ABSTRACT

ASSIGNMENT OF E-COMMERCE ORDERS TO FULFILLMENT WAREHOUSES

by
Ahmad Basem Zamka

For large e-commerce companies such as Amazon, when an order comes, this order might be available at more than one fulfillment centers. Therefore, the question of which fulfillment center this order should be fulfilled from would arise.

In a typical situation, customer demand is fulfilled from the closest fulfillment center. However, this approach does not always provide the optimal solution since there are so many factors that could be involved in making such a decision. These factors might include inventory balance, product correlations, and future demand.

Our decision model focuses on putting future orders in consideration while assigning orders to fulfillment centers. In order to get insights about future demand and orders, using historical data to forecast future orders is used. Different forecasting methods are used for different demand behaviors and different types of products. The objective of this thesis is to showcase the importance of considering future demand while assigning current demand to fulfillment centers and its effect on the total shipping cost.

We propose that for a singular product, when demand is uniformly distributed, and the total inventory level is higher than the current and expected demand, including future orders in consideration while allocating current orders would result in changing the allocation and reduce the total shipping costs when the right forecasting method is used.

ASSIGNMENT OF E-COMMERCE ORDERS TO FULFILLMENT WAREHOUSES

by
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ASSIGNMENT OF E-COMMERCE ORDERS TO FULFILLMENT WAREHOUSES

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This thesis is dedicated to my parents for their endless love, support, and encouragement.
My father, Basem Ahmad Zamka.
My mother, Najwa Abduljawwad.

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CHAPTER 1

INTRODUCTION

1.1 Background Information

Internet retailing and e-commerce is the process of selling product directly to the customers without having physical stores. The actual physical process of delivering these products called fulfillment (Onal, Zhang, & Das, 2017). Warehouses that are designed particularly for online retailing are different than warehouses that are designed for brick and mortar. Products usually spend less time and stored in less quantities. The average e-commerce demand is 1.6 items per order (Boysen, Schwerdfeger, & Weidinger, 2018). For large e-commerce companies, products might be available in more than one fulfillment center in order to satisfy demand in different geographical areas.

Consumers usually have access to websites that show all the products that are available at the fulfillment centers. One of the advantages that e-commerce has over brick and mortar is product variety, companies are able to offer more products without having these products in stores (Brynjolfsson, Hu, & Smith, 2003). However, consumers do not know which fulfillment center that these products will be delivered from, if the company has more than one. After the consumer chooses the product, they can be involved in picking one delivery option such as next day delivery, two days delivery, or no rush delivery. E-commerce companies are targeting next-day or even same-day delivery in order to stay competitive (Yaman, Karasan, & Kara, 2012). The sooner the customer wants the product, the most likely they will pay more.

After the consumer picks a delivery option, now all the work and decisions are transferred to the e-commerce company. The process of picking the right carrier, the process of picking the right fulfillment center to deliver from, and all the delivery options and decisions associated with this delivery. For large companies these decisions are made automatically by intelligent decision models. The main goal of these decision models is to minimize all the logistical costs such as transportation, inventory, and stockout costs.

Once the product is delivered to the customer, the customer checks if the product is not defective. If the product is defective or does not satisfy the consumer, the consumer can return the product, and this process called reverse logistics which is more complicated and more costly than forward logistics. These products that are returned will be checked in order to be remanufactured, or reused after assessment (Kokkinaki, Dekker, van Nunen, & Pappis, 2015). This research only considers the forward logistics.

1.2 Problem Description

Once the consumer chooses a product and a delivery option, based on how big the e-commerce company is, the product might be available at more than one fulfillment center. The first thing that comes to mind is to fulfill this order from the closest fulfillment center to where the product has to be delivered. The bigger the distance is, the higher the transportation cost will be. However, the distance is not the only factor that is involved in making such a decision. For small companies, it could be, but the bigger the e-commerce company, the more complex the process will get. For a company as big as Amazon, it is very likely to have a similar shipping cost from two different warehouses to the same destination. Therefore, other factors should be involved in the fulfillment process. For instance, a company might be expecting a lot of orders from a particular area, and they want to preserve that inventory at that location until the orders come. They do not wish to use this inventory for other orders. Another factor is inventory imbalance which means having a lot of inventory in one fulfillment center and a few in another. Then, an e-commerce company can think of transshipment which is moving the products between fulfillment centers or fulfilling the order from either of the fulfillment centers. Additionally, some products might be ordered together. Therefore, you want the inventory level of these products to be close to each other in order to minimize the order picking costs, packaging, and order consolidation time.

As we can see that there are so many factors that could be included in the process of picking which fulfillment center to fulfill orders from. Some of these factors could be more important than others based on the companies' strategies and their competitive advantage over other companies.

1.3 Research Objective

Among all the factors that could influence the process of picking the right fulfillment center to fulfill orders from, the one we would like to focus on is including the future orders while allocating received orders to fulfillment centers. The problem is that the future orders are unknown, and the only way to get insights about the future orders is the historical data. Using the historical data to forecast future orders would help us make better decisions and minimize costs. The main goal is to have the right inventory level in each fulfillment center so that the total shipping cost is minimized. We investigated if the future orders are included into the decision model, would the allocation be any different and what its effect would be on the total shipping costs. Varying scenarios with different inventory levels are tested for the objective of proving that including future orders into the current allocation process would change the allocation and minimize the total shipping cost.

CHAPTER 2

LITERATURE REVIEW

2.1 E-Commerce and Fulfillment Strategies

E-commerce market and online shopping have been growing over the last years. During the last three years, the online retail market has increased from 11.3% in 2016 to hit 15.2% in 2018 (Young, 2019). One of the main reasons for this growth of the online market is logistics. Online retailing is shifting from marketing to fulfillment logistics which is having the logistical abilities to deliver the products when the customer wants, the way they want it, and in low costs. In order to provide superior service and lower costs, online companies need to seek cost optimization in all the aspects of their supply chain. The success of consumer direct fulfillment can be related to the integration of four elements which are order-fulfillment planning, production execution, distribution management and cross-application integration (Ricker & Kalakota, 1999).

Choosing a fulfillment strategy would influence all the logistical decision that companies make. All companies seek to minimizing costs that are associated with their strength so that they can stay competitive and unique. For companies with dedicated fulfillment centers strategy, their major strength is fast delivery and reducing long-term costs of logistical operations which make them keen to reduce all the costs that are related to warehousing and shipping in order to compete with brick-and-mortar and stay competitive with companies that have similar strategies. Therefore, picking a fulfillment strategy is an important decision that every e-commerce company needs to make.

2.2 Cost Based Fulfilment

There are different factors that play a role in selecting which fulfillment center to fulfill an order from. The first and most important factor that comes to mind is the shipping cost, and shipping cost must be included all the decision models for picking which fulfillment center to fulfill an order from. One of the approaches that only considers the cost is the "greedy approach". The greedy approach as fulfilling an order from the closest fulfilment center to the order's destination. The concept behind the greedy approach is that the shipping cost from the nearest fulfillment center to an order would minimize the shipping cost. The expected cost is calculated for each delivery based on the inventory level that would result from fulfilling this order and the shipping cost (Raff & Li, 2013). This approach does not include any future factors such as upcoming demand. However, in some cases the expected cost from two fulfillment centers could be the same which forces the merchant to look at other factors that influence this decision or just select one of them randomly due to the limitation of the greedy approach. The greedy approach tries to minimize the current expected costs that are associated with current orders only.

For some e-commerce companies, the greedy approach could be the best choice. On the other hand, for companies who have multiple fulfillment centers in one region, other factors might be included beside the distance. For instance, customers might be presented multiple delivery dates based on future fulfillment plans that are made by system to minimize the total costs, a fulfillment plan usually considers future costs and future orders for a certain period of time (Braumoeller, Brinkerhoff, Holden, & Lee, 2007).

2.3 Customers and Fulfillment

Customers are getting more involved in businesses' decisions which helps achieving higher rate of customer satisfaction. However, listening to customers' needs would always create more challenges regarding availability, quality, and delivery (Field-Darragh, Olson, & Shiner, 2014). Customers can influence the process of choosing which fulfillment center to fulfill an order from. When a customer chooses a product, the customer is given more than one delivery dates. Each delivery date is associated with shipping and handling costs. The sooner the delivery date is, the more the shipping cost will be. Each one of these costs is associated with a fulfillment center. However, in all this the customer is not aware that this product is available at more than one fulfillment center. For example, a customer orders an order that is available at three fulfillment centers. Different costs are associated with different fulfillment centers such as next day delivery, two days delivery, or ground delivery. Therefore, in this scenario there are nine different costs, three for each fulfillment center. The customer will only see three costs, one cost for each date. After the customer selects a cost, the fulfillment center is assigned. E-commerce companies could recommend a delivery option or a delivery date to the customers which would decrease the total shipping cost for them and then the customer is rewarded by points or gifts (Albright, 2003).

2.4 Transshipment and Fulfillment

Another aspect that could influence and minimize the total logistic costs is transshipment. Transshipment is moving products between fulfillment centers. (Torabi, Hassini, &

Jeihoonian, 2015) Discusses how transshipment would influence the total logistic costs, when a customer places an order, the order goes to the nearest fulfilment center. However, in some cases, the order is not available at the fulfillment center or only part of it is available. Consequently, the order is moved to another fulfillment center, or transshipment is optimized with the objective of minimizing the total shipping costs while fulfilling the order from one location.

In some cases, transshipment is not possible or not allowed. Therefore, having more than one fulfillment center would reduce the risk of demand instability while serving each market by the nearest fulfillment center. Demand allocation and inventory problem should be solved together since inventory level is affected by the demand allocation. (Benjaafar, Li, Xu, & Elhedhli, 2008) explains how to find an optimal solution by balancing two trade-offs. First, assigning demand from sources to fulfillment centers by looking at the lowest transportation cost. Second, consolidate demand in fewest number of fulfillment centers. Demand is becoming more uncertain and companies are trying to balance holding costs and stockout costs by using transshipment within the same companies or between other companies (He, Zhang, & Yao, 2014).

2.5 Decision Models in E-Commerce Fulfillment

(Onal, Zhang, & Das, 2018) Discussed some decision models that are associated with internet fulfillment warehouses. They also have discussed the use of explosive storage and its effect on fast fulfillment. Additionally, they categorized the process flow into three categories which starts with receiving and stocking, followed by order picking and consolidation, and ending with truck assignment and loading.

They have also introduced some decision problems for the internet fulfilment control. One of the problems introduced is that fulfilling an order from the closest location is considered as simple and more factors could be involved in such a decision. Big data analytics could be used to make more effective and efficient allocations. Other problems that have been introduced are:

- Creating stocking lists and assign bins
- Creating order picking lists
- Assigning picking list totes to consolidators
- Creating truck docking schedule

Creating decision models would help online retailers to improve their fulfillment processes and minimize their logistical costs.

2.6 Forecasting and E-Commerce

For e-commerce companies to be competitive, they might consider some key performance indicators while forecasting. These KPI's are the number of website's visits, transactions, revenue, media spend. All these factors could be included in the forecast decision models for e-commerce companies in order to forecast demand accurately (Wan, 2017). Wan's base model uses the simple linear regression to forecast the KPI's. Additionally, introduces different forecasting models and compare them with each other to showcase the importance of these KPI's in e-commerce forecasting.

CHAPTER 3

MODEL

3.1 Problem Definition

If we consider an e-commerce company that has *i* fulfillment centers, each one of these fulfillment centers has an inventory level of *Si*. Additionally, there are *j* destinations which represent the customers, and for each *j* there is a weekly demand *Dj*. There is a cost of shipping the product from *i* to *j* which is represented as *Cij*. This company has only a singular product. Mainly, we would like to answer this question:

How much to allocate from each fulfillment center *i* to destinations *j* in order to minimize the total shipping cost?

Such a problem is very common in operation research and it is known as transportation problem. This could be solved by linear programming formulation that is represented below:

Minimize
$$\sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} X_{ij} \tag{1}$$
Subject to:

$$\sum_{i=1}^{m} X_{ij} \geq D_j \quad \forall ij \tag{2}$$

$$\sum_{j=1}^{n} X_{ij} \leq S_i \quad \forall ij \tag{3}$$

$$X_{ij} \geq 0 \quad \forall ij \tag{4}$$

The transportation model is very common and popular in solving transportation and inventory allocation problems. Let us assume the future demand is known, then, new questions will arise: would the allocation be any different if the future demand is known?

would we be able to minimize the total shipping cost; and if yes by how much?

In order to be able to answer these questions, we created three models which represent three cases. The first case, when demand is fulfilled on a weekly basis without looking at future or expected demand. The second, when future demand is known, and demand is fulfilled on a weekly basis. The final model, when future demand is unknown but forecasted, and demand is fulfilled on a weekly basis. After creating these models, we were able to see changes in order allocation to fulfillment center in these three models, and changes in the total shipping cost and compare between them.

3.2 Base Model

Let us assume that the demand Dj is fulfilled on a weekly basis. At the end of every week, you will have all the orders that are needed to be fulfilled in the upcoming week by destinations, also the inventory levels Si for each fulfillment center is given. Additionally, the shipping costs Cij from every fulfillment center to every destination is provided.

We solved the problem for every week demand separately and allocated the orders to the distribution centers at the end of each week for the upcoming week.

3.2.1 Base Model Assumptions

- There is only one type product.
- Demand Dj is uniformly distributed between predefined range.
- Demand is fulfilled on a weekly basis.
- Demand is known on a weekly basis.

- The total inventory level in all the fulfillment centers exceeds the total demand for all the destinations.

- The shipping costs are generated based on the assumption that each fulfillment center ships to at least one destination with a low cost since that they are in close proximity to each other. The further the destinations from the fulfillment centers, the higher the shipping cost would be.

- All fulfillment centers have the ability to send the products to all destinations.

3.2.2 Heuristic Solution Steps for the Base Model

1. For weekly orders of a singular product, Identify the inventory level *Si* at every fulfillment center.

2. Identify the shipping cost *Cij* from every fulfillment center *i* to every destinations *j*.

3. Allocate the demand *Dj* to the fulfillment center *i* with the minimum shipping cost *Cij* to destination *j*.

4. Check if the demand *Dj* for the product is less than or equal to the inventory level *Si*.

5. If yes, allocate the required quantity from the fulfilment center *i* to destination *j* and update the inventory level *Si* at the fulfillment center.

6. If no, allocate what is available at the fulfillment center *i* with the lowest cost and look for the next fulfillment center with the lowest shipping cost for the remaining quantity.

7. Repeat the process every week for the orders that need to be fulfilled the upcoming week.

3.2.3 Base Model Example

The demand *Dj* is uniformly distributed between one and fifty, the inventory level *Si* is generated randomly with assumption that it will always be higher than the demand. Finally, shipping costs are generated with the assumption that it would be cheaper to ship from some fulfillment centers to the closest destinations j. The same set of data are used for the other models in order to compare the results at the end. The data that are available for period one is as follow.

Table 3.1 Weekly Demand, Inventory Level, and Shipping Costs for Period One

Destinations	1	2	3	4	5	6	7	8	9	10	Total
Week One Demand	50	29	14	24	10	3	20	18	44	48	260
Fulfillment Centers	1	2	3	4	5						
Inventory Level	385	150	390	387	140						
Shipping Costs	1	2	3	4	5	6	7	8	9	10	
1	$2	$10	$15	$20	$25	$10	$15	$20	$10	$25	
2	$10	$15	$20	$25	$10	$15	$20	$10	$25	$2	
3	$15	$20	$25	$10	$15	$20	$10	$25	$2	$10	
4	$20	$25	$10	$15	$20	$10	$25	$2	$10	$15	
5	$25	$10	$15	$20	$10	$25	$2	$10	$15	$20	

We used excel solver to solve this problem as a linear programming problem with the formulation presented earlier. This transportation model is used to allocate orders to fulfillment centers. The allocated quantities and shipping costs for period one are as follow.

Table 3.2 Allocated Quantities, Shipping Costs, and Total Cost for Period One

Fulfillment Centers	1	2	3	4	5	6	7	8	9	10	TOTALS
1	50	29	0	0	0	0	0	0	0	0	79
2	0	0	0	0	0	0	0	0	0	48	48
3	0	0	0	24	0	0	0	0	44	0	68
4	0	0	14	0	0	3	0	18	0	0	35
5	0	0	0	0	10	0	20	0	0	0	30
Totals	50	29	14	24	10	3	20	18	44	48	260
Allocated Shipping Costs	1	2	3	4	5	6	7	8	9	10	
1	$100	$290	$0	$0	$0	$0	$0	$0	$0	$0	
2	$0	$0	$0	$0	$0	$0	$0	$0	$0	$96	
3	$0	$0	$0	$240	$0	$0	$0	$0	$88	$0	
4	$0	$0	$140	$0	$0	$30	$0	$36	$0	$0	
5	$0	$0	$0	$0	$100	$0	$40	$0	$0	$0	
Total Cost	$1,160										

After every week, the demand for the upcoming week is given, and is allocated for the upcoming week by doing the same thing for period one. The demand for the entire five periods is as follow.

Table 3.3 Five Weeks Demand

Weeks	1	2	3	4	5	6	7	8	9	10	Total
1	50	29	14	24	10	3	20	18	44	48	260
2	30	29	21	27	50	27	3	7	45	41	280
3	39	44	22	9	32	31	25	24	47	13	286
4	21	45	44	10	25	45	14	21	27	2	254
5	50	8	37	11	39	9	4	3	4	26	191
Total	190	155	138	81	156	115	66	73	167	130	1271

At the end of each week, we solved for the upcoming week, we calculated the total cost for all the five weeks at the end of week five, and we looked at the total allocated quantity from every fulfillment center to every destination. Then, compared these results with the second and third models which are presented next.

Table 3.4 Allocated Quantities, Shipping Costs, and Total Cost for Base Model

Fulfillment Centers	1	2	3	4	5	6	7	8	9	10	
1	140	147	0	0	0	98	0	0	0	0	385
2	0	0	0	0	25	0	0	0	0	125	150
3	50	8	0	81	39	0	18	0	167	5	368
4	0	0	138	0	0	17	0	73	0	0	228
5	0	0	0	0	92	0	48	0	0	0	140
Totals	190	155	138	81	156	115	66	73	167	130	1271
Fulfillment Centers	**1**	**2**	**3**	**4**	**5**						
Inventory Level	0	0	22	159	0						
Allocated Shipping Costs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
1	$280	$1,470	$0	$0	$0	$980	$0	$0	$0	$0	
2	$0	$0	$0	$0	$250	$0	$0	$0	$0	$250	
3	$750	$160	$0	$810	$585	$0	$180	$0	$334	$50	
4	$0	$0	$1,380	$0	$0	$170	$0	$146	$0	$0	
5	$0	$0	$0	$0	$920	$0	$96	$0	$0	$0	
Total Cost	$8,811										

After optimizing each period solely, we were able to get the total allocated quantity for the entire five periods per fulfillment center. Additionally, the total shipping cost per destination and per fulfillment center which are used later to compare the three models which each other. Inventory levels are updated after every week, and the shipping costs for all the periods are added up to get the final total cost.

3.3 Optimal Model

Our objective in this model is to show that when the demand for the entire five periods is known at the beginning of period one, we would be able to reduce the total shipping costs, and the allocation might be different from the base model. In the base model, we did not consider future demand in the optimization process which what we did for this model.

Let us assume that the demand *Dj* is fulfilled on a weekly basis. However, the demand for the entire five weeks is known at the beginning of period one. The inventory levels *Si* for each fulfillment center is given. Additionally, the shipping costs from every fulfillment center to every destinations *Cij*. We solved the problem and allocated the entire orders for the five weeks to the fulfillment centers. However, the fulfillment is weekly.

3.3.1 Optimal Model Assumptions

- There is only one type product.
- Demand D*j* is uniformly distributed between predefined range.
- Demand is fulfilled on a weekly basis.
- Future demand is known for the entire period which is five weeks.
- The total inventory level in all the fulfillment centers exceeds the total demand for all the destinations.
- The shipping costs are generated randomly based on the assumption that each fulfillment center ships to at least one destination with low cost since that they are in close proximity to each other. The farther the destinations from the fulfillment centers, the higher the shipping cost would be.
- All fulfillment centers have the ability to send the products to all the destinations.

3.3.2 Heuristic Solution Steps for the Optimal Model

1. For the total demand for the current and future periods of a singular product, Identify the inventory level *Si* at every fulfillment center.

2. Identify the shipping cost *Cij* from every fulfillment center to every destinations.

3. Allocate the total demand *Dj* for the entire periods to the fulfillment center with the minimum shipping cost *Cij*.

4. Check if the Demand *Dj* for the product is less than or equal to the inventory level *Si*.

5. If yes, allocate the required quantity from the fulfilment center *i* to destination *j* and update the inventory level *Si* at the fulfillment center.

6. If no, allocate what is available at the fulfillment center with the lowest cost and check the next fulfillment center with the lowest shipping cost for the remaining quantity.

7. This allocated quantity is for the entire period and fulfilling demand is on a weekly basis according to the allocated quantity.

3.3.3 Optimal Model Example

For the same set of data that was used for the base model. We solved the same problem with the same way. The only difference is that we allocated the inventory for the entire five periods under the assumption that the demand is known.

Table 3.5 Weekly Demand, Inventory Level, and Shipping Costs for Five Periods

Destinations	1	2	3	4	5	6	7	8	9	10	Total
Week One Demand	50	29	14	24	10	3	20	18	44	48	260
Week Two Demand	30	29	21	27	50	27	3	7	45	41	280
Week Three Demand	39	44	22	9	32	31	25	24	47	13	286
Week Four Demand	21	45	44	10	25	45	14	21	27	2	254
Week Five Demand	50	8	37	11	39	9	4	3	4	26	191
Total	190	155	138	81	156	115	66	73	167	130	1271
Fulfillment Centers	1	2	3	4	5						
Inventory Level	385	150	390	387	140						
Shipping Costs	1	2	3	4	5	6	7	8	9	10	
1	$2	$10	$15	$20	$25	$10	$15	$20	$10	$25	
2	$10	$15	$20	$25	$10	$15	$20	$10	$25	$2	
3	$15	$20	$25	$10	$15	$20	$10	$25	$2	$10	
4	$20	$25	$10	$15	$20	$10	$25	$2	$10	$15	
5	$25	$10	$15	$20	$10	$25	$2	$10	$15	$20	

Using excel solver to solve this problem as a linear programming problem with the formulation presented earlier for a typical transportation model, we allocated the demand for the entire five periods as follow.

Table 3.6 Allocated Quantities, Shipping Costs, and Total Cost for Optimal Model

Fulfillment Centers	1	2	3	4	5	6	7	8	9	10	
1	190	155	0	0	0	40	0	0	0	0	385
2	0	0	0	0	20	0	0	0	0	130	150
3	0	0	0	81	62	0	0	0	167	0	310
4	0	0	138	0	0	75	0	73	0	0	286
5	0	0	0	0	74	0	66	0	0	0	140
Totals	190	155	138	81	156	115	66	73	167	130	1271
Fulfillment Centers	**1**	**2**	**3**	**4**	**5**						
Inventory Level	0	0	80	101	0						
Allocated Shipping Costs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
1	$380	$1,550	$0	$0	$0	$400	$0	$0	$0	$0	
2	$0	$0	$0	$0	$200	$0	$0	$0	$0	$260	
3	$0	$0	$0	$810	$930	$0	$0	$0	$334	$0	
4	$0	$0	$1,380	$0	$0	$750	$0	$146	$0	$0	
5	$0	$0	$0	$0	$740	$0	$132	$0	$0	$0	
Total Cost	$8,012										

After allocating quantities for the entire period, we can see that the total shipping cost has decreased from $8,8011 on the base model to $8,012 on the optimal model. In this case the total shipping cost has decreased by 9.4%, we discussed this further in the experimentation chapter. The next graph shows the total shipping cost per destination for the base and optimal models.

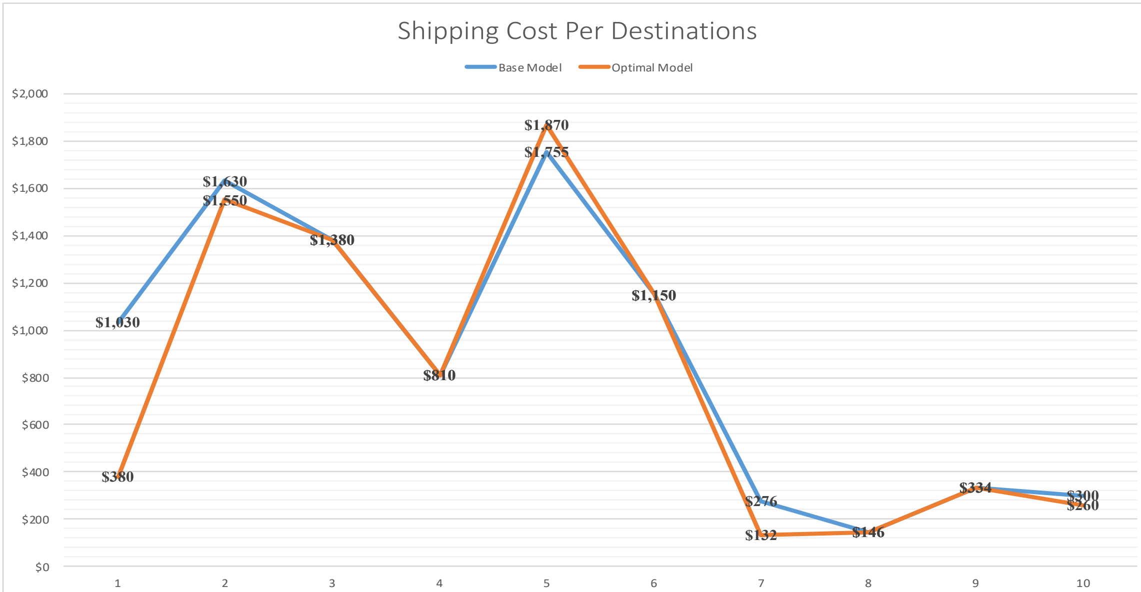

Figure 3.1 Comparison between shipping costs for the base and optimal models

Figure 3.1 shows that by including future demand in the optimization, we would be able to make better decisions which means different allocations. We can see that out of ten destinations, nine of which were less or equal than the base model. Every case is different based on the demand and shipping costs. What we tried to do in our next recommended model is to come up with a line that lies as close as possible to the optimal line. However, not lower than the base model through using historical data which will be discussed in the next section.

3.4 Suboptimal Model

In the last section, we were able to indicate that knowing future demand could influence our inventory allocation process. It could also help us make better decisions and reduce our total shipping costs. In business-to-business relations, customers might give you an estimation about how much they are going to need during the next period. This information would help organizations optimize and improve their inventory decisions. Conversely, in business-to-consumer relations. The best way to estimate future demand is by forecasting. Looking at historical data and trying to see patterns that would improve your demand estimations.

In the base model, we needed to wait for the orders to come and then do the allocation without looking at future orders at all. On the other hand, on our optimal model, the future demand was known which does not exist in business-to-consumer e-commerce market. Therefore, our objective is to find a suboptimal solution that uses historical data to predict future demand and orders, then, preserve inventory for expected orders in order to achieve better allocation and minimize the total shipping cost.

3.4.1 Suboptimal Model Assumptions

- There is only one type product.
- Demand D*j* is uniformly distributed between a predefined range.
- Historical demand is uniformly distributed between the same predefined range.
- The total inventory level for all the fulfillment centers exceeds the total demand for all the destinations.
- The shipping costs are generated randomly based on the assumption that each fulfillment center ships to at least one destination with low cost since that they are in close proximity to it. The farther the destinations from the fulfillment centers, the higher the shipping cost would be.
- All fulfillment centers have the ability to send the products to all the destinations

The assumptions for the base and recommended model are the same except that we needed to create a historical data for our recommended model to be used in the forecasting process. In our recommended suboptimal model, we used weighted moving average to forecast the demand. We gave higher weights to the most recent periods, these weights are 40%, 30%, 20%, and 10% respectively to the most recent period.

3.4.2 Heuristic Solution Steps for the Suboptimal Model

1. For weekly orders of a singular product plus the forecasted orders for the upcoming period, Identify the inventory level *Si* at every fulfillment center.
2. Identify the shipping cost *Cij* from every fulfillment center to every destination.
3. Allocate the actual demand in addition to the forecasted demand for the upcoming period to the fulfillment center with the minimum shipping cost *Cij*.
4. Check if the actual and forecasted demand *Dj* for the product is less than or equal to the inventory level *Si*.
5. If yes, allocate the required quantity from the fulfilment center to the destination, and update the inventory level *Si* at the fulfillment center by only the actual demand.
6. If no, allocate the actual demand to what is available at the fulfillment center with the lowest shipping cost and look for the next fulfillment center with the lowest shipping cost for the remaining quantity.
7. The first allocation is for the actual demand plus the forecasted demand. However, updating the inventory is only for the actual demand.
8. Repeat the process for the upcoming orders and update the forecasted demand.

3.4.3 Suboptimal Model Example

On our recommended model the demand is coming on a weekly basis, and the demand for the upcoming week is forecasted by a weighted moving average using historical data. We solved the model for one period only. However, we will be keeping the forecasted quantity for the upcoming week reserved. Moreover, when new demand comes, the forecast is updated, and the same allocation process happens again.

Table 3.7 Weekly and Historical Demand, Inventory Level, and Shipping Costs

Destinations	1	2	3	4	5	6	7	8	9	10
Previous Demand	50	29	14	24	10	3	20	18	44	48
Previous Demand	30	29	21	27	50	27	3	7	45	41
Previous Demand	39	44	22	9	32	31	25	24	47	13
Previous Demand	21	45	44	10	25	45	14	21	27	2
Week One Demand	50	29	14	24	10	3	20	18	44	48
Fulfillment Centers	**1**	**2**	**3**	**4**	**5**					
Inventory Level	385	150	390	387	140					
Shipping Costs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	$2	$10	$15	$20	$25	$10	$15	$20	$10	$25
2	$10	$15	$20	$25	$10	$15	$20	$10	$25	$2
3	$15	$20	$25	$10	$15	$20	$10	$25	$2	$10
4	$20	$25	$10	$15	$20	$10	$25	$2	$10	$15
5	$25	$10	$15	$20	$10	$25	$2	$10	$15	$20

In the suboptimal model we used weighted moving average forecast method in order to predict the future demand. Yet, we allocated the quantity that is expected to be used only for one upcoming forecasted period. We also gave higher weights to the most recent periods. As mentioned earlier we used 40%, 30%, 20%, and 10% respectively to the most recent period. Using the historical data presented earlier, future demand is forecasted and presented in the next table.

Table 3.8 Forecasted Table for the Optimal Model

Weight%	Period/Demand	1	2	3	4	5	6	7	8	9	10
0.1	**Previous Demand**	10	44	17	40	26	40	22	32	30	19
0.2	**Previous Demand**	41	46	2	35	1	37	25	5	7	9
0.3	**Previous Demand**	9	11	28	7	13	6	44	13	3	15
0.4	**Previous Demand**	37	10	30	8	50	20	7	40	17	37
	Week One Demand	27	21	23	16	27	21	23	24	12	23
	Week Two Forecast	28	18	24	14	29	19	23	25	11	24
	Week Three Forecast	28	17	25	13	31	19	22	27	12	25
	Week Four Forecast	29	17	25	13	32	20	21	27	12	26
	Week Five Forecast	28	18	25	14	31	20	22	26	12	25
	Week Six Forecast	28	18	25	14	31	20	22	26	12	25

We solved the problem with the formulation presented earlier as a transportation problem using excel solver. The demand D_j is used as the summation of the current actual demand and the expected forecasted demand for the next period that is presented in table 3.8. This method allows us to minimize the total shipping costs for two periods by preserving the expected demand in the fulfillment centers that would make the minimal shipping costs. The more accurate the forecast, the closer we would get to our optimal solution. As we did on our base model, tracking and updating the inventory level after every week and calculating the total shipping costs. Additionally, allocating the quantities in every fulfillment center to be sent to every destination.

Table 3.9 Allocated Quantities, Shipping and Total Costs for Suboptimal Period One

Fulfillment Centers	1	2	3	4	5	6	7	8	9	10	TOTALS
1	50	0	0	0	0	0	0	0	0	0	50
2	0	0	0	0	0	0	0	0	0	48	48
3	0	0	0	24	0	0	0	0	44	0	68
4	0	0	14	0	0	3	0	18	0	0	35
5	0	29	0	0	10	0	20	0	0	0	59
Totals	50	29	14	24	10	3	20	18	44	48	260
Allocated Shipping Costs	1	2	3	4	5	6	7	8	9	10	
1	$100	$0	$0	$0	$0	$0	$0	$0	$0	$0	
2	$0	$0	$0	$0	$0	$0	$0	$0	$0	$96	
3	$0	$0	$0	$240	$0	$0	$0	$0	$88	$0	
4	$0	$0	$140	$0	$0	$30	$0	$36	$0	$0	
5	$0	$290	$0	$0	$100	$0	$40	$0	$0	$0	
Total Cost	$1,160										

We allocated the demand for every week and preserved the demand for the upcoming week based on the forecast. After every period ends, the forecast will be updated, inventory levels are updated, and orders are allocated. After five period the total allocations and total shipping costs will be as follow.

Table 3.10 Allocated Quantities, Shipping Costs, and Total Cost for Suboptimal Model

Fulfillment Centers	1	2	3	4	5	6	7	8	9	10	
1	190	126	0	0	0	36	0	0	0	0	352
2	0	0	0	0	46	0	0	0	0	104	150
3	0	0	0	81	58	0	7	0	167	26	339
4	0	0	138	0	0	79	0	73	0	0	290
5	0	29	0	0	52	0	59	0	0	0	140
Totals	190	155	138	81	156	115	66	73	167	130	1271
Fulfillment Centers	1	2	3	4	5						
Inventory Level	33	0	51	97	0						
Allocated Shipping Costs	1	2	3	4	5	6	7	8	9	10	
1	$380	$1,260	$0	$0	$0	$360	$0	$0	$0	$0	
2	$0	$0	$0	$0	$460	$0	$0	$0	$0	$208	
3	$0	$0	$0	$810	$870	$0	$70	$0	$334	$260	
4	$0	$0	$1,380	$0	$0	$790	$0	$146	$0	$0	
5	$0	$290	$0	$0	$520	$0	$118	$0	$0	$0	
Total Cost	$8,256										

We can see that using the weighted moving average forecast method and put future orders in consideration while allocating current orders helped us finding a suboptimal solution that is between our base and optimal models' costs.

3.5 Models Comparison

We can see that the total shipping cost for the suboptimal model comes between our optimal and base models. The total shipping cost for the suboptimal model is $8,256 less than the base model by 6.3% and higher than the optimal model by 3.05%.

The next graph shows the total shipping cost per destination for the base, optimal, and suboptimal models.

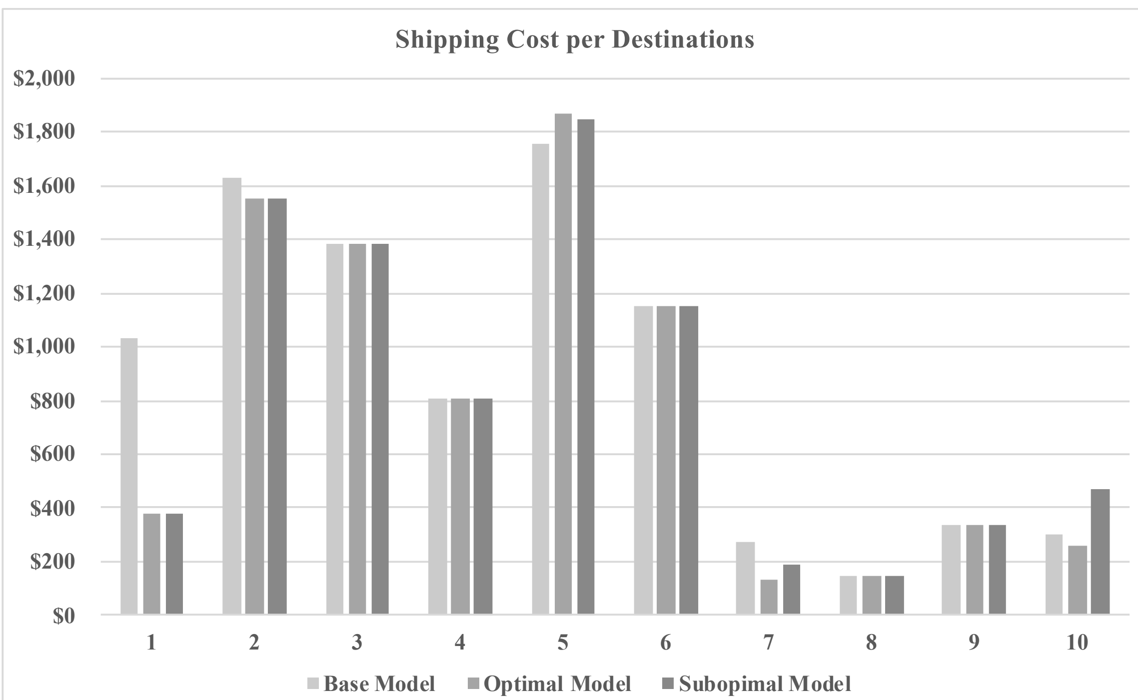

Figure 3.2 Comparison between shipping costs for the base, optimal, and suboptimal models per destinations.

It can be seen from figure 3.2 that the behavior of the suboptimal model is similar to the behavior of the optimal model in most of the destinations. In some cases, it came between the base and optimal model which is also good. However, the shipping cost for the suboptimal model can be higher than the base and optimal model as we can see for destination ten. The main objective is to have a total shipping cost that is close to the optimal cost for the entire period. We can also look at the shipping cost per fulfillment centers as follow.

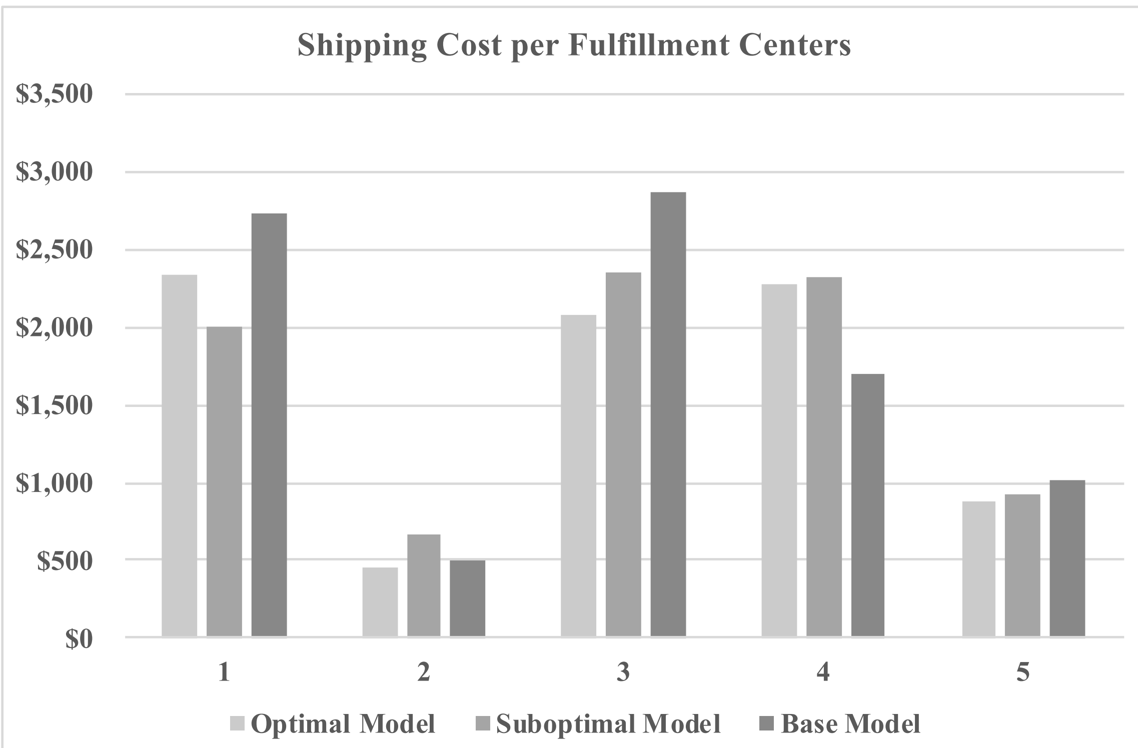

Figure 3.3 Comparison between shipping costs for the base, optimal, and suboptimal models per fulfillment centers.

When we look at the shipping cost from fulfillment centers perspective. It can be seen that the suboptimal model is lower than the base model in three of the cases, even lower than the optimal model for fulfillment one. This means, minimizing the costs at the current period to its minimal level might affect the shipping cost in the future, if future demand is not considered. Using the right forecasting method is very important too. For our case, when demand is uniformly distributed, a weighted moving average forecast method is used to predict future demand. In order to be able to validate this model, we did more experiments with different set of data for the variables that are demand, inventory levels, and historical data which is presented next in the upcoming experiment chapter.

CHAPTER 4

EXPERIMENTATION

4.1 Generation of Test Problems

In chapter two, we presented our recommended decision model which we call the suboptimal model. In the example presented earlier, our suboptimal model comes between our base and optimal model. In order to validate our suboptimal model, we need to create more examples by changing our variables which are the demand *Dj*, the inventory level *Si* for every fulfillment center, and the historical demand while keep the shipping costs constant throughout all the models. Additionally, as mentioned earlier, the total inventory level is always higher than the total demand for the entire period.

We tested different demand, and different inventory levels, to validate our model, and to get insights about which inventory levels could reduce the total shipping costs. Additionally, we did sensitivity analysis and created some special cases.

We categorized our test table into four categories based on the demand, and each category have five classes which present different inventory levels. In every case also the demand is changing. The values of the demand *Dj* are uniformly distributed for every category between (1, 50), (1, 100), (1, 500), and (1, 1000). Additionally, different inventory levels are presented with the assumption that inventory levels are controllable not like the demand. It is important to note that in our decision model transshipment is not allowed. The main goal of our model is to predict future demand and preserve required inventory for expected demand in order to minimize the total shipping cost and reduce costly assignments and allocations. As a concept, such a decision model would reduce the need of transshipment which will be very interesting to look at and will be recommended on this thesis for future research and expansion of the current model.

4.2 Experimentation Results and Explanations

As mentioned in chapter two, all the models are solved using excel solver as a linear programming problem. Our main comparison and experimentation table is presented as follow.

Table 4.1 Models Comparison and Experimentations Results

		Optimal Model	Suboptimal Model	Base Model	Opportunity Cost	New Opportunity Cost	Opportunity Cost Reduction %
RAND(1,50)	1	$8,437	$9,691	$9,857	$1,420	$1,254	11.69%
	2	$6,210	$6,505	$6,723	$513	$295	42.50%
	3	$9,900	$10,080	$10,166	$266	$180	32.33%
	4	$8,012	$8,256	$8,811	$799	$244	69.46%
	5	$8,970	$9,656	$9,828	$858	$686	20.05%
RAND(1,100)	1	$16,754	$17,195	$18,439	$1,685	$441	73.83%
	2	$12,819	$13,976	$14,156	$1,337	$1,157	13.46%
	3	$16,044	$17,505	$17,652	$1,608	$1,461	9.14%
	4	$16,765	$17,239	$17,767	$1,002	$474	52.69%
	5	$17,489	$17,983	$18,613	$1,124	$494	56.05%
RAND(1,500)	1	$83,831	$89,236	$90,823	$6,992	$5,405	22.70%
	2	$74,323	$75,813	$80,250	$5,927	$1,490	74.86%
	3	$87,551	$91,370	$92,416	$4,865	$3,819	21.50%
	4	$112,244	$117,289	$119,874	$7,630	$5,045	33.88%
	5	$97,284	$105,317	$109,809	$12,525	$8,033	35.86%
RAND(1,1k)	1	$175,092	$184,285	$184,520	$9,428	$9,193	2.49%
	2	$174,718	$191,198	$195,738	$21,020	$16,480	21.60%
	3	$144,922	$146,212	$149,587	$4,665	$1,290	72.35%
	4	$193,822	$201,268	$208,623	$14,801	$7,446	49.69%
	5	$241,332	$244,206	$248,495	$7,163	$2,874	59.88%

Table 4.1 shows four different categories, each category represents a different demand range, and within each category there are five classes and scenarios that follow the same demand with different inventory levels for each one of them. As mentioned earlier demand is uncontrollable, but inventory level is. Therefore, different inventory levels were presented to measure its effect on the total shipping costs. The first three columns present our optimal, suboptimal, and base models' total shipping costs. We always want to make

sure that our suboptimal model total shipping cost is as close as possible to the optimal model. The fourth column is the opportunity cost. The opportunity cost is the difference between the optimal and base models. Our objective is to minimize the opportunity cost as much as possible and to make it match the optimal cost. In order to measure how much our decision model is getting us closer to the optimal model, we added two more columns at the end which show the difference between the suboptimal model and the base model which should be lower than the difference in the opportunity cost. Lastly, how much we decreased the opportunity costs as a percentage. For example, in the first case it was 11.69% which means we were able to get closer to the optimal solution by 11.69% and there is 88.31% that could have been minimized more. This column is important if we want to test out other forecasting methods and see if we could get closer to the optimal solution. Table 4.1 looks complicated, we will break it down and analyze it in order to validate our recommended decision model.

4.3 Experimentation Results Analysis

In order to analyze this table, let us break it down and analyze each set of demand alone. The first thing we want to look at is the total shipping cost for each scenario for the three models.

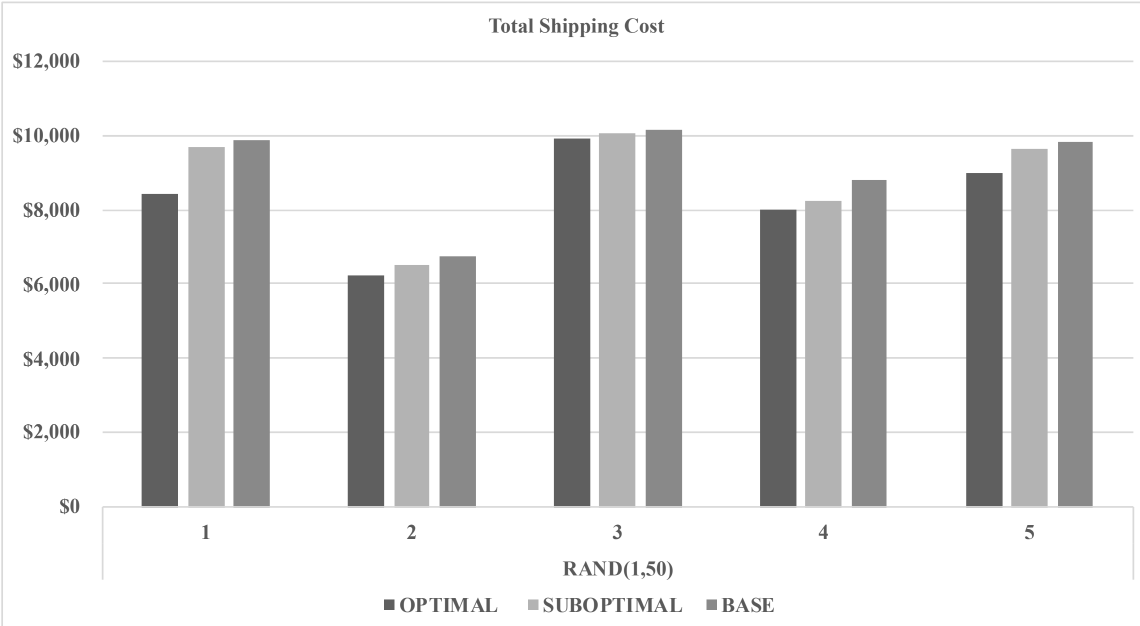

Figure 4.1 Comparison between shipping costs for the base, optimal, and suboptimal models for random distributed demand between (1, 50).

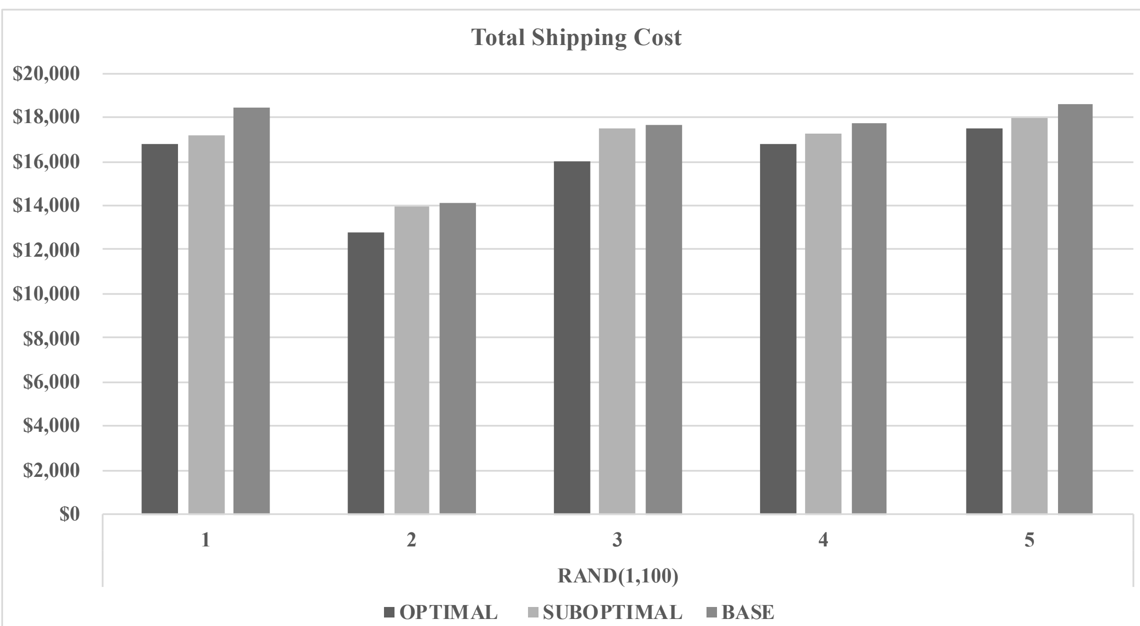

Figure 4.2 Comparison between shipping costs for the base, optimal, and suboptimal models for random distributed demand between (1, 100).

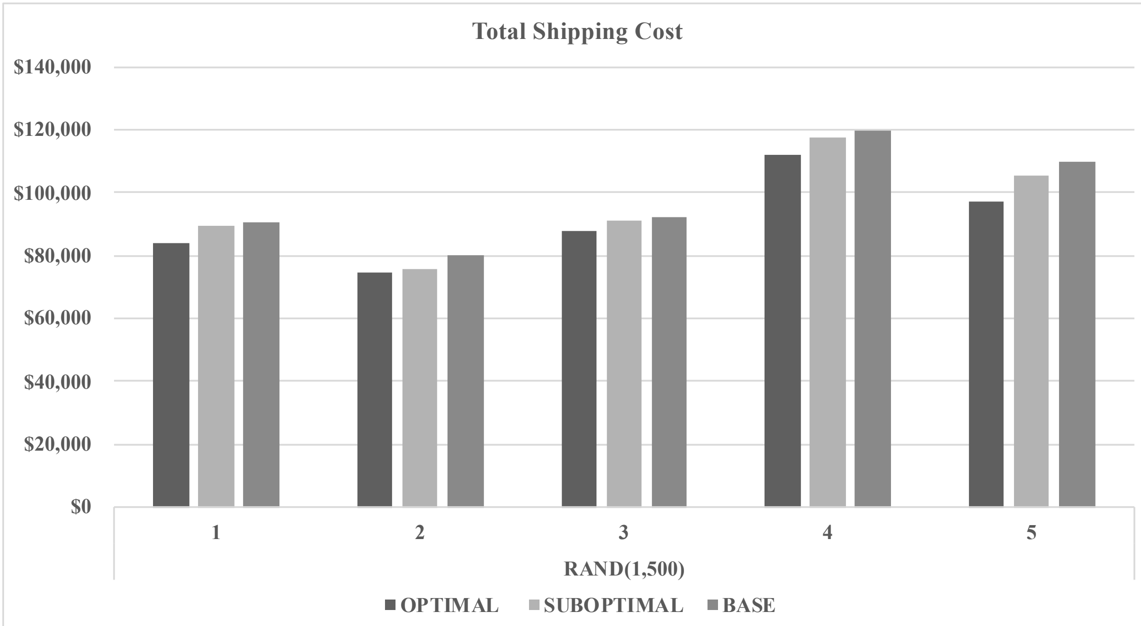

Figure 4.3 Comparison between shipping costs for the base, optimal, and suboptimal models for random distributed demand between (1, 500).

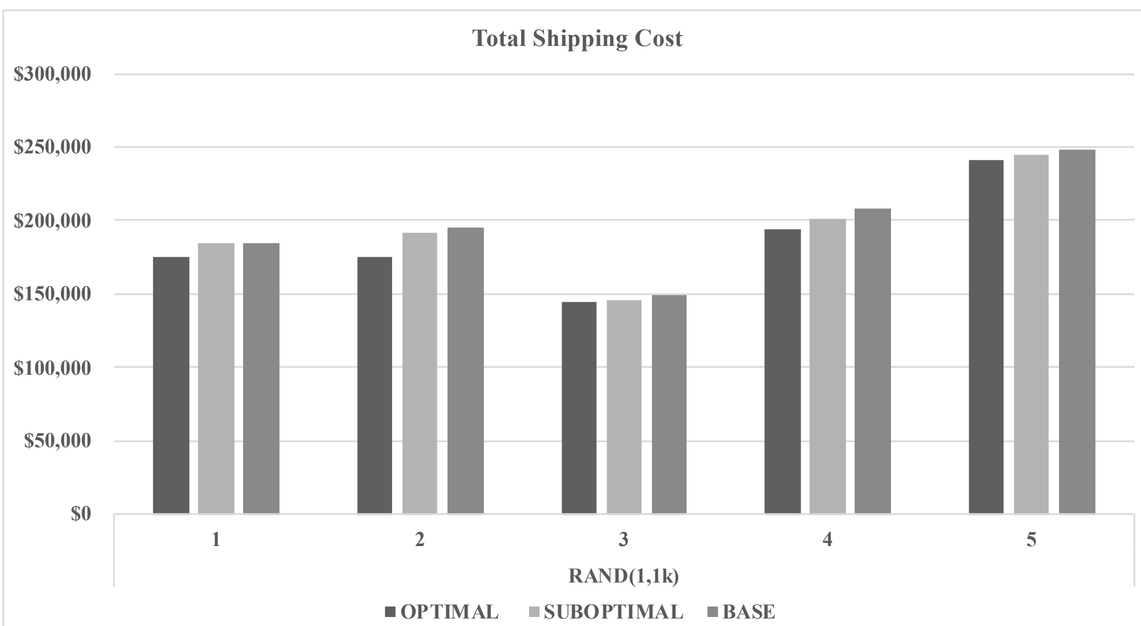

Figure 4.4 Comparison between shipping costs for the base, optimal, and suboptimal models for random distributed demand between (1, 1000).

In the previous figures, it can be seen that the total shipping cost for the suboptimal model is always coming lower than the base model which what we wanted to see here. The question of could our suboptimal model be worse than our base model, the answer to this question is yes, when the demand is not stable, or the forecasting method is not appropriate, we could end up making bad allocation even worse than optimizing every single period alone. It can be observed that the level of optimization is different in every case or scenario. In some cases, the optimization is minimal, and it could also equal to the base model. However, we can conclude that when demand is stable, and the right forecasting method is used, including future demand in the optimization process would reduce the total shipping cost.

By looking at some cases such as in 4.1 scenario 1, it can be observed that there is a large opportunity to minimize our shipping costs. Even though our suboptimal model minimized the total shipping cost, but still an additional minimization is possible. Of course, having a cost that is equal to the optimal cost is difficult, but we want to get as close as possible to the optimal model shipping cost. Conversely, by looking at figure 4.4 scenario 3, it can be observed that the opportunity cost is not big, and there is not a big area for improvement, and our suboptimal solution is very close to the base model. It can be concluded that every case is different, but we want to make sure that in some cases we might not minimize the cost a lot, but in most cases, we are.

Let us look at the opportunity costs and how much we were able to minimize it in terms of costs and percentages.

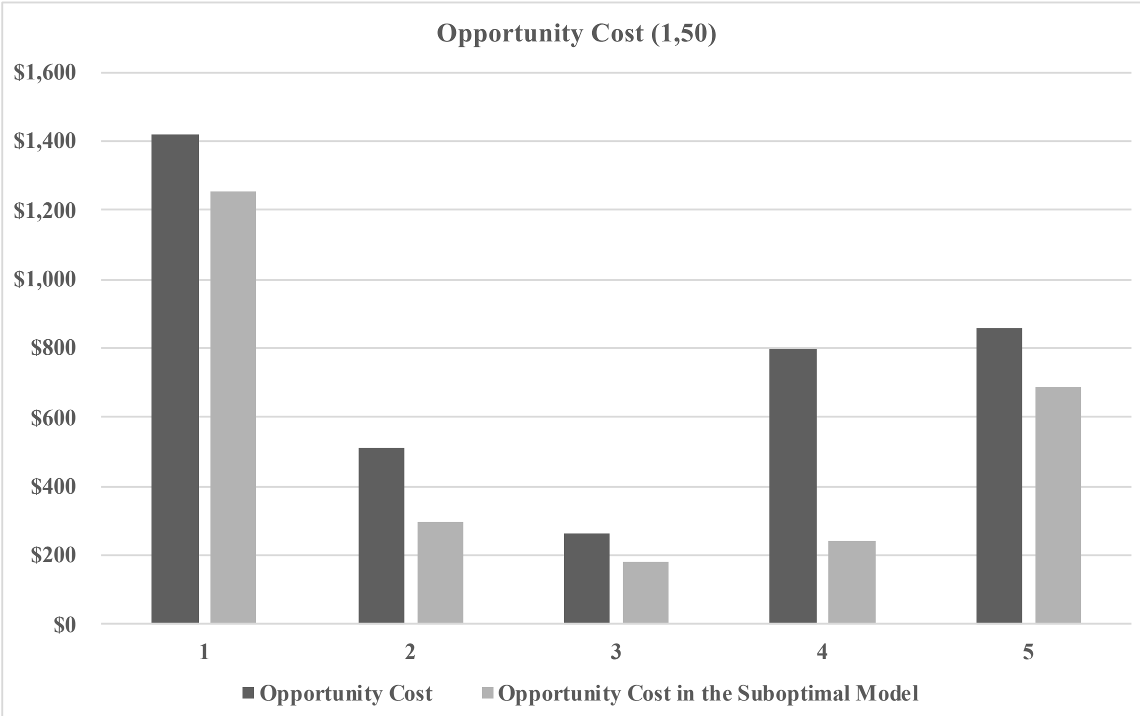

Figure 4.5 Opportunity cost in the base model and in the suboptimal model for random distributed demand between (1, 50).

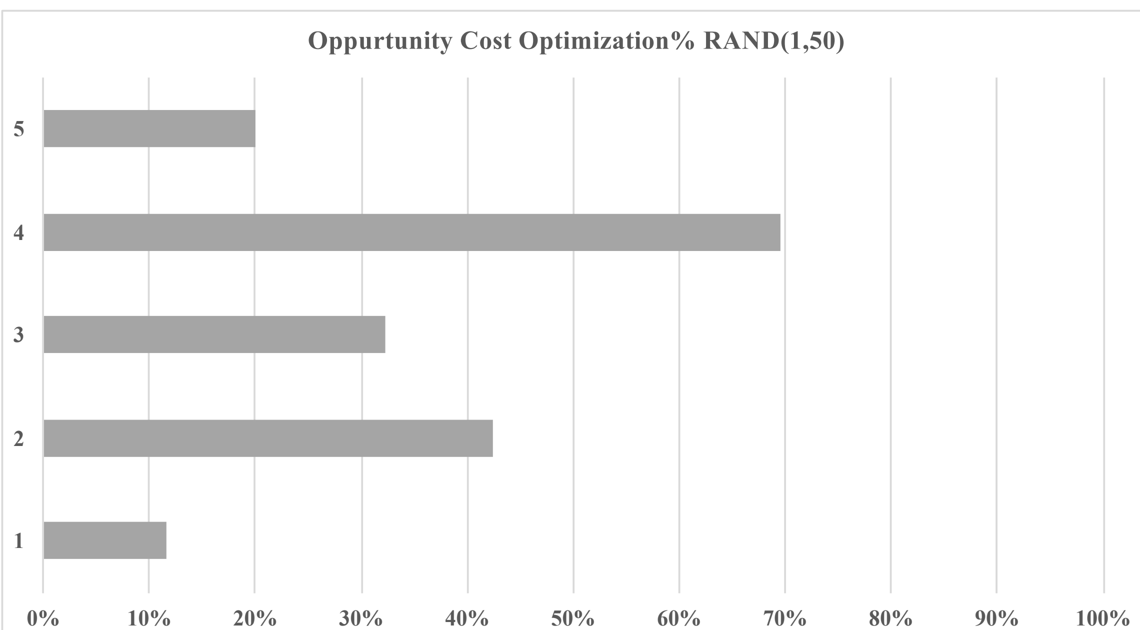

Figure 4.6 Opportunity cost optimization for random distributed demand between (1, 50).

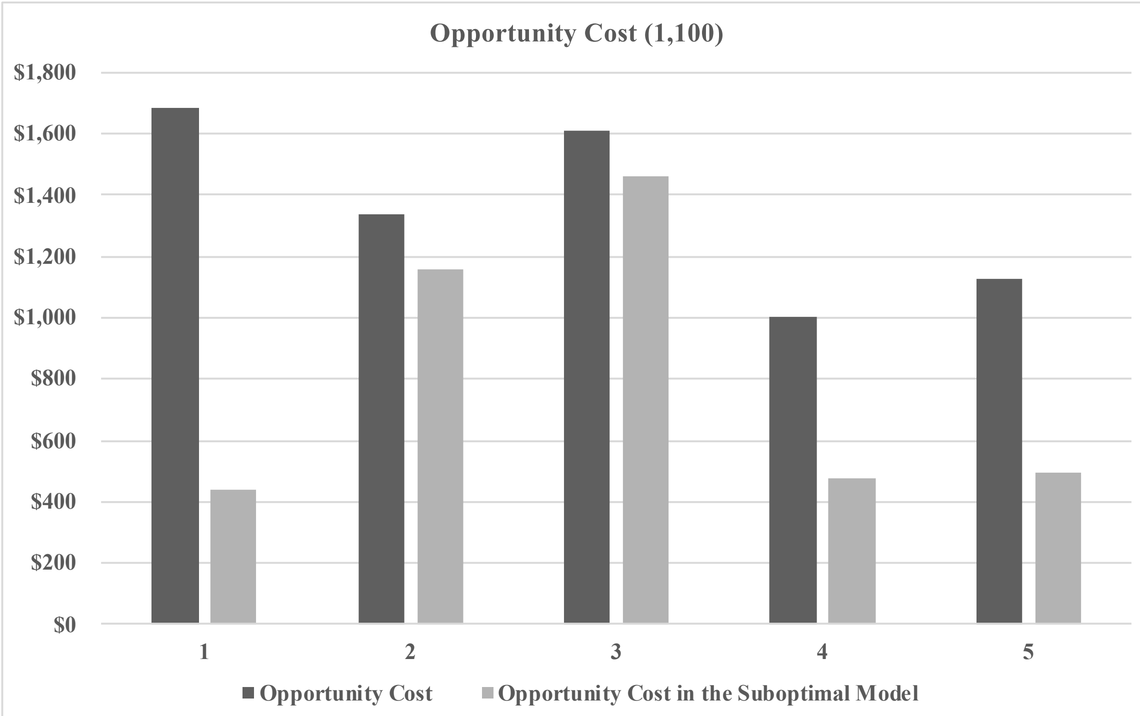

Figure 4.7 Opportunity cost in the base model and in the suboptimal model for random distributed demand between (1, 100).

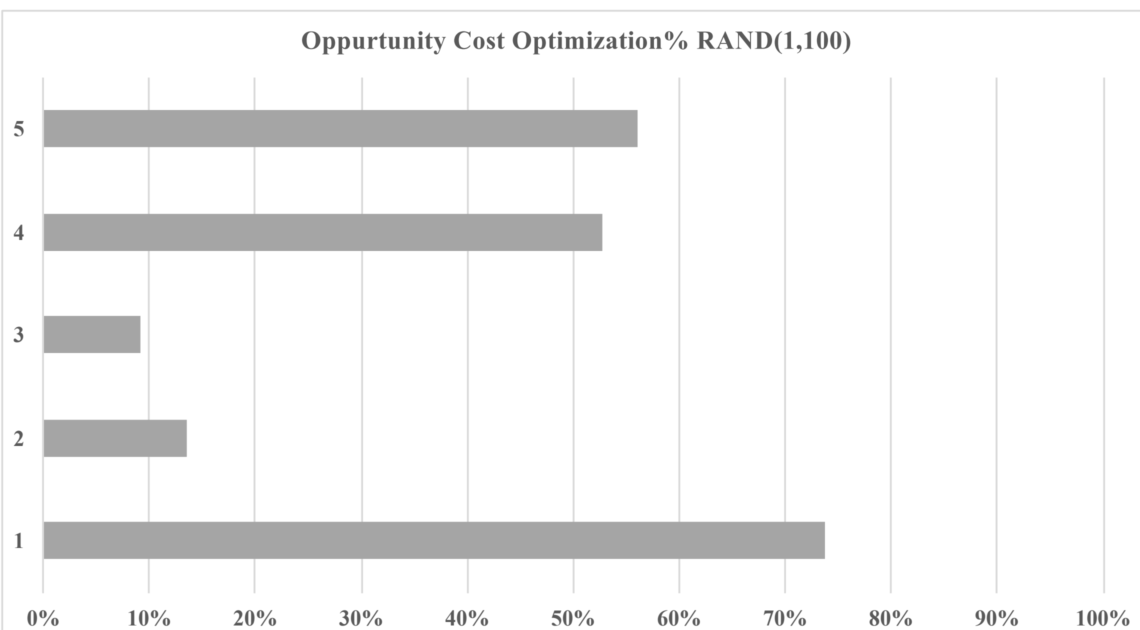

Figure 4.8 Opportunity cost optimization for random distributed demand between (1, 100).

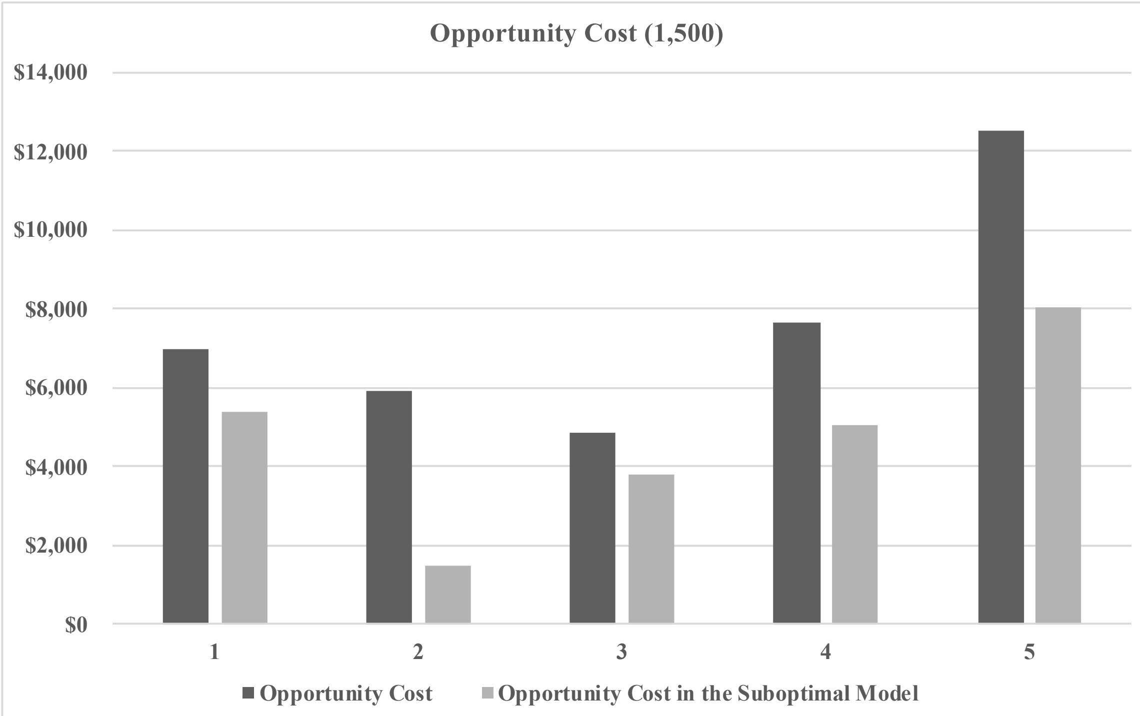

Figure 4.9 Opportunity cost in the base model and in the suboptimal model for random distributed demand between (1, 500).

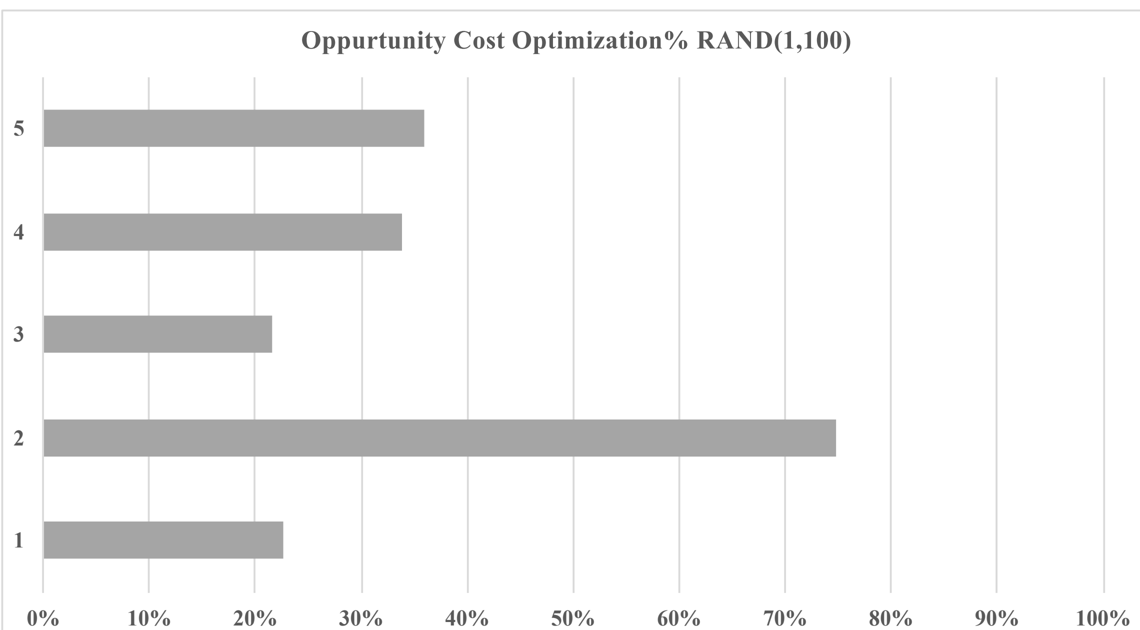

Figure 4.10 Opportunity cost optimization for random distributed demand between (1, 500).

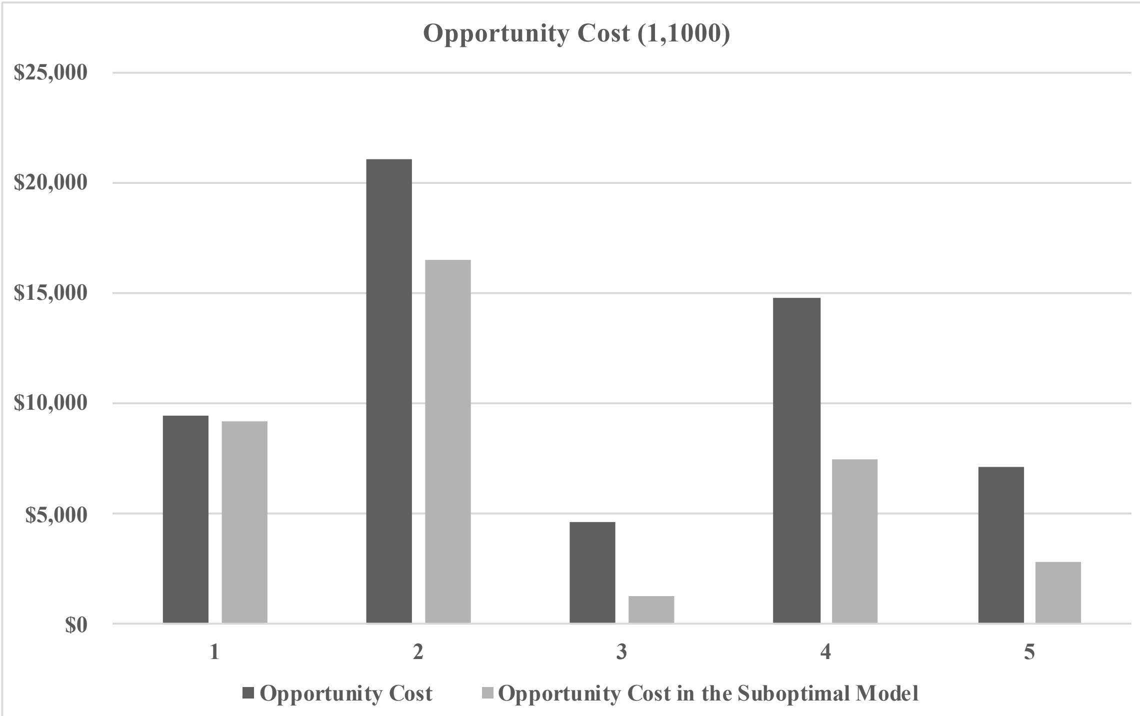

Figure 4.11 Opportunity cost in the base model and in the suboptimal model for random distributed demand between (1, 1000).

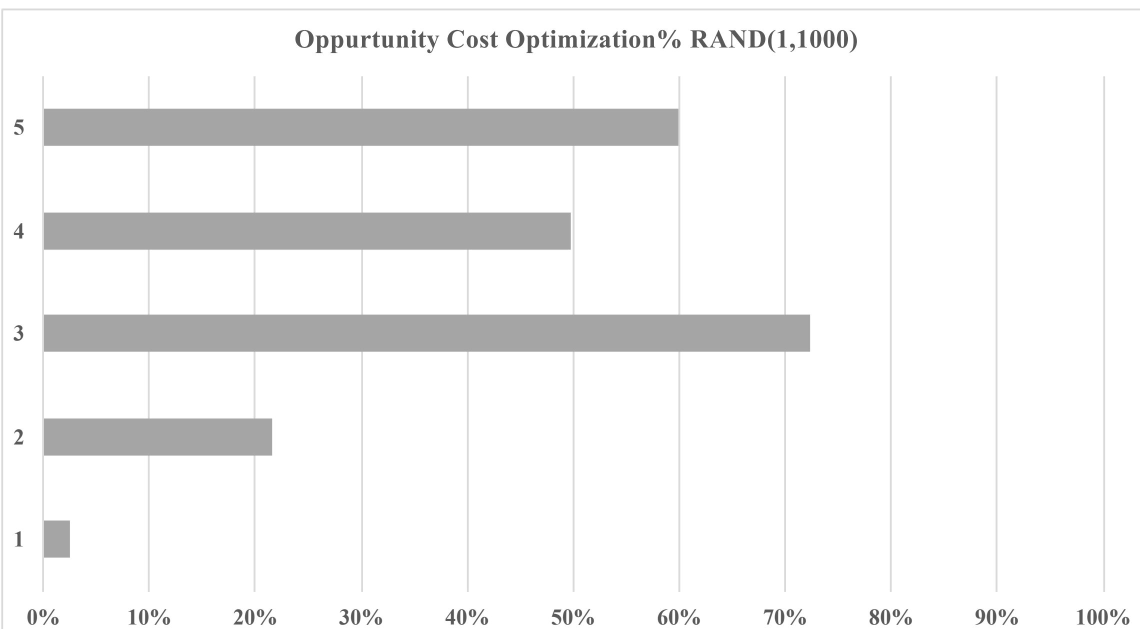

Figure 4.12 Opportunity cost optimization for random distributed demand between (1, 1000).

By looking at the previous figures, it can be seen that in every set of data and in every scenario, the opportunity cost is decreasing in different rates. When the opportunity cost is equal to zero, this means that the suboptimal solution is equal to the optimal solution which is difficult to achieve. However, we want to get closer to the optimal solution as much as possible. These set of graphs help us to see if there is a good chance for further improvement. Our main objective of our decision model is to make sure that in all scenarios we were able to minimize the total shipping cost compared to the base model. Furthermore, we are looking to see how far we are from the optimal solution. For instance, in figure 4.7 scenario one, it can be observed that the opportunity cost has decreased from around \$1,700 to around \$500. By looking at figure 4.10, it can be seen that this reduction has got us closer to 70% of the optimal solution which is very satisfactory. Conversely, by looking at figure 4.11 scenario one, it can be seen that the opportunity cost has not decreased a lot and it is almost the same, and by looking at figure 4.12, it can be observed that we only have got closer to our optimal solution by 2%. This result is not satisfactory and there is a big chance of further improvement. The reason behind this is that sometimes the historical data that are randomly generated is too optimistic or too pessimistic and conversely the real demand is. This causes different optimization rates.

To conclude this part, we can say that the suboptimal model is minimizing the total shipping costs in different rates. The forecasting method used has a big impact on the model. In our case, weighted moving average is used for a uniformly distributed demand, and we were able to minimize the total shipping costs in most of the scenario as presented in table 4.1.

4.4 Sensitivity Analysis

Sensitivity analysis is changing controllable factors and see its effect on the output. On our model the controllable factors are the inventory level and the forecasting method that is being used to predict future demand. Additionally, the shipping costs from fulfillment centers to destinations. When a company has more than one fulfillment center and they know the expected demand. They would be able to keep the right inventory level in every fulfillment center based on the geographical demand. However, in the e-commerce industry predicting demand and forecasting could be more challenging, and in order to minimize costly allocations and stockouts e-commerce companies always want to carry safety stock inventory. Therefore, in our model, when demand is uniformly distributed, we wanted to see the effect of balancing the inventory in all the fulfillment centers as a barrier for unexpected demand or too optimistic or too pessimistic forecast. What we tested was when the demand is uniformly distributed between (1, 500) for the same set of data that was used before, we kept the inventory balanced in all the fulfillment centers and looked to see if we were able to minimize the total shipping costs while using our recommended model. The results are as follow.

Table 4.2 Testing Balanced Inventory for Uniformly Distributed Demand (1, 500)

		SHIPPING COST	SUBOPTIMAL BALANCED INVENTORY	% DECREASED
RAND(1,500)	1	$89,236	$83,661	6%
	2	$75,813	$75,813	0%
	3	$91,370	$84,247	8%
	4	$117,289	$88,783	24%
	5	$105,317	$80,143	24%

It can be seen from table 4.1 that we were able to minimize our total shipping costs for the same set of data by keeping the inventory balanced. For case two, there is no improvement because it was balanced in the main example. Keeping the inventory balanced is a good idea if the demand is unknown, and there is no or few historical data. Once historical data is available, and the right forecasting method is used. The right amount of inventory should be kept in each fulfillment center.

Another concept that we have tested is when the demand is unstable. For example, let us assume that the demand for the last previous periods was uniformly distributed between (1, 20), and for some reason the demand has increased from (1, 20) to be (1, 50). This change would influence the forecasted demand. Consequently, the allocated quantities for destinations. We created two models and compared them to each other and looked at the effect of unstable demand on our model.

Figure 4.13 Total shipping cost comparison between stable and unstable demand.

Figure 4.13 shows the total shipping costs is different when the demand is unstable. The actual demand is uniformly distributed between (1, 50) in all models. However, what is different between the suboptimal models is that the historical data. When demand is stable, the historical data were uniformly distributed between (1, 50). On the other hand, when demand is unstable, the historical data were uniformly distributed between (1, 20) which means that the increase in demand has influenced the total shipping cost which showcase the importance of using the right forecasting method, for the right set of data. Like presented earlier, when historical data is not available or is not accurate different models might be used to forecast future demand, and different inventory levels might be used. The next figures show the total shipping cost per destinations and per fulfillment centers for unstable demand.

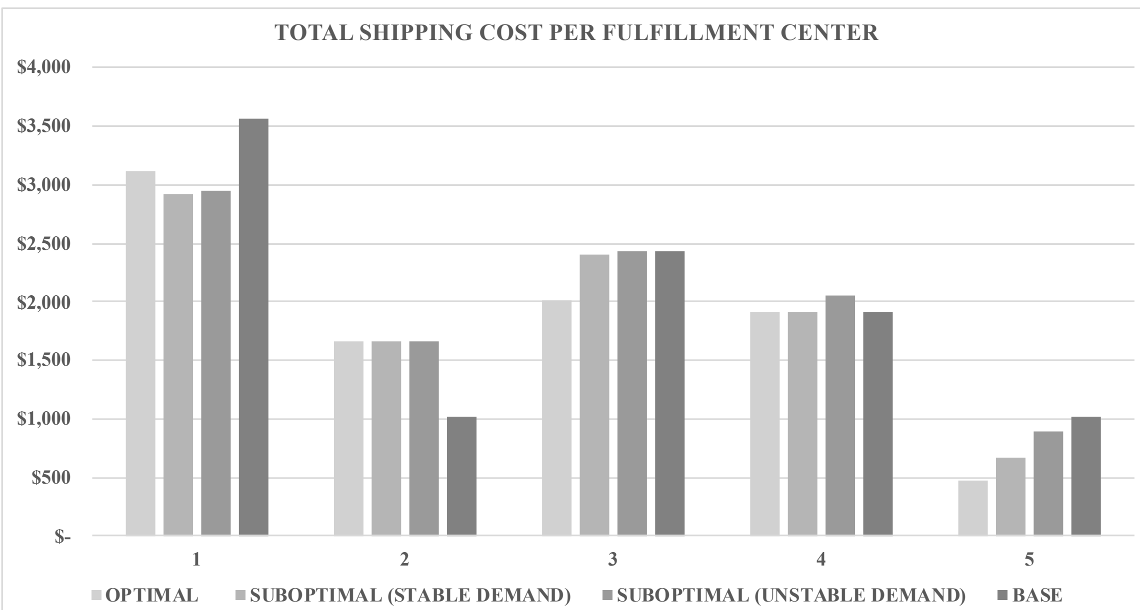

Figure 4.14 Total shipping cost comparison between stable and unstable demand per fulfillment center.

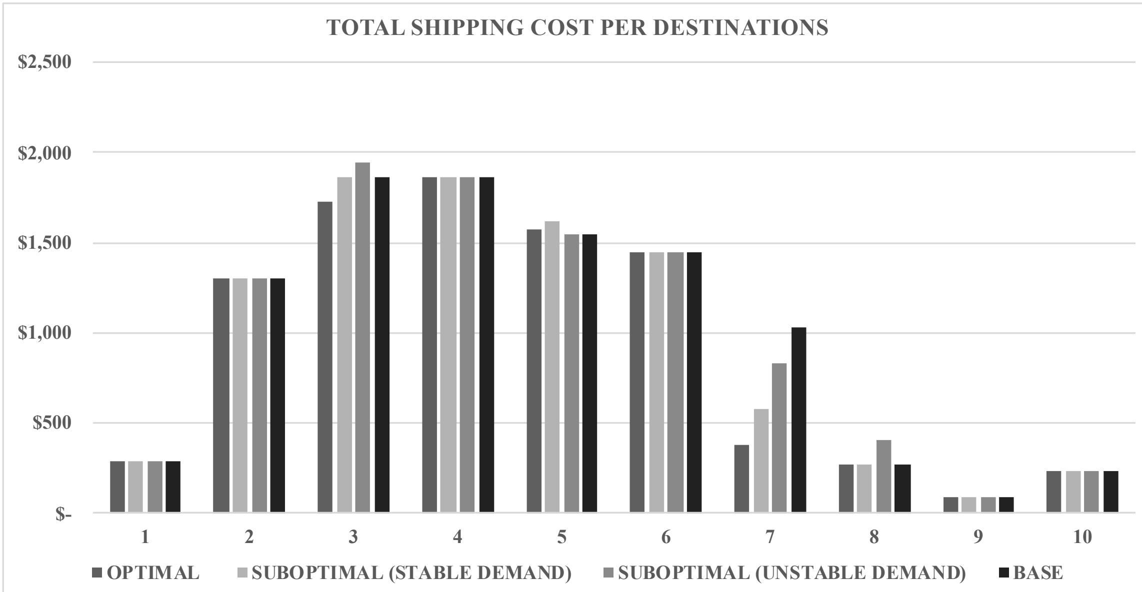

Figure 4.15 Total shipping cost comparison between stable and unstable demand per destination.

It can be observed from figure 4.14 and figure 4.15 that different allocations presents different shipping costs. Our recommended model assumed a stable demand with using weighted moving average to monitor any changes or trends in demand. However, e-commerce companies need to make sure that the data that they are using for forecasting is reliable and it gives real insights about the actual demand. Additionally, using the right forecasting methods. These are the most important factors in making the right allocation and assignment.

CHAPTER 5

SUMMARY

5.1 Conclusion and Remarks

In order for e-commerce to be competitive with brick and mortar, it has to be effective and efficient in all its logistics operations. Big e-commerce companies such as Amazon have different decision models for different operations and functions. The process of decision making is automated, and it is done in seconds. Once an e-commerce customer picks a product, and picks a delivery option, then it is the e-commerce company responsibility to deliver the product in the expected delivery date.

For companies such as Amazon, when an order comes there is a big probability that this order is available at more than one fulfillment center. Delivering the product from the closest fulfillment center to the order might be the first thing to come in mind. However, it is not always the right and optimal decision. There are different variables that are included in such a decision besides the distance such as future order and product correlations.

Our model shows that including future demand during the process of allocating received demand would change the allocation and minimize the total shipping costs. We presented three models, the first model which was called the base model. The base model allocates orders to fulfillment centers after they are received without considering future orders. The second model was to show that when the future demand is known the allocation is different and the total shipping cost is minimized, and we called this model the optimal model. However, in real life the future demand is unknown, but we could have insights about future demand by looking at historical data. For our recommended decision model, we were trying to find a solution that is better than the base model and as close as possible to the optimal model. For a uniformly distributed demand, we used weighted moving average to forecast future orders and including expected orders in our optimization process, we called this model, the suboptimal model. All the models were solved as a linear programming problem using excel solver. Different shipping costs, inventory levels and demands were presented to validate the model.

Additionally, once the model is developed, we tried to see the effect of balancing the inventory in all fulfillment centers. By testing that we were able to minimize the total shipping costs to be lower than other random inventory levels. Therefore, we think that balancing the inventory is a good idea when historical data is not available, or it is not reliable or when the demand is unpredictable and instable.

5.2 Future Work

Future research should consider including other factors to the model and looking at their effects on the total shipping cost. For example, assuming that two products are always ordered together, and there is a correlation between these two products and we want the quantity of these two products to be somewhat equal in the fulfillment centers. Would product correlation affect the allocation process or minimize the total shipping costs. Keeping two products that are usually ordered together would reduce the order picking time and also the packaging. One of the big challenges in e-commerce is order consolidation which mean objective is to minimize the shipped boxes for orders that have more than one product. Additionally, future research might test other forecasting methods, for different demand behaviors, different inventory levels and shipping costs knowing that each product is different, and one forecasting method might work well with certain type of products and work bad with others, and as we discussed earlier that bad forecasting would make companies make costly allocation.

In our model, the total inventory level is always higher than the demand, future studies could also look at when the demand is higher than the inventory level, what is the effect on the allocation and what how to involve and calculate stockout costs. Finally, testing how such a model would reduce transshipment between fulfillment centers. As mentioned earlier, transshipment is the process of moving products between fulfillment centers. Transshipment should be minimized as much as possible. Knowing the right amount of inventory needed in every fulfillment center would minimize transshipment.

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