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Kiva Robot Simulation in Automated Warehouse

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ABSTRACT

This research applies a customer order clustering strategy to develop a first come first serve strategy. In this system, customer orders will be classified based on the most dominant product for each order, then it will be allocated to the order-picking station base on the rules set. The aim is to minimize service time and task balancing at each picking station order and reduce the movement of Kiva to go to the same picking station. To find out about the work of this rule, the model is implemented using Python.

Keywords: Clustering, Order Picking Station, Customer Order

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CHAPTER 1
INTRODUCTION

1.1 Background and Motivation

A warehouse is an important entity in the supply chain system. This facility is something that must be considered to support success in business. Business advisors consider that the activity is in the warehouse which controls overall logistics costs (Dukic & Opetuk, 2008). Some of the activities in the warehouse are replenishment, handling of good, and order pickers. From some of these activities, order picking is an activity that requires the highest cost compared to other activities, 55% of operational costs are allocated for order picking (Theys et al, 2010). With a large allocation's costs, it's natural that order picking is given special attention by business people because it can directly influence the effectiveness of the warehouse.

In maximizing order picking productivity, companies must be able to determine the right method to be applied in the warehouse. Most warehouses still use the conventional method with the pick to part method. Using this method, order picking productivity reaches only 74.9%. The parameter to be considered in measuring the level of productivity of order picking is to look at the value of pick rate, which is the average of products that can be picked up per hour (Manikas & Terry, 2010). According to Flazelle, a way to increase productivity in order picking activities is to minimize the distance to the picking location. Order picking activities carried out conventionally are always related to mileage (Sadowsky & Hompel, 2011).

In industrial 4.0's era, e-commerce company growth with a significant escalation. The number of growth of e-commerce is also in line with the increasing number of customer orders. These conditions make activities in the e-commerce warehouse increasingly busy, especially from the throughput of material handling in order picking activities. This e-commerce business trend must be balanced with the selection of the right method for order picking. The conventional method or pick to a part method that is usually used is considered to have three main inefficiencies, including non-scalable and a sequential order pick flow. If companies continue to use conventional methods, e-commerce companies will have difficulty when customer orders are in peak demand conditions and will have a direct impact on customer satisfaction levels. depend on this constrains that makes some e-commerce companies begin to replace conventional methods by using Robotic Mobile Fulfillment System (RMFS)

RMFS is a new paradigm that integrates picking, packing, and shipping activities that can increase warehouse productivity and throughput capacity. Amazon is a company that pioneered the use of RMFS through its Kiva System. For now, several RMFS models have been developed, such as Carry Pick (Swisslog), Butler (Gray Orange), Racrew (Hitachi), and Suning start implementing RMFS.

This research aims to know the best strategy for creating efficiencies in smart warehouse. Improved efficiency is finished by applying assignments for Kiva by conducting heuristic routing taking into account the shortest distance and time. It also implements several rules using a heuristic method to provide an alternative in a warehouse operation.

1.2 Problem Definition

Here is the problem definition based on research topics raised:

1. How does the Robotic Mobile Fulfillment System (RMFS) and Kiva System work?
2. What are the problems commonly encountered during operating kiva robot?
3. What is the strategy to improve the warehouse's productivity?

1.3 Objectives

The objectives of this research are:

1. To understand the Robotic Mobile Fulfillment System (RMFS) work.
2. To understand the effect of using Kiva Robot on warehouse effectiveness.
3. To understand how to solve the problem in operating Kiva Robot at e-commerce warehouse.

CHAPTER 2
LITERATURE REVIEW

2.1 Kiva Robot

The rapid development of technology has a good impact on the industrial sector, especially for e-commerce companies. Innovations in implementing robots as a material handling tool can increase company profits. The use of robots has also been applied directly in the warehouse. Amazon as a pioneer in the use of robots in e-commerce companies (D'Adrean 2014).

Amazon claims that the use of the Kiva robot as a material handling tool is considered efficient because it can perform tasks without interference and has better performance than human workers (Guizzo, 2008). According to Baraks (2017), the use of robots in the industrial world has the advantage of being able to minimize the danger posed by industrial activities.

Although it has many benefits, the use of Kiva in e-commerce warehouses is also considered to have many challenges. The many types of goods stored in warehouses are the most frequently encountered challenges. Some products that have different dimensions such as books, USB drives, and DVDs, can make it difficult for e-commerce companies to design strategies for taking products using Kiva. It is necessary to design a Kiva robot operating algorithm that can be used to carry out tasks effectively (Kuffner & Diankov, 2008; Fuchs et al, 2010).

2.2 Application of Robot Kiva Technology

As a large e-commerce company, Amazon started the development of the Kiva robot, starting with the acquisition of the Kiva producer. The acquisition was carried out in 2012, solely to improve the efficiency of goods collection and packaging time. Within two years, Amazon began implementing Kiva robots in several fulfillment warehouse centers (Kim, 2015). The company's strategy in the use of Kiva as a material handling tool is assessed to increase effectiveness and productivity in the fulfillment warehouse. Kiva robots have to carry out freight from pod to order picking stations. Where the booked items will be taken manually and the pod will be returned to the storage location (Guizzo, 2008).

Figure 2.1 Kiva Robot Carrying a Pod to Picker

Besides Amazon, another company that provides Kiva robots for e-commerce warehouses is Swisslog. The benefits offered are the same as those of Amazon, which helps in increasing productivity and minimizing operational costs (Liang et al, 2015). In figure 2.2, is a robot designed by Swisslog.

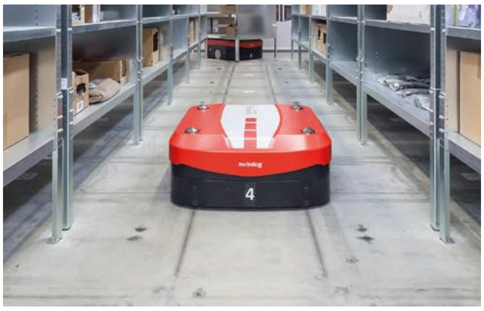

Figure 2.2 Good-to-picker concept

2.3 Warehouse

The warehouse is a facility that is used to maintain the availability of goods owned by the company. Several types of goods are stored in the warehouse, such as raw materials, semi-finished goods, finished goods, stems, and goods that are being prepared for the production process (Warman, 2012).

Warehouse is a storage area for various types of goods, both raw materials that will be used in the manufacturing process, and finished goods that are ready to be marketed. Warehousing activities not only focus on the storage of goods, but several other activities support warehouse operations. Warehousing activities begin with the activities of receiving goods, recording, inspection, storage, selection, sorting, labeling, and the last is the delivery of goods (Meyers and Stephens, 2009).

According to Mulcahy (1994), a warehouse is a storage place for various types of products in large or small quantities and with a storage period according to the product needed by the customer or work station.

2.3.1 Function of Warehouse

The warehouse has a function as a place to store raw materials, intermediate goods, and storage for finished products. The purpose of the storage area is to maximize the service of each existing order to achieve customer satisfaction**:**

According to Tompkins (2003), some warehouse functions are:

1. Receiving

   Activities that include receiving goods to be stored in a warehouse, checking the quality and quantity of goods, as well as allocating goods based on storage or will be sent directly.

2. Put away

   The process of moving goods from the receiving area to the pre-determined storage area.

3. Customer order picking

   The activity of moving goods from the storage to the order-picking station is then forwarded to the shipping process to fulfill the customer's order.

4. Packing

   The packing process is used to protect goods and collect goods in a container to facilitate the shipping process.

5. Cross docking

   Moving goods from the receiving area to the order-picking station without a storage process.

6. Shipping

The process of sending goods to consumers after through the packaging process.

2.4 Clustering

Clustering is a way of grouping the data to be more organized. According to Tan (2006), this method is a process for grouping data into several smaller classes that have a high level of similarity and data between clusters has a low level of similarity. Entities that are in a cluster environment have similar characteristics between each other and different from other clusters. Cluster formation is done using a clustering algorithm. So this method has the benefit of finding unknown groups in the data. Clustering is often used in several activities such as business intelligence, web search, the field of biology, and security. In the business world, clustering is used to classify customer orders into several groups that have similarities. In this method, many data sets are partitioned into many groups based on their similarity and can also be used as outlier detection.

2.4.1 Clustering Requirements

According to Han and Kamber (2012), several conditions that must be met in conducting clustering are:

1. Scalability

   The clustering method must be able to handle large amounts of data.
2. The ability to analyze various forms of data

   Clustering algorithms must be implemeCnted in various forms of data, such as: nominal and ordinal.
3. The ability to handle noise

   Data to be grouped is not always in good condition. There are times when the incoming data does not match the data we expect. A clustering algorithm is required to be able to handle data that is not appropriate.
4. Sensitive

   Adding input can cause changes to existing clusters

5. Able to do clustering for data with big dimensions

   Data groups that enter have different attributes. Thus a clustering algorithm is needed that can handle data with various dimensions.

6. Interpretation and useful

   The results of clustering must be interpretable and useful.

CHAPTER 3
METHODOLOGY

Simulation is the process of forming an imitation model of a real system. The purpose of the simulation is to understand the behavior of the system under investigation to determine the operating strategy of the system. Simulation methods can represent the system within a certain period of a model built with a mathematical model.

Kiva robot simulation is designed using Netlogo software. Netlogo is the modeling environment of a system that can be programmed to simulate. In particular, Netlogo is best used for modeling systems that are constantly evolving.

According to Wilensky (1999), NetLogo is an open-source environment for design and testing of models. Specifically, NetLogo can connect with Python (Head, 2017). That way the Python code allows it to be executed to the NetLogo model.

Following is the flow of interaction between NetLogo and Python:

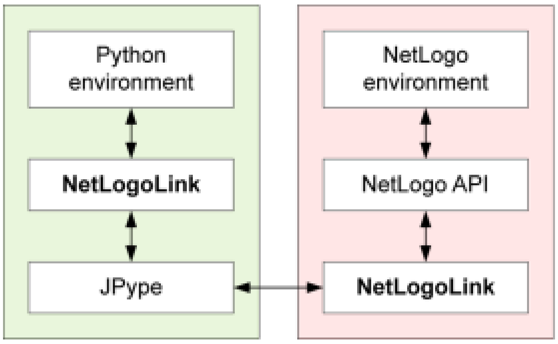

Figure 3.1 Interactions between Python and NetLogo

From the graph above, it can be seen when the interaction between Python and NetLogo takes place. In this research, we only focus on the activity of order picking and making the environment in Python.

3.1 Decision Hierarcy

In this section, the sequence of activities described in the robotic mobile fulfillment system is carried out in carrying out its operational activities. Figure 3.2

below is a decision hierarchy on order picking and replenishment activities.

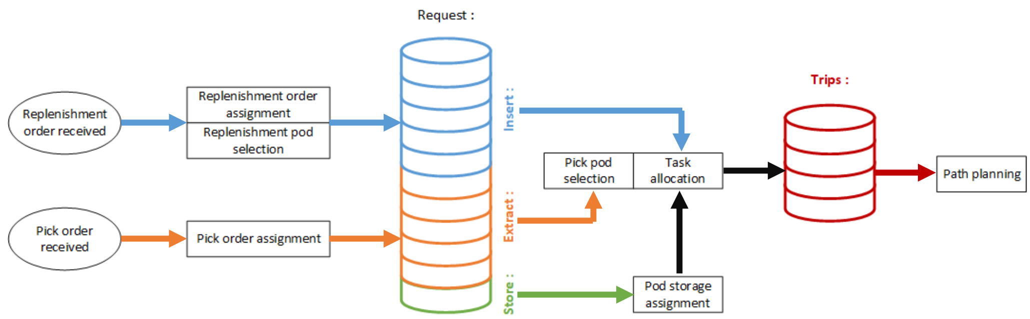

Figure 3.2 Order of Decision by Order Picking and Replenishment

From Figure 3.2, we can find out about the process that must be passed before Kiva can determine the route that must be chosen in carrying out order picking and replenishment activities. Because we only focus on order picking activities, several activities must be considered. Here are all the activities that exist in the order picking activity, namely: pick order assignment (POA), pod storage assignment (PSA), and pick pod selection (PPS).

3.2 Order Picking Process

In fulfilling customer orders, the order picking activity must carry out several steps to be able to take the pod from the storage zone and deliver it to the order-picking station. The following is a flow chart in the picking process in the robotic mobile fulfillment system.

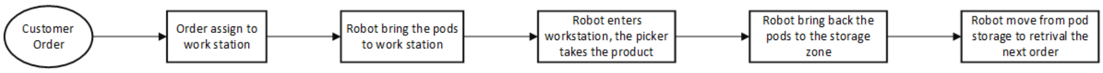

Figure 3.3 RMFS Picking Process

From Figure 3.3, we can know that after the customer order is entered as an input to this system. Then it will be processed to place an order assign to the work station. In this study, we try to develop a way that the order to assign work station process can run efficiently. The objective function is to minimize service time and balance the tasks of each order-picking station.

3.3 Customer Order Clustering Process

As we know, every warehouse must have an order that must be served. In general, the rules in service for customer orders use the law of first come first serve, but in this research, we try to improve it by adding a new rule, namely order clustering. The following is a general flow chart for conducting order clustering:

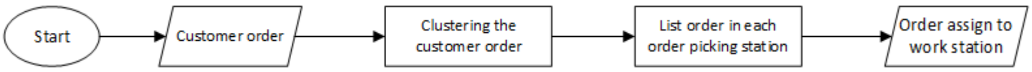

Figure 3.4 Order Assignment Process

CHAPTER 4
RESULT AND DISCUSSION

4.1 Problem's Focus

Before customer orders are grouped, the rules for each picking station are determined in advance. The objective function of the customer order clustering strategy is to minimize service time at each order-picking station and balance the tasks at each order-picking station in the warehouse. Based on the literature review on "A Simulation Framework for Robotic Mobile Fulfillment System", it shows that the activity in the area of the order-picking station has the highest density level compared to other activities in the warehouse.

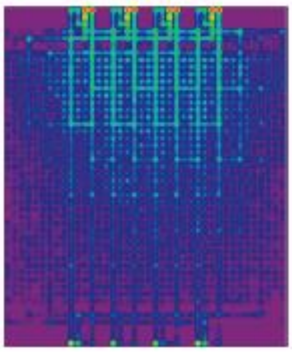

Figure 4.1 Heatmap Showing Robot Moving Behavior Over TIme

From Figure 4.1, the layout at the top is the order picking station activity and the bottom is replenishment. The red color indicates that the area has a high level of density and purple for a low-density level.

4.2 Model's Formulation

The first step in making the customer order clustering model formulation is to determine the rules that are applied to each order-picking station. In this study, we assume that the demand owned by the warehouse is 100 units, with the number of units for each order being five units. In this modeling, the warehouse has five stored products, namely pencils, rulers, books, erasers, and pupils. All products in the warehouse have the same probability to be ordered by customers. Each incoming order can contain all types of items owned by the warehouse, with the total product requirement for each order is five units.

In the customer order clustering strategy, we assumed that the warehouse has five order picking stations and each station has different characteristics. The difference between stations is the priority of the order served. The total unit for each order is five, with different types of items and can contain more than one unit with the same item. Each customer order must have a dominant product or the most ordered product. In this study, customer order clustering is applied by classifying the dominant product in each incoming entry.

The order-picking station classification is divided into five classes, namely station A for pencils, station B for rulers, station C for books, station D for erasers, and station E for pens. An order will be served at station A when the pencil product has the largest total unit in the order, will be served at station B when the number of rulers on an order has the most number, the order will be served at station C when the number of books on an order has the most number a lot, orders will be served at station D when the number of erasers has the highest number, and orders will be served at station E when the number of pens has the highest number of orders. For customer orders that do not have a dominant product or all items in an order have the same amount, it will be stored in the dummy station first. After all orders that have a dominant product enter their respective stations, then the total queues will be searched for the five stations. stations with the least number of queues will be assigned to serve customer orders, each waiting at the dummy station. In this case, the service time of each order is assumed to be the same, so the waiting time for each incoming order can be ignored.

To facilitate understanding of customer order clustering, the following is a flow chart in classifying the types of incoming orders:

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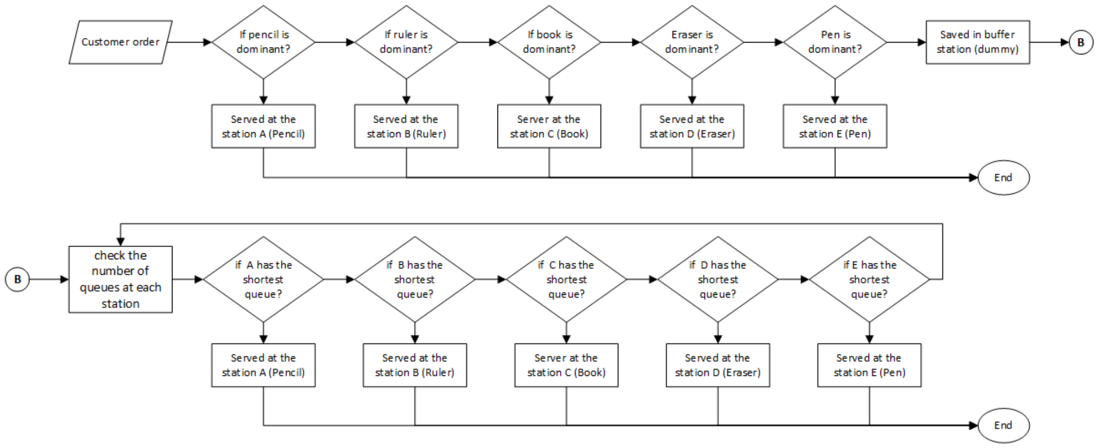

Figure 4.2 Flow Chart of Orders's Clustering

4.2.1 Illustration of Customer Order Clustering

To make it easier to understand how the work of the customer order clustering strategy is to illustrate on a smaller scale. In this illustration, it is assumed that the total customer orders that enter the system total of six orders. Each order that comes in includes three product units. Products available in warehouses are pencils, books, and pens. Each order that enters can load all items or some items available in the warehouse.

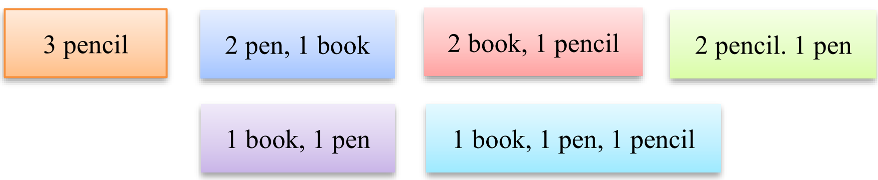

Figure 4.3 Customer Order

From Figure 4.3 it can be seen that six orders must be served and processed by the warehouse. In this system the number of order picking stations is three stations, this determination is based on the number of product items available in the warehouse. But that does not mean the number of order picking stations must always be the same as the number of items available in the warehouse. Determination of the number of stations can be influenced by the width of the existing warehouse and the throughput of the warehouse activity itself.

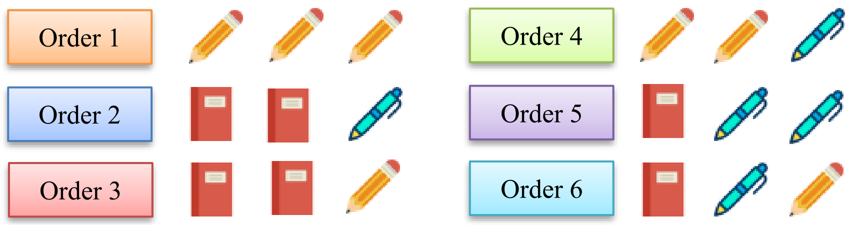

Figure 4.4 Customer Order Visualization

Figure 4.4 shows a visualization of every order that enters. From this visualization, it can be determined what products are dominant in each customer order. Based on Figure 4.4, the following is a recapitulation of the dominant product for each order:

Order	Dominant Product
1	Pencil
2	Book
3	Book
4	Pencil
5	Pen
6	No dominant product

Table 4.1 Recapitulation of Dominant Product

Table 4.1 is a recapitulation of the dominant products for each incoming order. From the six orders, there is one order that does not have a dominant product. Based on Figure 4.4, regarding the flow chart of the order's clustering, orders that do not have a dominant product will be temporarily stored at the dummy station and orders that have a dominant product will be allocated to the order-picking station according to the strategy.

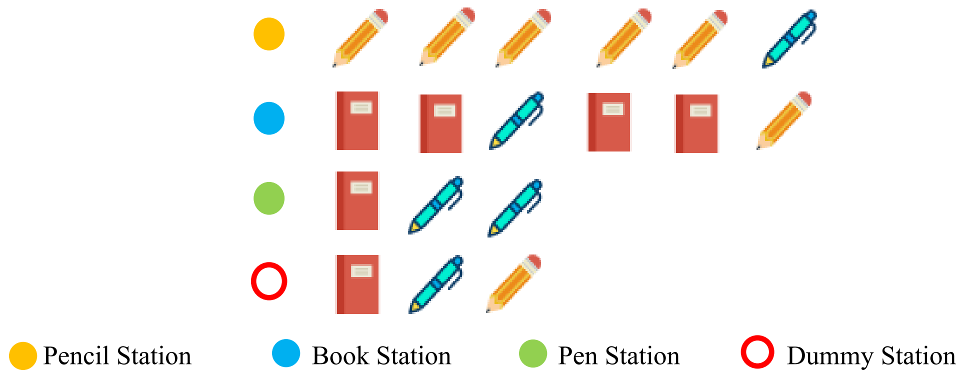

Figure 4.5 Order's Clustering 1

Figure 4.5 shows customer order clustering. But at this stage, there are still orders waiting at the dummy station. Order number six is still at the dummy station because the order does not have a dominant product.

The next step is to find out the shortest queue of all available picking station orders. The following is a recapitulation of the number of queues available for each order-picking station:

Station	Queue
Pencil	2
Book	2
Pen	1

Table 4.2 Number of Queue per Order Picking Station

From the recapitulation results in table 4.2, we can find out that the pen station has the shortest queue, one. Because the station has the fewest queues, order number six currently waiting at the dummy station will be allocated to the pen station to be served.

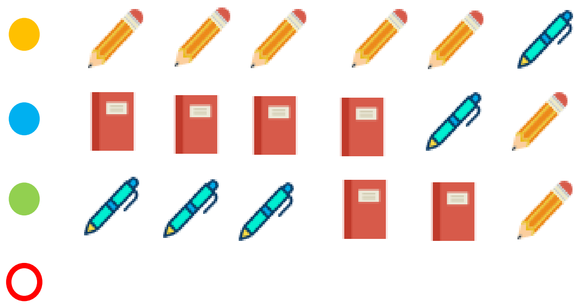

Figure 4.6 Order’s Clustering Final

Figure 4.6 shows the results of the final clustering order. In addition to balancing service time and equalizing tasks for each station, this strategy also reduces the intensity of officers at the order-picking station to pick up the same item and minimize the movement of the robot's kiva to travel to the same place to meet different orders. We can see in Figure 4.6, products with the same type of items are placed in the same order even from different order numbers. We take the example on the book station. The station serves two orders, orders number two and three have the following details: book, book, pen and book, book, pencil. If you do not use the customer order clustering strategy, kiva robot will visit the book station twice to fulfill order number one and order number two. But when using the customer order clustering strategy, products that have the same type of item will be grouped, and dominant products will be served first. So, in addition to balancing service time at each picking station order, the customer order clustering strategy can also minimize the activities of the robot kiva to visit the same picking station order, because officers at the station can pick up the same item to fulfill order number two and order number three in a relatively similar time span.

However, there are several challenges in implementing customer order clustering strategies, one of which is how to deal with fluctuating demands. There will be a period in which the demands that enter the system are the same type of item, one example is when the Christmas moment, most orders that enter are the same type. When still doing cluster distribution by considering the most dominant product, it will not run well. Because it will cause other stations to have a long idle time because no order type matches the specified classification. To resolve this problem, a different customer order clustering strategy can be used. Although the demand is something that cannot be predicted, we can do forecasting to predict the number and types of products that will be ordered by prospective customers. From the results of the forecasting, we can determine the appropriate clustering strategy to be applied at the order-picking station in the warehouse. The customer order clustering classification can be determined from one or more dominant product items. So that in one order-picking station can serve more than one dominant product type. That way, the chances of an idle picking station order will be reduced.

4.3 Python Result

The system model described earlier is implemented using Python. From several running, it produces the following results:

```
Order Picking Station
====================
Station Pencil : [0, 3, 10, 11, 14, 20, 23, 25, 26, 28, 34, 42, 45, 49, 50, 55, 58, 60, 69, 82, 86, 91, 93, 98]

Station Ruler : [1, 5, 7, 12, 15, 17, 18, 32, 33, 35, 41, 43, 46, 53, 54, 57, 66, 78, 99]

Station Book : [6, 21, 38, 40, 52, 59, 61, 65, 70, 71, 72, 81, 89, 94]

Station Eraser : [4, 8, 22, 24, 27, 36, 39, 47, 48, 64, 73, 75, 84, 85, 87, 88, 92, 96]

Station Pen : [2, 9, 16, 19, 30, 31, 37, 44, 51, 62, 63, 67, 68, 74, 76, 79, 80, 83, 95, 97]

Station Dummy : [13, 29, 56, 77, 90]
```

Figure 4.7 Task of Order Picking Station 1

```
Buffer Order Allocation
====================
Allocated for Station 2 = order number [13]
Update for Station 2 = [6, 21, 38, 40, 52, 59, 61, 65, 70, 71, 72, 81, 89, 94, 13]

Allocated for Station 2 = order number [29]
Update for Station 2 = [6, 21, 38, 40, 52, 59, 61, 65, 70, 71, 72, 81, 89, 94, 13, 29]

Allocated for Station 2 = order number [56]
Update for Station 2 = [6, 21, 38, 40, 52, 59, 61, 65, 70, 71, 72, 81, 89, 94, 13, 29, 56]

Allocated for Station 2 = order number [77]
Update for Station 2 = [6, 21, 38, 40, 52, 59, 61, 65, 70, 71, 72, 81, 89, 94, 13, 29, 56, 77]

Allocated for Station 2 = order number [90]
Update for Station 2 = [6, 21, 38, 40, 52, 59, 61, 65, 70, 71, 72, 81, 89, 94, 13, 29, 56, 77, 90]
```

Figure 4.8 Buffer Order Allocation 1

```
Order Picking Station
=====================
Station Pencil : [2, 7, 21, 33, 48, 54, 59, 64, 68, 75, 78, 82, 93, 95, 98]

Station Ruler : [10, 11, 16, 17, 19, 20, 24, 25, 26, 27, 31, 35, 44, 47, 50, 52, 57, 62, 73, 76, 84, 86, 87]

Station Book : [4, 5, 12, 13, 18, 22, 23, 28, 32, 38, 39, 41, 43, 46, 53, 55, 56, 60, 65, 67, 69, 74, 77]

Station Eraser : [3, 6, 8, 14, 15, 30, 36, 37, 42, 45, 66, 71, 72, 81, 88, 97, 99]

Station Pen : [0, 1, 9, 29, 34, 40, 49, 51, 58, 61, 63, 70, 79, 83, 89, 90, 91, 92, 94, 96]

Station Dummy : [80, 85]
```

Figure 4.9 Task of Order Picking Station 2

```
Buffer Order Allocation
====================
Allocated for Station 0 = order number [80]
Update for Station 0 = [2, 7, 21, 33, 48, 54, 59, 64, 68, 75, 78, 82, 93, 95, 98, 80]

Allocated for Station 0 = order number [85]
Update for Station 0 = [2, 7, 21, 33, 48, 54, 59, 64, 68, 75, 78, 82, 93, 95, 98, 80, 85]
```

Figure 4.10 Buffer Order Allocation 2

The figure above shows that the customer order clustering strategy can balance the tasks handled by each order-picking station. Also, we can know about the results of the allocation of the order that was first stored at the dummy station to wait for information about which stations are possible to serve the order.

CHAPTER 5
CONCLUSION

5.1 Conclusion

The implementation of the customer order clustering strategy is felt to be able to handle the problems in the warehouse, especially those owned by Kiva robots and order picking stations. Activities in the order picking station are the most populous activities in the warehouse, so other alternatives are needed in carrying out operations in the sector. The application of customer order clustering will help stabilize the service time available at the order-picking station. It also can balance the assignments for each station. This strategy can also reduce the possibility of Kiva robots visiting the same picking station order because items with the same type of item will be grouped, so that the warehouse labor only takes the goods at a time for certain items that are used to fulfill the first and second orders at the relevant order-picking station.

5.2 Suggestion

Some suggestions regarding Kiva robot simulation research:

1. In this study, researchers have not tried the proposed strategy into the simulation, so that for future research the proposed strategy can be implemented.
2. Examples of models developed are still limited, so it needs further development so that the issues raised can be following real conditions.

REFERENCES

[1] Merschformann, Marius; Xie, Lin, and Li, Hanyi, *RAW Sim O A Simulation Framework for Robotic Mobile Fulfillment Systems.* Econstor, 2018.

[2] Roy, Debjit; Nigam, Shobhit; de Koster, Rene; Adan, Ivo, and Resing, Jacques, *Robot-storage Zone Assignment Strategies in Mobile Fulfillment Systems.* Elsevier, 2019.

[3] Smyk, Vadim, *Minimizing Order Picking Distance Through the Storage Allocation Policy*. International Business Management, 2018.

[4] Singh, Balkeshwar; Sellapan, Kumaradhas, *Evolution of Industrial Robots ande their Applications,* IJEATAE, 2013.

[5] Gunaratne, Chanthika and Garibay, Ivan, *Agent-Based Modeling in Python with Parallezied NetLogo Workspace,* 2018.