The Behavior of Lean and the Theory of Constraints in the Wider Supply Chain: A Simulation-Based Comparative Study Delving Deeper into the Impact of Noise

J. C. Puche-Regaliza, B. Ponte, J. Costas, R. Pino, and D. de la Fuente

Abstract The design and implementation of *systems thinking* strategies for supply chains, based on collaboration among partners, is gaining ground as a key source of competitive advantages. Therefore, a growing number of companies is moving the scope of their lean management (LM) and theory of constraints (TOC) solutions from the production system to the wider supply chain. Building on prior research studies, we explore their robustness against noise in a supply chain setting. To this end, we consider the Kanban and drum-buffer-rope (DBR) control systems, respectively, from the LM and TOC paradigms; we model a four-echelon supply chain by means of an agent-based approach; and we measure the net profit of the supply chain under six scenarios with increasing level of noise. As can be expected, we observe that the net profit decreases significantly as the severity of the noise grows. This happens both for the LM- and TOC-based supply chains. However, it is relevant to note that the gradient of the curve is stronger for the Kanban system. This means that DBR makes the supply chain more robust against noise. As a result, we conclude that the benefits derived from implementing DBR, in comparison with Kanban, increase significantly as the noise becomes more demanding.

J. C. Puche-Regaliza (✉)
Department of Applied Economics, Faculty of Economics and Business, University of Burgos, Infanta Doña Elena Square, Infanta Doña Elena Square, S/N, 09001 Burgos, Spain
e-mail: jcpuche@ubu.es

B. Ponte · R. Pino · D. de la Fuente
Department of Business Administration, Polytechnic School of Engineering, University of Oviedo, Campus of Viesques, S/N, 33204 Gijón, Spain
e-mail: ponteborja@uniovi.es

R. Pino
e-mail: pino@uniovi.es

D. de la Fuente
e-mail: david@uniovi.es

J. Costas
Department of Engineering, Florida Centre de Formació, Florida Universitária, Rei en Jaume I, nº 2, 46470, 46470 Catarroja, Valencia, Spain
e-mail: jcostas@florida-uni.es

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1 Introduction

Lean management (LM) and the theory of constraints (TOC) define two different strategic approaches to management that are built on the same pillars: those of *systems thinking*.[1] The former emerged from the principles of the Toyota Production System, designed and developed by Taiichi Ohno [30] from the late 1940s to the early 1970s—although it did not become popular worldwide until the 1990s—[14, 44], while the latter became prominent after the publication of Eliyahu M. Goldratt's books in the 1990s [17, 41].

Given that they share the same pillars, there are strategic similarities between LM and TOC. Moore and Schinkopf [28] underscore four main similarities between them: (i) the *value* principle, according to which customer's perception of value is central to them; (ii) the key role of the *flow* in the management of the system; (iii) the endless *pursuit of perception* based on continuous improvement cycles; and (iv) the adoption of *pull* methods for controlling the flow of materials. In this regard, LM proposes the Kanban control system [21] for just-in-time production,[2] while TOC suggests the drum-buffer-rope (DBR) methodology [6].

At the same time, there are relevant divergences between LM and TOC, which mainly stem from their different operational goals. On the one hand, LM aims at increasing profits by minimizing waste. On the other hand, TOC places the focus on the maximization of the throughput [28]. Accordingly, Kanban focuses on eliminating unevenness and overburden regardless of where they are in the system, while DBR directly concentrates on the bottleneck of the system.

Both LM and TOC have widely proven to be efficient means for managing production systems; see Liker [23] and Hines et al. [14] for LM, and Mabin and Balderstone [24] and Gupta and Boyd [13] for TOC. But which one is best and what does their performance depend on? Several authors have addressed these questions, which would help managers direct redesign and investment efforts to maximize the performance of their systems. In this regard, we may claim that there are two main lines of conclusions in the literature. Some studies have concluded that TOC-based scheduling systems systematically offer higher performance than LM-based mechanisms, including Koh and Bulfin [22] and Watson and Patti [42]. At the same time, other researchers have observed that each one has its own region of superiority, such as Takahashi et al. [39] and Jodlbauer and Huber [20]. We highlight that this

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[1] This perspective highlights the need to understand systems as a whole rather than a collection of parts, plunging actors into a global optimisation environment, where they care about interrelationships among processes, interdependencies among decisions, patterns instead of snapshots, and root causes of the inefficiencies rather than their symptoms [36].

[2] Although less common, LM also employs CONWIP (the acronym of 'CONstant Work-In-Progress) as an alternative to Kanban. Interested readers are referred to Takahashi and Nakamura [40] for a comparison between them.

observation buttresses the findings by Grünwald et al. [11], one of the first comparisons between LM and TOC, claiming that Kanban works better in highly static or predictable scenarios, and DBR makes a difference in complex settings.

Nonetheless, it is important to highlight that all these analyses have been carried out for production systems. However, as the management of supply chains through *systems thinking* approaches becomes a crucial source of competitive advantages in the current business scene (see [31, 37]), both LM and TOC principles have started to be implemented in the wider supply chain setting. By way of example, we refer interested readers to Naylor et al. [29] and Martínez-Jurado and Moyano-Fuentes [27] for LM, and Simatupang et al. [38] and Puche et al. [34] for TOC.

In light of this, Puche et al. [33] broaden the LM versus TOC comparison to the area of supply chain management. They analyze the performance of the Kanban and DBR production schedules in two different supply chain scenarios. The first one, labeled as "*mild*", is characterized by favorable conditions—short and stable lead times, low unit costs, small amount of defective products, etc. The second one, labeled as "*acid*", has opposite features. They reveal that, in general terms, DBR outperforms Kanban in the wide parameter space. In addition, they point out an interesting observation: in the presence of acid noise, DBR achieves a net profit that is significantly higher than that obtained by Kanban (average net profit increase: 8.47%); however, relevant differences in the net profit do not emerge in the mild scenario. Importantly, the authors underline that Kanban can generally be implemented at a lower cost in supply chain settings, primarily as it requires less collaborative efforts; thus, it may be preferable in easy-to-manage supply chain scenarios.

Motivated by the previous considerations, in this work we delve deeper into the noise effects in LM- and TOC-based supply chains. In this way, we aim to obtain further insights on the relationship between the LM versus TOC decision and the noise affecting the supply chain by considering six different levels of noise. We aim to explore the robustness of both systems against noise—that is, how they lose profit as the noise becomes more demanding. Overall, our analysis is expected to provide managers with a richer understanding on the interplays between supply chain noise and performance in LM and TOC environments; which would help them make well-informed decisions in the context of their own supply chains.

2 Research Design and Model Implementation

Our methodological approach is based on modeling and simulation techniques, in line with many prior studies in the discipline of supply chain management that explore collaborative strategies; see, e.g. Holweg and Bicheno [16], Cannella and Ciancimino [1], and Costas et al. [3]. We investigate a single-product, serial supply chain with four nodes—named as factory, distributor, wholesaler, and retailer—like the one considered in the popular Beer Game[3] [18]. Traditionally, the Beer Game scenario assumes only one source of uncertainty, in particular, customer demand. To bring it closer to the real-world operation of supply chains, we also model other operational obstacles faced by these systems, specifically, defective products, capacity constraints, and lead time variabilities.

Likewise, we do not only consider the materials and information flows among the nodes but we also consider the financial flow in order to measure the economic performance of the supply chain. In this sense, we capture four sources of cost: buying raw materials (*provisioning* cost), elaborating new products (*production* cost), transporting products between nodes (*shipping* cost), and stocking up products (*storage* costs). In contrast, money is only made in the supply chain by selling the finished goods to the end customer.

Taking the above into account, we model ten noise factors. These include both operational and economic uncontrollable parameters that impact on the net profit of the supply chain. To investigate in depth the effects of noise, we define different levels for each of these factors. To explore the differences in performance between the Kanban and DBR systems under different noise scenarios, we group the factors into six *noise grades*: $Z \in [1, 6]$. Table 1 describes each grade by providing information on the level associated with each factor.

The rationale we used for defining the levels of the different factors is similar to the one described and followed in Puche et al. [33]. It should be noted that the definition of the extreme noise grades here, i.e. mild and acid, match those in that article for benchmarking purposes. In addition, it is important to highlight that the rest of the factors in the supply chain have been interpreted as fixed factors in the different simulations performed. These are (i) raw material cost: 0.4 \$/u, (ii) selling price: 1.5 \$/u; (iii) minimum order lead time: 0 days; (iv) minimum shipping lead time: 7 days; and (v) minimum production lead time: 3 days.

We quantify the financial performance of the supply chain via the net profit (NP). According to the Throughput Accounting (see [25, 15]), this metric is obtained as the difference between: (i) the *throughput* (T), measuring the money captured by the system, i.e. sales revenue minus provisioning costs, and (ii) the *operating expense* (OE), measuring the money spent to turn raw materials into finished products, i.e. the sum of production, shipping, and storage costs.

To better understand the results that we will obtain via simulation, we also use three additional, first-line metrics: (i) *total sales* (TS), providing indirect information of the customer service level in the supply chain; (ii) *average time* (AT) of products in the supply chain, in days, which informs about the supply chain agility; and (iii) *rolled throughput yield* (RTY), i.e. the ratio of sales to raw materials purchased, which decreases as the amount of defective products grows.

We have implemented the supply chain model in the form of a multi-agent system (MAS). The agent-based approach provides autonomy, robustness, and flexibility to models exploring dynamic large-scale problems, like the one considered here [35].

[3]A role-playing exercise, developed by the MIT more than half a century ago, that continuous to be a powerful tool to explore dynamics of supply chains, as discussed by Macdonald et al. [26].

Table 1 (a) Definition of the noise levels—Levels 1–3, (b) Definition of the noise levels—Levels 4–6

Noise factor	Noise grade		
	1 (Mild)	2 (Low)	3 (Moderate)
A.Defective products rate	250 ppm	500 ppm	1,000 ppm
B.Transport capacity constraint	120 u	140 u	170 u
C.Factory capacity constraint	120 u	140 u	170 u
D.Demand: standard deviation	5 u	10 u	15 u
E.Production cost	0.001 $/u/day	0.002 $/u/day	0.004 $/u/day
F.Shipping cost	0.001 $/u/day	0.002 $/u/day	0.004 $/u/day
G.Storage cost	0.001 $/u/day	0.002 $/u/day	0.004 $/u/day
H.Order lead time: Range	0 days	0 days	0 days
I.Production lead time: Range	1 day	1 day	2 days
J.Shipping lead time: Range	1 day	1 day	2 days
Noise factor	*Noise grade*		
	4 (High)	*5 (Very high)*	*6 (Acid)*
A.Defective products rate	3,000 ppm	6,000 ppm	12,000 ppm
B.Transport capacity constraint	300 u	9876 u	9876 u
C.Factory capacity constraint	300 u	9876 u	9876 u
D.Demand variability	25 u	30 u	45 u
E.Production cost	0.007 $/u/day	0.01 $/u/day	0.02 $/u/day
F.Shipping cost	0.007 $/u/day	0.01 $/u/day	0.02 $/u/day

(continued)

Table 1 (continued)

Noise factor	Noise grade		
	1 (Mild)	2 (Low)	3 (Moderate)
G.Storage cost	0.007 $/u/day	0.01 $/u/day	0.02 $/u/day
H.Order lead time: Range	1 day	1 day	2 days
I.Production lead time: Range	3 days	4 days	6 days
J.Shipping lead time: Range	3 days	4 days	6 days

For this reason, this approach has been widely used in supply chain studies over the last decade, see e.g. Chatfield and Pritchard [2], Dominguez et al. [5], Costas et al. [4], and Ghadimi et al. [7]. To model the dynamics of the supply chain, we have used unbounded and stochastic Colored Petri Nets [19]. To implement the agent-based model, we have used the NetLogo environment [43].[4] Ponte et al. [32] provide a detailed description of the agent-based model that we have employed in this article. Specifically, we refer interested readers to Sect. 2.4 (*Agent-based implementation of the model*), which describes the static architecture of the system, its dynamic behavior via Petri nets, and how it has been validated and verified.

3 Results, Analysis, and Discussion

In this work, we explore the six noise scenarios defined above both when the supply chain operates according to Kanban and when it operates with the DBR mechanism. A time window of 230 days has been simulated for each of the 12 resulting runs, from run I to run XII, with the first 30 days being a warm-up period that is aimed at minimizing the impact of the initial state of the supply chain. Thus, the results we report are based on 200 days.[5] These are shown in Table 2.

We now conduct an exploratory study based on a dot graph, which is displayed in Fig. 1, followed by an ANOVA in order to understand the interaction between the compound noise grades (i.e. the disturbance of the system) and the inventory policy (i.e. the controllable factor). The results of the ANOVA study are provided in Table 3. It should be noted that both variables, i.e. the noise grade and the inventory policy, are significant (at a significance level of 10%). We note that the adjusted R^2 obtained

[4]NetLogo is a programmable modeling environment for agent-based modelling and simulation developed at Northwestern's Center for Connected Learning and Computer-Based Modeling. Please visit https://ccl.northwestern.edu/netlogo/ for more information.

[5]We checked the stability of the response of the agent-based supply chain and the repetitiveness of the results for our (30 +)200-day approach according to common practices.

Table 2 Results of the 12 simulation runs

Run	Noise grade	Policy	NP [$]	TS [u]	AT [p]	RTY [%]
I	1 *(Mild)*	Kanban	20,245.83	19,377	24.11	99.46
II	1 *(Mild)*	DBR	20,357.65	19,174	18.97	99.48
III	2 *(Low)*	Kanban	19,438.00	19,129	24.42	98.62
IV	2 *(Low)*	DBR	19,993.10	19,177	19.81	99.13
V	3 *(Moderate)*	Kanban	18,325.70	19,250	28.02	97.28
VI	3 *(Moderate)*	DBR	18,921.57	19,300	22.11	97.7
VII	4 *(High)*	Kanban	16,173.50	19,815	30.55	90.98
VIII	4 *(High)*	DBR	17,296.70	19,860	26.85	92.19
IX	5 *(Very High)*	Kanban	12,387.30	19,599	34.21	82.02
X	5 *(Very High)*	DBR	14,671.00	20,304	26.55	84.56
XI	6 *(Acid)*	Kanban	-1,511.81	19,220	38.76	63.57
XII	6 *(Acid)*	DBR	3,144.98	19,677	32.25	68.59

for the model is 97.15%, confirming that it represents accurately the results obtained via simulation.

Figure 1, which displays the net profit obtained by the LM- and TOC-based supply chains in the six noise scenarios, shows that Kanban and DBR offer similar performance when the intensity of the noise is very low. In both cases, the net profit is close to the ideal net profit that can be achieved under such conditions. However, as the intensity of the noise grows, both supply chains suffer from a noticeable decrease in the net profit. Nonetheless, it can be seen that this decrease is more accentuated in the Kanban system. Thus, DBR begins to make a difference as the noise becomes

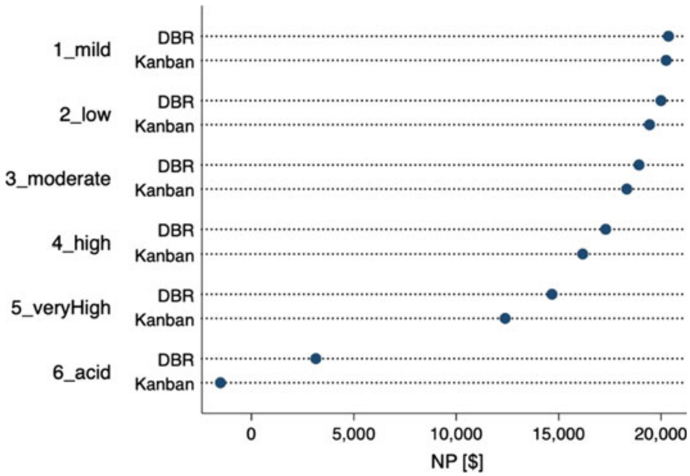

Fig. 1 Relationship between the net profit and the noise level for both supply chains

Table 3 Results of the ANOVA study

Source	Sum of Squares [Partial]	Degrees of Freedom	Mean Squares [Partial]	F ratio	P-value [Prob > F]
Model	5.469e + 08	6	91143407	63.55	0.0001
X_Policy	7248603.2	1	7248603.2	5.05	0.0744
Z_Noise grade	5.396e + 08	5	1.079e + 08	75.25	0.0001
Residual	7170526	5	1434105.2		
Total	5.540e + 08	11	50366451		

more intense. The more severe the noise conditions, the greater the difference in the net profit. That is, the sensitivity of the LM-based supply chain to the noise is higher, making it less robust to noise increases.

Looking at the last two rows (runs XI and XII) of Table 2, we observe that the net profit increase induced by the DBR methodology stems from a win–win solution. Through its bottleneck orientation, the inventory is appropriately allocated across the TOC-based supply chain, and hence this supply chain is able to achieve a higher service level (*TS* is higher) with greater agility (*AT* is lower) and less defective products (*RTY* is higher). From this perspective, we can conclude that the TOC-based supply chain becomes both more efficient and flexible.

It is important to note that our results are aligned with the second line of conclusions discussed in Sect. 1 (*Introduction*) for those papers comparing LM and TOC in the context of production systems. Also, the results in this work allow us to better understand some findings revealed in Puche et al. [33], through the consideration here of six scenarios of noise. We have seen the gradual increase of the difference between Kanban and DBR as the noise becomes more severe, which leads us to conclude that (i) the excess of complexity that the DBR methodology entails over the Kanban system may not be justified in easy-to-manage environments, but (2) adopting TOC-based solutions may be very rewarding when the supply chain operates in dynamic and uncertain contexts.

4 Conclusions

Supply chain managers now need to create, sustain, and maximize value in a complex business scene. Collaborative strategies for the supply chain, built on the pillars of *systems thinking*, are able to make a difference. In light of this, this work has compared the lean manufacturing (LM) and theory of constraints (TOC) holistic approaches to manage supply chains. Using agent-based modeling and simulation techniques, we have explored the performance of their pull rules to control the inventory, Kanban and drum-buffer-rope (DBR), in a four-echelon, single-product supply chain that faces a wide variety of noise sources.

We have observed that both systems lose significant net profit as the noise becomes more severe. However, the DBR methodology has proven to make the supply chain more robust against such noise. Interestingly, we have found that the difference in performance between DBR and Kanban, favorable to the former, grows noticeably as the noise becomes more demanding. Therefore, as regards the managerial implications of our work, we highlight that DBR proves to be a more appropriate alternative in uncertain and/or dynamic scenarios, while Kanban provides similar results at a lower implementation cost in foreseeable and/or static scenarios. In this sense, our findings have buttressed and extended prior research works in this area, from Grünwald et al. [11] and Takahashi et al. [39], in the context of production systems, to Puche et al. [33], in a supply chain scenario.

Having said that, it is important to emphasize again the exploratory nature of this work. Further studies are necessary to investigate in detail the link between net profit and supply chain noise. Ungrouping the noise grades (or compounds) into their individual components would allow for a more comprehensive understanding of the problem. Factor analyses may be of use in this regard. This is an important avenue for research taking into consideration that this study has provided clear evidence that the LM versus TOC dilemma in supply chain settings enormously depends on the severity of the environmental noise.

Another research avenue worth pursuing would be based on extending the application of LM and TOC principles from traditional, open-loop supply chains to the emerging closed-loop systems, which integrate forward and reverse flow of materials. Such closed-loop systems are gaining practical relevance in the current business environment due to current societies adopting more circular economic models in a bid to minimize environmental impacts and leverage economic opportunities [9, 10, 12]. From this perspective, investigating the LM versus TOC comparison in closed-loop settings with the aim of understanding how such closed-loop system can be optimized in practice would arguably help to accelerate the transition toward the desired circular economic models.

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