Product Mixture of SKU to Pod Assignment Policy in Robotic Mobile Fulfillment System Warehouse

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Keywords: RMFS, SKU to Pod Assignment Policy, Pile-On, ABC Classification, Association Rule.

Abstract: Robotic Mobile Fulfillment System Warehouse (RMFS) was purposefully created as a part-to-picker warehouse in response to the enormously good trend of e-commerce sales. There are numerous strategies to boost the warehouse's effectiveness. The SKU to the pod, or product assignment policy, will be the main topic of this study. Three situations are presented in this study: SKU to pod using random, mixed classes, and mixed classes with affinity. The second and third scenarios are designed utilizing the Weighted Support Count. The ideal policy to improve warehouse efficiency is then determined by comparing these scenarios using a simulation approach. By examining the quantity of pods transported under each policy, it may be determined. The SKU to pod approach generates a larger pile-on the fewer pods there are. Therefore, the final scenario produces the best pile-on, with an average of 6.59 pods being carried per order. In contrast, the outcomes of the first and second situations are 7.06 and 6.90, respectively. Even if just 8% of SKUs make up the association's rule, the figures indicate that the pile-on of the last scenario is 7% and 5% more than the other situations. The one-way ANOVA method is used to confirm this result.

1 INTRODUCTION

The global impact of the coronavirus has altered the nature of business. 52% of consumers, it has been found, steer clear of both in-person shopping and busy places. In addition, 36% postpone going shopping in person until they receive a coronavirus vaccination (Bhatti, et al., 2020). As a result, one of the most common internet activities in the world is shopping. E-commerce revenue is expected to increase to US$6.4 trillion by 2024 from its current level of US$4.28 trillion in 2020. (Chevalier, 2021).

The efficiency of warehouse operations must keep up with the expansion of e-commerce sales. The warehouse for the Robotic Mobile Fulfillment System (RMFS) was created especially for online shopping. This warehouse system can use robots or RMFS, commonly referred to as AGV (Automated Guided Vehicles), to transport the shelves, known as pods, to the picking stations in place of human operators (Merschformann, Lamballais, de Koster, & Suhl, 2019). Because the parts or goods are transported to the picking stations before the operator gathers the goods, this kind of warehouse can also be referred to as a part-to-picker warehouse (Murray, 2019). Order picking is typically the task that takes the longest in the entire warehouse compared to others (Frazelle E., 2016). As a result, improving order picking efficiency also improves warehouse efficiency.

There are numerous strategies to boost the warehouse's effectiveness. There are three tiers of decision-making issues. These are the levels of strategy, tactics, and operations (Merschformann, Lamballais, de Koster, & Suhl, 2019). Product assignment is a tactical choice that influences the effectiveness of order-picking (Li, Hua, Huang, Sheu, & Cheng, 2020). To achieve order-picking efficiency, it is crucial to create a good policy for product assignment (Silva, Roodbergen, Coelho, & Darvish, 2022). Product assignment by itself has three difficulty areas. These are the distribution of a product over several pods, pods to zones, and products (SKU) to pods (Mirzaei, Zaerpour, & de Koster, How to benefit from order data: correlated dispersed storage assignment in robotic warehouses, 2021). The first decision problem—products to pod or product assignment policy—will be the main focus of this study.

Hanifha, N., Chou, S. and Vanany, I.
Product Mixture of SKU to Pod Assignment Policy in Robotic Mobile Fulfillment System Warehouse.
DOI: 10.5220/0012103900003680
In *Proceedings of the 4th International Conference on Advanced Engineering and Technology (ICATECH 2023)*, pages 33-41
ISBN: 978-989-758-663-7; ISSN: 2975-948X

Random, dedicated, and class-based storage assignment rules are the three most used product assignment policies (Gu, Goetschalckx, & McGinnis, 2007).

The SKU randomly assigns the pod according to the clear and simple random assignment policy (Mirzaei, Zaerpour, & de Koster, how to benefit from order data: correlated dispersed storage assignment in robotic warehouses, 2021). A dedicated assignment policy, on the other hand, limits the use of each storage place to a single product. This policy will produce the shortest picking distance possible (Muppani & Adil, 2008). Between devoted and random assignment policies, Chan and Chan (2011) conducted a simulation. The outcome demonstrated that these regulations, in turn, aid in maximizing both system throughput and storage space usage. A smaller warehouse may be needed when using a random policy as opposed to one that is devoted, although proper inventory tracking may take more work (Gu, Goetschalckx, & McGinnis, 2007). After the products are classified into classes based on the frequency of orders, the class-based storage assignment policy assigns the products (Silva, Roodbergen, Coelho, & Darvish, 2022). This approach can produce the highest benefits with two or three courses (Yuan, Cezik, & Graves, 2018). Significant cost reductions and space sharing are the next two benefits (Muppani & Adil, 2008). (Mirzaei, Zaerpour, & Koster, The impact of integrated cluster-based storage allocation on parts-to-picker warehouse performance, 2021).

The cluster-based storage assignment policy is an additional product assignment policy in addition to those three well-liked ones. In order to reduce the cost of inventory and material handling, this policy groups correlated goods into clusters before assigning the products to the pods depending on the cluster (Kim K. H., 1993).

By grouping frequently ordered products on the same pod, RMFS warehouses can benefit (Mirzaei, Zaerpour, & Koster, The impact of integrated cluster-based storage allocation on parts-to-picker warehouse performance, 2021). This policy's implementation greatly cuts down on retrieval time and saves order-picking labor (Frazelle & Sharp, 1989). (Mirzaei, Zaerpour, & Koster, The impact of integrated cluster-based storage allocation on parts-to-picker warehouse performance, 2021).

Nearly all cluster-based policy studies demonstrate that, given their goals, cluster-based policies are superior to other types of policies for storage assignment. None of them, however, are looking for the ideal product combination that might be used in other instances with a similar problem. The ideal combination of product classes on pods is called a product mixture, which reduces the amount of delivered pods. Higher pile-on is achieved when there are fewer pods to transfer, which may result in fewer AGVs being required (Merschformann, Lamballais, de Koster, & Suhl, 2019). Pile-on is when the pods provide the majority of the units required to complete the orders (Merschformann, Lamballais, de Koster, & Suhl, 2019).

Order selection effectiveness is also increased with the right product classification (Chan & Chan, 2011). According to how frequently orders are placed, ABC classification is typically the method used to classify products in warehouses. However, the second assignment decision problem—pod to zones—is typically resolved by this classification. Additionally, they all adhere to the "one class, one pod" principle and make no effort to determine the ideal Product Class Mix (Products to Pod) for each pod. As a result, the goal of this research is to optimize pile-on by identifying the ideal product combination.

2 OBJECTIVE

In light of the background information provided, the following objectives of this study might be stated:

1. Choosing the optimal product mixture percentage for the warehouse.
2. Using a simulation method, the optimum policy for the SKU to pod decision problem is identified.

3 LITERATURE REVIEW

This chapter will show the literature review of this research related to robotic mobile fulfilment system (RMFS), SKU to pod assignment, ABC classification, and association rule.

3.1 Robotic Mobile Fulfillment System (RMFS)

Because it accommodates several SKUs and necessitates numerous small-quantity purchases, a robotic mobile fulfillment system (RMFS) warehouse is an answer to the problem of increasing e-commerce sales (Azadeh, Koster, & Roy, 2019). Robots that carry pods on traditional warehouse shelves with things in the pods are the RMFS company's proposed solution (Enright & Wurman, 2011). The RMFS warehouse has a number of advantages. Depending on the quantity of AGVs and SKUs, RMFS's throughput was discovered to be higher than AS/RS in 2016. (Beuters, Cock, Hollevoet, Dobbelaere, & Landeghem, 2016). When the inventory is divided over several pods, the warehouse has the right number of stations, and the pods are refilled before they run out, the throughput increases (Tessensohn, Roy, & De Koster, 2020).

3.2 SKU to Pod Assignment

Three common SKU-to-pod assignment policies are dedicated, random, and class-based storage assignments. In addition to these three well-liked policies, cluster-based storage assignment is another policy for product assignment. The efficiency of warehouse operations can be increased in a number of ways.

In order to reduce the number of groups accessed, Kress et al. (2016) investigated implementing a cluster-based storage assignment mechanism in a vertical warehouse (Kress, Boysen, & Pesch, 2016). Chuang et al. in 2012, Bindi et al. in 2014, Wang et al. in 2019, Li et al. in 2020, and Foroughi et al. in 2020 have all demonstrated that utilizing a cluster-based storage assignment policy results in a reduction in journey distance. Additionally, those researchers implemented the policy in several kinds of warehouses. Only two of them are used in traditional warehouses, with the remaining ones being one-block, one-aisle, RMFS, and movable racks warehouses (Chuang, Lee, & Lai, 2012) (Bindi, Manzini, Pareschi, & Regattieri, 2014) (Wang, Zhang, & Fan, 2019) (Li, Hua, Huang, Sheu, & Cheng, 2020) (Foroughi, Boysen, Emde, & Schneider, 2020).

By analyzing the robot's energy usage, Li et al. in 2020 sought to reduce energy consumption in addition to lowering trip distance in the RMFS warehouse. Along with Li et al., Mirzaei also studied the cluster-based implementation in RMFS and ASRS warehouses in 2021. According to the research, this policy is the fastest at picking orders than any other policy.

3.3 ABC Classification

Muppani & Adil and Yuan et al. conducted research in conventional and RMFS warehouses in 2007 and 2021, respectively, to reduce trip distance for class rack allocation in a conventional warehouse and ABC pod assignment in an RMFS warehouse (Yuan, Cezik, & Graves, 2018). Along with Muppani and Adil, rack allocation was also studied by Chan & Chan in 2011 and Ang & Lim in 2019. Their goals differ in that unit-load warehouses aim to reduce travel expenses whereas conventional warehouses want to reduce journey time (Chan & Chan, 2011). (Ang & Lim, 2019). The most recent study, Silva et al., 2022, found that ABC zone sizing increased the efficiency of order picking in the traditional warehouse (Silva, Roodbergen, Coelho, & Darvish, 2022).

3.4 Association Rule

In Yang 2022, Yang contrasts two approaches to an association rule. Jaccard Index and Weighted Support Count are these. The Jaccard Index evaluates similarities and differences between simple sets and was created by the Swiss mathematician Paul Jaccard.

This technique is also used to measure the relationship between the objects in storage assignment study. WSC, on the other hand, integrates the ideas of support and lift created by Ming et al. and reflects the relationship between any pair of products (Chiang, Lin, & Chen, 2014). The study's findings demonstrate that the Weighted Support Count outperforms the Jaccard Index (Yang, 2022).

4 METHODOLOGY

The next chapter will cover the research procedures. The steps act as a guide for the study so that it can move forward with the goals in mind.

4.1 Data Gathering

On the basis of an investigation of 55000 past orders with the same number of total SKUs, 10000 data orders with 5000 SKU numbers are generated. The order data history is then examined using @RISK software, a Microsoft Excel add-in tool. The distribution of the generated data is guaranteed to match that of the historical data.

4.2 Inventory Analysis

The next phase of this research is inventory analysis, which comes after creating new data orders. The SKU classification procedure and the computation of the number of slots are both included in this second stage.

4.2.1 SKU Classification

In this step, the SKU is divided into three classes based on the order frequency. 10%, 30%, and 60% of all SKUs are categorized according to classes A, B, and C using the ABC rule. However, A, B, and C each represent 60%, 25%, and 15% of the total order frequency, respectively.

4.2.2 Number of Slots Calculation

The SKU must be divided into three classes before determining how many slots are required for each SKU. The number of slots required will be the same for SKUs categorized into the same group. The number of slots is determined using the minimal level inventory formula in Equation (1) (Radasanu, 2016). The goal of determining the minimal stock is to keep track of inventories and lower operating expenses to prevent overstock.

$$\text{Minimum Level Inventory} = \bar{x}_D + (\sigma_D \sqrt{L}. Z_{SL}) \tag{1}$$

Notation:
$\bar{x}_D$ = Demand Average
σ_D = Demand Standard Deviation
Z_{SL} = Z score of Service Level
L = Lead Time

4.3 SKU to Pod Assignment Scenarios

Three different possibilities make up the SKU to pod assignment. These possibilities include random, mixed-class, and mixed-class affinity. The specifics of each case are described below.

4.3.1 Random Assignment Scenario

Based on the data order and inventory analysis performed in the preceding stage, the SKUs in this scenario are assigned at random. Despite the unpredictability, there is a rule in this scenario: each SKU is distributed among numerous pods.

4.3.2 Mixed-Class Assignment Scenario

To complete a mixed-class assignment scenario, three actions must be taken. First, use Equation (2) and (3) of Independent Event Probability to determine the product mixture percentage. The ordering between classes are independent of one another, hence this formula helps calculate the number of pods for each class combination in each pod. Therefore, the chance of each product mixture is calculated using independent event probability. Next, use Equation (4) to calculate the SKU in pod ratio to ascertain the number of slots required for each class assigned to each pod. Finally, distribute the SKUs according to the class.

$$P(X\ and\ Y\ and\ Z) = P(X \cap Y \cap Z) \tag{2}$$

$$P(X\ and\ Y\ not\ Z) = P(X \cap Y \cap Z') \tag{3}$$

$$\%X_{XY} = \frac{\%Slot_X}{\%Slot_X + \%Slot_Y} \tag{4}$$

4.3.3 Mixed-Class-Affinity Assignment Scenario

The previous scenario has led to the final scenario. Calculating the product mixing percentage and the SKU in pod ratio are the first two phases in this scenario, which are the same as the first two steps of the mixed-class assignment. The method used to allocate the SKU to the pod differs. The SKUs are assigned based on the affinity between the items based on the order data history, as opposed to the previous case when the SKU is just assigned based on the class.

In this instance, the third step is using Weighted Support Count to assess the link between each SKU and the support, confidence, and lift that can be determined using Equations (5), (6), and (7), respectively. To assess the degree of link between things, support is utilized. Confidence is used to show how likely it is that a set of SKUs will be ordered together. Lift, on the other hand, describes the kinds of connections between the SKUs.

$$P(A \cup B) = \frac{a}{N} \tag{5}$$

$$P(B|A) = \frac{P(A \cup B)}{P(A)} \tag{6}$$

$$Lift_{AB} = \frac{P(B|A)}{P(B)} = \frac{P(A \cup B)}{P(A)P(B)} \tag{7}$$

Notations and details:
P = Probability
a = frequency of SKU A and B are ordered together
Lift > 1, complementary
Lift = 1, independent
Lift < 1, substitutive

4.4 Simulation

The simulation will be run using the NetLogo program to identify which scenario has the greatest pile in comparison to the other two situations by counting the number of pods visited in each scenario.

4.4.1 Simulation Layout

The NetLogo warehouse arrangement is depicted in Figure 1 below. A picking station, a storage area, and a replenishment station make up the layout of the RMFS. The picking station is where the picker waits to take items out of AGV-transported pods, the storage area is where the pods are kept, and the replenishment station is where the empty pods are refilled.

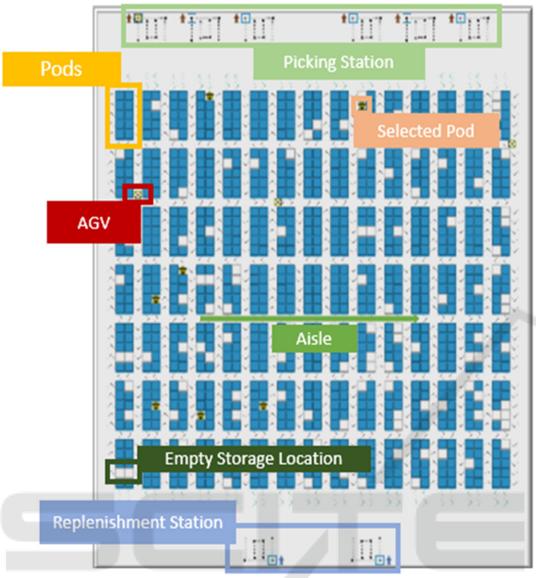

Figure 1: Simulation Layout.

There are various components on it in the storage section. Which are:
1. The items are kept in the pod.
2. The picked pod is the pod that matches the products to the given orders.
3. The AGV robot is responsible for transporting pods to the station for picking and refilling.
4. The aisle provides room for AGV movement.
5. The pod can be positioned in an open storage spot.

4.4.2 Simulation Parameter

This simulation makes use of a number of assumptions, which are represented as parameters in Table 1 below.

Table 1: Simulation Parameter.

Parameter	Value
Run Length	24 Hours
Replication	10 Replications
Inventory Area	1050 Locations
Inventory Capacity	935 Pods
Empty Storage	115 Locations
Pod Batch	2 x 5 Blocks
Picking Station	6 Stations
Replenishment Station	2 Replenishment Stations
Charging Station	7 Charging Stations
Pod Capacity	100 Slots
Number of AGV	50 AGVs
AGV Speed Without Load	2 m/s
AGV Speed With Load	1,5 m/s
Acceleration	1 m/s
Time for 90˚ turning	2,5 second
Time for 180˚ turning	3 second
Time for pod lifting	4 second
AGV to pod policy	Shortest Pod

4.5 Statistical Test

To verify that the simulation is accurate, a statistical test must be run. Replication adequacy testing is done initially to make sure there are enough replications. The second test uses Analysis of Variance to validate substantial changes across scenarios (ANOVA).

4.5.1 Replication Adequacy Test

Equations (8) and (9) are the formulas for the replication adequacy test (Harrel, Ghosh, & Bowden, 2012).

$$e = \frac{\left(t_{n-1,\alpha/2}\right) s}{\sqrt{n}} \tag{8}$$

$$n' = \left(\frac{(Z_{\alpha/2}) s}{e}\right)^2 \tag{9}$$

e = hw (halfwidth)
t = t value from student's t distribution table
α = confidence level
s = standard deviation
n = number of replication
n' = estimate the number of replication
$n > n' \rightarrow$ number of replication is sufficient

4.5.2 Hypothesis Test

The next step is to do a hypothesis test using One-Way ANOVA after verifying that the number of replications is adequate. This kind of ANOVA takes into account simulations with a solitary factor. The SKU to pod assignment policy is one element in this study. By comparing the means of three alternative situations and demonstrating that the results are significantly different, an ANOVA can validate the simulation's output.

$H_0: \mu_1 = \mu_2 = \mu_3$
H_A: At least two means are different

5 RESULT AND DISCUSSION

This chapter will show the result and discussion of this research starting from the data gathered to the statistical test.

5.1 Data Gathering

From the 55000 actual data order, this phase creates a 10000 data order. To make the simulation as realistic as feasible, the new data order must correspond to the actual data order. Both generated and real data are classified as having a lognormal distribution after being checked using @RISK.

5.2 Inventory Analysis

The 5000 SKUs can be divided into ABC classes based on the overall frequency of orders. Class A has 500 SKUs, or 10% of all SKUs, which account for 60% of all order frequency. Class B accounts for 1500 SKUs, or 30% of all SKUs, and 30% of all order frequencies. Additionally, SKUs that make up a small portion of the total order frequency are put into class C.

Table 2: ABC Classification.

Class	Number of SKU
A (10%)	500
B (30%)	1500
C (60%)	3000
	5000

The number of slots each SKU is based on the quantity of orders, not the frequency, unlike how ABC classification is determined. As a result of the variable order quantity, each class has a varying number of slots. Equation (1) is then applied to specify the total number of slots. Given that the confidence level is 95%, the Z score can be found in Appendix 1, and the slot capacity is ten units, the calculation below demonstrates how to estimate how many slots there should be.

The computation reveals that even though class A has the fewest SKUs (500 SKUs), it has the most slots (106 slots/SKU). The majority of the overall order's SKUs are in class A. In addition, classes B and C, each having 1500 and 3000 SKUs, respectively, call for 17 and 5 spaces per SKU.

Table 3: Slots Required.

Class	Number of SKU	Slots/SKU	Total Number of Slots
A (10%)	500	106	53000
B (30%)	1500	17	25500
C (60%)	3000	5	15000
	5000		93500

According to Table 3, each class needs 53000 seats for A, 25500 positions for B, and 15000 slots for C. This means that there are 935000 spaces in all in the warehouse. With each pod having a capacity of 100 slots, it can be calculated that 935 pods are required in total.

5.3 SKU to Pod Assignment Scenario

A data set must be satisfied in all three cases. The objects kept on the pods will be one column that varies between scenarios.

5.3.1 Random Assignment Scenario

5000 SKUs, of which the first 500 are grouped into class A, the following 1500 into class B, and the final 3000 into class C and distributed at random into 935 pods.

5.3.2 Mixed-Class Assignment Scenario

With a total of 10,000 orders, 9304 orders have SKUs from class A, whereas 7548 orders have SKUs from class B, and 4627 orders have SKUs from class C. The likelihood of orders including each class can be calculated by dividing the total orders of each class by the total number of orders. Equation (2) can be used to define the mixed-class order probability following the determination of the probability orders for each class. The product mixture percentage in the warehouse can then be calculated using this likelihood. The likelihood of mixed-class orders and the number of pods needed for each mixture are shown in Table 4.

Table 4: Product Mixture.

Product Mixture	Percentage	Pods
P(ABC) = ABC	32,5%	306
P(ABC') = AB	37,7%	352
P(ACB') = AC	10,6%	100
P(BCA') = BC	2,4%	24
P(AB'C') = A	12,3%	116
P(BA'C') = B	2,8%	27
P(CA'B') = C	0,8%	10
Total	100,0%	935

By a margin of 37.7%, the combination of class A and class B orders had the highest chance. From that percentage, 352 pods are required for the AB pod. By 32.5% or more pods, the combination of all three classes has the second-highest probability. Then, just A pod and AC pod were required, with 116 and 100 pods, respectively. Finally, with less than 3% in each, just B pod, BC mixed pod, and only C pod are the three lowest.

The number of slots for each class on each pod must be computed using Equation (4) once the number of pods for each mixture has been determined. It is clear that class A, which includes the ABC, AB, and AC pods, will always account for more than 50% of the product combination in each pod. A third of the ABC and AB pods and two thirds of the BC pod are dominated by Class B. Class C, on the other hand, makes up the least amount of each pod's product mixture, amounting to 16%, 22%, and 37% for the ABC, AC, and BC pods, respectively. With a capacity of 100 slots per pod, it will be simple to determine how many slots belong to each class on each product mixture pod. Table 5 illustrates this. The SKUs are then allocated at random using the number of slot rules.

Table 5: Product Combination of Pod.

Class	ABC	AB	AC	BC
A	57	68	78	0
B	27	32	0	63
C	16	0	22	37
	100	100	100	100

5.3.3 Mixed-Class Affinity Assignment Scenario

The first two steps of this scenario—determining the product combination and the slots percentage—are the same as they are in the second scenario. The method used to allocate the SKU to the pod differs. In this case, association analysis with the GoogleColab tool must be used to discover the rules. As a result, only 400 SKUs, or 8% of all SKUs, make up the rules. The majority of the SKUs in Classes B and C, however, do not have any rules because they are not ordered together frequently enough. The 400 SKUs must therefore be assigned close together, while the remaining SKUs are assigned at random.

5.4 Simulation

The number of pods transported for the entire order may be determined from the simulation output. The average number of pods transported for 10,000 orders can therefore be determined as the performance indicator for the simulation outcome. Higher pile-on are achieved when the average is lower.

5.4.1 Simulation Result Analysis

Each scenario, from replications one to ten, is contrasted in Table 6 below. It is clear that the final scenario, which had the lowest average number of pods moved, produced the best results. The baseline scenario is increased by 6.4% in the mixed affinity scenario but only by 3.49% in the mixed scenario.

Table 6: Simulation Result.

Sim	Number of Pods/Order		
	Scen 1	**Scen 2**	**Scen 3**
Rep 1	7,14	6,99	6,54
Rep 2	7,06	6,76	6,46
Rep 3	7,13	6,89	6,45
Rep 4	6,92	6,90	6,72
Rep 5	7,03	7,07	6,89
Rep 6	7,20	6,94	6,54
Rep 7	6,93	6,76	6,51
Rep 8	7,03	6,78	6,74
Rep 9	7,21	6,6	6,76
Re 10	7,18	6,67	6,69
Average	**7,08**	**6,84**	**6,63**

The outcome indicates that SKU to pod assignment policy's ABC classification also influences the quantity of pods transported. Because SKUs are too widely scattered in numerous pods without any restrictions, Scenario 1, or the baseline scenario, with random policy, has the highest average number of pods transported. As a result, the necessary pods are increased relative to other SKU to pod assignment policies. The simulation results show that using ABC categorization to the second and third scenario improves warehouse performance.

It would seem hard for the third scenario to produce the best simulation outcome, especially when compared to the second scenario, with only 8% or equal to 400 SKUs forming the association rules. Because the third situation just uses association rules, the second and third scenarios are comparable. But after examining the order data, it was discovered that those 400 SKUs made up the majority of the total order—55%. Therefore, even though just a small portion of all SKUs are related to one another, it still has a big impact on the pile-on if those SKUs predominate in the overall order.

According to the simulation findings and the research above, choose the proper SKU to pod assignment strategy can have an impact on the efficiency of the warehouse. The greatest strategy for maximizing pile-on is mixed class affinity policy when compared to random and mixed class policies. It can also be used in real e-commerce warehouses, where a high pile-on is necessary to increase warehouse productivity due to the volume of orders and the variety of SKUs in each order. SKUs and notes have relationships, and those SKUs dominate the overall orders.

5.5 Statistical Test

The next step is to determine whether the number of replications is adequate after receiving the simulation results. If it is still insufficient, more replications of the simulation are required. On the other hand, if it is already adequate, One-Way ANOVA is used to confirm the outcome.

5.5.1 Replication Adequacy Test

Only ten replications have been performed due to time constraints. Therefore, the replications adequacy test using Equation (8) and (9) must be performed to demonstrate that the 10 replications are sufficient. Given that the confidence level is 95%,. The number of replications required is at least eight times greater when compared to the mean and standard deviation of the simulation result. As a result, the 10 replications completed are adequate for this study.

5.5.2 ANOVA

One-way factor ANOVA must be used to validate the simulation result after confirming that the number of replications is adequate. The result of the hypothesis test is shown in Figure 2 below. As can be seen, the null hypothesis is rejected and the three scenarios are statistically different because the p-value, 0.000000182, is less than 0.05.

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Random	11	77,91955	7,0835953	0,010088
Mix	11	75,20078	6,8364346	0,019635
Mix Affinity	11	72,92997	6,629997	0,020014

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1,134673	2	0,5673366	34,21968	1,81672E-08	3,315829501
Within Groups	0,497377	30	0,0165792			
Total	1,632051	32				

Figure 2: ANOVA Test Result

6 CONCLUSION

The RMFS warehouse can be made more effective in a number of ways. The SKU to pod assignment policy is one of the decision-related issues. The policy with the fewest transported pods is the best to accomplish the greatest pile-on in the warehouse, despite the fact that different policies result in varying warehouse performances. In this study, three policies—Random—baseline, Mixed Class, and Mixed Class Affinity policy—are tested as a scenario. For each product composition, each policy has a different set of rules.

According to the simulation results, the final scenario produces the best pile-on, with an average of 6.63 pods being transported per order. In contrast, the outcomes of the first and second situations are 7.08 and 6.84, respectively. Even though just 8% of SKUs conform to the association's criterion, the figures indicate that the pile-on of the final scenario is 6.4% and 3.02% larger than that of the other two situations. However, it should be noted that 55% of the order data is dominated by the 8% SKUs.

The one-way ANOVA is used to validate the outcome. The three scenarios are significantly different because their p-values are less than 0.05. Therefore, it can be said that the SKU-to-pod scenarios have had an impact on the effectiveness of the RMFS warehouse. When compared to random and mixed-class policies, the mixed-class affinity policy is shown to be the most effective.

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