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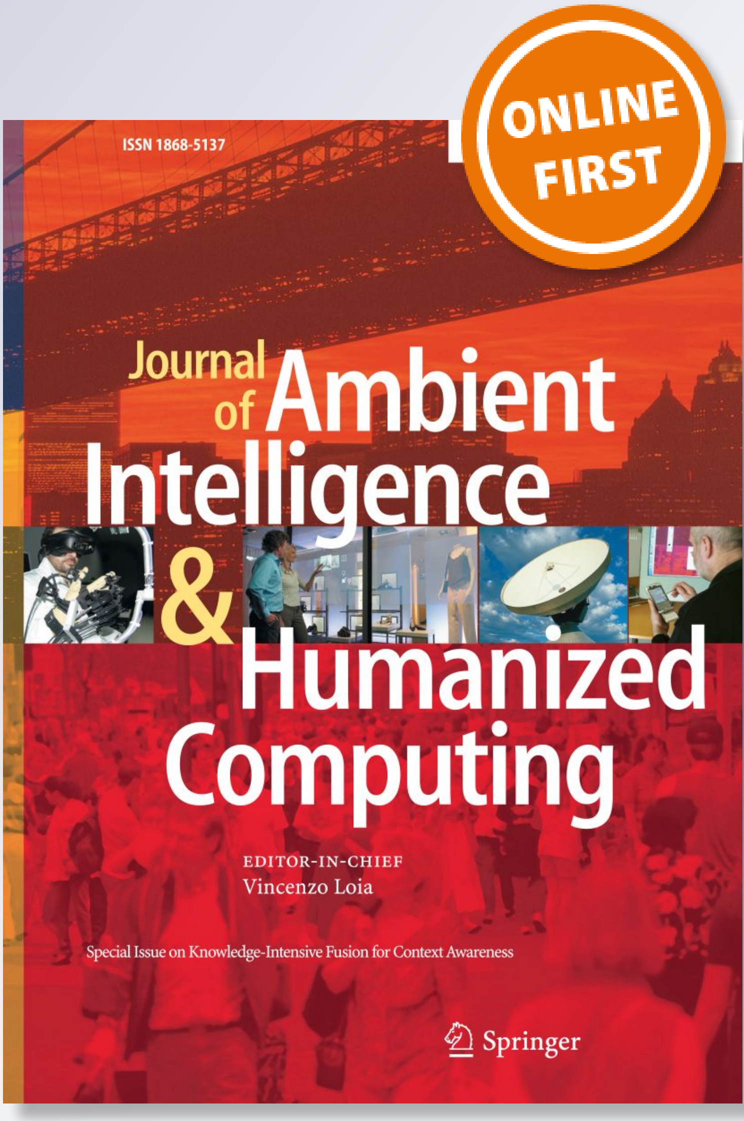

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ORIGINAL RESEARCH

Lead time performance in a internet product delivery supply chain with automatic consolidation

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Abstract Internet sales have increased exponentially in the last decade. Much of the internet sales are of physical products in urban areas that require product delivery transportation with a tight delivery lead time. With this challenge, a new type of transportation services has been developed aiming to cope with a strict control of transportation lead time. In this paper, an internet product delivery service with customer orders that are multi-item as well as single item is simulated. We address specifically the mismatch between supply and demand when retailers for any reason are unable to estimate the configuration of multi-item orders. Three scenarios of demand patterns are simulated (demand as forecasted, lower than forecasted and higher than forecasted) using discrete-event simulation to look at the effect on transportation lead time. Results show the positive effect on the mismatch between demand and resource capacity which is expressed in higher number delayed delivery orders. The excess of capacity in the product delivery supply chain has not a positive impact on delivery time of orders as technically orders are not delivered before the multi-item components are not available. This leads to think that the excess of resources are not an element that add value to customers waiting for their orders.

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1 Introduction

Transportation services in urban areas have changed in the last years in terms of collaboration, configuration, operational practices and performance expectations (Fisher and Raman 2010). These challenges come from several factors that have changed the rules for providing competitive transportation services. Changes in product transportation management can be attributed to three main driving forces: Customers are raising their service expectations including the delivery of perishable products (Choi 2016; Cronin et al. 2000). Customer demands for quick response and customized products are propagating along supply networks (Kibert 2016). Changes in life style of people require manufacturers and service providers to adjust to the new circumstances including futuristic configurations of homes where automatic replenishment of groceries and foods is executed by intelligent systems that evaluate stock at home and automatically order form supermarkets (Amiribesheli et al. 2015). Information technologies are providing more timely and detailed supply chain data that improves the performance of the transportation services (Waller and Fawcett 2013). Advances in information technologies in both connectivity and reach increase the potential for information sharing and enable tighter integration among supply chain partners (Zhang et al. 2011). Partnerships with transportation service providers allow manufacturers to focus on their core competences while taking advantage of the distribution efficiency and expertise of dedicated distributors (Yinan et al. 2016). In turn, distributors are offering their services beyond the traditional warehousing and transportation functions to

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include value-added activities e.g., repackaging, labeling, light assembly, and non-inventory distribution services of which cross-docking and merge-in-transit distribution are examples.

Merge-in-transit distribution (MiT) is a logistics process introduced to cope with consolidation of orders in the same shipment (O´Leary 2000). Merge-in-transit is a distribution process that brings together at in consolidation center multi-product order components, coming from different origins, consolidates them into a single order, and then ships it for final delivery to the end customers. Some of the advantages obtained with MiT are: higher customer satisfaction is obtained by delivering multi-product orders in one event instead of making more than one delivery, one for each component or partial group of them. Savings are achieved by not keeping inventories in the distribution process, since merge-in-transit centers just hold order components for a short time (usually less than 24 h) so the order is all the way in transit to its final delivery point. Holding costs associated with warehousing operations are avoided or at least minimized. Third, savings also arise by avoiding the risk of keeping obsolete inventories. MiT is normally applied to distribute orders where sometimes one component has been made-to-order. Those tailored components have been made for a specific need and are never kept in stock so there is no risk of keeping obsolete components (Ala-Risku et al. 2003; Camacho-Vallejo et al. 2015).

Product consolidation in the context of internet retiling has been researched with the name of Merge-in-Transit (Kopczak 1995), looking at logistics partnership and supply chain restructuring. Cole and Parthasarathy (1998) develop a linear programming model to design optimal MiT distribution networks and a decision support system for the same purpose. Croxton et al. (2003) developed an integer programming formulations and solution methods for addressing operational issues in MiT distribution. Cannella et al. (2016) have also studied the lead time performance of supply chains in the context of reverse logistics. The models account for various complex problem features, including the integration of inventory and transportation decisions, the dynamic and multimodal component of MiT distribution and the specific structure of particular cost functions that arise in MiT. Ala-Risku et al. (2003) developed a guideline for logistics managers on how to evaluate the applicability of MiT operations for their particular business situation. Karkkainen et al. (2003) presented a description of differences between MiT and cross-docking from the point of view of how operations are carried out in merging points and cross docks respectively, customer service implications and suitability for different business sectors. It can be seen after the literature review that MiT has not yet been researched concerning the stochastic behavior of the system. Monsreal and Cruz-Mejia (2014) have also integrated the solution of production and distribution systems in supply chains for improving operational performance in reverse logistics. MiT has implicit transportation operations, order assembly operations, inventory carrying and corresponding inventory management decisions, demand fluctuation estimation and demand pattern estimation.

Zhang (1997) was one the first to model manufacturing systems with multi-item orders in a assemble-to-order setting but his research was analytical developments.

Rabinovich and Evers (2003) were first to model product fulfilment internet retailing operations in supply chains to evaluate customer service based in economical logistics operations.

None of the research works in MiT has addressed all these sources of uncertainty in the operation of MiT and this is one of the novel contributions of this work. This work aims to fill the gap on studying stochasticity in MiT product delivery supply chains. In the next section we develop a prototypical scenario.

In prospective publications, Grewala et al. (2017) suggests that retailers have embraced a variety of technologies to engage their customers including the methods the product purchased is sent to customers. Internet retailing including logistics and mobile advertising have attracted large amounts of researchers in fields linked (Su et al. 2016).

1.1 Supply chain description

A typical transportation scenario that will represent a generalization of normal operation of MiT supply chains will be used. It is considered a customer that is online at home or office and makes the selection of items that he wants to buy in the same transaction. The information is sent to the retailer and the retailer sends the multi-item purchase order to the order consolidation center. The order consolidation center collects the items needed and a single multi-item package is assembled for the specific customer order. It may happen that some items required are not in stock because they are in transit to the consolidation center. Having products out of stock obviously causes delay in the delivery process. A graphic explanation of the supply chain can be seen in Fig. 1.

The stock of items at the consolidation center is replenished by a continuous review policy. The following logic is applied: if the stock level at the consolidation center goes below the reorder point, then place an order that replenishes the stock at the consolidation center. The replenishment shipments have an implicit transportation time. Finally, when all the items required for a multi-item order are available, a single shipment is transported and delivered at the customer location.

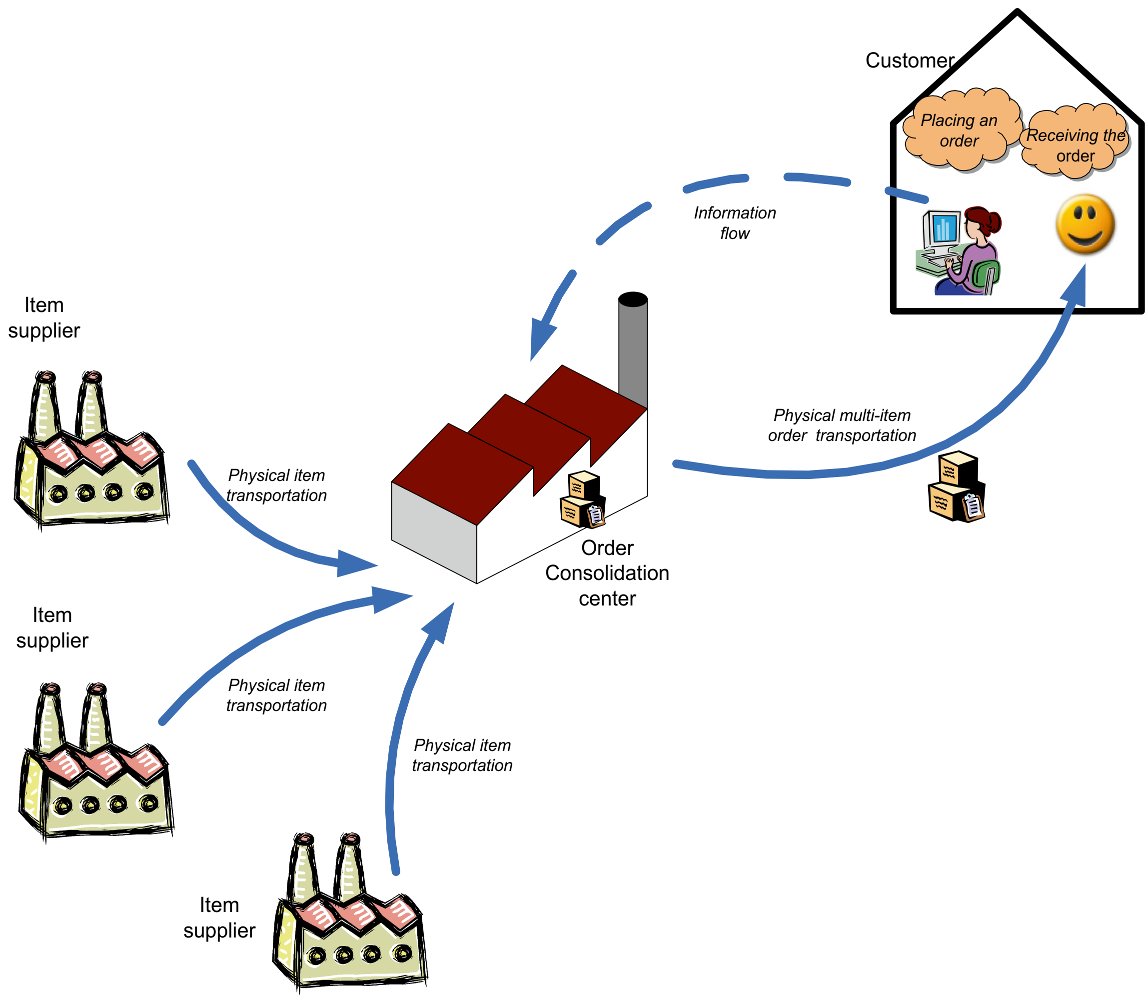

Fig. 1 Transportation model

1.2 Problem description

The transportation utilized can deliver up to three items for the same customer order and the supply chain structure and operating principles remain the same. For this case, we use three demand scenarios, each of them having different proportions of dependent orders. The three scenarios are: (a) demand with a high proportion of dependent orders, this type of demand will be called higher than expected, (b) demand with a medium proportion of dependent orders, we will call this type of demand as expected and (c) demand with a low proportion of dependent orders and this will be called lower than expected. These three prototypical scenarios represent the possible mismatch in the demand predicted for a product and the corresponding implication for the transportation delivery process. It is well known that demand prediction mismatch can cause late deliveries in transportation services (De Treville et al. 2014). In the three scenarios inventory inaccuracy is experimented in a similar way as Bruccoleri et al. (2014) test the effect of inventory variation in supply chains.

The key concept to explore in this simulation scenario is whether the supply chain operation is set to supply and cope with the delivery of orders to customers with an expected level of demand per individual item, which may be different to the demand received. Travel time and delivery time have been researched as a service performance indicator (Avila-Torres et al. 2017). Figure 2 shows the logic applied for handling multi-item orders and processing them in the simulation model. Since orders are not single-item and that the multi-item orders depend on customer choice, the real demand per item may be different from what was expected and consequently the capability of the supply chain to fulfil the delivery orders on time may be affected. By order configuration based on customer choice we mean the group of items requested per multi item order. Three order types will be defined: type A represents an order for item 3 only, type B represents

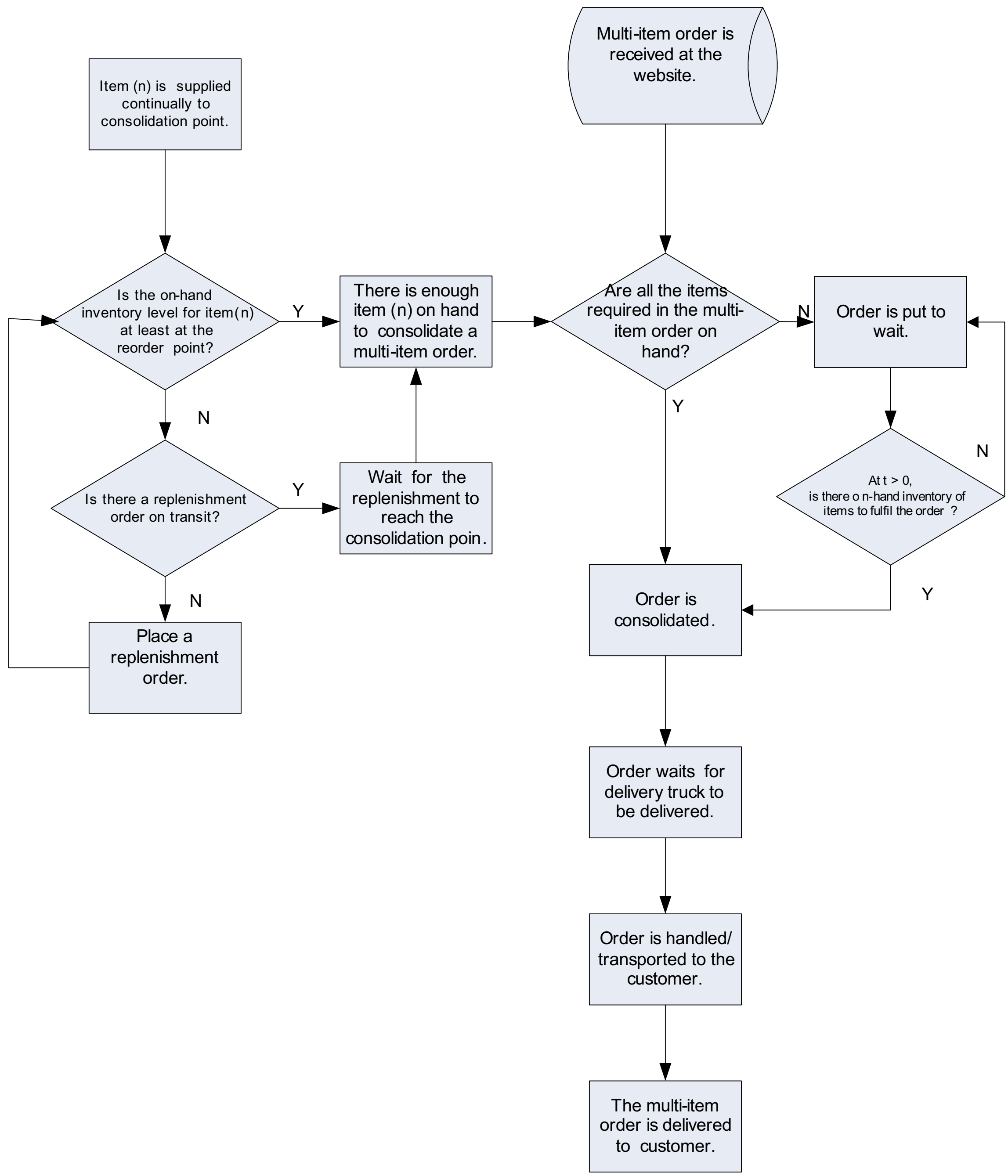

Fig. 2 Flowchart of the automatic merging operation

an order for items 2 and 3 and type C represents an order for items 1, 2 and 3. We assume a situation where we expect an equal proportion of orders from customers of types A, B and C. In this scenario, we use three customer demand configurations, each one representing levels of demand higher than expected, as expected, and lower than expected. In the higher than expected configuration, we assume that a higher proportion of orders are of type C and a lower proportion is for type A. In the lower than expected configuration, we assume that a lower proportion of orders are of type C and a higher proportion is for type A. In this condition, it is expected that the system will operate with excess of capacity.

The objective of this three-scenario experiment is to quantify the implications in the delivery supply chain when the demand for some items is significantly more or less than expected, due to different proportions of orders combining orders for different items.

The values used to generate each of the demand scenarios are shown in Table 1.

Up to this section, we have described the modeling considerations for simulating the MiT supply chain. We can list now the operations that together make the whole model: multi-item order processing operation, product sourcing operation, merging operation and order delivery operation.

1.3 Data and input parameters

The simulation model was run for 50 replications of 3 months of continuous operation, each 2196 h. The conditions of the model were: 50% of stock out risk, inbound and outbound transportation times were modelled following a Normal distribution with means of 24 and 72 h respectively. Standard deviations for the transportation times were 2.4 and 7.2 h, respectively. Table 2 summarize data and input parameters used for the simulation runs.

Table 1 Demand profiles

Order type	Item 1	Item 2	Item 3	% of orders per type
(a) Demand higher than expected				
A	0	0	1	15
B	0	1	1	15
C	1	1	1	55
(b) Demand as expected				
A	0	0	1	33
B	0	1	1	33
C	1	1	1	33
(c) Demand lower than expected				
A	0	0	1	55
B	0	1	1	30
C	1	1	1	15

Discrete-event simulation (DES) was used as the modeling methodology for the analysis of the supply chains under study (Cigolini et al. 2014). DES is a well-established technique for the study of operational scenarios in real world situations (Banks et al. 1995; Pidd 1998; Law and Kelton 2000). DES is a suitable analysis tool for the research objectives set for this work because of the following advantages: DES allows a high level of detail to be modeled for the operating scenarios under study while mathematic analytic models would only allow the simplified representations of real world scenarios (low level of detail) (Robinson 2004). Using DES can easily model alternative scenarios of operation (experimentation) of the supply chains under study and allow practical conclusions to be drawn. One of the main research aims in this work is the study of the composition of customers' multi-item orders when buying using the Internet. This order composition is a behavioral element that can be nicely modeled and experimented upon with DES. Supply chain problems involving behavioral issues use predominantly simulation over analytical methods as the primary research tool, since the complexity of human interaction with complex systems precludes analytical methods for examining customer election issues (Banks et al. 1995).

2 Results and analysis

Table 3 shows the results for the three scenarios of demand being higher than expected, as expected and lower than expected. The table includes the segregated values for orders delayed and non-delayed as well as all the orders.

We have claimed some differences in the system under study. To support these differences, we need to test the statistical significance as the outcomes of our simulations are results of probabilistic events. Next is presented the tests performed to demonstrate statistical significance related to our findings. The same seeds were used for the random

Table 2 Input parameters, control variables and experimental variables

Section of the model	Variable name	Variables	
		Control variable	Experimental variable
Order taking	Order inter-arrival time		Exp (0.15)
	Maximum number of different type of products	3	
	Order configuration (independent and dependent)		2
Inventory	Excess of supply factor	1.25	
	Reorder policy	(R, Q)	
	Induced stock-out probability		30%
	Inbound transportation time	N(24, 2.4)	
	Inbound transportation vehicle size	2MLTD	
Consolidation	Consolidation operation time	0.005/item	
Outbound transportation	Outbound transportation time		N (72, 7.2)

Table 3 Lead time table for mixed demand

% Orders of type A, B and C		Demand pattern condition		
		Higher	As expected	Lower
		15,30,55	33,33,33	55,30,15
Average time in system (1)	Delayed orders	279	110.41	110.17
Minimum time in system (1)		66.99	66.06	70.57
Maximum time in system (1)		1660.09	157.97	152.12
Standard deviation of (1)		214.64	21.94	21.01
CV		0.77	0.2	0.19
Items entered (delayed)	Non-delayed orders	6727.66	804.14	390.26
Average time in system (2)		108.81	108.53	108.52
Minimum time in system (2)		57.67	57.36	57.36
Maximum time in system (2)		164.07	164.38	164.39
Standard deviation of (2)		22.59	22.59	22.59
CV		0.21	0.21	0.21
Items entered (non-delayed)	All orders	6019.84	13847.14	14260.64
Average time in system		195.5	108.63	108.56
Minimum time in system		57.67	57.36	57.36
Maximum time in system		1660.09	164.68	164.43
St Dev of		175.95	22.58	22.57
CV		0.9	0.21	0.21
Number completed (all)	Performance	12763.88	14552.9	14553.4
% of orders delayed		52.80%	5.50%	2.70%
Average difference in lead time (LT) [delayed vs. non-delayed (h)]		170.19	1.88	1.64
% of difference in lead time (delayed vs non-delayed)		156.40%	1.70%	1.50%

number generation of demand values; therefore, it is possible to claim that these values are statistically dependent. We use a t-test for two paired samples to test statistical significance in the difference between means (Kvanli et al. 2000). As we are attempting to demonstrate the difference in the two means then a two-tailed test is needed.

Where μ_d= average difference in time in system between dependent and independent orders.

Our hypotheses are:

$$H_0{:}\mu_d = 0,$$

$$H_a{:}\mu_d \neq 0.$$

Using the t_D test statistic, the test will be to reject H_0 if $|t_D| > t_{\alpha/2,n-1}$.

A value of $\alpha = 0.05$ will be used.

The procedure to estimate the level of precision for estimating the mean, μ, based on the number of replications performed to calculate $\overline{X}$ is presented. The precision level of an estimated mean represents the degree of precision the estimated mean over the true mean.

The number of replications used to calculate the estimated mean will define the precision obtained to calculate the estimated mean. Here is presented a summary of the sequential procedure proposed by Law and Kelton (2000) that was used to verify precision levels obtained in simulation trials.

If the confidence interval for estimating means is given by:

$$\bar{X}(n) \pm t_{n-1,1-\alpha/2}\sqrt{\frac{S^2(n)}{n}}$$

and if the relative error of $\bar{X}$ is measured by:

$$\gamma = \left|\bar{X} - \mu\right| / |\mu|$$

Then, $\gamma' = \gamma/(1-\gamma)$ will be the adjusted relative error to obtain an actual error.

The objective of the procedure is to obtain an estimate of μ with a relative error of $\gamma(0 < \gamma < 1)$ and a confidence level of $100(1-\alpha)$ percent.

The procedure is as follows:

Chose an initial number of replications $n_0 \geqslant 2$ and let $\delta(n,\alpha) = t_{n-1,1-\alpha/2}\sqrt{\frac{S^2(n)}{n}}$ be the usual confidence interval half length.

Make n_0 replications of the simulation and set $n = n_0$.

Compute $\bar{X}(n)$ and $\delta(n,\alpha)$ from $X_1, X_2, \ldots, Xn$.

If $\delta(n,\alpha)/\left|\bar{X}(n)\right| \leqslant \gamma'$, use $\bar{X}(n)$ as the point estimate for μ and stop.

Otherwise, replace n by $n+1$, make an additional replication of the simulation, and go to step 1.

The average time in system for the case of orders with demand higher than expected is almost double (195.50) that for the as expected (108.63) and lower than expected (108.56) cases. The reason for this is the higher number of out of stocks registered under the higher than expected demand. The high coefficient of variation (CV) of time in system for orders with higher demand than expected (0.90) compared to the ones from as expected (0.21) and lower than expected (0.21) confirms the higher variability in delivery time of the system with higher demand than expected caused by the lack of stock. As orders with demand as expected or lower than expected have the same CV, we can argue that they expect the same degree of variation in the delivery time. The percentage of orders delayed for higher than expected, as expected and lower than expected demand is 52.8, 5.5, 2.7%, respectively.

More than half of the orders are delayed when demand is higher than expected. This value is ten times higher than when demand is as expected and almost 20 times higher than when demand is lower than expected. So this proportion can be very high and implies a potential high impact on the delivery time of the order and customer satisfaction. Again, the high proportion of orders delayed when demand is higher than expected is related to the lack of items to fulfill orders.

The average difference in lead time between delayed and non-delayed orders for the different scenarios show that when demand is higher than expected, the orders (170.19 h) have around a 100% longer delays compared to when demand is as expected (1.88 h) and lower than expected (1.64 h). This means that delays registered when demand is higher than expected are 100% longer on average than for the other types of demand.

The percentage of difference in lead time between delayed and non-delayed orders for runs with the same demand values show that when the demand is higher than expected a delayed order takes 156.4% more time to be fulfilled than a corresponding order that did not register delay. In the case when demand is as expected, the difference between delayed and non-delayed is only 1.7% more time, while when the demand is lower than expected, the delay is 1.5% time in excess.

For orders non-delayed the lead time in systems is the same for the three types of demand (108.53, 108.81, 108.52). This data confirms the correct operation of the simulation model including that the model is not blocking at the merge operation. The standard deviations for delayed orders are 214.64, 21.94, 21.01 for high, medium and low mix respectively. We can understand from this that orders delayed in when demand is higher than expected have a 10 times larger standard deviation in the delivery time.

3 Conclusions

The performance of product delivery systems can be measured by the lead time an order takes to make from the origin to destination. This research work evaluates the lead time in a simulated product delivery system using a computational program. If internet orders are multi-item it is common sense to expect a possible delay in the delivery if all the products conforming a multi-item order are not available at the time the order is placed. We call delayed orders those which have at least on item not available at the time an order is placed. Then, the degree of association between product ordered together is experimented in this work and what is its the impact of that delay. We found the more mismatch between the expected levels of demand and real demand cause more delayed in orders. For orders non-delayed, the lead time in system is the same for the three types of demand (108.53, 108.81, 108.52). This data confirms the correct operation of the simulation model including that the model is not blocking at the merge operation. The standard deviations for delayed orders are 214.64, 21.94, 21.01 for high, medium and low mix respectively. We can understand from this that orders delayed in when demand is higher than expected have a ten times larger standard deviation in the delivery time.

Based in this results in can be suggested that the better the expected demand and the degree of association in multi -item orders is forecasted the better the logistic system in charge of delivering items can fulfill orders in time. It can be mentioned that the aggregated demand in this type of scenarios will be how often and item is ordered when another item is also ordered. We conclude that the more the demand of multi-item orders is forecasted accurately taking in account the association with other items, the better performance the system will have.

4 Future research directions

This work simulated a logistic system when more than one product is ordered and fulfilled by a logistic system. However, the demand mismatch scenarios between expected demand and real demand is limited to 3 instances. It will be interesting seeing more instances of degrees of association with real-world scenarios patterns that can develop further the conclusions. One of the factors that makes and order delay is the lack of stock of a demanded order. Since a product delivery system is a dynamic system where the condition of inventory fluctuates along the elapsed time, the degree of lack of stock can be instantaneous of last for a extended period of time. If the logistic system simulated in the work can be experimented under different degrees of intensity of stock out more conclusion and managerial insights could be taken from how to handle the inventory management policies and the location of suppliers.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest The authors declare that they have no conflict of interest.

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