OPERATIONS AND SUPPLY CHAIN MANAGEMENT
Vol. 17, No.2, 2024, pp. 220 - 235
ISSN 1979-3561 | EISSN 2579-9363

Simulation-Based Optimization of Logistics Decisions under Horizontal Collaboration Following the Can-Order Policy

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ABSTRACT

In today's competitive and environmentally conscious business landscape, companies constantly seek more efficient ways to conduct their daily operations. Horizontal Logistics Collaboration (HLC), in which firms at the same supply chain level share resources such as trucks and information, has proven effective in achieving synchronized deliveries, optimizing transport equipment usage, and reducing carbon footprint. This study implements HLC between two neighboring companies ordering different products from the same supplier. The study adopts the can-order policy, employing three threshold values to define each company's ordering policy and potential joint orders. To better reflect real-world operational aspects, a simulation-based optimization approach is employed, allowing experimentation with various realistic scenarios. The developed model assumes stochastic demand and lead time for both companies and assesses the benefits of HLC from both economic and environmental standpoints, one at a time. Computational experiments consistently demonstrate cost savings through collaboration, especially when both companies are similar with low unit holding costs. From an environmental standpoint, adopting the collaborative model can reduce carbon emissions by up to 27%, particularly when both companies are identical and have low demand and low products' weight. Statistical analysis using paired t-tests confirms the significant differences in cost and carbon emissions after implementing HLC.

Keywords: *can-order policy, horizontal collaboration, lot-sizing, simulation-based optimization, stochastic environment*

1. INTRODUCTION

Road networks play a vital role in facilitating the movement of goods across diverse geographical locations where they currently constitute the leading transportation mode in the global logistics market. More specifically, the use of truck transport has a size of $1,663.34 billion globally and is expected to grow at a rate of 8.5% from 2021 to 2026. However, despite this rapid growth, several significant challenges persist. First, the loading rate of trucks stands at a mere 57% on average (Ferrell *et al*., 2020). This suboptimal utilization translates into an increased number of trucks on the road contributing to heightened traffic congestion, elevated noise levels, and more air pollution. Notably, transportation activities, in general, are responsible for a substantial portion of greenhouse gas emissions, surpassing even the energy consumption observed in the commercial and residential sectors (Hu *et al*., 2021). Furthermore, the fuel cost is increasing, and it contributes up to 30% of the total transportation cost (Cruijssen, 2006).

This multifaceted scenario underscores the critical need for innovative solutions to enhance the efficiency and sustainability of road-based logistics systems. Among the initiatives increasingly being adopted by companies to address these challenges is horizontal collaboration. According to Cruijssen (2006), horizontal logistics collaboration (HLC) is a form of collaboration established between at least two companies operating at the same supply chain level. It requires the sharing of crucial information such as product demand and assets such as trucks with the aim of achieving mutual, long-term benefits. While HLC is popular in maritime and aviation transportation, it remains a relatively emerging concept within road logistics (Pomponi *et al*., 2013). An early implementation of HLC in road transportation dates to the year 1993 when eight medium–sized Dutch producers of sweets joined forces to consolidate shipments for their common customers, who required a variety of products daily (Cruijssen, 2006). In essence, pooling transportation resources and warehousing facilities leads to a reduction in overall logistics costs including transportation and inventory holding costs (Cleophas *et al*., 2019). For instance, through economies of scale, logistics partners can jointly leverage the shared trucks, effectively splitting the fixed costs amongst them (Hacardiaux and Tancrez, 2022). Additionally, reducing the total number of trips achieved by sharing the same fleet enhances the efficient utilization of truck capacities while concurrently reducing CO_2 emissions generated by trucks as shown in (Soysal *et al*., 2018).

While HLC has proven successful through various sharing mechanisms, achieving synchronizing of partners' orders calls for careful consideration of multiple factors to maximize benefits for all involved parties. For instance, consider a HLC between two companies A and B, each with distinct demand requirements. In this context, each company would have in place its own optimized replenishment policy that determines when and how much to order. Consequently, if company A intends to share trucks with Company B, it may need to adjust its replenishment schedule, either ordering sooner or later than it would if operating independently. This adjustment introduces a delicate balance between the costs associated with holding inventory and those related to transportation within the shared fleet. In essence, there exists a trade-off between the expenses incurred for inventory storage and the costs associated with transportation when collaborating. For the collaboration to be economically viable, any savings achieved in one of these cost areas must offset any increase in the other, ensuring that overall benefits outweigh the added expenses.

This paper assesses the benefits of horizontal collaboration between two companies, where their orders are synchronized based on a joint replenishment policy called the can-order policy. Balintfy (1964) was the first to propose the use of a can-order system, a special type of continuous review systems for controlling coordinated items. Following such policy, each company i has three triggering points (S_i, c_i, s_i), where $s_i < c_i < S_i$ (Van Eijs, 1994). The "must-order point" s_i is equivalent to the reorder point in the continuous review model. Thus, when the inventory level of company i reaches its s_i level, it triggers an order. At the same time, company j can place an order if its inventory level reached its "can-order level" c_j or below. Then, the inventory levels of all companies in the joint order are replenished up to their own "order-up-to-level" S_i. In this case, company i will bear the major ordering cost K_i and the minor ordering cost k_i, whereas the joining companies j (where $j \neq i$) will pay only their minor ordering cost k_j. This is a complex problem that cannot be easily handled by optimization methods. Heuristics are usually used under restrictive assumptions (see for example Silver (1974)). To better capture the inherent complexity, uncertainties and the stochastic nature of the problem at hand, this paper adopts a simulation-optimization based approach using Arena simulation package to build the discrete event simulation model of the HLC scenario and compare the results with the standalone settings in which the two companies operate independently. Moreover, OptQuest is used to determine the optimal values of the can-order policy parameters minimizing the logistics cost and CO_2 emissions, one at a time. Hence, this research attempts to address the following questions:

RQ1. *Under different scenarios, what are the optimum can-order policy parameters that yield the minimum joint logistics cost?*

RQ2. *To what extent would the horizontal collaboration under the can-order policy result in cost reduction as compared to the standalone scenario?*

RQ3. *What is the impact of horizontal collaboration on CO_2 emissions?*

RQ4. *What are the favourable and unfavourable conditions for horizontal collaboration, considering both economic and environmental perspectives?*

2. LITERATURE REVIEW

The problem at hand is closely related to the two variants of the well-known joint replenishment problem (JRP), the item-based JRP and the retailer based JRP, where interested readers are referred to the work of Khouja and Goyal (2005) for a thorough review up to late 2005, and that of Peng *et al*. (2022) for an updated review of the JRP literature from 2006 till 2022. One of the well-known joint replenishment policies in the context of the continuous review system is the can-order policy (Balintfy, 1964). At first, an approach called the decomposition method was proposed by Silver (1974) to calculate the three thresholds of the can-order class. However, Van Eijs (1994) proved that the decomposition approach is not accurate, and suggested a can-order level that is less than the order-up-to-level by one unit only for instances where the major ordering cost is high. The results showed that the can-order policy performs well. Also, Kayiş *et al*. (2008) devised a semi-Markov decision approach and a search algorithm to find the solution of a two-item JRP following the can-order policy. Similarly, Liu and Yuan (2000) deployed Markov chain under correlated demand, and showed that the savings increase when the demand covariance increases. Johansen and Melchiors (2003) proposed a new class of the can-order policy that is periodic instead of continuous. Similarly, Nagasawa *et al*. (2015) used genetic algorithms to optimize only the can-order level of each item in a multi-item setting. Also, Noh *et al*. (2020) applied a periodic can-order policy where a Mixed Integer Linear Programming (MILP) model is employed to reduce logistics cost and carbon emissions simultaneously. Kouki *et al*. (2016) adopted Markov Chain for zero lead time case and then used the decomposition method for a positive lead time case. They demonstrated that the can-order policy performs better with high shortage costs. In another work, a compensation approach was proposed by Melchiors (2002) where an item initiating an order acquires compensation from the other joining items. The results show that such an approach enhances the performance of the can-order policy. Recently, a new greedy-optimal method that uses embedded Discrete-Time Markov chain was developed by Creemers and Boute (2022). This model considers the state of the system after an order is placed. Consequently, it significantly reduces the total number of states encountered by the traditional continuous-time Markov-chain model.

All of the aforementioned works only consider the joint replenishment of multiple items in the context of a single firm. Nevertheless, the can-order policy can effectively be employed for the joint replenishment of multiple companies, where this latter case is considered a form of HLC. Vanovermeire and Sörensen (2014) and Danloup *et al*. (2015) presented the bundling of orders via a fleet that goes from a shared warehouse to a common destination. Indeed, the synchronization of orders was done through changing the delivery dates of partners' orders within the limits of each order's time window. However, both papers have overlooked the effect of collaboration on inventory levels and its related holding costs. To account for the on-hand inventory using the can-order policy, Pukcarnon *et al*. (2014) developed a heuristic algorithm to find near optimum solution in a one-warehouse N-retailers case. Othman *et al*. (2012) utilized Excel spreadsheet simulation to model a three retailers setting whose orders are synchronized by a periodic can-order policy. The authors employed OptQuest to find the three threshold values that yield the minimum holding, shortage and major transportation cost. De Moor *et al*. (2023) combined proactive cooperative shipping using can-order policy and periodic review with modal split transport. A heuristic algorithm that splits the problem per company and solves each problem sequentially was devised. Boucherie *et al*. (2010) tackled the cases of two and three collaborative companies' having the same item on stock, where they jointly replenish their inventories when one of them reaches its reorder point, and showed that this strategy outperforms its non-collaborative counterpart. Nevertheless, the authors did not consider the minor transportation cost in their analysis. On the other hand, Tinoco *et al*. (2017) accounted for the minor shipping cost in their can-order policy, and reported that the economic performance of companies under collaboration is always better than the standalone case. In addition, it was shown that the savings increase when the major cost increases. As an extension to this work, Tinoco *et al*. (2018) explored a mechanism to find the optimal solution where both the reduction in logistics cost and transportation CO_2 emissions are investigated simultaneously.

It is important to point out that the last three works above (Boucherie *et al*., 2010; Tinoco *et al*., 2017, 2018) suffer from several limitations. First, the Markov Chain based solution approach suffers from the issue of excessively high computational time with increasing number of states. Although Boucherie *et al*. (2010) determined the optimal cost for the three companies' case, it considered small sized instances and only handles the case where all companies join the order when one of them reaches its reorder point. That is, instead of having three thresholds like in the typical can-order policy, it only considers one threshold which was assumed to be zero. On the other hand, the works of Tinoco *et al*. (2017, 2018) only varied two thresholds in the can-order policy assuming the must-order level to be zero (since the lead time is zero). Third, they did not consider the finite capacity of the trucks. Finally, except for Boucherie *et al*. (2010), these papers applied a full enumeration procedure to find the optimal values of both the can-order level and the order-up-to-level, which is deemed impractical for large problem instances. **Table 1** presents the related works, which are classified and compared based on several dimensions in order to identify the existing gap in the literature and position the work presented herein. Formally stated, this paper brings the following contributions:

1. Rather than adopting Markov Chains and full enumeration approaches utilized in the literature, this work devises a simulation-based optimization approach via a discrete-event model coupled with OptQuest that can accurately determine the optimum can-order policy parameters.
2. It extends existing models by including a positive and stochastic lead-time, homogenous fleet of trucks of finite capacity as well as service level.
3. It quantifies the CO_2 emissions generated by both transportation and warehousing activities, rather than considering only the transportation carbon footprint as typically found in the literature.
4. It provides a mean for quantifying the benefits obtained due to horizontal collaboration between the two companies versus the standalone settings in terms of the total logistics cost and CO_2 emissions, when considering these objectives one at a time.

3. SIMULATION-BASED OPTIMIZATION MODEL

Discrete event simulation (DES) is the adopted approach as it allows for testing the effectiveness of horizontal collaboration via the can-order policy under different scenarios. In essence, the use of simulation provides a mean for experimenting large number of instances under various practical settings while relaxing some of the simplifying assumptions made in the literature, such as that of a zero-lead time or a constant one. Furthermore, it is suitable for very complex systems (Goldsman & Goldsman, 2015) and hence enables building a fully stochastic model that captures the practical aspects of the problem under consideration. It has been adopted to address a wide spectrum of optimization problems having a stochastic nature, such as Aircraft boarding problem (Qureshi & Qureshi, 2022) and blood supply chain systems (Mansur *et al*., 2023) among many others. Hence, Arena simulation package is utilized in this work coupled with an optimization tool called OptQuest, which facilitates building the model and optimizing the three threshold values at the same time.

The problem presented here considers the case where 2 companies are in the proximity of one another with close origin and destination locations. The demand (D_i) of each company i follows a Poisson probability distribution. Unlike the work of Tinoco *et al.* (2017), an exponentially distributed lead time of mean (LT_i) is assumed, rendering the must-order level or the reorder point not equal to zero. The problem encompasses five types of costs. First, a holding cost (h_i) is accounted for each unit held in the stock of company i per unit time. The calculation of the holding cost depends on the unit cost (c_i) and the holding rate (r_h). Secondly, there are three types of transportation or ordering (being used interchangeably) costs that are considered; the major ordering cost (K), the minor ordering cost (k_i) and the variable transportation cost (V_i). All these costs are incurred each time company i initiates an order of (Q_i) units.

Table 1 Classification of related research works

Paper	Decision Problem		Inventory Review policy		Sustainability Measure						Constraints		No. of partners	No. of Products	Demand Uncertainty	Lead time	Partners always collaborating?	Solution approach
					Economic (cost)				Environmental (CO_2)									
	Horizontal Cooperative shipping	Can-order Policy	Continuous	Periodic	Major transportation	Inventory holding	Minor transportation	Shortage	Transportation	Warehouse activities	Service Level	Truck Capacity						
Boucherie *et al.* (2010)	×		×		×	×							3	1	×	0	yes	Markov Chain
Tinoco *et al.* (2017)	×	×	×		×	×	×						2	1	×	0	No	Markov Chain
Tinoco *et al.* (2018)	×	×	×		×	×	×		×				2	1	×	0	No	Markov Chain
Pukcarnon *et al.* (2014)		×	×		×	×	×						N	1	×	0	No	Simulation & Heuristic
Vanovermeire & Sörensen (2014)	×				×		×	×				×	3	1			No	Heuristic
Danloup *et al.* (2015)	×				×		×	×	×			×	2	N			No	Simulation
Van Eijs (1994)		×	×	×	×	×	×				×		1	4	×	Deterministic		Decomposition
Liu & Yuan (2000)		×	×		×	×	×	×					1	2	×	0		Markov Chain Model
Kayiş *et al.* (2008)		×	×		×	×	×	×					1	2	×	Deterministic		Semi-Markov Chain model & Enumeration
Melchiors (2002)		×	×	×	×	×	×	×					1	N	×	Deterministic		Decomposition & Simulation
Nagasawa *et al.* (2015)		×		×	×	×	×	×					1	N		Deterministic		Genetic Algorithm
Noh *et al.* (2020)		×		×	×	×	×	×		×			1	3		0		Mixed Integer Programming
Creemers & Boute (2022)		×	×		×	×	×	×					1	3	×	Deterministic		Markov Chain
Johansen & Melchiors (2003)		×		×	×	×	×	×					1	N	×	Deterministic		Decomposition
Kouki *et al.* (2016)		×	×		×	×	×	×					1	N	×	Deterministic		Decomposition & Markov Chain & Simulation
De Moor *et al.* (2023)	×	×		×	×	×	×	×					3	1	×		No	Decomposition
Othman *et al.* (2012)		×		×	×	×		×					3	1	×	Deterministic	No	Excel Spreadsheet & OptQuest optimization
This paper	**×**	**×**	**×**		**×**	**×**	**×**	**×**	**×**	**×**	**×**	**×**	**2**	**1**	**×**	**Stochastic**	**No**	**Simulation Optimization**

The major ordering cost consists of related administrative and bookkeeping costs that are independent of the lot size while the minor ordering cost accounts for the handling cost of the products. The variable transportation cost is the fuel cost incurred because of transporting the products, which depends on the load and the number of trucks used. Finally, there are two types of shortage costs that are considered which are the backorder cost per unit time (B_i) and the cost of lost sales per unit time (LS_i) for each unit of unsatisfied demand. The backorder cost is incurred when the company runs out of stock and the customer is willing to wait for his order unlike the lost sales scenario where the customer is not willing to wait for the replenishment to take place. Like the holding cost calculation, the unit backorder cost and lost sales cost per unit time are calculated based on the unit cost as well as the backorder rate (r_B) and lost sales rate (r_{LS}), respectively.

Given that transportation activities generate a high amount of CO_2 emissions and HLC provides a mean to curb such emissions, the environmental factor ought to be accounted for the analysis rather than solely relying on the economic measure. This paper adopts the equation provided by Cheng *et al.* (2017) to calculate the fuel consumption while considering the velocity of the truck (v), the engine displacement (P) and other factors as shown below:

$$F_{Ti} = \lambda \left(\frac{xNPd}{v} + (m + Q_i w_i)\gamma\alpha d + \beta\gamma d v^2 \right) \quad (1)$$

where (F_{Ti}) is the transportation fuel consumption in liters, (m) is the weight of the empty truck, (w_i) denotes the weight of one product unit of company i, and (d) is the distance travelled (see Cheng *et al.* (2017) for the full interpretation of all notations used). Accordingly, the transportation carbon footprint per order for company i (E_{Ti}) is calculated via multiplying **Eq. (1)** by the amount of CO_2 emitted per liter of fuel consumed (e_T). Similarly, multiplying **Eq. (1)** by the fuel cost per liter (f) gives the variable transportation cost. Note that in this work, the travelled distance is assumed to be 60 km and the velocity is 80 km/h.

Furthermore, storing the products in the warehouses consumes electricity in the form of cooling, lighting, maintenance, etc. This generates CO_2 emissions as well which shall be accounted for. According to Lewsuwan (2021), the warehouse generates an amount of carbon emissions per unit stored as follows:

$$E_{Wi} = e_W \times w_i \times \overline{OH}_i \quad (2)$$

where (E_{Wi}) is the daily CO_2 emissions from the operating warehouse of company i, (e_W) is the daily rate of emitted CO_2 to hold one unit in stock, and ($\overline{OH}_i$) is the time weighted average on-hand inventory level. According to Dobers *et al.* (2022), this number varies significantly among warehouses. Thus, the carbon emissions from ambient storage are set at 0.0012 $kg\ CO_2/kg$ (Dobers *et al.*, 2022).

Additionally, the developed model has the following assumptions:

1) Products need ambient storage conditions (no refrigeration requirements needed).
2) The demand rate and lead time follow Poisson and exponential distributions, respectively.
3) Without loss of generality, both companies are assumed to have the same major ordering cost, lead time, travelled distance and emit the same amount of CO_2 to hold one unit in stock (e_W).
4) Only one product from each company is considered.
5) A homogenous fleet of trucks is considered, specifically the light duty trucks having a capacity of 2585 kg.

3.1 The Standalone Model

The first step of the analysis is to investigate the performance of the two companies under the standalone case (no collaboration) as this represents the benchmark scenario for quantifying the savings obtained upon collaboration (Section 3.2). The replenishment of companies' inventories in this case follows the classical continuous review policy (Q_i,s_i). As such, when the inventory position I_i of company i drops to the reorder point s_i, it places an order of Q_i units. It should be noted that the inventory position I_i and the on-hand inventory OH_i are different. The on-hand inventory OH_i is the actual physical units in stock while the inventory position I_i considers the unsatisfied backordered units BO_i and the order quantities that have been ordered but did not arrive yet, thereafter referred to as quantities On Order OO_i. The formula used to calculate the inventory position I_i is as follows:

$$I_i = OH_i + OO_i - BO_i \quad (3)$$

According to Nahmias and Olsen (2015), the total logistics cost for a company i based on the classical (Q_i,s_i) policy includes ordering and/or transportation cost, holding cost and shortage cost. Thus, the logistics cost per unit time C_i^{sa} formula under the standalone case is:

$$C_i^{sa} = \frac{(K_i + k_i + V_i) \times n_i^{sa}}{\hat{n}} + h_i \times \overline{OH_\iota} + B_i \times \overline{BO}_i + LS_i \times \overline{LD}_i \quad (4)$$

where superscript sa stands for standalone, n_i^{sa} is the number of orders initiated by company i over a specific period of $\hat{n}$ days long. $\overline{BO}_i$, $\overline{OH_\iota}$, and $\overline{LD}_i$ are the time-weighted average of the backorder units, on-hand inventory and the lost demand (sales) units, respectively.

The standalone model consists of two sections: demand management part and inventory management part. Starting with the demand management part, this part includes the demand arrival, an inventory check, and the processing of unsatisfied demand as shown in **Figure 1**.

First, the "Create" module creates an entity indicating that a demand has arrived. The interarrival time between these entities is assumed to be one day. Then, a Poisson distributed demand of mean D is assigned to the entity in the "Assign" module, where this mean value is different between the two companies. Then, the entity goes into a "Decide" module to check if there is stock available to meet the demand. The expression to check is if the "On-hand Inventory" is greater than the "Demand" or not. If yes, the customer demand is satisfied, and the inventory gets decreased in the "Decrease Inventory assign" module. However, if the "On-hand Inventory" is less than the "Demand", then part of the demand will be met, and the rest will be either backordered or lost. The satisfied part will be equal to whatever is in stock as "On-hand Inventory", while the unsatisfied part of the demand will be divided into backorder units and lost demand units based on some variable σ, where σ can be any number between 0 and 1. Also, the "on-hand inventory" is then set to zero. After that, another check is made as to whether the "Inventory Position" is less than or equal to the "Reorder Point". If the condition is met, then the entity is transferred to the Inventory Management part of the model using "Label" and "Go to Label" modules. In case the condition is not met, then the entity is disposed. This section is needed when the "Inventory Position" does not reach the "Reorder Point" before the arrival of the last entity, whose demand is greater than the current stock.

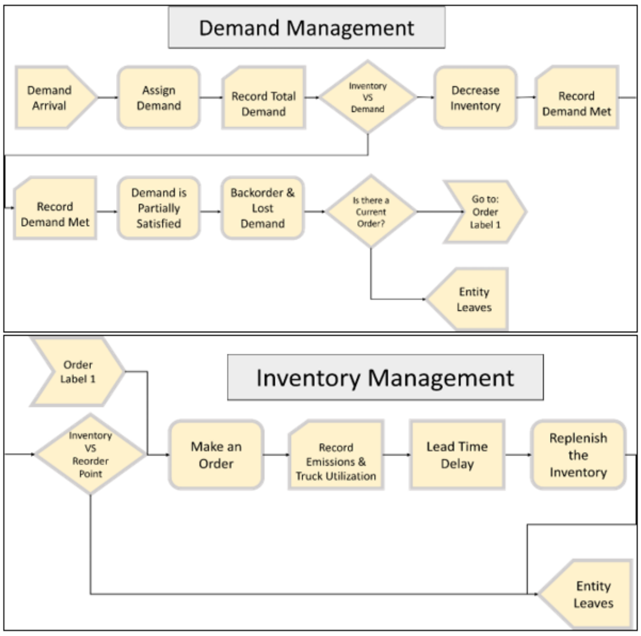

Figure 1 The standalone ARENA model

Moving on to the inventory management section, this part includes checking the inventory position and making orders as shown in **Figure 1**. It starts with a "Decide" module to check if the "Inventory Position" I is less than the "Reorder Point" s. If yes, then the entity proceeds to the "Make an Order" module. If no, then the entity disposes the model without making a new order. The "Inventory Position" formula as explained in **Eq. (3)** is written under the expression section which gets updated continuously. In the "Make an Order" module, the "On Order" is updated by adding the "Order Quantity" amount. Then, the "Transportation CO_2 Emissions" E_T^{sa}, "Variable Transportation Cost" V^{sa} and "Truck Utilization" U^{sa} tally variables as well as the Order Number, n^{sa}, count variable are calculated in the "Record" module. It should be noted that a tally variable is a variable that is calculated only when an entity passes through the record module. On the contrary, the count variable is a variable that gets incremented by one each time an entity passes through the record module. Moreover, the truck utilization is calculated as follows:

$$U^{sa} = \frac{Q_i w_i}{M} \tag{5}$$

where M is the capacity of one light duty truck in kg. Next, a "Delay" module is utilized to reflect the lead time, which is assumed to follow an exponential distribution with a mean of LT. The delay expression is written as:

$$Delay = Max(Expo(LT), Z) \tag{6}$$

where Z is the minimum possible delay duration in days. After the lead time is passed, the order arrives, and the following are computed in the "Replenish the Inventory" module in its respected order:

$$\begin{aligned} &Onhand\ Inventory\ (OH) \\ &= Max(0, Onhand\ Inventory\ (OH) \\ &+\ Order\ Quantity\ (Q) \\ &-\ Backorder\ Num\ (BO)) \end{aligned} \tag{7}$$

$$\begin{aligned} &Backorder\ Num\ (BO) \\ &=\ Max(0, Backorder\ Num\ (BO) \\ &- Order\ Quantity\ (Q)) \end{aligned} \tag{8}$$

These formulas allow for the flexibility of having more than one outstanding order. For the calculation of the "On-hand Inventory", it gets updated by the arrived "Order Quantity" after satisfying the backordered units. If the "Backorder Num" is greater than or equal to the "Order Quantity", the "On-hand Inventory" is set to zero. This means that there is more than one outstanding order. Next, the "Backorder Num" is updated. If the "Order Quantity" is greater than the "Backorder Num", this means that an order arrives and satisfies all the backorder units that were not satisfied by the previous orders. Thus, the "Backorder Num" is set to zero. By contrast, if the "Order Quantity" is less than the "Backorder Num", this means that when an order arrives, some of the backorder units are satisfied by the arrived "Order Quantity" and the "Backorder Num" gets updated to a new value. Also, the "Lost Demand" variable is set to zero when an order arrives as a new cycle begins. Note that the cycle time is the time between two consecutive orders. Then, the "On Order" variable gets decreased by the arrived "Order Quantity". This is essential to keep the "Inventory Position" updated when an order arrives and when there is more than one outstanding order. Finally, the entity leaves the system.

3.2 The Collaborative Model

In this model, the demand management part is like what was explained earlier in the standalone model. However, the inventory management part is different. For Company 1, the inventory management part, as displayed in **Figure 2**, starts with checking if the "Inventory Position" I_1 is less than or equal to the "Must Order Point" s_1. If yes, then the entity goes to the order initiation process, otherwise the entity leaves the system. In the "Make an Order 1" module, the "Order Quantity" Q_1^s is set to a new value $Q_1^s = S_1 - I_1$. Note that superscript "s" stands for self-initiated order, "J" stands for joined order and "cl" stands for the collaborative case. Obviously, a self-initiated order takes place when the inventory position of the company reaches its reorder point.

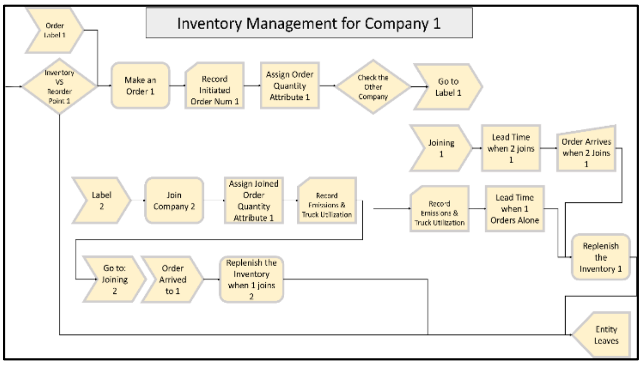

Figure 2 The collaborative ARENA model for the inventory management part of Company 1

In addition, like the standalone model, the "On Order" variable, OO_1, is updated by adding the "Order Quantity" Q_1^s . Moreover, the "Self-initiated Order Num" count variable, n_1^s, is increased by 1. Next, there is a "Decide" module called "Check the Other Company", where the "Inventory Position" of Company 2, I_2, is checked against its "Can Order Level" C_2. If the "Inventory Position" I_2 is less than or equal to the "Can Order Level" C_2, then Company 2 joins the order initiated by Company 1 and the entity goes into the first branch where a "Go to Label" module is used. The "Go to Label 1" module transfers the entity into "Label 1" module in the Company 2 part to place the joint order. In this part, the "Joined Order Quantity" Q_2^J is updated to $Q_2^J = S_2 - I_2$ in the "Assign" module. Next, the "Order Num Joined by 2" n_2^J count variable is increased by one. Also, the tally variables; "Joined Variable Transportation Cost" V_1^J and the "Joined Transportation CO_2 Emissions" E_{T1}^J are calculated as per (Cheng *et al.*, 2017). Note that $i = 1$ because Company 1 is the one who initiates the order. Furthermore, the "Joined Truck Utilization" U^J Tally variable is determined as follows:

$$\frac{(Q_2^j \times w_2 + Q_1^s \times w_1)}{M} \tag{9}$$

After that, the entity goes into another "Go to Label" module that transfers the entity into "Joining 01" label in Company 1 part, where it goes into the "Delay" module that represents the lead time. The lead time expression is the same as in the standalone model. When the lead time is passed, the "Clone" module duplicates the entity into two entities: one goes to the "Replenish the Inventory 1" module for Company 1 while the other entity goes to "Replenish the Inventory when company 2 Joins 1" module for Company 2. In both modules, the "On-hand Inventory" and the "Backorder Num" are updated like **Eqs. (7)** and **(8)** respectively. Then, the entities leave the system. Back to the "Decide" module in Company 1 part, where the "Can Order Level" C_2 is checked. If the expression is false, then the order is only for Company 1 and the entity goes through the same process as in the inventory management part of the standalone model.

This paper runs the models for 1460 days (4 years) with 40 replications and a warm-up period of 365 days. The validation of the standalone model is conducted by comparing the OptQuest results with the results of the classical continuous review model (Q_i, s_i). It is found that the logistics cost deviation is about 1.9%. Finally, a snapshot of the collaborative model output is shown in **Table 2**, which is like the standalone model output.

Table 2 Arena collaborative model output

Name	Expression in Arena	Notation
Holding Cost per day 1 (HC_1)	DAVG(Onhand Inventory 1)×Holding Cost per unit 1/365	$\frac{\overline{OH}_1 \times h_1}{365}$ *
Ordering Cost per day 1 (OC_1)	((Major Ordering Cost per order + Minor Ordering Cost per Order 1) × NC(Self Initiated Order Num 1)+Minor Ordering Cost per Order 1×NC(CL Order Num Joined by 1))/Days to Run	$\frac{(K+k_1)\times n_1^s + k_1 \times n_1^J}{\hat{n}}$
Transportation Cost per day 1 (TC_1)	(TVALUE (Variable Transportation Cost 1)+ TVALUE (Variable Transportation Cost when 2 joins 1))/Days to Run + OVALUE (Ordering Cost per day 1)	$\frac{(V_1^s + V_1^J)}{\hat{n}} + OC_1$
Backorder Cost per day 1 (BOC_1)	DAVG(Backorder Units 1) ×Backorder Cost per unit 1/365	$\frac{\overline{BO}_1 \times B_1}{365}$ *
Lost Demand Cost per day 1 (LDC_1)	DAVG(Lost Demand Units 1) ×Lost Demand Cost per unit 1/365	$\frac{\overline{LD}_1 \times LS_1}{365}$ *
Shortage Cost per day 1 (SC_1)	OVALUE(Backorder Cost per day 1) +OVALUE(Lost Demand Cost per day 1)	$BOC_1 + LDC_1$
Logistics Cost per day 1	OVALUE(Holding Cost per day 1)+ OVALUE(Shortage Cost per day 1) + OVALUE(Transportation Cost per day 1)	$HC_1 + SC_1 + TC_1$
Warehouse CO_2 Emissions 1 (E_{W1})	Warehouse Emissions per stored unit ×Weight of one product 1* DAVG(Onhand Inventory 1)	$e_W \times w_1 \times \overline{OH}_1$
Fill Rate 1	TVALUE (Demand Met 1)/TVALUE (Total Demand 1)	
Avg. Truck Utilization 1 ($\overline{U_1^s}$)	TAVG(Truck Utilization 1)	
Holding Cost per day 2 (HC_2)	DAVG(Onhand Inventory 2) ×Holding Cost per unit 2/365	$\frac{\overline{OH}_2 \times h_2}{365}$ *

Ordering Cost per day 2 (OC_2)	((Major Ordering Cost per order + Minor Ordering Cost per Order 2) ×NC(Self Initiated Order Num 2)+Minor Ordering Cost per Order 2×NC(CL Order Num Joined by 2))/Days to Run	$\frac{(K+k_2)\times n_2^s+k_2\times n_2^J}{\hat{n}}$
Transportation Cost per day 2 (TC_2)	(TVALUE (Variable Transportation Cost 2)+ TVALUE (Variable Transportation Cost when 1 joins 2))/Days to Run + OVALUE (Ordering Cost per day 2)	$\frac{(V_2^s+V_2^J)}{\hat{n}}+OC_2$
Backorder Cost per day 2 (BOC_2)	DAVG(Backorder Units 2) ×Backorder Cost per unit 2/365	$\frac{\overline{BO}_2\times B_2}{365}$ *
Lost Demand Cost per day 2 (LDC_2)	DAVG(Lost Demand Units 2) ×Lost Demand Cost per unit 2/365	$\frac{\overline{LD}_2\times LS_2}{365}$ *
Shortage Cost per day 2 (SC_2)	OVALUE(Backorder Cost per day 2)+OVALUE(Lost Demand Cost per day 2)	BOC_2+LDC_2
Logistics Cost per day 2	OVALUE (Holding Cost per day 2)+ OVALUE(Shortage Cost per day 2) + OVALUE(Transportation Cost per day 2)	$HC_2+SC_2+TC_2$
Warehouse CO_2 Emissions 2 (E_{W2})	Warehouse Emissions per stored unit × Weight of one product 2 × DAVG (Onhand Inventory 2)	$e_W\times w_2\times\overline{OH}_2$
Fill Rate 2	TVALUE (Demand Met 2)/TVALUE (Total Demand 2)	
Avg. Truck Utilization 2 ($\overline{U_2^s}$)	TAVG (Truck Utilization 2)	
Total Transportation CO_2 Emissions per day (E_T^{cl})	(TVALUE (Transportation CO_2 Emissions 1) +TVALUE(Transportation CO_2 Emissions 2) +TVALUE(Joined Transportation CO2 Emissions))/Days to Run	$\frac{(E_{T1}^s+E_{T2}^s+E_T^J)}{\hat{n}}$
Total CO_2 Emissions by companies 1 & 2 (E^{cl})	OVALUE(Total Transportation CO_2 Emissions per day)+ OVALUE(Warehouse CO_2 Emissions 1) +OVALUE(Warehouse CO_2 Emissions 2)	$E_T^{cl}+E_{W1}+E_{W2}$
Avg Joined Truck Utilization ($\overline{U^J}$)	TAVG(Joined Truck Utilization)	

* Divide by 365, if h_i, B_i, LS_i are annual. DAVG, OVALUE, TVALUE, NC, TAVG are Arena expressions. For instance, DAVG is the time-weighted average for time persistent variables, while TAVG is the average value of Tally variables.

As an extension to the standalone case, the logistics cost of Company i per unit time under collaboration C_i^{cl} is expressed as follows:

$$C_i^{cl}=\frac{(K_i+k_i)\times n_i^s+V_i^{cl}+k_i\times n_i^J}{\hat{n}}+h_i\times\overline{OH_i}+B_i\times\overline{BO}_i+LS_i\times\overline{LD}_i \quad (10)$$

where n_i^s is the number of orders initiated by Company i regardless of if Company j joins the order or not, and n_i^J is the number of orders that Company i joins the orders initiated by Company j.

4. COMPUTATIONAL EXPERIMENTS

The optimization of the standalone model involves determining the optimum reorder point and order quantity values under 13 different scenarios, where these scenarios are obtained by changing key model parameters such as unit cost, demand mean, and major ordering cost Each scenario is referred to hereafter as a trial (see **Table 3**). As shown in **Table 3**, the unit cost (c) assumes one of the three values (10, 50, 500), the demand mean (D) is set at 10 or 50 per day, unit major ordering cost (K) varies between (250, 500, 1000), unit minor ordering cost (k) is either 50, 100 or 200, product weight (w) is 2 or 10, holding rate (r_h) is 0.05 or 0.000584 (which is $\frac{0.2}{365}$) per day, backorder rate (r_B) is 0.06 or 0.000822 (which is $\frac{0.3}{365}$) per day, and lost sales rate (r_{LS}) is 0.07 or 0.0001096 (which is $\frac{0.4}{365}$) per day. Note that all these key parameters are tested with extreme limits of minimum and maximum values, except for the minor ordering cost. The minor ordering cost is linked with the major ordering cost and the weight of the products. For instance, if the weight of the product is 2, the minor ordering cost is set to be 10% of the major ordering cost. On the contrary, if the weight of the product is 10, then the minor ordering cost is assumed to be 20% of the major ordering cost.

Two objectives were tested separately for each trial, which are to minimize the logistics cost and total CO_2 emissions. In addition, a minimum fill rate value of 0.95 is specified as a constraint. The lead time is always set to have a mean $LT=2$ days and a minimum delay $Z=3$ days. Also, variable σ is set to 0.5 indicating equal likelihood of backordering and lost sales. Moreover, the upper and lower bounds used to optimize the control variables are determined for each trial. Note that in **Table 3**, LB stands for the lower bound and UB stands for the upper bound. The lower bound for the must order point, s, is always set to be equal to the demand in the respective trial. The bounds for the order quantity Q change according to the holding rate and the demand, since low holding rate and high demand values require larger bounds. Note that the step size chosen for the standalone optimization is one. It is worth mentioning that the optimization is performed using Intel Core i7-7700HQ CPU, 2.80 GHz, 8 GB of RAM laptop. It takes a minimum of one hour to complete one optimization run.

Table 3 Standalone optimization input parameters

SA Trial no.	D	w	K	k	r_h	r_B	r_{LS}	c	$OH_{t=0}$	$Q(LB, UB)$	$s(LB, UB)$
1	50	2	500	50	0.000548	0.000822	0.001096	10	800	(800, 3000)	(50, 350)
2	50	2	500	50	0.000548	0.000822	0.001096	50	800	(800, 3000)	(50, 350)
3	50	2	500	50	0.05	0.06	0.07	50	300	(100, 1000)	(50, 350)
4	10	2	500	50	0.000548	0.000822	0.001096	50	300	(50, 1500)	(10, 150)
5	50	2	500	50	0.05	0.06	0.07	10	300	(100, 1500)	(50, 350)
6	10	2	500	50	0.05	0.06	0.07	50	300	(50, 900)	(10, 150)
7	10	2	1000	100	0.05	0.06	0.07	50	300	(50, 1500)	(10, 150)
8	10	10	500	100	0.000548	0.000822	0.001096	500	250	(80, 800)	(10, 150)
9	50	10	500	100	0.000548	0.000822	0.001096	500	500	(100, 1000)	(50, 350)
10	10	10	1000	200	0.000548	0.000822	0.001096	500	250	(80, 800)	(10, 150)
11	50	10	1000	200	0.000548	0.000822	0.001096	500	500	(100, 1500)	(50, 350)
12	50	10	250	50	0.000548	0.000822	0.001096	500	500	(100, 1500)	(50, 350)
13	10	10	250	50	0.000548	0.000822	0.001096	500	250	(80, 800)	(10, 150)

A similar approach was used for the optimization of the collaborative model. However, the number of control variables in this case is six, which makes the optimization more complex leading to a much higher CPU time for each run. The control variables are the three can-order policy parameters for each company. **Table 4** shows the different tested trials along with the specified boundaries of the control variables. It should be noted that a combination of the standalone "SA" Trials is set to companies 1 and 2 in the collaborative "CL" trials as shown in **Table 4**. There is a total of 14 different CL Trials. Indeed, choosing the combination of SA Trials for companies 1 and 2 depends on testing what happens if a certain parameter increases/decreases. For instance, how the results might differ when companies have different characteristics compared to another trial where one of the companies increased its holding cost, or major ordering cost, or demand or unit cost. This can be seen in CL Trials 1 and 2 where unit cost of Company 1 is increased in Trial 2. Furthermore, it is essential to test the case where both companies are identical like in CL Trials 4, 7, and 13, or having different weight of products like in Trials 1, 2 and 3, etc. Unlike the standalone case, two optimization attempts were utilized for each trial. The first attempt includes the specified boundaries in **Table 3** with a step size of 5, while the second attempt involves taking a smaller boundary around the optimum solution found in the first attempt with a smaller step size. The boundary in this latter attempt is about ± 50 of the optimum first attempt's values for the can order level and order up to level with a step size of 2. On the contrary, the boundary for the must order point is ± 10 with a step size of 1. This approach is similar to that adopted by Kleijnen and Wan (2007). For the collaborative model, it takes about 10 to 11 hours to complete one optimization run including both attempts.

Table 4 Collaborative optimization input parameters

	Company 1				Company 2			
CL Trial no.	SA Trial no.	$S(LB, UB)$	$C(LB, UB)$	$s(LB, UB)$	SA Trial no.	$S(LB, UB)$	$C(LB, UB)$	$s(LB, UB)$
1	1	(800, 3000)	(700, 3000)	(50, 350)	8	(80, 800)	(80, 800)	(10, 150)
2	2	(800, 3000)	(700, 3000)	(50, 350)	8	(80, 800)	(80, 800)	(10, 150)
3	4	(100, 900)	(80, 800)	(10, 150)	8	(80, 800)	(80, 800)	(10, 150)
4	4	(100, 900)	(80, 800)	(10, 150)	4	(100, 900)	(80, 800)	(10, 150)
5	5	(100, 1000)	(100, 1000)	(50, 350)	8	(80, 800)	(80, 800)	(10, 150)
6	6	(50, 800)	(50, 800)	(10, 150)	8	(80, 800)	(80, 800)	(10, 150)
7	6	(50, 800)	(50, 800)	(10, 150)	6	(50, 800)	(50, 800)	(10, 150)

8	7	(50, 1000)	(50, 1000)	(10, 150)	10	(80, 800)	(80, 800)	(10, 150)
9	3	(100, 800)	(100, 800)	(50, 350)	8	(80, 800)	(80, 800)	(10, 150)
10	11	(200, 1500)	(100, 1500)	(50, 350)	10	(80, 700)	(80, 650)	(10, 150)
11	3	(100, 800)	(100, 800)	(50, 350)	9	(200, 1500)	(100, 1500)	(50, 350)
12	9	(200, 1500)	(100, 1500)	(50, 350)	8	(80, 700)	(80, 650)	(10, 150)
13	12	(100, 1500)	(100, 1500)	(50, 350)	12	(100, 1500)	(100, 1500)	(50, 350)
14	12	(100, 1500)	(100, 1500)	(50, 350)	13	(80, 800)	(50, 800)	(10, 150)

5. RESULTS AND DISCUSSION

There are two objectives to be minimized, one at a time, for each trial which are the cost and CO_2 emissions. As such, each trial number X has two sub-trials X.1 and X.2. The cost objective is represented by X.1 while X.2 represents the CO_2 objective. It should be noted that CO_2 emissions are affected by the demand and weight of the products. Thus, trials having similar demand and weight will yield the same minimum CO_2 emissions as shown in the Appendix. As a result, the total number of tested SA and CL trials are 19 and 21, respectively.

The first objective seeks to minimize the total logistics cost consisting of the transportation cost, holding cost and shortage cost. A comparative summary of the total logistics cost for the collaborative case of the two companies together C_{To}^{cl} and the standalone case C_{To}^{sa} is presented in **Table 5**. The table shows that cost savings are attained due to collaboration as opposed to the standalone setting across all 14 trials. The highest saving is achieved in Trial 4.1, where the two companies are identical and have low unit holding costs. By contrast, the least saving of 5.56% is obtained in Trial 9.1, where the unit holding cost per day is high for Company 1 ($h_1 = 2.5$) and the demand is low for Company 2. However, the cost saving is reduced to 14.6% in Trial 7.1 where the unit holding cost is high for the same characteristics as in Trial 4.1.

Furthermore, the high major ordering cost almost doubles the savings attained due to collaboration as shown in Trial 10.1 ($K = 1000$) once compared to Trial 12.1 ($K = 500$). In general, when the major ordering cost is high coupled with a low unit holding cost, the number of trucks to be used per order increases (recall that the major ordering cost is paid for each order regardless of the number of trucks used). This reduces the total number of orders compared to the standalone case, which means more savings in the major ordering cost. This finding aligns with what was concluded in (Tinoco *et al.*, 2017). Moreover, the logistics cost of one of the companies is less than the standalone case (the negative values) in Trials 5.1, 12.1, 13.1 and 14.1. However, because the logistics cost of the other company outweighs such reduction, the overall scenario is better than no collaboration.

Table 5 Standalone optimization input parameters

CL Trial no.	C_1^{cl}	C_2^{cl}	C_1^{sa}	C_2^{sa}	C_{To}^{cl}	C_{To}^{sa}	Saving
Trial 1.1	10.42	52.97	17.609	56.846	63.384	74.455	14.87%
Trial 2.1	28.17	46.98	38.602	56.846	75.149	95.448	21.27%
Trial 3.1	13.66	49.33	16.833	56.846	62.993	73.679	14.50%
Trial 4.1	13.28	12.30	16.833	16.833	25.577	33.667	24.03%
Trial 5.1	180.37	33.46	178.486	56.846	213.829	235.332	9.14%
Trial 6.1	183.89	28.31	184.902	56.846	212.201	241.748	12.22%
Trial 7.1	179.90	135.87	184.902	184.902	315.774	369.805	14.61%
Trial 8.1	240.74	39.77	243.764	79.603	280.512	323.366	13.25%
Trial 9.1	503.60	36.46	515.025	56.846	540.058	571.871	5.56%
Trial 10.1	176.30	44.38	183.726	79.603	220.681	263.329	16.20%
Trial 11.1	506.61	83.20	515.025	134.388	589.811	649.413	9.18%
Trial 12.1	137.97	37.46	134.388	56.846	175.430	191.234	8.26%
Trial 13.1	109.89	59.47	101.775	101.775	169.360	203.551	16.80%
Trial 14.1	79.57	49.34	101.775	41.465	128.909	143.241	10.01%

The results of the optimum solution of Trial 1.1 show that the logistics cost of each company decreases when they are collaborating compared to the standalone case as presented in **Figure 3**. However, the transportation cost decreases by

3.69 units per day while the holding cost increases by 2.4 units per day for Company 2 under collaboration. This is due to the reduction in the total number of collaborative orders (initiated + joined) of about 45 orders compared to the numbers initiated under the standalone case of about 49 orders. By contrast, Company 1 achieves lower costs by 52% and 33% for both holding and transportation, respectively, due to the increase in the total number of collaborative orders. In other words, increasing the frequency of orders leads to lower inventory holding cost and would normally increase the transportation cost. However, the transportation cost decreases as 78% of the orders are when Company 1 joins Company 2 in which case only the minor ordering cost is paid by such a company.

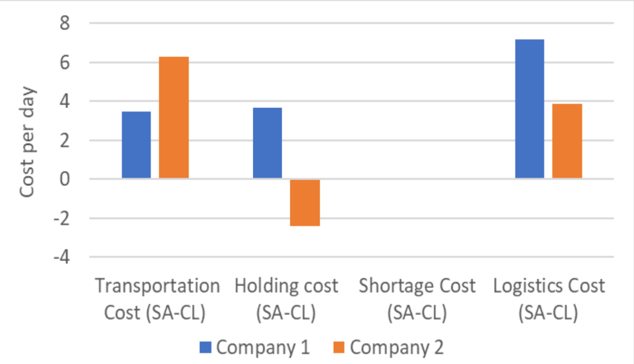

Figure 3 Cost analysis of the optimum solution of Trial 1.1

Similarly, the number of total collaborative orders in Trial 4.1 increases from 16 to 23 orders for both companies leading to savings in the holding cost. The transportation cost is reduced as well since the initiated number of orders by each company decreases compared to the orders initiated in the standalone case. Indeed, the number of self-initiated orders was 16 and becomes about 12 and 10 for Company 1 and Company 2, respectively. In addition, the truck utilization has improved from 0.494 to 0.713 due to collaboration.

Company 1 in Trial 6.1 initiates 99% of the collaborative orders due primarily to the fact that the unit holding cost of Company 1 is much higher than that of Company 2. Accordingly, Company 1 seeks to minimize its holding cost by lowering its inventory level through initiating more orders. Note that its “can order level” C_1 is closer to its “must order level” s_1 than to its “order up to level” S_1 in order to lower the on-hand inventory OH_1 in case Company 2 initiates an order and company 1 joins. Nevertheless, the logistics cost of company 1 decreases slightly compared to the standalone case due to the increase in transportation cost, which nearly offsets the savings in the holding cost. Overall, the situation is better off as the logistics cost of company 2 decreases significantly.

Likewise, Trial 9.1 presents an optimal solution where Company 1 initiates 93% of the orders and joins Company 2 whenever it initiates an order. It should be noted that Company 1 has a high unit holding cost, where its number of total collaborative orders increases by around 9% leading to a slight saving of 3.5% in the holding cost. Moreover, the saving in total logistics cost is less than Trials 5.1 and 6.1. Compared to Trial 5.1, the unit cost is increased in Trial 9.1 leading to a higher unit holding cost. Therefore, the order up to level S_1 in Trial 9.1 is less than that in Trial 5.1 in order to further decrease the order quantity and the holding cost per day accordingly. As such, the total number of collaborative orders increases by more than 60% in Trial 9.1 compared to Trial 5.1. On the other hand, the demand increases in Trial 9.1 as compared to Trial 6.1 leading to a higher order up to level S_1 in Trial 9.1. As a result, more orders are needed to meet the increase in demand and minimize the holding cost. However, the transportation cost increases for Company 1 due to initiating more orders than the standalone case.

It should be noted that in the first three trials shown in **Table 5**, the increase in the demand for Company 1 (from 10 in Trial 3 to 50 in Trial 2) and unit cost for Company 1 (from 10 in Trial 1 to 50 in Trial 2) yield higher savings in logistics cost. However, such an increase leads to lower savings in Trials 5, 6 and 9, which have similar characteristics as Trials 1, 3 and 2, respectively except for Company 1 holding rate r_h. After a thorough analysis, it has been found that if the demand and unit cost increase is associated with the company having a lower unit holding cost (remains lower even with the increase in unit cost), then this increase leads to higher savings as in Trial 1, 2 and 3. On the contrary, if the increase in demand and unit cost occurs for the company characterized by higher unit holding cost, then less cost savings will be attained. This observation can also be seen in Trials 9 and 11. The demand increases for Company 2 from 10 in Trial 9 to 50 in Trial 11, where Company 2 has lower unit holding cost ($h_1 = 2.5$, $h_2 = 0.274$). Consequently, the logistics cost saving in Trial 11.1 is higher than that in Trial 9.1. This is due to the fact that when the unit holding cost is high, the frequency of orders increases. This indicates that a smaller quantity is being ordered, which further decreases the truck utilization rate, eventually leading to an increase in the transportation cost.

Moving on to the second objective, which seeks to minimize the CO_2 emissions generated from transportation and warehousing related activities. **Figure 4** summarizes the savings attained in each distinct collaborative trial as compared to the standalone case. The highest saving of 27% is also achieved in Trial 4.2, where companies are identical and have low demand and low products’ weight. This is attributed to better truck utilization under collaboration once compared to the lower utilization rate when companies are working separately. Indeed, the standalone case is better than the collaborative case, from an environmental standpoint, when both companies have high demand and high weight of products. Closely examining each scenario, **Figure 5** summarizes the difference between the emissions of the standalone and collaborative cases, where negative values indicate that the standalone case generates lower carbon footprint. Indeed, the optimum solution of Trials 1.2, 5.2, 10.2 and 11.2 shows an increase in the total number of collaborative orders compared to the total number of standalone orders (for both companies) leading to higher transportation emissions but lower warehouse emissions for each company. This also takes place in Trial 13.2 but the increase in transportation emissions is higher than the savings in warehouse related emissions. Under this condition, collaboration leads to an increase in the generated CO_2 emissions by almost 4%.

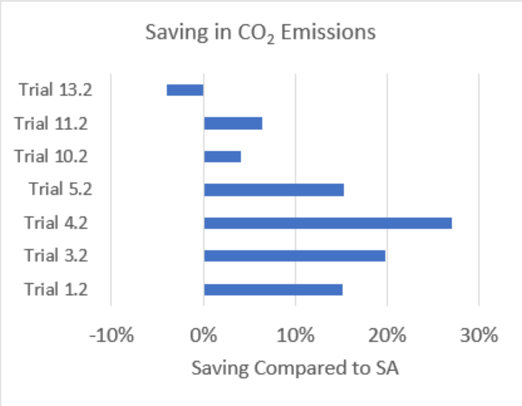

Figure 4 Emissions of the collaborative case vs the standalone (SA) case

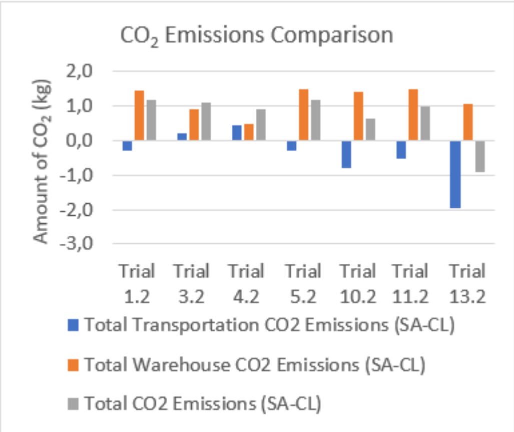

Figure 5 The difference in emissions generated by the standalone and collaborative models in each trial

In addition, paired t-test is conducted for each trial to see whether the differences in logistics cost and CO_2 emissions are statistically significant between the horizontal collaboration scenario and the no collaboration scenario. The results of the paired t-test revealed that the means of the trials are not equal (missing the zero value) and have positive values when subtracting the collaborative mean from the standalone mean. In other words, it can be concluded statistically that horizontal collaboration is beneficial.

6. CONCLUSION

This paper leverages simulation as a powerful tool for testing practical settings and conducting what- if analysis in a completely safe and virtual environment. Specifically, Arena simulation package is used to build both the standalone and the HLC models of two companies. Then, OptQuest is employed to optimize the can-order policy thresholds for the collaboration case as well as the continuous review policy parameters for the no collaboration setting. The results reveal that horizontal collaboration in logistics brings substantial economic and environmental benefits to the partners. The extent of these savings is contingent on key input parameters, including demand rate, holding cost and major ordering cost. In terms of logistics cost, it becomes evident that the collaborative arrangements outperform standalone operations for all tested scenarios. For instance, horizontal collaboration achieves savings of up to 24% compared to the standalone case when the unit holding cost is low and the major ordering cost is high. From an environmental standpoint, the saving in CO_2 emissions are the highest when the weight of the products and demand are both low.

These findings point out to the potential of attaining substantial benefits upon engaging in horizontal collaboration, particularly with partners having low unit holding costs or high major ordering cost. Additionally, synchronization of orders becomes crucial when both companies have low truck utilization when operating independently. Furthermore, if a company dealing with products of high unit holding costs considers horizontal collaboration, it is advisable to seek collaboration with a partner that shares similar cost and demand characteristics.

Future research could explore collaborations involving more than two companies and compare the outcomes with two-company collaborations versus non-collaborative scenarios. Additionally, a heterogeneous rather than a homogeneous fleet of trucks can be considered. Alternatively, varying the distance between the collaborating companies could also be investigated in order to check whether collaboration may outperform the standalone case when locations are different. Furthermore, exploring carbon regulatory policies like the carbon cap policy, which impose upper limits on carbon footprint, presents another promising avenue for future research.

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APPENDIX 1: OPTQUEST RESULTS FOR THE STANDALONE MODEL

SA Trial no.	Q	s	Fill Rate	Avg. Truck Utilization	n_i^{sa}	Holding cost	Transportation Cost	Shortage Cost	Logistics Cost C_i^{sa}	Transportation Emissions	Warehouse Emissions	Total Emissions E_i^{sa}
Trial 1.1	2729	52	0.95	2.11	19.03	7.05	10.53	0.03	17.61	3.52	3.09	6.61
Trial 1.2	1250	50	0.89	0.97	41.10	2.99	21.36	0.07	24.42	2.60	1.31	3.91
Trial 2.1	1509	116	0.95	1.17	35.05	19.70	18.79	0.12	38.60	4.27	1.73	5.99
Trial 2.2	1250	50	0.89	0.97	41.10	14.94	21.36	0.35	36.65	2.60	1.31	3.91
Trial 3.1	209	209	0.95	0.16	255.55	373.00	132.47	9.55	515.02	14.88	0.36	15.23
Trial 3.2	1285	50	0.89	0.99	40.10	280.70	20.85	4.78	306.32	2.55	1.35	3.89
Trial 4.1	639	10	0.96	0.49	16.35	8.32	8.49	0.03	16.83	0.99	0.73	1.71
Trial 4.2	750	10	0.96	0.58	14.03	9.79	7.28	0.03	17.09	0.85	0.86	1.71
Trial 5.1	397	180	0.95	0.31	134.68	106.33	69.85	2.30	178.49	7.96	0.51	8.47
Trial 5.2	1285	50	0.89	0.99	40.10	280.70	20.85	4.78	306.32	2.55	1.35	3.89
Trial 6.1	77	39	0.95	0.06	138.80	110.69	71.93	2.29	184.90	7.99	0.11	8.10
Trial 6.2	750	10	0.96	0.58	14.03	9.79	7.28	0.03	17.09	0.85	0.86	1.71
Trial 7.1	101	36	0.95	0.08	105.75	133.80	107.92	2.05	243.76	6.10	0.13	6.23
Trial 7.2	750	10	0.96	0.58	14.03	9.79	7.28	0.03	17.09	0.85	0.86	1.71
Trial 8.1	217	28	0.95	0.84	49.13	28.84	27.77	0.23	56.85	3.07	1.26	4.33
Trial 8.2	258	10	0.89	1.00	40.18	30.85	22.72	0.79	54.35	2.55	1.35	3.90

Trial 9.1	509	172	0.95	1.97	105.00	71.53	61.22	1.64	134.39	13.32	3.13	16.46
Trial 9.2	258	50	0.57	1.00	166.53	18.37	48.55	13.91	80.83	10.58	0.80	11.38
Trial 10.1	297	24	0.95	1.15	35.78	38.96	40.41	0.24	79.60	4.35	1.71	6.06
Trial 10.2	258	10	0.89	1.00	40.18	30.85	22.72	0.79	54.35	2.55	1.35	3.90
Trial 11.1	718	156	0.95	2.78	74.38	97.20	85.40	1.13	183.73	14.07	4.26	18.33
Trial 11.2	258	50	0.57	1.00	166.53	18.37	48.55	13.91	80.83	10.58	0.80	11.38
Trial 12.1	397	181	0.95	1.54	134.73	58.64	41.54	1.60	101.78	16.72	2.57	19.29
Trial 12.2	258	50	0.57	1.00	166.53	18.37	48.55	13.91	80.83	10.58	0.80	11.38
Trial 13.1	155	32	0.95	0.60	68.93	21.17	20.05	0.25	41.47	4.20	0.93	5.13
Trial 13.2	258	10	0.89	1.00	40.18	30.85	22.72	0.79	54.35	2.55	1.35	3.90

APPENDIX 2: OPTQUEST RESULTS FOR THE COLLABORATIVE MODEL (PART 1)

CL Trial no.	s_1	C_1	S_1	s_2	C_2	S_2	Fill Rate 1	Fill Rate 2	Avg. Joined Truck Utilization	Avg. Truck Utilization 1	Avg. Truck Utilization 2	n_1^s	n_2^s	n_1^J	n_2^J
Trial 1.1	78	955	1355	26	255	260	0.96	0.95	1.83	0.000	0.000	10.10	35.25	35.25	10.10
Trial 1.2	50	455	725	10	120	125	0.88	0.79	0.91	0.000	0.000	28.98	56.50	56.50	28.98
Trial 2.1	106	1160	1205	24	205	239	0.95	0.95	1.62	0.000	0.000	23.03	27.78	27.78	23.03
Trial 2.2	50	455	725	10	120	125	0.88	0.79	0.91	0.000	0.000	28.98	56.50	56.50	28.98
Trial 3.1	30	250	252	26	230	231	0.98	0.95	0.95	0.000	0.000	16.98	35.45	35.45	16.98
Trial 3.2	10	170	245	10	190	210	0.95	0.87	0.94	0.000	0.000	9.80	40.88	40.88	9.80
Trial 4.1	19	190	491	10	150	484	0.97	0.96	0.71	0.000	0.000	12.45	10.60	10.60	12.45
Trial 4.2	10	549	549	10	246	551	0.96	0.96	0.82	0.000	0.000	9.98	10.08	10.08	9.98
Trial 5.1	195	450	485	30	110	214	0.95	0.97	0.48	0.000	0.000	163.60	8.58	8.58	163.60
Trial 5.2	50	601	730	10	46	123	0.89	0.79	0.91	0.014	0.011	23.63	61.85	61.83	23.60
Trial 6.1	39	52	105	13	111	200	0.95	0.96	0.33	0.003	0.020	149.40	1.08	1.03	149.35
Trial 6.2	10	170	245	10	190	210	0.95	0.87	0.94	0.000	0.000	9.80	40.88	40.88	9.80
Trial 7.1	40	105	107	24	110	113	0.95	0.95	0.11	0.000	0.000	135.93	15.13	15.13	135.93
Trial 7.2	10	549	549	10	246	551	0.96	0.96	0.82	0.000	0.000	9.98	10.08	10.08	9.98
Trial 8.1	35	65	140	11	90	148	0.95	0.95	0.51	0.009	0.041	93.03	4.40	4.33	92.85
Trial 8.2	10	170	245	10	190	210	0.95	0.87	0.94	0.000	0.000	9.80	40.88	40.88	9.80
Trial 9.1	214	358	383	29	64	154	0.95	0.97	0.58	0.152	0.000	259.73	17.98	17.98	77.95
Trial 9.2	50	601	730	10	46	123	0.89	0.79	0.91	0.014	0.011	23.63	61.85	61.83	23.60
Trial 10.1	155	853	859	16	155	180	0.95	0.96	3.35	0.000	0.000	64.88	9.10	9.10	64.88
Trial 10.2	50	192	200	10	66	80	0.43	0.90	0.87	0.000	0.000	218.58	0.25	0.25	218.58
Trial 11.1	209	387	388	182	419	438	0.95	0.97	0.94	0.000	0.000	255.13	12.25	12.25	255.13
Trial 11.2	50	332	333	50	205	205	0.77	0.44	0.88	0.000	0.000	3.18	213.13	213.13	3.18
Trial 12.1	163	712	752	16	175	200	0.95	1.00	2.86	0.000	0.000	86.93	0.00	0.00	86.93
Trial 12.2	50	192	200	10	66	80	0.43	0.90	0.87	0.000	0.000	218.58	0.25	0.25	218.58
Trial 13.1	199	235	456	106	425	463	0.95	0.95	2.19	0.000	0.000	188.30	0.50	0.50	188.30
Trial 13.2	50	178	179	50	155	176	0.38	0.37	0.81	0.013	0.000	179.05	179.80	179.80	179.03
Trial 14.1	144	556	556	41	108	110	0.95	0.96	1.64	0.000	0.000	37.23	114.35	114.35	37.23
Trial 14.2	50	192	200	10	66	80	0.43	0.90	0.87	0.000	0.000	218.58	0.25	0.25	218.58

APPENDIX 2: OPTQUEST RESULTS FOR THE COLLABORATIVE MODEL (PART 2)

CL Trial no.	Holding Cost per day 1	Holding Cost per day 2	Transportation Cost per day 1	Transportation Cost per day 2	Shortage Cost per day 1	Shortage Cost per day 2	Logistics Cost C_1^{cl}	Logistics Cost C_2^{cl}	Total Transportation Emissions	Warehouse Emissions 1	Warehouse Emissions 2	Total Emissions by companies 1 and 2 E_W
Trial 1.1	3.36	31.25	7.04	21.47	0.02	0.25	10.42	52.97	5.71	1.47	1.37	8.55
Trial 1.2	1.54	12.06	17.64	34.60	0.08	1.42	19.26	48.08	5.43	0.67	0.53	6.63
Trial 2.1	14.42	28.46	13.63	18.28	0.12	0.24	28.17	46.98	6.33	1.26	1.25	8.84
Trial 2.2	1.54	12.06	17.64	34.60	0.08	1.42	19.26	48.08	5.43	0.67	0.53	6.63
Trial 3.1	3.21	27.49	10.44	21.62	0.01	0.22	13.66	49.33	3.39	0.28	1.20	4.88
Trial 3.2	3.03	23.57	6.96	24.01	0.03	0.86	10.02	48.44	3.20	0.27	1.03	4.50
Trial 4.1	6.31	6.20	6.95	6.07	0.02	0.03	13.28	12.30	1.42	0.55	0.54	2.52
Trial 4.2	7.07	7.11	5.64	5.69	0.02	0.02	12.74	12.83	1.25	0.62	0.62	2.49
Trial 5.1	92.28	13.43	85.29	19.78	2.80	0.24	180.37	33.46	10.37	0.44	0.59	11.41
Trial 5.2	142.45	11.82	15.10	37.13	4.75	1.45	162.31	50.40	5.40	0.68	0.52	6.60
Trial 6.1	103.98	13.79	77.54	14.25	2.37	0.28	183.89	28.31	8.92	0.10	0.60	9.63
Trial 6.2	3.03	23.57	6.96	24.01	0.03	0.86	10.02	48.44	3.20	0.27	1.03	4.50
Trial 7.1	106.44	119.75	71.14	14.05	2.32	2.08	179.90	135.87	8.74	0.10	0.11	8.96
Trial 7.2	7.07	7.11	5.64	5.69	0.02	0.02	12.74	12.83	1.25	0.62	0.62	2.49
Trial 8.1	143.32	17.63	95.40	21.86	2.02	0.28	240.74	39.77	5.89	0.14	0.77	6.80
Trial 8.2	3.03	23.57	6.96	24.01	0.03	0.86	10.02	48.44	3.20	0.27	1.03	4.50
Trial 9.1	359.63	18.98	135.51	17.27	8.46	0.20	503.60	36.46	16.41	0.35	0.83	17.59
Trial 9.2	142.45	11.82	15.10	37.13	4.75	1.45	162.31	50.40	5.40	0.68	0.52	6.60
Trial 10.1	97.66	21.68	77.25	22.44	1.40	0.26	176.30	44.38	18.46	4.28	0.95	23.69
Trial 10.2	9.27	7.80	243.42	40.20	18.11	0.54	270.80	48.54	13.91	0.41	0.34	14.65
Trial 11.1	364.04	52.18	133.88	30.42	8.69	0.59	506.61	83.20	20.19	0.35	2.29	22.83
Trial 11.2	235.63	9.73	11.38	120.79	32.75	17.61	279.76	148.13	13.65	0.23	0.43	14.31
Trial 12.1	84.15	29.48	52.27	7.94	1.54	0.05	137.97	37.46	16.78	3.69	1.29	21.76
Trial 12.2	9.27	7.80	243.42	40.20	18.11	0.54	270.80	48.54	13.91	0.41	0.34	14.65
Trial 13.1	47.22	48.90	60.79	8.76	1.89	1.81	109.89	59.47	33.26	2.07	2.14	37.47
Trial 13.2	6.24	5.95	60.48	60.61	14.24	14.58	80.97	81.14	23.13	0.27	0.26	23.66
Trial 14.1	61.36	12.12	16.79	36.92	1.43	0.29	79.57	49.34	19.03	2.69	0.53	22.24
Trial 14.2	9.27	7.80	243.42	40.20	18.11	0.54	270.80	48.54	13.91	0.41	0.34	14.65

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