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Sequential Model of FSN Classification with Zabls Slotting and Vehicle Routing Problem Using Hybridization of Ant Colony Optimization and Tabu Search to Reduce Picking Time

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Abstract:

Purpose: The research purpose is to enhance picking performance by developing a hybrid algorithm that classifies SKU, determines slot, and routes the process for Delivery Order (DO).

Design/methodology/approach: FSN classification is used for categorizing the products into three groups: fast-moving, slow-moving, and not-moving based on the consumption rate and average stay of each SKU. The result of classification is continued with ZABLS Slotting for product placement on warehouse shelves based on the quickest to the longest picking time on each slot. Slotting results are used for VRP addresses with Ant Colony Optimization and Tabu Search hybridization algorithms. Due to the high process and cost to move the goods storage location because of the use of FSN and ZABLS method, hybridization algorithms are compared to pre-slotting and post-slotting conditions. Method verification uses 30 random sampling DO, and based on existing storage locations, it took 757.14 seconds average picking time.

Findings: On pre-slotting condition, it reduced 17.74% to 626.34 seconds, and on post-slotting condition it reduced 25.75% to 557.64 seconds. The reduced picking time gives PT. XYZ better performance on fulfilling delivery orders in a day; theoretically, based on standard time, PT. XYZ can fulfill 40 orders in a day, and based on current performance, PT. XYZ can only fulfill 31 DO in a day. The uses of ACO-TS hybridization algorithms on pre-slotting condition PT. XYZ can fulfill 45 DO in a day and on post-slotting condition PT. XYZ can fulfill 51 DO in a day, increasing 27.5% from current performance.

Originality/value: The novelty of this research is the use of hybridization algorithms of Ant Colony Optimization and Tabu Search (ACO-TS) to design sequential model of FSN-ZABLS to VRP to minimize picking time on each Delivery Order (DO).

Keywords: ant colony optimization, fast-moving consumer goods, FSN analysis, tabu search, vehicle routing problem, ZABLS slotting

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1. Introduction

Logistics is an aspect of Supply Chain Management (SCM) that serves the functions of transferring and handling materials from upstream to downstream, including raw materials and finished goods. Logistics also encompasses planning, execution, and control of the flow of goods within a system (Christopher, 2023). Picking time is an aspect of logistics that refers to the time required for retrieving goods from the storage location to fulfill customer needs (Frazelle, 2015).

Inaccurate handling and strategy for picking can lead to cost inefficiency or worker utilization (Johan & Sunardi, 2023).

PT. XYZ is a Fast-Moving Consumer Goods (FMCG) company operating in the food and beverage sector. In the FMCG Industry, rapid and accurate availability of products is important for business operations. In the case study of PT. XYZ, the assessment of logistics performance involves not only picking time but also includes receiving, storing, and shipping.

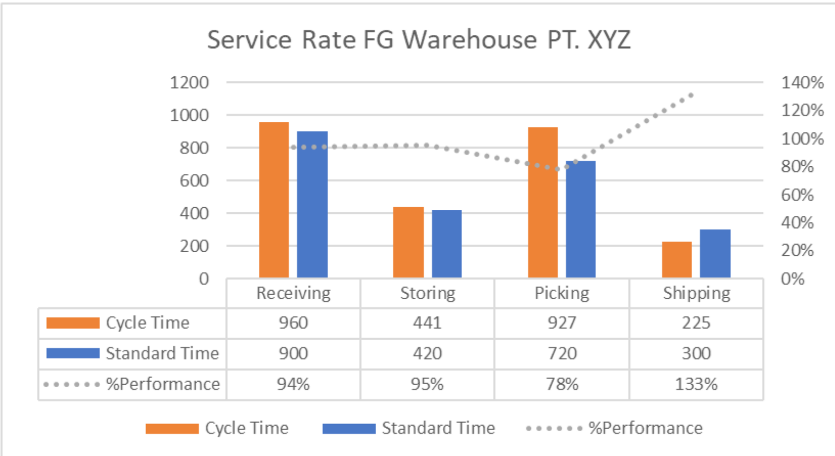

Figure 1. Service Rate FG Warehouse PT. XYZ (seconds)

Standard time is used as a reference in the calculation of finished goods warehouse service rate of PT. XYZ. Cycle time is obtained by averaging the time of each transaction in every process. Both compare to calculating the percentage of each process performance at a minimum of 98%. The reception process includes physical check and product sampling by the QC/QA department. Incompetencies in this process are due to products that don't meet the criteria that have been determined and require re-verification. This process is also beyond the control of warehouse. The storing process includes delivering products from the receiving area to available rack slots. Incompetencies in this process are due to the need to search for empty slots. The picking process includes activities of searching and checking product variants and the batch number due to the implementation of First-In-First-Out (FIFO). FIFO is a method of taking goods that prioritizes which item entered the warehouse first (Hidayat & Al-Amin, 2018). The shipping process includes delivering goods from the MHE area to the staging area. Of the four warehouse performance criteria, the worst one is the picking process with an achievement of only 78%. Therefore, the focus of the research was to achieve picking process performance according to the standard time. In the picking process, PT. XYZ uses 3 reach truck with 1 pallet jack each that can collect 3 pallets. Therefore, the maximum pallet capacity for picking is 4 pallets per reach truck.

Poor performances of the picking process at the finished product warehouse of PT. XYZ are divided into several categories. "Man" category has a close relationship with "Method" category, the operator doesn't know about what's inside the shelf slots in the warehouse because the data collection process of the goods in the warehouse hasn't been implemented with a Warehouse Management System (WMS) to find out which and where items need to be taken from certain shelves. It requires more time because they need to apply the FIFO concept even though the warehouse has been classified based on the SKU. Meanwhile, the lack of training of Reach Truck operators causes the picking-goods process from the shelf to take longer than the trained operator because of the need for focus and knowledge of the fork reach on the Reach Truck. The "machine" category is limited by warehouse capacity where the occupancy is close to 100% as well as Reach Truck specifications for horizontal and vertical speed. The "Money" category is limited by the company's budget because investing in the WMS system and purchasing a Reach Truck with a higher specification is not the main consideration for budgeting.

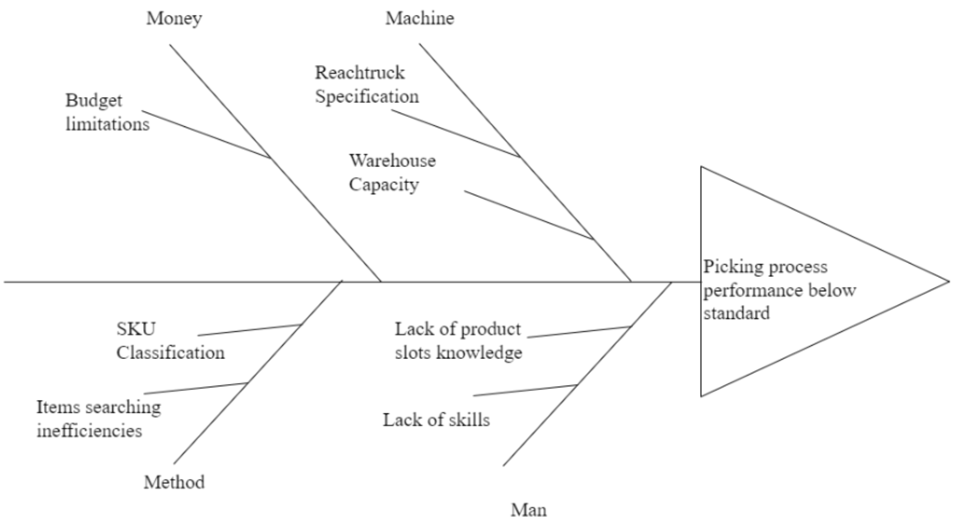

Figure 2. Fishbone Diagram

The FSN Classification Method could be used for solving the problem where this method will divide categories into Fast Moving, Slow Moving, and Not Moving that consider Consumption Rate and Average Stay from its SKU (Bose, 2006). Research conducted by Arini (2016) using the FSN and Slotting ZABLS Method on solving the problem of delays in releasing materials shows that it could be optimized by 8,14%. Another research conducted by Hazaghi (2016) using FSN and Slotting OPITZ Method to optimize 2,72% picking process time to solve fulfillment of picking times problem at warehouse. Research using the FSN method tends to optimize picking time and/or delay at the warehouse; however, research conducted by Tadestarika (2015) to solve the fulfillment of picking time at the warehouse using the FSN and Slotting ZABLS methods optimizes 7% for the picking time and 13,53% for operational cost.

The picking list owned by PT. XYZ depends on the delivery order (DO) received by the warehouse, so there's a routing process for picking up goods at the warehouse. We can implement an additional concept for decreasing picking time at the warehouse with Vehicle Routing Problem (VRP), where to the author's knowledge that no one has conducted research using FSN, ZABLS, and VRP. VRP is an optimizing process to choose which optimal route should be chosen for one or more depots that can serve one or more customers (Toth & Vigo, 2014). In completing VRP research, there are a few algorithmic methods that can be used, such as the exact and approximation methods. The exact method is a method that produces an optimal global solution for maximation or minimization solutions. Some examples of exact algorithms methods that are used are linear and dynamic programming (Kunche & Reddy, 2016). The approximation method is a method that produces optimal local solutions for maximation or minimization. This method can be divided into two kinds of types, heuristic and metaheuristic, where the heuristic method is designed to solve specific problems and the metaheuristic method is designed to solve global problems (Talbi, 2009). To support the use of metaheuristic algorithms to get closer to global optimal results, it is necessary to hybridize both algorithms. For example, research conducted by Kurniati, Rahmatulloh and Rahmawati (2019) combines both Genetic Algorithms and Tabu Search (GA-TS) where the results show that the hybridize algorithm gets 11% better solutions than ACO algorithms results. But ACO has 33% better performance in using memory and 82% better process time. In research conducted by Xu, Pu and Duan (2018), hybridization from ACO algorithms and Nearest Distance Cluster to Particle Swamp Optimization (PSO) algorithms and Genetic Algorithms (GA) results. It shows that hybrid algorithms have 12 best solutions, where GA only produces 4 solutions and PSO only produces 3 solutions. But it needs 11.3% longer than GA and

1.8% longer than PSO. Research conducted by Pratama, Utomo and Wibowo (2022) compares problem solving using TS and ACO algorithms, where the result shows that the TS method produces 0.8% better solutions than ACO does. But ACO algorithms have a runtime that is 12% better than the TS method. In this research, there's going to be a hybridization of the ACO and TS algorithms.

The problems that PT. XYZ faced in fulfilling DO completion in one of its assessment's components, namely picking time, can use FSN and Slotting ZABLS methods. The use of these methods is supported by other research with similar problems in solving. To ensure problem solving and optimization of the picking time, the design was continued with VRP using the hybrid algorithm from Tabu Search and Ant Colony Optimization and Tabu Search (ACO-TS). In this VRP modeling, nodes from the ZABLS Slotting results will be used for the process of picking goods from DO that are owned by the warehouse.

2. Literature Review

2.1. FSN Classification

FSN classification is a method where goods are classified based on the movement in the warehouse. The method classified goods into 3 categories: fast-moving, slow-moving, and not-moving based on calculations of consumption rate and average stay of each goods. Consumption rate is a calculation that shows how often inbound and outbound of each goods. Average stay is a calculation that shows how long goods are stored in the warehouse. There are several steps to calculate FSN classification (Bose, 2006):

1. Calculate the average storage and turnover rate of goods in the warehouse.
2. Calculate the cumulative percentage of average stock and turnover rate of goods.
3. Final classification based on the result of step 2.

2.2. Vehicle Routing Problem

Vehicle Routing Problem (VRP) according to Caric and Gold (2008) is a problem that states a number of m vehicles that are placed at a depot or zero point to deliver goods to a number of n consumers. As stated by Prasetyo and Tamyiz (2017), VRP is a distribution problem from starting point to ending point, which will produce an optimal route depending on how to solve it. The statement is aligned with Toth and Vigo (2014) that VRP is an optimization problem is used to determine the optimal route of a vehicle from one or more depots to serve several customers. There are several types of VRP:

1. Capacitated VRP (CVRP)
2. Heterogeneous Fleet VRP (HFVRP)
3. VRP with Backhauls (VRPB)
4. VRP with Time Windows (VRPTW)
5. Multiple Depots VRP (MDVRP)
6. Split Deliveries VRP (SDVRP)

2.3. Ant Colony Optimization

Ant Colony Optimization (ACO) is an algorithm that is inspired by ants' behavior in the process of looking for foods. Ant colony can get the shortest route from the nest to the food source based on the tracks they have taken before, and from the distribution of the ants, the shortest route to the food source will be known (Risqiyanti, Yasin & Santoso, 2019). Each ant releases pheromone in the process of looking for food and evaporation that occurs. After the ants found the shortest route to the food source, they will repeat using that route and the pheromone level remains strong so that route remains chosen (Bell & McMullen, 2004). There are several variables that are used for ACO algorithms, including (Nugroho & Permadi, 2020):

1. Amount of Ants

   It affects the algorithm in looking for solutions. The more ants, the better the solution exploration will be.

2. Alpha (α)

   A parameter to control the weight of pheromone. The higher of the value will change the ant's behavior in looking for another path.

3. Beta (β)

   It is a distance control parameter. The higher of the value will change the ant's behavior in looking for the possibility of new paths based on the possibility of the solutions the ant has already traversed.

4. Rho (ρ)

   It is a pheromone evaporation parameter. The higher the value will evaporate the pheromone longer.

2.4. Tabu Search

Tabu Search (TS) is an algorithm that was first introduced by Glover in 1986 and can be used when we have many datasets (Prajapati, Jain & Chouhan, 2020). This algorithm is also widely used because of its efficiency in finding solutions, the concept of this algorithm is the same as Nearest Neighbor (Du & He, 2012). Tabu Search looks for solutions around the existing solutions and stores them in a tabu list that contains potential solutions that have been obtained. It is not only accepting better solutions but also can accept the worst solutions (Hakim, Ardiansyah & Yulianti, 2023). There are several parameters that are used for Tabu Search algorithms, including (Hindriyanto, 2012):

1. Tabu List

   It is a potential solution list that has already been implemented before. The aim of using this list is to avoid using the same solution. The higher the value, the better the algorithm results will be. But it requires longer processing time.

2. Aspiration Criteria

   This criterion is used to produce potential solutions that's better than the tabu list.

3. Intensification (Medium-term memory)

   It will have stored the best solutions and given priority to solutions that have been produced.

4. Diversification (Long-term memory)

   It will have stored the best solutions that have been visited and will be exploited in that memory.

3. Research Design

There are 3 stages of conducting the research. The first stage is data gathering that consists of initial stock 2021, inbound and outbound SKU 2021, warehouse layout, and reachtruck specifications. The second stage is data processing that consists of SKU classification based on FSN analysis, SKU slotting based on ZABLS analysis, and VRP using hybridization algorithms of ACO and TS. The third stage is result analysis; the result from VRP will be compared based on two situations, the pre-slotting condition and the post-slotting condition.

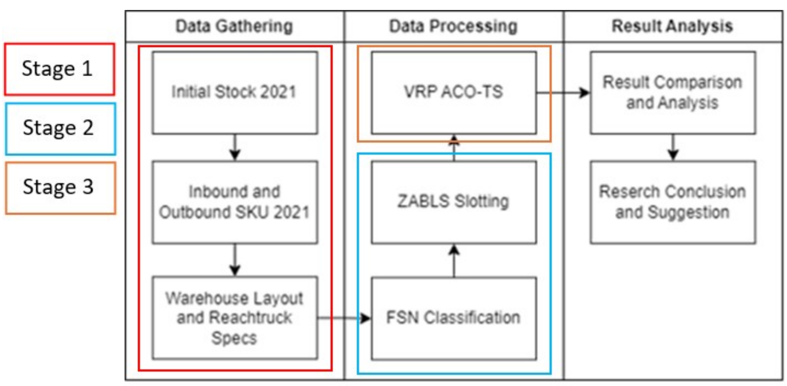

Figure 3. Research Stages

The first step to do the research after all the data gathered is determining FSN classification based on consumption rate and average stay for each of the SKUs. To calculate the consumption rate on each SKU, we can use calculations (Bose, 2006):

$$\sum_{m=1}^{12} \frac{OB_{s_m}}{m} \quad (1)$$

Ob_s = Sum of Outbound SKU s in the warehouse
m = The period (in month) used (1,2, ..., 12)

From the calculation results, the consumption rate on each SKU will be cumulated and sorted from the largest to the lowest. The cumulative result will determine FSN classification from each SKU based on consumption rate.

% Consumption Rate	Category	Classification
$0 < x \leq 70\%$	Fast Moving	F
$70\% < x \leq 90\%$	Slow Moving	S
$90\% < x \leq 100\%$	Non-Moving	N

Table 1. FSN by Consumption Rate

The process of determining FSN classification based on consumption rate can be seen in Table 1, where if the cumulative results are 0%–70%, it is determined as fast-moving category. If the cumulative results are 70%–90%, it is determined as slow-moving category. But if the cumulative results are 90%–100%, it will be determined as not-moving category. To calculate the average stay on each SKU, we can use the calculations (Bose, 2006):

$$\sum_{m=1}^{12} \frac{St_{s_m}}{OB_{s_m} + IB_{s_m}} \quad (2)$$

St_s = Sum of SKU s stock in the warehouse
IB_s = Sum of Inbound SKU s in the warehouse

The same thing is done with the average stay results on each SKU, and the FSN classification is determined based on the average stay.

% Average Stay	Category	Classification
$90\% < x \leq 100\%$	Fast Moving	F
$70\% < x \leq 90\%$	Slow Moving	S
$0 < x \leq 70\%$	Non-Moving	N

Table 2. FSN by Average Stay

The process of determining FSN classification based on average stay can be seen in Table 2, where the cumulative results are reserved if compared to calculation by consumption rate. If the cumulative results are 0%–70%, it will be determined as not-moving. But if the cumulative results are 70%–90%, it will be determined as a slow-moving category. And if the cumulative results are 90%-100%, it will be determined as the fast-moving category.

The final results of the FSN classification are seen based on categories of the consumption rate and average stay following the reference in Table 3, where if the classification results both from CR and AS are fast-moving categories, then the results will be fast-moving categories too. But if the classification of CR is a slow-moving category and AS is a fast-moving category, then the results will be slow-moving category or so on. The final results of the FSN classification will be used for the Slotting ZABLS process, where the process will calculate the rectilinear distance on each shelf. The illustration of the rectilinear distance can be seen in Figure 4.

Criteria	Category								
FSN (%CR)	F	F	F	S	S	S	N	N	N
FSN (%AS)	F	S	N	F	S	N	F	S	N
Final FSN	F	F	S	S	S	N	S	N	N

Table 3. Final FSN Classification

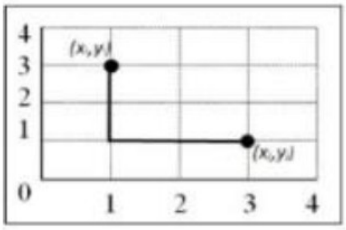

Figure 4. Rectiliner Distance Illustration

Rectilinear distance is a distance that can be calculated with a perpendicular line, the method for calculating this measurement (Nursyanti, & Rahayu, 2019):

$$Dij = |x - a| + |y - b|$$

The results of the Slotting ZABLS process are the allocation of SKUs that are sorted from the lowest to the highest picking time, and the SKUs are placed from the fast-moving category to the not-moving category from the final classification results. The allocation of SKU is used as a node on the VRP calculation process. The modeling and rationale of the VRP process are identified and illustrated using an influence diagram that is categorized into control input, uncontrollable input, and output.

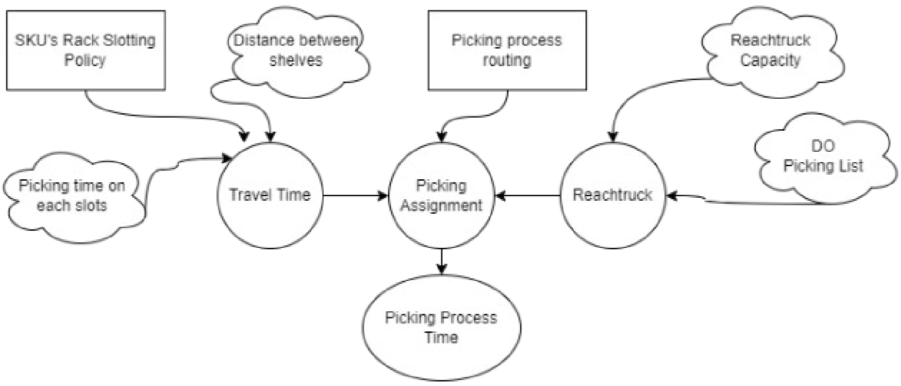

Figure 5. Influence Diagram

From the influence diagram, the main objective of this modeling is to minimize the picking process time, which is a result of the routing carried out by each truck based on supervision in the field that is influenced by travel time and vehicle. The travel time itself can be influenced by the distance between the item slot on the shelf and picking time in each slot. Meanwhile, the vehicle can be influenced by the capacity for picking up goods and demand for items on Delivery Orders (DO). The flowchart of the algorithm hybridization from Ant Colony Optimization (ACO) and Tabu Search (TS) can be seen in Figure 6.

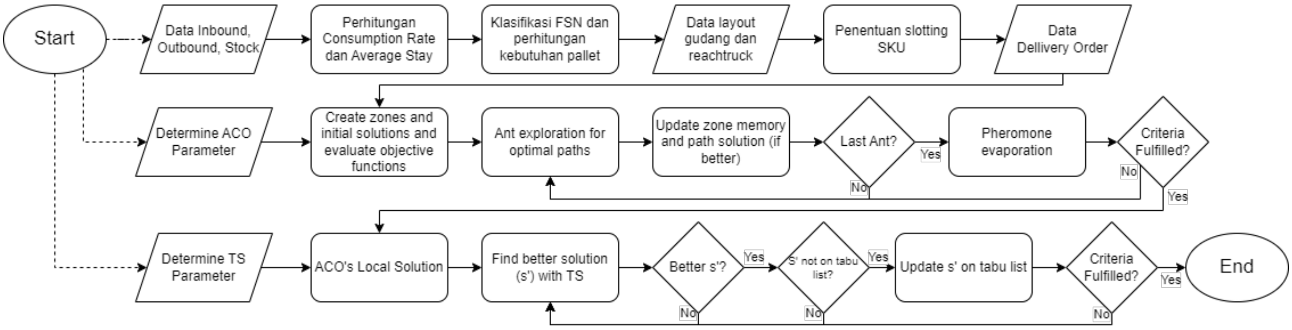

Figure 6. Research Flowchart

The Tabu Search algorithm method generally uses a random initial solution. But, in the flowchart the initial solution for the Tabu Search algorithm is obtained from the results of the Ant Colony Optimization (ACO) algorithm. The hybridization of these two algorithms aims to obtain better results than if we did it with one of the methods and the acceptable runtime. A mathematical model of this research is created based on references to Muna's research (2022):

Objective Function:

$$\min \sum_{i \in Nd} \sum_{j \in Nd} \sum_{v \in V} X_{ijv} D_{ij} + \sum_{j \in Nd} \sum_{v \in V} X_{0jv} \qquad \forall\, i \in Nd, j \in Nd, v \in V \tag{3}$$

Constraint:

$$\sum_{v \in V} X_{ijv} = 1 \qquad \forall\, i \in Nd, v \in V \tag{4}$$

$$\sum_{j \in Nd} X_{0jv} = 1 \qquad \forall\, v \in V \tag{5}$$

$$\sum_{i \in Nd} X_{ijv} \leq Q_v \qquad \forall\, v \in V \tag{6}$$

$$\sum_{j \in Nd} X_{0jv} = \sum_{i \in Nd} X_{ijv} \qquad \forall\, v \in V \tag{7}$$

$$\sum_{i \in Nd} \sum_{j \in Nd} \sum_{v \in V} X_{ijv} D_{ij} C_v + \sum_{j \in Nd} \sum_{v \in V} X_{0jv} \leq Z \qquad \forall\, i \in Nd, j \in Nd, v \in V \tag{8}$$

$$X = 25, Y = 15$$

$$A = 3, \alpha = 0.8, \beta = 2, \rho = 0.3, q0 = 0.3$$

$$\min(\alpha) = 0.001, \max(\alpha) = 0.5$$

Equation (3) is the objective function of this research, that is to minimize travel time. On Equation (4), there is a constraint so each node can be visited by one vehicle only. Equation (5) is a constraint for each vehicle that departs from 0 point and returns with the same amount. The Equation (6) is a constraint, so the amount of cargo intended does not exceed the capacity of the vehicle. Equation (7) is used to maintain the consistency of the departures and arrival amounts at 0 points. And the Equation (8) is a constraint to maintain the maximum value of the solution (Z), which is 720 seconds or 12 minutes.

4. Findings and Discussion

4.1. Stage 1

FSN analysis was carried out based on the historical data of 2021 that is owned by PT. XYZ. The data required in the FSN analysis process are:

a) Early Stock of 2021
b) Production Results of 2021
c) Delivery Order (DO) of 2021

From these 3 data, it can be concluded the inbound, outbound, and stock in each month situation. Inbound is obtained from the production results from each month in 2021. Outbound is obtained from the DO from each month in 2021. Stock is obtained from the calculations:

$$S_n = S_{n-1} + I - O \tag{9}$$

The data needs during 2021 from PT. XYZ for applying FSN analysis that can be seen from Table 4.

SKU	Inbound (Ctn)	Outbound (Ctn)	Stock (Ctn)
A1	310,963	310,108	129,995
A2	35,541	37,408	13,875
A3	656,622	652,420	275,693
A4	2,503,662	2,480,870	845,950
A5	752,024	750,843	313,934
A6	1,802,991	1,786,785	458,851
A7	811,736	807,414	340,385
A8	5,373,922	5,322,917	1,368,983
A9	488,122	487,990	203,450
A10	31,133	31,496	10,196
A11	518,693	520,176	215,381
A12	1,811,103	1,794,005	612,250
A13	49,019	48,748	16,475
A14	1,061,213	1,049,615	271,102
A15	35,674	35,883	11,787
A16	1,049,798	1,046,836	438,896
A17	3,086,388	3,057,146	786,218
A18	46,315	46,311	15,440

Table 4. SKUs Data

Inbound, outbound, and stock data will be used later for the consumption rate and average stay calculations on FSN classification analysis. For slotting ZABLS calculations, the following data are required:

1. Layout and specification of the warehouse shelves
2. Different picking times at each level
3. Horizontal and vertical speed specifications for reach trucks

Criteria	Distance (m) by Criteria
Row	1.25
Column	2
Level	1.5

Table 5. Racks Specification

Each level or grade has a different picking process time due to the need for different concentrations and sense in directing the reach truck to pick up the goods.

Level	Picking Time (s)
1	7
2	17
3	27
4	37
5	47
6	57
7	67
8	77

Table 6. Picking Time by Level

Table 6 shows the difference in time required by the reach truck operator in picking up goods at every level, while to find out the total amount of picking process time needed in each slot of the shelf, one needs to calculate the horizontal and vertical distance on each shelf along with the horizontal and vertical reach truck speed.

R	C	L	Horizontal Distance (m)	Vertical Distance (m)
R1	C1	1	6	0
R2	C1	1	7.25	0
R1	C1	2	5	1.5
R1	C1	4	5	4.5
R1	C4	5	9	6
R8	C1	3	13.75	3
R2	C1	2	6.25	1.5
R1	C6	4	11	4.5
R2	C1	6	6.25	7.5

Table 7. Slot Distance Examples

Table 7 shows an example of the distance for each slot owned by the PT. XYZ warehouse. After knowing the horizontal and vertical distance in each slot of the shelves, the distance will be divided by the specification of the horizontal and vertical speed on each reach truck and the picking time added in Table IV.3 to find out the time needed for the picking process time of the slot.

Criteria	Speed (m/s)
Horizontal	3.75
Vertical	0.59

Table 8. Horizontal and Vertical Speed Criteria

Table 8 shows MHE's speed specifications at the PT. XYZ warehouse. To find out the picking process time on each slot, data from the table is divided by horizontal and vertical speed and then added by picking time from Table 6.

Row	Column	Level	Horizontal Time (s)	Vertical Time (s)	Picking Time (s)	Total Time(s)
R1	C1	1	1.6	0	7	8.6
R2	C1	1	1.93	0	7	8.93
R1	C1	2	1.60	2.54	17.00	21.14
R1	C1	4	1.60	7.63	37.00	46.23
R1	C4	5	3.20	10.17	47.00	60.37
R8	C1	3	3.93	5.08	27.00	36.02
R2	C1	2	1.93	2.54	17.00	21.48
R1	C6	4	4.27	7.63	37.00	48.89
R2	C1	6	1.93	12.71	57.00	71.65

Table 9. Picking Time by Slots Examples

4.2. Stage 2

The first step of doing FSN analysis is to classify the product based on the consumption rate and average stay. Based on the data that was received from Table 4, using calculations to calculate consumption rate.

The %Consumption Rate column is obtained by the results of the consumption rate calculation of the SKU with total accumulation of all SKUs. After getting the percentage of the consumption rate from each SKU, then the SKU is sorted based on the highest to the lowest and calculated cumulatively to determine the FSN classification. If the percentage of the cumulative is 0%–70%, it is determined as a fast-moving category. But if the percentage of the cumulative is 70%–90%, it is determined as a slow-moving category. And if the percentage of the cumulative is 90%–100%, it is determined as a Not Moving category. The average stay calculations can be seen in Table 11.

SKU Code	Cons.	% Cons.	Cum. Cons.	Class
A8	447,827	26.31%	26.31%	F
A17	257,199	15.11%	41.42%	F
A4	208,639	12.26%	53.68%	F
A12	150,925	8.87%	62.55%	F
A6	150,249	8.83%	71.37%	S
A14	88,434	5.20%	76.57%	S
A16	87,483	5.14%	81.71%	S
A7	67,645	3.97%	85.68%	S
A5	62,669	3.68%	89.37%	S

SKU Code	Cons.	% Cons.	Cum. Cons.	Class
A3	54,718	3.21%	92.58%	N
A11	43,224	2.54%	95.12%	N
A9	40,677	2.39%	97.51%	N
A1	25,914	1.52%	99.03%	N
A13	4,085	0.24%	99.27%	N
A18	3,860	0.23%	99.50%	N
A15	2,973	0.17%	99.67%	N
A2	2,962	0.17%	99.85%	N
A10	2,594	0.15%	100.00%	N

Table 10. FSN Class by Consumption Rate

SKU Code	Avg. Stay	% Avg. Stay	Cum. Average Stay	Class
A3	0.211	6.65%	6.65%	N
A7	0.210	6.63%	13.28%	N
A16	0.209	6.61%	19.89%	N
A1	0.209	6.61%	26.49%	N
A5	0.209	6.59%	33.08%	S
A9	0.208	6.58%	39.66%	S
A11	0.207	6.54%	46.20%	S
A2	0.190	6.00%	52.21%	S
A12	0.170	5.36%	57.57%	S
A4	0.170	5.36%	62.92%	F
A13	0.169	5.32%	68.24%	F
A18	0.167	5.26%	73.50%	F
A15	0.165	5.20%	78.70%	F
A10	0.163	5.14%	83.84%	F
A14	0.128	4.05%	87.89%	F
A8	0.128	4.04%	91.93%	F
A17	0.128	4.04%	95.97%	F
A6	0.128	4.03%	100.00%	F

Table 11. FSN Class by Average Stay

The %Average Stay column is obtained from the results of the Average Stay calculations on the SKU with total accumulation of the entire SKU. After getting the percentage of the average stay from each SKU, then the SKU is sorted based on the highest to the lowest and calculated cumulatively to find out the FSN classification that has been delivered in Chapter II.1.5 FSN Analysis. If the cumulative percentage is 0%–30%, it is determined as a Not Moving category. But if the cumulative percentage is between 30% and 60%, it is determined to be a slow-moving category. And if the cumulative percentage is 60%–100%, it is determined to be a fast-moving category. The consumption rate and average stay calculations categories were then combined to find out the final FSN classification on each SKU. The results of the final classification can be seen in Table 12.

SKU Code	FSN by CR	FSN by AS	FSN Classification
A1	N	N	N
A2	N	S	N
A3	N	N	N
A4	F	F	F
A5	S	S	S
A6	S	F	S
A7	S	N	N
A8	F	F	F
A9	N	S	N
A10	N	F	S
A11	N	S	N
A12	F	S	F
A13	N	F	S
A14	S	F	S
A15	N	F	S
A16	S	N	N
A17	F	F	F
A18	N	F	S

Table 12. Final Classification FSN

From the results of the final classification based on the stock in the carton unit, it needs to be converted to the pallet due to storage on the shelf using a pallet to proceed with the Slotting ZABLS process.

SKU Code	Pallet Capacity (Carton)	Average Stock (Carton)	Pallet Requirement	Round-Up Req. Pallet	Final FSN
A8	90	114,082	1,267.58	1,268	F1
A17	60	65,518	1,091.97	1,092	F2
A4	90	70,496	783.29	784	F3
A12	90	51,021	566.90	567	F4
A6	90	38,238	424.86	425	S1
A14	60	22,592	376.53	377	S2
A16	90	36,575	406.39	407	N1
A7	90	28,365	315.17	316	N2
A5	90	26,161	290.68	291	S3
A3	90	22,974	255.27	256	N3
A11	90	17,948	199.43	200	N4
A9	90	16,954	188.38	189	N5
A1	90	10,833	120.37	121	N6
A13	80	1,373	17.16	18	S4
A18	80	1,287	16.08	17	S5

SKU Code	Pallet Capacity (Carton)	Average Stock (Carton)	Pallet Requirement	Round-Up Req. Pallet	Final FSN
A15	80	982	12.28	13	S6
A2	90	1,156	12.85	13	N7
A10	90	850	9.44	10	S7
Total Pallet Needed				**6,364**	
Capacity Pallet Existing				**6,400**	

Table 13. Pallet Requirement of SKUs

Table 13 will be a reference to place the SKU in slot from the results of Table 9 calculations, where it will be sorted from the lowest to the highest total time. In Table 13, SKU A8 that is categorized as a F1 needs 1,268 pallet positions on the shelf, SKU A6 that is categorized as a S1 needs 425 pallet positions on the shelf, and so on.

Row	Column	Level	Total (s)	Zone	Aisle	Bay	Level	Slot	(ZABLS)	SKU Code	Node
R1	C1	1	8.60	F1	1	1	L1	1	F1-1-1-L1-1	A8	A8-R1-C1-L1-F1
R2	C1	1	8.93	F1	1	1	L1	2	F1-1-1-L1-2	A8	A8-R2-C1-L1-F1
R1	C2	1	9.13	F1	1	1	L2	1	F1-1-1-L2-1	A8	A8-R1-C1-L2-F1
R3	C1	1	9.27	F1	2	1	L1	1	F1-2-1-L1-1	A8	A8-R1-C2-L1-F1
R2	C2	1	9.47	F1	2	2	L1	1	F1-2-2-L1-1	A8	A8-R1-C3-L1-F1
R4	C1	1	9.60	F1	1	1	L1	3	F1-1-1-L1-3	A8	A8-R3-C1-L1-F1
R1	C3	1	9.67	F1	1	1	L2	2	F1-1-1-L2-2	A8	A8-R2-C1-L2-F1
R3	C2	1	9.80	F1	2	1	L1	2	F1-2-1-L1-2	A8	A8-R2-C2-L1-F1
R5	C1	1	9.93	F1	2	2	L1	2	F1-2-2-L1-2	A8	A8-R2-C3-L1-F1

Table 14. SKUs Slot Examples

4.2. Stage 3

This research method test is using ACO-TS algorithm hybridization with a sample of 30 Delivery Orders (DO). Where the testing process will be compared with the before and after conditions of the FSN-ZABLS classification stage.

No	SKU	Loc (Before FSN)	Loc (After FSN)
1	A8 #484	R21-C17-L7	R2-C11-L2
2	A16 #118	R35-C15-L3	R7-C1-L8
3	A8 #711	R8-C18-L5	R27-C10-L1
4	A17 #292	R20-C11-L3	R40-C5-L2
5	A4 #669	R6-C4-L3	R18-C16-L4
6	A8 #735	R32-C18-L5	R3-C15-L2
7	A4 #333	R30-C3-L2	R4-C19-L4
8	A16 #135	R12-C15-L4	R32-C14-L6
9	A4 #698	R35-C4-L3	R30-C9-L4
10	A17 #623	R31-C12-L3	R25-C20-L2
11	A8 #788	R5-C18-L7	R14-C9-L2

Table 15. DO #1 Nodes

Table 15 shows the location of each SKU on the 1st DO sampling before and after FSN-ZABLS. This location changes following the Slotting ZABLS results but with the codification changes, it will be easier to do the proofing and identification process.

DO #	Existing			Before FSN+Slotting			After FSN + Slotting		
	V	R	T (s)	V	R	T (s)	V	R	T (s)
1	1	1-3-5-7	261.26	1	1-6-2-10	279.68	1	5-10-7-6	187.35
	2	4-6-10-9	230.18	2	11-3-8-4	282.22	2	4-8-9-3	192.01
	3	2-8-11	285.22	3	5-9-7	132.32	3	2-11-1	175.96
	Total		**776.66**	**Total**		**694.22**	**Total**		**555.32**

Table 16. ACO-TS Result on DO #1

Table 16 shows the results of the existing conditions combined with before and after the FSN-ZABLS process. The existing conditions take 776.66 seconds, or 12.9 minutes of the picking process time. While the routing process is being improved using the ACO-TS hybridization algorithm without changing the SKU address on the shelf, it takes 694.22 seconds or 11.6 minutes. The minimization obtained without changing the address is 10.61%. But if we combine the after-classification process along with the slotting, it will obtain the picking process time needed of 555.32 seconds, or 9.26 minutes. Improving 28.5% based on the existing condition.

No	SKU	Loc (Before FSN)	Loc (After FSN)
1	A12 #431	R24-C9-L7	R19-C11-L5
2	A8 #837	R14-C18-L8	R32-C9-L1
3	A16 #48	R5-C15-L2	R26-C2-L7
4	A11 #153	R26-C8-L3	R31-C5-L8
5	A16 #85	R2-C15-L3	R21-C20-L6
6	A8 #316	R13-C17-L3	R9-C3-L2
7	A3 #251	R12-C2-L2	R16-C11-L8
8	A12 #80	R33-C8-L6	R40-C20-L3
9	A3 #118	R39-C1-L6	R20-C20-L7
10	A8 #269	R6-C17-L2	R19-C6-L1
11	A17 #675	R3-C12-L5	R36-C14-L2

Table 17. DO #2 Nodes

Table 17 shows the location of each SKU on the 2nd DO sampling, the same as the results of the previous number that represent the routing results from the ACO-TS hybridization algorithm.

DO #	Existing			Before FSN+Slotting			After FSN + Slotting		
	V	R	T (s)	V	R	T (s)	V	R	T (s)
2	1	1-3-6-4	247.65	1	9-8-4-7	246.59	1	5-9-8-11	273.27
	2	8-10-11-5	255.39	2	1-2-6-10	284.89	2	6-3-4-2	244.06
	3	2-7-9	301.76	3	11-5-3	149.81	3	1-7-10	193.83
	Total		**804.81**	**Total**		**681.29**	**Total**		**711.16**

Table 18. ACO-TS Result on DO #2

Table 18 shows that the existing condition takes 804.81 seconds, or 13.41 minutes of the picking process time. Meanwhile, if the routing process is improved using the ACO-TS hybridization algorithm without changing the SKU address on the shelf, the picking process time will be 681.29 seconds or 11.35 minutes. The minimization without changing the address that obtained is 18.13%. But if we combined the after-classification with the slotting process, the picking process time that is required to fulfill the orders is 711.16 seconds, or 11.85 minutes. Improving 13.17% based on the existing condition. On the 2nd DO sampling case, the results of the after-slotting with FSN-ZABLS do not provide greater improvisation than without. It is due to the SKU that is categorized as slow moving or not moving in the location for fast moving area. Therefore, the slotting results didn't improve a lot more than they should in this case. For all 30 DO sampling test results can be seen in Table 19.

DO	Exist (s)	B (s)	A (s)	% B	% A	Gap
1	776.66	694.22	555.32	10.61%	28.50%	17.88%
2	804.81	681.29	711.16	15.35%	11.64%	**-3.71%**
3	935.81	769.56	550.72	17.77%	41.15%	23.38%
4	704.26	629.42	527.47	10.63%	25.10%	14.48%
5	502.65	372.12	360.37	25.97%	28.31%	2.34%
6	829.47	681.86	567.63	17.80%	31.57%	13.77%
7	539.13	439.16	347.35	18.54%	35.57%	17.03%
8	740.21	659.44	607.00	10.91%	18.00%	7.08%
9	997.16	929.92	692.03	6.74%	30.60%	23.86%
10	931.78	769.15	562.48	17.45%	39.63%	22.18%
11	814.17	668.73	691.58	17.86%	15.06%	**-2.81%**
12	964.19	852.26	730.19	11.61%	24.27%	12.66%
13	866.63	711.46	693.58	17.91%	19.97%	2.06%
14	759.72	677.88	657.73	10.77%	13.42%	2.65%
15	674.99	594.17	470.08	11.97%	30.36%	18.38%
16	946.18	812.77	598.21	14.10%	36.78%	22.68%
17	941.30	835.79	736.78	11.21%	21.73%	10.52%
18	635.04	543.13	565.55	14.47%	10.94%	**-3.53%**
19	787.16	508.20	447.89	35.44%	43.10%	7.66%
20	602.31	507.20	472.90	15.79%	21.48%	5.69%
21	362.54	248.70	293.14	31.40%	19.14%	**-12.26%**
22	593.89	577.49	528.11	2.76%	11.08%	8.31%
23	864.55	739.09	485.71	14.51%	43.82%	29.31%
24	719.17	595.11	582.16	17.25%	19.05%	1.80%
25	752.99	493.19	649.69	34.50%	13.72%	**-20.78%**
26	639.10	521.57	514.50	18.39%	19.50%	1.11%
27	798.73	514.50	431.75	35.58%	45.95%	10.36%
28	561.46	415.65	385.35	25.97%	31.37%	5.40%
29	802.48	610.89	739.53	23.87%	7.84%	**-16.03%**
30	865.73	736.18	573.26	14.96%	33.78%	18.82%
AVG	757.14	626.34	557.64	17.74%	25.75%	

Table 19. ACO-TS Recapitulation Result

Based on Table 19, the 2nd, 11th, 18th, 21st, 25th, and 29th DO samplings show that the results for the before-slotting condition are better than the after-slotting condition with FSN-ZABLS. The average picking time on the existing sample is 757.14 seconds, or 12.62 minutes. By using the ACO-TS hybridization algorithm on the before-slotting condition with FSN-ZABLS, it improves 17.74% to 626.34 seconds, or 10.43 minutes. Meanwhile, if the ACO-TS hybridization algorithm is used on the after-slotting condition with FSN-ZABLS, it improves 25.75% to 557.64%, or 9.29 minutes. Although the average of the entire picking time of the 30 samples on both conditions is under 12 minutes and is fulfilled for the picking assessment criteria owned by the company, the use of the ACO-TS hybridization algorithm after slotting improvisation gives better results for the picking process.

Criteria	ACO-TS (s)	ACO (s)	TS (s)
Solution (Avg)	557.64	589.82	670.63
Runtime (Avg)	186.64	0.37	0.05

Table 20. Algorithm Performance Comparison

The model is compared to single use of ACO and TS algorithms to acknowledge the performance of hybridization ACO and TS algorithms. The comparison criteria are solution average on post-slotting condition and average on algorithm runtime. The use of ACO gives solution 589.82 seconds in average, or 5.77% larger than ACO-TS, but it only needs 0.37 seconds average on runtime, or 99.8% better than ACO-TS. The use of TS gives solution 670.63 seconds in average, or 20.26% larger than ACO-TS, but it only needs 0.05 seconds average on runtime, or 99.98% better than ACO-TS. Even though the hybridization algorithm of ACO-TS needs much larger runtime to determine the route of picking on every DO, it is still acceptable for the company because on every cycle on completion DO, the warehouse staff can already determine 3 more routes for the next DO.

The current condition PT. XYZ can only fulfill 31 DO in a day. Theoretically, based on the standard time determined by the company, it should fulfill 40 DO. The uses of the ACO-TS algorithm showed it can fulfill 45 DO in a day on a pre-slotting condition and 51 DO in a day on a post-slotting condition, increasing 27.5% from current performance. If the post-slotting condition is compared to the use of single algorithms ACO and TS, the single use of ACO algorithm can fulfill 48 DO in a day, or 5.9% worse than the use of ACO-TS hybridization, and the single use of TS algorithm can fulfill 42 DO in a day, or 17.6% worse than the use of ACO-TS hybridization.

Another approach that can be used and is viable is Fuzzy Algorithm with Multi Criteria Decision Making (MCDM) method or Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to evaluate the performance of PT. XYZ warehouses. Research conducted by Ebrahimi and Fathi (2017) that uses Fuzzy and DEMATEL methods focuses on proposing a suitable model for Human Capital (HC) performance evaluation based on the 7 indicators determined for the questionnaire. Jindal, Sharma, Sangwan and Gupta (2021) also conducts research that uses Fuzzy and DEMATEL methods and focuses on modeling the Supply Chain Agility based on the 7 dimensions determined for the questionnaire. Büyüközkan and Güler (2021) research uses Fuzzy and MCDM methods to propose a new Supply Chain Analytics tool evaluation with 6 main criteria and a total of 30 sub-criteria. Research conducted by Sufiyan, Haleem, Khan and Khan (2019) also uses a fuzzy algorithm with a combination of the MCDM and DEMATEL methods that evaluates the performance of the food supply chain with 6 indicators. Even though the research conducted that using Fuzzy Algorithm with MCDM or DEMATEL method doesn't concern the routing optimization, it can be used to know the problem root cause for the lacking performance of PT. XYZ warehouses so the next steps to improve the performance can be identified correctly to improve the performance.

5. Conclusion

PT. XYZ is a Fast-Moving Consumer Goods (FMCG) company operating in the food and beverage sector that has 18 SKUs. Rapid and accurate availability of products is considered in business operations, and with the current warehouse performance criteria, the picking process is the worst, with only a 78% achievement rate.

To improve picking time performance, the 18 SKUs were classified using FSN (Fast moving, Slow moving, and Not moving) based on consumption rate and average stay of each SKU. The results of FSN continued with ZABLS to determine the storage location for each SKU on warehouse shelves.

The slotting results will be used for the routing process using hybridization algorithms from Ant Colony Optimization and Tabu Search (ACO-TS) as the initial and destination nodes, where the ACO algorithm will be used as initial solutions that will be evaluated by the TS algorithm to find the better alternative solution.

The routing process results of the hybridization of Ant Colony Optimization and Tabu Search (ACO-TS) algorithms were compared with the conditions of pre-slotting and post-slotting by ZABLS on 30 random sampling DO, where the average picking time on the pre-slotting condition is 626.34 seconds or 10.43 minutes, which improves 17.74% from the existing conditions that need 757.14 seconds or 12.62 minutes. Meanwhile, in the post-slotting condition, the average picking time obtained was 557.64 seconds or 9.29 minutes, it improves 25.75% from the current condition. The average picking time after slotting is under 12 minutes, so the assessment criteria are met. To evaluate the uses of ACO-TS hybridization algorithms, it is compared to the single use of ACO and TS algorithms by solution, and the runtime needs to run the algorithm. The use of single ACO algorithms gives solution 589.82 seconds in average, or 5.77% larger than ACO-TS with 99.8% faster runtime, and the single use of TS algorithms gives solution 670.63 seconds in average, or 20.26% larger than ACO-TS with 99.98% faster runtime.

VRP results will affect the amount of completion DO in each day. Based on standard time, theoretically the company can fulfill 40 DO in a day, and in the current condition, it only fulfills 31 DO in a day. The use of ACO-TS algorithms on pre-slotting conditions can fulfill 45 DO in a day, and on post-slotting conditions, they can fulfill 51 DO in a day. If it compares to the use of single algorithm ACO, it can fulfill 48 DO in a day, and TS can fulfill 42 DO in a day. ACO-TS algorithms on post-slotting conditions give the best results, even though the runtime of the algorithms takes a much longer time. It is still acceptable for the company due to the fact that the fact that on each completion DO it still can determine the next 3 DO routes.

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