THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

SCHOOL OF ENGINEERING

DYNAMIC GROUP TECHNOLOGY ALGORITHM FOR INVENTORY MANAGEMENT

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Spring 2023

A thesis
submitted in partial fulfillment of the requirements
for a baccalaureate degree in Industrial Engineering
with honors in Industrial Engineering

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ABSTRACT

The management and control of inventory is a challenging job for modern manufacturing systems. Due to the complexity of these systems, poor management can result in high expenses, disgruntled customers, and eventually a loss of competitiveness and business. The majority of businesses use computerized management information systems, which gather and display data on various parts of their operations, to deal with this problem. This data, which includes details on the demand for materials and parts, machine status, and defect rates, is dynamic and needs to be managed successfully using the right analytic techniques. One such strategy is Group Technology (GT), a management theory that organizes things according to their properties. In this research, a dynamic GT-based framework is presented for classifying inventory items according to a set of attributes specific to the inventory. The method is implemented in a case study that groups inventory based on item type, order type, sales channels, and Stock Keeping Unit (SKU) to reduce the transportation time of the items in a warehouse. Managers may be able to improve inventory management within a warehouse with the aid of the resulting classification. The method is portable and accessible because it is developed in MATLAB and can be incorporated into a business's information system.

Keywords

Group Technology; Inventory Management; Dynamic Grouping; Manufacturing Systems

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ACKNOWLEDGEMENTS

First, I would like to thank Dr. Ashour, my thesis supervisor. Dr. Ashour's dedication to creating an enlightening environment for his students is unmatched. He guided me through my academic career and reviewed my research, and thesis every week. Dr. Ashour's passion for teaching has encouraged me, along with all of his students to achieve academic success. I am honored to have had the chance to work alongside such an amazing professor and industrial engineer. Thank you Dr. Ashour for making an amazing impact on my academic career.

Moreover, I would like to thank Dr. Onipede, my honors advisor for guiding me through my academic journey at Penn State Behrend. Dr. Onipede was the first faculty member that I met during my transfer to Penn State Behrend. He assisted me through the process and has been an amazing advisor ever since. Dr. Onipede leaves an incredible mark on all of his students as he inspires them to reach their full potential. Thank you Dr. Onipede for guiding me during my time at Penn State Behrend, and for advising me to reach my full potential both inside and outside of the classroom.

Furthermore, I would like to thank Dr. Brown, and Dr. Amy, who have made sure that scholars Schreyer scholars at Penn State Behrend receive all the resources needed in order to gain the Schreyer experience. The Schreyer faculty members at Penn State Behrend make sure that all scholars are well-surrounded and guided. They have made Schreyer one of the best experiences I have ever had.

I would like to thank my family and friends who have encouraged me to reach my full potential.

Finally, I would like to thank the Schreyer Honors College for giving me the opportunity to write this thesis. It has been a great learning experience for me, and I have gained a great amount of knowledge and skill throughout the process.

Chapter 1 Background

Modern manufacturing systems confront a significant challenge in managing and controlling inventory, which is getting harder as system complexity, inventory size, and globalization increase. Inventory management mistakes could lead to several problems, including inefficient use of floor space, lost revenue, damaged reputations, and dissatisfied customers. However, improvements in technology and information systems have made it possible to overcome these difficulties. Managers can reduce inventory costs and promptly meet customer needs by using data analytics and data warehouse management. Companies use a classification system to efficiently group things in order to manage the thousands of inventory items with various characteristics.

Inventory classification methods have been studied extensively for the past decade, as researchers' goal is to develop various methods effectively and efficiently classify inventory. This topic has been divided into two broad categories: single-criterion inventory classification, and multi-criteria inventory classification. The most popular classification method that has been studied is the single-criterion ABC classification method which divides inventory into three categories: (A) items are classified with tight control, (B) items are less lightly controlled, and (C) items are classified with the simplest control. The ABC method is simple to implement, yet it has many limitations. Its most common limitation is that the method classifies inventories based on a singular criterion, which can result in the misclassification of items.

To overcome the challenges of a singular-criterion classification method, researchers developed a cross-tabulate matrix to solve a bi-criteria inventory classification problem [1]. In their study, the authors used the example of a consumer goods manufacturer and classified inventory based on two criteria: lead time and item cost. The cross-tabulate matrix method has helped the manufacturers to reduce the number of inventories, which in turn reduces the inventory cost. However, this method has two major constraints: the computation becomes too complex when the number of criteria exceeds two, and it assumes that the weights of the different criteria are equal, which again can result in the misclassification of items.

To resolve the singular-criterion and bi-criteria limitations, Multi-Criteria Inventory Classification (MCIC) methods have been developed. Flores et al. developed an analytic hierarchy process (AHP) that takes into consideration all criteria of importance and arranges items based on the hierarchy of their importance [2]. In their study, however, as Torabi et al. identified, the determination of weight criteria is based on experts' subjective opinions which can create unreliable results [3]. Moreover, this method requires a large amount of managerial and computational time to develop the information needed for each inventory item, which increases resource costs significantly. To resolve these limitations, inventory grouping methods were developed. Researchers proposed the use of meta-heuristics such as genetic algorithms and artificial neural networks(Partovi & Anandarajan, n.d.,2001) and [5]. Unfortunately, meta-heuristics are complex and require a long computational time.

Moreover, multiple MCIC methods have been designed based on optimization. Ramanathan developed a weighted linear optimization model (R-model) that generated a set of criterion weights for every inventory item and assigns an inventory score [6]. Items are then classified using the ABC classification with the criterion being the normalized score of each item. To eliminate weight-assignment subjectivity, this model was based on the Data Envelopment Analysis (DEA) concept where the model weights are generated by a DEA optimization technique [7]. The DEA technique is a linear mathematical programming technique that aims to evaluate the performances of a group of complex objects referred to as Decision-Making Units (DMUs). However, the R-model has two major limitations. First, the probability that items share the same optimal score is high, and second, there is significant flexibility when weighting multi-criteria which can result in unbalanced weights between criteria causing the misclassification of items. Many models have been developed to solve the limitations of the R-model. Other researchers proposed models to create inventory scores without employing a linear optimizer [8], [9]. However, these models follow an independent evaluation approach which means that they disregard relative evaluation between inventory items. Zhou and Fan developed a model that determines the least and most favorable weights that are combined with a control parameter determined by the decision maker (ZF-model) [10].

Park et al. developed the cross-evaluation-based weighted linear optimization which has important advantages in terms of inventory management performance and costs [11]. Millstein et al., developed a generalized and enhanced ABC inventory grouping method based on the optimization of profit, inventory investment, and customer satisfaction [12]. However, this method has various limitations, as the model is a one-period static model, which means that the time factor is not explicitly considered; every time new inventory is introduced to the warehouse, a worker needs to run the model and redetermine the classification of every item. Not only is this complex, but it is also time-consuming, which is a direct link to the increase in costs. Park et al. developed a cross-evaluation-based weighted linear optimization (CE-WLO) for multi-criteria ABC classification [11]. The purpose of the model is to produce a finer classification of inventory by incorporating cross-efficiency evaluation into weighted linear optimization. However, this method's limitation, like many of the previous limitations described, is a long computational time.

Andrew Kusiak evaluates a generalized Group Technology (GT) technique by considering two clustering techniques: integers, and matrices. It was concluded that GT has an important implication on the layout of machines, disposition of workers, and storage location of inventory items within a warehouse. This research presents a dynamic inventory grouping model that directly optimizes the grouping decisions by using a GT technique. This feature solves the previous models' limitation: our model is a dynamic classification model that rearranges inventories every time a new item is introduced into the system. This new feature reduces the computational time as the system needs to be set up only once.

This thesis is organized as follows: Chapter 1 provides a background on the related work and differences between different classification methods. Chapter 2 describes the proposed approach. Chapter 3 presents a case study that is used as an example of how to use the proposed approach. Chapter 4 draws conclusions and provides directions for future research.

Chapter 2 Methodology

The goal of the proposed algorithm is to dynamically group items as orders arrive at a warehouse location. The algorithm considers different characteristics of a product; these characteristics are determined by a warehouse manager. Examples of characteristics include the order type, product type, sales channel, and SKU. Once the characteristics of the grouping are determined, the algorithm forms clusters following the logic explained in the sections below.

2.1 Group Technology

Lee-Post describes GT as a management philosophy that stresses the value of understanding groups in order to solve problems effectively (Anita Lee-Post, 2000).This implies that, in order to save time and effort, a single answer can be used to solve a collection of issues that are related in terms of their concepts, guiding principles, and tasks. Green and Sadowski contend that GT can also raise productivity (T. J. Green & R. P. Sadowski, 1984).while Mitrofanov indicates that it can improve the effectiveness of manufacturing systems (SP Mitrofanov, 1959).

Manufacturing systems, which are a combination of actions and processes used for the production of any good, can also be improved through the improvement of the quality of the workforce, capital recovery, and production technology. Each of these improvements adds 15%, 25%, and 60%, respectively to the productivity of manufacturing systems [16]

GT is thought of as a component of manufacturing technology [16]. Information analytics and data warehousing are examples of technologies that can be included in the advancement of manufacturing technology.

The two main stages of the general GT approach consist of two steps. The first step entails finding the key product characteristics that can be used to cluster (or group) the population's constituents. Part groups can be created in a manufacturing setting using routing or design data (J. L. Burbidge, 1996; O. F. Offodile, 1991). Table 1 in Groover and Zimmers (1984) shows examples of component attributes that can be used to categorize parts according to their similarity. Part categories can be created in inventory management based on factors like pick frequency, product age, price, etc.

Table 1. Attributes for Part Groups Formation.

Design Attributes	**Manufacturing Attributes**
Shape	Process
Length/diameter ratio	Operations
Material type	Machine tool
Part function	Operation Sequence
Dimensions	Annual production
Tolerances	Fixtures needed
Surface finish	Batch size

Implementing an effective process to group parts based on their similarity to the chosen attributes is the second stage in GT. Production Flow Analysis (PFA) and the Classification and Coding (CC) scheme are the two primary grouping methods that have been employed. Based on part similarity and machine and/or operation criteria, the PFA classifies groups. As a result, each group's components would be handled using machinery or techniques that are related to one another (J. L. Burbidge, 1996).The CC system, on the other hand, gives each component a numerical code (Anita Lee-Post, 2000). This code might be an alphanumeric string or character that refers to a feature of the part's design or manufacturing (Anita Lee-Post, 2000).

2.2 Problem Formulation

Two essential stages are involved in implementing the GT approach: 1) developing a CC scheme based on pertinent inventory item attributes to produce meaningful and distinct groups of items, and 2) using an effective grouping algorithm to identify these groups. These procedures are thoroughly explained in the sections that follow.

2.2.1 Classification and Coding (CC) Scheme

The employed CC system is comparable to the conventional GT part CC schemes. The use and type of the items that are kept in the inventory determine the essential set of item attributes. In this research, our attributes are: Item type, order type, sales channel, and SKU. The chain-type structure has been chosen. Each number in this code structure conveys a unique piece of information, and each digit is independent of the others. The first number of the code denotes the item type, the second one denotes the order type, the third one denotes the sales channel, and the last one denotes the SKU frequency.

Each attribute has a set of options, and each option has a different code based on the frequency of that option. For instance, the item type has a set of 2 options: “Footwear,” and “Apparel,” and the footwear option is more frequent than the apparel option, so the footwear option has a score of 1, and the apparel option has a score of 2. Table 2 represents all the options and socres for each attribute.

Table 2. Classification and Coding Scheme.

Item Type	Order Type	Sales Channel	SKU
1.Footwear 2.Apparel	1.Future US 2.Present US 3.B2B 4.Future MEX 5.Present MEX 6.INTL	1.RAS 2.USA 3.Nonstop 4.Mexico 5.Stop 6.Non-USA	1.0 – 29 2.20-99 3.100- 249 4.250 - 3000

Below is an example of how the raw data is coded into the coded data based on the attribute scores.

Table 3. Example of the Raw Data.

Item Type	Order Type	Sales Channel	SKU
Footwear	Future US	RAS	312
Apparel	Present US	USA	51
Footwear	Present Mexico	Non-USA	1

Based on the ranges of each attribute, this set of data would turn into the coded data below:

Table 4. Example of the coded data.

Item Type	Order Type	Sales Channel	SKU
1	1	1	1
2	2	2	3
1	5	6	4

2.2.2 Algorithm

The recommended approach effectively arranges a large number of ambiguous inventory items whose properties might alter over time. Ben-Arieh and Sreenivasan introduced the distributed dynamic GT algorithm to deal with this dynamic situation (D. Ben-Arieh & R. Sreenivasan, 1999).This algorithm uses a bidding process between agents representing groups of related products. If a new item is sufficiently similar to the group, as decided by a similarity measure, this agent would accept it into the group. Each agent engages in repeated negotiations with others to exchange their most distinctive item for a comparable item from a different agent's group. When no agent is ready to trade its items, the algorithm ends.

The algorithm used in this research for identifying groups is depicted in Figure 1. The process starts by gathering all relevant information related to inventory items, such as the item type, order type, sales channel, and SKU. After collecting this data, the grouping algorithm is applied to cluster the items based on how similar they are in terms of their attributes.

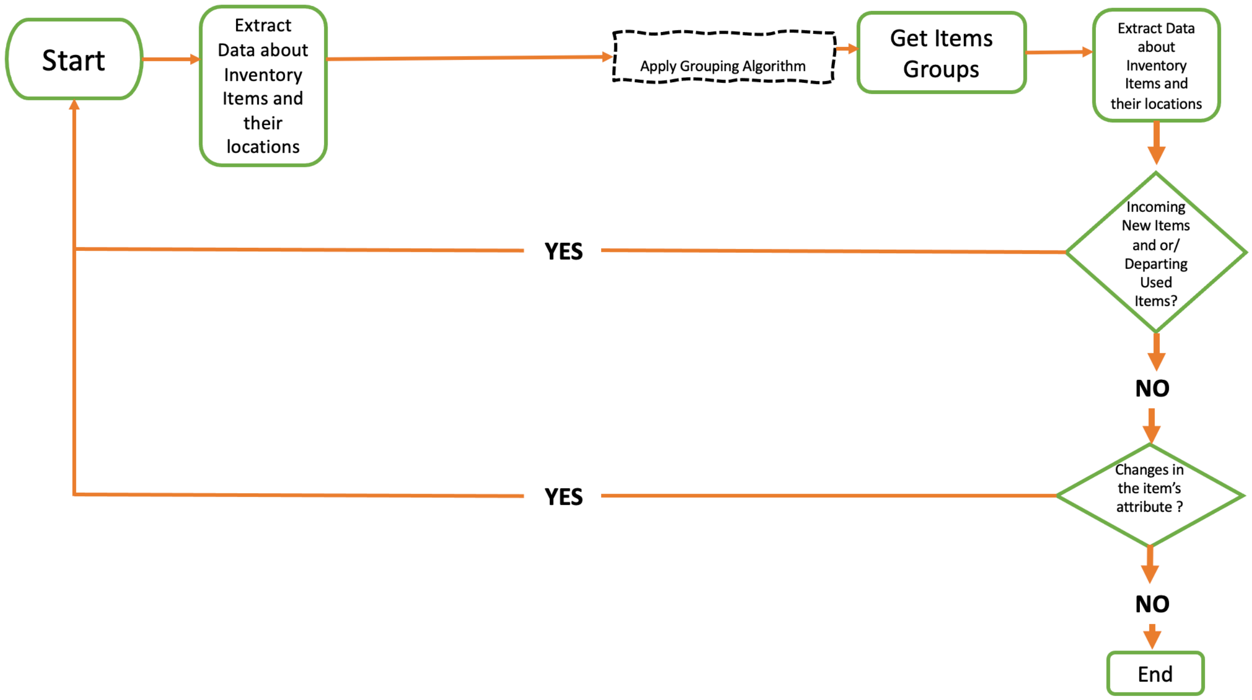

Figure 1.Overall Grouping Algorithm.

The following describes the notations and definitions used in the algorithm.

Definitions, Indexes, and Variables

l: is the group index, and $l = 1, 2, ..., L$.

i: represents item i, and $i = 1, 2, ..., N$

j: represents item j, and $j = 1, 2, ..., N$

k: represents attribute k, and $k = 1, 2, ..., K$

$\boldsymbol{A_l}$: Agent for group *l*. the agent is the item group representative. It calculates and stores information about the group such as dissimilarities between itself and all the items in the group. The agent negotiates with other agents to exchange items.

$\boldsymbol{d_{ij}}$: Dissimilarity between items *i* and *j*. The dissimilarity is calculated using the following set of equations. Equation 2 presents the Offodile similarity measure between items *i* and *j*:

$$S_{ij} = \sum_{k=1}^{K} w_k S_{ijk} \tag{1}$$

Where, w_k is the weight of attribute *k*, and

$$S_{ijk} = 1 - \frac{|p_{ik} - p_{jk}|}{R_k} \tag{2}$$

Where,

S_{ijk}: the similarity measure between item *i* and item *j* on attribute *k*,

p_{ik}: coding for item *i* on attribute *k*,

p_{jk}: coding for item *j* on attribute *k*,

R_k: the range of attribute *k* over the population space of items.

Then, dissimilarity can be calculated as the complement of S_{ij}:

$$d_{ij} = 1 - S_{ij} \tag{3}$$

$\boldsymbol{C_l}$: Center of a group. The center of a group is calculated using Equation 4:

$$C_{kl} = (\frac{1}{nl})*\sum_{m=1}^{nl} Pmkl \tag{4}$$

Where,

C_{kl}: the center of group *l* over the dimension *k*,

p_{mkl}: coding for item *m* on attribute *k* in group *l*,

n_l: the number of items in group *l*.

Then,

$$C_l = [C_{1l}\, C_{2l} \ldots C_{KL}] \tag{5}$$

G: Global center. The global center is calculated using Equation 6:

$$G_k = \frac{1}{nl} *\sum_{m=1}^{N} Pmk \tag{6}$$

Where,

Gk: global center on attribute *k*,

pmk: coding for item *m* on attribute *k*,

$$G=[G_1\ G_2 \ldots G_K] \tag{7}$$

$\boldsymbol{T_l}$: Threshold for group *l*. threshold is the dissimilarity between the group center and the global center.

$\bar{d}$: This is the average dissimilarities between the items and their group, calculated as follows:

$$\bar{d} = \frac{2}{nl_*(nl-1)} \sum_{i=2}^{nl} \sum_{j=i+1}^{nl} \mathrm{d}_{ij} \tag{8}$$

Dissimilarity between an item and a group: The dissimilarity between the item and the group center.

Different item: The item that has the greatest dissimilarity from the group center.

Code of location: The CC code for a location in the inventory. The CC code represents the most desired items that should be stored in this location.

Dynamic Items Grouping Algorithm

A distributed dynamic GT algorithm with two phases was suggested by Ben-Arieh and Sreenivasan [19]. This research adds a third phase that organizes and ranks the groups formed as a result of phases one and two in accordance with the warehouse's intended placement. Each of these three phases is described in the following sections.

Phase 1: Initial item groups formation

The algorithm originally assigns an agent to each freshly arrived item in the first stage. An existing agent or a new one may be given to the item. The threshold, global enter, and group center are updated following each assignment. Until a predetermined time period has passed or a certain number of items have arrived, this procedure is repeated. When the limit is reached, the first step is finished and the initial item groups are formed.

Phase 2: Group optimization phase

A similarity measure is used in phase two to distinguish unique items among the groups. Their agents exchange these various items with other agents. The agent with the largest average dissimilarity offers their unique item for bid and trade with the other agents. If the different item's dissimilarity is below the agent's threshold, the other agents would approve it. The agent that is most similar to the item, will win the trade. Until there are no more agents ready to trade any items, which indicates convergence, the algorithm's second phase continues.

Phase 3: Ranking phase

Items are ranked based on their difference to the worst alternative. The worst alternative being [1,1,1,1], it is the best possible combination for an item to be placed in the "most important" cluster. Items are measured based on their similarity to the worst alternative. Based on their similarity to the worst alternative, and how closely items' combinations are to each other, they are assigned the items are assigned to a cluster.

Figure 2 below represents a flowchart of the logic followed by the dynamic item grouping algorithm.

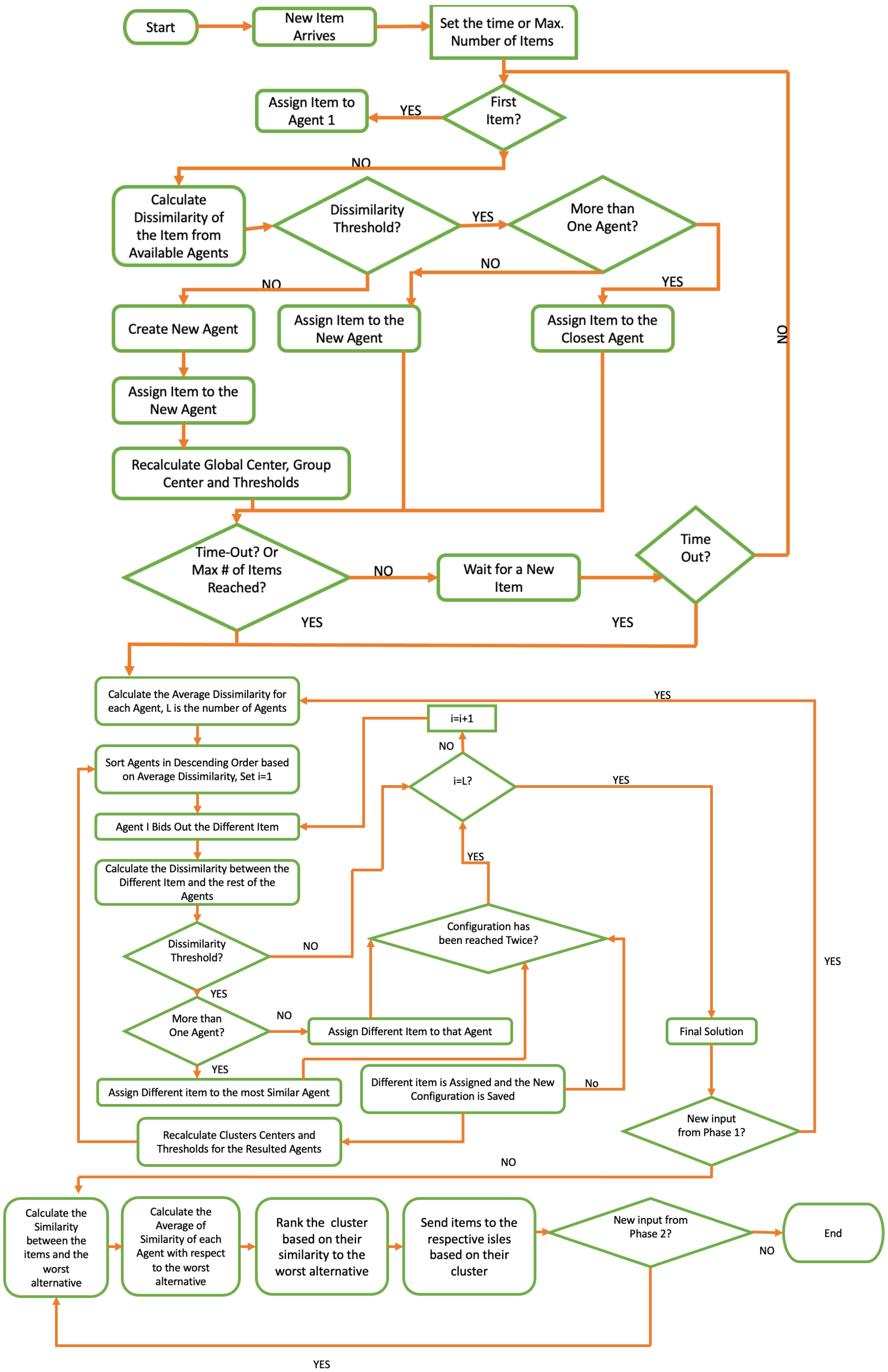

Figure 2. Dynamic Item Grouping Algorithm.

Chapter 3 Case Study

3.1 Background

A discrete-event simulation model of a warehouse was used to study the effectiveness of the developed algorithm. In addition, the Silhouette score was used as a metric to measure the goodness of the resulting clusters [20]. The simulation model was built for a warehouse that stores footwear and apparel items. The warehouse receives customer orders and the ordered items are shipped out directly to the customers. The warehouse runs 24 hours per day, 5 days per week. The warehouse is 200 meters long and 140 meters wide, and it is split into two main sets of aisles: 9 isles on the north side of the warehouse and 10 aisles on the south side of the warehouse. Figure 3 presents the layout of the warehouse.

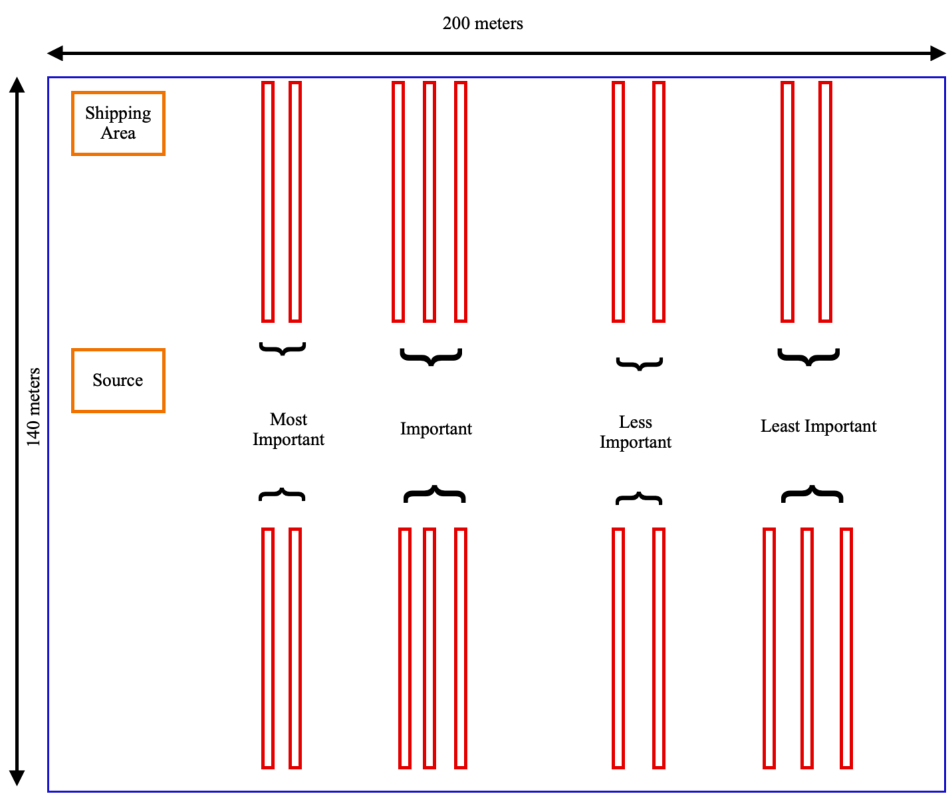

Figure 3. Layout of warehouse.

Currently, the warehouse uses a random storage technique to store the orders in the aisles. The goal of the study is to organize the items within the warehouse to reduce transportation time. The items that are ordered more frequently will be located in the aisles closest to the shipping area, and the less frequently ordered items will be located in the aisles farthest from the shipping area. The ranked clusters of the items are determined by the GT algorithm using four attributes for the orders. The first attribute is the item type, which is either "footwear" or "apparel." The second attribute is order type, which indicates whether the order should be fulfilled directly, or not. This attribute contains six different options: "Future US," "Present US," "B2B," "Future MEX," "Present MEX, "and "INTL." The third attribute is the Sales Channel. A channel is defined as a direct consumer web order or a wholesale restock order. The sales channel contains six different options "Mexico," "Nonstop," "Stop," "USA" "RAS" "Non-USA" Finally, the fourth attribute is the SKU of each order.

3.2 Formation of the Ranked Clusters

For this research, the algorithm was run for a dataset spanning over five days. Four clusters were formed. The clusters were labeled as most important, important, less important, and least important.

3.2.1 Performance of GT Algorithm

To measure the goodness of the GT algorithm, the Silhouette score was calculated for the resulting clusters. The Silhouette score is a metric used to measure the goodness of a clustering technique. The values of the Silhouette score range from -1 to 1. A score of 1 indicates that the clusters are well apart and clearly separated. On the other hand, a score of zero indicates that the clusters are indifferent, or the distance between them is not significant.

Table 5 shows the Silhouette scores for sample datasets.

Table 5. Silhouette Scores.

Sample	Silhouette Score
1	0.505
2	0.656
3	0.651

Figures 4, 5 and 6 are the silhouette plots of the 3 data points samples.

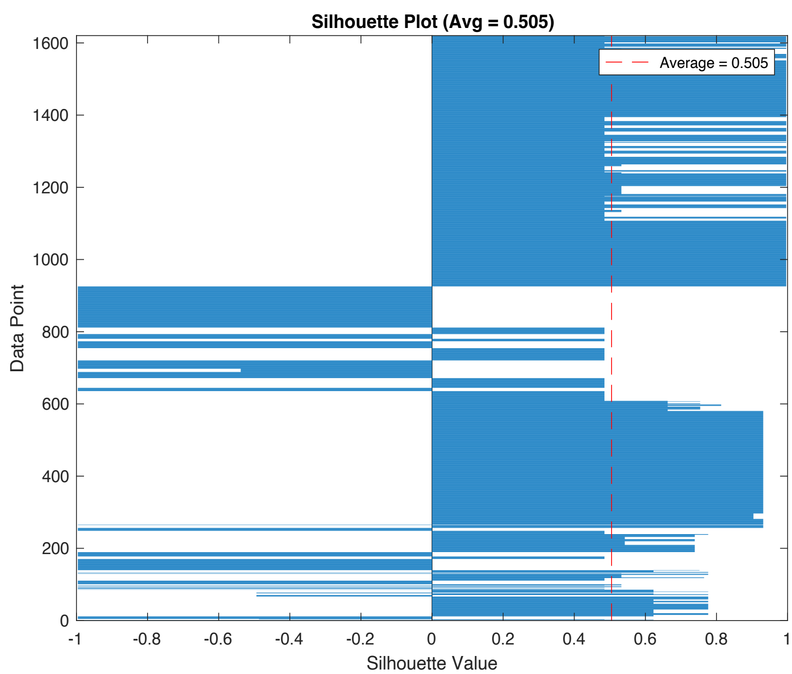

Figure 4. Silhouette Plots for Sample 1 Datapoints.

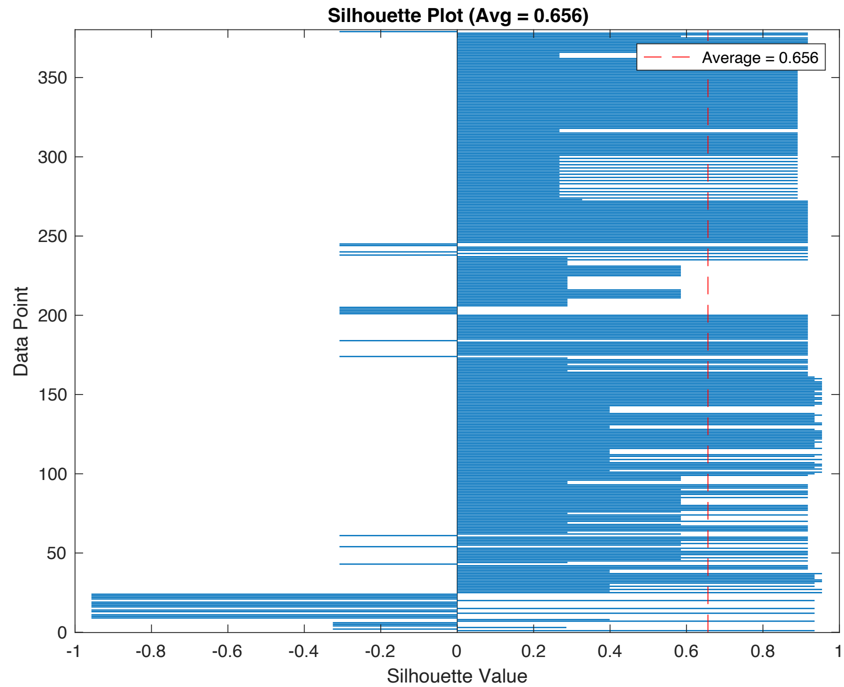

Figure 5. Silhouette Plot for Sample 2 Datapoints.

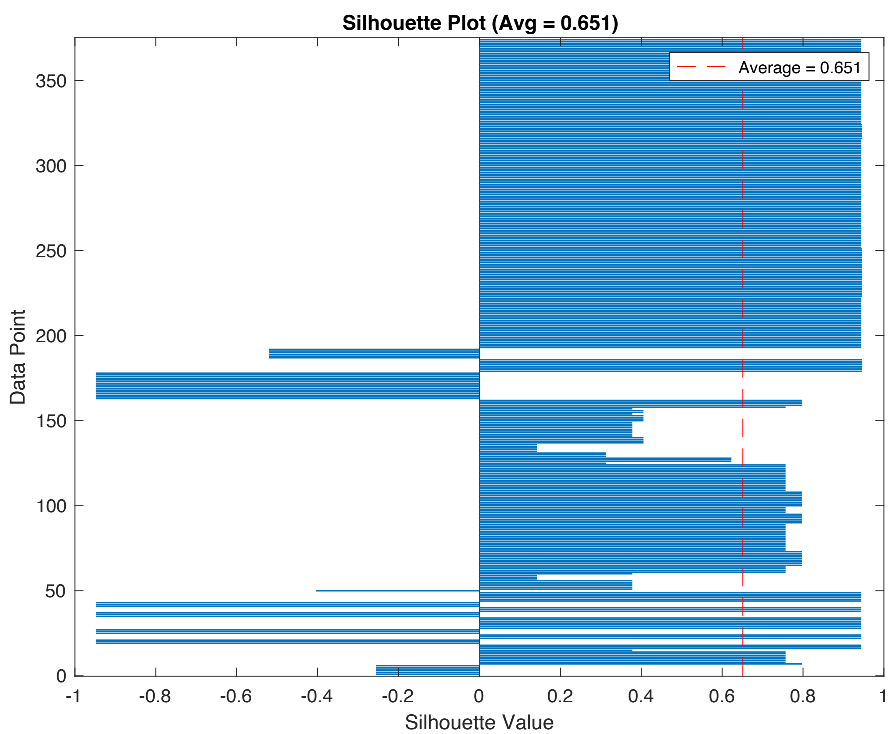

Figure 6. Silhouette Plof for sample 3 datapoints.

Figures 7, 8 and 9 are the silhouette plots of the 3 data points sample clusters.

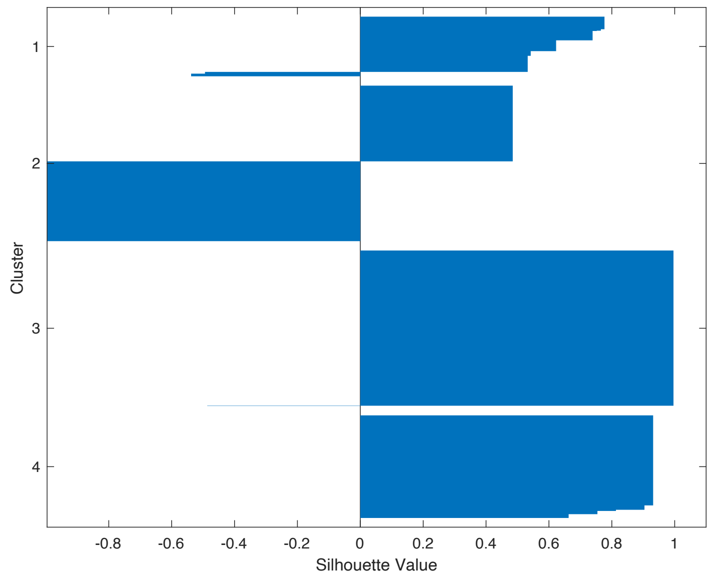

Figure 7. Silhouette Plot for the Sample 1 Clusters

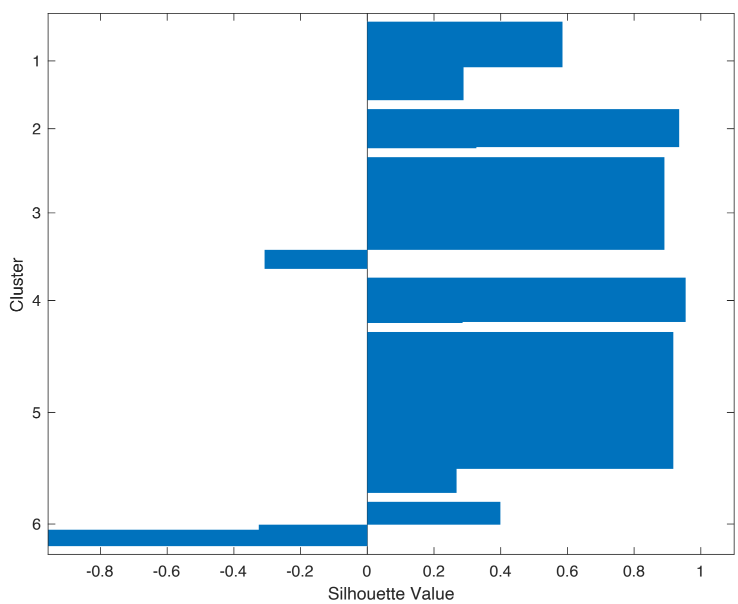

Figure 8. Silhouette Plot for the Sample 2 Clusters

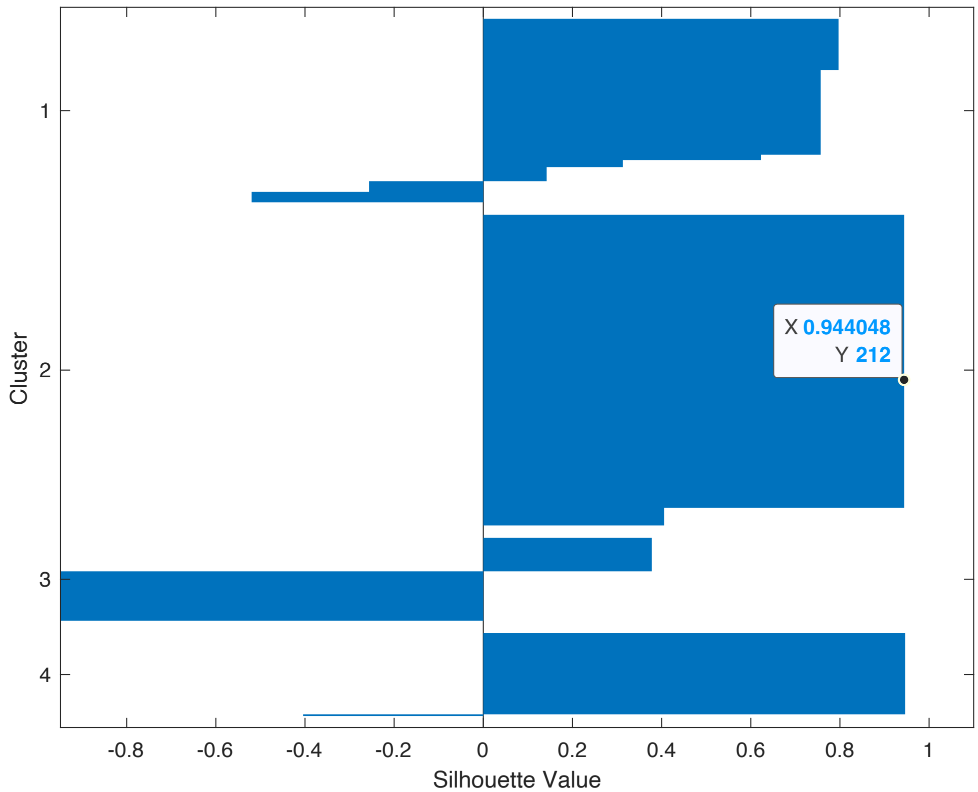

Figure 9. Silhouette Plot for the Sample 3 Clusters

The Silhouette scores for the sample datasets are above 0.505. To improve the score, the weights of the attributes can be changed.

3.3 Operational Performance

After identifying the ranked clusters, the dataset was imported into the simulation model of the warehouse. Figure 7 shows the simulation model snapshot:

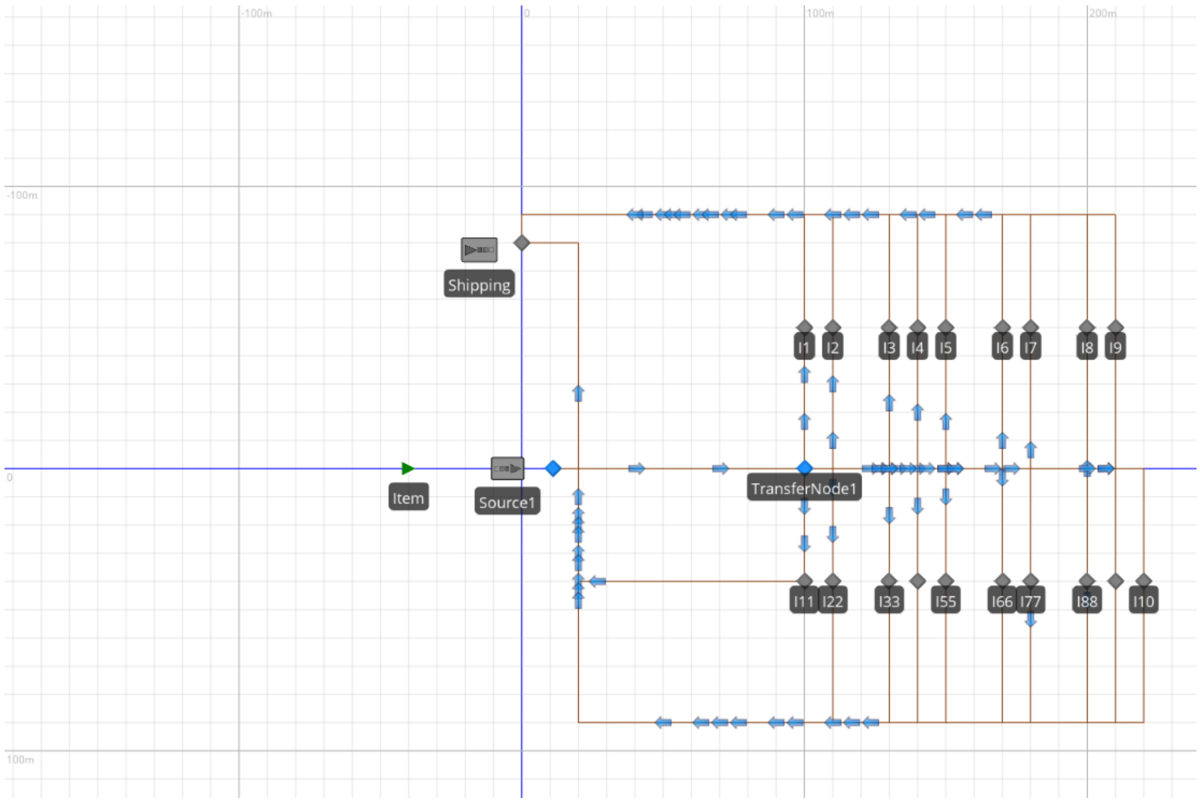

Figure 10. Simulation Model Snapshot.

Two scenarios were developed. The first scenario did not consider the clusters; items were randomly stored in the aisles. This scenario represents the current situation of the warehouse. The second scenario considers the resulting ranked clusters. The items are stored in the warehouse based on their clusters: the most important items are stored in the aisles that are closest to the shipping area, and the items in the least important cluster are stored in the aisles that are the furthest from the shipping area. The distance between the group of aisles and the shipping area can be found in Table 6.

Table 6. Distance between the isles and the shipping area.

Cluster Type	Average Distance Travelled (in meters)
Most Important	185
Important	260
Less Important	300
Least Important	344

The average transportation time from the isles to the shippin area is measured for each scenario. The simulation was run for 5 days, and for 30 replications for scenario. The simulation output is shown in Table 7.

Table 7. Average Transportation time for the two different scenarios.

	Average Transportation Time (in minutes)	Average Number of Orders in the System
Current Model	6.7815	12.02478
Modified Model	4.87788	8.649296

Figures 8 and 9 show snapshot of the output of the simulation runs.

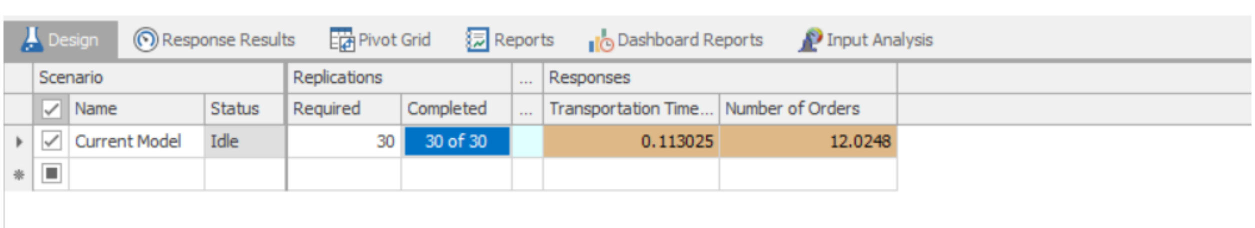

Figure 11. Snapshot of the Simulation Output for the Current Model.

Scenario			Replications		...	...	Responses	
✓	Name	Status	Required	Completed	...	...	Transportation Time...	Number of Orders
✓	Modified Model	Comple...	30	30 of 30		...	0.0812979	8.6493
■								

Figure 12. Snapshot of the Simulation Output for the Modified Model.

Chapter 4 Results and Discussion

A paired t-test is employed in order to determine the impact of the modification on the system performance. The average transportation time is used to measure the performance. The sample data is collected from 30 replications and the simulation is for for 5 days for each scenario: the current model, and the modified model.

4.1.Results

There is a significant difference between the two scenarios, as the transportation time drops by 1.9 minutes on average, which is a 28.0708% decrease. . The number of order in the system system drops by 3.375484 items on average, which is a 28.0711% decrease. The modification in the system affected the transportation time and the number of items in the system alsmot equally.

Table 8. Sample Data of the Transportation Time.

Replication	Transportation Time in minutes (Current)	Transportation Time in minutes (Modified)
1	6.763	4.891
2	6.826	4.888
3	6.784	4.877
4	6.753	4.877
5	6.809	4.873
6	6.754	4.876
7	6.737	4.866
8	6.771	4.879
9	6.792	4.880
10	6.758	4.873
11	6.761	4.870
12	6.826	4.891
13	6.809	4.881
14	6.807	4.876
15	6.806	4.881
16	6.788	4.883
17	6.798	4.873
18	6.815	4.887
19	6.780	4.876
20	6.726	4.874
21	6.754	4.884
22	6.816	4.887
23	6.757	4.872
24	6.801	4.884
25	6.740	4.877
26	6.791	4.869
27	6.763	4.868
28	6.848	4.878
29	6.734	4.873
30	6.779	4.873
Average	6.782	4.878
SD	0.031	0.007

Table 9. Sample Data of the Number of Orders in the System.

Replication	Average Number of Items (Current)	Average Number of Items (Modified)
1	11.992	8.673
2	12.103	8.668
3	12.029	8.649
4	11.974	8.647
5	12.073	8.642
6	11.976	8.647
7	11.946	8.628
8	12.007	8.651
9	12.043	8.652
10	11.983	8.640
11	11.988	8.635
12	12.104	8.673
13	12.074	8.655
14	12.069	8.646
15	12.067	8.655
16	12.037	8.658
17	12.053	8.640
18	12.085	8.665
19	12.023	8.645
20	11.927	8.642
21	11.976	8.660
22	12.087	8.665
23	11.981	8.638
24	12.059	8.660
25	11.952	8.648
26	12.041	8.634
27	11.993	8.633
28	12.142	8.650
29	11.940	8.641
30	12.020	8.640
Average	12.025	8.649
SD	0.054	0.012

The paired t-test is done on the sample data present in the secontion above. The paired t-test is conducted in Excel. The results of the paired t-test for the transportation time are shown in Table 10.

Table 10.Paired t-Test for the Average Transportation Time.

	Current Model	*Modified Model*
Mean	0.113025	0.081298
Variance	2.68E-07	1.25E-08
Observations	30	30
Pearson Correlation	0.494198	
Hypothesized Mean Difference	0	
df	29	
t Stat	367.6857	
P(T<=t) one-tail	4.68E-55	
t Critical one-tail	1.699127	
P(T<=t) two-tail	9.37E-55	
t Critical two-tail	2.04523	

Below is our hypothesis for the paired t-test (two-tailed):

- Ho: $\mu_{current} = \mu_{modified}$
- H1: $\mu_{current} \neq \mu_{modified}$

The paired t-test shows that the transportation time decreased from the current model ($\mu_{current}$ =0.113 hours; $\sigma_{current}$ = 2.68Ex10^{-7}) to the modified model ($\mu_{modified}$ =00.081hours; $\sigma_{modified}$ = 21.25x10^{-8})

With p-value ≈ 0 being smaller than the significance level of 0.05, we can reject the null hypothesis, hence there is a statistically significant difference between the two scenarios.

The results of the paired t-test for the average number of orders in the system are shown in Table 11

Table 11.Paired t-Test for the Average Number of Orders in the System.

	Current Model	*Modified Model*
Mean	12.02478	8.649296
Variance	0.003035	0.000142
Observations	30	30
Pearson Correlation	0.494198	
Hypothesized Mean Difference	0	
df	29	
t Stat	367.6858	
P(T<=t) one-tail	4.68E-55	
t Critical one-tail	1.699127	
P(T<=t) two-tail	9.37E-55	
t Critical two-tail	2.04523	

Below is our hypothesis for the paired t-test (two-tailed):

- Ho: $\mu_{current} = \mu_{modified}$
- H1: $\mu_{current} \neq \mu_{modified}$

The paired t-test shows that the number of orders in the system decreased from the current model ($\mu_{current}$ =12.024; $\sigma_{current}$ = 0.0030) to the modified model ($\mu_{modified}$ =8.649; $\sigma_{modified}$ = 1.4×10^{-4})

With p-value = 9.37E-55 being smaller than the significance level of 0.05, we can reject the null hypothesis, hence there is a statistically significant difference between the two scenarios.

4.3 Discussion

The objective of this research is to develop an algorithm that can improve the material handling cost of warehouses. This research develops a GT dynamic grouping approach that groups inventory based on the frequency of their attributes.. The more frequent the attribute is, the more likely it is for an item to be grouped within the “most important” cluster. Attributes can be chosen by warehouse managers, and in theory, there is no limit to the number of attributes that can be chosen. After the grouping of inventory, the inventory is stored in the isles based on their group; The “most important” items will be placed in the isles closest to the shipping area. Similarly, the “least important” items will be placed in the isles that are the furthest from the shipping area.

The algorithm provided a coded data that was imported within a simulation that represented a footwear warehouse. The simulation was run for a 5 day period, for 30 replications and measured the average transportation time from the isles to the shippin area, as well as the number of oders. The output of the simulation were compared with the output of the current scenario where inventory is stored randomly. The two sets of data were analyzed using the paired t-test.

Based on the paired t-test, there is a statistically significant difference between the current scenario and the proposed scenario. Hence, the proposed method in this research proves that when items are stored in aisles based on the chosen attributes, the average transportation time between the storing aisles and the shipping area is significantly reduced. Moreover, the number of orders in the warehouse is also reduced. The decrease of transportation time and the number of items in the system leads to a reduction of the overall material handling cost, as well as an increase in shipping the orders on time.

Chapter 5 Conclusion

This research represents a dynamic inventory grouping technique, where warehouse managers can efficiently store inventory within the warehouse based on attributes that they can choose.

In this research, we tested the GT algorithm using a simulation in order to see if the GT dynamic grouping approach would have a statistical difference in the outcome of the simulation which means that the performance of the system has a positive outcome on the operational performance of the warehouse. It was proven that grouping inventory based on attributes such as item type, order type, sales channel, and SKU, and storing them in the warehouse based on their ranked clusters will reduce the transportation time and the number of orders within the warehouse.

This research is different than other studies as it permits the warehouse managers to choose as many attributes as they would like. Moreover, the grouping is dynamic and it adjusts the clusters as new items arrive at the warehouse.

There are some limitations to this research: when the data set exceed 2500 data points, the computational system slows down and does not output any clusters. If the grouping is dynamic, then it is possible that some clusters are way larger than others, which can result in some aisles being overcrowded while others are not. However, that can be solved by redesigning some warehouses based on their inventory.

Future work and development to this research include developing an algorithm that can sustain large amounts of data. The algorithm is currently coded in MatLab, other languages could be able to process larger amounts of data. Moreover, in this research, the attributes were given equal weights. Different weights could be tested based on the importance of each attribute; that could improve the grouping of inventory, and the cluster performance.

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Academic Vitae

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Work Experience

West Monroe (New York, NY) June 2022 – August 2022 *M&A Consulting Intern*

- Enhanced the client's enterprise value by 37 % by recommending projects focused on the improvement of the company's corporate infrastructure, and cybersecurity
- Reduced the client's buying offer by $ 145,000 by performing an IT due diligence on the target company and identifying areas of improvements within the IT department
- Improved employees' participation to office events by 45% by creating an internal website that contains all the summer events hosted by the New York office

Amazon (Albany, NY) May 2021 - July 2021

Area Manager Intern

- Increased the overall inbound operations' effectiveness by 30% and reduced monetary losses by 35%; redesigned and implemented the transship operations process
- Increased the associate engagement by 23%, creating a feedback delivery system
- Increased the percentage of the total outbound results by 27%, created a non-inventory list of all the appropriate shipping equipment and dividing associate work accordingly

Education

Schreyer Honors College, Pennsylvania State University (Erie, PA)

May 2023 *Bachelor's Degree, Industrial Engineering, Supply Chain Management (Minor)*

- GPA: 3.94 (Dean's list since enrollment)
- Teaching Assistant for the engineering economy course; peer tutor for engineering and French courses.
- Recipient of the Eric and Josephine Walker award
- Recipient of the Freshman's award, awarded to 5% of the freshmen by earning a 4.00 during my first semester

College Notre Dame de Nazareth (Beirut, Lebanon) Aug 2004 - Jun 2019

French Baccalaureate, Math Focus

17/20 Highest Honors

Leadership and Extracurricular Experience

Multi-Cultural Council (Erie, PA) August 2021-May 2023

President

- Managed all the affinity clubs on campus, and improved the International Student Office, the Student Government Association, and faculty members
- Organized monthly events to spread diversity, equity, and inclusion on campus

Skills & Interests

- **Skills:** French and Arabic, EXCEL
- **Interests: Campus clubs** (Engineering Ambassador, B.E.S.T mentoring, Society of Women Engineers), **Discovering new cultures** (Traveling, culinary interests)