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Agents playing the Beer Distribution Game: Solving the Production Dilemma through the Drum-Buffer-Rope Methodology

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Abstract The Beer Distribution Game (BDG) is a widely used experiential learning simulation game aimed at teaching the basic concepts around Supply Chain Management (SCM). The goal in this problem is to minimize inventory costs while avoiding stock-outs –hence the players face the dilemma between storage and shortage. Human players usually get confused giving rise to significant inefficiencies in the supply chain, such as the Bullwhip Effect. This research paper shows how artificial agents are capable of playing the BDG effectively. In order to solve the dilemma, we have integrated supply chain processes (*i.e.* a collaborative functioning) through the Drum-Buffer-Rope (DBR) methodology. This technique, from Goldratt's Theory of Constraints (TOC), is based on bottleneck management. In comparison to traditional alternatives, results bring evidence of the great advantages induced in the BDG by the systems thinking. Both the agent-based approach and the BDG exercise have proved to be very effective in illustrating managers the underlying structure of supply chain phenomenon.

Keywords: Beer Game, Supply Chain Management, Drum-Buffer-Rope methodology, Multi-Agent System, Production

1 Introduction

The Beer Distribution Game (BDG) is a role-playing simulation exercise of a simple supply chain that has been used in countless management courses since it was developed at the MIT Sloan School of Management (Jarmain, 1963). It aims at teaching the main principles of Supply Chain Management (SCM), as provides

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practical evidence of the generation of inefficiencies along the production and distribution system (Sterman, 1988). The experimental nature of this game has proved to be very effective in helping managers to understand the causal relationships between decision-making and supply chain behaviour (Goodwin and Franklin, 1994). For this reason, it has been widely studied in the literature, especially in the last two decades given the strategic importance of SCM in the current competitive environment.

The BDG scenario is defined by a single-product linear supply chain, composed of four main levels: factory, distributor, wholesaler, and retailer (*e.g.* Kaminsky and Simchi-Levi, 1998). At the beginning of each turn (a simulated week), the different levels receive the product from the previous level (material flow) and an order from the next level (information flow). Then, they try to ship the requested amount from its inventory. If it is not possible, a backorder is created and the remainder quantity will be fulfilled as soon as possible. Finally, they order an amount of beer from their supplier –in the case of the factory, these are manufacturing orders.

Under this context (*e.g.* Strozzi *et al*., 2007), there are only two sources inefficiencies: uncertainty in customer demand (simulated through random distributions) and lead time (fixed delay between orders and products are sent and received, *e.g.* three turns for both). It should be noted that production, storage, and transportation capacities are considered unconstrained.

The only goal for the participants in the BDG is to minimise costs. These are incurred in two ways (*e.g.* Chaharsooghi *et al*., 2008): carrying inventory and back-ordering, *e.g.* respectively $0.5 and $1 per unit of beer per period, creating an incentive to carry some inventory rather than back-order. As explained before, the only decision that each member must make is how much to order. Hence, the BDG dilemma emerges: if the purchase order is high (low), the stock-out risk reduces (surges) but the inventory costs tend to increase (decrease).

The results tend to be counterintuitive for the participants, as the small variations in consumer's demand are greatly amplified along the supply chain –this is the Bullwhip Effect (Lee *et al*., 1997). Sterman (1989) showed that the interaction of individual decisions produces aggregate dynamics in the supply chain which diverge from optimal behaviour. Therefore, the observed performance of human beings in the BDG is usually far from the optimal from a system-wide perspective (Lee and Whang, 1999).

This paper shows how an electronic supply chain managed by artificial agents has been developed. The aim is to provide evidence that they can play the BDG effectively (*i.e.* outperforming classical alternatives) from a collaborative approach, which is the main contribution of this research. More specifically, the Drum-Buffer-Rope (DBR) technique, detailed in section 2, has been used to implement the holistic functioning within the production and transportation system. The agent-based development of the system is described in section 3. Section 4 shows the main results of this research study, while section 5 presents a discussion of the results regarding the stated objectives.

2 Managing the Supply Chain through the DBR methodology

The Theory of Constraints (TOC) is a management philosophy coined by Goldratt (1990) that views any production system as being limited in achieving a higher level of performance by only one restriction. Thereby, it is aimed at achieving breakthrough improvements focusing on its constraint, which may vary over time. The logical thinking of this theory is based on a continuous improvement cycle (Goldratt and Cox, 1992): (1) Identify the bottleneck; (2) Decide how to exploit the bottleneck; (3) Subordinate everything else in the system to the previous decision; (4) Implement measures to elevate the bottleneck; and (5) Evaluate if the bottleneck has been broken, and return to the beginning.

Within operations management, the TOC proposes the Drum-Buffer-Rope (DBR) methodology, named for its components (Goldratt and Cox, 1992). The *drum* is the physical constraint of the system, *i.e.* the node that limits its performance. The rest of the nodes follow the drum beat. Hence, the *buffer* protects the drum against variability, so that the full capacity in the bottleneck is exploited. The *rope* is required for subordinating the system to the drum –it is the release mechanism. That is to say, orders are released according to the buffer time before they are due. It should be underlined that the DBR configuration (planning state) must be complemented with the buffer management (monitoring stage). It implies administrating the buffer along the different nodes, in order to guide how the system is tuned for peak performance.

Although DBR technique was first oriented to the manufacturing process of the company, further development incorporates solutions for other areas. SCM is an emerging one of them. The early work deals with managing the whole system from a single company perspective (*e.g.* Cox and Spencer, 1998). Later studies have used TOC to promote supply chain collaboration. Simatupang et al. (2004) provided a conceptual work for using this approach to assist the members to realise the potential benefits. Wu *et al*. (2010, 2014) developed two enhanced DBR-based replenishment models under capacity constraints, in order to facilitate plants and central warehouses to implement TOC. Costas *et al*. (2015) demonstrated that the DBR methodology induced signify operational improvements in the supply chain –as the Bullwhip Effect is greatly reduced–, without any collateral damage.

When implementing the DBR method, the first question deals with identifying the bottleneck. In a real supply chain, it could be in any part of the system, depending on which one is limiting system performance. In the BDG, customer demand is the bottleneck –*i.e.* the other nodes cannot be the bottleneck due to the assumption of infinite production, storage, and transportation capacities. Thus, the *drum* is placed at the retailer.

According to TOC logical thinking, the next step is to decide how to fully exploit the bottleneck. In the BDG, it is exploited by selling the product at the retailer. This node beats out the rate at which the whole supply chain can work at. To maximize the bottleneck flow means to decrease the missing sales.

This leads to the last key point[2]: factory, distributor, and wholesaler must work subordinated to the bottleneck. That is to say, the drum must be protected against process variation –*i.e.* from shortages. In other words, we need to buffer the constraint. Hence, the *buffer* is the material release duration (time interval by which the release of work is predated), while the *rope* is the release timing (it could be as a real-time feedback between the drum and the gating operation). Therefore, *e.g.* in the case of the factory the buffer is 9 turns (it is followed by three levels, and the lead time is 3 turns for every member). The rope length is the same as the buffer duration, and trying the rope ensures that excess flow cannot be admitted.

Thereby, at each turn, the factory decides the manufacturing orders that are issued, after analyzing the evolution of customer demand. Afterwards, each supply chain member (except the retailer) carries out buffer management. It means compensating the flow dissipated towards the following member. The DBR orders are dosage orders into the buffer, which are dissipative. Each agent decides what to dose subordinated to the bottleneck, so backorders creation does not make sense.

Figure 1 outlines the DBR implementation in the BDG explained above[3].

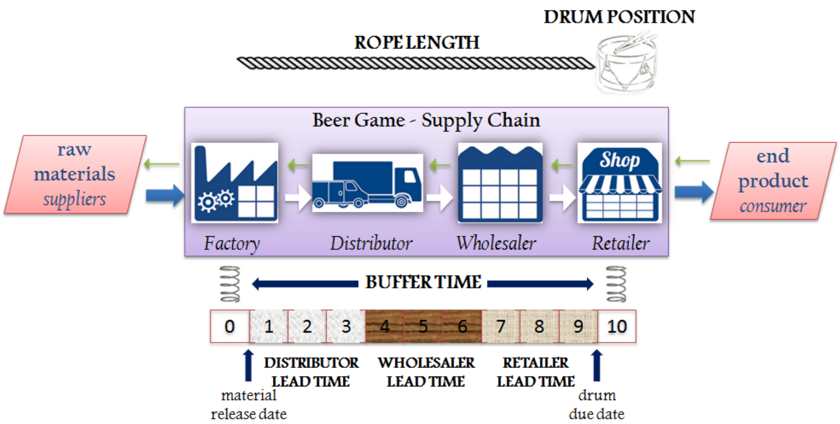

Fig. 1 Scheme of the supply chain when working according to the DBR methodology

3 Description of the Multi-Agent System

Agent-Based Modeling and Simulation (ABMS) is the computational method that enables to create, analyze, and experiment with models composed of agents that

[2] Note that, according to BDG assumptions, it is not possible to elevate the bottleneck. It is an external constraint, which is beyond the supply chain's sphere of influence. Hence the bottleneck will not be broken, and the continuous improvement cycle is reduced to three steps.

[3] Youngman (2009) elaborated an excellent guide that can be consulted to get more detail in the implementation process.

interact within an environment (Gilbert, 2008). When the system is composed by intelligent agents that cooperate in order to achieve collective goals, it is called Multi-Agent System (MAS) (Wooldridge, 2002). These emerging techniques are optimal for the study of SCM, because of the intrinsic characteristics of this problem (De la Fuente and Lozano, 2007). They allow studying the effective of collaborative solutions in the supply chain, as many authors did -*e.g.* Moyaux *et al*. (2004) proposed the Quebec Wood Supply Game. Kimbrough *et al*. (2002) explored the concept of a supply chain managed by artificial agents, and demonstrated that they were capable of playing the BDG more effectively than humans.

We have used KAOS methodology to devise the conceptual model (Dardenne *et al.*, 1993) robust software engineering techniques (Taguchi *et al.*, 2000) to build the system, and NetLogo (Wilensky, 1999) to implement it. An interface window provides the experimenter with the control to set-up parameters and to run each experimenter, as well as the graphics and monitoring to track the system. By way of example, figure 2 is a screenshot of the three-dimensional graphical simulator. It shows the product street (horizontal), through which the material flows from west to east –the patch closest to each node represent the on-hand inventory–, and the orders street (vertical), through which the orders move from the south to the north. The other regions of the simulation are the future event list (space for agents who act as events), the sink for the system (for tangible facts), and the accounting zone (for statistical purposes.

Each supply chain node functions according to a finite state machine schema: (1) Idle state, where it waits until the drum triggers it; (2) Serve backorders state, where it completes past orders if remain at the node; (3) Shipping orders state, aimed at moving material downstream; (4) Sourcing state, when it takes care of the information flow; and (5) Reporting state, when it updates the results and exports information. In this way, the various supply chain members carry out the usual BDG operations according to the DBR methodology.

Fig. 2 Three-dimensional image of the graphical simulator

4 Numerical Results

As usual in the BDG, we have simulated customer demand through a normal distribution with a mean of 12, while the standard deviation has been changed in order to evaluate the results in different scenarios: 1 (low variation), 3 (moderate variation), and 5 (high variation). We have carried out simulations of 330 periods. The first 30 are considered as warm-up period, hence they are not taken into account for the exposed results.

The first step is to check system stability according to common practices. We checked that the results behave stable using IR-charts, and replicated the same experiment to conduct ANOVA tests. We verified that p-value is greater than 5% in the Levene test. Thereby, we failed to reject the null hypothesis (*H0: var(replica1) = var(replica2)*) and we consider the results to be statistically representative.

With the aim of simulating the human's behaviour in the BDG, we have implemented the order-up-to policy[4] in the system using three-period moving averages to forecast. After carrying out the BDG experiments with real students, we have observed that they obtain the best results when using this simple method – although they tend to be more impulsive in their purchase orders.

Table 1 report the final results of the system in the three scenarios when using both methods. According to TOC's philosophy, we understand backlog costs as missing sales cost. That is to say, each level assumes a cost of $1 per unit of beer when there is shortage in the retailer. It must also be noted that inventory costs ($0.5 per unit of beer per period) considers the entire amount of product that is in the node's material flow (both on-hand inventory and product being transported).

Broadly speaking, table 1 provides evidence of agents' high effectiveness when playing the BDG using the DBR methodology. They are able to dramatically reduce inventory costs at all levels without increasing missing sales.

Table 1 Results of the tests

Supply Chain Performance	Demand ~ N(12,1)		Demand ~ N(12,3)		Demand ~ N(12,5)	
	Agents	Humans	Agents	Humans	Agents	Humans
Inventory _ Factory	$3,641	$21,662	$4,258	$22,240	$4,538	$39,636
Inventory _ Distributor	$1,900	$8,209	$2,119	$14,405	$2,225	$20,997
Inventory _ Wholesaler	$524	$2,546	$696	$3,939	$772	$5,793
Inventory _ Retailer	$346	$452	$628	$719	$819	$1,308
Missing sales _ Overall	$4	$652	$216	$496	$328	$344
Total Supply Chain Costs	$6,415	$33,521	$7,917	$41,799	$8,682	$68,078

[1] Note that 'agents' refers to the DBR method, and 'humans' refers to the OUT policy.

[4] This replenishment method is based on a basic periodic review system for issuing orders depending on incoming demand and inventory position, aimed at bringing this position up to a defined level. See Chen *et al.* (2000) for more detail of this widely studied policy.

5 Discussion

The DBR method has demonstrated to be a highly effective technique to play the BDG. In other words, as expected, agents clearly outperform humans when facing this classic distribution game. It should be highlighted the huge difference: cost reduction is enormous. It is mainly due to the large reduction in the average inventory position of chain members –the Bullwhip Effect generated by human behaviour punishes the system, especially those nodes which are far from the client. Nevertheless –and paradoxically–, even working with lower inventory levels, TOC philosophy displayed by agents leads to missing sales reduction.

How can this be explained? Playing the BDG with the OUT policy –even more with impulsive purchasing– causes large variations along the supply chain. Members tend to panic by shortage and thus contribute to information distortion. The peaks in orders received translate into larger peaks in orders issued (see left part of figure 3). These inefficiencies –provoked by the combined effect of lead times and demand uncertainty– lead to a poor performance. The more demand variability, the more costs are assumed –as the members overprotect themselves. They reduce missing sales at the expense of unavoidable storage costs.

Conversely, this issue is under control when managing the supply chain from a systemic perspective. In this case, amplification also occurs along the system –and hence the factory supports the higher costs– but is much lower (see right part of figure 3 and note the difference between both scales). The supply chain is also damaged when demand variability increases, but the growth has been heavily damped (both in absolute and in relative terms). In summary, managing the system through the bottleneck results in a much better solution, in comparison with that one where the various levels selfishly seek the best solution for themselves.

Finally, we would like to insist on the importance of simulation as a way to educate students and managers in the comprehension process of the underlying effects of decision-making. The BDG draws an optimal context to study them.

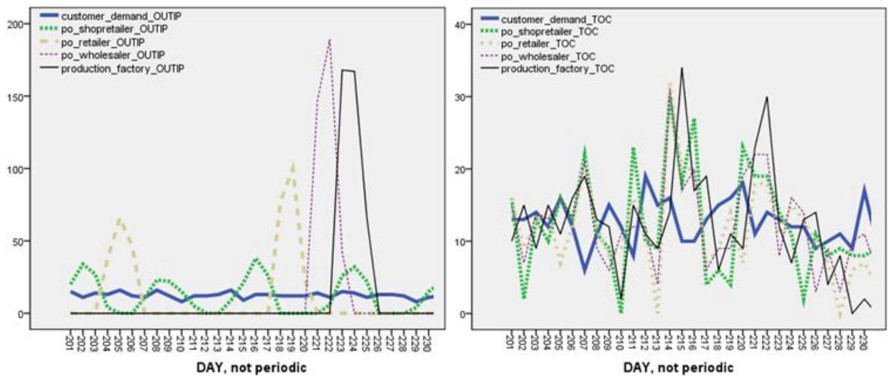

Fig. 3 Demand, orders, and production in the tests carried out with a N(12,3) demand from turn 201 to 231 when the supply chain is managed by the OUT policy (left) and by the DBR (right).

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