fifty numbers $D^{\text{lumber}} = \{16, 13, 16, 11, 15, \ldots, 15, 15, 12, 16, 15\}$ and $D^{\text{paper}} = \{15, 15, 14, 15, 14, \ldots, 13, 14, 14, 11, 13\}$, where the w^{th} number represents the market demand in Week w, e.g., $D_2^{\text{lumber}} = 13$ means that 13 units are requested to the LumberRetailer in Week 2. We only consider $|M| = 10$ instances of the distribution, because $|M| * |S|^{|I|}$ simulations are required to build the corresponding ten games in the normal form. However, **simAllConfig** carries out $|M| = 10$ times these $|S|^{|I|}$ simulations with one of the ten instances of M in order to build a game. In each of the obtained games, **anaSimOut** changes the ratio ϵ between the u^i_{dir} and u^i_{soc} when Gambit looks for Nash equilibria.

Ordering strategy	Level of collaboration	Type of communication
μ	No collaboration	No communication
β	Information sharing with direct neighbours	Point to point
γ	Information centralization	Bulletin board

Table 1: The three ordering strategies.

3.2 Simulation model

In this case study, we use exactly the same simulation model with $|I| = 6$ agents as in [3]: a LumberRetailer buys from a LumberWholesaler, which buys from a Sawmill, which itself is the only company managing both lumber and paper units. In fact, besides lumbers, the Sawmill can also sell paper units to the PulpMill, which then sells to the PaperWholesaler, which finally sells to the PaperRetailer. Each retailer sells in a different market (lumber and paper), and the Sawmill buys from an infinite source.

Next, each of the six companies i makes its ordering decisions by applying one of $|S| = 3$ ordering strategies s^i called α, β and μ. Once set, s^i remains the same for the fifty weeks of a simulation run. Table 1 outlines these three strategies:

- With ordering strategy μ, company-agents make their decision on their own and can only rely on their incoming orders and shipping to decide what order to place. The only information transmitted with μ are orders and no additional information is shared to help other agents place their own orders. In practice, μ is an (s, S) policy, which is classic in Inventory Management, and in which a company orders $(S - InvP)$ items when the level of its inventory position $InvP$ falls below s. We showed in [3] that taking $s = 0$ and S equals to the current incoming order is optimal.

- There is slight collaboration with strategy β, because agents now transmit the market consumption information to their supplier, which allows every agent to place orders in a more accurate way. From a technical viewpoint, every placed orders is a two-dimension vector, and the quantity ordered is equal to the sum of its two elements: the first element corresponds to the market consumption transmitted by each company to its direct supplier, and the second element represents the products to be ordered in more or in less than the market

Value of ϵ	Nash equilibria
$\epsilon = 1/6$	$(\gamma,\mu,\gamma,\mu,\gamma,\gamma)$, $(\gamma,\gamma,\gamma,\mu,\mu,\gamma)$
$\epsilon = 2/6$	$(\gamma,\mu,\gamma,\mu,\mu,\beta)$, $(\gamma,\gamma,\gamma,\mu,\mu,\gamma)$
$\epsilon = 3/6$	$(\gamma,\beta,\gamma,\mu,\mu,\beta)$, $(\gamma,\gamma,\gamma,\mu,\gamma,\gamma)$
$\epsilon = 4/6$	$(\gamma,\gamma,\gamma,\gamma,\gamma,\gamma)$
$\epsilon = 5/6$	$(\beta,\mu,\beta,\mu,\mu,\beta)$, $(\beta,\beta,\beta,\beta,\beta,\beta)$ $(\beta,\gamma,\beta,\gamma,\beta,\gamma)$, $(\beta,\gamma,\beta,\gamma,\gamma,\beta)$ $(\gamma,\beta,\gamma,\beta,\beta,\beta)$, $(\gamma,\gamma,\gamma,\gamma,\beta,\beta)$

Table 2: Results for Instance m_A.

consumption. Notice that the first element indicates the past market consumption, since this information travels the SC as slowly as orders.

- The highest level of collaboration is implemented in strategy γ, in which retailer-agents write the market consumption information on a bulletin board, and the rest of agents can read this information (this is information centralization). In practice, γ works as β, except that companies take the first element of their two-dimension orders equal to the current market consumption (while it is equal to past data with β).

3.3 Results and analysis

Table 2 enumerates all the Nash equilibria obtained with different values of ϵ with the particular instance m_A of the market demand M. For example, for $\epsilon = 5/6$, there are 6 Nash equilibria, and the first one is the *strategy profile* $(s^1, s^2, s^3, s^4, s^5, s^6) = (\beta,\mu,\beta,\mu,\mu,\beta)$; in this equilibrium, the LumberRetailer ($i = 1$), the LumberWholesaler ($i = 3$) and the Sawmill ($i = 6$) use Strategy β, while all other agents use γ. Note that μ occurs 15 times, β 29 times and γ 40 times in overall Table 2, which represents respectively to frequencies of 20%, 29% and 51%. Therefore, the highest level of collaboration γ occurs in half of the found Nash equilibria.

Next, the question addressed in this paper is to determine at which value of ϵ the Nash equilibria switch from a full-collaborating system (that is, most companies collaborate at the highest level, e.g., $(\gamma,\gamma,\gamma,\beta,\gamma,\gamma)$) to a full non-collaborating one (that is, most companies disagree to collaborate, e.g., $(\mu,\beta,\mu,\mu,\mu,\mu)$). To answer this question, we check if the Nash equilibria with low ϵ (selfish agents) often apply the non-collaborative μ, and/or if the Nash equilibria with high ϵ (benevolent agents) frequently use the highly collaborative γ. To see this, we calculate the frequency at which every strategy is used depending on the value of ϵ. That is, we calculate the central column about m_A in Table 3 based on the numbers in Table 2. This calculation is achieved in the following way. In line '$\epsilon = 5/6$' in Table 2, there are 6 equilibria that count a total of 3 μ, 20 β and 13 γ. These three numbers are reported in line $\epsilon = 5/6$ in Table 3 as '$3/36 = 8\% \rightarrow \mu$', which means that 3 of the 36 (=3+20+13) strategies used in a Nash equilibrium are μ. Next, the right column of Table 3 contains the same results, but with the nine other instances m_B to m_J of market consumption. To calculate every frequency in the right column, we take the average of the frequencies obtained with the ten market demands, i.e., these frequencies are not weighted by the number of equilibria: to obtain '$7\% \rightarrow \mu$' with $\epsilon = 5/6$ in the right column of Table 3, the 8% obtained with m_A has the same importance as the percentages obtained with $m_B, \ldots, m_J$, even though they do not represent the same quantity of equilibria.

With both center and right columns in Table 3, we can see that μ only has low occurence frequencies, and that these frequencies do not depend on ϵ. This means that the decision of collaborating does not depend on the level of social

Value of ϵ	Frequency of μ,β and γ under Instance m_A	Average frequency of μ,β and γ over Instances m_A to m_J
$\epsilon = \frac{1}{6}$	$4/12 = 33\% \rightarrow \mu$ $0/12 = 0\% \rightarrow \beta$ $8/12 = 67\% \rightarrow \gamma$	$27\% \rightarrow \mu$ $9\% \rightarrow \beta$ $64\% \rightarrow \gamma$
$\epsilon = \frac{2}{6}$	$5/12 = 42\% \rightarrow \mu$ $1/12 = 8\% \rightarrow \beta$ $6/12 = 50\% \rightarrow \gamma$	$22\% \rightarrow \mu$ $6\% \rightarrow \beta$ $72\% \rightarrow \gamma$
$\epsilon = \frac{3}{6}$	$3/12 = 25\% \rightarrow \mu$ $2/12 = 17\% \rightarrow \beta$ $7/12 = 58\% \rightarrow \gamma$	$17\% \rightarrow \mu$ $14\% \rightarrow \beta$ $69\% \rightarrow \gamma$
$\epsilon = \frac{4}{6}$	$0/6 = 0\% \rightarrow \mu$ $0/6 = 0\% \rightarrow \beta$ $6/6 = 100\% \rightarrow \gamma$	$9\% \rightarrow \mu$ $16\% \rightarrow \beta$ $75\% \rightarrow \gamma$
$\epsilon = \frac{5}{6}$	$3/36 = 8\% \rightarrow \mu$ $20/36 = 56\% \rightarrow \beta$ $13/36 = 36\% \rightarrow \gamma$	$7\% \rightarrow \mu$ $43\% \rightarrow \beta$ $50\% \rightarrow \gamma$

Table 3: Relative frequency of the occurence of μ,β and γ in the incurred Nash equilibria.

consciousness ϵ. The interpretation of this may be that every company-agent is so strongly *dependent* on each other, that they should all collaborate.

4. CONCLUSION

This paper studied the impact of social consciousness on individual decision making. As an illustration, we studied if companies in a supply chain would collaborate by sharing the demand when they are more or less benevolent. We found that the benevolence level does not have a great impact, perhaps because companies are tightly linked in our simulation.

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