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Abstract:

The transportation industry contributed around one trillion dollars to the economy in 2016 accounting for 8.9% percent of the GDP. In 2017, it was responsible for 1.5 billion tons of CO_2 emissions. With the American Trucking agency predicting a 35% growth in the trucking industry between 2016 and 2027, there are rising concerns about the impact the trucking industry will have on the economy and the environment. The trucking industry is also very inefficient with many trucks driving with empty loads or with less than full capacity loads. There is potential to save billions of dollars and cut back on millions of tons of CO_2 emissions by improving the efficiency of the trucking industry. To accomplish this task, we will explore the existing ideas surrounding collaborative logistics. Collaborative logistics is the integration of planning, resource allocation and operational decisions between independent companies. This research will seek to quantify the benefits associated with introducing collaboration in a supply chain. To accomplish this, two optimization models will be developed to model a non-collaborative and a collaborative supply chain. Various cost and performance metrics will be collected to compare the operational efficiencies of both supply chains. The results produced from this research provides motivation for implementing collaboration within supply chains in order to save billions of dollars and cut back on millions of CO_2 emissions.

1. Background and Significance

The volume of truck freight on the road in the United States has increased drastically over the past few years with $772 billion in freight being shipped by trucks alone in 2018 [1]. This growth over the past few decades has triggered various problems: truck congestion is increasing, transportation expenditures are rising, and carbon emission levels are intensifying. With on-road vehicles emitting 1.5 billion tons of CO_2 in 2017 [2] and with the transportation industry accounting for 8.9% of the GDP by contributing roughly $1.5 trillion in 2016 [3], a solution to these growing costs on the economy and the environment is crucial. The cause for these high numbers is correlated with the inefficiencies in the supply chain.

Supply chains unfortunately suffer from a lack of coordination that result in cost, operational, and labor inefficiencies. According to the Environmental Defense Fund (2014), it is estimated that 15-20% of the miles driven by trucks in the US are empty, and when the trucks are not empty, they are 36% underutilized, meaning the trucks are filled 64% to capacity. Capturing just half of this underutilization would cut carbon emissions by 100 million tons per year, and reduce expenses by $30 billion a year [4]. To achieve this, collaborative logistics is one solution that has been proposed and studied extensively [5].

Collaborative logistics "describes the practice where companies work together to improve efficiency in their supply chains rather than operate in isolation and accept the inefficiency that frequently results" [6]. The two types of collaboration are vertical and horizontal. Vertical collaboration occurs when multiple organizations such as the manufacturer, the distributer, the carrier, and the retailer share their responsibilities, resources, and information to serve the customers [5]. Horizontal collaboration occurs when multiple unrelated or competing organizations cooperate to share their private information or resources such as joint distribution centers between two retailers [5]. Presently, in the absence of collaboration, there exists *incentive misalignment*. This occurs when "a player makes decisions considering only local rewards and penalties, which typically often differ from maximizing the overall profitability – sometimes at the expense of others" [5]. Discovering a way to promote collaboration within is a promising opportunity for the transportation industry to reduce inefficiencies and negative impacts of excessive trucks on the highways.

This research aims to quantify the benefits associated with a collaborative supply chain. First, a review of the literature related to collaboration, the Physical Internet, and the vehicle routing problem (VRP) is discussed. Next, in Section 3, a mixed integer program is formulated to model a supply chain with and without collaboration. Section 4 describes how the supply chain is structured, and how the parameters used within the model are randomly generated. Then, Section 5 discusses how the experiment is setup and tested on over 2,500 randomly generated supply chains. Finally, in Section 6, conclusions and future work are discussed.

2. Literature Review

To combat the growing inefficiencies within the supply chain, a growing number of approaches connected to horizontal collaboration have been researched such as on-demand logistics, information sharing, and resource sharing [6]. On-demand logistics is an uber-like business model in which transportation service providers (TSP) are matched up with a shipment whenever the demand arises [7].

Due to the cost-effectiveness and convenience of shipping many of the largest e-commerce companies such as Amazon Inc. and Walmart Inc. are turning away from long-term agreements with TSP's and turning to on-demand logistics [8]. Information sharing is where companies share information such as demand, capacity, inventory, production data, and more [9]. A study conducted in 2002 examined the effects of different types of information sharing within a supply chain, and the lowest total cost was realized with all information being shared between the companies [10]. Resource sharing, in a transportation logistics setting, can be defined as multiple companies sharing their resources. Some of these resources include trucks, equipment, and inventory capacity. Becker and Stern conducted a simulation study to determine the impact of resource sharing in manufacturing. They found resource sharing had a beneficial impact on all key performance measures, and it leads to superior performance when compared to non-resource sharing scenarios [11]. Another simulation study conducted by Erdmann researched the impact of resource sharing in transportation by measuring the impact on mileage, tours, and vehicle utilization. She found resource sharing yields an improvement in these key figures [12]. These three concepts are initiatives under a concept commonly known as the Physical Internet (PI).

Pioneered by Benoit Montreuil, the physical internet (PI) is the concept of applying the technologies of the digital internet to the physical world of logistics. The following list describes the primary initiatives the physical internet calls for [13]:

- Shipping – Standardize modular containers to optimize storage and handling.
- Network – An interconnected and open logistics network shared by all companies.
- Routing – Allow for the dynamic routing of containers to allow for more flexibility in shipments.
- Information System – Allow for information sharing for all stakeholders in the PI network.
- Standardization – Standardize the information within organizations to allow for connecting and interfacing between other organizations.
- Storage – Allow for decentralized storage in the network where products can be stored throughout the network.
- Capacity Management – Vehicle, resources, and storage capacities are shared across all organizations in the network.

This research will focus on the network, routing, storage, and capacity management initiatives by estimating the cost savings associated with implementing these initiatives in a supply chain.

The vehicle routing problem (VRP) is a common optimization problem used in transportation to optimally assign a set of vehicles to a route as a means to minimize the total travel time associated with that set of vehicles. This problem is an NP-hard problem meaning that the solution time to solve the problem increases exponentially as the number of trucks and possible routes increases [14]. Numerous variants of the VRP have been formulated since its initial conception. This following list describes some of the most popular variants of the VRP [15]:

- Capacitated VRP (CVRP) – Vehicles have a finite capacity of goods than can be delivered.
- VRP with Time Windows (VRPTW) – Each customer must be visited with a certain time frame.
- VRP with Pick-up and Delivery (VRPPD) – Vehicles can pick-up and deliver goods at each stop along its route.
- VRP with Multiple Trips (VRPMT) – Vehicles can take multiple routes within the same modeling time horizon.

This research will leverage aspects from each these variants in an attempt to accurately model a realistic supply chain scenario.

3. Modeling

The model is developed for a supply chain with multiple companies ranging from manufacturers, retailers, and 3PL's. Depending on the company type, a company can have numerous nodes such as manufacturing plants, distribution centers (DC's), and stores. Two models will be developed: a Vertical Collaboratory model that models a supply chain in which only vertical collaboration is present and a Horizontal Collaboratory model that models a supply chain with both vertical and horizontal collaboration is present.

3.1 Modeling Context

There are three classes of nodes used in this supply chain: plants, DC's, and stores. Let, *M* represent the set of all plant and DC nodes (*i)* while *N* represents the set of all DC and store nodes (*j* or *k*). The plant and DC nodes (*i*) will be assigned a fleet of vehicles. Each of the plants will produced a single type of unit that is unique to each plant, so let *U* represent the set of all units (*u*) produced in the supply chain. The number of vehicles will vary depending on the volume of demand or production. Let V_i represent the set of all vehicles (*v*) assigned to node *i*. Each vehicle will have restrictions on which nodes and which types of units it is allowed to carry. Let $Home_v$ represent the node (*i*) vehicle *v* is assigned to, let $Node_v$ represent the set of all nodes (*i, j, or k*) vehicle *v* can travel to let R_v represent the set of all routes (*r*) a vehicle can take, and let $Deliver_v$ represent the set of all unit's (*u*) vehicle *v* can carry. All of these indices and sets can be seen in Table X.

Discrete-Time Model

The two models will utilize a discrete-time model where *T* represents the set of all time periods (*t*), and *TI* represents the time between the time periods. I have adapted an approach used in the chemical engineering community for the scheduling of chemical process in which they used a key decision variable that denotes whether or not a unit begins processing a task at a given time period [16]. This decision variable has been translated into a supply chain context in which $X_{r,v,t}$ is a binary decision variable that indicates whether or not a route (*r*) has been taken by vehicle *v* starting at time *t*. Furthermore, if a vehicle (*v*) begins a route at time *t*, then no other route can be taken by that vehicle until that route is finished. This rule is enforced in the equation below where the parameter α_r is the travel time route (*r*), and *M* is a very large positive number.

$$\sum_{r\prime \in R_v} \sum_{t\prime = t}^{t+\alpha_{r,v}} X_{r',v,t'} - 1 \leq M\left(1 - X_{r,v,t}\right) \quad \forall v \in V, \forall r \in R_v, \forall t \in T \tag{1}$$

Vehicle Constraints

Whenever a vehicle begins its route, it is allowed to pick up any available goods located in inventory at the starting node. The decision variable $A_{u,i,v,t}$ is a decision variable that represent the volume (ft^2) of goods (u) picked up at node i by vehicle v at time t. Similarly, when a vehicle arrives at a node, it is allowed to drop off goods at the node. Therefore, the decision variable $B_{u,i,v,t}$ is introduced to represent the volume of goods (u) dropped off at node j by vehicle v during time t. *Equation 4* ensures goods (u) can only be picked up by vehicle v at node i during time t only if the vehicle starting a route at that node during that time. Similarly, *Equation 5* ensures goods (u) can only be dropped off to node j by vehicle v if the vehicle is arriving to node j at a certain time. Note that $\beta_{i,r,v}$ represents the time periods for a vehicle (v) to arrive at node i on route r after the route has been started.

$$\sum_{u \in Del_v} A_{u,i,v,t} \leq Q_v \sum_{r \in R_v | i \in S_r} X_{r,v,t-\beta_{i,r,v}} \quad \forall v \in V, \forall i \in S_r, \forall t \in T \tag{2}$$

$$\sum_{u \in Del_v} B_{u,i,v,t} \leq Q_v \sum_{r \in R_v | i \in S_r} X_{r,v,t-\beta_{i,r,v}} \quad \forall v \in V, \forall i \in S_r, \forall t \in T \tag{3}$$

To track the volume of goods on any given vehicle, the decision variable $Z_{u,v,t}$ is introduced to represent the volume of goods (u) on vehicle v during time t. The following constraint is a vehicle inventory balance that ensures the current inventory of goods (u) is equivalent to the previous time periods inventory plus the ingoing and outgoing of goods.

$$Z_{u,v,t-1} - Z_{u,v,t} + \sum_{i \in Node_v} A_{u,j,v,t} - \sum_{j \in Node_v} B_{u,j,v,t} = 0 \quad \forall v \in V, \forall u \in Del_v, \forall t \in T \tag{4}$$

A vehicle has a limit to the volume of goods it can carry at a given time. This is denoted by the parameter Q_v which represents the max volume capacity of vehicle v. The following constraint ensures the total volume of goods on a vehicle at any time period does not exceed the max capacity of the vehicle.

$$\sum_{u \in Del_v} Z_{u,v,t} \leq Q_v \quad \forall v \in V, \forall t \in T \tag{5}$$

The final vehicle constraint ensures that if a vehicle is not currently traveling, then it cannot carry any goods. This is to prevent goods from being stored on a non-utilized vehicle.

$$Q_v \sum_{r \in R_v} \sum_{t\prime - \alpha_{r,v}}^{t} X_{r,v,t\prime} \geq \sum_{u \in Del_v} Z_{u,v,t} \quad \forall v \in V, i = Home_v, \forall t \in T \tag{6}$$

Inventory Constraints

The next batch of constraints ensure the inventory levels at each plant and DC node is balanced each time period, and to ensure the demand of the retailers is being met. The decision variable $I_{u,i,t}$ denotes the volume of goods (u) is being stored at node i during time t. Additionally the parameter $P_{u,i,t}$ is the volume of goods (u) produced at plant i during time t. The following is an inventory balance constraint for all plant nodes where *Plant* is the set of all plant nodes.

$$P_{u,i,t} + I_{u,i,t-1} - I_{u,i,t} - \sum_{v \in V | i \in Node_v \wedge u \in Del_v} A_{u,i,v,t} = 0 \quad \forall u \in U, \forall i \in Plant, \forall t \in T \tag{7}$$

A similar inventory balance constraint is needed for the DC nodes. The following constraint ensures the current inventory is equivalent to the previous time periods inventory plus the ingoing an outgoing of goods that are either picked up or dropped off by vehicles. Additionally, *DC* is the set of all DC nodes.

$$I_{u,i,t-1} - I_{u,i,t} + \sum_{v \in V | i \in Node_v \wedge u \in Del_v} \left(-A_{u,i,v,t} + B_{u,i,v,t}\right) = 0 \quad \forall u \in U, \forall i \in DC, \forall t \in T \tag{8}$$

The parameter $D_{u,j,t}$ is used to represent a node's (j) demand for a good (u) at time t. This demand will always take place in the time period that represents the very end of the day. For example, if there were 20 time periods in a day, then the stores demand must be met before $t=20$. This is to ensure the vehicles have plenty of time to deliver to the stores on time. The following constraint ensures the demand of a store is always met where *Store* is the set of all store nodes.

$$\sum_{t'=0}^{t} \sum_{v \in V | j \in Node_v \wedge u \in Del_v} B_{u,j,v,t'} \geq \sum_{t'=0}^{t} D_{u,j,t'} = 0 \quad \forall u \in U, \forall j \in Store, \forall t \in T \tag{9}$$

The following two constraints set the initial inventory of a node as well as a vehicle. The initial inventory of a vehicle is simply 0, but the initial inventory of a node is calculated based off the estimated volume of goods that will flow through the node. Section 4 will explain how this data is calculated. Let $I^0_{u,i}$ represent the initial inventory of goods u at node i.

$$Z_{u,v,0} = 0 \quad \forall v \in V, \forall u \in Del_v \tag{10}$$

$$I_{u,i,0} = I^0_{u,i} \quad \forall u \in U, \forall i \in M \tag{11}$$

Objective Function

There are two main costs incurred within this supply chain: the holding cost per ft^3 of goods and the cost per mile of operating a vehicle. The holding cost per ft^3 of goods for each time period at node i is denoted by H_i, and the total cost of a vehicle taking route r is denoted by C_r which is derived from the product of the cost per mile of operating a truck (C_v) and the total distance in miles of route r ($dist_r$). The following equation denotes the objective function which is to minimize the total cost.

$$Minimze: \qquad \sum_{u \in U} \sum_{i \in M} \sum_{t \in T} H_i I_{u,i,t} + \sum_{v \in V} \sum_{r \in R_v} \sum_{t \in T} C_r X_{r,v,t} \tag{12}$$

It is assumed that the cost parameter h_i includes all operating and overhead costs associated with holding inventory. Similarly, it is also assumed c_v captures all operating and overhead costs associated with operating a vehicle. The entire model can be seen in table 1.

Complete Model Formulation

mix
$$\sum_{u\in U}\sum_{i\in M}\sum_{t\in T} H_i I_{u,i,t} + \sum_{v\in V}\sum_{r\in R_v}\sum_{t\in T} C_r X_{r,v,t} \tag{12}$$

s.t.
$$\sum_{r'\in R_v}\sum_{t'=t}^{t+\alpha_{r,v}} X_{r',v,t'} - 1 \le M\left(1 - X_{r,v,t}\right) \quad \forall v \in V, \forall r \in R_v, \forall t \in T \tag{1}$$

$$\sum_{u\in Del_v} A_{u,i,v,t} \le Q_v \sum_{r\in R_v | i\in S_r} X_{r,v,t-\beta_{i,r,v}} \quad \forall v \in V, \forall i \in S_r, \forall t \in T \tag{2}$$

$$\sum_{u\in Deliver_v} B_{u,i,v,t} \le Q_v \sum_{r\in R_v | i\in S_r} X_{r,v,t-\beta_{i,r,v}} \quad \forall v \in V, \forall i \in S_r, \forall t \in T \tag{3}$$

$$Z_{u,v,t-1} - Z_{u,v,t} + \sum_{i\in Node_v} A_{u,j,v,t} - \sum_{j\in Node_v} B_{u,j,v,t} = 0 \quad \forall v \in V, \forall u \in Del_v, \forall t \in T \tag{4}$$

$$\sum_{u\in Del_v} Z_{u,v,t} \le Q_v \quad \forall v \in V, \forall t \in T \tag{5}$$

$$Q_v \sum_{r\in R_v}\sum_{t'-\alpha_{r,v}}^{t} X_{r,v,t'} \ge \sum_{u\in Del_v} Z_{u,v,t} \quad \forall v \in V, i = Home_v, \forall t \in T \tag{6}$$

$$P_{u,i,t} + I_{u,i,t-1} - I_{u,i,t} - \sum_{v\in V | i\in Node_v \wedge u\in Del_v} A_{u,i,v,t} = 0 \quad \forall u \in U, \forall i \in Plant, \forall t \in T \tag{7}$$

$$I_{u,i,t-1} - I_{u,i,t} + \sum_{v\in V | i\in Node_v \wedge u\epsilon Del_v} \left(-A_{u,i,v,t} + B_{u,i,v,t}\right) = 0 \quad \forall u \in U, \forall i \in DC, \forall t \in T \tag{8}$$

$$\sum_{t'=0}^{t}\sum_{v\in V | j\in Visit_v \wedge u\epsilon Del_v} B_{u,j,v,t'} \ge \sum_{t'=0}^{t} D_{u,j,t'} = 0 \quad \forall u \in U, \forall j \in Store, \forall t \in T \tag{9}$$

$$Z_{u,v,0} = 0 \quad \forall v \in V, \forall u \in Del_v \tag{10}$$

$$I_{u,i,0} = I^0_{u,i} \quad \forall u \in U, \forall i \in M \tag{11}$$

$$X_{r,v,t} \in \{0,1\} \quad \forall v \in V, \forall r \in R_v, \forall t \in T \tag{13}$$

Table 1. Complete formulation of supply chain model

3.2. Collaborative Model

The primary difference between the collaborative and the non-collaborative model is the vehicles have no restrictions on what nodes they can travel to and what products they can carry. Suppose node 1 is a plant node; node 2 and 3 are DC nodes; node 4, 5, and 6 are store nodes; and a vehicle is stationed at node 1 (Figure 1). Suppose the company that owns node 1 has a competitor that owns node 3. In a network with no collaboration, that vehicle is not allowed to travel to that node. However, in a network with collaboration, that same vehicle is allowed to travel to node 3, and this creates additional routes the vehicle can take (colored in blue). It can be hypothesized that these additional routes within the collaborative network might yield savings in the travel cost.

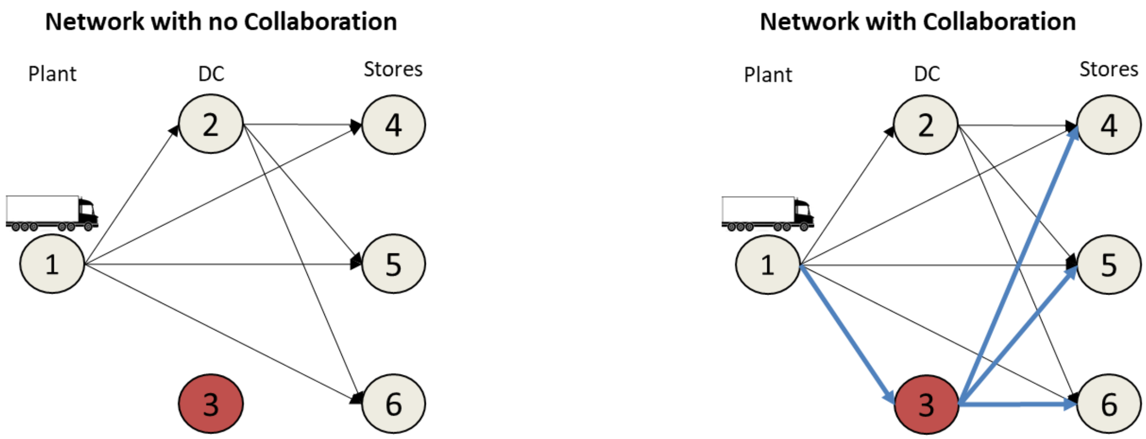

Figure 1. Vehicles in the network with collaboration are allowed to travel to any forward node within the network. The connections, seen in blue, are the additional routes the vehicles in the network with full collaboration can take.

Additionally, in collaborative network, that vehicle stationed at node one, can now collaborate with a competitor by making a stop at node 3 to pick up and deliver its competitors goods stored at node 3. This ability has the potential to further reduce the total operating cost of a supply chain.

4. Data Generation

With the lack of real life supply chain data, this research will rely on randomly generated supply chain data to test both the collaborative and non-collaborative models. Section 4.1 will describe how the nodes are generated, section 4.2 will explain how supply and demand is derived, and Section 4.3 will discuss how the initial inventory and number of vehicles are produced.

4.1. Node Generation

As previously mentioned, this supply chain is made up of three different types of companies: retailers, manufacturers, and 3PL's. Each of these companies have a different set of resources. For example, a manufacturer may have a plant, a distribution center, and a fleet of trucks; a retailer may have numerous stores, a distribution center, and a fleet of trucks; and a 3PL may have a distribution center, and a fleet of trucks. In order to capture the realities of a diverse supply chain, both the manufacturers and retailers are classified as being either a large, medium, or small company. Each classification comes with a different number of resources (Figure 2).

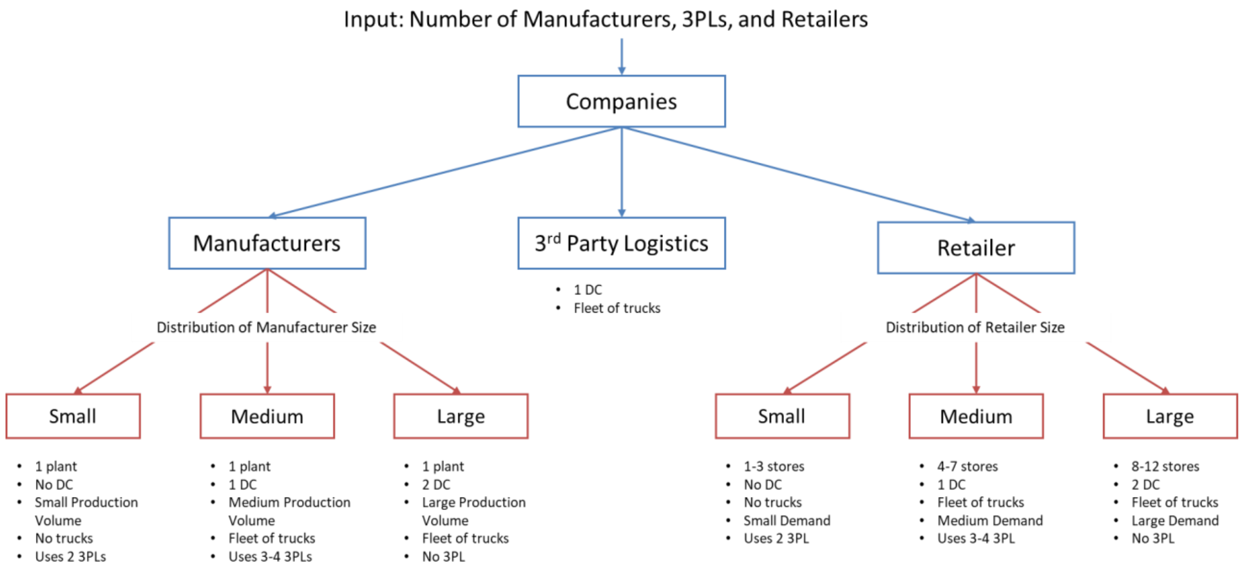

Figure 2. The supply chain contains three types of companies: manufacturers, 3PLs, and retailers. The manufacturers and retailers have different amounts of resources depending on the size of the company.

The supply chain will be generated based off of the number of manufacturers, 3PLs, and retailers specified. The manufacturers and retailers are categorized as either small, medium, or large which is dependent on a distribution that is provided. The experiments discussed in section 5 will be tested with various distributions. The 3PLs will be of the same size, and will all have a single distribution center and trucks that can be contracted out to the manufacturers and retailers.

As mentioned, a manufacturer will have a different set of resources based on the size. A small manufacturer has one plant, no DC, small production volume, no fleet of trucks, and will depend on two 3PLs. A medium manufacturer has one plant, one DC, a medium production volume, a fleet of trucks, and will use three to four 3PLs. A large manufacturer has one plant, two DCs, a large production volume, a fleet of trucks, and will not use 3PLs.

Similarly, a retailer will have a different set of resources depending on the size. A small retailer has one to three stores, no DC, no trucks, a small level of demand, and will depend on two 3PLs. A medium retailer has four to seven stores, one DC, a fleet of trucks, a medium level of demand, and will use three to four 3PLs. A large retailer has eight to twelve stores, two DCs, a fleet of trucks, a large level of demand, and will not use 3PLs.

The 3PL a company uses will be randomly selected from the list of all 3PLs. Also, supply chain network will be within a rectangular region with a fixed height and width. The experiments in section 5 will test the model on different region sizes. The location of a node (plant, DC, or store) within this region is a randomly generated (x,y) coordinate. From these coordinates, the distances between all nodes can be calculated. For the sake of simplicity, the Euclidean distance will be used. All of the company types and its associated resources are shown in table 2.

Company Type	Company Size	Number of Plants	Number of Stores	Number of DC's	Production Levels	Demand Levels	Vehicles	3PLs Used
Manufacturer	Small	1	0	0	Low		No	2
Manufacturer	Medium	1	0	1	Medium		Yes	3-4
Manufacturer	Large	1	0	2	High		Yes	0
3PL		0	0	1			Yes	
Retailer	Small	0	1-3	0		Low	No	2
Retailer	Medium	0	4-7	1		Medium	Yes	3-4
Retailer	Large	0	8-12	2		High	Yes	0

Table 2. The breakdown of the types of companies, the sizes, and the resources associated them.

4.2. Production and Demand

A manufacturer and retailer has a different volume of production and demand depending on the size of the company. As previously mentioned, a manufacturer serves every store in the network, and there are three variables that go into calculating the daily demand (*DD*) of goods (*u*) from plant *i* for store *j*: the average daily demand (*ADD*) for all stores, the supply volume multiplier of plant *i* (SVM_i), and the demand volume multiplier of store *j* (DVM_j).

$$DD_{u,j} = ADD \times SVM_i \times DVM_j \quad \forall i \in Plant, \forall u \in i, \forall j \in Store \tag{14}$$

The daily production rate for each plant *i* ($DP_{u,i}$) is derived from the total daily demand (*DD*) for each customer of *i* multiplied by a daily safety stock percentage (*SS*). The production rate per time period ($P_{u,i,t}$) is simply $DP_{u,i}$ divided by the number of time periods in a single day (T^D). The daily production rates per time period for all plants (*i*) is derived from the following equation.

$$DP_{u,i} = \sum_{j \in Store} DD_{i,j}(1 + SS) \quad \forall i \in Plant, \forall u \in i \tag{15}$$

$$P_{u,i,t} = \frac{DP_{u,i}}{T^D} \quad \forall i \in Plant, \forall u \in i, \forall t \in T \tag{16}$$

An average daily demand of 500 cubic feet is used in the daily demand calculations. The supply and demand volume multiplier for each retailer and manufacturer size is based off of a uniform distribution. Since this model is based off a 10 hour (600 minute) workday and a 30 minute time period interval, the number of time periods in a single day is 20 (600 minutes / 30 minutes). A variety of safety stocks will be used during the final experiments: 5%, 10%, and 25%. All of these values can be seen in table 3.

Variables in Production and Demand Calculations	
Average Retailer Daily Demand	500 cubic feet of goods
Demand Volume Multiplier of Small Retailers	X ~ u(0.3, 0.7)
Demand Volume Multiplier of Medium Retailers	X ~ u(0.9, 1.1)
Demand Volume Multiplier of Large Retailers	X ~ u(1.5, 1.9)
Supply Volume Multiplier of Small Manufacturers	X ~ u(0.3, 0.7)
Supply Volume Multiplier of Medium Manufacturers	X ~ u(0.9, 1.1)
Supply Volume Multiplier of Large Manufacturers	X ~ u(1.5, 1.9)
Safety Stock Percentage	5%, 10%, or 25%
Number of Time Periods in a Single Day	20

Table 3. The values of the variables used in the production and demand calculations.

4.3. Initial Inventory and Number of Vehicles

An initial inventory of goods at each plant and DC is first populated to replicate a supply chain in a steady state. There are three different types of nodes that require an initial inventory: a plant used by a manufacturer, a DC used by a manufacturer, and a DC used by a retailer. The equations that initialize these three initial inventories is shown in table 4.

Initial Inventory Calculations		
Plant used by Manufacturer	$I_{u,i,0} = DP_{u,i} \times Inventory\ Multiplier \quad \forall i \in Plant, \forall u \in i$	(17)
DC used by Manufacturer	$I_{u,i,0} = DP_{u,i} \times Inventory\ Multiplier \quad \forall i \in DC, \forall u \in i$	(18)
DC used by Retailer	$I_{u,i,0} = \sum_{j \in Store} DD_{u,j} \times Inventory\ Multiplier \quad \forall i \in DC, \forall u \in i$	(19)

Table 4. Equations for calculating the initial inventory of all plants and DC's in the supply chain.

The initial inventory of a plant and a DC used by a manufacturer is derived from the daily production of goods (u) that plant i produces multiplied by an inventory multiplier, and the initial inventory of a DC used by a retailer is calculated from the sum of daily demand from each store that the retailer owns multiplied by the inventory multiplier. An inventory multiplier of 1 is used as the control, and the final tests will experiment with different multipliers.

As section 4.1 mentioned, a manufacturer and a retailer can either own a vehicle or rent a vehicle from a 3PL. A vehicle capacity of 3,000 square feet is used for each vehicle, and a company will have enough vehicle capacity to carry an entire day of either production or demand depending on if the company is a manufacturer or retailer. Then the number of vehicles determined is evenly distributed between the company's plants, DC's, and stores.

5. Experiment

This section presents the computational results produced from the two models tested on over 2,500 generated supply chains. Section 5.1 will describe how the instances are generated based on the different parameters. Section 5.2 will discuss and compare the results produced from the non-collaborative and collaborative models.

All tests were performed through the Arkansas High Performance Computing Center on an Intel E5-4640 2.4 GHz CPU with 32 processors and 768 GB of memory. The experiment was programmed in Python using the Google OR-Tools python library to formulate and solve the model. The open source MIP solver Solving Constraint Integer Programs (SCIP) version 7.0 [17] is used to solve the models. Additionally, the multiprocessing library in Python *concurrent.futures* library is used to take advantage of the processors on the High Performance Computer. A time limit of one hour is used to solve each instance.

5.1. Test Instances

The experiment consists of 2,662 test instances. During each instance a supply chain is generated based off of certain parameters, both a collaborative and a non-collaborative model is built based on the supply chain data generated, and both models are solved. Additionally, metrics such as total miles driven, total cost, total travel cost, total inventory cost, average truck utilization, and number of trucks used are calculated after a model is solved.

There are many parameters that determine the configuration of the supply chain generated during each instance. The primary ones that are altered to produce a variety of instances are:

- Number of Companies – includes the number of retailers, manufacturers, and 3PLs.
- Retailer Size Distribution – includes the percentage of large, medium, and small retailers.
- Manufacturer Size Distribution – includes the percentage of large, medium, and small manufacturers.
- Region Square Miles – the square miles of the supply chain region.
- Max Vehicle Stops – The maximum nodes a truck is allowed to visit on a single route.

All the parameters and the associated values can be seen in table 5.

Supply Chain Parameters	
Number of Companies ([Retailers, Manufacturers, 3PLs])	{[1,2,2], [2,5,5], [5,10,10]}
Number of Time Periods	20
Minutes Between Time periods	30
Minutes in a Day	600 (10 hours)
Retailer Size Distribution ([large, medium, small])	{[0.33,0.33,0.33], [0.2,0.3,0.5], [0.5,0.3,0.2], [0.1,0.4,0.5], [0.1,0.1,0.8], [0.8,0.1,0.1], [0.1,0.8,0.1]}
Manufacturer Size Distribution ([large, medium, small])	{[0.33,0.33,0.33], [0.2,0.3,0.5], [0.5,0.3,0.2], [0.1,0.4,0.5], [0.1,0.1,0.8], [0.8,0.1,0.1], [0.1,0.8,0.1]}
Square Miles of Region	{25, 250, 1000}
Average Daily Demand	500
Safety Stock Percentage	{5%, 10%, 25%}
Truck Speed Limit (mph)	60
Truck Cost Per Mile ($/mile)	1.821
Truck Capacity (sq ft)	3,000
Max Route Time (time periods)	20
Max Stops	{1, 2, 3}
Storage Cost ($/sq ft)	0.001

Table 5. This table contains all the parameters and its values that are used to generate the supply chain instances that populate the parameters of the model.

The next section will compare the results from running the non-collaborative and collaborative model on the different supply chain configurations generated. The main attributes to compare are the number of companies, the square miles of the region, and the maximum number of stops allowed by the vehicles.

5.2. Results

After the generation of a single supply chain instances, both the non-collaborative and collaborative model will run, and then metrics such as total miles driven, total cost, total travel cost, total inventory cost, average truck utilization, and number of trucks used are collected to compare the results from the two models. The final results are displayed in table 6, and in almost all cases, the collaborative model outperforms the non-collaborative model across all metrics. An instance will have no feasible solution if either the non-collaborative or collaborative fail to find a feasible solution within the 1 hour time limit, and due to the complexity of the model as the number of companies increases, this experiment was only able to model small supply chains with under 15 companies. The instances generated with 5 retailers, 10 manufacturers, and 10 3PL's failed to find a feasible solution in the allotted time due to the time and space complexity of the models. Also, of the 882 instances tested using a region area of 1,000 square miles, only about 15% of the instances were able to find a feasible solution. For that reason, these instances were discarded, but it is worth noting for the few instances that found a feasible solution, there was a slight improvement across all performance metrics.

Number of Companies	Region Size	Max Stops	Total Instances	No Feasible Solutions	Total Cost % Decrease	Total Travel Cost % Decrease	Total Inventory Cost % Decrease	Average Truck Utilization % Increase	Number of Trucks Used % Decrease
[1,2,2]	25	1	147	90	$5.05^{(0, 38.47)}$	$3.26^{(-60.16, 45.05)}$	$6.33^{(-23.11, 54.21)}$	$17.24^{(0, 35.26)}$	$1.75^{(0, 33.33)}$
[1,2,2]	25	2	147	9	$14.07^{(-1.38, 35.68)}$	$-8.52^{(-83.43, 49.53)}$	$20.86^{(-46.49, 71.04)}$	$17.03^{(-1.91, 48.80)}$	$5.92^{(0, 50)}$
[1,2,2]	25	3	147	3	$11.54^{(-6.60, 43.84)}$	$3.45^{(-85.16, 52.63)}$	$14.23^{(-31.63, 67.08)}$	$14.46^{(-12.56, 44.25)}$	$4.81^{(0, 50)}$
[1,2,2]	250	1	147	74	$6.25^{(0, 50.70)}$	$8.05^{(0, 56.77)}$	$-2.70^{(-59.70, 22.99)}$	$0.24^{(-4.57, 5.91)}$	$6.13^{(0, 33.33)}$
[1,2,2]	250	2	147	13	$12.14^{(-2.04, 61.21)}$	$14.91^{(-6.87, 66.59)}$	$0.26^{(-28.55, 38.48)}$	$3.20^{(-13.20, 23.98)}$	$10.52^{(0, 50)}$
[1,2,2]	250	3	147	9	$10.95^{(-43.31, 56.77)}$	$11.89^{(-132.37, 62.67)}$	$2.89^{(-23.04, 44.35)}$	$3.18^{(-17.25, 28.06)}$	$8.05^{(0, 50)}$
[2,5,5]	25	1	147	53	$6.47^{(-0.02, 55.15)}$	$23.28^{(-70.41, 60.13)}$	$3.98^{(0, 63.50)}$	$24.40^{(7.56, 46.65)}$	$0.35^{(0, 20)}$
[2,5,5]	25	2	147	11	$13.60^{(-7.33, 55.05)}$	$-3.39^{(-135.09, 74.01)}$	$17.28^{(-7.46, 62.79)}$	$19.53^{(-3.31, 41.86)}$	$1.57^{(0, 28.57)}$
[2,5,5]	25	3	147	88	$16.38^{(-18.79, 50.09)}$	$-0.67^{(-238.49, 69.07)}$	$21.78^{(-50.49, 64.65)}$	$21.47^{(-0.70, 41.67)}$	$3.72^{(0, 57.89)}$
[2,5,5]	250	1	147	36	$16.63^{(-6.56, 69.78)}$	$29.74^{(-19.98, 82.75)}$	$-2.15^{(-19.76, 16.70)}$	$1.44^{(-6.09, 28.66)}$	$12.94^{(0, 57.14)}$
[2,5,5]	250	2	147	79	$11.15^{(-72.74, 65.37)}$	$13.15^{(-129.74, 71.88)}$	$1.43^{(-16.64, 26.55)}$	$0.96^{(-20.44, 26.18)}$	$7.93^{(0, 57.14)}$
[2,5,5]	250	3	147	103	$19.67^{(-10.02, 47.38)}$	$28.37^{(-17.26, 64.55)}$	$2.31^{(-14.50, 16.43)}$	$1.87^{(-10.21, 16.68)}$	$3.24^{(0, 50)}$

Table 6. Final results produced from comparing the metrics from the non-collaborative and collaborative model for each instance. The metric values shown are averaged across the total instances in each category, and are structured as $average^{(minimum,\ maximum)}$

Based on the results in table 6, it appears that collaboration is most impactful for smaller region sizes since the region size of 25 seems to have larger improvements. Also, as the number of companies increases from [1,2,2] to [2,5,5], it appears collaboration also allows for a greater level of improvements. It is worth noting that the majority of these solutions are feasible and not optimal due to the time complexity of these models It can be hypothesized that the improvements shown in table 6 could potentially be greater if the optimal solutions were found.

6. Conclusions

This paper quantifies the benefits associated with a collaborative supply chain. The results discovered lower costs and improved vehicle utilization in a collaborative supply chain. The idea of collaboration and the physical internet has tremendous potential to significantly improve the efficiency and operating costs of a supply chain. This research was able to estimate the potential cost savings in small supply chains with less than 15 companies, but the cost savings of large supply chains with hundreds or thousands of companies has yet to be determined. It can be hypothesized that as this similar methodology is scaled up to larger supply chains, there will be more opportunities for collaboration, and therefore the cost savings and efficiency will increase with size. To get results for larger supply chains, a heuristic will likely need to be created, for the time and space complexity of a mixed integer program will likely be too severe to find solutions.

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