YAŞAR UNIVERSITY

GRADUATE SCHOOL

MASTER'S THESIS

THE EFFECT OF LATERAL TRANSSHIPMENT POLICIES FOR MULTI-OBJECTIVE OPTIMIZATION AND SIMULATION MODELS IN SUPPLY CHAIN NETWORKS

SERKAN BAYRAM

THESIS ADVISOR: ASSIST. PROF. DR. GIZEM MULLAOĞLU

INDUSTRIAL ENGINEERING

PRESENTATION DATE: 13.11.2020

BORNOVA / İZMİR
NOVEMBER 2020

ABSTRACT

THE EFFECT OF LATERAL TRANSSHIPMENT POLICIES FOR MULTI-OBJECTIVE OPTIMIZATION AND SIMULATION MODELS IN SUPPLY CHAIN NETWORKS

Bayram, Serkan
MSc, Industrial Engineering
Advisor: Assist. Prof. Gizem MULLAOĞLU
November 2020

Supply chain systems play a crucial role to meet customer demands on time, especially in competitive markets. Nowadays, these systems have to consider the environment as much as economical perspectives because of the increase in carbon emission awareness and possible future regulations. Therefore, in this thesis, we developed a multi-objective mixed-integer programming and simulation models while allowing lateral transshipment distribution strategy which provides product transportation within the echelons. Also, electric vehicles are considered in these models to give more opportunities to reduce carbon emissions. As a result of these models' computational studies, it has been observed that lateral transshipment could increase the efficiency of the supply chain. However, it has been noticed that when carbon emission is more superior to the total cost, less lateral transshipment occurs. Therefore, we can conclude that even though lateral transshipment provides efficiency in the total cost, it is less favorable when carbon emission is more important. Moreover, it has been observed that electric vehicles have a positive effect on total carbon emission and total cost as expected. Hence, electric vehicles can play a crucial role in the supply chain system if they can be integrated more in line with lateral transshipment policies.

Key Words: lateral transshipment, multi-echelon supply chain, multi-objective mixed integer programming, simulation, carbon emission

ÖZ

YANAL AKTARMA POLİTİKALARININ TEDARİK ZİNCİRİ AĞLARI İÇİN ÇOK AMAÇLI EN İYİLEME VE BENZETİM MODELLERİNE ETKİSİ

Bayram, Serkan
Yüksek Lisans, Endüstri Mühendisliği
Danışman: Dr. Öğr. Üyesi Gizem MULLAOĞLU
Kasım 2020

Tedarik zinciri sistemleri, özellikle rekabetçi pazarlarda, müşteri taleplerini zamanında karşılamada önemli bir rol oynamaktadır. Günümüzde, artan karbon emisyonu hassasiyeti nedeniyle bu sistemlerin karbon emisyonlarını da dikkate alması gerekmektedir. Bu nedenle, bu tezde, tedarik zincirinin esnekliğini attırmak için kademeler arasında ürün aktarımını sağlayan yanal aktarma dağıtım stratejisine olanak sağlayan ve karbon emisyonunu dikkate alan çok amaçlı tamsayı karışık doğrusal programlama ve benzetim modelleri geliştirilmiştir. Ayrıca, karbon emisyonunu azaltmaya yönelik daha fazla seçenek sunmak için bu modellerde elektrikli araç seçenekleri de dikkate alınmıştır. Bu modellerin sonuçlarına göre, yanal aktarma seçeneğinin, tedarik zincirinin verimliliğini arttırabileceği gözlemlenmiştir. Ancak, karbon emisyonunun öneminin daha baskın olduğu durumlarda, bu seçeneğin kullanımının azaldığı fark edilmiştir. Bu nedenle, yanal aktarma seçenekleri toplam maliyet açısından hala faydalı bir seçenektir, ancak karbon emisyonu daha önemli hale gelirken kullanımı azalmaktadır. Ayrıca, elektrikli araçların beklenildiği gibi toplam karbon emisyonu ve toplam maliyet üzerinde olumlu bir etkisi olduğu gözlemlenmiştir. Dolayısıyla elektrikli araçlar tedarik zinciri sisteminde yanal aktarmaya uyumlu olacak şekilde kullanılabilirse önemli bir rol oynayabilir.

Anahtar Kelimeler: yanal aktarma, çok kademeli tedarik zinciri, çok amaçlı tamsayı karışık doğrusal programlama modeli, benzetim, karbon emisyonu

ACKNOWLEDGEMENTS

First of all, I would like to express my sincere gratitude to my supervisor Gizem Mullaoğlu for her guidance, patience and great support during this study.

I also would like to thank the jury members Banu Yetkin Ekren and Ali İrfan Mahmutoğulları for reading my thesis and accepting to participate in my thesis defense.

I express my gratitude to my closer friends for their unconditional support at any moment of my life.

Last, but not least, I would like to express my enduring love to my parents Nurdan Bayram and Ahmet Bayram, who are always supportive, loving and caring to me in every possible way in my life.

Serkan BAYRAM

İzmir, 2020

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

Growing population of the world raises the demand and also increase in the number of suppliers fosters competition. This gives more importance to supply chain systems because companies must reach customer demands right on time to survive in the competitive market. Given that, supply chain and inventory-related costs constitute a large proportion of total costs. For instance, the ratio of logistics costs to the gross national product in the United States is approximately 8% (CSCMP, 2018). Hence, increased competition, globalization, and growth of the current market push companies to be more reactive over growing customer demands. Since, traditional design of a supply chain systems allow only product flows from one echelon to the next, lateral transshipment distribution strategy can give more opportunity to improve these systems' performance because it allows product flow within the echelon (Paterson et al., 2011). On the other hand, while satisfying the customer demands and improving supply chain systems performance, systems are using more transportation flow. Thus, increasing transportation flows brings more vehicles on the roads which cause more carbon emission. This is one of the serious environmental problems nowadays. For instance, road freight transportation reached a transportation share of 72% and released 93% of the CO2 emissions from surface freight transport in Germany (Hütter et al., 2013). As a result of this recent undesirable progress, many of the governments established regulations to reduce carbon emission and it forces companies to be more responsible for the environment. At this point, electric vehicles can help to reduce carbon emission amounts because it has been found that electric trucks can reduce carbon emission and applicable to as a road freight vehicle in the industry (Liimatainen et al.,2019). But the companies still have to tackle creating an effective supply chain and inventory management while caring environmental pollution to satisfy the customer demands. Therefore, the aim of the thesis is to provide insights about lateral transshipment policy effectiveness and electric vehicle usage impact in the supply chain network while considering carbon emission with the common total cost structure including transportation, holding, and lost sales. Multi-objective mixed-integer linear programming optimization models (MOMILP) and simulation models are developed to achieve this aim.

The multi-objective mixed-integer linear programming optimization models are used when the demand is known by certainty. It may not be totally practical for some applications where certain demand information is not possible. Yet, there can be some other applications in which our proposed model may work quite well where uncertainty is not present most of the time. For instance, precious metals, tobacco products, and beer & liquor industries are examples where uncertainty is observed to be low (Dyer et. al, 2014). This model minimizes cost and carbon emission in a given multi-echelon supply chain network which contains lateral transshipment and multi-sourcing options by considering lead times.

The simulation models are employed for the uncertain demands. (s, S) policy is used to overcome demand uncertainty and satisfy demands in models.

In both models, we present electric vehicles options besides gasoline vehicles to prevent more carbon emissions. Since electric vehicle development and battery technologies are improving, we can expect that they will play a crucial role in the supply chain transportation part in the future.

The remainder of this thesis is organized as follows. Literature review over multi-echelon inventory optimization, inventory policies, lateral transshipment, carbon emission sensitive supply chain systems, and electric vehicles are provided in Chapter 2. In Chapter 3, problem definition and assumptions of the supply chain are described for MOMILP models. In Chapter 4, MOMILP models are constructed. The results of MOMILP models and comparison of MOMILP models are represented in Chapter 5. In Chapter 6, simulation models and algorithms are presented. The results of the simulation models and comparison of simulation models are represented in Chapter 7. Managerial insight is provided in Chapter 8. Finally, in Chapter 9 conclusion and future work are provided.

CHAPTER 2
LITERATURE REVIEW

The supply chain is a system that deals with flows of products based on customer demands. The generalized structure of the supply chain is a multi-echelon network structure which is usually composed of a supplier, distribution centers, and retailers. Inventory has a crucial role in the supply chain because the optimal stock level should be determined so that the customer demands can be satisfied right on time. Otherwise, unsatisfied demand occurs which may result in customer loss, especially for the competitive markets. Our research focus on multi-echelon supply chain networks and inventory management optimization. Furthermore, we consider lateral transshipment and electric vehicles to reduce carbon emissions. As a result, we intend to provide important studies in this section that shed light into our research.

Initially, studies over traditional supply chain systems were provided. These systems are only allowed product flow between echelons. Therefore, transportation flows occur only from one echelon to the next, i.e. from manufacturers to distribution centers and from distribution centers to retailers. For instance, You and Grossman (2010) created a mixed-integer non-linear programming model for the chemical industry. The represented multi-echelon network consists of plants, distribution centers, and wholesalers. In the study, product distribution is allowed only between echelons. They proposed a decomposition algorithm based on Lagrangian relaxation and piecewise linear approximation to solve the model and their algorithm can obtain a global optimal solution or near optimum. Similarly, Keskin et al. (2010) proposed a solution to vendor selection and inventory replenishment decision problems. They used (Q, R) policy as an inventory replenishment policy. In this problem, their goal is to find the minimum total cost which includes transportation cost, holding cost, backorder cost, and procurement cost. They developed an MINLP model and solved it by metaheuristic powered simulation-optimization approach. Therefore, they determine optimum inventory levels and the selection of vendors to achieve their goal. They conclude that this approach can be useful in determining the best vendors and optimum inventory levels. In another study, Amiri Aref et al. (2018) studied two-echelon supply chain networks. Their objective is to find the minimum cost in a location-inventory optimization problem. They applied (s, S) policy to deal with the demand uncertainty. They developed a mathematical model to achieve this goal and they solved the model by using the sample average approximation approach. According to their results, their modeling approach is can be useful to deal with practical cases efficiently and creates more powerful design solutions under uncertainty.

So far, we described research over the ‘traditional’ design of supply chain systems which are hierarchical. Therefore, transportation flows occur only from one echelon to the next, i.e. from manufacturers to distribution centers and from distribution centers to retailers. To make these systems more flexible, some of the supply chain network systems allow lateral transshipment. Lateral transshipment allows the product flow within the echelon, i.e. between distribution centers or retailers (Paterson at al.). Therefore, our investigations over multi-echelon supply chain network with lateral transshipment include optimization models, analytical models, and simulation models as follows:

Chartniyom et al. (2007) proposed a new lateral transshipment policy which is called service level adjustment (SLA). SLA policy determines the amount of transshipment quantity by considering emergency lateral transshipment with preventive lateral transshipment. They used (Q, R) policy in retailer inventories. They applied their policy to a two-echelon supply chain which is composed of a supplier and retailers. According to their results, they found that SLA policy is better than other policies. In another study, Reddy et al. (2011) proposed a linear programming model to minimize the total cost in the two-stage supply chain network. The supply chain network is composed of one warehouse and three retailers. Lateral transshipment among retailers is allowed in the supply chain network. They applied the linear programming model to the confectionery industry. According to their experiment results, they get better results than the existing total cost results. Also, simulation optimization is used to find optimum lateral transshipment amounts. For instance, Yücesan et. al, (2012) proposed a solution to optimal multi-location transshipment problem by considering the base stock quantities. Their supply chain system is composed of one supplier and N distinct stocking locations. Their purpose is to minimize the total cost. They used simulation optimization combined with an LP/network flow formulation and IPA (infinitesimal perturbation analysis) to reach their purpose.

In another study, Vicente et al. (2015) presented a multi-echelon supply chain network that is composed of a central warehouse, regional warehouses retailers. The network allows lateral transshipment among warehouses and retailers. They used Mixed Integer Linear Programming (MILP) to optimize the multi-product flow among nodes. In this study, they compared continuous review, periodic review, and proposed an inventory management system. According to their model results, proposed inventory management gave the best result.

Lateral transshipment studies are also connected to a new business model that is called Offline to Online. For instance, Zhao et al. (2015) tried to find an optimal policy for a new business model called Offline to Online (OTO) by checking the centralized OTO, decentralized OTO, and with/without lateral transshipment policy options. Their supply chain model is composed of one manufacturer, one retailer, and one e-store. Lateral transshipment is allowed between e-store and retailer in the model. According to their model results, they found that lateral transshipment can be always beneficial for the supply chain. In another study, Nakandala et al. (2017) investigated the lateral transshipment (LT) effect in the supermarket chain over perishable products. They used a periodic review policy in inventories. As a result of their research, implementing LT to the perishable inventory management increased the performance of inventory management.

Lateral transshipment studies also link to Physical Internet (PI) phenomenon. For instance, Yang et al. (2017) compared the classical inventory models with PI (Physical Internet) which is an interconnected logistic system. Hence, PI allows multisourcing. Their network is composed of a plant, three hubs, and four retailers. They applied a simulation-based optimization modeling method to minimize the cost. The model uses (Q, R) policy to satisfy the uncertain demand. Therefore, it finds the optimal Q and R levels. As a result of this optimization model, they found that PI model is better than the classical inventory models. Similarly, Ekren et al. (2018) proposed a solution to PI based inventory control model in a multi-echelon supply chain. Their supply chain network is composed of one supplier, three distribution hubs, and two retailers. Each of them has an inventory. They used (s, S) policy on the inventory management side and they used lateral transshipment option among distribution hubs to minimize the total cost. Their aim is to find optimum lateral transshipment policy and they tried to answer the question of “Is the lateral transshipment option beneficial for the supply chain?” question. According to their experiment results, the lateral transshipment option more beneficial than without the lateral transshipment option. Also, dynamic programming approach is used to compare the lateral transshipment efficiency in supply chain management. For example, Meissner et al. (2018) tried to answer questions like “When to order?’’, “From which location?’’ and “How much to transport?” with a multi-location inventory system under periodic review with a proactive lateral transshipment option. They developed a dynamic programming model to answer these questions and they found that the approximate dynamic programming policy more efficient compared to a no transshipment and other known heuristics. Moreover, Feng et al. (2018) studied emergency lateral transshipment (ELT) policy and preventive lateral transshipment (PLT) policy in a two-echelon supply chain network. The supply chain network is composed of one supplier and two-retailer. According to their model results, they obtained more benefit with higher customer patience and lower backorder cost with ELT. Last but not least in LT research, Firoozi et al. (2020) tried to answer the multi-echelon inventory optimization under non-stationary demand. Their multi-echelon supply chain network is composed of suppliers, production distribution centers, distribution centers, and customer zone stages. Single sourcing, multi-sourcing, and with/ without lateral transshipment options compared in this study. They proposed a MILP model to optimize the network. They used the sample average approximation method to find a solution. According to model results, lateral transshipment and multi-sourcing options considerably useful to improve the supply chain performance.

Because of the recent developments, supply chain models do not only focus on traditional objectives like cost or customer satisfaction but also considers the environmental impact. This is mainly because of global warming and its increasing negative effects. Therefore, governments established regulations over carbon emissions. As a result of environmental concerns and regulations, companies must be more sensitive to carbon emissions. Hence, our investigations over carbon sensitive supply chain network as follows:

Soysal et al. (2014) studied the international beef logistics chain, which is operating in Nova Andradina, Mato Grosso do Sul, Brazil, and exporting beef to European Union.

The supply chain is composed of production regions, third-party logistics (3PL) firms, slaughterhouses, and export ports. In the represented network system, trucks are rented from a 3PL firm and there are two types of trucks old ones and new ones. New trucks are more efficient than old trucks. In this article, the aim is to minimize the total cost and total greenhouse gas emission in representing the supply chain by developed a multi-objective linear programming model. According to experiment results, they found that there is a trade-off between logistics cost and amount of CO2 emissions from transportation and decreasing fuel efficiency of trucks increase the logistics cost and CO2 emissions. Therefore, they conclude that the developed model can help as a decision support tool and it can improve the supply chain network in the aspect of greenhouse gas emission and total cost. Some studies also investigate carbon policies such as carbon emission tax, carbon cap, and carbon cap and trade. For instance, Hammami et al. (2015) developed a multi-echelon single product production-inventory model under carbon emission policies. Carbon emission tax and carbon emission cap are used in the model as carbon emission policies. The article shows how carbon emissions are correlated to lead time, the inventory policy, and the multi-echelon context. Similarly, Peng et al. (2016) proposed a one-stage supply chain network that is composed of factories and sales points. They developed a multi-objective mixed-integer linear programming model to minimize total cost and carbon emission. According to their network, carbon emission is generated by factory allocation and product transportation. They applied carbon tax and carbon emission cap methodology to their model. They applied their model to a household electric appliance manufacturing industry in China. As a result of the experiment, they conclude that both of the methods incentivize a reduction of carbon emissions to the environment. Moreover, Manupati et al. (2018) developed a non-linear mixed-integer programming model over a multi-echelon supply chain. The proposed model has two objectives which are minimizing cost and minimizing CO2 emission. Thus, they investigated carbon tax, strict carbon capping, and carbon cap and trade policies. According to their experiment, they found that the carbon cap and trade policy is the most cost-effective one.

Lateral transshipment and cap-and-trade policy relationship is investigated as well. For instance, Wang et al. (2019) studied a large transnational manufacturer in a global garment supply chain which is consisting of a manufacturer, retailers, and customers.

Two countries are involved in this supply chain and both of them have manufacturer, retailers, and customers as a part of the global garment supply chain. Lateral transshipment is allowed between these two countries manufacturer's subsidiary and the retailer in the represented supply chain. For instance, the demand in country B has a sudden increase, transshipment from country A to country B is considered. Hence, they tried the find solution to manufacturing planning, transshipment, and carbon trading problem for the supply chain which is explained above. They developed mixed-integer linear programming to solve the problem and maximize the profit. As a result of the model solution, they conclude that transshipment among countries can improve the profit but for international emission reduction regulators, the transnational enterprise's lateral transshipment with the purpose of utilizing the difference in carbon trading mechanisms should be suppressed because it may result in an increase in carbon emissions worldwide.

According to our investigations over carbon sensitive supply chain, we observed that the main reason for carbon emission is road freight transportation (Stern, 2006). Therefore, we investigated electric vehicles to reduce carbon emissions and create an alternative to conventional vehicles. For instance, Feng and Figliozzi (2012) compared electric and conventional commercial fleets using the integer programming model. The model considers vehicle purchase cost, operating costs, maintenance costs, and salvage revenue. According to the proposed model results, they found that electric vehicles can be competitive. In another study, Lee et al. (2013) studied electric urban delivery trucks (EUDT) which have 3-ton payload capacity. They compared gasoline urban delivery trucks (GUDT) and EUDT. According to the article, they conclude that EUDTs emit 32-61% less carbon emission than GUDT, and its 22% less total cost than GUDT. Similarly, Mareev et al. (2017) studied electric heavy-duty trucks (EHDT) for long-haul transportation. They compare gasoline and electric heavy trucks by considering the life cycle cost. According to research, EHDT is more beneficial in energy costs but EHDT is not beneficial in vehicle costs due to batteries and charging infrastructure. In the total life cycle cost aspect, both of them can perform at the same cost level. Therefore, they conclude that if the battery prices decrease EHDT could become a profitable option. Moreover, Liimatainen et al. (2019) examined the potential of the medium and heavy-duty electric trucks in Switzerland and Finland.

They found that electric trucks can reduce carbon emission and applicable as road freight vehicles in the industry.

According to the research, our motivation is to find optimum product distribution and inventory levels under demand uncertainty and certainty while caring carbon emissions. In addition to this, we aim to investigate the usage of electric vehicles in the supply chain systems and their effects on carbon emission and total cost.

CHAPTER 3
THE ASSUMPTIONS OF THE SUPPLY CHAIN NETWORK

3.1 Problem Definition and Assumptions

Supply chain product flows can occur between echelons, i.e. product flow between supplier to distribution centers in the base model and hybrid model. In addition to the base and hybrid model, in the lateral transshipment model, product flows can occur within and between the echelon. Echelons can be feeding from the lower echelon and/or the same echelon (lateral transshipment) to satisfy the demand. Hence, the distribution of multi-products is provided by these transportation options.

The demand amounts follow a normal distribution for each product, each retailer, and each time period. When the demands are not satisfied lost sales occur. The distribution centers and retailers have an inventory and they do not have any restrictions.

Products are transported with two types of vehicles in the base model. The vehicle types are gasoline medium-duty vehicles (MDV) and gasoline heavy-duty vehicles (HDV). In addition to the base model, electric medium-duty vehicles and electric heavy-duty vehicles are given as an option in the hybrid model and the lateral transshipment model. Electric vehicles have limited distances and longer refilling times according to gasoline vehicles. In long distances, electric vehicles' lead times are more than gasoline vehicles but transportation costs and carbon emissions less than gasoline vehicles. The models can use both of them to meet customer demands right on time. According to the research, our motivation is to find optimum product distribution and inventory levels under demand uncertainty and certainty while caring carbon emissions. In addition to this, we aim to investigate the usage of electric vehicles in the supply chain systems and their effects on carbon emission and total cost.

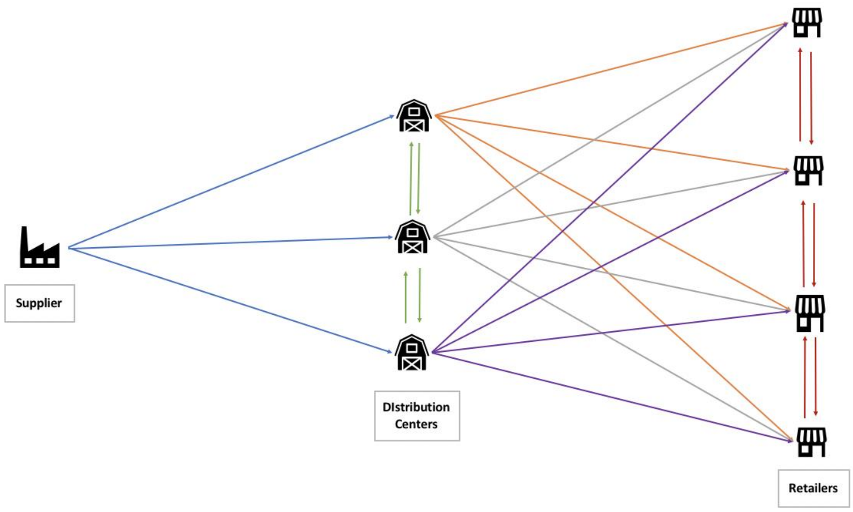


Figure 3.1. Supply Chain Network

In the supply chain, there are several costs which are transportation, order, lost sale, and inventory holding cost and it considers the carbon emissions as well.

The aim of this thesis is to minimize the total cost and total carbon emission under different scenarios which are named as base model, hybrid model, and lateral transshipment model. Therefore, we will be able to compare the scenarios and have an insight over this type of supply chain network problems.

We divided the problem into two separate parts which are under demand certainty and uncertainty. For demand certainty, we developed a multi-objective mixed-integer linear programming model for each scenario, and we determine the order quantities and vehicle types that are used to send products while minimizing the total cost and total carbon emission according to specified assumptions.

The assumptions of problem for MOMILP model as follows:

- Transportation costs are known between all nodes.
- Lead times are deterministic and known between all nodes.
- Distribution centers (DC) and retailers hold inventory.
- Initial inventory levels of distribution centers and retailers are known.
- Unitary holding costs of DC and retailer inventories are known.
- Order costs are known for supplier, distribution centers and retailers.
- When product flows occur between nodes order cost occurs for each vehicle used.
- Retailer order cost occurs when a vehicle travels between retailers.

- Distribution center order cost occurs when the product flow occurs from DC to retailer (R) or between DC.
- Supplier order cost occurs when the product flow occurs from supplier to DC.
- 12 planning time horizons are taking into account.
- Customer demands for each product in all time periods are known and the amounts are assumed to follow normal distribution with a given mean and standard deviation.
- Four types of a vehicle exist in the supply chain which are heavy duty vehicle (HDV) and medium duty vehicle (MDV) and each of them has electric and gasoline version.
- The carbon emissions are known for electric vehicles and gasoline vehicles for per kg CO_2 (e)/kg*km.
- Unit product weight is equal to 200kg for each product type.
- The carbon emission of electric vehicle is 50% less than gasoline vehicle.
- Electric HDVs' and gasoline HDVs' transportation cost per unit are the same.
- Gasoline MDVs' transportation cost per unit is 50% less than HDVs. Electric MDVs' transportation cost per unit is 20% less than gasoline MDVs.

For demand uncertainty, we developed simulation models for each scenario, and the assumptions of the problem for simulation models contain all MOMILP model assumptions.

The MOMILP models and simulation models are particularly explained in Chapter 4 and Chapter 6, respectively.

3.2 Experiment Data and Parameters

In this work, the supply chain network is composed of a supplier, three distribution centers, and four retailers as illustrated in Figure 3.1. Three types of products are considered. The time horizon is composed of twelve time periods. Distribution centers and retailers hold inventory. HDVs have 120 SKU capacities and MDVs have 20 SKU capacities. Demands are come to retailers according to a normal distribution with parameters as shown in Table 3.1.

In this experiment, we consider three scenarios which are base model, hybrid model, lateral transshipment model. All parameters of the supply chain model are given in

Table 3.1 to 3.11. Data are taken from the research of Vicente et al. (2015) except carbon emission data. Carbon emission data are based on the research of ECTA (2011), ADEME (2010) and DEFRA (2012).

Table 3.1. Customer Demands

	Average Demand			Standard Deviation		
	Product1	**Product2**	**Product3**	**Product1**	**Product2**	**Product3**
Retailer1	12	8	4	4	4	2
Retailer2	11	7	4	4	4	3
Retailer3	10	6	4	6	3	1
Retailer4	9	5	5	3	3	1

Table 3.2. Holding Cost, Order Cost and Lost Sale Cost

Holding cost for distribution centers	0,2
Holding cost for retailers	0,6
Order cost	50
Lost sale cost	300

Table 3.3. Transportation Cost Nodes for Gasoline and Electric Heavy-Duty Vehicle

	DC1	**DC2**	**DC3**	**R1**	**R2**	**R3**	**R4**
Supplier	1.3	0.84	1	-	-	-	-
DC1	-	0.4	1	0.44	1.4	0.8	0.5
DC2	0.4	-	0.8	1.36	1.04	0.68	0.2
DC3	1	0.8	-	1.9	0.2	0.64	0.76
R1	-	-	-	-	0.4	0.8	0.7
R2	-	-	-	0.4	-	0.3	0.8
R3	-	-	-	0.8	0.3	-	0.36
R4	-	-	-	0.7	0.8	0.36	-

Table 3.4. Transportation Cost between Nodes for Gasoline Medium Duty Vehicle

	DC1	DC2	DC3	R1	R2	R3	R4
Supplier	0.65	0.42	0.5	-	-	-	-
DC1	-	0.2	0.5	0.22	0.7	0.4	0.25
DC2	0.2	-	0.4	0.68	0.52	0.34	0.1
DC3	0.5	0.4	-	0.95	0.1	0.32	0.38
R1	-	-	-	-	0.2	0.4	0.35
R2	-	-	-	0.2	-	0.15	0.4
R3	-	-	-	0.4	0.15	-	0.18
R4	-	-	-	0.35	0.4	0.18	-

Table 3.5. Transportation Cost between Nodes for Electric Medium Duty Vehicle

	DC1	DC2	DC3	R1	R2	R3	R4
Supplier	0.6	0.336	0.4	-	-	-	-
DC1	-	0.16	0.4	0.176	0.56	0.32	0.2
DC2	0.16	-	0.32	0.544	0.416	0.272	0.08
DC3	0.4	0.32	-	0.76	0.08	0.256	0.304
R1	-	-	-	-	0.16	0.32	0.28
R2	-	-	-	0.16	-	0.12	0.32
R3	-	-	-	0.32	0.12	-	0.144
R4	-	-	-	0.28	0.32	0.144	-

Table 3.6. Distance between Nodes

	DC1	DC2	DC3	R1	R2	R3	R4
Supplier	900	1000	950	-	-	-	-
DC1	-	310	290	350	400	300	500
DC2	310	-	300	600	700	350	300
DC3	290	300	-	900	400	600	650
R1	-	-	-	-	330	280	290
R2	-	-	-	330	-	350	310
R3	-	-	-	280	350	-	320
R4	-	-	-	290	310	320	-

Table 3.7. Lead Times between Nodes for Gasoline HDV

	DC1	DC2	DC3	R1	R2	R3	R4
Supplier	2	1	2	-	-	-	-
DC1	-	1	1	1	2	1	2
DC2	1	-	1	2	2	1	1
DC3	1	1	-	3	1	2	2
R1	-	-	-	-	1	1	1
R2	-	-	-	1	-	1	1
R3	-	-	-	1	1	-	1
R4	-	-	-	1	1	1	-

Table 3.8. Lead Times between Nodes for Electric HDV

	DC1	DC2	DC3	R1	R2	R3	R4
Supplier	3	3	3	-	-	-	-
DC1	-	1	1	1	3	1	3
DC2	1	-	1	3	3	1	1
DC3	1	1	-	5	1	3	3
R1	-	-	-	-	1	1	1
R2	-	-	-	1	-	1	1
R3	-	-	-	1	1	-	1
R4	-	-	-	1	1	1	-

Table 3.9. Lead Times between Nodes for Gasoline MDV

	DC1	DC2	DC3	R1	R2	R3	R4
Supplier	2	1	2	-	-	-	-
DC1	-	1	1	1	2	1	2
DC2	1	-	1	2	2	1	1
DC3	1	1	-	3	1	2	2
R1	-	-	-	-	1	1	1
R2	-	-	-	1	-	1	1
R3	-	-	-	1	1	-	1
R4	-	-	-	1	1	1	-

Table 3.10. Lead Times between Nodes for Electric MDV

	DC1	DC2	DC3	R1	R2	R3	R4
Supplier	3	2	3	-	-	-	-
DC1	-	1	1	1	3	1	3
DC2	1	-	1	3	3	1	1
DC3	1	1	-	4	1	3	3
R1	-	-	-	-	1	1	1
R2	-	-	-	1	-	1	1
R3	-	-	-	1	1	-	1
R4	-	-	-	1	1	1	-

Table 3.11. Carbon Emission Factor of Vehicle Types

Gasoline HDV	Electric HDV	Gasoline MDV	Electric MDV
2.6	1.3	2.6	1.3

CHAPTER 4
OPTIMIZATION MODELS

In this section, three different optimization models are proposed which are the base model, hybrid model, and lateral transshipment model. All models contain multi-product, multi-sourcing policy, lead time, and carbon emissions sensitivity.

All sets, indices, parameters, and variables used in these models' formulations are listed as follows:

Sets

$p \in P$: Products

$i \in I$: Suppliers

$j \in J$: Distribution centers

$k \in K$: Retailers

$t \in T$: Time periods

$v \in V$: Vehicle types

Parameters

$D_{p,k,t}$ = Demand of product $p \in P$ from retailer $k \in K$ at the period $t \in T$

H_j = Holding cost at DC $j \in J$

HR_k = Holding cost at Retailer $k \in K$

O_i = Order cost from Supplier $i \in I$

OC_j = Order cost from DC $j \in J$

$TR_{v,j,k}$ = Transportation cost from DC $j \in J$ to retailer $k \in K$ with vehicle $v \in V$

$TDC_{v,i,j}$ = Transportation cost from supplier $i \in I$ to DC $j \in J$ with vehicle $v \in V$

$MaxCap_v$ = Maximum load capacity of vehicle $v \in V$

$IL_{p,j}$ = Initial inventory level of product $p \in P$ at DC $j \in J$

$IniR_{p,k}$ = Initial inventory of product $p \in P$ at retailer $k \in K$

LSC_k = Lost sale cost at retailer $k \in K$

$LTDC_{v,i,j}$ = Lead Time from supplier $i \in I$ to DC $j \in J$ with vehicle $v \in V$

$LTR_{v,j,k}$ = Lead Time from DC $j \in J$ to retailer $k \in K$ with vehicle $v \in V$

$DDis_{j,k}$ = Distance from DC $j \in J$ to retailer $k \in K$

$DSDis_{i,j}$ = Distance from supplier $i \in I$ to DC $j \in J$

E_v = Empty vehicle $v \in V$ fuel consumption amount per km

Dif_v = Difference between empty and full load $v \in V$ fuel consumption amount per km

CE_v = Carbon emission factor of vehicle $v \in V$

Decision Variables

$SQ_{v,p,i,j,t}$ = Shipping quantity of product $p \in P$ from supplier $i \in I$ to DC $j \in J$ with vehicle $v \in V$ at the beginning of period $t \in T$

$SQR_{v,p,j,k,t}$ = Shipping quantity of product $p \in P$ from DC $j \in J$ to retailer $k \in K$ with vehicle $v \in V$ at the beginning of period $t \in T$

$I_{p,j,t}$ = Inventory level of product $p \in P$ at DC $j \in J$ at the end of period $t \in T$

$IR_{p,k,t}$ = Inventory level product $p \in P$ at Retailer $k \in K$ at the end of period $t \in T$

$LS_{p,k,t}$ = Number of lost sale product $p \in P$ at retailer $k \in K$ at the end of period $t \in T$

$Vb_{v,i,j,t}$ = Number of vehicles from type $v \in V$ going from Supplier $i \in I$ to DC $j \in J$ at period $t \in T$

$VDb_{v,j,k,t}$ = Number of vehicles from type $v \in V$ going from DC $j \in J$ to Retailer $k \in K$ at period $t \in T$

$LF_{v,i,j,t}$ =Load factor of vehicle $v \in V$ going from Supplier $i \in I$ to DC $j \in J$ at period $t \in T$

$LFR_{v,j,k,t}$=Load factor of vehicle $v \in V$ going from DC $j \in J$ to Retailer $k \in K$ at period $t \in T$

4.1 Base Model

The base model represents the multi-echelon supply chain by considering lead time. The aim of this model is to find the optimal order quantities and inventory levels while minimizing the total cost and carbon emission by using weighted sum method for both objectives. The weighted sum method scales the set of objectives into a single objective by multiplying each objective with a user-specified weight. The weight of an objective is chosen in proportion to the relative importance of the objective. Therefore, objective function of the model is as follows:

Objective Function = $\beta * \mathrm{TC} + (1-\beta) * \mathrm{TCE}$

where β is the coefficient of total cost, TC is total cost and TCE is total carbon emission.

$$
\begin{aligned}
\text{minimize TC} = & \sum_{v\in V}\sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} \mathrm{TDC}_{v,i,j} \times \mathrm{SQ}_{v,p,i,j,t} \\
& + \sum_{v\in V}\sum_{p\in P}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} \mathrm{TR}_{v,j,k} \times \mathrm{SQR}_{v,p,j,k,t} \\
& + \sum_{p\in P}\sum_{j\in J}\sum_{t\in T} \mathrm{H}_{j} \times \mathrm{I}_{p,j,t} + \sum_{p\in P}\sum_{k\in K}\sum_{t\in T} \mathrm{HR}_{k} \times \mathrm{IR}_{p,k,t} \\
& + \sum_{v\in V}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} \mathrm{OC}_{j} \times \mathrm{VDb}_{v,j,k,t} + \sum_{v\in V}\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} \mathrm{O}_{i} \times \mathrm{Vb}_{v,i,j,t} \\
& + \sum_{p\in P}\sum_{k\in K}\sum_{t\in T} \mathrm{LS}_{p,k,t} \times \mathrm{LSC}_{k} \quad (1)
\end{aligned}
$$

The first and second expressions of the objective function (1) are transportation costs according to shipping quantities from suppliers to distribution centers and distribution centers to retailers. The third and fourth expressions represent the inventory holding costs of distribution centers and retailers. The fifth and sixth terms express the order costs of distribution centers and the supplier. Lastly, the eighth term represents the lost sale costs.

$$
\begin{aligned}
\text{minimize TCE} = & \sum_{v\in V}\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} (\mathrm{Vb}_{v,i,j,t} \times \mathrm{E}_{v} + \mathrm{LF}_{v,i,j,t} \times \mathrm{Dif}_{v}) \times \mathrm{DSDis}_{i,j} \times \mathrm{CE}_{v} \\
& + \sum_{v\in V}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} (\mathrm{VDb}_{v,j,k,t} \times \mathrm{E}_{v} + \mathrm{LFR}_{v,j,k,t} \times \mathrm{Dif}_{v}) \times \mathrm{DDis}_{j,k} \\
& \times \mathrm{CE}_{v} \quad (2)
\end{aligned}
$$

The expressions of the objective function (2) represent the total carbon emissions respect to the distance between two nodes, vehicle usage and load factor. For instance, when the vehicle goes from supplier to distribution center carbon emission occurs according to the distance between the nodes and payload amount because carbon emission is not constant, it may change according to payload amount and distance. Total carbon emission calculated by total number of vehicles used times unloaded vehicle fuel consumption plus load factor (i.e., shipment amount dividing by payload capacity) times difference between fully load and unload vehicle fuel consumption times distance and carbon emission factor (kg CO2(e) per liter fuel). (ADEME, 2010; DEFRA, 2012b).

Constraints

$$I_{p,j,t} = IL_{p,j} + \sum_{v \in V}\sum_{i \in I} SQ_{v,p,i,j,t-LTDC_{v,i,j}} - \sum_{v \in V}\sum_{k \in K} SQR_{v,p,j,k,t} \qquad \forall p \in P, \forall j \in J, \; t = 1 \qquad (2)$$

$$I_{p,j,t} = I_{p,j,t-1} + \sum_{v \in V}\sum_{i \in I} SQ_{v,p,i,j,t-LTDC_{v,i,j}} - \sum_{v \in V}\sum_{k \in K} SQR_{v,p,j,k,t} \qquad \forall p \in P, \forall j \in J, \; t \in T \setminus \{1\} \qquad (3)$$

The distribution center's inventories constraints (2) and (3) show the inventory levels at the end of the period by calculating input and output flows considering the lead time. Input flows are shipment amounts from the supplier to distribution centers and the previous inventory. Output flows are shipment amounts from the distribution center to retailers. The difference of constraint (2) is initial inventory levels because inventories have an initial inventory level at time t equals to 1.

$$IR_{p,k,t} = IniR_{p,k} + \sum_{v \in V}\sum_{j \in J} SQR_{v,p,j,k,t-LTR_{v,j,k}} - D_{p,k,t} + LS_{p,k,t} \qquad \forall p \in P, \forall j \in J, \; t = 1 \; (4)$$

$$IR_{p,k,t} = IR_{p,k,t-1} + \sum_{v \in V}\sum_{j \in J} SQR_{v,p,j,k,t-LTR_{v,j,k}} - D_{p,k,t} + LS_{p,k,t} \qquad \forall p \in P, \forall j \in J, \; t \in T \setminus T\{1\} \; (5)$$

The retailer's inventories constraints (4) and (5) show the inventory levels at the end of the period by calculating input and output flows considering the lead time. Input flows are shipment amounts from distribution centers to retailers and the previous inventory. Output flows are customer demands and lost sale amounts. The difference of constraint (4) is initial inventory levels because inventories have an initial inventory level at time t equals to 1.

$$\sum_{p \in P} SQ_{v,p,i,j,t} \leq MaxCap_v * Vb_{v,i,j,t}\,, \quad v \in V, \forall i \in I, \forall j \in J, \forall t \in T \ (6)$$

$$\sum_{p \in P} SQR_{v,p,j,k,t} \leq MaxCap_v * VDb_{v,j,k,t} \quad v \in V, \forall j \in DC, \forall k \in K, \forall t \in T \ (7)$$

Vehicle maximum transportation capacity is provided by constraint (6) and (7) for each vehicle. The constraints (6) and (7) trigger the order cost of supplier and distribution centers when the vehicle flows occurred.

$$LF_{v,i,j,t} = \sum_{p \in P} SQ_{v,p,i,j,t} \,/\, Cap_v \qquad \forall v \in V, \forall i \in I,, \forall j \in J, \forall t \in T \ (8)$$

$$LFR_{v,j,k,t} = \sum_{p \in P} SQR_{v,p,j,k,t} \,/\, Cap_v \qquad \forall v \in V, \forall j \in J, \forall k \in K, \forall t \in T \ (9)$$

Payload portions are provided by constraint (8) and (9). Therefore, the model will be able to calculate the carbon emission amount according to the payload amount.

$$SQ_{v,p,i,j,t}\,, SQR_{v,p,j,k,t}\,, VDb_{v,j,k,t}\,, Vb_{v,i,j,t}, I_{p,j,t}\,, IR_{p,k,t}, LS_{p,k,t} \geq 0, \text{for all indices.} \ (10)$$

The constraint (10) is non-negativity constraints on the values of variables.

4.2 Hybrid (Electric and Gasoline Engine Vehicle) Model

The hybrid model differs from the base model by additional vehicle types. In this model, the supply chain has four types of vehicles which are gasoline engine heavy-duty vehicle, gasoline engine medium-duty vehicle, electric engine heavy-duty vehicle, and electric engine medium-duty vehicle. Electric vehicles give less transportation cost and less carbon emission opportunities, but these vehicles have limited distance and their charging times increase the lead time. Therefore, the supply chain is considering the gasoline engine vehicles option as well to avoid more lost sale costs. We extend vehicle type sets to add these vehicle options into the model. Therefore, all the parameters and decision variables that contain vehicle indices are changed with the new extended vehicle types set.

The hybrid model is composed of the objective function (1), (2) and constraints (3), (4), (5), (6), (7), (8), (9) and (10) with the replacement of extended parameters and decision variables.

4.3 Lateral Transshipment Model

In this model, the supply chain model allows lateral transshipment among distribution centers and retailers. To apply this option, we add order cost of retailers, transshipment cost and lead time parameters among distribution centers and retailers which are as follows:

$TSDC_{v,j,m}$ = Transshipment cost form DC $j \in J$ to DC $m \in J$, $j \neq m$ with vehicle $v \in V$

$TSR_{v,k,l}$ = Transshipment cost form retailer $k \in K$ to retailer $l \in K$, $k \neq l$ with vehicle $v \in V$

$LTLDC_{v,j,m}$ = Lead Time from DC $j \in J$ to DC $j \in J$, $j \neq m$ with vehicle $v \in V$

$LTLR_{v,k,l}$ = Lead Time from retailer $k \in K$ to retailer $l \in L$, $k \neq l$ with vehicle $v \in V$

OCR_k = Order cost from Retailer $k \in K$

$DDisLR_{k,l}$ = Distance from retailer $k \in K$ to retailer $l \in K$

$DSDisLD_{j,m}$ = Distance from DC $j \in J$ to DC $m \in J$

We also add variables to represent shipment amounts among the same echelons, we add variables to check order cost of within echelons and we add load factor variables.

$SQDL_{v,p,j,m,t}$ = Shipping quantity of product $p \in P$ from DC $j \in J$ to DC $m \in J$ with vehicle $v \in V$ at the beginning of period $t \in T$, $j \neq m$

$SQRL_{v,p,k,l,t}$ = Shipping quantity of product $p \in P$ from Retailer $k \in K$ to Retailer $l \in K$ with vehicle $v \in V$ at the end of period $t \in T$, $j \neq m$

$VDLb_{v,j,m,t}$= Number of vehicles from type $v \in V$ going from DC $j \in J$ to DC $m \in J$, $m \neq j$, at period $t \in T$

$VRLb_{v,k,l,t}$=Number of vehicles from type $v \in V$ going from Retailer $k \in K$ to Retailer $l \in K$, $k \neq l$, at period $t \in T$

$LFRL_{v,j,k,t}$ = Load factor of vehicle $v \in V$ going from Retailer $k \in K$ to Retailer $l \in K$, $k \neq l$, at period $t \in T$

$LFDL_{v,j,k,t}$ = Load factor of vehicle $v \in V$ going from DC $j \in J$ to DC $m \in J$, $m \neq j$, at period $t \in T$

According to the lateral transshipment option objective function (1) and (2) are changed. We added transshipment cost (1.1) and order cost of within echelons (1.2) to the objective function (1) and carbon emission amount according to lateral transshipment (2.1) to objective function (2). All these changes in objective functions are shown below:

$$\sum_{v \in V}\sum_{p \in P}\sum_{k \in K}\sum_{l \in K}\sum_{t \in T} TSR_{v,k,l} \times SQRL_{v,p,k,l,t} + \sum_{v \in V}\sum_{p \in P}\sum_{j \in J}\sum_{m \in J}\sum_{t \in T} TSDC_{v,j,m} \times SQDL_{v,p,j,m,t} \quad (1.1)$$

$$\sum_{v \in V}\sum_{k \in K}\sum_{l \in K}\sum_{t \in T} OCR_k \times VRLb_{v,k,l,t} + \sum_{v \in V}\sum_{m \in J}\sum_{j \in J}\sum_{t \in T} OC_j \times VDLb_{v,j,m,t} \quad (1.2)$$

$$\sum_{v \in V}\sum_{j \in J}\sum_{k \in K}\sum_{t \in T} (VDLb_{v,j,m,t} \times E_v + LFDL_{v,j,m,t} \times Dif_v) \times DDisLD_{j,m} \times CE_v + \sum_{v \in V}\sum_{j \in J}\sum_{k \in K}\sum_{t \in T} (VRLb_{v,k,l,t} \times E_v + LFRL_{v,k,l,t} \times Dif_v) \times DDisLR_{k,l} \times CE_v \quad (2.1)$$

Constraints (2), (3), (4) and (5) are changed as well.

$$I_{p,j,t} = IL_{p,j} + \sum_{v \in V}\sum_{i \in I} SQ_{v,p,i,j,t-LTDC_{v,i,j}} + \sum_{v \in V}\sum_{m \in J \wedge j \neq m} SQDL_{v,p,m,j,t-LTDL_{v,m,j}} - \sum_{v \in V}\sum_{m \in J \wedge j \neq m} SQDL_{v,p,j,m,t} - \sum_{v \in V}\sum_{k \in K} SQR_{v,p,j,k,t} \quad \forall p \in P, \forall j \in J, t = 1 \quad (2)$$

$$I_{p,j,t} = I_{p,j,t-1} + \sum_{v \in V}\sum_{i \in I} SQ_{v,p,i,j,t-LTDC_{v,i,j}} + \sum_{v \in V}\sum_{m \in J \wedge j \neq m} SQDL_{v,p,m,j,t-LTDL_{v,m,j}} - \sum_{v \in V}\sum_{m \in J \wedge j \neq m} SQDL_{v,p,j,m,t} - \sum_{v \in V}\sum_{k \in K} SQR_{v,p,j,k,t} \quad \forall p \in P, \forall j \in J, t \in T \setminus \{1\} \quad (3)$$

In constraints (2) and (3), shipment amounts among distribution centers are added to input flows and output flows to provide proper inventory balancing constraints. For instance, when distribution center 1 sent products to distribution center 2, this is an output flow for distribution center 1 inventory, or when distribution center 2 sent product to distribution center 1, this is an input flow for distribution center 1 inventory. Therefore, adding $\mathrm{SQDL}_{v,p,m,j,t-\mathrm{LTDL}_{v,m,j}}$ and subtracting $\mathrm{SQDL}_{v,p,j,m,t}$ to represent these scenarios. The new constraints are shown in the above.

$$\mathrm{IR}_{p,k,t} = \mathrm{IniR}_{p,k} + \sum_{v \in V} \sum_{j \in J} \mathrm{SQR}_{v,p,j,k,t-\mathrm{LTR}_{v,j,k}} + \sum_{v \in V} \sum_{l \in K \wedge k \neq l} \mathrm{SQRL}_{v,p,l,k,t-\mathrm{LTRL}_{v,l,k}} - \sum_{v \in V} \sum_{l \in K \wedge k \neq l} \mathrm{SQRL}_{v,p,k,l,t} - \mathrm{D}_{p,k,t} + \mathrm{B}_{p,k,t} \qquad \forall p \in P, \forall j \in J, \; t = 1 \quad (4)$$

$$\mathrm{IR}_{p,k,t} = \mathrm{IR}_{p,k,t-1} + \sum_{v \in V} \sum_{j \in J} \mathrm{SQR}_{v,p,j,k,t-\mathrm{LTR}_{v,j,k}} + \sum_{v \in V} \sum_{l \in K \wedge k \neq l} \mathrm{SQRL}_{v,p,l,k,t-\mathrm{LTRL}_{v,l,k}} - \sum_{v \in V} \sum_{l \in K \wedge k \neq l} \mathrm{SQRL}_{v,p,k,l,t} - \mathrm{D}_{p,k,t} + \mathrm{B}_{p,k,t} \quad \forall p \in P, \forall j \in J, \quad t \in T \setminus T\{1\} \quad (5)$$

Same as in inventory balancing constraints (2) and (3), shipment amounts among retailers added to input flows and output flows to provide a proper inventory balancing constraint in constraint (4) and (5). Hence, the new constraints are shown in the above.

Vehicle maximum transportation capacity is provided by constraint (11) and (12) for each vehicle.

$$\sum_{p \in P} \mathrm{SQDL}_{v,p,m,j,t} \leq \mathrm{MaxCap}_v * \mathrm{VDLb}_{v,j,m,t} \;, \qquad \forall v \in V, \forall m \in J, \forall j \in J, \forall t \in T, m \neq j \; (11)$$

$$\sum_{p \in P} \mathrm{SQRL}_{v,p,k,l,t} \leq \mathrm{MaxCap}_v * \mathrm{VRLb}_{v,k,l,t} \;, \qquad \forall v \in V, \forall k \in K, \forall l \in K, \forall t \in T, k \neq l \; (12)$$

The constraint (11) triggers the order cost of distribution centers when the vehicle flows occurred between distribution centers (DC). For instance, vehicle flows from DC 1 to DC 2. Similarly, to constraint (11), constraint (12) triggers the order cost of retailers when the vehicle flows occurred between retailers. For instance, vehicle flows from retailer 1 to retailer 2.

$$LFRL_{v,k,l,t} = \sum_{p \in P} SQRL_{v,p,k,l,t} \,/\, Cap_v \qquad \forall v \in V, \forall k \in K, \forall l \in K, \forall t \in T \ (13)$$

$$LFDL_{v,j,m,t} = \sum_{p \in P} SQDL_{v,p,j,m,t} \,/\, Cap_v \qquad \forall v \in V, \forall j \in J, \forall m \in J, \forall t \in T \ (14)$$

Payload portions within echelons are provided by constraint (13) and (14). Therefore, the model will be able to calculate the carbon emission amount according to payload amount.

The lateral transshipment model is composed of the objective function (1), (2) and constraints (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13) and (14).

CHAPTER 5
EXPERIMENTAL RESULTS OF OPTIMIZATION MODELS

Base model, hybrid model, and lateral transshipment model results are given in this section. Problems are solved in a 64-bit operating system with an Intel CORE i5 CPU 2.9 GHz processor and 8 GB RAM. To optimize the model IBM ILOG Cplex Optimization Studio 12.10 is used. Computational statistics are given in Table 5.1. The weighted sum method is used to handle multi-objective optimization. Therefore, we define β as the weight of total cost and we choose three different β levels which are 0.9, 0.5, and 0.1. These weights are chosen to reflect different importance levels to each objective function. For instance, when β is equal to 0.9 total cost is more important than carbon emission; whereas when β is equal to 0.1, the relation is reversed.

Table 5.1. Computational Statistics of Models

	β	Gap	Time	Variables
Lateral Transshipment Model	0.9	3.49%	14176.7 sec.	9996
	0.5	1.73%	14187.5 sec.	9996
	0.1	0%	4021.8 sec	9996
Hybrid Model	0.9	0%	1472.4 sec.	3996
	0.5	0%	710.1 sec.	3996
	0.1	0%	170.5 sec.	3996
Base Model	0.9	0%	485.1 sec	2196
	0.5	0%	383.9 sec	2196
	0.1	0%	2562.1 sec.	2196

5.1 Base Model

In the base model, we only consider gasoline engine heavy-duty vehicle (HDV) and gasoline engine medium-duty vehicle (MDV) as vehicle types. Also, we only consider the multi-sourcing option as a distribution strategy. All the results of this base model experiment are given in Table 5.2.

Table 5.2. Base Model Results

	β Level		
	0.9	**0.5**	**0.1**
Total Carbon Emission	9553,7	8373,95	8227,48333
Supplier to DC Transportation Cost	708,52	778,88	812,38
DC to Retailer Transportation Cost	358,44	457,56	595,96
Total Transportation	1066,96	1236,44	1408,34
Holding DC In. Cost	23,6	55,4	72,6
Holding R In. Cost	688,2	985,8	935,4
Total Holding	711,8	1041,2	1008
Order S to DC Cost	350	300	300
Order DC to Retailer Cost	700	600	600
Total Order Cost	1050	900	900
Lost Sale Cost	0	0	300
Total Cost	2828,76	3177,64	3316,34

According to Table 5.2, we see that when the β level decreases, the total cost increases and total carbon emissions decreases as expected.

As shown in Figure 5.1, when the β level decreases, the order cost decreases. The model tries to use fewer vehicles to avoid more carbon emission due to the increasing total carbon emissions coefficient.

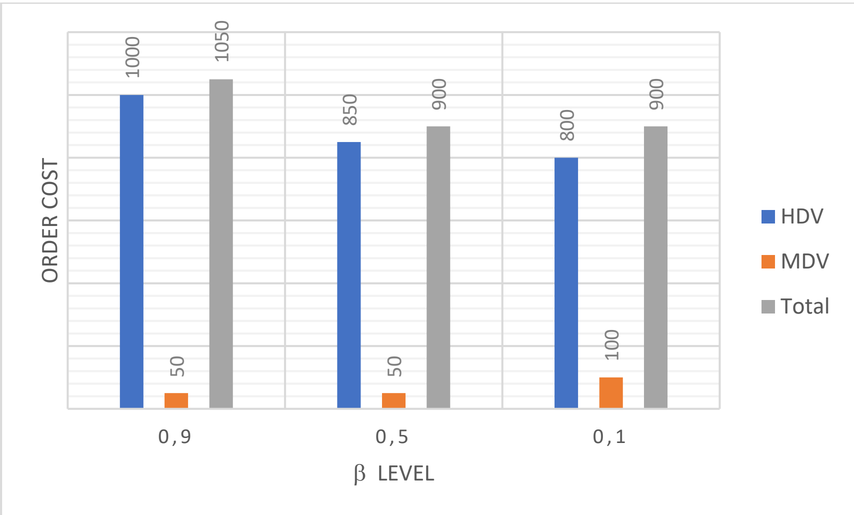


Figure 5.1. Base Model - Order Cost vs. β level

When the β level decreases, HDV's usage decreases as well because HDV has more carbon emission when shipment amounts are small. HDV has the highest value because it has more capacity than MDV. Hence, the model chose them because of their capacity. Also, they cause less order cost when the shipment amounts massive.

In total holding cost, when the β level decreases, holding cost increases because the model tries to use fewer vehicles. As a result of this choice, the model is sending large number of products to avoid loss sales and it increases the holding cost. However, when the level is equal to 0.1, the model uses more MDV and this choice decreases the holding cost because MDV has less lead times between some nodes according to HDV.

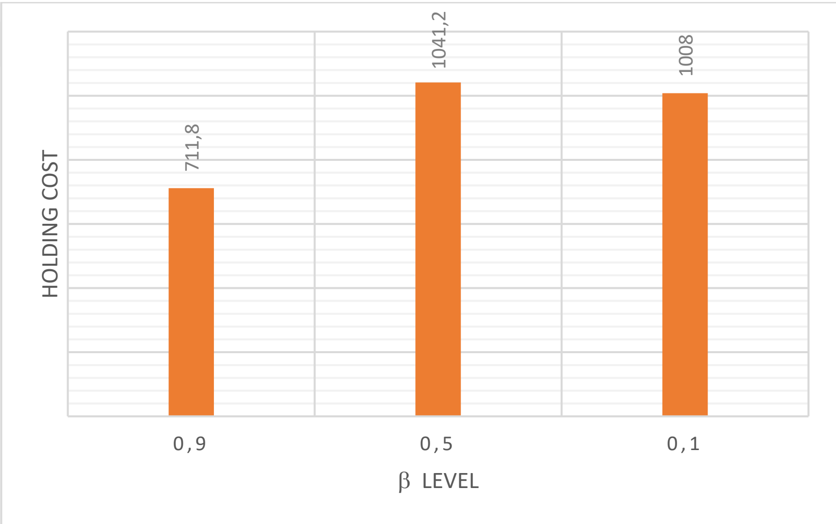


Figure 5.2. Base Model - Holding Cost vs. β level

As a result of total transportation cost values, when the β level decreases total transportation cost increases. When we look at the Figure 5.3, we can see that total order quantities almost equal at each β level and we can understand that when the β level decreases the model generally chooses to use a path that has less distance because of carbon emission. However, these paths mostly have more unit transportation cost because of the road fees.

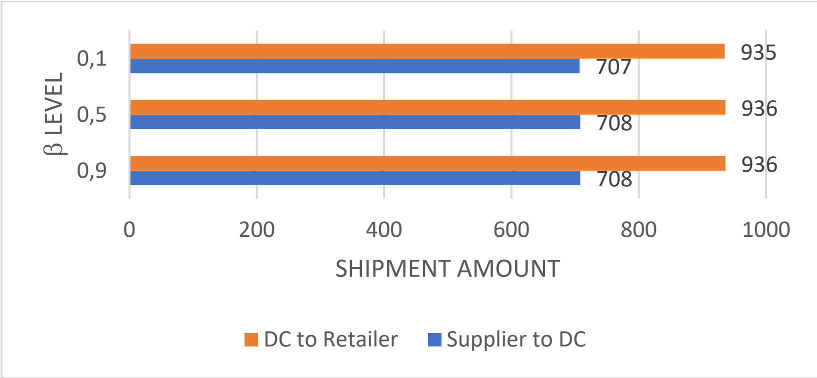


Figure 5.3. Base Model - Shipment Amounts between Nodes vs. β level

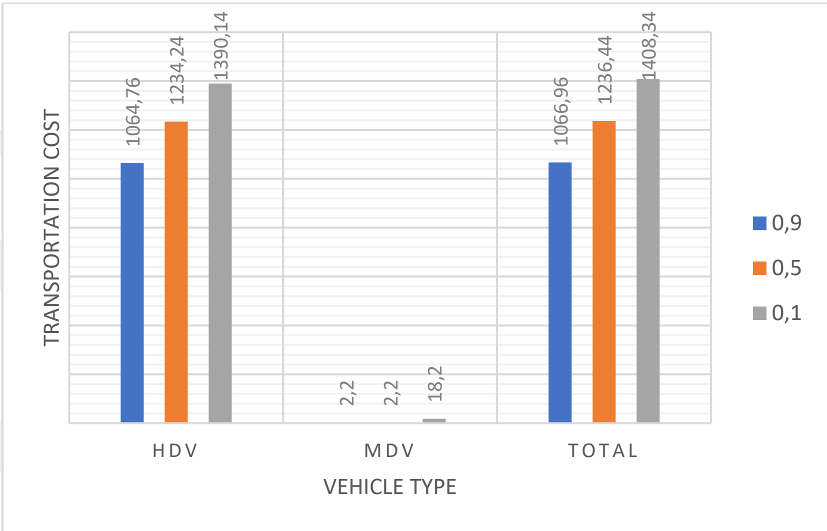


Figure 5.4. Base Model - Transportation Cost for Different Vehicle Types vs. β level

HDV's and MDV's transportation cost increases when the β coefficient decreases because the model becomes more sensitive to carbon emission.

As we can see in Figure 5.5, when the total cost coefficient β decreases, the model chooses to send products with MDV because it more beneficial for small shipment amounts. The model sends more products with HDV because it has eight times more capacity than MDV. Therefore, it becomes more beneficial costly. Also, when the shipment amount is large, it becomes more beneficial in the aspect of carbon emission.

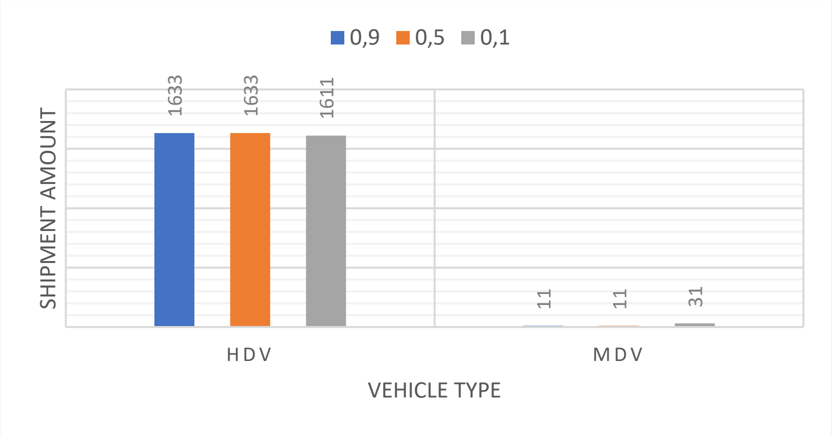


Figure 5.5. Base Model - Shipment Amounts vs. Vehicle Type

5.2 Hybrid Model

In the hybrid model, we use four different types of vehicles to reduce carbon emissions. Vehicle types are electric HDV, gasoline HDV, electric MDV and gasoline MDV. Electric engine vehicles have less transportation costs, and less carbon emissions in their life cycle, but they have limited distance and relatively long charging times. According to their limited distance and long charging times, electric vehicles have more lead time in long distances.

All the results of this hybrid model experiment are given in Table 5.3.

Table 5.3. Hybrid Model Results

	β Level		
	0.9	**0.5**	**0.1**
Total Carbon Emission	5286,34167	4688,66667	4626,15833
Supplier to DC Transportation Cost	705,76	777,92	779,52
DC to Retailer Transportation Cost	349,2	445,32	442,56
Total Transportation	1054,96	1223,24	1222,08
Holding DC In. Cost	25,4	62,4	58,4
Holding R In. Cost	631,8	842,4	1005,6
Total Holding	657,2	904,8	1064
Order S to DC Cost	350	300	300
Order DC to Retailer Cost	750	700	650
Total Order Cost	1100	1000	950
Lost Sale Cost	0	0	0
Total Cost	2812,16	3128,04	3236,08

According to Table 5.4, we can say that when the β level decreases, the total cost increases and total carbon emissions decreases.

As shown in Figure 5.6, when the β level decreases, the order cost decreases. The model tries to use fewer vehicles to avoid more carbon emission due to the increasing total carbon emissions coefficient.

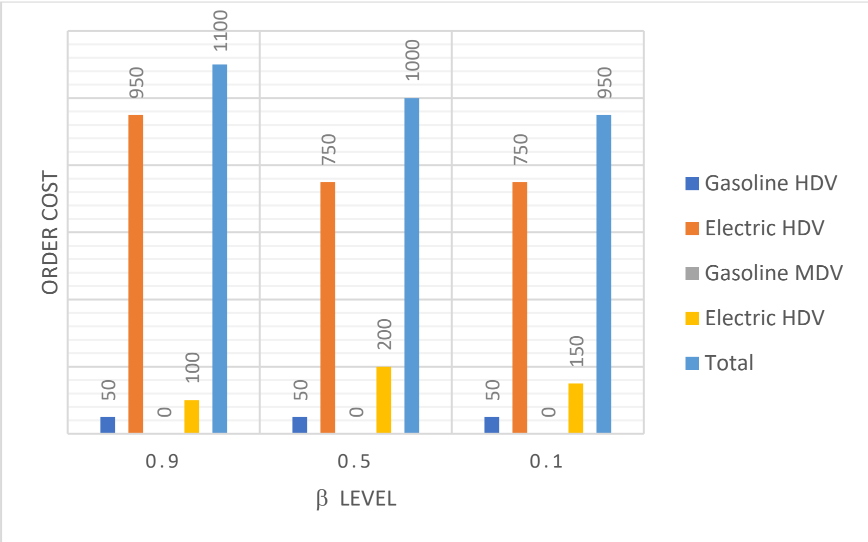


Figure 5.6. Hybrid Model - Order Cost vs. β level

HDVs cause more order cost because they have more capacity than MDVs. Hence the model chooses them because of their capacity, and it causes less order cost and carbon emission when the shipment amounts massive.

When the β level is equal to 0.5 and 0.1, the model chooses electric MDV more because it is more beneficial for small shipment amounts. Also, MDVs can be helpful to prevent more holding cost and lost sale cost because if the model chooses to send products with HDVs, it sends more products to avoid lost sale due to HDVs lead times more than MDVs lead times between some nodes.

In total holding cost, when the β level decreases, holding cost increases because the model tries to use fewer vehicles. As a result of this choice, the model is sending large number of products to avoid loss sale and it increases the holding cost.

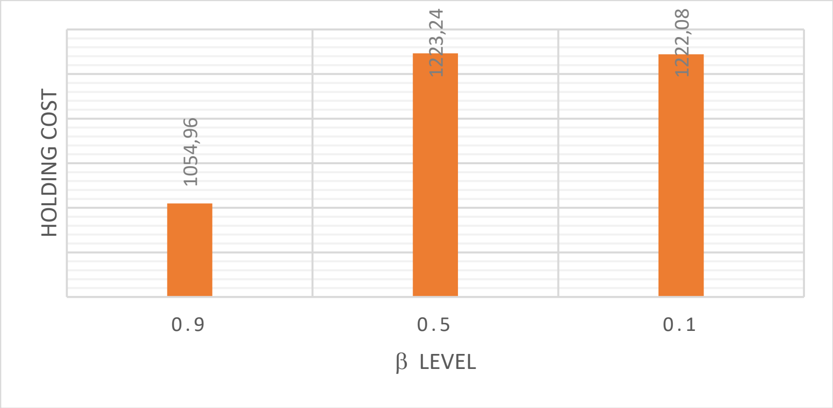


Figure 5.7. Hybrid Model - Holding Cost vs. β level

As a result of total transportation cost values, when β level is 0.9, total transportation cost has the lowest value than other β levels because when the model sends products, it chooses nodes that have less transportation cost mostly.

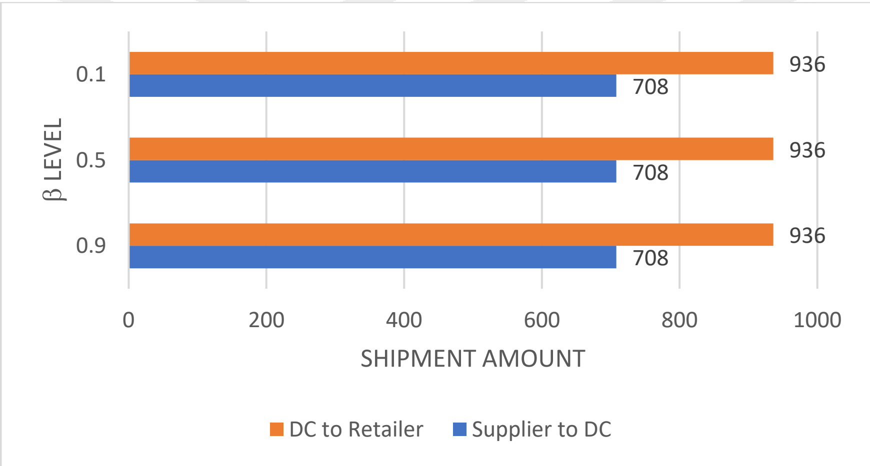


Figure 5.8. Hybrid Model - Shipment Amounts between Nodes vs. β level

When the β levels are equals to 0.5 and 0.1, models have more transportation cost because the model cares the carbon emission more than cost. Therefore, it uses mostly paths that have the least distances. However, these nodes generally have more transportation cost. As a result of these choices, the model provides less carbon emissions but it increases the transportation cost.

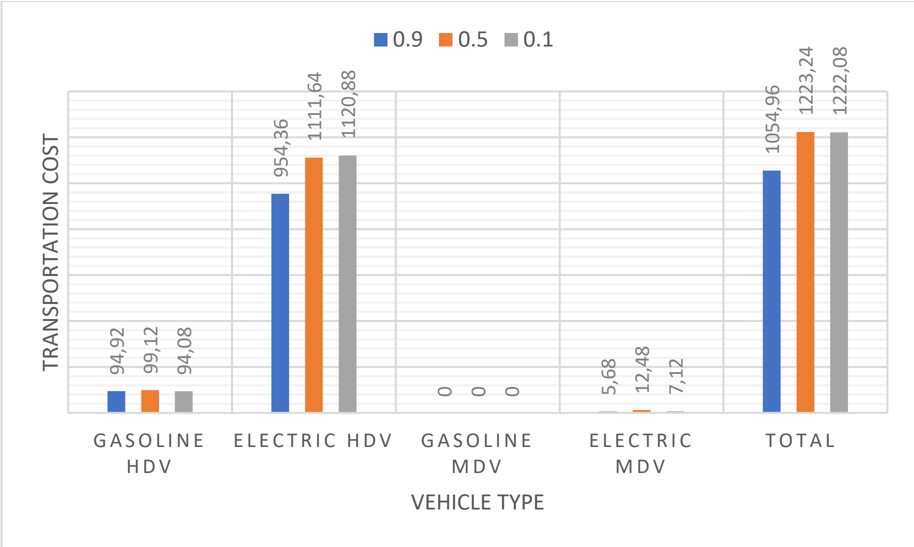


Figure 5.9. Hybrid Model - Transportation Cost for Different Vehicle Types vs. β level

Finally, we can say that total electric vehicle transportation cost increases when the β coefficient decreases because the model becomes more carbon sensitive.

As we can see in Figure 5.10, when the total cost coefficient β decreases, the model generally chooses to send products with electric vehicles even they have more lead times because they release less carbon emission. The model sends more products with electric HDV because it has eight times more capacity than electric MDV and it's more beneficial than gasoline HDV in the aspect of carbon emission. Therefore, it becomes more beneficial in aspects of cost and carbon emission.

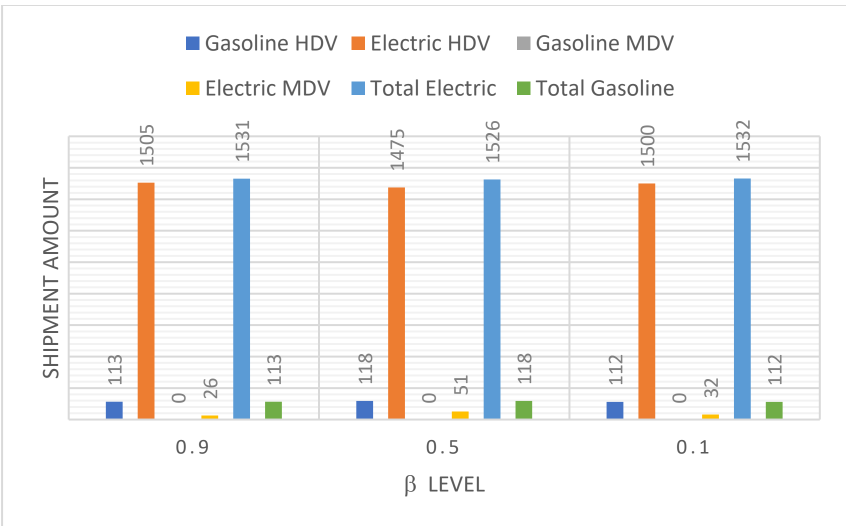


Figure 5.10. Hybrid Model - Shipment Amounts According to Vehicle Types vs. β level

5.3 Lateral Transshipment Model

In this model, we added lateral transshipment policy among retailers and among distribution centers to extend the hybrid policy and give more flexibility to the supply chain.

All the results of the lateral transshipment model experiment are given in Table 5.4.

Table 5.4. Lateral Transshipment Model Results

	β Level		
	0.9	**0.5**	**0.1**
Total Carbon Emission	5592,51333	4733,18083	4626,15833
Supplier to DCs Transportation Cost	674,56	688,32	779,52
DC to Retailer Transportation Cost	299,16	335,4	442,56
Retailer Transshipment Cost	59,6	24,32	0
DC Transshipment Cost	0	0	0
Total Transportation	1033,32	1048,04	1222,08
Holding DC In. Cost	10,4	8,8	58,4
Holding R In. Cost	534	1054,2	1005,6
Total Holding	544,4	1063	1064
Order R Cost	150	100	0
Order S Cost	0	0	0
Order DC Cost	350	300	300
Order D Lateral Cost	700	550	650
Total Order Cost	1200	950	950
Lost Sale Cost	0	0	0
Total Cost	2777,72	3061,04	3236,08

According to Table 5.4, we can say that when the β level decreases, the total cost increases and total carbon emission decreases.

As shown in Figure 5.11, when the β level decreases, the order cost decreases. The model tries to use fewer vehicles to avoid more carbon emissions due to the increasing total carbon emissions coefficient.

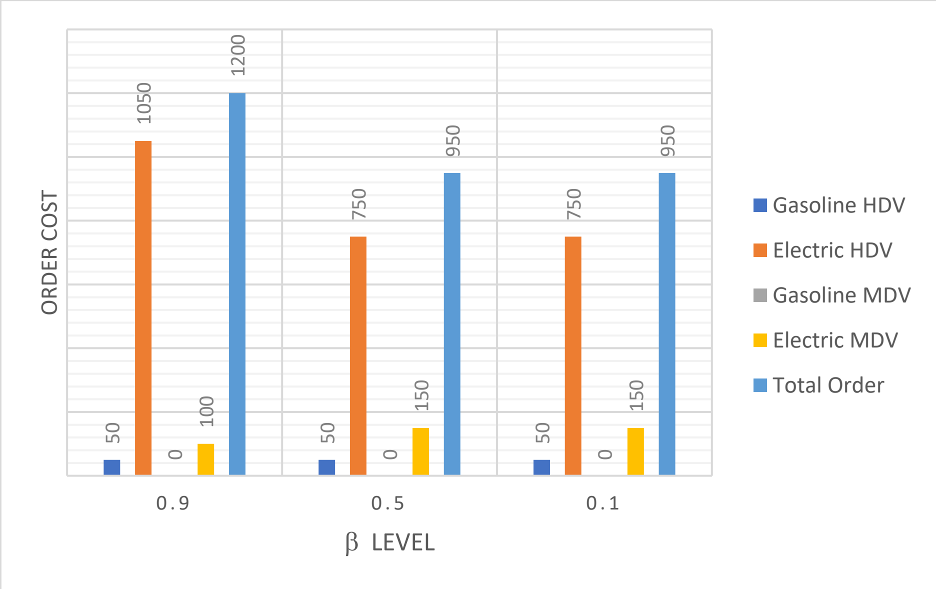


Figure 5.11. Lateral Transshipment Model - Order Cost According to Vehicle Type vs. β level

HDVs cause more order cost because they have more capacity than MDVs. Hence the model chooses them because of their capacity, and it causes less order cost and carbon emission when the shipment amounts massive.

When the β level is equal to 0.5 and 0.1, the model chooses more electric MDV because it is more beneficial for small shipment amounts. Also, MDVs can be helpful to prevent more holding cost and lost sale cost because if the model chooses to send products with HDVs, it sends more products to avoid lost sale due to HDVs lead time more than MDVs lead time between some nodes.

In total holding cost, when the β level decreases, holding cost increases because the model tries to use fewer vehicles. As a result of this choice, the model is sending large number of products to avoid loss sale and it increases the holding cost.

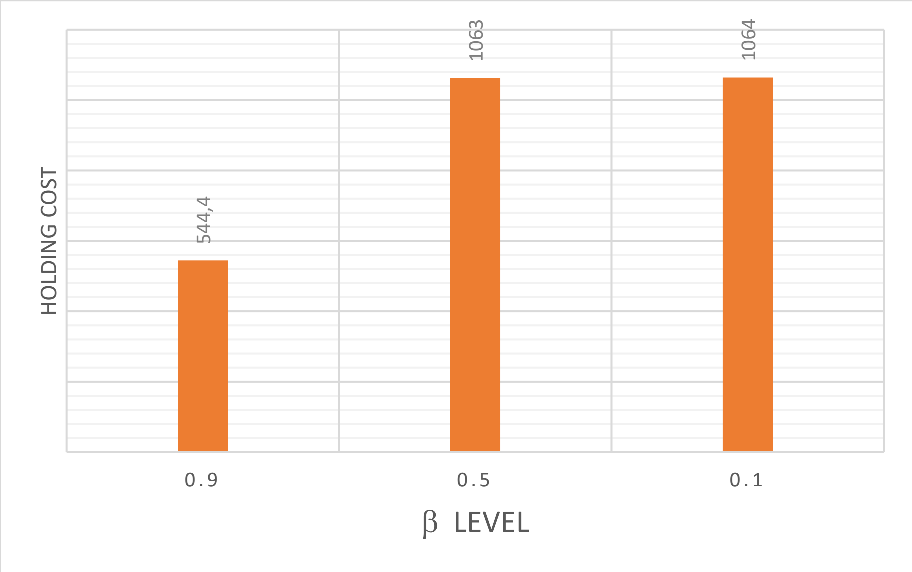


Figure 5.12. Lateral Transshipment Model - Holding Cost vs. β level

As a result of total transportation cost values, when the β level decreases total transportation cost increases even shipment amount decreases because when the β level is equal to 0.9, it chooses nodes that have less transportation cost mostly. Also, lateral transshipment option helps to reduce this cost because as we can see in Figure 5.13, lateral transshipment amount has the highest value when the β level is 0.9.

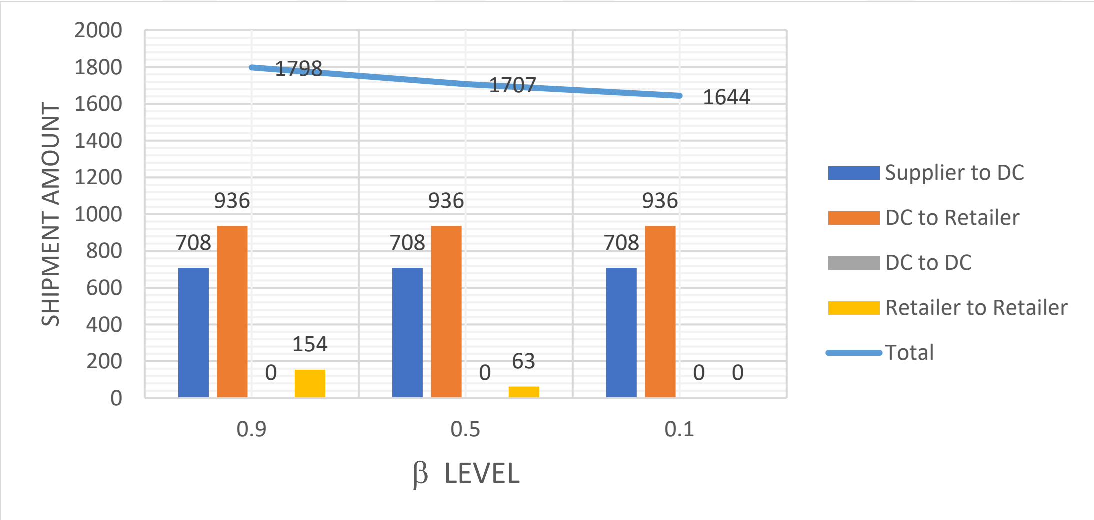


Figure 5.13. Lateral Transshipment Model - Shipment Amounts between Nodes vs. β level

Electric vehicles' transportation cost increases when the β level decreases as we can see in Figure 5.14 because the model becomes more carbon sensitive.

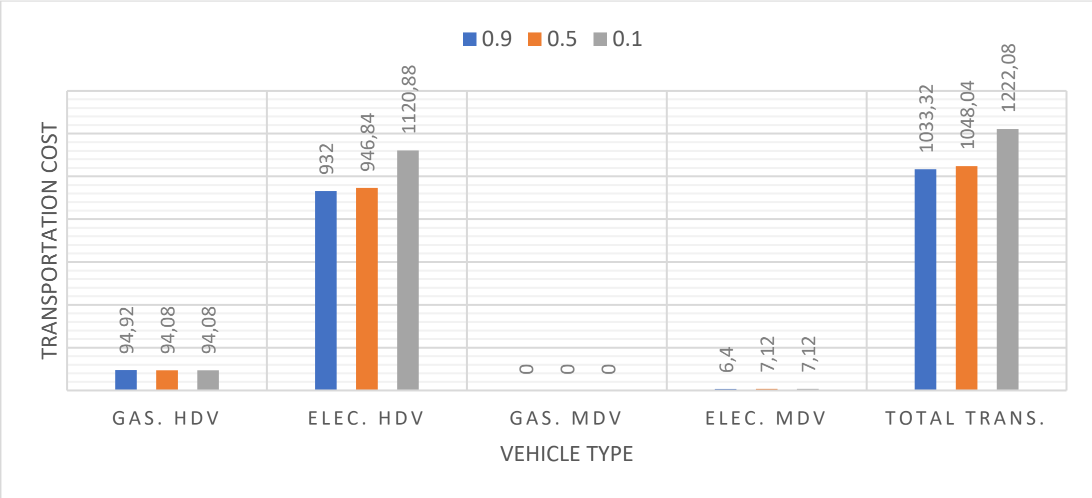


Figure 5.14. Lateral Transshipment Model - Transportation Cost for Different Vehicle Types vs. β level

As we can see in Figure 5.15, when the total cost coefficient β decreases, the model chooses to send products with electric vehicles even they have more lead times. The model sends more products with electric HDV because it has eight times more capacity than electric MDV and it's more beneficial than gasoline HDV in the aspect of carbon emission. Therefore, it becomes more beneficial in aspects of cost and carbon emission.

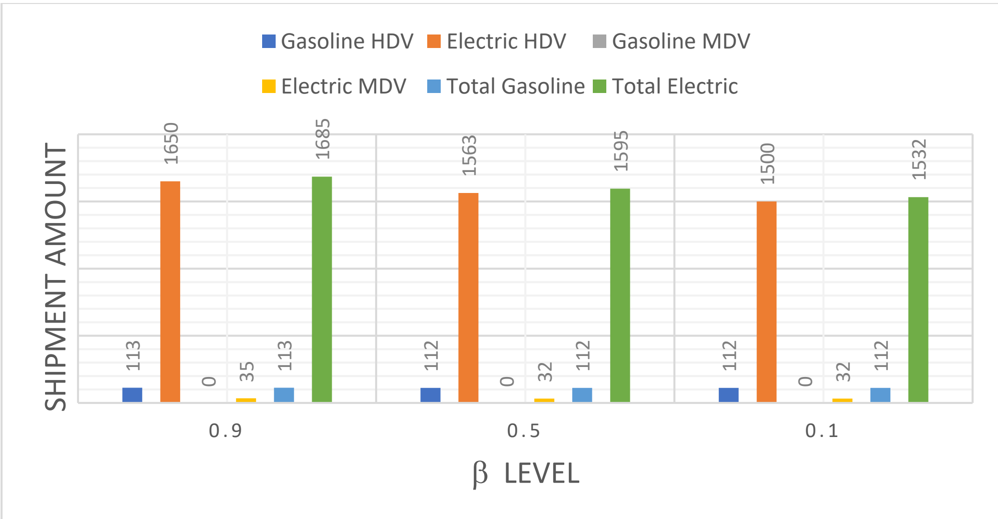


Figure 5.15. Lateral Transshipment Model - Shipment Amounts According to Vehicle Types

5.4 Sensitivity Analysis

Lateral transshipment cost is one of the crucial parameters for the supply chain system with lateral transshipment. It is useful to see lateral transshipment cost variation over the total cost. Therefore, three different lateral transshipment cost are applied to the system which are given cost, 25% more and 50% more.

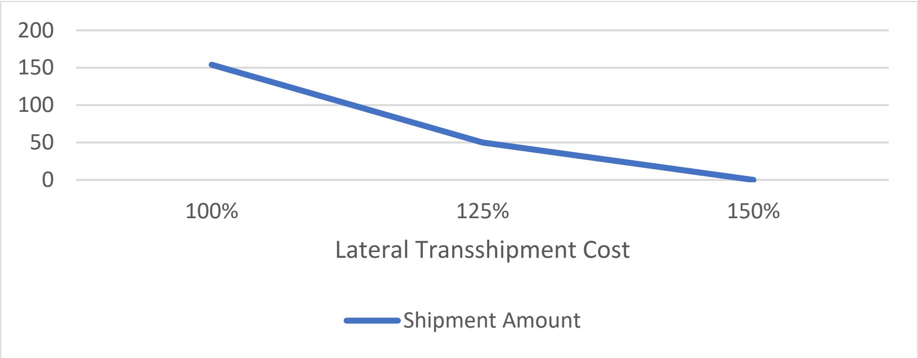


Figure 5.16. Lateral Transshipment Shipment Amounts According to Transshipment Costs

In this case, when the lateral transshipment cost is increasing, the lateral transshipment is decreasing as in Figure 5.16. Eventually, the lateral transshipment model does not prefer to make lateral transshipment. Therefore, the model gives the same results as the hybrid model.

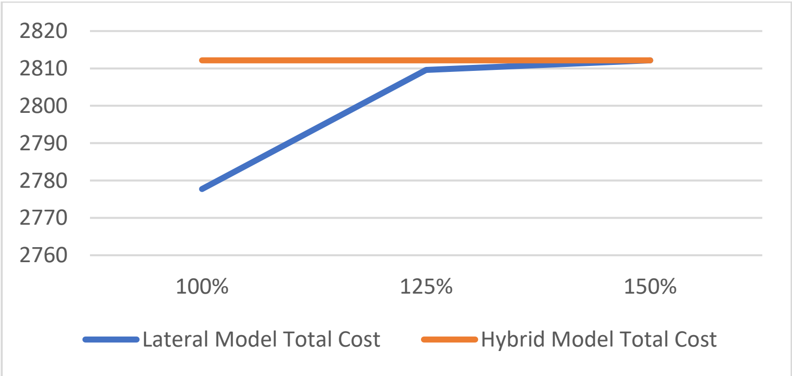


Figure 5.17. Lateral Transshipment Total Cost vs. Hybrid Model Total Cost According to Transshipment Costs

5.4 Comparison of Models

Comparison of optimization models' experimental results is given in this section. According to each β level, experimental results of models are given in Table 5.5 to Table 5.7.

Table 5.5. All Model Results When β Level is 0.9

	Base Model	Hybrid Model	Lateral T. Model
Total Carbon Emission	9553.7	5286.341667	5592.513
Supplier to DCs Transportation Cost	708.52	705.76	674.56
DC to Retailer Transportation Cost	358.44	349.2	299.16
Retailer Transshipment Cost	0	0	59.6
DC Transshipment Cost	0	0	0
Total Transportation	1066.96	1054.96	1033.32
Holding DC In. Cost	23.6	25.4	10.4
Holding R In. Cost	688.2	631.8	534
Total Holding	711.8	657.2	544.4
Order R Cost	350	350	350
Order S Cost	700	750	700
Order DC Cost	0	0	150
Order D Lateral Cost	0	0	0
Total Order Cost	1050	1100	1200
Lost Sale Cost	0	0	0
Total Cost	2828.76	2812.16	2777.72

Table 5.6. All Model Results When β Level is 0.5

	Base Model	Hybrid Model	Lateral T. Model
Total Carbon Emission	8373.95	4688.666667	4733.180833
Supplier to DCs Transportation Cost	778.88	777.92	688.32
DC to Retailer Transportation Cost	457.56	445.32	335.4
Retailer Transshipment Cost	0	0	24.32
DC Transshipment Cost	0	0	0
Total Transportation	1236.44	1223.24	1048.04
Holding DC In. Cost	55.4	62.4	8.8
Holding R In. Cost	985.8	842.4	1054.2
Total Holding	1041.2	904.8	1063
Order R Cost	300	300	300
Order S Cost	600	700	550

Table 5.6(cont'd). All Model Results When β Level is 0.5

	Base Model	Hybrid Model	Lateral T. Model
Order DC Cost	0	0	100
Order D Lateral Cost	0	0	0
Total Order Cost	900	1000	950
Lost Sale Cost	0	0	0
Total Cost	3177.64	3128.04	3061.04

Table 5.7. All Model Results When β Level is 0.1

	Base Model	Hybrid Model	Lateral T. Model
Total Carbon Emission	8227.483	4626.158333	4626.158333
Supplier to DCs Transportation Cost	812.38	779.52	779.52
DC to Retailer Transportation Cost	595.96	442.56	442.56
Retailer Transshipment Cost	0	0	0
DC Transshipment Cost	0	0	0
Total Transportation	1408.34	1222.08	1222.08
Holding DC In. Cost	72.6	58.4	58.4
Holding R In. Cost	935.4	1005.6	1005.6
Total Holding	1008	1064	1064
Order R Cost	300	300	300
Order S Cost	600	650	650
Order DC Cost	0	0	0
Order D Lateral Cost	0	0	0
Total Order Cost	900	950	950
Lost Sale Cost	300	0	0
Total Cost	3316.34	3236.08	3236.08

5.4.1 Total Carbon Emission

According to the evaluation of the models by carbon emission aspect, the base model has more carbon emission than the hybrid model and the lateral model, because this model provides transportation with only gasoline vehicle types which have higher carbon emissions than electric vehicle types. In the lateral transshipment model, we have all kinds of vehicles and lateral transshipment option. Therefore, this model has the second-lowest carbon emission value in all β levels. When we compare this model with the hybrid model, this model lateral transshipment options gives more flexibility to the transportation of products. Therefore, the optimization model generally sends more products, and it causes more carbon emissions than the hybrid model. According to these results, we can conclude that the hybrid model is the least carbon emission value in all β levels.

5.4.2 Total Order Cost

Base Model has the lowest value in all β levels because in this model has only gasoline vehicle options because it tries to use fewer vehicles to reduce carbon emission but in other models, electrical vehicles already decrease the carbon emission so they can use more vehicle.

Lateral transshipment model and hybrid model have the same vehicle options. However, as we can see in Figure 5.18 lateral transshipment option reduced distribution center to retailer order cost because the model can make product flow between retailers.

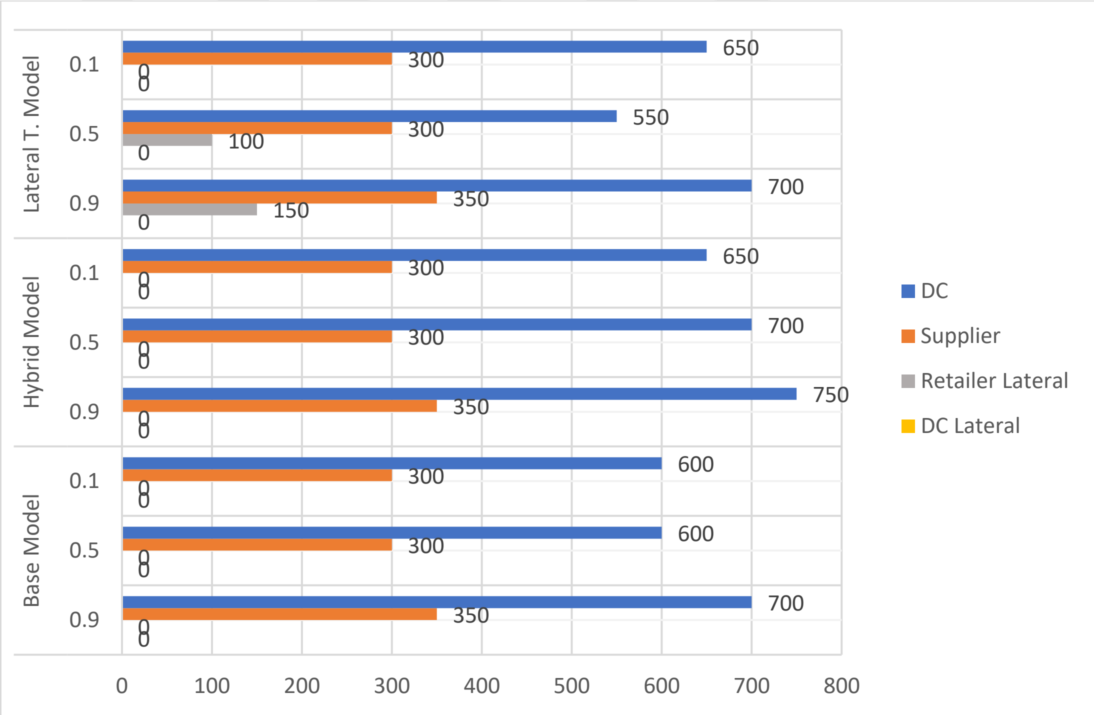


Figure 5.16. Order Cost of All Models

5.4.3 Total Transportation Cost

For the total transportation case, the base model is more than the hybrid model for each beta level because, in hybrid model, we have more vehicle options. For instance, electrical HDV has the same transportation cost as the gasoline HDV but the MDVs have less transportation cost. Therefore, the usage of MDVs makes difference in total transportation and the hybrid model becomes more beneficial.

The lateral transshipment model has less than the base and the hybrid models for all β levels because of lateral transshipment options give more opportunity to product transportation. Therefore, the lateral transshipment model can use only the least transportation cost paths then it may share these products within the echelons. However, when the β level is 0.1, it is not less than the hybrid model because the total carbon emission gains more importance. Therefore, the model does not choose to send products with lateral transshipment options because these options cause more carbon emissions.

5.4.4 Total Holding Cost

The base model has more total holding cost than the hybrid model for all β levels because the model sends massive products to avoid more vehicle usage. Therefore, this model chooses to send fully load vehicles because of the carbon emission and this choice increases the holding cost. As we can see in the order cost part, the hybrid model has more order cost when the level is equal to 0.5. Therefore, we can understand that vehicle traffic is more than the lateral model and it decreases the holding cost. As a result of these, we can conclude that there is a tradeoff between order cost and holding cost in model decisions.

5.4.5 Total Cost

As a result of all models, the hybrid model better than the base model, the lateral transshipment model better than the hybrid model in the aspect of total cost in the whole same β levels. Hence, we can conclude that each option gives more opportunities to minimize the total cost.

CHAPTER 6
SIMULATION MODELS

In this chapter, three different simulation models are developed which are base simulation model, hybrid simulation model, and lateral transshipment simulation model. All models contain multi-product, multi-sourcing policy, lead time and carbon emission sensitivity. We prefer to use (s, S) policy as an inventory control policy to overcome demand uncertainty in retailer and distribution center inventories. In (s, S) policy, when the inventory level drops under reorder point 's' order must be placed number of products to reach the order up point 'S' as we can see in Figure 6.1.

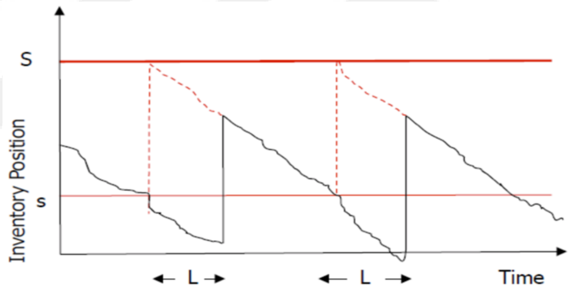


Figure 6.1. (s, S) Inventory

The supply chain network, assumptions and data are given in Chapter 3.

Simulation model assumptions are listed as follows:

- The run length of simulation models is considered to be 6 months with 60 days of warm-up period for each scenario.
- Warm-up periods determined by total cost divided by total demand value graphic. As we can see in the Figure 6.2, models reach the steady state at time 60.
- 10 independent replications are completed in each scenario run.
- Since it is a popular and useful variance reduction technique, Common Random Numbers (CRN) variance reduction technique is used in the simulation models. Note that in CRN, the same random number stream is used for all other configurations. Thus, variance reduction is ensured.

- The OptQuest is run several times by narrowing the search space of decision variables by utilizing previous run's result as suggested solution.

Figure 6.2. Warm-up Period Determination

OptQuest evaluates the responses from the current simulation run, analyzes and integrates these with responses from the previous simulation runs, and determines a new set of values for the controls, which are then evaluated by running the Arena model. This optimization tool is a heuristic-based optimization tool combining the meta-heuristics of tabu search, neural networks, and scatter search into a single search heuristic (Kleijnen,2007). It allows the user to define integer and linear constraints for the simulation inputs. It requires to specify the lower, suggested, and the upper values for variables to be optimized. The suggested values are determining the starting points in the search procedure. In this search, first an initial optimization is run by heuristically determined suggested solution. Then, we utilize this initial optimization's result as suggested solution in the second optimization run to find a better solution.

All sets, indices, parameters, and variables used in the formulation of the models are listed below:

Sets

$p \in P$: Products

$i \in I$: All nodes

$j \in J$: All nodes

$v \in V$: Vehicle types

Parameters

$D_{p,i,t}$ = Demand of product $p \in P$ from $i \in$ {all nodes} at period $t \in T$.

CapHDV = Maximum load capacity of HDV.

CapMDV = Maximum load capacity of HDV.

$GMDVLT_{ij}$ = Gasoline MDV's lead time from node $i \in$ {all nodes} to $j \in$ {all nodes}.

$EMDVLT_{ij}$ = Electric MDV's lead time from node $i \in$ {all nodes} to $j \in$ {all nodes}.

$GHDVLT_{ij}$ = Gasoline HDV's lead time from node $i \in$ {all nodes} to $j \in$ {all nodes}.

$EHDVLT_{ij}$ = Electric HDV's lead time from node $i \in$ {all nodes} to $j \in$ {all nodes}.

Decision Variables

$s_{p,i}$ = Reorder point of product $p \in \{1,2,3\}$ in inventory $i \in \{1,2,3,4,5,6,7\}$.

$S_{p,i}$ = Order up point of product $p \in \{1,2,3\}$ in in inventory $i \in \{1,2,3,4,5,6,7\}$.

$LS_{p,i}$ = Number of lost sale product $p \in \{1,2,3\}$ at retailer $i \in \{1,2,3,4\}$.

$AD_{p,i,j,t}$ = Arriving demand of product $p \in \{1,2,3\}$ from node $i \in \{1,2,3,4,5,6,7\}$ to $j \in \{1,2,3,4,5,6,7\}$ the period $t \in T$.

$I_{p,i,t}$ = Inventory level of product $p \in \{1,2,3\}$ at node $i \in \{1,2,3,4,5,6,7\}$ at the end of period $t \in T$.

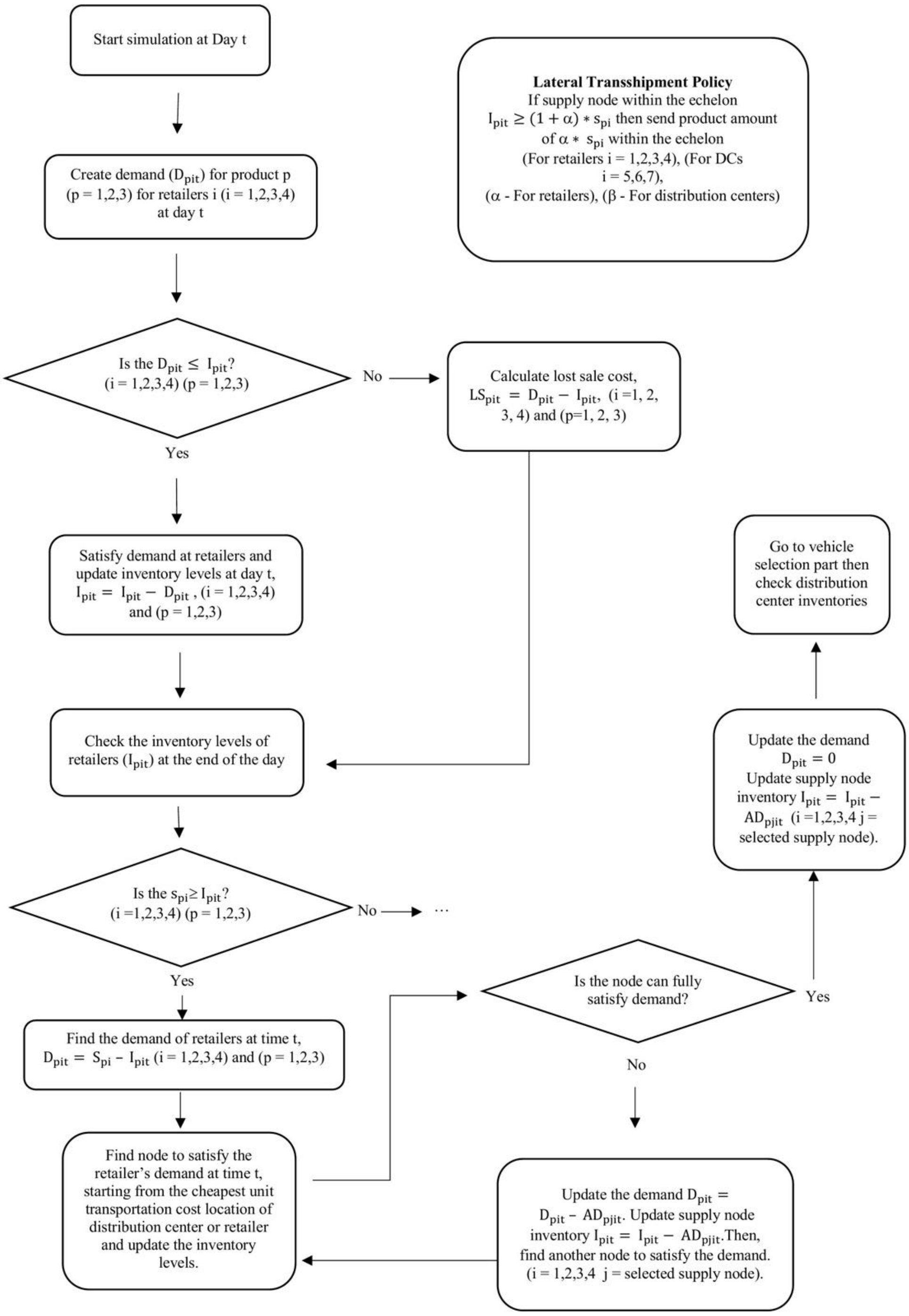
θ = Level represents the portion of reorder point of inventories to send product with electric.

δ = Level represents the portion of reorder point of inventories to send product with electric MDV.

α = Level determines the amount of product more than reorder point to make lateral transshipment between retailers.

ɣ = Level determines the amount of product more than reorder point to make lateral transshipment between distribution centers.

The general flowchart of all the simulation models are given in Figure 6.3.



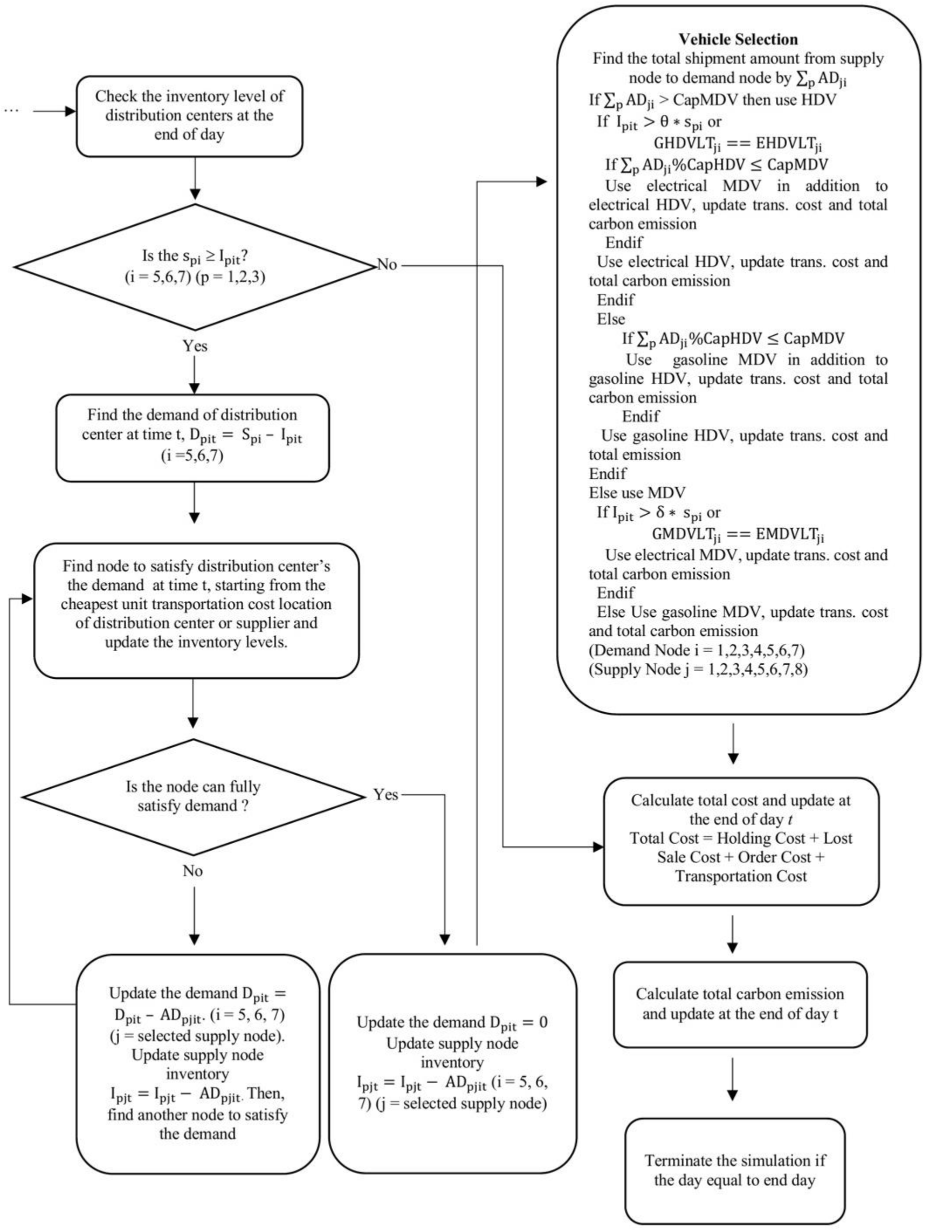


Figure 6.3. Simulation Model Flow Chart

In these models, demands come to retailers beginning of the day for each product type. If the retailer cannot satisfy the demand, lost sale cost occurs.

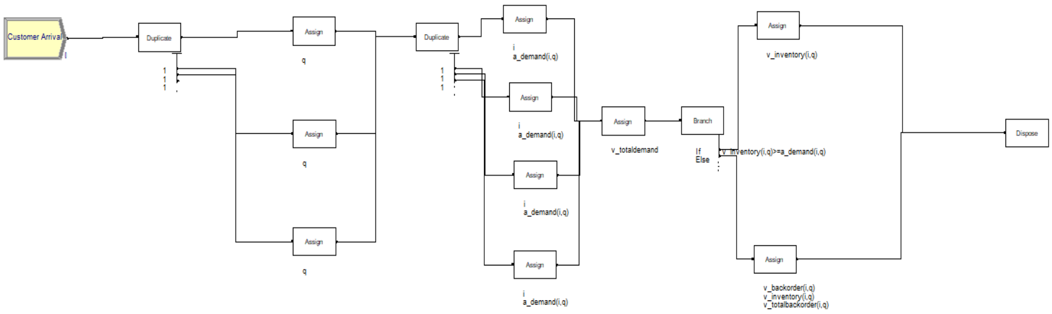


Figure 6.4. Customer Demand Satisfaction Part

After that, the model firstly checks the retailer inventories, if their inventories under the reorder point, order occurs at the amount of product to reach the order up point by subtracting the current inventory level from the order up level.

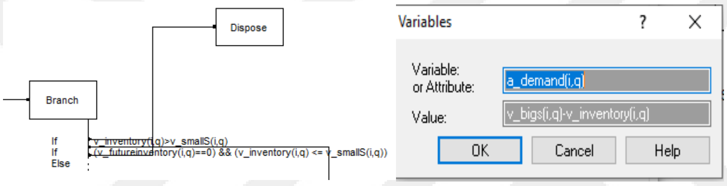


Figure 6.5. Retailer Inventory Checking Part

The model is sorting the supply nodes according to transportation cost, then feeds the demand node until satisfying the demand. However, the model is sorting the supply nodes by distance to give importance to total carbon emission in the b level 0.5 and 0.1.

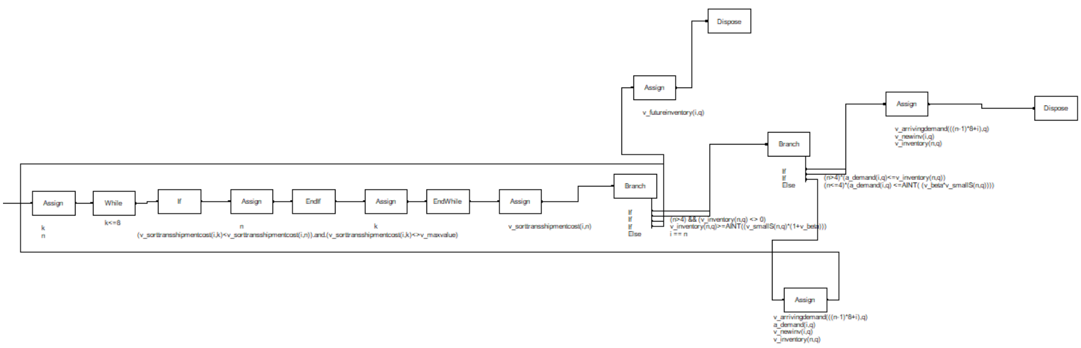


Figure 6.6. Supply Node Selection for Retailer Part

After feeding the retailers, the model checks the distribution center inventories in the same manner as retailer inventories.

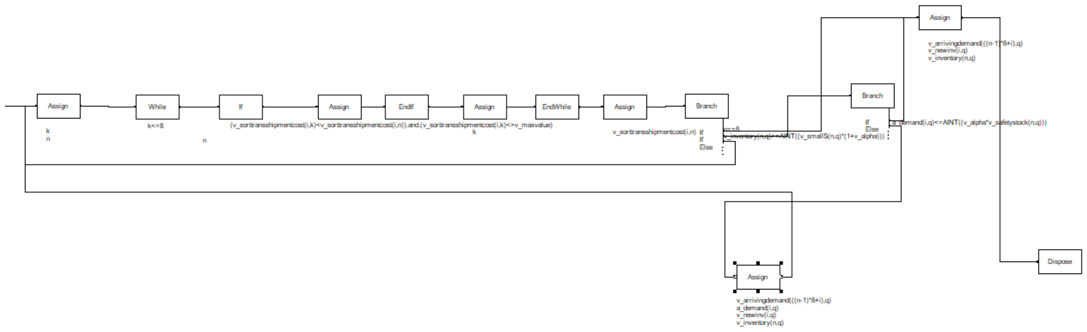


Figure 6.7. Supply Node Selection for Distribution Center Part

In the base model, the vehicle selection algorithm decides gasoline HDV and gasoline MDV usage. Therefore, when the total shipment amount more than MDV’s capacity, the model sends HDV because if we choose MDV, we must use more vehicles, and this choice will increase order cost drastically. For instance, let's think that the model sends 119 units of items from the supplier to the distribution center. If the model uses MDV, the order cost increases six times more than HDV usage. In some cases, the algorithm uses both of them. For instance, when it is sending 137 units of product model can send 120 units of products with HDV, 17 units of products with MDV instead of sending all of them with HDV because MDV’s unit transportation cost is less than HDV. Therefore, the model chooses to transport products with HDV and MDV, when the total shipment amount mod HDV’s capacity is less than or equal to MDV’s capacity. In the hybrid and lateral transshipment model, the vehicle selection algorithm decides electric versions of HDV and MDV in addition to the base model. Electric vehicles lead times more than gasoline vehicles for some distances and we know that the reorder point and lead time are strongly related because the reorder point represents the stock amount until the new product flow arrives. Therefore, the hybrid and lateral models determine levels that represent the portion of the reorder point of inventories to send products with electric vehicles. Hence, we can be sure that if we choose the electric vehicle, it can transport the products right on time by determining these levels.

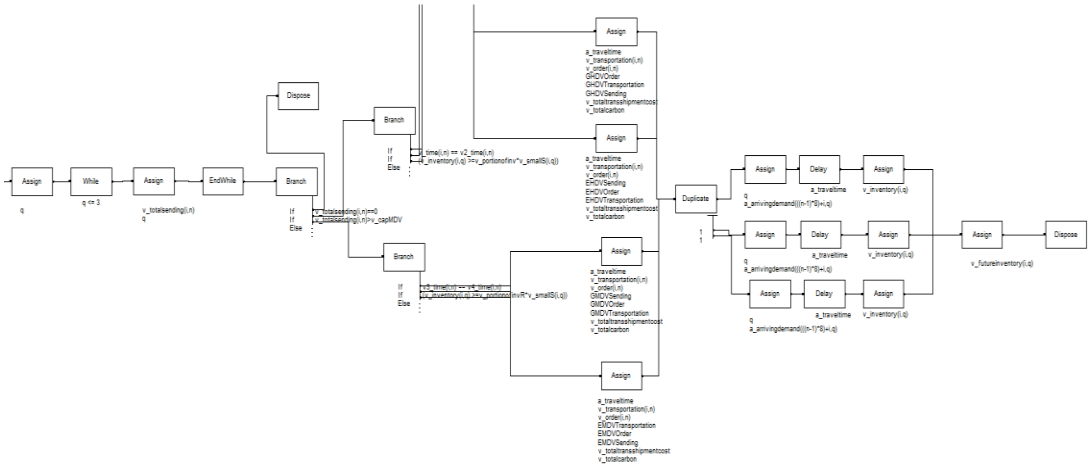


Figure 6.8. Vehicle Selection Part

In the lateral transshipment model, we determine levels that represent the portion of the reorder point to allow product flow within the echelon. In other words, transshipment occurs when the supply node inventory more than (1+α) times reorder point. Therefore, supply node inventory must be more than the reorder point to send products to the demand node within the same echelon.

6.1 Verification and Validation

Verification is the process of confirming that a model operates as intended (Pegden et al., 1990). Therefore, debugger tools of Arena simulation modeling software, such as Command, Break and Watch were used for checking models' status. Also, models' animation was watched. In this way, models' verification process was done.

Validation is usually defined to mean "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Schlesingeret et al., 1979). There are several methods for validation process such as event validity, face validity, historical data validation, Turing tests, parameter variability (i.e. sensitivity analysis) etc. (Sargent, 2011). In this thesis, sensitivity analysis is applied to models. This technique consists of changing the values of the input and internal parameters of a model to determine the effect upon the model's behavior or output. This technique can be used qualitatively directions only of outputs and quantitatively both directions and (precise) magnitudes of outputs. Those parameters that are sensitive, i.e., cause significant changes in the model's behavior or output, should be made sufficiently accurate prior to using the model. Thus, sensitivity analysis over total cost coefficient showed that models are valid because while total cost coefficient decreasing model give more importance to the total carbon emission. In addition, sensitivity analysis over lateral transshipment cost shows that when the lateral transshipment cost increased lateral transshipment amount decreased as expected so, the model was validated.

CHAPTER 7
EXPERIMENTAL RESULTS OF SIMULATION MODELS

The base simulation model, the hybrid simulation model, and the lateral transshipment simulation model results are given in this section. As in Chapter 5, the problem objectives are the same and we use the same β levels which is the coefficient of the total cost. To optimize the problem objectives and determine the (s, S) levels OptQuest tool is used and we developed the model in ARENA 14.0 software. The OptQuest is run several times by narrowing the search space of decision variables by utilizing the previous run's result as a suggested solution. Screenshots of the OptQuest run and its result are shown in Figure 7.1. Decision variables are determined as reorder and order up inventory levels (s, S) each retailer and distribution center for each product. So, total cost and total carbon emission amounts are minimized by optimizing (s, S) values and the same logic is used in all models.

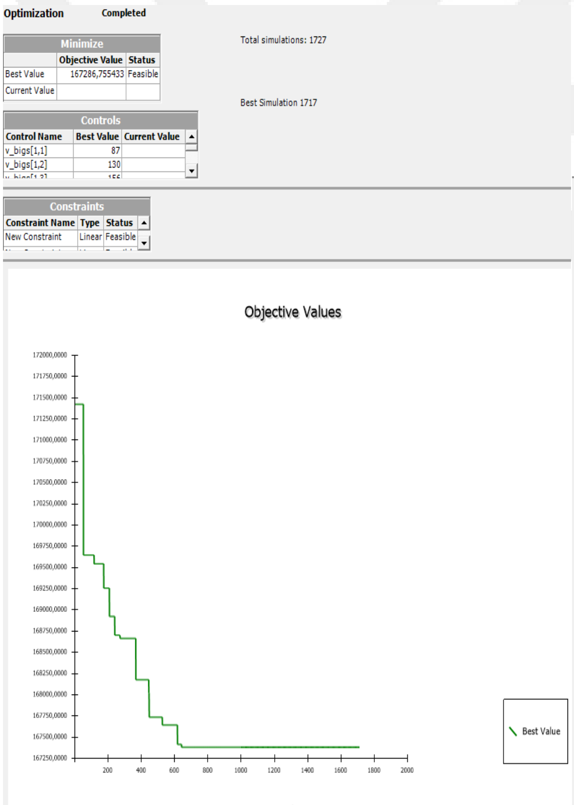
User Specified Summary

Included	Control	Element Type	Type	Low Bound	Suggested Value	High Bound	Step
✔	v_bigs[1,1]	Variable	Discrete	80	84	88	1
✔	v_bigs[1,2]	Variable	Discrete	130	134	138	1
✔	v_bigs[1,3]	Variable	Discrete	156	160	164	1
✔	v_bigs[2,1]	Variable	Discrete	50	60	70	1
✔	v_bigs[2,2]	Variable	Discrete	170	180	190	1
✔	v_bigs[2,3]	Variable	Discrete	191	201	211	1
✔	v_bigs[3,1]	Variable	Discrete	45	55	65	1
✔	v_bigs[3,2]	Variable	Discrete	67	77	87	1
✔	v_bigs[3,3]	Variable	Discrete	7	17	27	1
✔	v_bigs[4,1]	Variable	Discrete	184	194	204	1
✔	v_bigs[4,2]	Variable	Discrete	68	78	88	1
✔	v_bigs[4,3]	Variable	Discrete	25	35	45	1
✔	v_bigs[5,1]	Variable	Discrete	406	416	426	1
✔	v_bigs[5,2]	Variable	Discrete	101	111	121	1
✔	v_bigs[5,3]	Variable	Discrete	95	105	115	1
✔	v_bigs[6,1]	Variable	Discrete	0	0	10	1
✔	v_bigs[6,2]	Variable	Discrete	118	128	138	1
✔	v_bigs[6,3]	Variable	Discrete	67	77	87	1
✔	v_bigs[7,1]	Variable	Discrete	197	207	217	1
✔	v_bigs[7,2]	Variable	Discrete	0	0	10	1
✔	v_bigs[7,3]	Variable	Discrete	474	479	483	1

(a)

User Specified Summary							
Included	Control	Element Type	Type	Low Bound	Suggested Value	High Bound	Step
☑	v_smallS[1,1]	Variable	Discrete	17	27	37	1
☑	v_smallS[1,2]	Variable	Discrete	39	49	59	1
☑	v_smallS[1,3]	Variable	Discrete	0	3	13	1
☑	v_smallS[2,1]	Variable	Discrete	2	12	22	1
☑	v_smallS[2,2]	Variable	Discrete	46	56	66	1
☑	v_smallS[2,3]	Variable	Discrete	10	20	30	1
☑	v_smallS[3,1]	Variable	Discrete	43	53	63	1
☑	v_smallS[3,2]	Variable	Discrete	16	26	36	1
☑	v_smallS[3,3]	Variable	Discrete	5	15	25	1
☑	v_smallS[4,1]	Variable	Discrete	14	24	34	1
☑	v_smallS[4,2]	Variable	Discrete	36	46	56	1
☑	v_smallS[4,3]	Variable	Discrete	0	4	14	1
☑	v_smallS[5,1]	Variable	Discrete	288	298	308	1
☑	v_smallS[5,2]	Variable	Discrete	0	0	10	1
☑	v_smallS[5,3]	Variable	Discrete	51	61	71	1
☑	v_smallS[6,1]	Variable	Discrete	0	0	10	1
☑	v_smallS[6,2]	Variable	Discrete	16	26	36	1
☑	v_smallS[6,3]	Variable	Discrete	19	29	39	1
☑	v_smallS[7,1]	Variable	Discrete	99	109	119	1
☑	v_smallS[7,2]	Variable	Discrete	0	0	10	1
☑	v_smallS[7,3]	Variable	Discrete	106	116	126	1

(b)



Constraints

Constraints Summary				
Included	Name	Type	Description	Expression
☑	New Constraint	Linear		[v_bigs[1,1]] >= [v_smallS[1,1]]
☑	New Constraint	Linear		[v_bigs[1,2]] >= [v_smallS[1,2]]
☑	New Constraint	Linear		[v_bigs[1,3]] >= [v_smallS[1,3]]
☑	New Constraint	Linear		[v_bigs[2,1]] >=[v_smallS[2,1]]
☑	New Constraint	Linear		[v_bigs[2,2]] >= [v_smallS[2,2]]
☑	New Constraint	Linear		[v_bigs[2,3]] >= [v_smallS[2,3]]
☑	New Constraint	Linear		[v_bigs[3,1]] >= [v_smallS[3,1]]
☑	New Constraint	Linear		[v_bigs[3,2]] >= [v_smallS[3,2]]
☑	New Constraint	Linear		[v_bigs[3,3]] >= [v_smallS[3,3]]
☑	New Constraint	Linear		[v_bigs[4,1]] >= [v_smallS[4,1]]
☑	New Constraint	Linear		[v_bigs[4,2]] >= [v_smallS[4,2]]
☑	New Constraint	Linear		[v_bigs[4,3]] >= [v_smallS[4,3]]
☑	New Constraint	Linear		[v_bigs[5,1]] >= [v_smallS[5,1]]
☑	New Constraint	Linear		[v_bigs[5,2]] >= [v_smallS[5,2]]
☑	New Constraint	Linear		[v_bigs[5,3]] >= [v_smallS[5,3]]
☑	New Constraint	Linear		[v_bigs[6,1]] >= [v_smallS[6,1]]
☑	New Constraint	Linear		[v_bigs[6,2]] >= [v_smallS[6,2]]
☑	New Constraint	Linear		[v_bigs[6,3]] >= [v_smallS[6,3]]
☑	New Constraint	Linear		[v_bigs[7,1]] >= [v_smallS[7,1]]
☑	New Constraint	Linear		[v_bigs[7,2]] >= [v_smallS[7,2]]
☑	New Constraint	Linear		[v_bigs[7,3]] >= [v_smallS[7,3]]

(c) (d)

Figure 7.1 OptQuest screenshots for Base Model: (a) and (b) control part of the (s, S) values; (b) Visualized (s, S) values of Base Model OptQuest; (c) Part represents constraints which are added to OptQuest.

7.1 Base Simulation Model

In the base model, we only consider gasoline engine heavy-duty trucks and gasoline engine medium-duty trucks as vehicle types. According to the OptQuest results, we define (s, S) levels that are given in Table 7.1 to Table 7.3 for each β level.

Table 7.1. (s, S) Levels when β is 0.9 in Base Simulation Model

β = 0.9	s			S		
	P1	P2	P3	P1	P2	P3
R 1	31	44	4	87	130	156
R 2	16	60	14	64	176	197
R 3	57	22	15	58	73	17
R 4	24	42	8	190	80	39
DC 1	302	0	56	410	107	101
DC 2	0	22	33	0	124	81
DC 3	105	0	112	203	0	483

Table 7.2. (s, S) Levels when β is 0.5 in Base Simulation Model

β = 0.5	s			S		
	P1	P2	P3	P1	P2	P3
R 1	100	19	125	161	102	223
R 2	28	92	32	102	92	32
R 3	87	9	69	152	45	89
R 4	13	38	129	120	149	183
DC 1	104	55	28	305	500	497
DC 2	120	36	12	120	114	295
DC 3	108	0	0	108	0	0

Table 7.3. (s, S) Levels when β is 0.1 in Base Simulation Model

β = 0.1	s			S		
	P1	P2	P3	P1	P2	P3
R 1	163	56	135	250	250	150
R 2	31	85	147	178	195	250
R 3	10	41	112	110	142	236
R 4	132	45	210	240	250	250
DC 1	208	260	110	470	315	398
DC 2	0	255	173	349	299	499
DC 3	125	125	147	409	205	231

Base model simulation output file screenshots are given in Figure 7.2 to Figure 7.4.

ARENA Simulation Results
Serkan - License: 7328734345

Output Summary for 10 Replications

Project: Unnamed Project — Run execution date :10/16/2020
Analyst: Rockwell Automation — Model revision date:10/16/2020

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
Total Cost	1.5958E+05	1129.2	1.5744E+05	1.6296E+05	10
Total Carbon Emission	2.3666E+05	2584.3	2.2950E+05	2.4170E+05	10
DC Inv.Holding Cost	35289.	863.33	34105.	38406.	10
Retailer Inv.Holding Cost	74320.	398.23	73263.	75107.	10
Total Holding	1.0961E+05	910.27	1.0792E+05	1.1276E+05	10
DC to Retailer Transportation Cost	7858.0	177.72	7342.3	8234.6	10
Supplier to DC Transportation Cost	16180.	228.95	15545.	16601.	10
Total Transportation Cost	24038.	392.66	22888.	24740.	10
DC Order Cost	16040.	237.71	15250.	16500.	10
Supplier Order Cost	8990.0	167.58	8600.0	9300.0	10
Total Order Cost	25030.	330.90	24050.	25650.	10
Lost Sale Cost	900.00	74.480	.00000	2100.0	10
GMDV Order Cost	3385.0	200.23	3000.0	3800.0	10
GHDV Order Cost	21645.	247.47	20950.	22050.	10
GHDV Shipment Amount	29773.	362.83	28764.	30461.	10
GMDV Shipment Amount	1167.6	54.988	988.00	1327.0	10
GMDV Transportation Cost	534.89	32.174	466.97	595.26	10
GHDV Transportation Cost	23503.	395.23	22356.	24207.	10
StoDC Shipment Amount	15466.	198.36	14934.	15882.	10
DCtoR Shipment Amount	15474.	180.54	14934.	15773.	10
Entity 1.NumberIn	17033.	12.980	17008.	17064.	10
Entity 1.NumberOut	17023.	11.215	17002.	17049.	10
System.NumberOut	.00000	.00000	.00000	.00000	10

Simulation run time: 0.03 minutes.
Simulation run complete.

Figure 7.2. Base Model Simulation Output File When β is 0.9

ARENA Simulation Results
Serkan - License: 7328734345

Output Summary for 10 Replications

Project: Unnamed Project — Run execution date :10/16/2020
Analyst: Rockwell Automation — Model revision date:10/16/2020

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
Total Cost	2.0471E+05	946.79	2.0028E+05	2.0444E+05	10
Total Carbon Emission	1.8403E+05	2552.1	1.7959E+05	1.9101E+05	10
DC Inv.Holding Cost	42443.	366.31	41561.	43253.	10
Retailer Inv.Holding Cost	1.0857E+05	154.92	1.0823E+05	1.0888E+05	10
Total Holding	1.5102E+05	367.39	1.5033E+05	1.5194E+05	10
DC to Retailer Transportation Cost	10781.	144.33	10292.	10979.	10
Supplier to DC Transportation Cost	17984.	235.37	17373.	18674.	10
Total Transportation Cost	28766.	306.31	27996.	29557.	10
DC Order Cost	14330.	577.24	13550.	16400.	10
Supplier Order Cost	7055.0	154.01	6800.0	7550.0	10
Total Order Cost	21385.	620.63	20500.	23350.	10
Lost Sale Cost	3550.00	85.880	.00000	3600.0	10
GMDV Order Cost	2730.0	67.780	1700.0	5850.0	10
GHDV Order Cost	18655.	358.62	17500.	19450.	10
GHDV Shipment Amount	29736.	307.11	28893.	30350.	10
GMDV Shipment Amount	813.10	17.020	539.00	1376.0	10
GMDV Transportation Cost	495.23	10.330	335.10	881.25	10
GHDV Transportation Cost	28270.	336.92	27437.	28956.	10
StoDC Shipment Amount	15091.	200.65	14587.	15687.	10
DCtoR Shipment Amount	15457.	140.82	15041.	15703.	10
Entity 1.NumberIn	14448.	23.362	14404.	14520.	10
Entity 1.NumberOut	14442.	22.628	14401.	14514.	10
System.NumberOut	.00000	.00000	.00000	.00000	10

Simulation run time: 0.02 minutes.
Simulation run complete.

Figure 7.3. Base Model Simulation Output File When β is 0.5

```
                          ARENA Simulation Results
                       Serkan - License: 7328734345

                       Output Summary for 10 Replications

Project: Unnamed Project                                 Run execution date :10/16/2020
Analyst: Rockwell Automation                             Model revision date:10/16/2020

                                   OUTPUTS

Identifier                          Average    Half-width Minimum    Maximum # Replications
_______________________________________________________________________________________

Total Cost                           3.2990E+05 2394.9     3.2405E+05 3.3723E+05 10
Total Carbon Emission                1.6421E+05 2577.6     1.5929E+05 1.7029E+05 10
DC Inv.Holding Cost                  89555.     1305.0     85128.     91257.     10
Retailer Inv.Holding Cost            1.8935E+05 388.95     1.8857E+05 1.9028E+05 10
Total Holding                        2.7890E+05 1422.0     2.7391E+05 2.8084E+05 10
DC to Retailer Transportation Cost   10998.     166.52     10504.     11398.     10
Supplier to DC Transportation Cost   17951.     308.00     17496.     18764.     10
Total Transportation Cost            28950.     525.35     28000.     30163.     10
DC Order Cost                        10375.     170.48     10050.     10950.     10
Supplier Order Cost                  6925.0     140.30     6700.0     7300.0     10
Total Order Cost                     17300.     295.41     16850.     18250.     10
Lost Sale Cost                       4740.0     126.50     .00000     10800.     10
GMDV Order Cost                      2350.0     93.700     2100.0     3000.0     10
GHDV Order Cost                      14950.     184.69     14450.     15350.     10
GHDV Shipment Amount                 29511.     385.84     28755.     30506.     10
GMDV Shipment Amount                 804.30     71.961     698.00     1050.0     10
GMDV Transportation Cost             233.32     33.162     188.28     337.74     10
GHDV Transportation Cost             28717.     455.31     27736.     29945.     10
StoDC Shipment Amount                14857.     260.43     14393.     15435.     10
DCtoR Shipment Amount                15458.     169.37     15071.     15891.     10
Entity 1.NumberIn                    14236.     10.875     14218.     14274.     10
Entity 1.NumberOut                   14233.     10.621     14218.     14268.     10
System.NumberOut                     .00000     .00000     .00000     .00000     10

Simulation run time: 0.03 minutes.
Simulation run complete.
```

Figure 7.4. Base Model Simulation Output File When β is 0.1

The results of the base simulation model experiment are given in Table 7.4.

Table 7.4. Base Simulation Model Results

	β Level		
	0.9	**0.5**	**0.1**
Total Carbon Emission	236660	184030	164210
Supplier to DC Transportation Cost	16180	17984	17951
DC to Retailer Transportation Cost	7858	10781	10998
Total Transportation	24038.	28765	28949
Holding DC In. Cost	35289	42443	89555
Holding R In. Cost	74320	108570	189350
Total Holding	109609	151013	278905
Order S to DC Cost	8990	7055	6925
Order DC to Retailer Cost	16040	14330	10375
Total Order Cost	25030	21385	17300
Lost Sale Cost	900	3550	4740
Total Cost	159577	204713	329894

According to Table 7.4, we see that when the β level decreases, the total cost increases and total emission decreases.

As shown in Figure 5.1, when the β level decreases, the order cost decreases. The model tries to use fewer vehicles to avoid more carbon emissions due to the increasing total carbon emissions coefficient. According to this behavior, order up and reorder point levels differences getting wider while β level decreases.

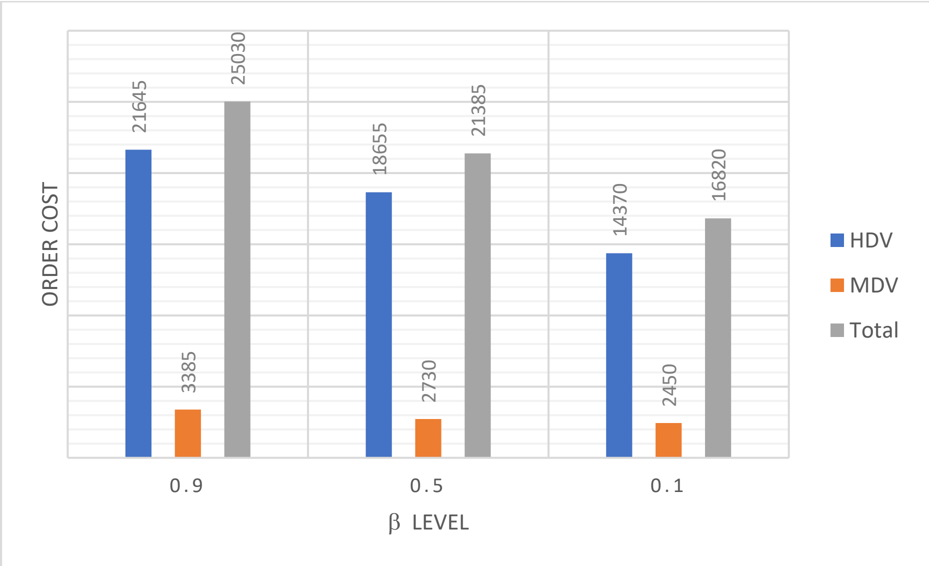


Figure 7.5. Base Simulation Model - Order Cost vs. β level

When the β level decreases, HDV's usage decreases as well because HDV has more carbon emission when shipment amounts are small. HDV's usage has the highest value because it has more capacity than MDV. Hence, the model chose them because of their capacity. Also, they cause less order cost when the shipment amounts are massive.

The total holding cost increases when the β level decreases because the model tries to use fewer vehicles. As a result of this choice, the model is sending large number of products to avoid loss sale and it increases the holding cost. Therefore, reorder point and order up levels difference getting wider when β level is decreasing.

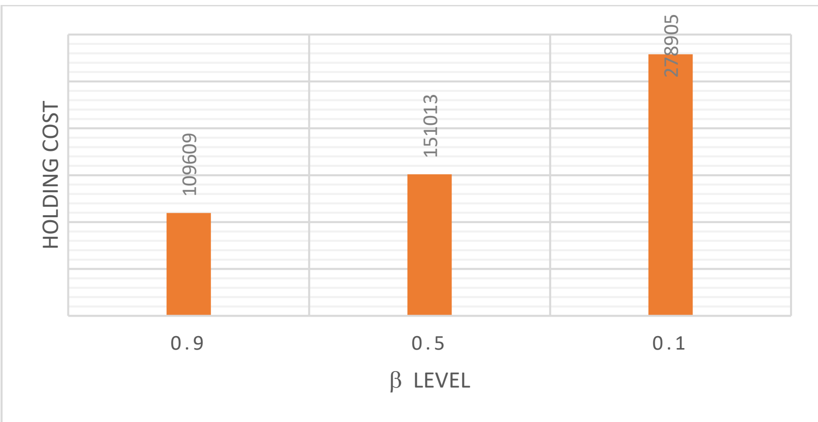


Figure 7.6. Base Simulation Model - Holding Cost vs. β level

As a result of total transportation cost values, when the β level decreases total transportation cost increases. When we look at Figure 7.7, we can see that the total shipment amount has the highest value when β level is 0.9. However, it has the lowest transportation cost because cost has more priority at this level and it chooses paths that have less unit transportation cost.

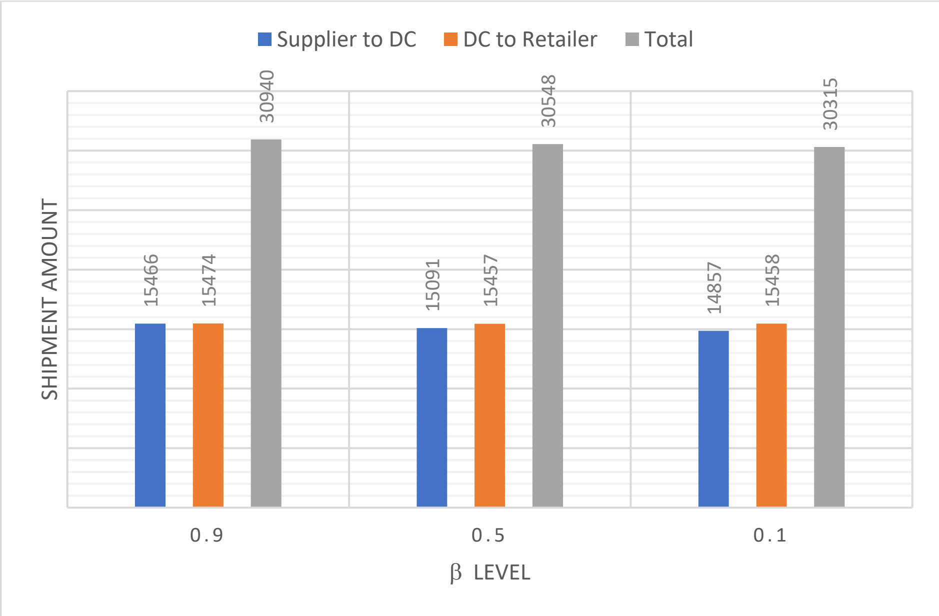


Figure 7.7. Base Simulation Model - Shipment Amounts between Nodes vs. β level

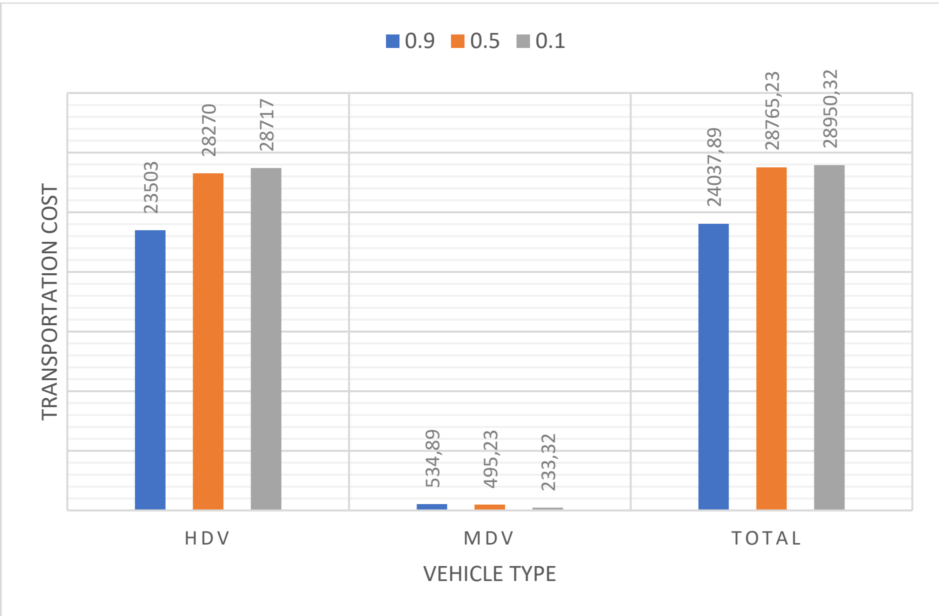


Figure 7.8. Base Simulation Model - Transportation Cost for Different Vehicle Types vs. β level

HDV’s transportation cost increases when the β coefficient decreases because the model sending massive shipment amounts. Thus, HDV’s transportation cost increase because it has more capacity than MDV.

7.2 Hybrid Simulation Model

In the hybrid simulation model, we use two different types of vehicles to reduce carbon emissions. Each vehicle type has an electric engine version and a gasoline engine version same as in the Chapter 5 hybrid model.

According to the OptQuest result, we defined (s, S) levels for the hybrid simulation model. The levels are given in Table 7.5 to Table 7.7 for each β level.

Table 7.5. (s, S) Levels When β is 0.9 in Hybrid Simulation Model

β = 0.9	**s**			**S**		
	P1	**P2**	**P3**	**P1**	**P2**	**P3**
R 1	16	10	6	49	58	23
R 2	61	23	36	69	62	69
R 3	19	24	29	92	153	29
R 4	70	16	8	135	40	57
DC 1	95	99	23	380	107	70
DC 2	0	0	61	97	155	128
DC 3	0	400	19	53	418	105

Table 7.6. (s, S) Levels When β is 0.5 in Hybrid Simulation Model

β = 0.5	**s**			**S**		
	P1	**P2**	**P3**	**P1**	**P2**	**P3**
R 1	20	27	37	87	122	47
R 2	73	28	23	73	62	153
R 3	33	22	18	88	69	25
R 4	15	6	118	35	37	122
DC 1	217	179	104	482	411	209
DC 2	36	140	47	262	270	417
DC 3	59	68	284	83	68	284

Table 7.7. (s, S) Levels When β is in Hybrid Simulation Model

β = 0.1	**s**			**S**		
	P1	**P2**	**P3**	**P1**	**P2**	**P3**
R 1	74	83	147	173	151	184
R 2	109	74	83	109	76	83
R 3	83	33	26	128	96	98
R 4	55	45	74	161	153	122
DC 1	198	135	102	400	306	278
DC 2	173	96	93	269	348	155
DC 3	30	0	234	38	0	267

According to OptQuest results, we defined θ, δ levels for the hybrid simulation model. θ level represents the portion of the reorder point of inventories to send products with electric HDV when the lead time of electric HDV is not equal to gasoline HDV. δ level represents the portion of the reorder point of inventories to send products with electric MDV when the lead time of electric MDV is not equal to gasoline MDV. As a reminder, they represent the portion of the reorder point because the reorder point represents the point that satisfies the demand until new products come. Thus, we define these levels because electric vehicles lead times more than or equal to gasoline vehicles. Therefore, if the inventory level can satisfy the demand until the electric vehicle brings new products, the model can send products with electric vehicles. The levels are given in Table 7.8 for each β level.

Table 7.8. θ and δ Levels

	β level		
	0.9	**0.5**	**0.1**
θ	0.483	0.197	0
δ	0.334	0.214	0

According to these values, the model prefers to send products only with electric vehicles when β level is 0.1. So, we can observe that when the β decreases model chooses electrical vehicles more.

Hybrid model simulation output file screenshots are given in Figure 7.9 to Figure 7.11.

ARENA Simulation Results
Serkan - License: 7328734345

Output Summary for 10 Replications

Project: Unnamed Project
Analyst: Rockwell Automation

Run execution date :10/16/2020
Model revision date:10/16/2020

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
Total Cost	1.4363E+05	1165.5	1.4202E+05	1.4675E+05	10
Total Carbon Emission	1.4581E+05	1366.8	1.4277E+05	1.4823E+05	10
DC Inv.Holding Cost	34346.	265.25	33730.	35063.	10
Retailer Inv.Holding Cost	51710.	256.07	51210.	52281.	10
Total Holding	86056.	363.55	85535.	87152.	10
DC to Retailer Transportation Cost	5735.4	97.382	5554.9	5959.3	10
Supplier to DC Transportation Cost	16412.	175.10	16029.	16850.	10
Total Transportation Cost	22147.	222.22	21584.	22649.	10
DC Order Cost	22935.	126.22	22700.	23250.	10
Supplier Order Cost	11595.	126.67	11350.	11900.	10
Total Order Cost	34530.	217.35	34200.	35050.	10
Lost Sale Cost	900.00	57.500	.00000	5100.0	10
EMDV Order Cost	9345.0	243.42	8900.0	9950.0	10
EHDV Order Cost	21420.	322.19	20600.	22150.	10
GMDV Order Cost	415.00	13.587	300.00	600.00	10
GHDV Order Cost	1925.0	59.270	1550.0	2300.0	10
GHDV Shipment Amount	3251.3	130.80	2556.0	4140.0	10
GMDV Shipment Amount	140.00	11.013	104.00	202.00	10
EHDV Shipment Amount	25326.	454.10	23822.	25802.	10
EMDV Shipment Amount	2186.8	81.164	1998.0	2342.0	10
EMDV Transportation Cost	541.79	19.240	474.51	569.16	10
EHDV Transportation Cost	18390.	462.55	16883.	19015.	10
GMDV Transportation Cost	47.402	4.0430	33.280	73.880	10
GHDV Transportation Cost	3178.4	393.88	2266.5	4353.1	10
StoDC Shipment Amount	15443.	146.73	15141.	15828.	10
DCtoR Shipment Amount	15461.	112.15	15220.	15655.	10
Entity 1.NumberIn	15000.	9.3932	14978.	15026.	10
Entity 1.NumberOut	14988.	9.6279	14966.	15014.	10
System.NumberOut	.00000	.00000	.00000	.00000	10

Simulation run time: 0.03 minutes.
Simulation run complete.

Figure 7.9. Hybrid Model Simulation Output File When β is 0.9

ARENA Simulation Results
Serkan - License: 7328734345

Output Summary for 10 Replications

Project: Unnamed Project — Run execution date :10/16/2020
Analyst: Rockwell Automation — Model revision date:10/16/2020

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
Total Cost	1.8380E+05	2065.6	1.8095E+05	1.8964E+05	10
Total Carbon Emission	1.1088E+05	1908.5	1.0756E+05	1.1643E+05	10
DC Inv.Holding Cost	59234.	241.46	58618.	59677.	10
Retailer Inv.Holding Cost	60120.	196.79	59723.	60456.	10
Total Holding	1.1935E+05	320.73	1.1874E+05	1.1999E+05	10
DC to Retailer Transportation Cost	10640.	125.27	10427.	10830.	10
Supplier to DC Transportation Cost	18222.	182.26	17896.	18815.	10
Total Transportation Cost	28862.	235.61	28480.	29532.	10
DC Order Cost	23755.	192.56	23100.	24050.	10
Supplier Order Cost	8280.0	129.72	8000.0	8600.0	10
Total Order Cost	32035.	249.53	31250.	32350.	10
Lost Sale Cost	3550.0	185.00	1800.0	9300.0	10
EMDV Order Cost	11050.	183.14	10600.	11400.	10
EHDV Order Cost	19825.	338.14	18750.	20500.	10
GMDV Order Cost	65.000	3.9300	.00000	150.00	10
GHDV Order Cost	870.00	44.440	450.00	1700.0	10
GHDV Shipment Amount	1342.1	46.900	722.00	2895.0	10
GMDV Shipment Amount	26.000	3.5720	.00000	60.000	10
EHDV Shipment Amount	27557.	502.27	25894.	28448.	10
EMDV Shipment Amount	1975.1	49.511	1815.0	2067.0	10
EMDV Transportation Cost	477.02	12.505	442.92	505.82	10
EHDV Transportation Cost	26616.	601.44	24560.	27515.	10
GMDV Transportation Cost	17.340	1.3836	.00000	40.000	10
GHDV Transportation Cost	1770.3	87.100	950.80	3808.5	10
StoDC Shipment Amount	15346.	150.72	15034.	15802.	10
DCtoR Shipment Amount	15554.	124.72	15342.	15793.	10
Entity 1.NumberIn	14847.	12.072	14814.	14866.	10
Entity 1.NumberOut	14841.	10.649	14813.	14857.	10
System.NumberOut	.00000	.00000	.00000	.00000	10

Simulation run time: 0.03 minutes.
Simulation run complete.

Figure 7.10. Hybrid Model Simulation Output File When β is 0.5

ARENA Simulation Results
Serkan - License: 7328734345

Output Summary for 10 Replications

Project: Unnamed Project — Run execution date :10/16/2020
Analyst: Rockwell Automation — Model revision date:10/16/2020

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
Total Cost	2.2103E+05	785.76	2.1551E+05	2.1931E+05	10
Total Carbon Emission	89810.	1515.6	87813.	95187.	10
DC Inv.Holding Cost	51660.	363.05	51158.	52851.	10
Retailer Inv.Holding Cost	1.1638E+05	223.44	1.1595E+05	1.1687E+05	10
Total Holding	1.6804E+05	460.95	1.6743E+05	1.6963E+05	10
DC to Retailer Transportation Cost	11107.	118.27	10716.	11318.	10
Supplier to DC Transportation Cost	18365.	154.40	17975.	18717.	10
Total Transportation Cost	29472.	171.17	28976.	29805.	10
DC Order Cost	11430.	743.40	10850.	14350.	10
Supplier Order Cost	7490.0	115.33	7300.0	7750.0	10
Total Order Cost	18920.	815.78	18200.	22100.	10
Lost Sale Cost	4600.0	136.50	.00000	11400.	10
EMDV Order Cost	780.00	727.36	250.00	3650.0	10
EHDV Order Cost	18130.	143.26	17900.	18550.	10
GMDV Order Cost	.00000	.00000	.00000	.00000	10
GHDV Order Cost	.00000	.00000	.00000	.00000	10
GHDV Shipment Amount	.00000	.00000	.00000	.00000	10
GMDV Shipment Amount	.00000	.00000	.00000	.00000	10
EHDV Shipment Amount	30542.	167.60	30048.	30853.	10
EMDV Shipment Amount	242.40	18.780	94.000	948.00	10
EMDV Transportation Cost	119.86	8.0310	35.008	503.60	10
EHDV Transportation Cost	29361.	194.25	28928.	29714.	10
GMDV Transportation Cost	.00000	.00000	.00000	.00000	10
GHDV Transportation Cost	.00000	.00000	.00000	.00000	10
StoDC Shipment Amount	15323.	150.26	14976.	15748.	10
DCtoR Shipment Amount	15461.	94.405	15175.	15647.	10
Entity 1.NumberIn	14354.	34.335	14320.	14488.	10
Entity 1.NumberOut	14351.	33.762	14317.	14482.	10
System.NumberOut	.00000	.00000	.00000	.00000	10

Simulation run time: 0.03 minutes.
Simulation run complete.

Figure 7.11. Hybrid Model Simulation Output File When β is 0.1

All the results of this hybrid model experiment are given in Table 7.9.

Table 7.9. Hybrid Simulation Model Results

	β Level		
	0.9	**0.5**	**0.1**
Total Carbon Emission	145810	110880	89810
Supplier to DC Transportation Cost	16412	18222	18365
DC to Retailer Transportation Cost	5735.4	10640	11107
Total Transportation	22147.4	28862	29472
Holding DC In. Cost	34346	59234	51660
Holding R In. Cost	51710	60120	116380
Total Holding	86056	119354	168040
Order S to DC Cost	11595	8280	7490
Order DC to Retailer Cost	22935	23755	11430
Total Order Cost	34530	32035	18920
Lost Sale Cost	900	3550	4600
Total Cost	143633	183801	221040

According to Table 7.9, we can say that when the β level decreases, the total cost increases and total emission decreases.

As shown in Figure 7.12, when the β level decreases, the order cost increases because the model tries to use fewer vehicles to avoid more carbon emissions due to the increasing total carbon emissions coefficient.

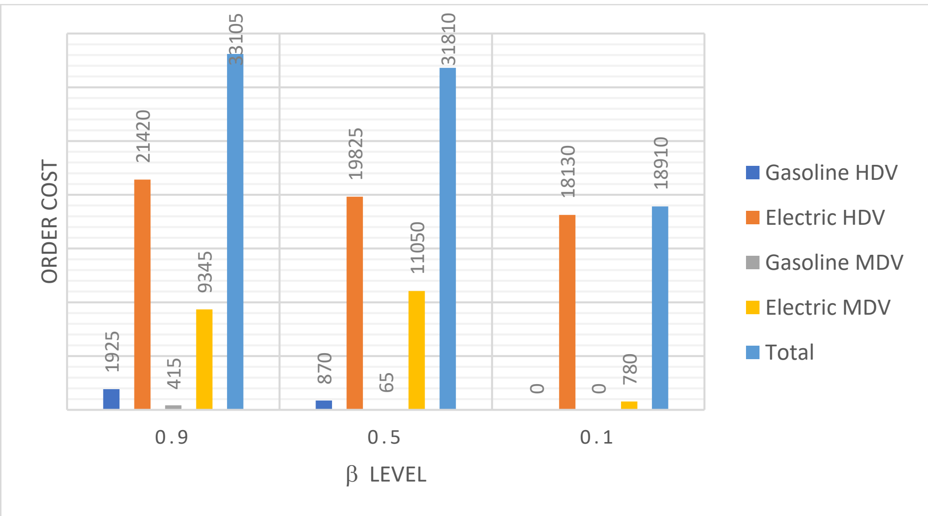


Figure 7.12. Hybrid Simulation Model - Order Cost vs. β level

In each β level, HDVs cause more order costs because they have more capacity than MDVs. Therefore, the model chose them to avoid huge order cost. Also, it causes less carbon emission when the shipment amounts are massive.

According to these results, we know that when the β level decreases, the model gives more priority to carbon emission. Therefore, gasoline HDV and MDV usage become not beneficial when the β level decreases. Thus, the model will be able to decrease total carbon emission.

In total holding cost, when the β level decreases, holding cost increases because the model tries to use fewer vehicles. As a result of this choice, the model is sending large number of products to avoid loss sale and it increases the holding cost.

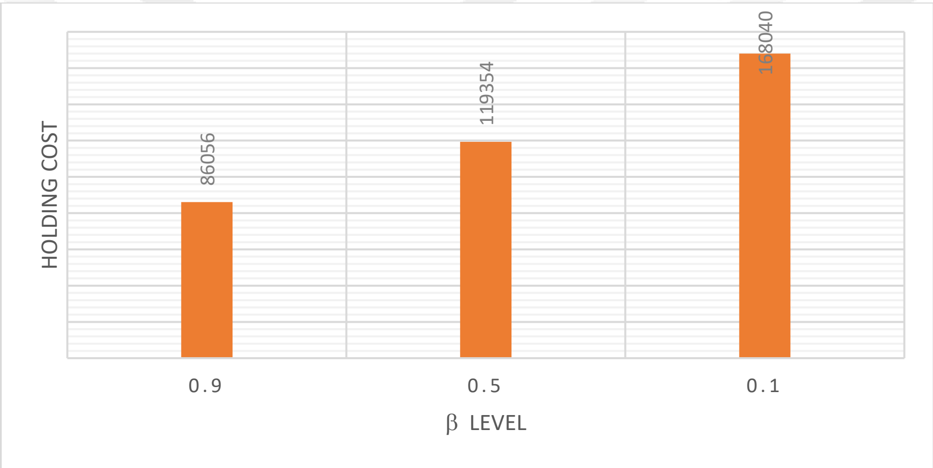


Figure 7.13. Hybrid Simulation Model - Holding Cost vs. β level

As a result of total transportation cost values, when the β level decreases total transportation cost increases. For instance, when the β level is 0.9, the total transportation cost has the lowest value than other β levels because when the model sends products, it chooses nodes that have less transportation cost mostly. However, total cost does not have priority in other level. Thus, the model chooses nodes that have less distance and it increases the total transportation cost.

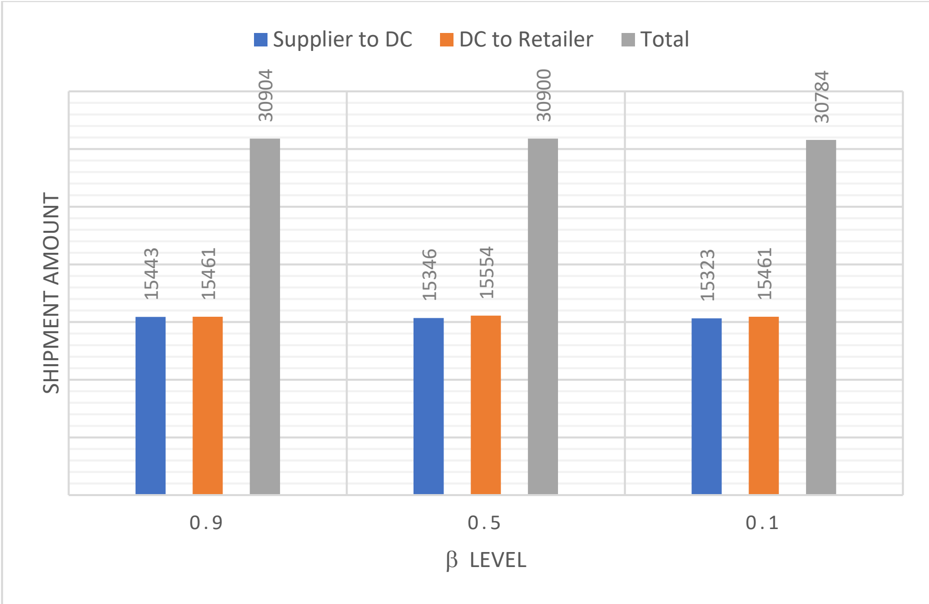


Figure 7.14. Hybrid Simulation Model - Shipment Amounts between Nodes vs. β level

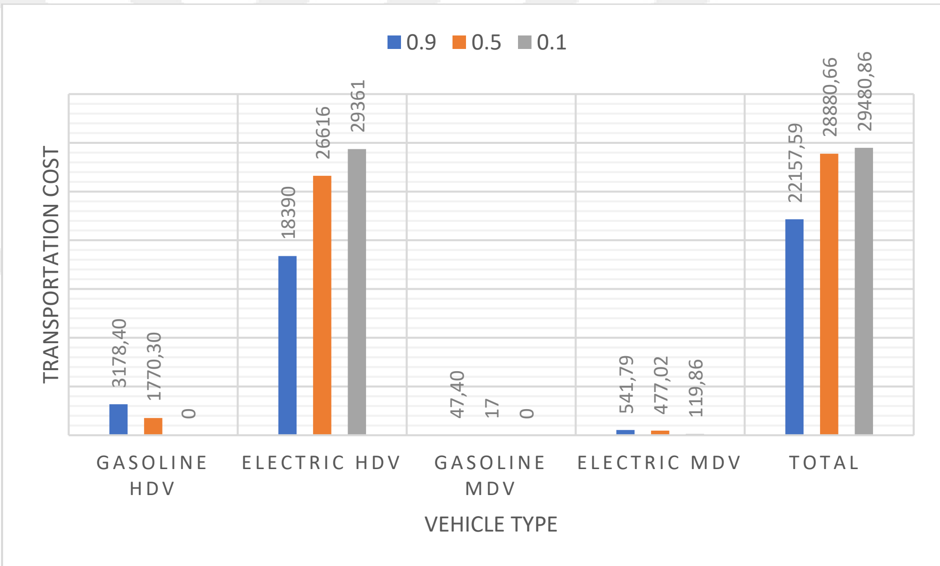


Figure 7.15. Hybrid Simulation Model - Transportation Cost for Different Vehicle Types vs. β level

Gasoline HDV and MDV transportation cost decreases when the β coefficient decrease because the model becomes more sensitive to carbon emission. Electric HDV's transportation cost increases when β level is decreases because it has less carbon emissions than gasoline HDV. Also, it has less carbon emission than MDVs when the shipment amounts are massive.

As we can see in Figure 7.16 when the total cost coefficient β decreases the model chooses to send products with electric vehicles, even they have more lead times. The model sends more products with electric HDV because it has more capacity than

MDVs. Therefore, it becomes more beneficial costly. Also, when the shipment amount is large, it becomes more beneficial in the aspect of carbon emission.

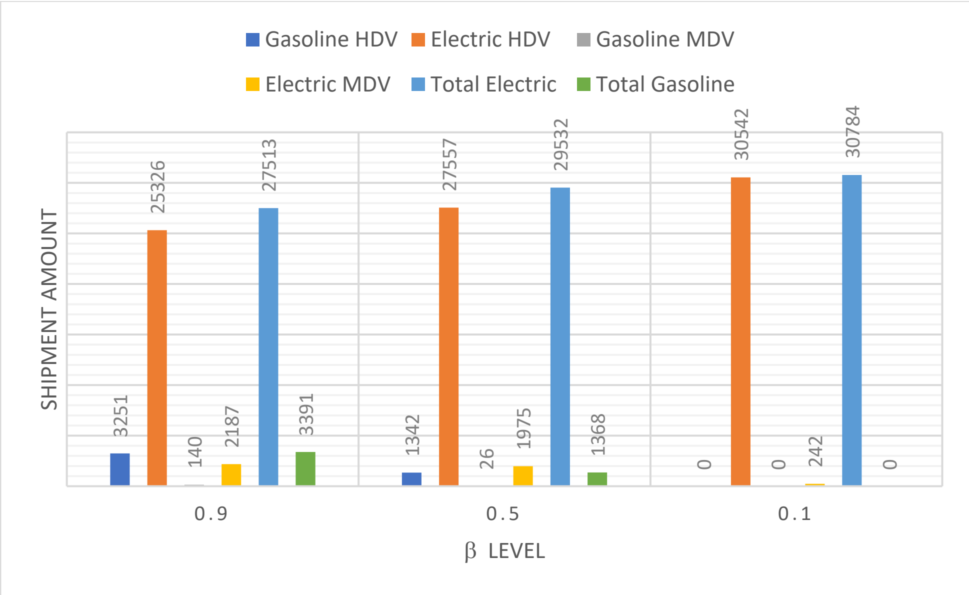


Figure 7.16. Hybrid Simulation Model - Shipment Amounts According to Vehicle Types vs. β level

Finally, we can see that when the sensitivity of carbon emission increases, electric vehicles become a more preferred option for the model.

7.3 Lateral Transshipment Simulation Model

In this model, we add lateral transshipment policy among retailers and distribution centers to the hybrid simulation model to extend hybrid policy and give more flexibility to the supply chain. According to OptQuest results, we defined (s, S) levels for the lateral transshipment simulation model. The levels are given in Table 7.10 to Table 7.12 for each β level.

Table 7.10. (s, S) Levels when β is 0.9 in Lateral Transshipment Simulation Model

β = 0.9	**s**			**S**		
	P1	**P2**	**P3**	**P1**	**P2**	**P3**
R 1	22	40	18	35	55	45
R 2	43	17	11	87	60	26
R 3	29	29	59	96	54	62
R 4	21	11	10	54	34	34
DC 1	48	30	46	135	98	87
DC 2	139	68	33	210	150	92
DC 3	61	0	35	61	230	100

Table 7.11. (s, S) Levels when β is 0.5 in Lateral Transshipment Simulation Model

β = 0.5	**s**			**S**		
	P1	**P2**	**P3**	**P1**	**P2**	**P3**
R 1	20	27	37	87	122	47
R 2	73	28	23	73	62	153
R 3	33	22	18	88	69	25
R 4	15	6	118	35	37	122
DC 1	217	179	104	482	411	209
DC 2	36	140	47	262	270	417
DC 3	59	68	284	83	68	284

Table 7.12. (s, S) Levels when β is 0.1 in Lateral Transshipment Simulation Model

β = 0.1	**s**			**S**		
	P1	**P2**	**P3**	**P1**	**P2**	**P3**
R 1	74	83	147	173	151	184
R 2	109	74	83	109	76	83
R 3	83	33	26	128	96	98
R 4	55	45	74	161	153	122
DC 1	198	135	102	400	306	278
DC 2	173	96	93	269	348	155
DC 3	30	0	234	38	0	267

According to OptQuest results, we defined θ, δ, α, ɣ levels for the lateral transshipment simulation model. The θ level represents the portion of the reorder point of inventories to send products with electric HDV when the lead time of electric HDV is not equal to gasoline HDV. The δ level represents the portion of the reorder point of inventories to send products with electric MDV when the lead time of electric MDV is not equal to gasoline MDV. The α level determines the amount of product more than the reorder point to make lateral transshipment among retailers. ɣ level determines the amount of product more than the reorder point to make lateral transshipment among distribution centers.

The levels are given in Table 7.13 for each β level.

Table 7.13. θ, δ, α, ɣ Levels

	β level		
	0.9	0.5	0.1
θ	0.09	0.197	0
δ	0.88	0.214	0
$\boldsymbol{\alpha}$	0.149	0	0
ɣ	0.04	0	0

According to α and ɣ levels, the model doesn't prefer to make lateral transshipment within the echelons in β level 0.5 and 0.1. The model prefers to send products with only electric vehicles when β level is 0.1. So, we can observe that when the β decreases model chooses electrical vehicles more.

Lateral transshipment model simulation output file screenshots are given in Figure 7.17 to Figure 7.19.

ARENA Simulation Results
Serkan - License: 7328734345

Output Summary for 10 Replications

Project: Unnamed Project
Analyst: Rockwell Automation

Run execution date :10/18/2020
Model revision date:10/18/2020

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
LateralTModel	1.2850E+05	1370.9	1.2709E+05	1.3326E+05	10
Total Carbon Emission	1.6467E+05	1051.1	1.6260E+05	1.6713E+05	10
DC Inv.Holding Cost	20188.	159.83	19795.	20516.	10
Retailer Inv.Holding Cost	40396.	181.77	40029.	40866.	10
Total Holding	60584.	262.56	59962.	61104.	10
Retailer L.Transsipment Cost	12.447	.54615	10.960	13.440	10
DC L.Transshipment Cost	171.81	5.3228	160.32	180.40	10
DC to Retailer Transportation Cost	7112.9	79.584	6992.7	7293.5	10
Supplier to DC Transportation Cost	15545.	114.94	15290.	15727.	10
Total Transportation Cost	22842.	173.62	22481.	23206.	10
Retailer Order Cost	4425.0	166.26	3950.0	4800.0	10
DC Order Cost	24330.	276.62	23850.	24900.	10
DC Lateral Order	6115.0	141.11	5850.0	6500.0	10
Supplier Order Cost	10935.	169.48	10700.	11500.	10
Total Order Cost	39690.	330.73	38950.	40350.	10
Lost Sale Cost	900.0	87.700	.00000	6300.0	10
EMDV Order Cost	16530.	404.00	15950.	17850.	10
EHDV Order Cost	22890.	355.98	22000.	23550.	10
GMDV Order Cost	2210.0	72.470	1800.0	2600.0	10
GHDV Order Cost	2195.0	72.419	2100.0	2400.0	10
GHDV Shipment Amount	3837.3	132.12	3630.0	4191.0	10
GMDV Shipment Amount	486.90	19.855	399.00	568.00	10
EHDV Shipment Amount	24890.	304.06	24094.	25534.	10
EMDV Shipment Amount	2581.3	101.06	2371.0	2889.0	10
EMDV Transportation Cost	481.61	24.131	434.43	548.04	10
EHDV Transportation Cost	18358.	252.43	17953.	18871.	10
GMDV Transportation Cost	165.20	2.1050	131.20	206.04	10
GHDV Transportation Cost	3842.1	137.71	3589.8	4210.2	10
StoDC Shipment Amount	15481.	114.08	15257.	15754.	10
DCtoR Shipment Amount	15511.	117.59	15197.	15801.	10
DCtoDC Shipment Amount	714.40	21.544	659.00	749.00	10
RtoR Shipment Amount	88.800	3.1596	80.000	96.000	10
Entity 1.NumberIn	15452.	15.865	15424.	15488.	10
Entity 1.NumberOut	15437.	16.843	15407.	15482.	10
System.NumberOut	.00000	.00000	.00000	.00000	10

Simulation run time: 0.03 minutes.
Simulation run complete.

Figure 7.17. Lateral Transshipment Model Simulation Output File When β is 0.9

ARENA Simulation Results
Serkan - License: 7328734345

Output Summary for 10 Replications

Project: Unnamed Project
Analyst: Rockwell Automation

Run execution date :10/18/2020
Model revision date:10/18/2020

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
Total Cost	1.8380E+05	2065.6	1.8095E+05	1.8964E+05	10
Total Carbon Emission	1.1088E+05	1908.5	1.0756E+05	1.1643E+05	10
DC Inv.Holding Cost	59234.	241.46	58618.	59677.	10
Retailer Inv.Holding Cost	60120.	196.79	59723.	60456.	10
Total Holding	1.1935E+05	320.73	1.1874E+05	1.1999E+05	10
Retailer L.Transsipment Cost	.00000	.00000	.00000	.00000	10
DC L.Transshipment Cost	.00000	.00000	.00000	.00000	10
DC to Retailer Transportation Cost	10640.	125.27	10427.	10830.	10
Supplier to DC Transportation Cost	18222.	182.26	17896.	18815.	10
Total Transportation Cost	28862.	235.61	28480.	29532.	10
Retailer Order Cost	.00000	.00000	.00000	.00000	10
DC Order Cost	23755.	192.56	23100.	24050.	10
DC Lateral Order	.00000	.00000	.00000	.00000	10
Supplier Order Cost	8280.0	129.72	8000.0	8600.0	10
Total Order Cost	32035.	249.53	31250.	32350.	10
Lost Sale Cost	3550.0	185.00	1800.0	9300.0	10
EMDV Order Cost	11050.	183.14	10600.	11400.	10
EHDV Order Cost	19825.	338.14	18750.	20500.	10
GMDV Order Cost	65.000	3.9300	.00000	150.00	10
GHDV Order Cost	870.00	44.440	450.00	1700.0	10
GHDV Shipment Amount	1342.1	46.900	722.00	2895.0	10
GMDV Shipment Amount	26.000	3.5720	.00000	60.000	10
EHDV Shipment Amount	27557.	502.27	25894.	28448.	10
EMDV Shipment Amount	1975.1	49.511	1815.0	2067.0	10
EMDV Transportation Cost	477.02	12.505	442.92	505.82	10
EHDV Transportation Cost	26616.	601.44	24560.	27515.	10
GMDV Transportation Cost	17.340	1.3836	.00000	40.000	10
GHDV Transportation Cost	1770.3	87.100	950.80	3808.5	10
StoDC Shipment Amount	15346.	150.72	15034.	15802.	10
DCtoR Shipment Amount	15554.	124.72	15342.	15793.	10
DCtoDC Shipment Amount	.00000	.00000	.00000	.00000	10
RtoR Shipment Amount	.00000	.00000	.00000	.00000	10
Entity 1.NumberIn	14847.	12.072	14814.	14866.	10
Entity 1.NumberOut	14841.	10.649	14813.	14857.	10
System.NumberOut	.00000	.00000	.00000	.00000	10

Simulation run time: 0.03 minutes.
Simulation run complete.

Figure 7.18. Lateral Transshipment Model Simulation Output File When β is 0.5

```
                    ARENA Simulation Results
                  Serkan - License: 7328734345

                Output Summary for 10 Replications

Project: Unnamed Project                       Run execution date :10/18/2020
Analyst: Rockwell Automation                   Model revision date:10/18/2020

                              OUTPUTS

Identifier                         Average    Half-width Minimum    Maximum # Replications
_______________________________________________________________________________________

Total Cost                          2.2103E+05 785.76     2.1551E+05 2.1931E+05 10
Total Carbon Emission               89810.     1515.6     87813.     95187.     10
DC Inv.Holding Cost                 51660.     363.05     51158.     52851.     10
Retailer Inv.Holding Cost           1.1638E+05 223.44     1.1595E+05 1.1687E+05 10
Total Holding                       1.6804E+05 460.95     1.6743E+05 1.6963E+05 10
Retailer L.Transsipment Cost        .00000     .00000     .00000     .00000     10
DC L.Transshipment Cost             .00000     .00000     .00000     .00000     10
DC to Retailer Transportation Cost  11107.     118.27     10716.     11318.     10
Supplier to DC Transportation Cost  18365.     154.40     17975.     18717.     10
Total Transportation Cost           29472.     171.17     28976.     29805.     10
Retailer Order Cost                 .00000     .00000     .00000     .00000     10
DC Order Cost                       11430.     743.40     10850.     14350.     10
DC Lateral Order                    .00000     .00000     .00000     .00000     10
Supplier Order Cost                 7490.0     115.33     7300.0     7750.0     10
Total Order Cost                    18920.     815.78     18200.     22100.     10
Lost Sale Cost                      4600.0     136.50     .00000     11400.     10
EMDV Order Cost                     780.00     727.36     250.00     3650.0     10
EHDV Order Cost                     18130.     143.26     17900.     18550.     10
GMDV Order Cost                     .00000     .00000     .00000     .00000     10
GHDV Order Cost                     .00000     .00000     .00000     .00000     10
GHDV Shipment Amount                .00000     .00000     .00000     .00000     10
GMDV Shipment Amount                .00000     .00000     .00000     .00000     10
EHDV Shipment Amount                30542.     167.60     30048.     30853.     10
EMDV Shipment Amount                242.40     18.780     94.000     948.00     10
EMDV Transportation Cost            119.86     8.0310     35.008     503.60     10
EHDV Transportation Cost            29361.     194.25     28928.     29714.     10
GMDV Transportation Cost            .00000     .00000     .00000     .00000     10
GHDV Transportation Cost            .00000     .00000     .00000     .00000     10
StoDC Shipment Amount               15323.     150.26     14976.     15748.     10
DCtoR Shipment Amount               15461.     94.405     15175.     15647.     10
DCtoDC Shipment Amount              .00000     .00000     .00000     .00000     10
RtoR Shipment Amount                .00000     .00000     .00000     .00000     10
Entity 1.NumberIn                   14354.     34.335     14320.     14488.     10
Entity 1.NumberOut                  14351.     33.762     14317.     14482.     10
System.NumberOut                    .00000     .00000     .00000     .00000     10

Simulation run time: 0.03 minutes.
Simulation run complete.
```

Figure 7.19. Lateral Transshipment Model Simulation Output File When β is 0.1

Results of lateral transshipment policy are given in Table 7.14.

Table 7.14. Lateral Transshipment Simulation Model Results

	β Level		
	0.9	**0.5**	**0.1**
Total Emission	164670	110880	89810
Supplier to DCs Transportation Cost	15545	18222	18365
DC to Retailer Transportation Cost	7112.90	10640	11107
Retailer Transshipment Cost	12.45	0	0
DC Transshipment Cost	171.81	0	0
Total Transportation	22842.157	28862	29472
Holding DC In. Cost	20188	59234	51660
Holding R In. Cost	40396	60120	116380
Total Holding	60584	119354	168040

Table 7.15(cont'd). Lateral Transshipment Simulation Model Results

	β Level		
	0.9	**0.5**	**0.1**
Order R Cost	4425	0	0
Order D Lateral Cost	6115	0	0
Order S Cost	10935	8280	7490
Order DC Cost	24330	23755	11430
Total Order Cost	45805	32035	18920
Lost Sale Cost	900	3550	4600
Total Cost	128680	183650	221040

According to Table 7.14, we can say that when the β level decreases, the total cost increases and total emission decreases.

As shown in Figure 7.20, when the β level decreases, the order cost decreases. The model tries to use fewer vehicles to avoid more carbon emissions due to the increasing total carbon emissions coefficient. According to this behavior, order up and reorder point levels differences getting wider while β level decreases.

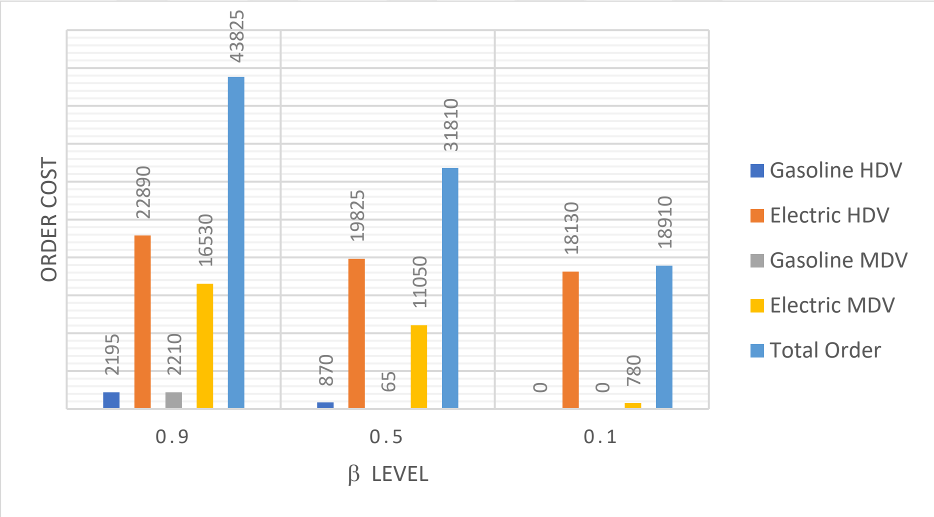


Figure 7.20. Lateral Transshipment Simulation Model - Order Cost vs. β level

According to these results, gasoline vehicles order cost decreases when the β coefficient decreases because the model gives more priority to carbon emission.

The holding cost increases when the β level decreases because of order cost values. For instance, the model has the highest order cost value when the β level is 0.1, it means that model is trying to send fewer vehicles. In order to achieve that the model must keep more products on hand.

Contrary to this, the model keeps fewer products on hand when the β level is 0.9, but it uses more vehicles to send products. Therefore, we can conclude that there is a strong relationship between order cost and holding cost.

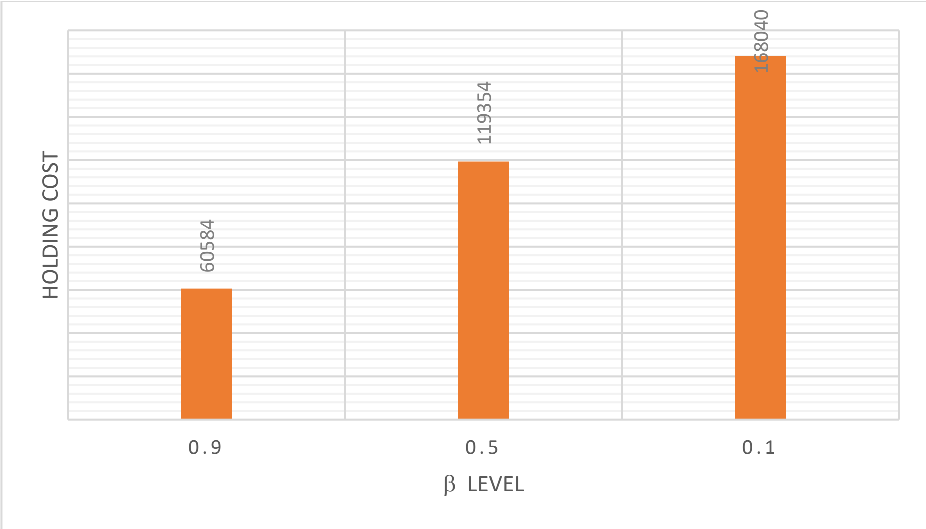


Figure 7.21. Lateral Transshipment Simulation Model – Holding Cost vs. β level

As a result of total transportation cost values, when the β level is 0.9, the total transportation cost has the lowest value than other β levels because when the model sends products, it chooses nodes that have less transportation cost mostly.

When we looked at the total shipment amounts, we can see that the model does not prefer to send products within the echelons when β levels are 0.5 and 0.1. Therefore, we can conclude that transshipment between echelons may not be beneficial for carbon emission while using (s, S) policy.

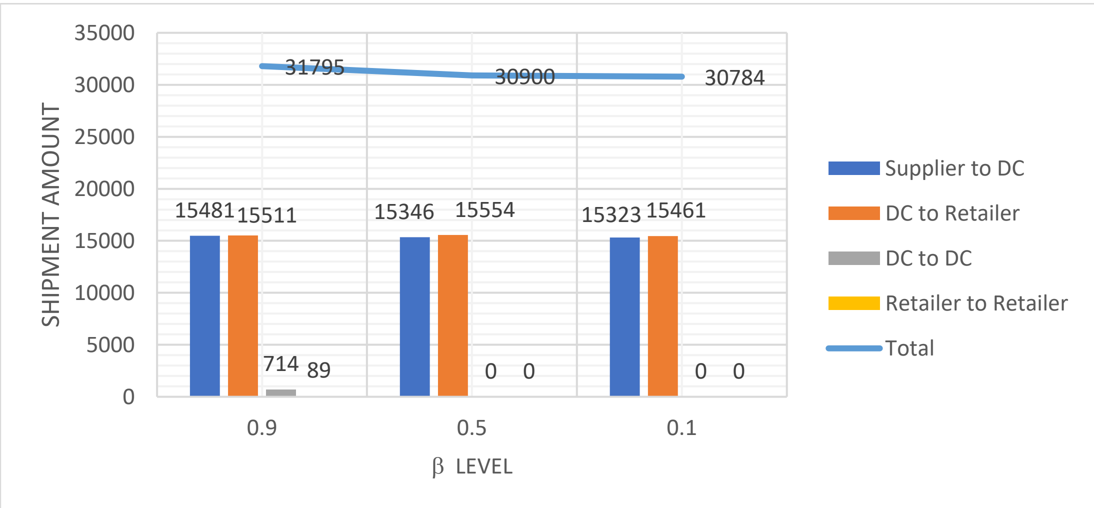


Figure 7.22. Lateral Transshipment Simulation Model - Shipment Amounts between Nodes vs. β level

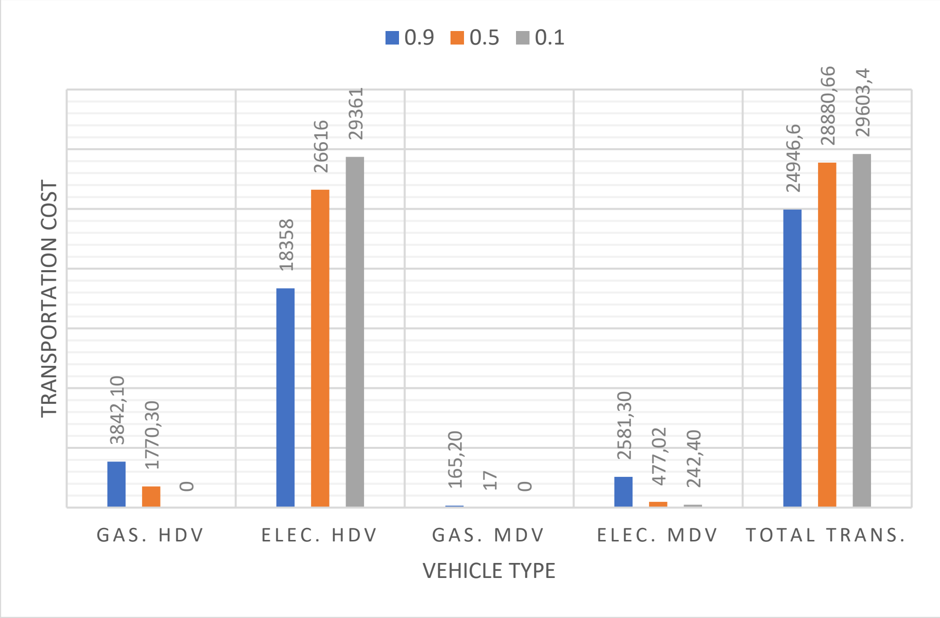


Figure 7.23. Lateral Transshipment Simulation Model - Transportation Cost for Different Vehicle Types vs. β level

Gasoline vehicles' transportation cost decreases when the β coefficient decreases because the model becomes more carbon sensitive. Contrary, the electric HDV's usage increases when the β level decreases because shipment amounts are increasing. Therefore, it becomes more beneficial in the aspect of total cost and total carbon emission.

According to Figure 7.24, the model sends more products with HDVs because they have more capacity than MDVs. Therefore, they become more beneficial costly.

When the total cost coefficient β decreases, the model chooses to send more products with electric vehicles instead of gasoline vehicles due to its less carbon emission although it has more lead times.

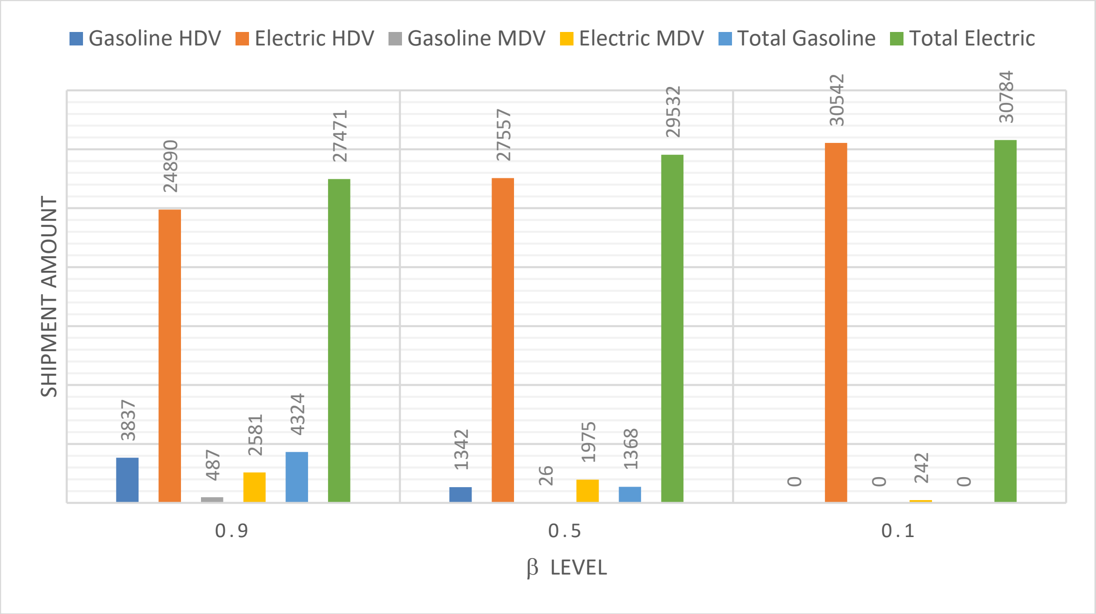


Figure 7.24. Lateral Transshipment Simulation Model - Shipment Amounts According to Vehicle Types vs. β level

Finally, we can say that electric vehicles have a critical role in the model.

7.4 Sensitivity Analysis

Lateral transshipment cost is one of the crucial parameters for the supply chain system with lateral transshipment. It is useful to see lateral transshipment cost variation over total cost. Therefore, three different lateral transshipment cost are applied to the system which are given cost, 25% more and 50% more.

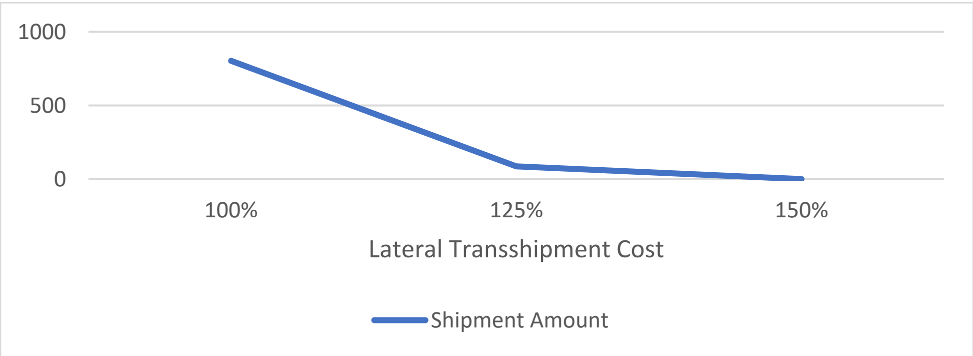


Figure 7.25. Lateral Transshipment Shipment Amounts According to Transshipment Costs

In this case, when the lateral transshipment cost is increasing, the lateral transshipment is decreasing as in Figure 7.25. Eventually, the lateral transshipment model does not prefer to make lateral transshipment. Therefore, the model gives the same results as the hybrid model.

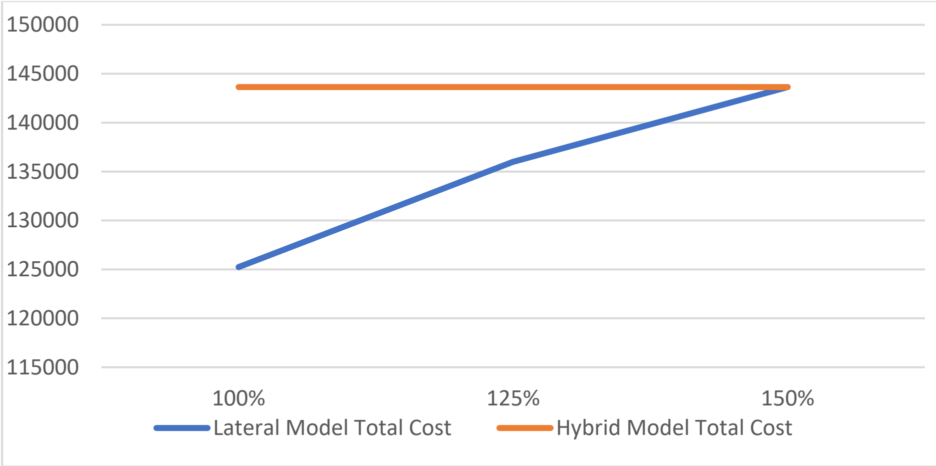


Figure 7.26. Lateral Transshipment Total Cost vs. Hybrid Model Cost According to Transshipment Costs

7.5 Comparison of Models

Comparison of optimization models' experimental results is given in this section. According to each β level, experimental results of models are given in Table 7.15 to Table 7.17.

When we applied paired t-test to models, as we can see in Figure 7.27, we can conclude that there is a (statistically) significant difference on all models' output performance measures when the β is 0.9. The first test is applied to the base model and hybrid model and we see that there is a significant difference between both model total costs because p-value is not less than 0.05. The second test is applied to the lateral transshipment model between the hybrid model, we see that there is a significant difference between both model total costs because the p-value is not less than 0.05. The third test is applied to the lateral transshipment model between the base model we see that there is a significant difference between both model total costs because the p-value is not less than 0.05.

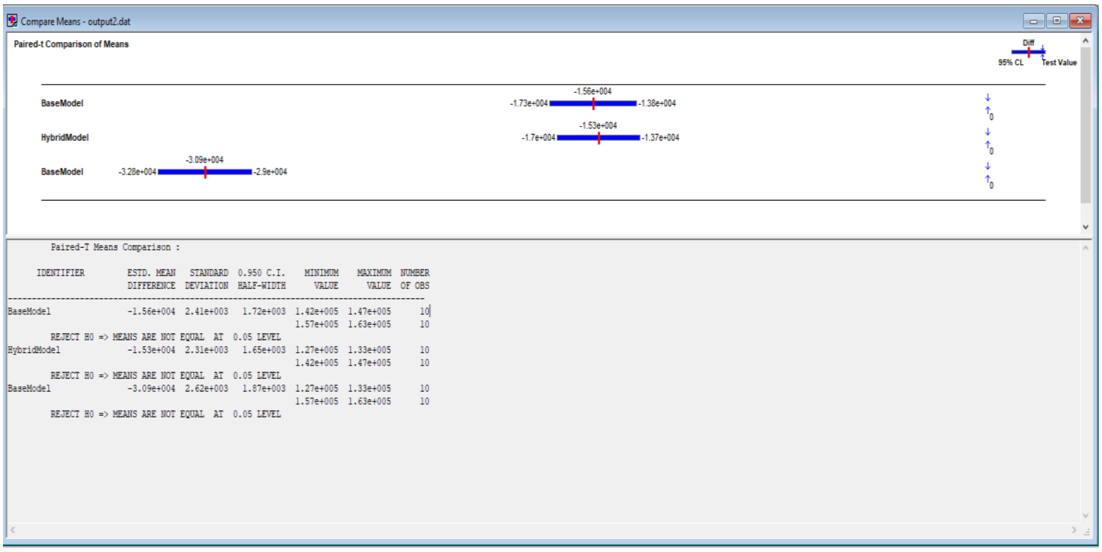


Figure 7.27. Paired t test comparison of means when the β is 0.9

Table 7.16. All Model Results When β Level is 0.9

	Base Model	Hybrid Model	Lateral T. Model
Total Carbon Emission	236660	145810	164670
Supplier to DCs Transportation Cost	16180	16412	15545
DC to Retailer Transportation Cost	7858	5735.4	7112.90
Retailer Transshipment Cost	0	0	12.45
DC Transshipment Cost	0	0	171.81
Total Transportation	24038	22147.4	22842.157
Holding DC In. Cost	35289	34346	20188
Holding R In. Cost	74320	51710	40396
Total Holding	109609	86056	60584
Order R Cost	0	0	4425
Order D Lateral Cost	0	0	6115
Order S Cost	8990	11595	10935
Order DC Cost	16040	22935	24330
Total Order Cost	25030	34530	45805
Lost Sale Cost	900	900	900
Total Cost	159577	143633.4	128680

When we applied paired t-test to models, as we can see in Figure 7.28, we can conclude that there is a (statistically) significant difference on all models' output performance measures when the β is 0.5. The first test is applied to the base model and the hybrid model and we see that there is a significant difference between both model total costs because p-value is not less than 0.05. The second test is applied to the lateral transshipment model between the hybrid model and we see that there is not a significant difference between both model total costs because the p-value is less than 0.05. The third test is applied to the lateral transshipment model between base model and we see that there is a significant difference between both model total costs because the p-value is not less than 0.05.

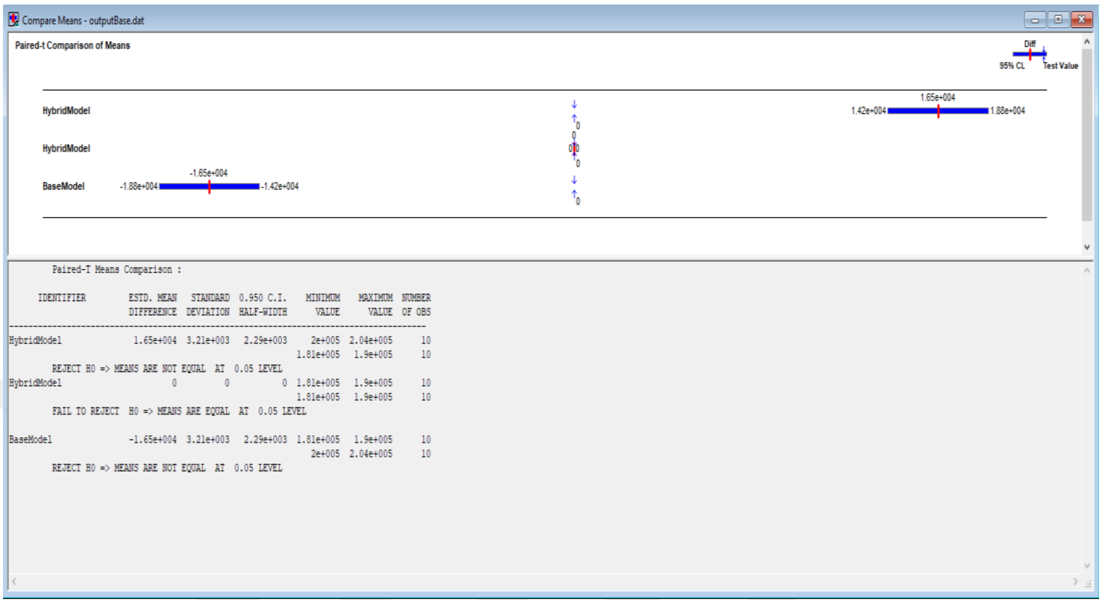


Figure 7.28. Paired t test comparison of means when the β is 0.5

Table 7.17. All Model Results When β Level is 0.5

	Base Model	**Hybrid Model**	**Lateral T. Model**
Total Carbon Emission	184030	110880	110880
Supplier to DCs Transportation Cost	17984	18222	18222
DC to Retailer Transportation Cost	10781	10640	10640
Retailer Transshipment Cost	0	0	0
DC Transshipment Cost	0	0	0
Total Transportation	28765	28862	28862
Holding DC In. Cost	42443	59234	59234
Holding R In. Cost	108570	60120	60120
Total Holding	151013	119354	119354
Order R Cost	0	0	0
Order D Lateral Cost	0	0	0
Order S Cost	7055	8280	8280
Order DC Cost	14330	23755	23755
Total Order Cost	21385	32035	32035
Lost Sale Cost	3550	3550	3550
Total Cost	204713	183650	183650

When we applied paired t-test to models, as we can see in Figure 7.29, we can conclude that there is a (statistically) significant difference on all models output performance measures when the β is 0.1. The first test is applied to the base model and the hybrid model and we see that there is a significant difference between both model total costs because p-value is not less than 0.05. The second test applied to the lateral transshipment model between the hybrid model and we see that there is not a significant difference between both model total costs because the p-value is less than 0.05. The third test is applied to the lateral transshipment model between the base model we see that there is a significant difference between both model total costs because the p-value is not less than 0.05.

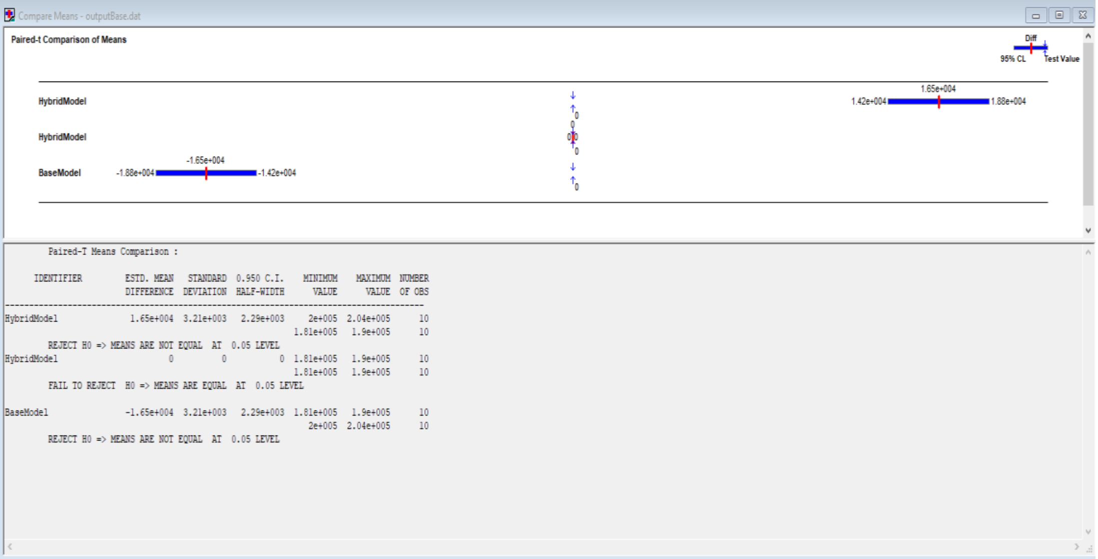


Figure 7.29. Paired t test comparison of means when the β is 0.1

Table 7.18. All Model Results When β Level is 0.1

	Base Model	**Hybrid Model**	**Lateral T. Model**
Total Carbon Emission	164210	89810	89810
Supplier to DCs Transportation Cost	17951	18365	18365
DC to Retailer Transportation Cost	10998	11107	11107
Retailer Transshipment Cost	0	0	0
DC Transshipment Cost	0	0	0
Total Transportation	28949	29472	29472
Holding DC In. Cost	89555	51660	51660
Holding R In. Cost	189350	116380	116380
Total Holding	278905	168040	168040
Order R Cost	0	0	0

Table 7.19(cont'd). All Model Results When β Level is 0.1

	Base Model	Hybrid Model	Lateral T. Model
Order S Cost	0	0	0
Order DC Cost	6925	7490	7490
Order D Lateral Cost	10375	11430	11430
Total Order Cost	17300	18920	18920
Lost Sale Cost	4740	4600	4600
Total Cost	329894	221040	221040

7.4.1 Total Carbon Emission Cost

According to the evaluation of the models by carbon emission aspect, the base model has more carbon emission than the hybrid model and the lateral model, because this model provides transportation with only gasoline vehicle types which are higher carbon emission than electric vehicle types. In the lateral transshipment model, we have all kinds of vehicles and lateral transshipment option within the echelons. Therefore, this model has the second lowest carbon emission cost when the β level is 0.9. However, the model doesn't choose the lateral transshipment option when the β levels are 0.5 and 0.1. Hence, we can see that when the model more carbon sensitive, lateral transshipment options become not beneficial options. Finally, we can conclude that the hybrid model has the least carbon emission value for all β levels.

7.4.2 Total Order Cost

Base Model has the lowest value in all β levels because this model has only gasoline vehicle options because it tries to use fewer vehicles to reduce carbon emission but in other models, electrical vehicles already decrease the carbon emission so they can use more vehicle. Therefore, this option makes (s, S) values wider than other models, and order cost occurs less than others.

When the β level is 0.9, the hybrid model order cost better than the lateral transshipment simulation model. Since the lateral transshipment simulation model doesn't use the lateral option when β levels are 0.5 and 0.1, and the hybrid and lateral transshipment simulation models have the same results.

7.4.3 Total Transportation Cost

In the aspect of total transportation cost case, the base model has a higher total transportation cost than other models because, in other models, the system has more vehicle options. For instance, electrical HDV has the same transportation cost as the gasoline HDV but the MDVs have less transportation cost. Therefore, the usage of MDVs makes difference in total transportation. The lateral transshipment simulation model has more transportation cost than the hybrid model when the β level is 0.9 because it sends more product. However, the lateral transshipment option gives an opportunity to send products within echelons and it has less unit transportation cost than between echelons mostly. Therefore, the difference is not so much. The hybrid model and lateral transshipment models have the same results when β levels are 0.5 and 0.1.

7.4.4 Total Holding Cost

The base model has more total holding cost than the hybrid model for all β levels because the model sends massive products to avoid more vehicle usage. Therefore, this model chooses to send fully load vehicles because of the carbon emission and this choice increases the holding cost. The lateral transshipment and hybrid simulation models have the same values except when the β level is 0.9. When the β level is 0.9, the lateral transshipment simulation model gives a better total holding cost. Since its total shipment amount less than the hybrid simulation model, it can decrease the holding cost. Also, its total order cost more than the hybrid model. Hence, this can show us, the lateral model uses more transportation traffic than the hybrid model and it can decrease holding cost.

7.4.5 Total Cost

The hybrid and lateral transshipment simulation models are better than base simulation model in the whole same β levels in terms of the total cost. The lateral transshipment simulation model is better than the hybrid simulation model only in β level 0.9. However, lateral transshipment and hybrid model have the same results in other β levels. Therefore, we can conclude that each option gives more opportunities to improve the total cost. However, the lateral transshipment option may be unnecessary to use when carbon sensitivity has the same or more priority than the total cost.

CHAPTER 8
MANAGERIAL INSIGHT

Nowadays, the world is trying to tackle global warming because of carbon dioxide and other air pollutants. Supply chain systems are one of the crucial factors of carbon emissions. For instance, road freight transport accounts for 22% of the CO2 emissions from the transport sector in the United Kingdom (Stern, 2006). The conventional supply chain models consider only the economic aspect, in other words, cost minimization or profit maximization. Therefore, they are not fully capable of satisfying the current needs.

In this thesis, we consider carbon emission and cost minimization at the same time in all models with and without lateral transshipment. Therefore, we can observe carbon emission effects over the cost minimization decisions. In order to reduce carbon emissions more, electric vehicle options are available in our supply chain system because the carbon emissions of electric vehicles are less than that of gasoline vehicles. In spite of less carbon emissions of electric vehicles, their lead limes are generally more than gasoline vehicles because they have less range and long charging times. Therefore, we developed two models; one has only gasoline vehicles (Base Model), the other one has electric and gasoline vehicles (Hybrid Model). Thus, we are able to observe their effectiveness in the supply chain systems. In addition, we add lateral transshipment policy to the hybrid model to see lateral option effectiveness in the carbon sensitive system. Moreover, we developed these models for demand certainty and demand uncertainty cases. Hence, we can have insight over both demand cases.

In summary, the base model represents the traditional supply chain, the hybrid model represents electrical vehicles option and the lateral transshipment model represents the transshipment option within the hybrid model. According to the obtained results, we can benefit from using lateral transshipment in the supply chain. However, when carbon emission has high importance and there are possibilities of holding high inventories, it’s usage may not be so profitable. Also, it is efficient to use electric vehicles in supply chain systems in terms of carbon emissions. In spite of their long lead times, their integration to the supply chain can drastically decrease carbon emissions and they do not affect the service level of the supply chain while using them with the conventional vehicles especially while using lateral transshipment. Therefore, we can say that if charging times and battery technologies become more efficient and improved, electric vehicles will become more widespread in the future in supply chain networks. As a result, this thesis provides insights over electrical vehicles usage and lateral transshipment effectiveness in carbon emission sensitive systems for certain and uncertain demand cases.

CHAPTER 9

CONCLUSION AND FUTURE RESEARCH

This thesis presents a solution to tackle a multi-echelon supply chain optimization problem under demand uncertainty and certainty while considering the carbon emission. Lateral transshipment and multi-sourcing options have been considered in the supply chain optimization to increase efficiency. Additionally, electric vehicles have been considered to reduce carbon emissions. Three optimization and simulation models are developed to see improvements of lateral transshipment and electric vehicle usage in the system. Based on the experimental results of all models, we observed that electric vehicles have a positive effect on total carbon emissions and total cost, even it has a limited range and long charging time. Therefore, we can conclude that electric vehicles will be a crucial part of product transportation in the future when we consider the technological improvements and investments in this field.

Moreover, results show that the lateral transshipment is a beneficial option to reduce total cost. However, it is observed that when the carbon emission becomes more important, the amount of lateral transshipment decreases in both demand cases because with this option vehicle usage and transported product amount increases. Therefore, carbon emission amount increases. So, we can conclude that lateral transshipment options are useful in the traditional cost minimization models, yet there is still a room for improvement for it to be considered seriously in environmentally conscious models.

Future studies could investigate lateral transshipment effects to the supply chain with carbon policies such as carbon tax, strict carbon capping, and carbon cap-and-trade. Furthermore, other than the applied (s, S) policy in simulation models in this thesis, different inventory policies may be employed in future models.

REFERENCES

Amiri-Aref, M., Klibi, W., & Babai, M. Z. (2018). The multi-sourcing location inventory problem with stochastic demand. *European Journal of Operational Research*, 266(1), 72-87.

Chartniyom, S., Lee, M. K., Luong, L., & Marian, R. (2007, December). Multi-location inventory system with lateral transshipments and emergency orders. In *2007 IEEE International Conference on Industrial Engineering and Engineering Management* (pp. 1594-1598). IEEE.

Council of Supply Chain Management Professionals. (2018). 29th Annual State of Logistics Report

Dyer, J., Furr, N., Lefrandt, C. (2014). The industries plagued by the most uncertainty. *Harvard Business Review.* Retrieved 21 May 2020 from https://hbr.org/2014/09/the-industries-plagued-by-the-most-uncertainty

European Chemical Transport Association (2011). Guidelines for measuring and managing CO_2 emission from freight transport operations. Retrieved 2 May 2020 from https://www.ecta.com/resources/Documents/Best%20Practices%20Guidelines/guideline_for_measuring_and_managing_co2.pdf

Ekren, B. Y., Akpunar, A., & Sağol, G. (2018). Inventory Control Models towards Physical Internet: Lateral Transshipment Policy Determination by Simulation, In *5th International Physical Internet Conference.*

Feng, P., Wu, F., Fung, R. Y., & Jia, T. (2018). Evaluation of two transshipment policies in a two-location decentralized inventory system under partial backordering. *Transportation Research Part E: Logistics and Transportation Review*, *118*, 207-224.

Feng, W., & Figliozzi, M. A. (2012). Conventional vs electric commercial vehicle fleets: A case study of economic and technological factors affecting the competitiveness of electric commercial vehicles in the USA. *Procedia-Social and behavioral sciences, 39,* 702-711.

Firoozi, M., Babai, M. Z., Klibi, W., & Ducq, Y. (2016). A Scenario-Based Inventory Optimization Approach for a Multi-Echelon Network Considering Lateral Transshipment. In *Proceedings of the 6th international conference on information systems logistics and supply chain, ILS conference* (pp. 1-4).

Firoozi, M., Babai, M. Z., Klibi, W., & Ducq, Y. (2020). Distribution planning for multi-echelon networks considering multiple sourcing and lateral transshipments. *International Journal of Production Research, 58*(7), 1968-1986.

Hammami, R., Nouira, I., & Frein, Y. (2015). Carbon emissions in a multi-echelon production-inventory model with lead time constraints. *International Journal of Production Economics*, *164*, 292-307.

Hütter, A. (2013). Verkehr auf Einen Blick. *Statistisches Bundesamt*. Wiesbaden, Germany.

Keskin, B. B., Melouk, S. H., & Meyer, I. L. (2010). A simulation-optimization approach for integrated sourcing and inventory decisions. *Computers & Operations Research, 37*(9), 1648-1661.

Lee, D. Y., Thomas, V. M., & Brown, M. A. (2013). Electric urban delivery trucks: Energy use, greenhouse gas emissions, and cost-effectiveness. *Environmental science & technology, 47*(14), 8022-8030.

Liimatainen, H., van Vliet, O., & Aplyn, D. (2019). The potential of electric trucks– An international commodity-level analysis. *Applied Energy, 236*, 804-814.

Manupati, V. K., Jedidah, S. J., Gupta, S., Bhandari, A., & Ramkumar, M. (2019). Optimization of a multi-echelon sustainable production-distribution supply chain system with lead time consideration under carbon emission policies. *Computers & Industrial Engineering*, 135, 1312-1323.

Mareev, I., Becker, J., & Sauer, D. U. (2017). Battery dimensioning and life cycle costs analysis for a heavy-duty truck considering the requirements of long-haul transportation. *Energies*, *11*(1), 1-23.

Meissner, J., & Senicheva, O. V. (2018). Approximate dynamic programming for lateral transshipment problems in multi-location inventory systems. *European Journal of Operational Research*, 265(1), 49-64.

Nakandala, D., Lau, H., & Shum, P. K. (2017). A lateral transshipment model for perishable inventory management. International *Journal of Production Research, 55*(18), 5341-5354.

Peng, Y., Ablanedo-Rosas, J. H., & Fu, P. (2016). A multiperiod supply chain network design considering carbon emissions. *Mathematical Problems in Engineering*, *2016*.

Reddy, K. B., Narayanan, S., & Pandian, P. (2011). Single-Echelon Supply Chain Two Stage Distribution Inventory Optimization Model for the Confectionery Industry. *journal of Applied Mathematical Sciences*, 5(50), 2491-2504.

Soysal, M., Bloemhof-Ruwaard, J. M., & Van Der Vorst, J. G. (2014). Modelling food logistics networks with emission considerations: The case of an international beef supply chain. *International Journal of Production Economics*, 152, 57-70.

Stern, N. (2006). The Economics of Climate Change - *The Stern Review.* Cambridge: Cabinet Office - HM Treasury, Cambridge University Press.

Vicente, J. J., Relvas, S., & Póvoa, A. P. B. (2015). Multi-period and Multi-product Inventory Management Model with Lateral Transshipments. In *Operational Research* (pp. 425-444). Springer, Cham.

Wang, M., Ouyang, J., & Zhao, L. (2019). Production planning with transshipment in a global supply chain under different carbon trading mechanisms. *Operational Research*, 1-23.

Yang, Y., Pan, S., & Ballot, E. (2017). Innovative vendor-managed inventory strategy exploiting interconnected logistics services in the Physical Internet. *International Journal of Production Research*, *55*(9), 2685-2702.

You, F., & Grossmann, I. E. (2010). Integrated multi-echelon supply chain design with inventories under uncertainty: MINLP models, computational strategies. *AIChE Journal*, 56(2), 419-440.

Yücesan, E. (2012). Stochastic optimization for transshipment problems with positive replenishment lead times. *International Journal of Production Economics*, 135(1), 61-72.

Zhao, F., Wu, D., Liang, L., & Dolgui, A. (2016). Lateral inventory transshipment problem in online-to-offline supply chain. *International Journal of Production Research*, *54*(7), 1951-1963.

DEFRA (Department for Environment, Food and Rural Affairs), 2012b. *Guidelines to Defra/DECC's GHG Conversion Factors for Company Reporting. Methodology Paper for Emission Factors*. Retrieved 31 August 2020 from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/69568/pb13792-emission-factor-methodologypaper-120706.pdf.

ADEME (Agence de l'environnement et de la maîtrise de l'energie), 2010. *Bilan Carbon e Guide des facteurs d'emission (Version 6.1).* Retrieved 31 August 2020 from http://www. associationbilancarbone.fr

Kleijnen, Jack & Wan, Jie. (2007). Optimization of simulated systems: OptQuest and alternatives. *Simulation Modelling Practice and Theory*. *15*. 354-362.