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SIMULATION-BASED OPTIMIZATION OF LOGISTICS DECISIONS UNDER HORIZONTAL COLLABORATION

by

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Declaration of Authorship

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Dedication

To my family and friends…

Abstract

Logistics operations nowadays are facing challenges pertaining to the increase of fuel cost, underutilized trucks capacity, and rising environmental concerns. As such, companies are continuously looking for solutions to address those challenges, where horizontal collaboration has proved to be one such effective strategy. Horizontal collaboration in logistics is typically formed between at least two companies working on the same level. It allows supply chain partners to exploit the economies of scale of consolidating their orders. However, synchronizing the orders of these partners to be shipped using the same fleet of trucks is a complex problem. This requires making trade-offs between the inventory holding cost on one end, and the transportation cost on another. Therefore, this thesis intends to provide a resolution using a joint replenishment inspired strategy referred to in the literature as the can-order policy. For the case of two parties, the can-order policy has three thresholds that enable each company to initiate its own order or join the order of the other company or do nothing. For instance, when a company initiates an order, another company can join the order if its inventory level reached a threshold value called the can-order level. Indeed, determining the values of these three thresholds that minimize the total logistics cost coupled with the CO_2 emissions is a challenging task. To that end, this thesis adopts a simulation-based optimization approach to build the collaborative shipping model between two companies and optimize the can-order policy parameters. The model is built considering demand and lead time uncertainties, homogeneous truck capacity and service level constraint. The result of the "what if analysis" shows that the can order policy is able to synchronize the orders in a horizontal collaboration setting. In particular, the horizontal collaboration yields higher cost savings as compared to the standalone case when the unit holding cost is low and companies are identical in the sense that they have the same demand, unit cost, and holding rate values. Also, it results in significant reduction in CO_2 emissions when both the demand and weight of the products are low.

Keywords: Horizontal Collaboration; Can-order Policy; Simulation; Collaborative Shipping, Optimization

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List of Abbreviations

DES	Discrete Event Simulation
HLC	Horizontal Logistics Collaboration
IPS	Inventory Problem Solver
JRP	Joint Replenishment Problem
LSP	Logistics Service Provider
UCC	Urban Consolidation Centers
V&V	Verification and Validation

Chapter 1. Introduction

1.1. Introduction

In this chapter, an overview of the importance of logistics activities and the associated challenges are presented. The chapter also defines horizontal collaboration and highlights its effectiveness in solving those challenges. Moreover, the objectives and research contributions are presented. Finally, this chapter concludes with an overview of the thesis organization.

1.2. Overview

Logistics is a business function that deals with the transportation of goods among suppliers, manufacturers, retailers, customers, and other players in the supply chain. The main objective is to deliver the products on time at the right place with the right quantity at the least cost. According to the market research report [1], the global logistics market size attained a value of approximately USD 9,525.1 billion in 2021, which is forecasted to rise by a rate of 5.7% in 2027. In fact, roadways represent the leading transportation mode segment in the market [1]. Specifically, the truck transport market has a size of $1,663.34 billion globally and is expected to grow at a rate of 8.5% from 2021 to 2026 [2]. Such a rapid growth is attributed to the emerging markets growth, rapid urbanization, digital transformation, and online shopping [2].

Despite the rapid growth of the logistics sector, especially truck transport, and its contribution to the economy, there are a number of challenges that this sector continues to face. First, the loading rate of trucks is about 57% on average [3] and trucks are not efficiently loaded in Europe due to high market segmentation [4]. This translates into more trucks on the road contributing to traffic congestion, noise and air pollution. Also, traffic congestion increases the delivery time of trucks which causes higher transportation costs and more harmful emissions. Indeed, transportation emits a significant amount of greenhouse gases, and its energy consumption exceeds that for the commercial and residential usage since the past 70 years [5]. There has been an increasing awareness about saving the environment through lowering the greenhouse gases emissions. Thus, companies are facing mounting pressure to limit their carbon footprint by purchasing new trucks that are electric/hybrid or inserting soot filters [6] which increase their costs. Furthermore, the fuel cost is increasing, and it contributes up to 30% of the total transportation cost [6]. Hence, fuel cost, traffic congestion, the environmentally friendly assets and the road pricing mechanisms [6] lower companies' profits.

The aforementioned challenges have pushed companies to adopt new approaches to increase their profitability and lower their carbon footprint. Therefore, one of the initiatives implemented to improve the logistics industry is horizontal collaboration. Horizontal logistics collaboration (HLC), as defined by Cruijssen [6], is a form of collaboration that is established between at least two companies working on an equivalent supply chain echelon. Moreover, Xu [7] added that it is a gradually developed process where collaborators share information, resources, and gains in order to meet their ultimate performance goal. It differs from vertical collaboration whereby the coalition occurs at different levels of the supply chain, e.g. between a supplier and a manufacturer [8]. In addition, Björnfot et al. [9] stated that horizontal collaborators can be competitors or non-competitors. To sum up, horizontal collaboration happens across the supply chain in which it requires sharing of information (e.g. products' demand) and assets (e.g. trucks) in order to attain a mutual long-term gain.

In essence, horizontal collaboration has a number of benefits. First, sharing transportation means, consolidation centers and warehouses decrease the total logistics cost including the transportation cost and inventory holding cost [10]. For instance, logistics partners can benefit from the scale of economies by dividing the fixed cost of the shared trucks [11]. Also, Wadhwa et al. [12] argued that horizontal collaboration is capable of reducing the inventory holding cost. Second, the vehicles loading rate could be improved under collaboration by more than 15% as obtained by Hacardiaux and Tancrez [11]. Third, reducing the total number of trips through sharing the same fleets leads to a decrease in CO_2 emissions emitted by trucks. Indeed, the results of papers [11] [13] [14] [15] [16] [17] showed a considerable reduction in carbon footprint under different vehicle-routing collaboration models compared to the standalone case. Finally, HLC acts as a promising approach that facilitates meeting the desired customers service level. Indeed, it is a substantial objective in inventory management [12] due to the high expectation level of customers and their requirements of more frequent and quicker deliveries [18]. For instance, an increase in service level from two delivery days per week into three days was attained by Kimberly-Clark and Unilever-

HPC companies [19]. These suppliers collaborate to bundle their orders from a shared warehouse to a number of common customers. In addition, this cooperative shipping led to reductions in the number of trips and the handling costs of 50% and 20% respectively. To sum up, HLC can reduce the number of trucks on road leading to social, environmental and economic advantages.

HLC proved to be successful in multiple sharing mechanisms. However, planning such a coalition and synchronizing partners' orders require careful consideration of multiple factors in order to achieve the maximum gain for all partners involved. For instance, consider two companies A and B operating on the same level and seeking to collaborate. Each company has its own warehouse (not shared), different customers that are geographically close to each other. Each company has its own demand requirements and replenishment policy that determines when to order and what the optimum order quantity is. Therefore, for company A to join company B on the same fleet, it has to replenish its inventory sooner or later than its standalone reorder level (explained in Section 2.2). Indeed, this flexibility is not unlimited, as company A cannot replenish needlessly when it has enough items in stock. There is a trade-off to be made between the inventory holding cost and the transportation cost of the joined fleet. A saving in any of these two costs should justify the increase in the other cost. Also, in all cases, the collaboration cost should be less than the cost of the standalone scenario in order to avail benefits out of the cooperation.

This thesis intends to assess the benefits of the horizontal collaboration between two companies, where their orders are synchronized based on a joint replenishment policy called the can-order policy. The can-order policy of every item *i* has three triggering points (S_i, c_i, s_i), where $s_i < c_i < S_i$ [20]. That is to say, the "must-order point" s_i is equivalent to the reorder point in the continuous review model. Thus, when an item *i* reaches to its s_i level, it triggers an order where any other item *j* who has reached its "can-order level" c_i or below joins the order. Then all of these items in the joint order are replenished up to their own "order-up-to-level" S_i. This policy is commonly used in inventory management. In a similar fashion, it can be adopted in horizontal collaboration. As such, when the inventory level of a product in company *i* reaches its must-order level, company *i* initiates an order. If the inventory level of a product in company *j* reaches its can-order level, then company *j* can join the order with company

i, otherwise it will not join the order of this particular shipment. As a result, companies are given the flexibility to join or not to join as per their inventory levels and demand requirements. As such, the optimum values of the parameters of the can-order policy that minimize the total logistics cost and CO_2 emissions should be determined. Accordingly, this thesis utilizes Arena simulation package to build the discrete event simulation model of this collaboration scenario and compare the results with the standalone setting where the two companies operate as silos. Moreover, OptQuest is used to determine the optimal values of the can-order policy parameters minimizing the logistics cost and CO_2 emissions independently. In addition, a sensitivity analysis is conducted through varying key model parameters such as the unit holding rate, demand and transportation cost.

1.3. Thesis Objectives

Driven by the opportunities that horizontal collaboration provides to companies in terms of cost savings, CO_2 emissions as well as the improvement in truck utilization and customer service level, the aim of this research is to develop a discrete-event simulation model of two companies collaborating horizontally under the can-order replenishment policy using Arena simulation package. Therefore, the objectives of this work are as follows:

- Minimize the total logistics cost including the major and minor transportation costs, the inventory holding cost and shortage cost, through optimizing the can-order policy thresholds under a positive lead time, truck capacity and service level constraint using OptQuest tool.
- Quantify the savings in cost as well as CO_2 emissions under collaboration compared to the standalone scenario.

1.4. Research Contribution

The contributions of this research work can be summarized as follows:

- Develop a discrete-event simulation model that can accurately determine the optimum can-order policy parameters instead of using Markov Chains and full enumeration approaches adopted in the literature.
- Extend existing models by including a positive lead-time, homogenous truck fleet and service level.

- Quantify the CO_2 emissions generated by both the transportation and warehouse activities, unlike considering only the transportation carbon footprint as found in the literature.
- Compare the collaboration of two companies and the standalone settings in terms of the total logistics cost and CO_2 emissions. The first case is minimizing only the logistics cost while the second case involves minimizing only the CO_2 emissions.

1.5. Thesis Organization

The rest of this thesis is organized as follows: Chapter 2 provides background about horizontal collaboration in logistics, joint replenishment problem and can-order policy. Moreover, works related to this research are discussed. The problem formulation of the standalone and the collaborative settings are defined in Chapter 3. Additionally, the simulation model and the optimization approaches are discussed in Chapter 4 along with the verification and validation of the simulation models. Chapter 5 discusses the results and findings of the applied methodology. Finally, Chapter 6 concludes the thesis and outlines avenues for future research work.

Chapter 2. Background and Literature Review

In this chapter, the types of horizontal collaboration and implementation requirements are explained. Then, the joint replenishment problem is briefly introduced followed by an explanation of one of its policies, which is the can-order policy. Finally, the related works to this field of research are discussed.

2.1. Horizontal Collaboration: Types and Enablers

In fact, HLC is popular in maritime and aviation transportation, and it is a relatively emerging concept on road logistics [21]. Horizontal collaboration has been used as a mean to increase the efficiency of processes and be able to withstand in this evolutionary era where the competition level is high. Back in 1993, one of the first implementations of HLC on road transportation has been between eight competing medium-sized Dutch producers of sweets [6]. These companies have a high number of mutual customers whose demand are daily. The cooperation between these suppliers was to consolidate the shipments and deliver them to these customers via a logistics service provider (LSP). This led to an increase in the customers satisfaction because of facilitating the accessing of a variety of products. This example shows that collaboration can exist between competing companies (manufacturers). Also, a third neutral party, which is the LSP, was needed. In addition, it illustrates that there are similarities between these producers such as the type of products as well as the customers. As a result, a number of questions are raised, i.e., what type of collaboration can exist and on what basis? Also, what are the enablers that facilitate the implementation of HLC and assist in selecting the collaboration type? The answer to the first question can be found in Section 2.1.1, whereas Section 2.1.2 illustrates the enablers of HLC implementation.

2.1.1. Horizontal collaboration types

There are different types of HLC, which are classified based on the shared activities [22], collaborative decisions' level [23]-[21]-[24], collaboration intensity [25] and collaboration structure [4]. Any horizontal collaboration between partners can take a combination of these various typologies. For instance, the type of the shared activity or asset can involve all or one decision level(s) of a certain intensity and based on one of the collaboration structures.

2.1.1.1. Shared activities

First, the horizontal collaboration typology based on the shared activity could be shipping consolidation, warehouse(s) or distribution center(s) consolidation, collaboration in manufacturing as well as collaboration in procurement [22].

As stated by [26], collaboration in procurement occurs when at least two companies consolidate in purchasing orders, negotiation, contracting and other procurement activities. This aids in exchanging knowledge between partners and decrease the procurement cost. By contrast, in shipping or transportation collaboration, companies, i.e., shippers, share transportation information and trucks' capacity in order to improve delivery time, cost, service level, trucks' loading rate as well as the inventory holding cost through increasing delivery [27].

On the contrary, collaborative warehouse(s) refer to sharing the storage areas (warehouses) among different suppliers and/or carriers to increase the utilization of warehouses capacities and facilitate load consolidation in shipping collaboration [28]. However, there are some challenges in sharing warehouses where handling and storing different types of products requires advanced storing technologies [28].

On the other hand, collaboration in manufacturing is a horizontal collaboration type but not in logistics. This type refers to capacity sharing in production plants or sharing production processes or product design [29]. This type improves machines' utilization, but it requires high coordination and similarity in the products requirements [29].

2.1.1.2. Collaboration level of decisions

Second, the level of decisions involved in collaboration could be strategic, tactical or operational [23]-[21]-[24]. At the strategic level, long-term decisions are made for designing the collaborative distribution networks such as the consolidated distribution centers' allocation [23] and partners selection [21]. On the other hand, the tactical level focuses on such midterm decisions as the collaborative shipping size, inventory management and cost allocation between partners [23]-[24]. Finally, the operational level is concerned with short-term decisions like setting up delivery schedules, and vehicle routing plans [24].

2.1.1.3. Collaboration intensity

The third classification, namely collaboration intensity, means the degree of involvement and information sharing between the partners [25]. Indeed, indicators of the intensity level can be the number of shared assets and the amount of time spent on maintaining the collaboration [6]. Thus, the intensity levels can be low-cooperative, semi-cooperative or fully cooperative as examined by Nataraja et al. [30]. In a low cooperative case, there is a limited number of shared activities (usually only one) for a limited period of time between partners [6]. This particular type involves only the operational decision level. For instance, a low cooperative setting can occur where companies only share their warehouses to a certain extent while each company uses its own trucks to deliver to its own customers [30]. By contrast, semi-cooperative type involves integrating a limited part of partners' business planning for a considerable long period [6]. Also, Nataraj et al. [30] shows a semi-cooperative scenario, where companies share the capacities of their warehouses and their fleets. In this case, the decision planning of routings to deliver products to all customers is required. On the other hand, the collaboration level is the maximum under the fully cooperative type, where each company regards itself as an extension to the other company as if they are all one company [6]. This type involves all the decision levels of strategic, tactical and operational. This is illustrated by [30] too, where companies decided to invest into a new cooperative central warehouse, namely Urban Consolidation Center (UCC) as explained in the next section. This requires a high level of agreement among partners to decide upon the location of this center and the routings plan.

2.1.1.4. Collaboration structure

The collaboration structure means how the collaboration is formed and executed. This may take one of three forms. The first form is through an open electronic marketplace platform, where different competing or non-competing companies i.e., suppliers, and logistics service providers, are connected to collaborate through this web-based information system [4]. As such, this is a temporary collaboration on spot and no formal documentation is needed [4].

On the other hand, the coalition structure can be for a long-term that requires contractual agreements [21]. This is called the strategic alliance. This type involves making the three levels of decisions, the strategic, tactical, and operational decisions [4]. Similar to the electronic marketplace, any two or more companies working on the same level can form the collaboration. As a result, there are such types of alliances as carrier alliances, and supplier alliances [4]. For instance, shipper alliances are formed between at least two raw material suppliers, where their loads are consolidated using the same vehicle [4]. Indeed, this type is regarded to be the fully cooperative intensity level [6].

Furthermore, the third structure that is widely used is based on UCCs. UCCs are shared distribution centers located in or near cities to enable sharing distribution networks among a number of firms [31]. In this structure, multiple suppliers consolidate their shipments via trucks that go to a consolidation center, where these shipments are sorted and then grouped in a number of freights [30]. Finally, these freights are delivered to customers or receivers at various locations across the city. This reduces the distance travelled by trucks and saves fuel as a result. According to [30], the implementation of HLC through UCCs requires deciding on their number, size and locations, which is a strategic decision level. Moreover, the tactical decision involves deciding upon which customers will be served by which available UCC. Also, there is an operational decision level regarding the assignment of delivery routes from shippers to UCCs and from UCCs to customers or retailers.

2.1.2. Horizontal collaboration enablers

There are some factors that should be considered for a successful implementation of horizontal collaboration. These factors are called enablers or facilitators. The collaboration enablers differ depending on the collaboration intensity, type of the shared activity or asset(s) and who the partners are (e.g., manufacturers, or suppliers or carriers) [29]. In general, according to Cruijssen [6], Badraoui et. al. [29] and Rodrigues et al. [32], some of these facilitators are classified as follows: trust and commitment among partners, partners' similarity and products' compatibility, collaboration procedures and structure, information system and industry, country and organization characteristics.

First, a successful long-term collaboration requires trust and commitment among partners which enable them to share confidential information about their ordering quantities, demand, etc. Also, the high accuracy of the shared information is vital. Therefore, an information system that provides timely and complete data, facilitates an effective collaboration. In addition, collaboration as mentioned earlier leads to economic and environmental gains. Thus, a collaboration structure and procedures that determine the gain allocation mechanisms among partners is highly essential. Indeed, a third-party facilitator is advocated to manage the collaboration neutrally and effectively. Besides, it has been argued that partners should be similar in various aspects like pallets' size, products storage requirements, location, delivery routes, scheduling flexibility and other operational processes. This similarity facilitates the collaboration planning in utilizing the current available resources rather than investing in new assets. [6] [29] [32]

However, such similarity is not deemed necessary for the success of HLC. For instance, the collaboration between Scania, LKAB and SSAB companies requires temperature-controlled containers for Scanias' goods only [33]. Thus, new containers were purchased, and companies had to change their schedule to fit each other's lead time requirements. Nevertheless, the collaboration was successful and increased deliveries frequencies and service levels. That is to say, the decision to purchase new asset(s) in order for the HLC to work successfully for dissimilar companies is based on partners' agreement and trust as well as the collaboration intensity.

Finally, the country, industry and organization characteristics such as specific regulations, laws and rules, country's economic state, machinery requirements, products attributes and the organization collaborative structure, can influence the collaboration and partners' selection [6] [29] [32].

2.2. Joint Replenishment Problem

Joint Replenishment Problem (JRP) is an inventory management strategy that seeks to minimize the total inventory cost of ordering multiple products from the same supplier simultaneously [34]. In other words, the inventory managers want to decide upon the optimum ordering quantity of each item in order to minimize the ordering cost and the inventory holding cost that are incurred when ordering the multiple items using the same fleet. There are two types of ordering cost in this joint case: major ordering cost and minor ordering cost [35]. The former is the one that is paid for each time the order is placed regardless of the number of items. In contrast, the latter one is the handling cost of each item type, and it depends on the number of items. In general, one of the advantages of using JRP is that it exploits the economies of scale through ordering the items together and paying the major ordering cost only once [36].

A large variety of models, solution approaches and applications have been implemented to handle the complexity of such a problem [35]. In fact, JRP models can be of deterministic or stochastic demand type and associated with a periodic or continuous review replenishment policy [35]. Indeed, a replenishment policy determines the time to place an order and the amount to be ordered. The periodic review policy type monitors the inventory level every time *T* and replenishes the inventory up to a certain level called order-up-to level *S* [37]. However, the monitoring in the continuous review policy is an ongoing process and the replenishment happens whenever the inventory level reaches a predefined point called the reorder point [37]. One of the well-known joint replenishment policies in the continuous review system is the can-order policy explained next.

2.2.1. Can-order policy

The can order policy was first introduced by Balintfy [38] in 1964. According to Ignall [39], finding the optimal values of such parameters that minimizes the total logistics cost is not a straightforward task. At first, an approach called the decomposition method was proposed by Silver [40] to calculate the three thresholds of the can-order class. The decomposition method is an iterative method that splits the multi-item replenishment problem into multiple single-item problems, where the reduced ordering cost for a certain item is the superposition of the ordering processes initiated by the other items [41]. However, Van Eijs [42] proved that the previously claimed low performance of the can-order policy under a high major transportation cost situation is because of the decomposition theory, not due to the policy itself. Consequently, he 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 compared to the minor ordering cost. This forces all items to join an order that is initiated by any one of them. The results showed that the can-order policy performs well similar to other replenishment policies such as the periodic review policy.

Many other algorithms and approaches have been employed to get over the error that the decomposition method incurs [43]. For instance, Kayis et al. [44] used a semi-Markov decision approach and a search algorithm to find a solution of a two-item joint replenishment problem in order to avoid the error produced by the decomposition algorithms. The results were compared with the results of decomposition method proposed by [41]. It was shown that decomposition results are not even close to the optimal can-order policy solution. Also, Liu and Yuan [45] deployed a Markov chain model to optimize the can-order policy for a two-item scenario under correlated demand. The results revealed that can-order policy reduces the logistics cost, especially when the demand of the items is correlated. Indeed, more savings are realized when the demand covariance increases.

Johansen and Melchiors [46] proposed a new class of the can-order policy that is periodic instead of the continuous check. They claimed that periodic is better since the number of joint replenishment opportunities is limited. Hence, there is no need for a continuous check of the inventory. Nevertheless, this new class had great impact on cost savings. For periodic review systems, Nagasawa et al. [43] used genetic algorithms to optimize only the can-order level of each item in a multi-item setting. The main objectives are to minimize the number of orders, number of items in the inventory, and number of units short. Similarly, Noh et al. [47] applied a periodic can-order policy for a case where a single retailer orders multiple items from the same supplier under deterministic demand. This proposed policy determines the order-up-to-level S_t in each planning period, which means that this level is different from one period to another. A Mixed Integer Linear Programming model is employed to reduce logistics cost and carbon emissions simultaneously under storage capacity and budget constraints. Indeed, the buyer has a certain carbon cap; if exceeded he would pay a carbon tax, otherwise he would get a reward.

Kouki et al. [48] studied the continuous review can-order policy for the joint replenishment of perishable items under a zero-lead time first using Markov Chain. Then, it used the decomposition method for a positive lead time case. Simulation was used as well to verify the results that were compared with the periodic review model $P(s, S)$. This periodic type checks the inventory level every time T. All items that their stocks reach the reorder point s will be replenished up to level S. It was demonstrated that the can-order policy performs better in a case where the shortage cost is high.

In addition, a compensation approach was proposed by Melchiors [49] where an item initiating an order acquires a compensation from the other joining items. The author used the decomposition approach and simulation to compare the cost performance of the can-order policy and periodic review policy when the compensation approach is used. The results show that such an approach enhances the performance of the can-order policy under multi-item settings.

Recently, a new greedy-optimal method that uses embedded Discrete-Time Markov chain was developed by Creemers and Boute [50]. This model considers the state of the system after an order is placed. Consequently, this significantly reduces the total number of states encountered by the traditional continuous-time Markov-chain model. Hence, this study was able to determine the best can-order parameters of three items by considering a deterministic lead time, shortage cost and lost sales.

All of these papers showed that the can-order policy can attain significant savings in logistics cost compared to non-coordinated items replenishment case. However, they study only the joint replenishment of items within a single firm. As a matter of fact, the can-order policy can be used for the joint replenishment of multiple companies as illustrated in the next section. This case is considered as a form of horizontal collaboration in logistics.

2.3. Related Works

For collaborative shipping, Vanovermeire and Sörensen [19] presented the bundling of orders among three companies in a fleet that goes from a shared warehouse to a common destination. Indeed, the synchronization of orders were done by changing the delivery dates of partners' orders within the limits of each order's time window. Thus, the proposed heuristic model minimizes the total transportation cost, and changes the delivery dates only if the gain is greater than the penalty cost of such a change. Similarly, Danloup et al. [51] proposed a model for trucks' sharing among two companies based on the time window and historical customers' orders. Unlike Vanovermeire and Sorensen [19], the study minimizes the CO_2 emissions and the transportation cost independently and considers a heterogenous fleet and multiple items. These papers did not include the effect of collaboration on inventory levels and its related holding costs. They only analyzed the transportation related cost and penalty costs of late deliveries.

To account for the inventory, Otero and Rene [52] tested a collaborative transportation model among a number of suppliers and retailers considering the joint replenishment of multiple items on a periodic inventory check. The results showed that both the limited resources' companies and the firms with over capacity received benefits from the coalition of resources. Likewise, Vanvuchelen et al. [53] synchronized the collaborative shipping orders of two shippers through a periodic inventory review policy. The optimal solutions are approached through using a machine learning algorithm namely, proximal policy optimization. Indeed, the replenishment of multiple items, the backorder cost as well as the full truckload capacity are included in the comparison of different scenarios. The results were compared with the periodic review minimum order quantity and dynamic order-up-to heuristics, where the proposed approach excels.

As an extension to [52], Otero et al. [54] used genetic algorithm to minimize the collaborative logistics cost when multiple buyers jointly order multiple products from multiple suppliers. The transportation mean is through cargo and the products are stored in a warehouse next to the importers (the buyers). In fact, the approach tends to determine the optimum replenishment frequency for each collaborating firm based on periodic inventory review policy. The results showed that the cost saving increases with the rise in the number of collaborating partners.

These papers combined the joint replenishment problem with horizontal collaboration; however, they used periodic review model. In fact, the can-order policy is more efficient for several reasons. First, it is easy to implement and comprehend among the partners. In addition, the can-order policy is a continuous review replenishment policy, which can easily detect any sudden changes in inventory levels as compared to the periodic replenishment policies. Also, the can-order level gives an opportunity to companies to join the order whenever it is economic to do so. Therefore, the can-order policy is selected in this thesis due to its superiority and promising results.

The following papers used the chosen replenishment policy in an HLC setting where inventory is considered. For example, Pukcarnon et al. [55] developed a heuristic algorithm to find the close-to optimum solution in a one-warehouse N-retailers case. The inventory at both echelons was monitored and the joint replenishment is based on the can-order policy. Othman et al. [56] used Excel spreadsheet simulation to model the single supplier three retailers setting, whose orders are synchronized by a periodic can-order policy. Then, OptQuest was employed to optimize the three thresholds that results in minimum holding, shortage and major transportation cost. The results were compared with the exact solution generated by brute-force approach where they were very close. Both [55] and [56] handle the problem of having a common supplier or warehouse among the partners.

De Moor et al. [57] combined proactive cooperative shipping using can-order policy and periodic review with modal split transport. These are applied for synchronizing the orders between three companies solved using a heuristic algorithm that splits the problem per company and solves each problem sequentially. Indeed, the modal split, where multiple transport modes are used, is utilized to further decrease the number of trucks on road. The results showed that such combination leads to an additional saving in logistics cost.

Boucherie et al. [58] studied first the collaboration among two companies that order as soon as their joint inventory positions reach to a certain level. However, this policy led to higher costs compared to the standalone case. Then, the authors tested the two and three companies' cases who have the same item on stock, where they jointly replenish their inventories when one of them reaches its reorder point. This strategy outperforms the non-collaborated case. Nevertheless, [58] did not consider the minor transportation cost in their analysis.

On the other hand, Tinoco et al. [59] accounted for the minor shipping cost in their can-order policy. This allows the companies to decide whether to join the shipping or not based on their inventory levels and avoid replenishing needlessly. As such, the study intended to decrease the overall number of shipping trips and redistribute the monetary benefits of such collaboration using different allocation methods (e.g. Shapley Value). Indeed, they tried different allocation scenarios like redistribution of the major transportation cost only, the total shipping cost including the minor ordering cost as well as the total logistics cost among the two companies. Hence, they 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. [60] tried to find the optimal solution when both the reduction in logistics cost and transportation CO_2 emissions are investigated simultaneously. Also, the study considered the storage capacity as a constraint to limit the search of feasible solutions in the adopted full enumeration procedure.

It is important to point out that papers [58] [59] [60] suffer from several limitations. First, they used Markov Chain solution approach which cannot handle more than two partners due to the excessively high computational time required to compute the steady-states of three or more companies. Although [58] determined the optimal cost of the three companies' case, it considered small instances while varying only the holding cost, the major ordering cost and the demand. In addition, it 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 can-order policy, it only considers one threshold which was assumed to be zero. By contrast, the rest of the papers [59] [60] 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 capacity of the trucks. Finally, all of these papers except [58] applied a full enumeration procedure to find the optimal values of both the can-order level and the order-up-to-level, which is not practical for large problem instances.

To sum up, Table 2-1 presents the related works, which are classified and compared based on several dimensions in order to identify the existing gap in the literature. It also shows the dimensions that this thesis will take into consideration. The empty cells indicate that the corresponding dimension was either not considered or not applicable in the associated study.

Table 2-1: Related works classification.

Paper	Decision Problem				Inventory Review Model		Sustainability Measure						Constraints		No. of partners	No. of Products	Demand Uncertainty	Lead time	Partners always collaborating?	solution approach
							Economic (cost)				Environmental (CO_2)									
	One warehouse - N Retailers	One-supplier N Retailers	Horizontal Cooperative shipping	Can order Policy	Continuous	Periodic	Major transportation	Inventory holding	Minor transportation	Shortage	transportation	warehouse activities	Service Level	Truck Capacity						
[53]			×			×	×	×	×	×				×	2	N	×		yes	Machine Learning
[58]			×		×		×	×							3	1	×	0	yes	Markov Chain
[59]			×	×	×		×	×	×						2	1	×	0	No	Markov Chain
[60]			×	×	×		×	×	×		×				2	1	×	0	No	Markov Chain
[52]	×		×			×	×	×						×	4	N	×	Deterministic		Heuristic
[55]	×			×	×		×	×	×						N	1	×	0	No	Simulation & Heuristic
[54]	×		×			×	×	×	×					×	N	N	×	Deterministic	No	Heuristic
[19]			×				×		×	×				×	3	1			No	Heuristic
[51]			×				×		×	×	×			×	2	N			No	Simulation

Paper	Decision Problem				Inventory Review Model		Sustainability Measure						Constraints		No. of partners	No. of Products	Demand Uncertainty	Lead time	Partners always collaborating?	solution approach
							Economic (cost)				Environmental (CO_2)									
	One warehouse - N Retailers	One-supplier N Retailers	Horizontal Cooperative shipping	Can order Policy	Continuous	Periodic	Major transportation	Inventory holding	Minor transportation	Shortage	transportation	warehouse activities	Service Level	Truck Capacity						
[42]				×	×	×	×	×	×				×		1	4	×	Deterministic		Decomposition
[45]				×	×		×	×	×	×					1	2	×	0		Markov Chain Model
[44]				×	×		×	×	×	×					1	2	×	Deterministic		Semi-Markov Chain model & Enumeration
[49]				×	×	×	×	×	×	×					1	N	×	Deterministic		Decomposition & Simulation
[43]				×		×	×	×	×	×					1	N		Deterministic		Genetic Algorithm
[47]				×		×	×	×	×	×		×			1	3		0		Mixed Integer Programming
[50]				×	×		×	×	×	×					1	3	×	Deterministic		Markov Chain
[46]				×		×	×	×	×	×					1	N	×	Deterministic		Decomposition
[48]				×	×		×	×	×	×					1	N	×	Deterministic		Decomposition & Markov Chain & Simulation
[57]			×	×		×	×	×	×	×					3	1	×		No	Decomposition

Paper	Decision Problem				Inventory Review Model		Sustainability Measure						Constraints		No. of partners	No. of Products	Demand Uncertainty	Lead time	Partners always collaborating?	solution approach
							Economic (cost)				Environmental (CO_2)									
	One warehouse - N Retailers	One-supplier N Retailers	Horizontal Cooperative shipping	Can order Policy	Continuous	Periodic	Major transportation	Inventory holding	Minor transportation	Shortage	transportation	warehouse activities	Service Level	Truck Capacity						
[56]		×		×		×	×	×		×					3	1	×	Deterministic	No	Excel Spreadsheet & OptQuest optimization
This Thesis			×	×	×		×	×	×	×	×	×	×	×	**2**	**1**	×	**Stochastic**	**No**	**Simulation Optimization**

Chapter 3. Methodology

This chapter provides the problem formulation of synchronizing the orders using can-order policy for a horizontally collaborated multi-company model. Also, the problem formulation in terms of the logistics cost and CO_2 emissions for the standalone case are presented. Moreover, it highlights the assumptions taken into consideration while building the models.

3.1. Problem Formulation

The problem presented here considers the case where 2 companies in a set of H = {1 , 2}, have close origin and destination locations. The demand D_i of each company i follows a Poisson probability distribution. Unlike the work of [59], 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 has five types of costs. Firstly, a holding cost per unit h_i is accounted for each unit held in the stock of company i per unit time. Secondly, there are three types of transportation or ordering (they are 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. The major ordering cost consists of drivers' wages and other related administrative costs that are independent of the number of items or load. This cost is assumed to be equal for the two companies. By contrast, the minor ordering cost accounts for the handling cost of the products. However, the variable transportation cost is the fuel cost incurred as a result of transporting, which depends on the load and the number of trucks used. The formula used to calculate the variable transportation cost will be shown in Section 3.2. Finally, there are two types of shortage cost that are considered which are the backorder cost per unit time B_i and lost demand cost per unit time LS_i for each unsatisfied unit of demand. The backorder cost is incurred when the company is running out of stock and the customer is willing to wait for his order. The lost demand cost, however; is incurred when the customer is not willing to wait for the coming order and the demand will be lost in this case.

3.2. The Environmental Factor

Given that transportation emits a high amount of CO_2 emissions and HLC reduces such amount, the environmental factor will also be accounted for. Several equations are used to quantify the CO_2 emissions emitted because of shipping using trucks. For instance, [14] and [16] used the formulation suggested by the European studies COST (European Co-operation in the field of Scientific Research) and MEET (Methodologies for Estimating Air Pollutant Emissions from Transport). Also, Tinoco et al. [60] quantified the emissions based on the formulation provided by the Global Logistics Emissions Council (GLEC). Both formulas consider the CO_2 emissions due to the travelled distance as well as the load of the trucks. However, Cheng et al. [61] [61] used a more detailed formula that calculates the fuel consumption by considering the velocity of the truck v, the engine displacement P and other factors as shown in the following equation.

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

where F_{Ti} is the transportation fuel consumption in $(Liters)$, m is the weight of the empty truck, w_i is the weight of one product unit of company i, and d is the distance travelled. Table 3-1 illustrates further the parameters used in the formula along with their values as adopted from [61]. In order to calculate the transportation CO_2 emissions, Eq. 1 is then multiplied by the amount of CO_2 emitted by the unit fuel consumption e_T as shown below:

$$E_{Ti} = F_{Ti} e_T \tag{2}$$

E_{Ti} is the transportation CO_2 emissions per one order in ($kg\ CO_2$) and e_T is the amount of CO_2 emitted by unit fuel consumption in ($kg/Liters$).

Similarly, the variable transportation cost per order V_i is calculated as follows:

$$V_i = F_{Ti} f \tag{3}$$

where f is the unit fuel cost in (£$/Liters$).

Table 3-1: Parameters for the fuel consumption equation. [61]

Notation	Description	Values
m	Empty Truck Weight (kg)	4672
M	Maximum truck load (kg)	2585
x	Engine friction factor ($kJ/rev/Liters$)	0.25
N	Engine speed (rev/s)	39
P	Engine displacement ($Liters$)	2.77
µ	Coefficient of aerodynamics drag	0.6
A	Frontal surface area (m^2)	9
∀	Vehicle drive train efficiency	0.4
ε	Fuel-to-air mass ratio	1
g	Gravitational Constant (m/s^2)	9.81
ρ	Air Density (kg/m^3)	1.2041
R	Coefficient of rolling resistance	0.01
η	Efficiency for diesel engines	0.45
e_T	CO2 emitted by unit fuel consumption ($kg/Liters$)	2.669
f	Unit Fuel Cost per Liters	0.7382
κ	Heating value of a typical diesel fuel (kJ/g)	44
ν	velocity (m/s)	22.222
ψ	conversion factor (g/s to $Liters/s$)	737
θ	Road angle	0
τ	Acceleration (m/s^2)	0
d	Travel distance (m)	60000
λ	$\varepsilon/\kappa\psi$	3.08375E-05
γ	$1/(1000\forall\eta)$	0.005555556
α	$\tau + gsin(\theta) + gRcos(\theta)$	0.0981
β	$0.5\mu\rho A$	3.25107

Eq. 1 is rearranged in such a way to be in terms of Q_i and w_i. Thus, let:

$$a_1 = \lambda\left(\frac{xNPd}{v}\right) \tag{4}$$

And

$$a_2 = \lambda(\gamma\alpha D) \tag{5}$$

And

$$a_3 = \lambda(\beta\gamma d v^2) \tag{6}$$

Then,

$$a_4 = a_1 + a_3 + m \times a_2 \tag{7}$$

As such,

$$E_1 = a_4 \times e_T \tag{8}$$

and

$$E_2 = a_2 \times e_T \tag{9}$$

where $E_1$is the first term of the transportation CO_2 emissions, which is equivalent to 62.6212 $kg\ CO_2$. In addition, E_2 is the second term of the transportation CO_2 emissions, which is equivalent to 0.0026914 $kg\ CO_2/kg$. As a result, Eq. 3 can be rewritten as:

$$E_{Ti} = E_1 \times roundup(\frac{Q_i w_i}{M}) \ \ + Q_i w_i E_2 \tag{10}$$

where M is the maximum truck capacity in kg. Thus, the term $\frac{Q_i w_i}{M}$ indicates the number of homogenous trucks per one order when it is rounded up, while it is the truck utilization rate without rounding. The term should be rounded up in this equation.

Likewise, the variable transportation cost has two terms; V_{f1} and V_{f2} as shown below:

$$V_{f1} = a_4 \times f \tag{11}$$

and

$$V_{f2} = a_2 \times f \tag{12}$$

where $V_{f1}$is the first term of the fuel cost, which is equal to 17.3199 £. In addition, V_{f2} is the second term of the fuel cost, that is equal to 0.00074439 $£/kg$. As a result, Eq. 3 becomes:

$$V_i = V_{f1} \times roundup(\frac{Q_i w_i}{M}) \ \ + Q_i w_i V_{f2} \tag{13}$$

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 should be quantified. According to [62], the warehouse emits CO_2 per unit stored and the equation is as follows:

$$E_{Wi} = e_W \times w_i \times \overline{OH}_i \tag{14}$$

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 the stock. According to [63], this number varies significantly among warehouses. Thus, the emissions from ambient storage was selected as 0.0012 $kg\ CO_2/kg$ [63]. w_i is the weight of one product unit of company i, $\overline{OH}_i$ is the time weighted average of the on-hand inventory level as will be explained in Section 3.3.1.

3.3. Problem Statement

Ideally, the horizontal collaboration in logistics between companies should be managed smoothly allowing all the partners to get advantage of such initiative. However, synchronizing the orders between companies is challenging because of the characteristics of the products, demand requirements and companies' different objectives and preferences. This necessitates having a policy that monitors the inventory levels at all companies, and accordingly determines when these companies should collaborate and how much each collaborating company should order. Indeed, a company should not join an order when it has enough products in stock. Furthermore, a saving attained in one dimension (e.g. the number of transportation trips) leads to an increase in another dimension (e.g. the inventory holding cost) when following the collaborative scheme. Therefore, this thesis seeks to build a simulation model, where the can-order policy is applied for synchronizing the orders between horizontally collaborated companies. The goal is to achieve the best trade-offs between the transportation cost and the inventory holding cost through minimizing the total logistics cost. Additionally, the environmental gains due to collaboration is tested.

3.3.1. The standalone setting

The first part of the problem is to investigate the performance of the two companies under the standalone case. The standalone setting indicates that each company is ordering independently. The replenishment of companies' inventories in this case is based on the 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 there are two types of inventory levels, which are the inventory position I_i and on-hand inventory OH_i. On-hand inventory OH_i is the actual physical units in stock while the inventory position I_i takes into account the unsatisfied backordered units BO_i and the order quantities that have been ordered but did not arrive yet. These order quantities called On Order OO_i. The inventory position is the one to be checked when placing an order. The formula used to calculate the inventory position I_i is as follows:

$$I_i = OH_i + OO_i - BO_i \tag{15}$$

According to [64], the total logistics cost for a company based on (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 standalone case is:

$$C_i^{sa} = \frac{(K_i + k_i + V_i) \times n_i^{sa}}{\hat{n}} + h_i \times \overline{OH_i} + B_i \times \overline{BO}_i + LS_i \times \overline{LD}_i \tag{16}$$

where 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, $\overline{OH_i}$ is the time-weighted average on-hand inventory level of company *i*, $\overline{BO}_i$ is the time-weighted average backorder units of company *i*, $\overline{LD}_i$ is the time-weighted average lost demand units of company *i*. Note that h_i, B_i, S_i can be expressed in terms of the unit cost c_i as follows:

$$h_i = r_h c_i \tag{17}$$

$$B_i = r_B c_i \tag{18}$$

$$LS_i = r_{LS} c_i \tag{19}$$

where r_h, r_B, r_{LS} are holding rate, backorder rate, and lost demand rate respectively. Also, based on [65], the values are selected to be $r_h \leq r_B \leq r_{LS}$.

Furthermore, the total CO_2 emissions generated by company *i* per unit time E_i^{sa} in the standalone case, can be written as follows:

$$E_i^{sa} = \frac{E_{Ti} \times n_i^{sa}}{\hat{n}} + E_{Wi} \tag{20}$$

where the first term of the equation represents the emissions generated from transportation per unit time. Therefore, transportation emissions per order E_{Ti} is multiplied by the number of initiated orders n_i^{sa} over the period $\hat{n}$ in order to obtain the emissions generated per unit time. E_{Wi} is already the warehouse emissions per unit time because of the weighted average $\overline{OH_i}$.

3.3.2. The collaborative setting

The second case to be tested is the performance under collaboration. The collaborative setting is when companies work together and place joint orders. Under collaboration, the synchronization of orders is based on the can-order replenishment policy. Accordingly, when the inventory position I_i of company *i* reaches its must-order level (reorder point) s_i, it initiates an order such that its inventory position reaches its order-up-to level S_i. Therefore, the ordering quantity is $Q_i = S_i - I_i$. In this case, company *i* pays the major transportation cost K, the variable transportation cost V_i and its own minor transportation cost k_i. If the inventory position of company *j* reaches its can-order level C_j, it joins the order of company *i* where its order quantity is $Q_j = S_j - I_j$. In such a case, company j pays its minor transportation cost k_j only. However, if company *j* did not reach its can-order level C_j, then it does not join the order of company *i*. This means that company *j* has enough items in the stock and it is costly to collaborate.

Therefore, the logistics cost of company *i* per unit time under collaboration C_i^{cl} (as an extension to the standalone cost) is expressed as follows:

$$C_i^{cl} = \frac{(K_i + k_i) \times n_i^s + V_i^{cl} + k_i \times n_i^J}{\hat{n}} + h_i \times \overline{OH_i} + B_i \times \overline{BO}_i + LS_i \times \overline{LD}_i \quad (21)$$

where cl stands for the collaborative case, *J* stands for joined order whereas s stands for self-initiated order, n_i^s is the number of orders initiated by company *i* regardless if company *j* joins the order or not, n_i^J is the number of orders that company *i* joins the orders initiated by company *j*, and V_i^{cl} is the accumulated total variable transportation cost of company *i* under collaboration. Note that the variable transportation cost V_i is only for one self-initiated order. In the standalone case, the variable transportation cost V_i is the same for each initiated order because the order quantity Q_i is constant. However, in the collaborative case, V_i is changing according to the changing value of Q_i and whether there is a joined order from company j or not. Consequently, if company *j* joins the order initiated by company i, V_i in Eq. 13 becomes as follows:

$$V_i^J = V_{f1} \times \frac{(Q_i^s w_i + Q_j^J w_j)}{M} + (Q_i^s w_i + Q_j^{cl} w_j) V_{f2} \quad (22)$$

where V_i^J is the joined variable transportation cost under collaboration. Q_i^s is the order quantity of company *i* when it initiates an order, and Q_j^J is the joined order quantity of company *j*. In case company *j* did not join company *i*, then the formula to calculate V_i will still be Eq. 13. However, the order quantity will be changing according to the inventory position and so does V_i. Therefore, the total variable transportation cost V_i^{cl} over period $\hat{n}$ for company *i* will be the accumulation of the variable transportation cost for each self-initiated order by company *i* (V_i^s) (without having a joint order with company *j*) as well as the joined variable transportation cost under collaboration V_i^J. Thus, let *t* be the time when company *i* initiates an order, then the total variable transportation cost V_i^T is:

$$V_i^{cl} = \sum_t^{\hat{n}} (V_i^s + V_i^J) \tag{23}$$

Similarly, the joined transportation CO_2 emissions for company *i* per order E_{Ti}^J is:

$$E_{Ti}^J = E_1 \times \frac{(Q_i^s w_i + Q_j^J w_j)}{M} + (Q_i^s w_i + Q_j^J w_j) E_2 \tag{24}$$

and the transportation emissions generated when company *i* initiates the order alone E_{Ti}^s can be obtained using Eq. 10. Thus, the total transportation emissions E_{Ti}^{cl} over period $\hat{n}$ is:

$$E_{Ti}^{cl} = \sum_t^{\hat{n}} (E_{Ti}^s + E_{Ti}^J) \tag{25}$$

Finally, the emissions generated by company *i* per unit time $E_i^{cl}$is:

$$E_i^{cl} = \frac{E_{Ti}^{cl}}{\hat{n}} + E_{Wi} \tag{26}$$

Chapter 4. Simulation and Optimization

In this chapter, Arena simulation package and OptQuest are introduced. Specifically, both the standalone model and the collaborative model are developed, and their outputs are explained. Additionally, the validation of the models is presented along with the optimization technique using OptQuest.

4.1. Arena Simulation Package

Discrete event simulation (DES) is the selected approach to test the effectiveness of the can-order policy in solving such an HLC problem in a safe and virtual environment. Indeed, the joint replenishment problem is complex, and the proposed approaches in the literature have several limitations such as the long computational time. On the contrary, simulation allows experimenting large number of instances while relaxing some of the simplifying assumptions made in the literature such as zero-lead time. Furthermore, it is suitable for very complex systems [66] and hence enables building a fully stochastic model.

Indeed, in this particular problem, the demand arrives at discrete points in time. Therefore, the DES approach is employed to detect the change in the state of the inventory level as a result of this discrete event (the arrival of demand). According to Altiok and Melamed [67], DES handles the systems where "the simulation state remains unchanged unless an event occurs, at which point the model undergoes a state transition". Hence, Arena simulation package is utilized, especially that it is coupled with an optimization tool called OptQuest. This facilitates building the model and optimizing the thresholds at the same time. Arena software is a commercial general-purpose simulation tool that includes a variety of "functional modules, full visualization of model structure and parameters, improved input and output analysis tools, run control and animation facilities, and output reporting" [67]. The standalone and collaborative models are built using Arena.

4.2. Model Assumptions

The model has the following assumptions:

- Products need ambient storage conditions (no refrigeration requirements needed).

- Both companies emit the same amount of CO_2 to hold one unit in the stock, e_W.
- Lead time is the same for both companies.
- The demand amount and lead time follow Poisson and exponential distributions, respectively.
- Both companies have the same major ordering cost.
- Only one product from each company is considered.
- Only homogenous fleet of trucks is considered, specifically the light duty truck of capacity of 2585 kg.
- The distance travelled by company i equals the distance travelled by company j, which is assumed to be 60 km.

4.3. The Standalone Model

The standalone model consists of two sections; demand management part and inventory management part. Figure 4-1 shows the full model.

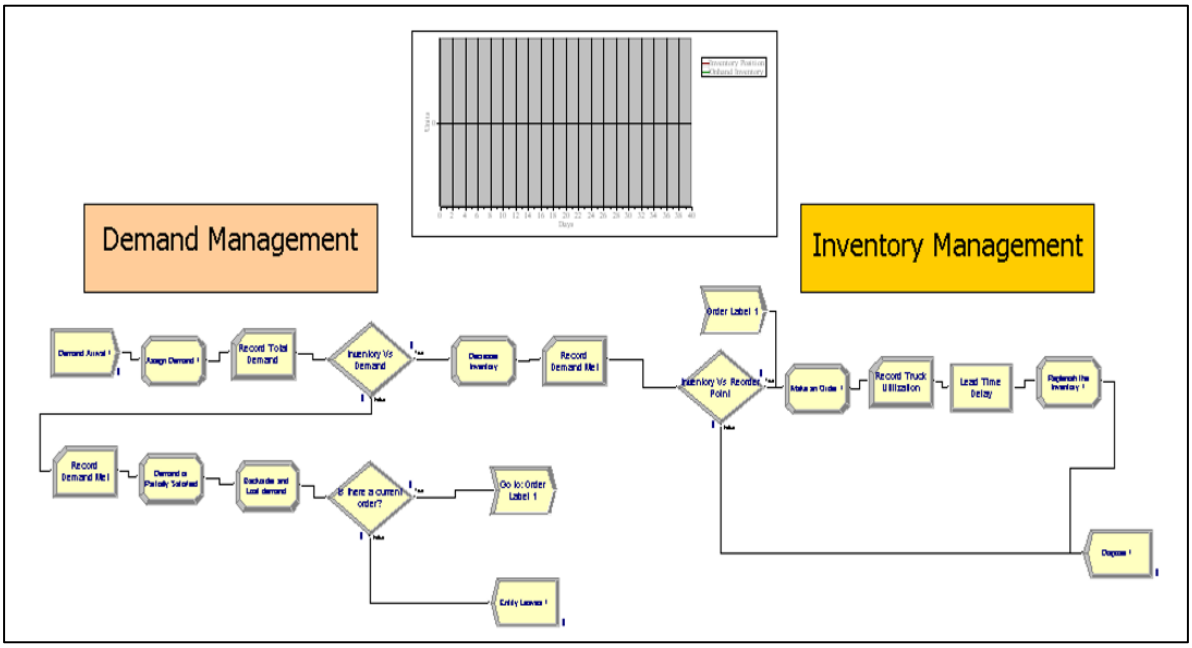

Figure 4-1: The standalone model in Arena.

4.3.1. Demand management sub model

Starting with the demand management part, this section includes the demand arrival, an inventory check, and processing of unsatisfied demand as shown in Figure 4-2.

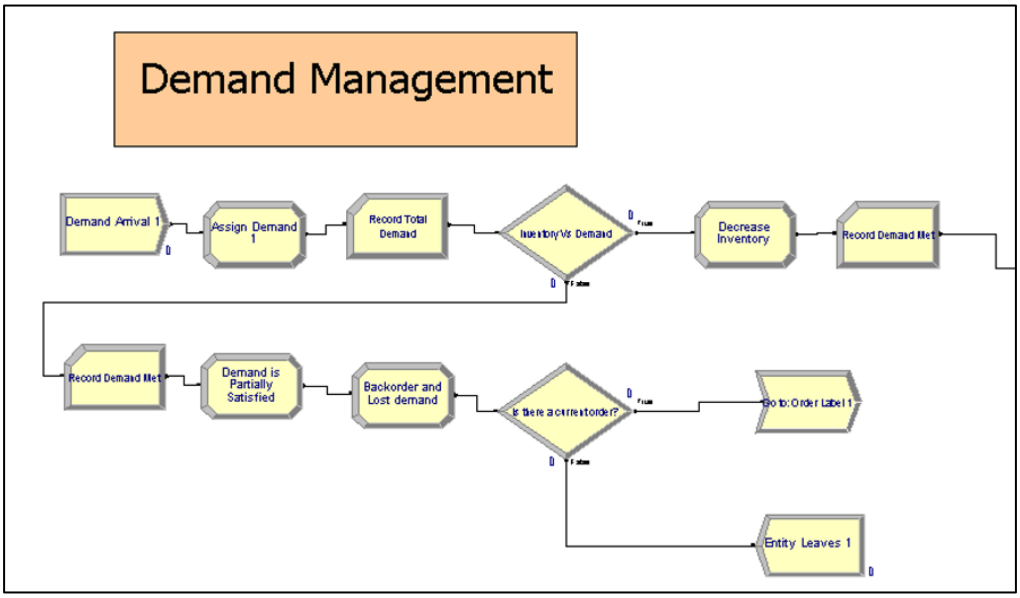

Figure 4-2: Standalone demand management part.

First, the "Create" module creates an entity indicating that a demand has arrived (not necessarily one customer, it can be a group of customers). The interarrival time between these entities is one day. Then, a Poisson distributed demand of mean D is assigned to the entity in the "Assign" module. Also, the "Total Demand" variable gets incremented by the newly arriving demand as follows:

$$Total\ Demand\ =\ Total\ Demand\ +\ Demand \tag{27}$$

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 is updated in the Decrease Inventory assign module as shown below:

$$On\ hand\ Inventory = \ On\ hand\ Inventory - \ Demand \tag{28}$$

$$Demand\ Met\ =\ Demand\ Met\ +\ Demand \tag{29}$$

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 the stock as "On-hand Inventory". The unsatisfied part of the demand will be divided into backorder units and lost demand units based on variable σ. Variable σ can be any number between 1 and 0. Thus, the formulas are as follows in their respected order:

$$Unsatisfied\ Demand = Demand - Onhand\ Inventory \tag{30}$$

$$Demand\ Met = Demand\ Met + Onhand\ Inventory \tag{31}$$

$$Backorder\ Num = Backorder\ Num + Unsatisfied\ Demand \times \sigma \tag{32}$$

$$Lost\ Demand = Lost\ Demand + Unsatisfied\ Demand \times (1 - \sigma) \tag{33}$$

Also, the on-hand inventory is set to zero. After that, another check is made which is to check if there is no current order or if the “Inventory Position” is less than or equal to the “Reorder Point”. If any of these conditions is met, then the entity is transferred to the Inventory Management part of the model using “Label” and “Go to Label” modules. If the conditions are not met, then the entity is disposed. This section is needed when the “Inventory Position” did not reach the “Reorder Point” before the arrival of the last entity, whose demand is greater than the current stock.

4.3.2. Inventory management sub model

Moving on to the inventory management section, this part includes checking the inventory position and making orders as shown in Figure 4-3. After the demand arrival and updating of the inventory, a “Decide” module checks 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 Section 3.3.1 is written under the expression section which gets updated continuously.

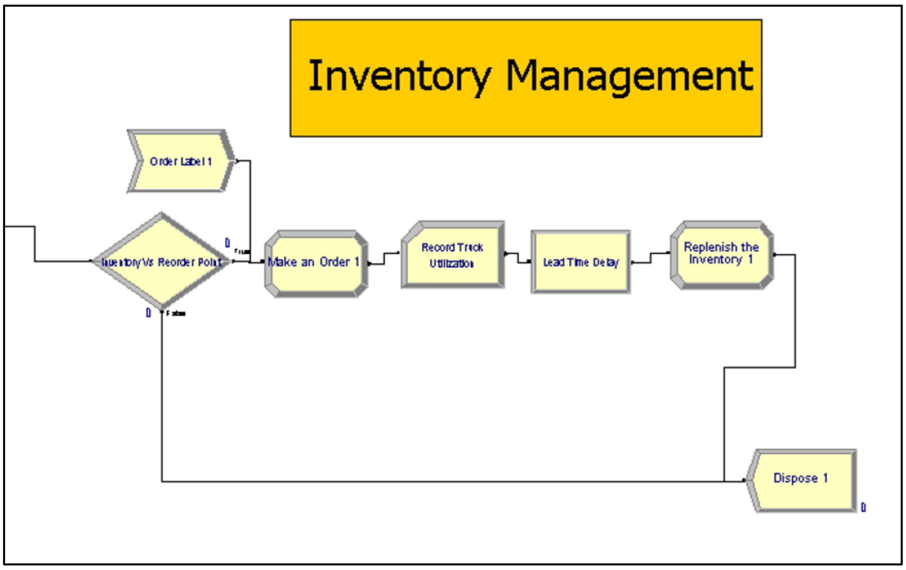

Figure 4-3: Standalone inventory management part.

In the “Make an Order” module, the “On Order” and “Order in Progress” variables get updated as follows:

$$On\ Order\ (OO) = On\ Order\ (OO) +\ Order\ Quantity\ (Q) \tag{34}$$

$$Order\ in\ Progress = Order\ in\ Progress +\ 1 \tag{35}$$

The “On Order” variable, as explained in Section 3.3.1, is the number of units ordered and still did not arrive, while the “Order in Progress” variable shows the number of orders that are placed but have not arrived yet.

Then, the “Transportation CO_2 Emissions” E_T, “Variable Transportation Cost” V and “Truck Utilization” 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. It does not change based on time. On the contrary, the count variable is a variable that gets incremented each time an entity passes through the record module. Eqs. 10 and 13 in Section 3.2 are the equations used to calculate the Transportation CO_2 Emissions and the Variable Transportation Cost, respectively. Moreover, the truck utilization is calculated as follows as mentioned earlier in Section 3.2:

$$Truck\ Utilization = \frac{Q_i w_i}{M} \tag{36}$$

Next, a “Delay” module is utilized to reflect the Lead Time. The lead time is assumed to follow an exponential distribution with a mean of LT. The delay expression is written as:

$$Delay = Max(Expo(LT), Z) \tag{37}$$

Which means that there is a minimum delay of Z 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:

$$\begin{aligned} &Onhand\ Inventory\ (OH) \\ &\quad = Max(0, Onhand\ Inventory\ (OH)\ + Order\ Quantity\ (Q) \\ &\quad - Backorder\ Num\ (BO)) \end{aligned} \tag{38}$$

$$\begin{aligned} &Backorder\ Num\ (BO) \\ &\quad =\ Max(0, Backorder\ Num\ (BO) - Order\ Quantity\ (Q)\ ) \end{aligned} \tag{39}$$

$$On\ Order\ (OO) = On\ Order\ (OO) -\ Order\ Quantity\ (Q) \tag{40}$$

$$Order\ in\ Progress = Order\ in\ Progress -\ 1 \tag{41}$$

These formulas allow for the flexibility of making 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 by the second equation which can be explained as follows:

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 "Order in Progress" variable is decreased by one as well as 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.

4.3.3. Standalone output

The simulation runs for $\hat{n}$ days in one replication. After the completion of one replication, all outputs are calculated as shown in Figure 4-4. The outputs are calculated per day since the time base unit is days.

First, the holding cost per day is calculated based on the time weighted average of the on-hand inventory as illustrated in Section 3.3.1. Therefore, the On-hand Inventory variable is stored as a time persistent variable called "Inventory". Time persistent variable is the type that changes over time. This step is needed in order to calculate the time weighted average using the Arena function "DAVG". The calculation of backorder cost per day and lost demand cost per day is carried out in a similar fashion. Also, as explained in Section 3.3.1, the holding cost per unit *h* is calculated based on the holding rate r_h and unit cost c_i. The holding cost per unit h is calculated in the expression section along with the backorder cost per unit and the lost demand per unit. If these rates are annual (different values are used as will be shown in Section 4.6.2), then the forumlas should be divided by the number of days per year.

Statistic - Advanced Process

	Name	Type	Expression
1	Holding Cost per day	Output	DAVG(Inventory)*Holding Cost per unit/365
2	Transportation Cost per day	Output	NC(Order Num)* (TVALUE(Tally Variable Transportation Cost)+Major Ordering Cost per order+Minor Ordering Cost per order01)/Days to Run
3	Backorder Cost per day	Output	DAVG(TP Backorder Units)*Backorder Cost per unit/365
4	Lost Demand Cost per day	Output	DAVG(TP Lost Demand)*Lost Demand Cost per unit/365
5	Shortage Cost per day	Output	OVALUE(Backorder Cost per day)+OVALUE(Lost Demand Cost per day)
6	Warehouse CO2 Emissions in kg	Output	Warehouse CO2 emissions per kg stored unit* Weight of one Product01*DAVG(Inventory)
7	Transportation CO2 Emissions in kg	Output	TVALUE(Tally Transportation CO2 Emissions)/Days to Run
8	Daily CO2 Emissions by Company	Output	OVALUE(Transportation CO2 Emissions in kg)+OVALUE(Warehouse CO2 Emissions in kg)
9	Logistics Cost per day	Output	OVALUE(Holding Cost per day)+OVALUE(Transportation Cost per day)+OVALUE(Shortage Cost per day)
10	Fill Rate	Output	TVALUE(Demand Met)/TVALUE(Total Demand)
11	Avg Truck Utilization	Output	TAVG(Truck Utilization01)

Figure 4-4: Standalone model output.

Furthermore, the transportation cost per day is calculated using the first term in Eq. 16. The backorder cost per day and the lost demand cost per day are added to give the shoratge cost per day. Then, the total of transportation cost, inventory holding cost, and shortage cost. The warehouse CO_2 emissions is calculated using Eq. 14 whereas the transportation CO_2 emissions per day is calculated using the first term in Eq. 20. Moreover, the fill rate (a way to express the customer service level) is calculated by dividing the "Demand Met" variable over the total demand over the period $\hat{n}$. Finally, the truck utilization rate is stored as an output by taking the average of all recorded values of this tally variable.

4.4. The Collaborative Model

The collaborative model consists of the demand management and inventory management sections for each company as shown in Figure 4-5. The demand management part is similar to what has been explained in the standalone model. However, the inventory management part is more complex as there is an interaction between the two companies.

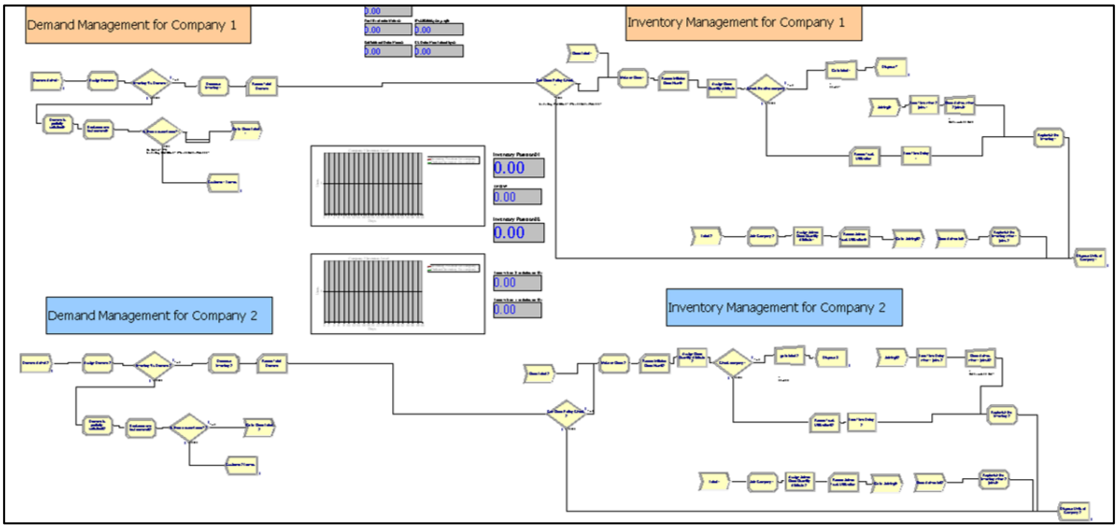

Figure 4-5: The collaborative model in Arena.

4.4.1. Inventory management sub model

For company 1, the inventory management part, as displayed in Figure 4-6, starts with checking if the inventory position 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 disposes the system. In the "Make an Order 1" module, the "Order Quantity" Q_1^s is set to a new value as follows:

$$\begin{aligned} &\mathit{Order\ Quantity}\ (Q_1^s) \\ &\qquad = \mathit{Order\ UpTO\ Level}\ (S_1) - \mathit{Inventory\ Position}\ (I_1) \end{aligned} \tag{42}$$

In addition, similar to the standalone model, the "On Order" variable, OO_1, is updated by adding the "Order Quantity" Q_1^s and the "Order in Progress 1" variable gets incremented by one. Then, an "Assign Attribute" module is used to assign each "Order Quantity" Q_1^s amount as an attribute to its respected entity. This is essential when there is more than one outstanding order as the "Order Quantity" is not constant as in the standalone model. Moreover, the "Self-initiated Order Num" count variable, n_1^s, increases by 1 in the "Record Initiated Order Num 1" record module.

Next, there is a "Decide" module called "Check the Other Company", where the "Inventory Position" of company 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.

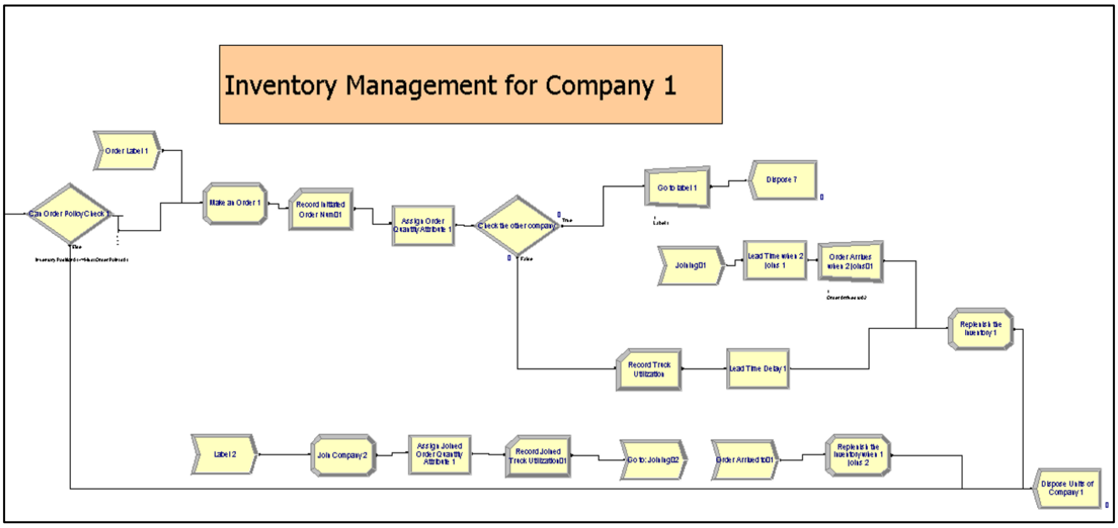

Figure 4-6: Collaborative inventory management part of company 1.

The entity will go via “Go to Label 1” into “Label 1” in company 2 part to place the joint order as shown in Figure 4-7. In this part, there is an assign module called “Join Company 1” where the following are calculated:

$$Joined\ Order\ Quantity\ (Q_2^J) = Order\ Up\ TO\ Level\ (S_2) - Inventory\ Position\ (I_2) \tag{43}$$

$$On\ Order\ (OO_2) = On\ Order(OO_2) + Joined\ Order\ Quantity\ (Q_2^J) \tag{44}$$

$$Order\ in\ Progress2 = Order\ in\ Progress2 + 1 \tag{45}$$

Next, similar to company 1, the “Joined Order Quantity” Q_2^{cl} is assigned to each entity as an attribute using “Assign Attribute” module.

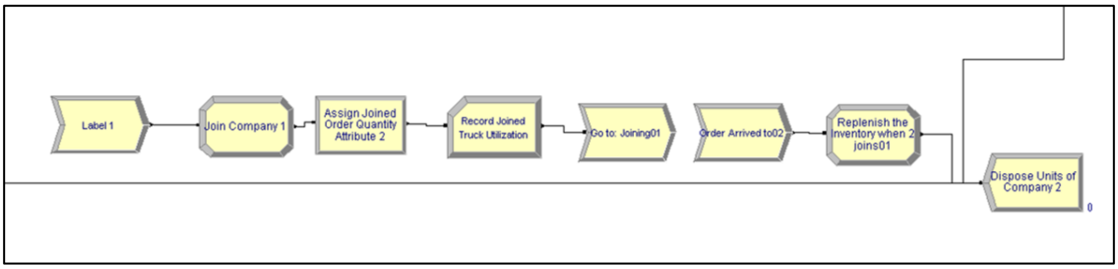

Figure 4-7: Company 2 joins the order of company 1 in the inventory management sub model of company 2.

Then, in the “Record” module, the “Order Num Joined by 2” n_2^{cl} count variable increases 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 using Eqs. 22 and

24 respectively. Note that $i = 1$ because company 1 is the one who initiates the order. Furthermore, the "Joined Truck Utilization" Tally variable will be determined as follows:

$$Joined\ Truck\ Utilization\ = \frac{(\ Q_2^j \times w_2 + Q_1^s \times w_1)}{M} \tag{46}$$

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 the "Replenish the Inventory 1" module, the following are calculated similar to the standalone model:

$$\begin{aligned} Onhand\ Inventory\ (OH_1) \\ = Max(0, Onhand\ Inventory\ (OH_1) \\ + Order\ Quantity\ (Q_1^s) - Backorder\ Num\ (BO_1)) \end{aligned} \tag{47}$$

$$\begin{aligned} Backorder\ Num\ BO_1 \\ =\ Max(0, Backorder\ Num\ (BO_1) - Order\ Quantity\ (Q_1^s)\ ) \end{aligned} \tag{48}$$

$$On\ Order\ (OO_1) = On\ Order\ (OO_1) -\ Order\ Quantity\ (Q_1^s) \tag{49}$$

$$Order\ in\ Progress1 = Order\ in\ Progress1 -\ 1 \tag{50}$$

Also, the "Lost Demand" LD_1 is set to zero. Similarly, the same variables are updated with respect to company 2 in the "Replenish the Inventory when 2 Joins 1" module. 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 "Record Truck Utilization" module, where the "Transportation CO_2 Emissions" E_{T1}^s, "Variable Transportation Cost" $V_1^s$and "Truck Utilization 1" are calculated similar to the standalone model.

Finally, when the order arrives after the lead time has passed, the entity goes to the "Replenish the Inventory 1" module that has Eqs. 47, 48, 49 and 50, which was mentioned earlier. Indeed, the same algorithm is applied for company 2 part.

4.4.2. Collaborative output.

Similar to the standalone model, the simulation runs for $\hat{n}$ days where the outputs are computed at the end of each run. The collaborative output is shown in Figure 4-8.

Statistic - Advanced Process

	Name	Type	Expression
1	Holding Cost per day01	Output	DAVG(Inventory01)*Holding Cost per unit01/365
2	Backorder Cost per day01	Output	DAVG(TP Backorder Units01)*Backorder Cost per unit01/365
3	Warehouse CO2 Emissions in kg01	Output	Warehouse CO2 emissions per kg stored unit* Weight of one Product01 *DAVG(Inventory01)
4	Total Transportation CO2 Emissions in kg per day	Output	(TVALUE(Transportation CO2 Emissions01) +TVALUE(Transportation CO2 Emissions02)+ TVALUE(Joined Transportation CO2 Emissions))/Days to Run
5	CL Total CO2 Emissions by companies 1 and02	Output	OVALUE(Total Transportation CO2 Emissions in kg per day)+OVALUE(Warehouse CO2 Emissions in kg01)+OVALUE(Warehouse CO2 Emissions in kg02)
6	Logistics Cost per day01	Output	OVALUE(Holding Cost per day01)+OVALUE(Shortage Cost per day01)+OVALUE(Transportation Cost per day01)
7	Lost Demand Cost per day01	Output	DAVG(TP Lost Demand01)*Lost Demand Cost per unit01/365
8	Shortage Cost per day01	Output	OVALUE(Backorder Cost per day01)+OVALUE(Lost Demand Cost per day01)
9	Ordering Cost per day01	Output	((Major Ordering Cost per order +Minor Ordering Cost per order01)*NC(Self Initiated Order Num01)+Minor Ordering Cost per order01*NC(CL Order Num Joined by01))/Days to Run
10	Holding Cost per day02	Output	DAVG(Inventory02)*Holding Cost per unit02/365
11	Ordering Cost per day02	Output	((Major Ordering Cost per order +Minor Ordering Cost per order02)*NC(Self Initiated Order Num02)+Minor Ordering Cost per order02*NC(CL Order Num Joined by02))/Days to Run
12	Backorder Cost per day02	Output	DAVG(TP Backorder Units02)*Backorder Cost per unit02/365
13	Logistics Cost per day02	Output	OVALUE(Holding Cost per day02)+OVALUE(Transportation Cost per day02)+OVALUE(Shortage Cost per day02)
14	Lost Demand Cost per day02	Output	DAVG(TP Lost Demand02)*Lost Demand Cost per unit02/365
15	Shortage Cost per day02	Output	OVALUE(Backorder Cost per day02)+OVALUE(Lost Demand Cost per day02)
16	Warehouse CO2 Emissions in kg02	Output	Warehouse CO2 emissions per kg stored unit* Weight of one Product02 *DAVG(Inventory02)
17	Transportation Cost per day01	Output	(TVALUE(Variable Transportation Cost01)+TVALUE(Variable Transportation Cost when 2 joins01))/Days to Run + OVALUE(Ordering Cost per day01)
18	Transportation Cost per day02	Output	(TVALUE(Variable Transportation Cost02)+TVALUE(Variable Transportation Cost when 1 joins02))/Days to Run + OVALUE(Ordering Cost per day02)
19	Fill Rate01	Output	TVALUE(Demand Met01)/TVALUE(Total Demand01)
20	Fill Rate02	Output	TVALUE(Demand Met02)/TVALUE(Total Demand02)
21	Avg Truck Utilization01	Output	TAVG(Truck Utilization01)
22	Avg Truck Utilization02	Output	TAVG(Truck Utilization02)
23	Avg Joined Truck Utilization	Output	TAVG(Joined Truck Utilization)

Figure 4-8: Collaborative model output.

The holding cost per day, backorder cost per day, lost demand cost per day, shortage cost per day and fill rate for each company are calculated similar to the standalone model. The ordering cost per day is calculated using the first term of Eq. 21 but without the variable transportation cost. The transportation cost per day output includes the variable transportation cost that is calculated using Eq. 23. as well as the ordering cost per day output. The total transportation CO_2 emissions per day is aggregated for both companies together by adding their last recorded values (using TVALUE function) of their respected transportation emissions tally variables. The warehouse CO_2 emissions per day is calculated for each company similar to the standalone model. The CL total CO_2 emissions by companies 1 and 2 output adds all the emissions output for both companies. The logistics cost per day adds all the cost output for each company separately as per Eq. 21. Finally, Avg Truck Utilization01 and Avg Truck Utilization02 are the average values of the truck utilization when each company is ordering alone. On the contrary, Avg Joined Truck Utilization output is the average value when a joined order happens regardless of whom has initiated the order.

4.5. Model Validation and Verification

There are two processes that should be applied for any simulation model to be accepted. These two fundamental steps are Verification and Validation (V&V), which should be done throughout the entire model building process [68]. In principle, verification is "the process of determining that a model or simulation implementation and its associated data accurately represent the developer's conceptual description and specifications" [66]. Using a debugger helps in detecting errors while building the model and aids in the verification process [66]. On the other hand, the validation process tends to assess the accuracy of the model and its representation of the real system [68].

There are various techniques to validate and verify the simulation model such as animation, comparison to other models, degenerate tests, event validity, traces, extreme condition tests, Sargent internal validity, and operational graphics (see [69] for more techniques). Due to the lack of real system data, this thesis uses traces, Sargent internal validity, operational graphics, animation and comparison to other models. Traces is used for both V&V processes, and it means that the entities of the system are followed through the model to check if the behavior, and performance is correct and logical [69]. Traces is coupled with animation and operational graphics. Animation aids in visualizing the model behavior while operational graphics shows the values of performance measures graphically during the simulation run time [69]. The operational graphs of the on-hand inventory and the inventory position for each company of both models are built in Arena. In addition, the simple deterministic cases of the model during model building is compared to the results of the known analytic models like the classical EOQ model. This is the comparison to other models' technique. This technique is used to validate the standalone model as will be illustrated in Section 4.6.1.

Moreover, several replications are run to determine the variability of the model and assess the validity. This method is called Sargent internal validity. Large variability indicates that the model produces inconsistent results among the runs. This method is used to assess the variability of both, the standalone model and the collaborative model by looking into the standard deviation and half width of each output. Finally, a warm-up period is set, which is the time where the simulation runs before starting the collection of statistics [70]. This is essential to allow the simulation system to get into the normal real running conditions as collecting data during this period might affect the results [70]. This thesis runs the models for 1460 days (4 years) with 40 replications and a warm-up period of 365 days.

4.6. OptQuest

OptQuest is used to optimize the reorder point and order quantity for the standalone model and can-order policy parameters for the collaborative model. OptQuest is an optimization add-in built into Arena software that searches for optimal solutions using scatter search, tabu search strategies and neural networks [71].

There are several parameters that the user should determine when optimizing a model in OptQuest (see the OptQuest users' guide [72]). These parameters are controls, responses, constraints, and objective. Controls are the decision variables, where their upper, lower bounds and the step size are set according to the user. The step size is the difference between the successive values within the specified boundary. Moreover, responses are the outputs of the simulation model or variables defined in the model. In general, responses are used to set the constraints (linear or non-linear) and objective function of the optimization problem. Constraints can be defined with different right-hand side bounds, and they are optional in OptQuest. Moreover, in terms of objective function, OptQuest tests only one objective at a time. In this thesis, there are two independent objective functions to be tested. First objective function is to minimize the total logistics cost, while the amount of CO_2 emissions will be calculated as a-posteriori. The second objective function is to minimize the CO_2 emissions only.

4.6.1. Standalone model validation

The validation of the standalone model is conducted by comparing the OptQuest results with the results of the IPS (Inventory Problem Solver) software. The parameters of the two trials that were tested are shown in Table 4-1. Note that IPS does not have the option to include the variable transportation cost and the lost demand cost. Thus, they were excluded from the test. In Arena, variable σ was set to 1 to include only the backordered units' option while the output section is updated by excluding the variable transportation cost. Also, the lead time LT is set to a constant value of 2 days.

Table 4-1: Input parameters for the validation trials.

Parameters	Validation Trial 1	Validation Trial 2
K	250	250
k	50	50
D	Pois(5)	Pois(5)
LT	2	2
Demand during Lead time	10	10
c	500	250
r_h (per year)	0.2	0.2
r_B (per day)	0.3	0.3
h	0.273972603	0.136986301
B	150	75

Figure 4-9 shows the input of Trial 1 to IPS and its solution. In IPS, the theoretical distribution of the continuous review problem under stochastic problems was selected given that it matches the characteristics of the standalone model. The demand during lead time is needed in IPS input under the Mean μ section. On the contrary, Figure 4-10 displays the optimization section of OptQuest while it is optimizing Trial 1. The controls are the reorder point and the order quantity, where their boundaries are set to (min 40, max 300) and (min 5, max 30), respectively. Also, the step size of both is set to one. The objective is to minimize the logistics cost per day and there is no constraint. Indeed, the number of replications is 40, the simulation runs for 1460 days (4 years) and the warmup period is 365 days.

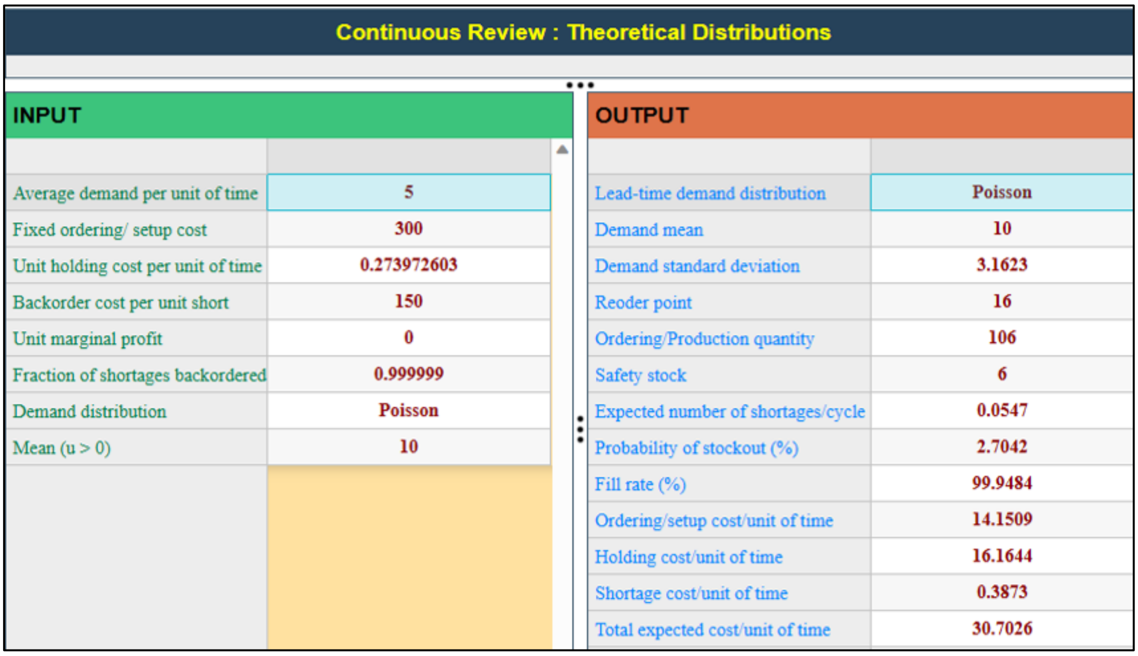

Figure 4-9: Input and output of validation Trial 1 in IPS.

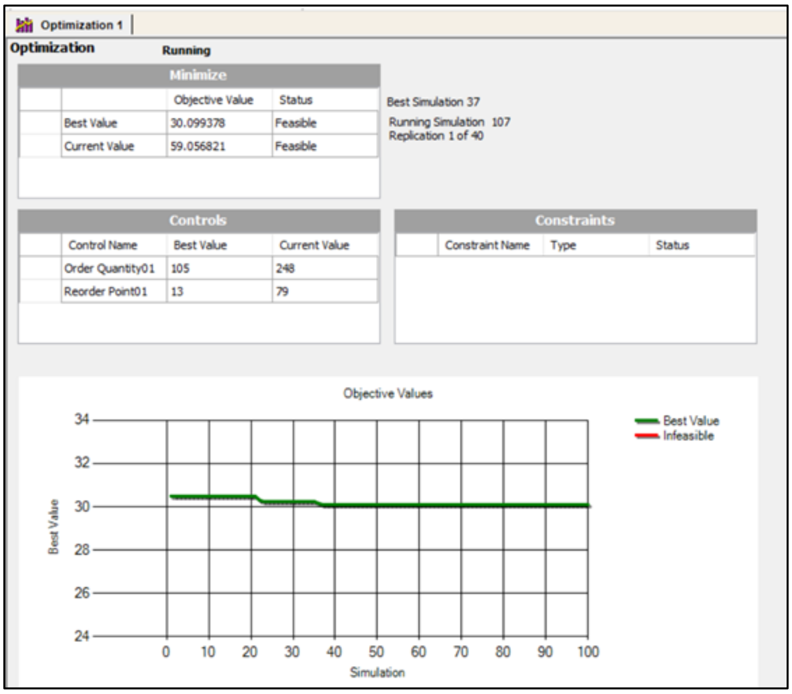

Figure 4-10: Optimization of validation Trial 1 in OptQuest.

Table 4-2 shows the results for trials 1 and 2 using the two methods. It is clear that the logistics cost deviation reaches 1.9% and 1.5% in trials 1 and 2 respectively. The deviation is very small. Therefore; the standalone model is successfully validated.

Table 4-2: Validation results of Trial 1 and 2 in IPS and OptQuest.

	Validation Trial 1		Validation Trial 2	
Solution	IPS	OptQuest	IPS	OptQuest
s	16	13	15	13
Q	106	105	150	147
Holding Cost per day	16.1644	15.363	10.9589	10.55
Ordering Cost per day	14.1509	14.294	10	10.178
Shortage Cost per day	0.3873	0.44178	0.2587	0.16096
Logistics Cost per day	30.703	30.099378	21.218	20.889
Logistics Cost Deviation	0.0196		0.01548	

4.6.2. Standalone model optimization

The optimization of the standalone model involves determining the optimum reorder point and order quantity values for different scenarios. Table 4-3 presents different scenarios by changing key model parameters such as unit cost, demand mean, and major ordering cost. Each scenario is called a trial. Two objectives were tested separately for each trial, which are to minimize the logistics cost and total CO_2 emissions. Also, a minimum value of fill rate 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. Moreover, the upper and lower bounds used to optimize the control variables are determined for each trial. Note that in the table L stands for the lower bound and U 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 standalone optimization is one. Specifically, the optimization is performed using Intel Core i7-7700HQ CPU, 2.80 GHz, 8 GB of RAM laptop. It takes a minimum of an hour to complete one optimization run.

Table 4-3: Standalone optimization input parameters.

Trial no.	D	w	K	k	r_h	r_B	r_S	c	$OH_{t=0}$	$Q(L,U)$	$s\ (L,U)$
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)

4.6.3. Collaborative model optimization

A similar approach was used for the optimization of the collaborative model. However, the number of control variables is six, which makes the optimization more complex and requires a much longer time. The control variables are the three can-order policy parameters for each company. Table 4-4 shows the different tested trials along with the specified boundaries of the control variables. It should be noted that each trial is a combination of the standalone trials represented in company 1 and company 2. This helps in comparing the results between the standalone case and the collaborative case. Unlike the standalone case, two optimization attempts were utilized for each trial. The first attempt includes the specified boundaries in Table 5.4 with a step size of 5. 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 of 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 what Kleijnen and Wan used in [71]. The optimization is performed using an Intel Core i7-10510U CPU, 2.30 GHz, 8 GB of RAM laptop. It takes about 10 to 11 hours to complete the optimization including both attempts.

Table 4-4: Collaborative optimization input parameters.

	Company 1				Company 2			
CL Trial no.	SA Trial no.	$S\ (L,U)$	$C\ (L,U)$	$s\ (L,U)$	SA Trial no.	$S\ (L,U)$	$C\ (L,U)$	$s\ (L,U)$
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)

Chapter 5. Results and Analysis

In this chapter, the optimization results for the standalone and collaborative models are presented. Accordingly, the performance is evaluated, the variability is checked, and conclusions are made.

5.1. Optimization Results

The full optimization results for all trials for the standalone case are presented in Table 5-1 whereas the results for the collaborative case are divided into two parts; part 1 and part 2 that are presented in Table 5-2 and Table 5-3 respectively. Part 1 shows the can order policy optimum parameters, truck utilization values as well as the number of order values for each company. On the side, the cost and CO_2 emissions output values are presented in part 2. Note that CL stands for collaborative and SA denotes standalone. Also, there are two objectives to be minimized separately for each trial, which are the cost and CO_2 emissions. As such, each trial number X has two sub-trials as 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, the trials that have similar demand and weight will have the same minimum CO_2 emissions. As such, some trials do not have Trial X.2 results, where it is indicated that the results are similar to another trial. In addition, the optimum results of the majority of the trials show that the two companies are collaborating all the time (this can be seen when the Avg. Truck Utilization of each company equals zero). As a result, other non-optimal solutions for selected trials are shown in Table 5-4 and Table 5-5. These are not optimal, but they have better results compared to the standalone case where they do not collaborate all the time. These trials are expressed as i.e. Trial X.1.a.

Table 5-1: 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	same as 5											
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	same as 4											
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	same as 4											
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	same as 12											
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	same as 8											
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	same as 12											
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	same as 8											

Table 5-2: 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	same as 1.2														
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	same as 3.2														
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	same as 4.2														
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	same as 3.2														
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	same as 5.2														
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	same as 10.2														
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	same as 10.2														

Table 5-3: 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												
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												
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												
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												
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												

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												
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												

Table 5-4: OptQuest results for the non-optimal solution of 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.a	200	800	1500	30	100	300	0.99	0.98	1.99	0.10	0.11	27.33	15.63	15.13	26.80
Trial 1.2.a	50	430	735	10	120	120	0.90	0.78	0.90	0.00	0.01	17.43	69.15	69.13	17.43
Trial 2.1 .a	200	600	1500	35	120	301	0.99	0.99	1.98	0.15	0.16	25.10	18.33	17.45	24.23
Trial 3.1 .a	40	100	560	40	185	275	0.99	0.98	0.93	0.06	0.32	20.15	34.58	33.48	19.50
Trial 3.1 .b	34	200	452	25	245	245	0.99	0.95	1.06	0.00	0.87	21.38	30.05	4.95	21.38
Trial 3.2 .a	12	125	300	12	200	205	0.98	0.88	0.86	0.00	0.69	9.03	48.33	39.25	9.03
Trial 4.1 .a	30	500	507	30	120	506	0.99	0.99	0.72	0.03	0.00	11.25	11.88	11.88	11.18
Trial 4.1 .b	45	600	660	40	100	650	1.00	1.00	0.92	0.34	0.19	8.58	10.63	10.18	7.50
Trial 4.2.a	10	500	600	10	100	560	0.98	0.95	0.86	0.01	0.01	4.35	15.18	15.15	4.33
Trial 5.1.a	200	320	485	30	85	214	0.95	0.98	0.86	0.24	0.04	162.05	14.70	14.65	51.30
Trial 5.1.b	200	500	500	30	80	214	0.96	0.97	0.88	0.25	0.00	146.48	24.53	24.53	39.25
Trial 6.1.a	40	65	110	15	120	200	0.95	0.99	0.54	0.06	0.00	141.98	0.23	0.23	88.05
Trial 7.1.a	40	120	120	25	90	125	0.96	0.95	0.13	0.00	0.00	109.58	19.88	19.88	109.55

Trial 8.1.a	35	50	140	35	145	150	0.95	0.97	0.45	0.08	0.46	72.43	42.73	27.70	67.00
Trial 9.1.a	205	400	401	40	50	120	0.95	0.97	0.43	0.17	0.32	193.35	94.63	91.35	36.83
Trial 10.1.a	200	879	879	28	129	286	0.98	0.97	3.35	2.72	0.00	52.15	30.75	30.75	11.25
Trial 10.1.b	145	345	860	48	150	190	0.96	0.99	3.16	2.21	0.45	38.95	43.95	39.63	36.05
Trial 10.2.a	50	80	200	10	50	80	0.43	0.89	0.88	0.57	0.19	217.78	3.08	1.58	212.65
Trial 11.2.a	50	224	329	50	155	205	0.75	0.44	0.86	0.09	0.39	12.03	210.20	198.90	11.55
Trial 13.1.a	203	231	468	107	427	483	0.95	0.96	2.26	0.03	0.04	183.25	0.40	0.38	183.23

Table 5-5: OptQuest results for the non-optimal solution of 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.a	3.80	38.17	15.56	11.72	0.01	0.11	19.37	50.00	6.70	1.66	1.67	10.04
Trial 1.2.a	1.61	11.57	12.21	40.68	0.06	1.44	13.88	53.69	5.45	0.70	0.51	6.66
Trial 2.1 .a	19.12	38.56	14.44	13.03	0.04	0.08	33.59	51.68	6.56	1.67	1.69	9.92
Trial 3.1 .a	3.32	30.73	12.00	21.34	0.01	0.13	15.33	52.20	3.49	0.29	1.35	5.13
Trial 3.1 .b	5.93	29.94	11.57	19.02	0.01	0.24	17.51	49.20	4.36	0.52	1.31	6.20
Trial 3.2 .a	4.30	23.10	6.48	28.14	0.01	0.74	10.79	51.98	3.59	0.38	1.01	4.97
Trial 4.1 .a	6.66	6.64	6.39	6.68	0.01	0.01	13.06	13.32	1.43	0.58	0.58	2.59
Trial 4.1 .b	8.97	8.66	4.92	5.86	0.00	0.00	13.89	14.53	1.21	0.79	0.76	2.75
Trial 4.2.a	8.04	7.21	2.95	8.08	0.01	0.03	11.00	15.32	1.22	0.70	0.63	2.56
Trial 5.1.a	93.07	28.00	84.75	13.00	2.59	0.13	180.41	41.13	10.64	0.45	1.23	12.31
Trial 5.1.b	96.51	27.38	77.12	17.45	2.57	0.20	176.20	45.02	10.31	0.46	1.20	11.97
Trial 6.1.a	110.38	28.98	73.66	8.17	2.55	0.07	186.58	37.22	8.45	0.11	1.27	9.83
Trial 7.1.a	122.66	133.61	57.70	15.30	2.09	2.14	182.45	151.05	7.51	0.12	0.13	7.75
Trial 8.1.a	141.44	18.05	76.48	59.77	2.17	0.19	220.09	78.02	6.90	0.14	0.79	7.83
Trial 9.1.a	372.42	13.93	104.42	56.78	8.56	0.29	485.40	71.00	17.00	0.36	0.61	17.96
Trial 10.1.a	106.14	35.69	65.69	37.79	0.79	0.17	172.62	73.65	17.92	4.65	1.56	24.13
Trial 10.1.b	98.83	24.35	52.56	57.23	1.16	0.09	152.55	81.67	18.52	4.33	1.07	23.92
Trial 10.2.a	9.26	7.78	242.77	42.26	17.89	0.56	269.93	50.60	14.02	0.41	0.34	14.76

Trial 11.2.a	230.10	9.70	15.32	119.90	36.17	17.17	281.59	146.76	13.97	0.22	0.42	14.62
Trial 13.1.a	49.20	52.83	59.49	8.50	1.87	1.66	110.56	62.99	33.56	2.15	2.31	38.03

5.1.1. Cost minimization results

The first objective is to minimize the total logistics cost that consists of the transportation cost, holding cost and shortage cost. A summary of the logistics cost comparison between the collaborative case and standalone case are presented in Table 5-6. The table shows that cost savings are attained by collaborating against the standalone setting. The highest saving is achieved in Trial 4.1, where the two companies are identical and have low unit holding cost. By contrast, the least saving of 5.56% is obtained in Trial 9.1, where the unit holding cost per day is high in company 1 (h_1=2.5 per day) and the demand is low in company 2. In addition, Figure 5-1 presents the amount of difference in logistics cost between the standalone case and collaborative case for all the trials. It is clear that Trial 11.1 has the highest cost difference given that it is the most expensive scenario (C_{To}^{cl}=589 and $C_{To}^{sa} = 649$), where To here indicates total cost of companies 1 and 2 together. In Trial 11.1, note that collaboration decreases the cost by 9.18%. By contrast, the amount of cost difference is around 8 units per day (C_{To}^{cl}=33.7 and $C_{To}^{sa} = 25.6$) in Trial 4.1, but it has the highest saving percentage of 24% as shown in Table 5-6. 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. The reason is discussed later in this section.

Table 5-6: Logistics cost under collaboration vs. standalone.

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%

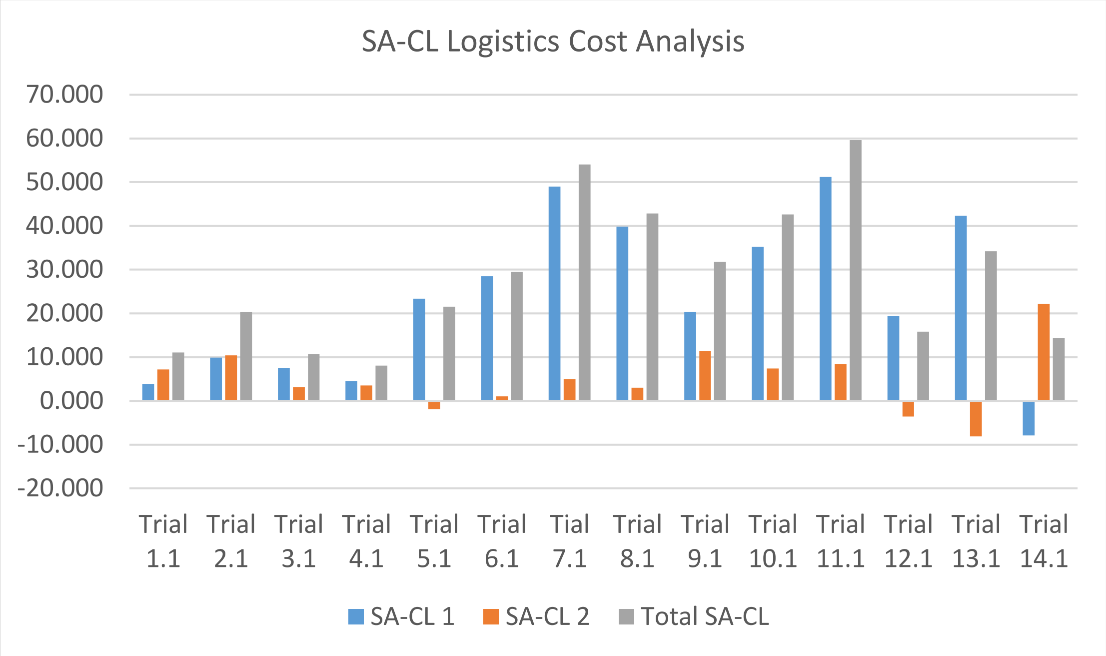

Figure 5-1: The difference between the standalone logistics cost and collaborative logistics cost in all 14 trials.

The results of the optimum solution of Trial 1.1 show that logistics cost of each company decreases when they are collaborating compared to the standalone case as presented in Figure 5-2. 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 normally increases the transportation cost. However, the transportation cost decreases as 78% of the orders are when company 1 joins company 2 at which only the minor ordering cost is paid by such a company.

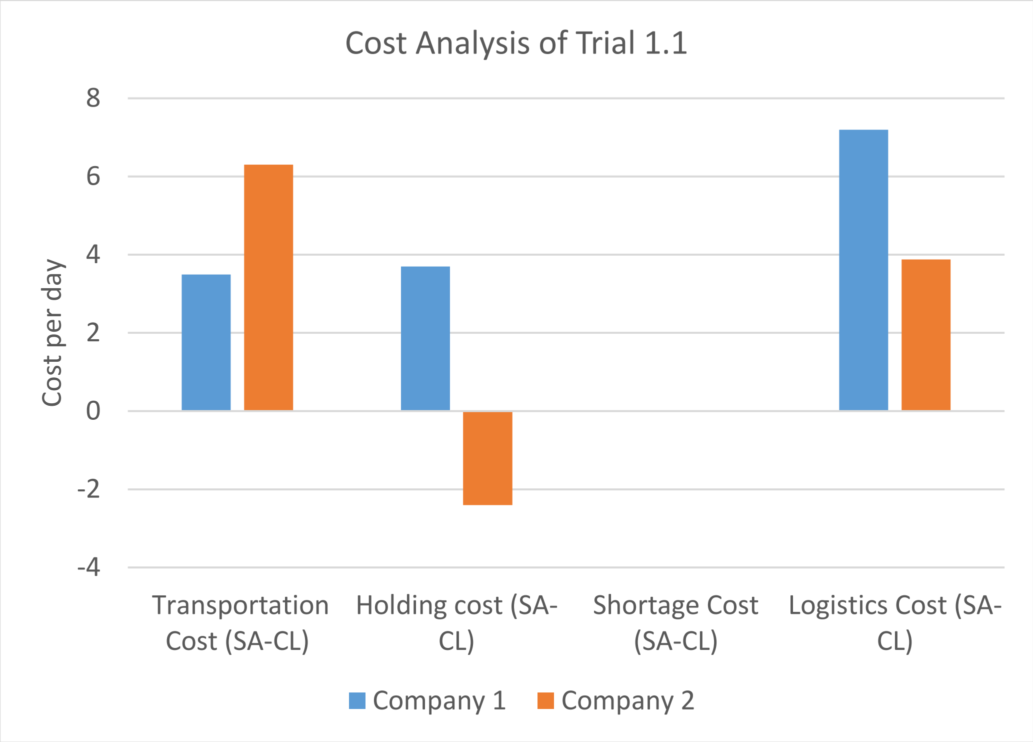

Figure 5-2: Cost analysis of the optimum solution of Trial 1.1.

By contrast, Trial 2.1 results in an optimum solution where savings occur in almost all dimensions at different magnitudes. Note that Trial 2.1 has higher cost savings compared to Trial 1.1 as shown in Table 5-6. This is because the increase in the units cost for company 1 will still make its unit holding cost cheaper than that for company 2 (h_1=0.0274, h_2=0.274). Thus, the amount of savings in terms of the holding cost is higher in Trial 2.1, where the savings are about 12% in Trial 2.1 and 3.6% in 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 holding cost. The transportation cost is reduced as well because 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 when collaborating as one truck is used instead of two.

The logistics cost of company 1 under collaboration increases slightly by 1% in Trial 5.1. There is an increase in the number of initiated orders by company 1 which leads to an increase of about 15.4 units in the transportation cost and decrease by 14 units in the holding cost. By contrast, the outputs of company 2 have improved except for the shortage cost. Overall, the increase in company 1's logistics cost is offset by the decrease in company 2's logistics cost.

Indeed, company 1 in Trial 6.1 is the one who initiates 99% of the collaborative orders. However, why is it that company 2 is not the one who initiates the orders. The answer is because the unit holding cost of company 1 is much higher than that of company 2. Thus, company 1 tries 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 it wants to join. Nevertheless, the logistics cost of company 1 decreases slightly compared to the standalone case due to the increase in transportation cost that offsets the savings in holding cost. Overall, the situation is better off as the logistics cost of company 2 decreases significantly.

In Trial 7.1, there is an increase of about 8% in the holding cost of company 2 even though the number of collaborative orders increases. This is because almost 90% of the orders are initiated by company 1 (where company 2 is joining) while the can order level C_2 is close to the order up to level S_2. This means that the on-hand inventory OH_2 is relatively high when joining the other company leading to higher holding cost compared to the standalone case. Also, note that the shortage cost of company 2 is less than that under the standalone case which supports why the holding cost increases.

Likewise, Trial 9.1 presents an optimal solution where the two companies are not always collaborating but 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 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 increases in Trial 9.1 which leads 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 Trials 1, 2 and 3, the increase in the demand and unit cost leads to more savings in logistics cost. However, such an increase leads to lower savings in Trials 5, 6 and 9. After a thorough analysis, it has been found that if the demand and unit cost increase happens to the company who have 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 that has 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 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 means low order quantity is ordered which further decreases the truck utilization rate. Thus, the transportation cost increases.

The logistics cost of company 1 in Trial 12.1 increases as compared to the standalone. Its total number of orders decreases leading to savings in transportation cost but much higher holding cost. For company 2, however, the number of joined orders increases where no orders are initiated leading to a significant saving in transportation cost. Nevertheless, the holding cost increases slightly as the can order level C_2 is close to the order up to level S_2 leading to an increase in the average on-hand inventory OH_2. This is similar to what happened in Trial 7.1. Note that both companies have the same unit holding cost.

Indeed, the major ordering cost is 1000, 500 and 250 in Trials 10, 12, and 14, respectively. This leads to increasing the order up to levels of both companies (but specifically company 1, who has higher demand) which corresponds to the reduction in the number of orders as the major ordering cost increases. This can be shown in Figure 5-3, where the lowest number of orders is in Trial 10.1. Moreover, unlike Trials 10.1 and 12.1, company 2 initiates the majority of orders in Trial 14.1 leading to a higher logistics cost compared to the standalone case. This might be because of the fill rate constraint as well as the low major ordering cost which leads to more orders compared to Trials 10 and 12. A lower number of orders is initiated by company 1 as its demand is higher. If it is the one who initiates more orders as in the aforementioned trials, then the proportion of demand that might not be met will be higher leading to unsatisfied fill rate. Because when the number of orders with low order quantities is high, the chance of getting a shortage will be high as well.

In general, when the major ordering cost is high compared to a low unit holding cost, the number of trucks to be used per order increases (remember 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 [59].

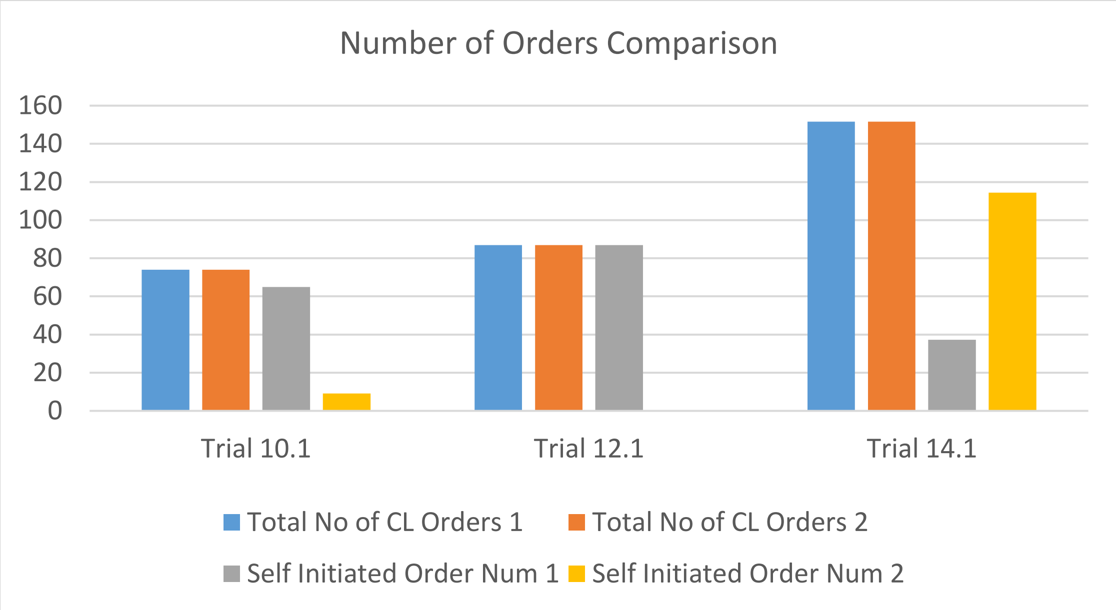

Figure 5-3: Number of orders in Trials 10.1, 12.1 and 14.1.

In Trial 13.1, the companies are identical. The optimum solution is to let company 1 initiate 99% of the orders leading to a considerable increase in transportation cost but saving in holding cost. The situation is better off by improving the situation significantly for company 2. The details are presented in Figure 5-4, where the logistics cost of company 2 gets lowers considerably under collaboration compared to a slight increase in the logistics cost of company 1.

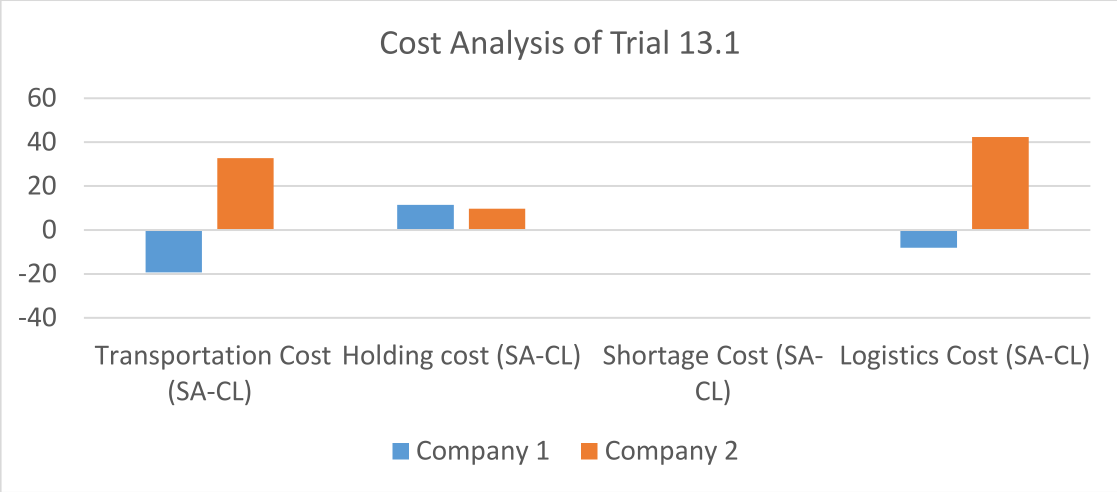

Figure 5-4: Cost analysis of Trial 13.1.

5.1.2. CO2 minimization results

The second objective is to minimize the CO_2 emissions generated from transportation and warehouses. Figure 5-5 summarizes the savings attained in each 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. By contrast, Trials 10.2 and 11.2 have low savings of about 4.1% and 6.4%, respectively. This is because the companies in Trial 10.2 have high products' weight but one of the companies has low demand. On the other hand, companies in Trial 11.2 have high demand but one of the companies has low weight for its product. Indeed, the standalone case is better than the collaborative case when the companies have both high demand and high weight of products.

By looking at each scenario, Figure 5-6 summarizes the difference between the emissions of the standalone and collaborative cases. Negative values indicate that the standalone case emits lower CO_2 than the collaborative setting. 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 happens in Trial 13.2 but the increase in transportation emissions is higher than the savings in warehouse emissions. Thus, the standalone outperforms the collaborative case.

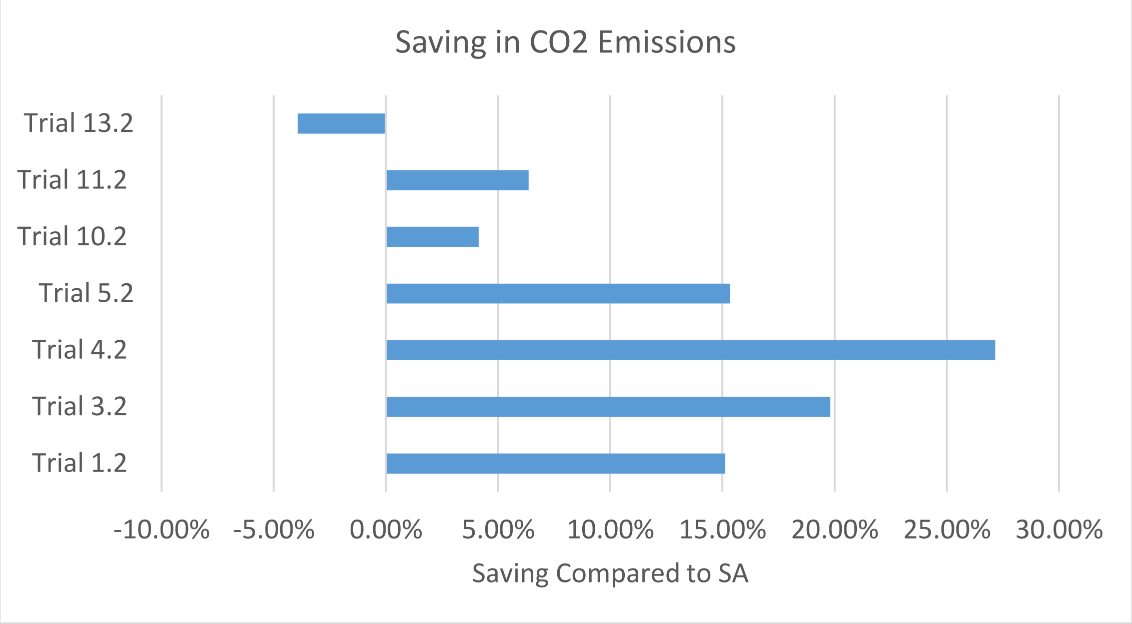

Figure 5-5: CO_2 emissions of the collaborative case vs the standalone case.

In Trials 3.2 and 4.2, the total number of collaborative orders is less than the total number of standalone orders (both companies together). This leads to lower total transportation emissions. Moreover, the number of collaborative orders for each company is higher than the standalone case leading to lower on-hand inventory and lower warehouse emissions accordingly. Unlike other trials, trials 3.2 and 4.2 improve truck utilization significantly.

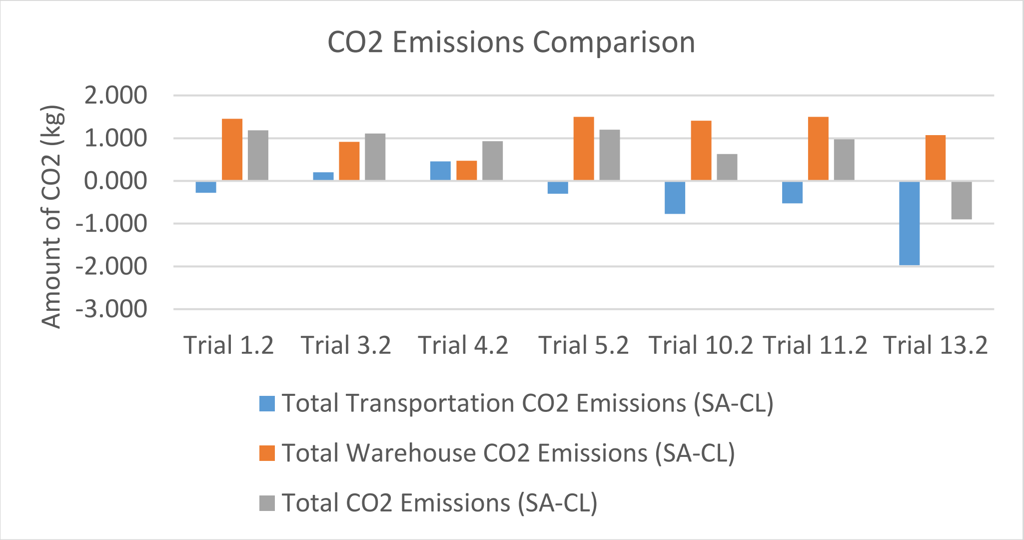

Figure 5-6: The difference in CO_2 emissions generated by the standalone and collaborative models in each trial.

5.2. Mean Comparison Test

The aforementioned results are comparisons based on the average result of all the 40 replications. In order to check whether the difference in logistics cost and CO_2 emissions between the trials is statistically different, Output Analyzer is utilized. Output analyzer is another built-in tool in Arena, where the outputs of the models can be further analyzed. This thesis uses "Compare Means" analysis feature to compare the means of the different scenarios. Precisely, the Paired t-test approach is used. In this test, Output Analyzer compares the means based on 95% confidence interval. It subtracts the means in the direction A-B, where A is the standalone output while B is the collaborative output. As such, it is expected based on the previous observations from OptQuest that the sign of the difference is positive for the logistics cost comparison (the standalone tends to cost more money compared to the standalone case).

Figure 5-7 shows the hypothesis paired t-test results for Trials 1.1, 6.1, 8.1, 9.1, 11.1 and 12.1. Since the difference between the standalone logistics cost and the collaborative logistics cost are greater than zero, then it can be concluded that the outputs of the standalone and collaborative cases are statistically significantly different. Therefore, the collaborative setting is able to reduce the logistics cost.

Figure 5-7: Paired t-test on the expected difference in logistics cost between the standalone and collaborative settings.

Furthermore, Figure 5-8 shows the results of the paired t-test of two CO_2 minimization trials. The one on the left is for Trial 12.2, where the null hypothesis of having the two means to be equal is rejected. Furthermore, the difference value is positive indicating that collaboration outperforms the standalone case based on 95% confidence interval. However, the difference value is negative for trial 13.2, which indicates that the standalone case outperforms the collaborative setting in this particular scenario. This was expected as per the OptQuest results. Note that the difference is not equal to zero so the means are statistically different.

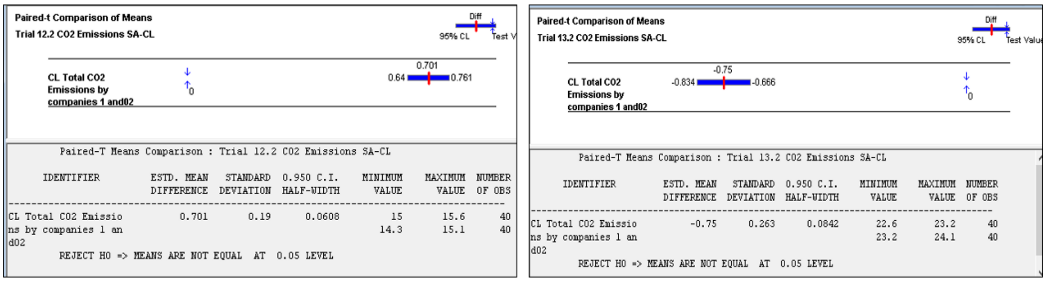

Figure 5-8: Paired t-test on the expected difference in CO_2 emissions between the standalone and collaborative settings.

Chapter 6. Conclusion and Future Work

It has been found that horizontal collaboration in logistics brings substantial economic and environmental benefits to the partners. However, in collaborative shipping, there is a problem of when companies can join their orders, and how much each company can order so that the benefits of HLC are maximized. Thus, this thesis uses the can-order policy in synchronizing the replenishment of the inventories of the collaborated companies. The can-order policy has three parameters namely; the must-order level, can-order level and order-up-to-level. Therefore, this research aims to optimize these levels such that the total logistics cost and companies' footprint are independently minimized. This is done through first building a simulation model of two horizontally collaborating companies under stochastic environment using Arena. Then, the optimization of the can-order policy parameters is performed using OptQuest, that is built in Arena. Unlike previous studies, stochastic lead time, truck capacity, service level and warehouse footprint are considered.

The findings of the optimization of the standalone and collaborative models for 14 different scenarios in terms of logistics cost and CO_2 emissions are presented. In terms of logistics cost, the collaborative case outperforms the standalone in all cases at different magnitudes. For instance, horizontal collaboration leads to higher savings of 24% compared to the standalone case when the unit holding cost is low and companies are identical as shown in Trial 4.1. By contrast, the cost saving is reduced to 14.6% in Trial 7.1 when the unit holding cost is high for the same characteristics as in Trial 4.1. In addition, the lowest saving of 5.6% is attained when the demand is high for a company that has a high unit holding cost. Also, the high major ordering cost almost doubles the savings compared to the standalone case as shown in Trial 10.1 compared to Trial 12.1.

On the other side, horizontal collaboration reduces the CO_2 emissions in all trials except for one trial, where the demand and weight of the products are high. Under this condition, collaboration leads to an increase in the generated CO_2 emissions by almost 4%. As such, the lower the demand and the weight of the products, the higher is the saving, which can reach up to 27%. This is due to better truck utilization under collaboration compared to the low rate when the companies are working separately. In addition, paired t-test is conducted for each trial to see whether the difference in logistics cost and CO_2 emissions are statistically significant between the horizontal collaboration scenario and the no collaboration scenario. The results indicate 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 that horizontal collaboration is beneficial.

These findings suggest that a company should better select a partner that has a low unit holding cost (or high major ordering cost). Also, two companies should consider consolidating when they both have low truck utilization. Indeed, if a high unit holding cost company wants to collaborate horizontally, it is preferred to do so with a company that has similar cost and demand characteristics.

As a future research work, the collaboration of more than two companies can be tested by comparing the results with the two companies' collaborating vs. the no collaboration scenario. Additionally, a heterogeneous fleet of trucks can be considered. Finally, varying the distance between the collaborating companies could be tested to check whether collaboration can outperform the standalone case when the locations are different. Lastly, some of the carbon regulatory policies, such as the carton cap policy whereby an upper limit on the amount of carbon footprint generated, can be explored as a future research avenue.

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Vita

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