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paper text:

3**Vehicle routing problem simultaneous deliveries and pickups with split loads and time windows**

with genetic algorithm (case study in shipping company) ABSTRACT Background: This research addresses the VRPSDPSLTW problem, which involves

13**vehicle routing** for **simultaneous deliveries and pickups with split loads and time windows. The**

main goal is to enhance the optimal utilization of vessel capacity in the field of shipping transportation and logistics. Methods: In this research, the VRPSDPSLTW problem is adapted for Company X, a shipping company based in Surabaya. The optimization approach employed is the Genetic Algorithm, serving as a metaheuristic to effectively optimize vessel capacity utilization. The algorithm uses One Point Crossover and Swap Mutation operators and analyzes various mutation parameters to determine the best configuration. Results: The research generates several outputs, including route plans, loaded and unloaded Twenty-Foot Equivalent Units (TEUs), travel times, and trip utility from the point of loading (POL) to the point of delivery (POD). Based on experimentation, it is found that employing

11**1000 generations** along **with a mutation probability of 0**

.2 produces improved solutions. As a result, the Genetic Algorithm solution enhances average vessel capacity utilization to 80.93%. This marks a substantial 21.23% increase compared to the global average of 59.7% observed for similar vessel usage scenarios. Conclusions: Furthermore, through the introduction of novel route opportunities, it effectively enhances the contributions of each vessel. This achievement results in reaching an optimal average vessel capacity utilization that meets the demand. The findings strongly advocate for the utilization of the Genetic Algorithm, highlighting its potential to substantially improve vessel capacity utilization. As a consequence, this approach

28**plays a** pivotal **role in** elevating **the** efficiency **of** transportation **and logistics** operations **for**

Company X. Keywords:

3**vehicle routing problem, simultaneous deliveries and pickups, split loads, time windows**

, optimization, genetic algorithm INTRODUCTION

15**The Vehicle Routing Problem (VRP**) originated **by Dantzig and Ramser [1959] as a**

solution for fuel delivery. It's now crucial for efficient cargo and travel services, covering various vehicles and customer demands, including sea and air transport. Optimizing delivery routes minimizes costs, travel time, and maximizes vessel capacity use in shipping. This involves sequencing visits using multiple vehicles from a central depot [D.M. Utama et al. 2020]. Depot and vehicle capacities, along with customer requests, influence route design [F. Arnold and K. Sörensen 2019]. VRP has evolved into variations like VRPPDTW, explored by researchers like Sitek et al. [2021] and Dewi and Utama [2021]. This research examines Shipping Company X, operating in Surabaya (Indonesia) since 1984, aiming to enhance its shipping services and economic impact. While offering various services, including port-to-port and international shipping, the company seeks to optimize cargo routes for greater vessel capacity utilization. Current manual processes hinder route efficiency, as evidenced by some vessels operating below 60% capacity. With a fleet of over 40 vessels of varying capacities, simultaneous pickup and delivery, travel time considerations, and load distribution complexities challenge the route optimization for Company X. Genetic Algorithm (GA), by John Holland [1975], optimizes via genetic selection and natural processes, using crossover and mutation. GAs streamline function modeling, reduce errors, and are effective in engineering [J. Protopopova and S. Kulik 2020]. Applied to routing problems [S. Karakatič 2021], GAs address VRP variants, like enhanced solutions by M. A.

20**Mohammed et al**. [2017], W. **Ho et al**. [2008], **and** P. R. **de Oliveira da Costa**

[2018], for delivery efficiency and cost reduction. GA handles capacitated vehicle routing [H. Nazif and L. S. Lee 2012, R. Saxena et al. 2020], fleet size [S. Liu et al. 2009], and improves VRPTW solutions with decomposition [C.-B. Cheng and K.-P. Wang 2009], relevant to VRPSDPSLTW. This research introduces a customized Genetic Algorithm (GA) to tackle VRPSDPSLTW challenges for Shipping Company X, optimizing vessel capacity use while respecting split-load, vessel capacity, and travel time restrictions. Using historical data (January 2018 to February 2023), this research classifies VRP, focusing on VRPSDPSLTW, utilizing route-specific details like demand, distances, travel times, and vessel attributes. The analysis pertains to Surabaya- based vessels of Company X, considering uniform speed, exclusive vessel use, and a one-week testing period. R is utilized for GA, Power BI for visualization, and Minitab for statistical analysis. The research assumes equal port accessibility and excludes size-based limitations at specific ports.
METHODOLOGY

9**The NP-Hard Vehicle Routing Problem (VRP) has**

drawn significant research interest for improving efficiency. Traditionally, it assumes a single depot, single-visit customers, and capacity limits. However, real-world scenarios require adjustments.

22**Dror and Trudeau [1989] and Dror et al. [1994**] introduced **the**

Split Delivery VRP (SDVRP), dividing customer demands among vehicles to reduce distance and vehicle count. Overcoming

1**traditional VRP** constraints, **the Vehicle Routing Problem** with **Simultaneous** Delivery **and** Pickup, **Split Loads, and Time Windows (VRPSDPSLTW**

) model emerges. It involves vehicles from a depot, serving customers while considering

12**simultaneous delivery and pickup** within **time windows**

. This applies even when demand surpasses vehicle capacity, enabling multiple visits or multiple-vehicle service. In a research by Wang et al. [2013], the VRPSDPLTW method was utilized, with ordered elements denoted as J = 1,2,3,...,n,N0 (where N0 includes the depot marked as 0 and 1,2,3,...,n represent customers). Routes involved sequential visits by individual vehicles, connecting successive customers. All routes shared the same depot for departure and return, leading to consistent origins and destinations. Table 1. Notations and mathematical models used in VRPSDPLTW model Source : Wang et al. 2013 Notations:

1Q **capacity of each vehicle** V **set of vehicles, where** $i \in V$ Vi **1 if vehicle** i **is** selected **to serve** a customer, **0 otherwise** J **set of customers {1, 2, 3, . . . ,** n**}** $\forall i$, $i \in J$**, and** $i \neq i$ dii **travel cost (travel distance) between customer** i **and customer** i tii **travel time between customer** i **and customer** i tii **travel speed between customer** $i$and customer i

Di

1**delivery demand at customer** i Qi **pickup demand at customer** i $xiii$ **1 if vehicle** i **travels directly from customer** i **to** customer i, **0 otherwise** $xiii$ amount **of goods delivered**

by vehicle i using the route

24**from customer** i **to customer** i $xiii$ **amount of** goods taken **from customer** i

by vehicle i using

1the route from customer i to customer i $x'iii$ remaining amount of goods

to be delivered form

2customer i to customer i for vehicle i $[Zi, Zi]$ time window for each customer $\forall i \in N0$ rii time when vehicle i starts serving customer i

. Objective functions: min $F1(x) = \sum i \in V|Vi| \sum i \in N0\ x0jj$ (1) min $F2(x) = \sum \sum \sum dii\ xiii$ (2)

31$i \in V$ $i \in N0$ $i \in N0$ Constraints: i

$\in N0 \sum x0jj =$

181 $\forall i \in V$ (3) $\sum xiui - \sum xuii = 0$ $\forall t \in J$, $\forall i \in V$ $i \in N0$ $i \in N0$ (4) i

$\in N0 \sum xiii \geq 1\ \forall$

27$i \in J$, $\forall i \in V$ (5) $n \sum \sum xii = Di$ $\forall i \in J$ $i \in V$ i

=0,$i \neq i$ (6) $n \sum \sum Zii = Qi$ $\forall i \in J$

26$i \in V$ i=0,$i \neq i$ (7) $\sum \sum xiii \geq 1$ $\forall i \in J$, $\forall i \in V$ (8) i

$\in V i \in N$ n $x'iii + \sum Ziii \leq$

7Q $\forall i \in J$, $\forall i \in V$ i=0,i

$\neq i$ (9) $dii\ tii = tii$ $\forall i, i \in J$ (10) $rii + tii - (Zi + tii - Zi)(1 - xiii) \leq rii$ $\forall i \in$

1J, $\forall i \in N0$, $\forall i \in V$ (11) $Zi \leq rii \leq Zi$ $\forall i \in N0$, $\forall i \in V$ (12

) $rii + ti0 - (Zi + ti0 - Z0)(1 - xi0i) \leq Z0$ $\forall i \in J$, $\forall i \in V$ (13) $r0i = Z0$ $\forall i \in V$ (14) $xiii = 0$ $\forall$

7$i \in N0$, $\forall i \in V$ (15) $xiii \in \{0,1\}$ $\forall i$, $i \in N0$, $\forall i \in V$

(16) Objective (1) is to minimize vehicles in delivery routes, and objective (2) is to minimize travel costs. Constraint (3) ensures each of the k vehicles goes from the depot to customer i in set J. Constraint (4) mandates vehicles to serve customers in sequence before returning to the depot. Constraint (5) permits

1a single vehicle to serve a customer multiple

times. Constraints (6) and (7) define

1total delivery and pickup demands at customer

i. Constraint (8) allows multiple vehicles to serve a customer in varying quantities. Constraint (9) ensures vehicle i 's remaining delivery and pickup fit its capacity. Constraint (10) calculates travel time using distance and speed. Constraint (11) regulates

17the arrival time of vehicle i at customer i after the time $rii + tii$ if vehicle i chooses the

route

2from customer i to customer i or earlier than the difference between $Zi - Zi$ if vehicle i does not choose that route

5 days 1000 , if OverTime ≥ 5 days } (25) Penalty Demand = Total Failed Demand (26) Fitness Value = %Utility - Penalty Demand - Penalty Time (27) Company X does not enforce a specific time limit for

completing a trip, but it does provide standard estimates for sailing hours and port time at each port. For the purpose of this research, an ideal total travel time per trip is defined as not exceeding 31 days. Any days that surpass this limit will be deemed as overtime, resulting in a penalty. The implementation of penalty time through a Genetic Algorithm (GA) aims to attain the shortest travel time per trip (penalties are applied to steer the solution towards the 31-day mark), thereby optimizing utility while minimizing unfulfilled demand. Integrating these elements into the fitness value enables GA to assess route performance. The selection favors higher %Utility and lower Penalty Demand and Time, progressively refining solutions for optimal routes and enhanced vessel capacity utilization. Generated solutions are verified, validated, and adjusted for Company X's needs. Result analysis aims for high-performance solutions aligned with goals. Comparing to historical data and constraints evaluates the effectiveness of improving cargo delivery vessel capacity use. RESULTS AND DISCUSSION Data Collection and Analysis Scenario testing utilizes Company X's demand data over a one-week period, which is used as input for the GA. Table

30**1 shows the first** 5 **rows of the** booking **data**

that will be used as forecast demand and further processed. One TEUS is equal to one 20 feet container. The total data collected for forecast demand consists of 1518 rows of data. Table 3. Forecast demand for scenario testing Source : Own work Row POL POD TOTALTEUS 1 IDSUB IDSSS 57 2 IDGGG IDSUB 9 3 IDSSS IDSUB 5 4 IDSSS IDSUB 1 5 IDSSS IDSUB 10 The subsequent action involves adding up the TOTAL TEUS values for matching POL and POD pairs. This sums the TEUs for each corresponding POL-POD combination, leading to a data transformation as depicted in Table 4. Table 4. Aggregated forecast demand based on POL and POD pairs Source : Own work POL POD TEUs POL POD TEUs POL POD TEUs POL POD TEUs IDZZZ IDSUB 7 IDSUB IDFFF 199 IDNNN IDSUB 328 IDFFF IDSUB 352 IDYYY IDSUB 323 IDSUB IDGGG 367 IDNNN IDXXX 1 IDEEE IDSUB 268 IDXXX IDSUB 702 IDSUB IDHHH 70 IDMMM IDSUB 117 IDDDD IDSUB 156 IDVVV IDABC 201 IDSUB IDJJJ 40 IDLLL IDSUB 383 IDCCC IDSUB 33 IDVVV IDALM 161 IDSUB IDKKK 375 IDKKK IDABC 7 IDBBB IDSUB 892 IDVVV IDSUB 116 IDSUB IDLLL 372 IDKKK IDAEF 18 IDAVW IDSUB 22 IDVVV IDXXX 10 IDSUB IDMMM 207 IDKKK IDALM 43 IDANO IDSUB 5 IDSUB IDAAA 89 IDSUB IDNNN 123 IDKKK IDCCC 8 IDAMN IDSUB 63 IDSUB IDABC 86 IDSUB IDPPP 26 IDKKK IDDDD 53 IDAKL IDSUB 595 IDSUB IDAEF 217 IDSUB IDQQQ 193 IDKKK IDGGG 35 IDAJK IDQQQ 3 IDSUB IDAEG 14 IDSUB IDSSS 693 IDKKK IDMMM 48 IDAJK IDSUB 545 IDSUB IDAGH 236 IDSUB IDUUU 54 IDKKK IDNNN 21 IDAHI IDSUB 236 IDSUB IDAHI 238 IDSUB IDVVV 217 IDKKK IDQQQ 30 IDAGH IDSUB 2 IDSUB IDAJK 117 IDSUB IDWWW 2 IDKKK IDSSS 63 IDAEF IDSUB 125 IDSUB IDALM 90 IDSUB IDXXX 158 IDKKK IDSUB 140 IDAEF IDYYY 261 IDSUB IDAMN 94 IDSUB IDYYY 302 IDKKK IDUUU 6 IDAEF IDZZZ 40 IDSUB IDAUV 9 IDSUB IDZZZ 35 IDKKK IDVVV 42 IDABC IDSUB 18 IDSUB IDBBB 639 IDSSS IDSUB 774 IDKKK IDYYY 26 IDABC IDXXX 9 IDSUB IDCCC 203 IDQQQ IDSUB 217 IDJJJ IDSUB 94 IDAAA IDBBB 1 IDSUB IDDDD 150 IDPPP IDSUB 36 IDGGG IDKKK 1 IDAAA IDSUB 562 IDSUB IDEEE 114 IDOOO IDSUB 90 IDGGG IDSUB 336 To determine port visit counts, identify the maximum TEUs achieved from past booking and vessel journey data (2018-2022). This calculates the highlighted maximum TEUs (Table 4) by finding the most transported TEUs from POL to POD in a single vessel journey. Next, assign unique identifiers to ports and determine their visit count (VISIT). VISIT represents required visits per port. Calculate VISITNR by dividing TOTALTEUS (demand) by MAXTEUSPERVISIT (highlighted), giving estimated visits. VISIT column contains rounded VISITNR values. For example, In Table 5, the highest VISIT of 3 for port IDYYY (POD) means 3 visits. Table 6 shows resulting visits for forecasted ports. This leads to 85 port visits, exceeding the initial 35, as some ports are visited multiple times (except Surabaya, dividing or serving as home base). Table 5. Example of calculating the number of visits for IDYYY Source : Own work POL POD TOTALTEUS MAXTEUSPERVISIT VISITNR VISIT IDYYY IDSUB 323 668 0.484 1 IDAEF IDYYY 261 523 0.499 1 IDKKK IDYYY 26 47 0.553 1 IDSUB IDYYY 302 111 2.721 3 Table 6. The required number of visits (count) to each port (35 ports in demand data, except for idsub as the home base) for each chromosome Source : Own work

16**Port Count Port Count Port Count Port Count Port Count Port Count**

IDAAA 2 IDXXX 2 IDFFF 3 IDKKK 5 IDPPP 1 IDAJK 2 IDBBB 7 IDYYY 3 IDGGG 4 IDLLL 4 IDAEG 1 IDAKL 3 IDCCC 2 IDAUV 1 IDAVW 1 IDMMM 3 IDAGH 3 IDALM 3 IDDDD 3 IDZZZ 1 IDHHH 2 IDNNN 2 IDQQQ 2 IDAMN 2 IDVVV 3 IDANO 1 IDABC 2 IDOOO 1 IDAHI 2 IDUUU 2 IDWWW 1 IDEEE 1 IDJJJ 2 IDAEF 3 IDSSS 5 Total Count = 85 Genetic Algorithm Here, the decision is to establish an initial population with 16 chromosomes, each representing port collections. Genes in a chromosome follow Table 6's visit count. Notably, IDSUB is different; it acts as both starting and ending points, dividing chromosomes into trips. Initial Population generates 16 random gene combinations. This ensures diverse starting points. Each chromosome includes 35 ports, totaling 85 visits. Genes in a chromosome initially count 87 (85 visits + 2 IDSUBs at the beginning and end of the chromosome). However, gene count grows with each generation. Chromosomes are split into trips via trimming, randomly picking 3 to 7 genes (excluding IDSUB) per trip. "SubKel" column labels trips, with IDSUBs marking partitions. This breaks 1 chromosome into 15 trips (115 genes), adding 28 new IDSUB genes. Data reshapes for journey analysis, streamlining structure for fitness calculation from POL to POD. Table 8 demonstrates this transformation, simplifying the original format. Table 7. Original data set format Source : Own work Table 8. Data set format after transformation Source : Own work Port Chromosome SubKel IDSUB 1 A IDAGH 1 A IDAUV 1 A IDBBB 1 A IDSUB 1 A Table 9. Demand from IDSUB to IDAEF and number of visits to IDAEF Source : Own work POL POD TOTALTEUS POD VISIT IDSUB IDAEF 217 3 POL POD Chromosome SubKel IDSUB IDAGH 1 A IDAGH IDAUV 1 A IDAUV IDBBB 1 A IDBBB IDSUB 1 A Fig. 2. Concept of split loads for demand from IDSUB to IDAED Source : Own work Load-unload quantities are determined based on total TEUs in demand data and visits from relevant ports. For instance, if there's a demand of 217 TEUs from POL IDSUB to POD IDAEF this week, with IDAEF visited three times within a chromosome, successful transport requires IDSUB (POL) preceding IDAEF

(POD). Proportional cargo allocation is crucial, achieved by dividing total TEUs by required visits. With 217 TEUs from IDSUB to IDAEF over three visits, allocation is 72 TEUs, 72 TEUs, and 73 TEUs. Unsuccessful visits result in untransported demand (145 TEUs if 2nd and 3rd fail, or 73 TEUs if only 3rd fails). Loading involves direct loading of subsequent ports' demands at each POL. At POD, a specific portion unloads. This continues until trip cargo is 0. Shipping load calculation considers TEUs from POL to POD. Next, vessel placement maximizes each trip's cargo. Each chromosome is assigned a vessel sequentially, matching cargo to closest vessel capacity. If between ideal and historical capacity, utility calculations use maximum cargo. Vessel assignment proceeds until each trip has a vessel. Table 10 demonstrates this process for a trip in one chromosome, outlining load, unload, shipping load, and vessel placement. Table 10. Example calculation results: load, unload, shipping cargo, and vessel placement in a trip for a single chromosome Source : Own work POL POD Chromosome SubKel LOAD UNLOAD Shipping Load Max Shipping Load VESSEL ID VESSEL NAME PAY LOAD IDSUB IDAGH 1 A 188 80 188 188 BBB BBBBBB 208 IDAGH IDAUV 1 A 2 9 110 188 BBB BBBBBB 208 IDAUV IDBBB 1 A 0 99 101 188 BBB BBBBBB 208 IDBBB IDSUB 1 A 136 138 138 188 BBB BBBBBB 208 In Table 11, the evaluation results of fitness value for all chromosomes in the initial population are presented, along with a detailed breakdown of the components contributing to the fitness value. Table 11. Fitness value calculation results for all chromosomes in the initial population Source : Own work Chromosome %Utility FAILED PENALTYDEMAND OVERTIME PENALTYTIME fitness value 1 80.23 880 880 166 1000 -1799.77 2 77.2 943 943 130 1000 -1865.8 3 77.22 589 589 147 1000 -1511.78 4 73.91 960 960 145 1000 -1886.09 5 76.67 862 862 131 1000 -1785.33 6 75.76 1024 1024 127 1000 -1948.24 7 75.64 811 811 116 1000 -1735.36 8 79.88 909 909 90 1000 -1829.12 9 78.6 927 927 108 1000 -1848.4 10 76.07 928 928 143 1000 -1851.93 11 80.01 867 867 141 1000 -1786.99 12 76.52 799 799 105 1000 -1722.48 13 73.09 759 759 115 1000 -1685.91 14 77.09 898 898 129 1000 -1820.91 15 75.74 729 729 111 1000 -1653.26 16 74.62 777 777 109 1000 -1702.38 Subsequently,

10**selection probability is calculated by dividing** an individual's **fitness value by the total fitness value of** the **population**, establishing chances **for**

the mating pool. Employing the roulette wheel method, individuals are chosen for the pool using a random number in the "rand" column. The first chromosome with a "cumulative_prob" exceeding the random number enters the pool. After pool selection, individuals are paired as parent pairs for crossover or genetic recombination if criteria are fulfilled, as shown in Table 12. Table 12. Roulette wheel results and parent pairs for crossover Source : Own work rand Chromosome cumulative_prob Pair rand Chromosome cumulative_prob Pair 0.722 12 0.738 1 0.966 16 1 5 0.08 2 0.1277 1 0.378 7 0.4059 5 0.041 1 0.0657 2 0.316 6 0.3477 6 0.814 14 0.8675 2 0.489 9 0.5381 6 0.597 10 0.6041 3 0.468 8 0.4716 7 0.497 9 0.5381 3 0.239 4 0.2439 7 0.663 11 0.6693 4 0.969 16 1 8 0.131 3 0.1915 4 0.408 8 0.4716 8 After obtaining chromosome pairs, the subsequent step is selecting pairs for crossover using a crossover probability (Pc) set at 0.9. Crossover occurs if the randomly generated number for each pair is below 0.9. Employing one-point crossover, a random cutting point is assigned to each pair. Chromosomes serve as "parents," yielding two offspring or "children" with equal chromosomes. Initial mutation probability (pm) ranges from 0.01 to 0.2 for real-world optimization. Following crossover, each chromosome's randomly generated number between 0 and 1 determines mutation. If the number is below pm, the chromosome mutates, exchanging two random gene points (swapping mutation) and forming a new offspring chromosome. New offspring resulting from crossover and mutation are merged with the initial population, then evaluated for fitness. Retaining the two best chromosomes, merged chromosome averages are calculated. If the target generation isn't reached, chromosomes ranked 3rd to 100th become the next generation's initial population, ensuring genetic diversity and optimal outcomes. Optimization Results of Scenario Testing In this research, the optimization of GA solutions for the VRPSDPSLTW problem consists of three key variables: population size, mutation probability, and crossover probability.

21**The crossover probability** is **set** at **0.9**, and the initial **population size** is 16 **individuals. The**

mutation probability is tested at 0.01 and 0.2, each repeated five times with the same initial population size and 500 generations per trial. Analysis of the best fitness value graphs in Fig. 5 and Fig. 6 reveals convergence at the 500th generation for both mutation probabilities. Consequently, it can be inferred that, under these conditions, mutation probabilities of 0.01 and 0.2 yield similar qualities, facilitating a meaningful comparison. Table 13. Analysis of mutation probability parameters Source : Own work Pengujian Ke- First Best Fitness Value %Utility Failed Demand (TEUs) OverTime (Days)

6**pm = 0**.01 **pm = 0.2 pm** = 0.01 pm = **0.2 pm = 0**.01 **pm = 0.2 pm = 0**.01 **pm = 0.2**

1 -978.6 -920.85 76.4 81.15 55 2 141 101 2 -980.8 -929.72 72.2 79.28 53 9 103 125 3 -931.05 -921.18 79.95 79.82 11 1 115 127 4 -938.98 -919.11 79.02 80.89 18 0 153 116 5 -939.78 -928.74 80.22 80.26 20 9 124 79 Mean -953.84 -923.92 77.56 80.28 31.4 4.2 127.2 109.6 Worst -980.8 -929.72 72.2 79.28 55 9 153 127 Best -931.05 -919.11 80.22 81.15 11 0 103 79 Based on the findings in Table 13, a mutation probability of 0.2 demonstrates the highest potential for achieving optimal fitness values. In this research, higher fitness values indicate improved performance and closer alignment with objectives. Remarkably, the peak fitness value of -919.11 was achieved with a 0.2 mutation probability, surpassing the 0.01 probability results. The subsequent sections will delve deeper into these optimal fitness value variables and compare them with the current conditions. The consistency of testing with a mutation probability of 0.2 is evident as the best

solution (-919.11) closely matches the average of all tests (-923.92). Fig. 3 and Fig. 4 provide supporting visuals, showcasing the best fitness values for mutation probabilities of 0.01 and 0.2, respectively. Fig. 4.

4The best fitness values for each generation

with 500 Fig. 3.

4The best fitness values for each generation

with

5500 generations and a mutation probability of 0.01 for each

test

5generations and a mutation probability of 0.2 for each

test Source : Own work Source : Own work The optimal fitness value achieved after 500 generations of testing was -919.11, representing a substantial improvement of 21.13%. This signifies that the average % capacity utilization of the tested vessels reached 80.89%, exceeding the historical average % capacity utilization of all vessels in Company X's history, which was 59.76% based on the data from previous operations. A mutation probability of 0.2 exhibits a higher likelihood of producing better results compared to 0.01. Although convergence solutions have been achieved using 500 generation, the solution still show sloping increasing trend, therefore number of generations are increased to be 1000. Generations are also increased to further reduce the number of overtime days. Fig. 5 presents

4the best fitness values for each generation with 1000 generations for

each test, while Table 14 provides detailed results for each test with 1000 generations. Fig. 5. Best fitness values across

111000 generations with a mutation probability of 0

.2 for each test Source : Own work Table 14. The results of 5 tests with a mutation probability of 0.2 and 1000 generations Source : Own work Testing - First Best Fitness Value %Utility Failed Demand OverTime

14pm = 0.2 pm = 0.2 pm = 0.2 pm = 0.2 1

-919.07 80.93 0 94 2 -923.6 78.4 2 138 3 -918.61 82.39 1 123 4 -917.54 83.46 1 115 5 -922.23 79.76 2 76 Mean (1000 generations) -920.21 80.99 1.2 109.2 Current Best Solution: First Best Fitness Value %Utility Failed Demand OverTime -919.11 80.89 0 116 Mean of mutation probability 0.2 with 500 Generations (all tests) First Best Fitness Value %Utility Failed Demand OverTime -923.92 80.28 4.2 109.6 Test 4 with 1000 generations outperformed the current best solution with higher %Utility (+2.57%), lower OverTime (-1 day), and improved fitness value (+1.57). However, it experienced unmet demands, impacting %Utility. As a result, Test 1 was chosen as the best solution, showing increased %Utility (+0.04) and reduced OverTime (-22 days) compared to the previous best solution, with no failed demands, providing more consistent results than Test 4. Although Test 500 met individual requirements, Test 1000 showed potential for better overall solutions with higher %Utility, lower demand failure rate, and shorter delivery times. The increase in fitness value per generation from the optimal solution will be visualized in Fig. 6. The visualization will include the second

19best fitness value and the average fitness value of the entire population for

each generation. Fig. 6. Trend of fitness value per generation for the optimal solution Source : Own work Table 15 provides a detailed breakdown of the output from the GA process that led to the optimal fitness value from a total of 15 trips (the table displays 1 sample trip). Fig 7. represents the practical results obtained from these 1 sample trip out of the total of 15 trips. It presents the planned routes to fulfill the designated demand, including the load and unload quantities, utility, and time required for each journey between POL and POD. Furthermore, the output also provides information regarding the average % capacity utilization of the vessel for the entire voyage (80.93%), no failed demand (0 TEUs), and the total sum of overtime for the entire journey (94 days). The following section will present a comprehensive analysis of these variables. Table 15. Output of GA process for optimal fitness value (1 out of 15 trips) Source : Own work POL POD Chro moso me Sub Kel LOAD UNLOAD Shipping Load VESSEL ID VESSEL NAME PAY LOAD % UTILITY TRIP TOTAL TIME DAYS IDSUB IDAMN 66 A 193 46 193 TTT TTTTTTT 453 42.6 6.14 IDAMN IDFFF 66 A 31 67 178 TTT TTTTTTT 453 39.29 5.7 IDFFF IDAKL 66 A 118 0 229 TTT TTTTTTT 453 50.55 5.51 IDAKL IDAGH 66 A 199 80 428 TTT TTTTTTT 453 94.48 4.48 ADAGH IDSUB 66 A 2 350 350

TTT TTTTTTT 453 77.26 2.07 Fig. 7. Practical illustration of GA solution (1 out of 15 trips) Source : Own work The case study results displayed successful TEUs demand, but various scenario tests uncovered potential forecast demand failures. In such cases, unmet demands and their POL and POD origins can be identified. Solutions include adapting forecast targets or allocating unmet demands to future trips. Table 16 shows the required time for each trip to return to the home base in the proposed solution can be observed. This total time includes travel time from all POL to POD on the trip, added with port time (idle time of the vessel), and measured in days. Currently, the company does not have an ideal figure to determine how long 1 trip should take to fulfill the demand. Therefore, in the implemented GA program, the authors apply high penalties to solutions with significant total overtime (days > 31) across all trips. This

23**is to minimize the total time of** each journey **as** close **as possible**

to the ideal figure. The results show that to meet the demand in the real-case scenario test, 15 trips are required with an average delivery time of 35.57 days. The case study results revealed no failed TEUs demand in the utilized scenario, yet various tests demonstrated potential forecast demand inaccuracies. In such instances, unfulfilled demands and their POL and POD origins can be displayed. Addressing this entails options like refining forecast targets or allocating unfulfilled demands to future trips, requiring careful consideration of utility maximization, demand fulfillment, and travel time trade-offs during the GA optimization process. Optimization focus adjustments can be realized by reevaluating parameters and penalty functions. Table 16. The time taken by each trip from homebase to return to homebase Source : Own work Trip VESSELID VESSELNAME TOTALTIME (Days) %UTILITY TRIP 1 A TTT TTTTTT 23.90 60.8389 2 B GGG GGGGGG 25.01 71.8056 3 C ABO ABOABO 30.38 81.7243 4 D WWW WWWWWW 40.53 93.6330 5 E ABY ABYABY 54.22 68.3165 6 F PPP PPPPPP 46.16 79.2683 7 G ABU ABUABU 36.18 74.1385 8 H OOO OOOOOO 36.72 87.8021 9 I BBB BBBBBB 31.02 91.4530 10 J ABS ABSABS 48.54 79.9195 11 K ABR ABRABR 32.32 80.1060 12 L QQQ QQQQQQ 37.86 91.1635 13 M RRR RRRRRR 36.61 77.6126 14 N ABI ABIABI 24.51 86.2894 15 O YYY YYYYYY 29.51 89.8960 Mean 35.57 80.93 The GA program penalizes solutions exceeding 31 days of overtime across trips to align with benchmarks, due to the absence of a standard trip duration. Real-case testing demands 15 trips for demand fulfillment and successfully achieves an average trip time close to 31 days, specifically averaging 35.57 days, representing optimal results. In the same table, the average vessel capacity utilization percentage for all trips is presented. This data offers a clear overview of trip-level utilization. Notably, each trip's average utilization surpasses 60%, with an overall average of 80.93%. These findings indicate a fairly optimal ship capacity utilization level from the GA algorithm. In the detailed analysis, the GA solution's utilization will be compared with historical data to assess improvements in ship capacity utilization. Table 17. Results of utilization evaluation for the involved vessels in solving scenario tests with GA Source : Own work % % VESSELID VESSELNAME Result History Utility Utility ABS ABSABS 79.92% 68.12% TTT TTTTTT 60.84% 55.54% ABR ABRABR 80.11% 54.64% ABY ABYABY 68.32% 57.36% YYY YYYYYY 89.90% 61.49% BBB BBBBBB 91.45% 66.23% GGG GGGGGG 71.81% 54.65% RRR RRRRRR 77.61% 52.20% ABI ABIABI 86.29% 76.32% ABO ABOABO 81.72% 53.46% PPP PPPPPP 79.27% 59.19% OOO OOOOOO 87.20% 63.22% Fig. 8. Clustered Column Chart: Historical % Utility vs. % QQQ QQQQQQ 91.16% 60.36% WWW WWWWWW 93.63% 46.76% Utility Results Using GA ABU ABUABU 74.14% 65.67% Mean 80.93% 59.70% Table 17 shows the utility evaluation results for the selected vessel in GA scenario testing. "Result Utility" indicates post-GA optimization, while "History Utility" portrays historical usage (2019-2022) without GA, reflecting actual fulfillment rates. Notably, a 21.23% increase is observed. Fig. 8 further illustrates the positive impact of GA, with improved vessel performance in capacity utilization. All vessels experience enhanced utility after GA optimization, showcasing its positive contribution to effective vessel capacity utilization for cargo delivery. When a t-test is conducted statistically, the null hypothesis (H0) assumes no difference between the population means of Result %Utility and History %Utility. On the other hand, the alternative hypothesis (H1) suggests a higher mean for Result %Utility. The t-

8**test results (P- Value (0.000) < alpha (0.05**

)) lead to the rejection of H0 and the acceptance of H1. This indicates a substantial increase in the mean of Result %Utility in comparison to History %Utility. Conclusion The Genetic Algorithm (GA) effectively tackled the complex

29**VRP with simultaneous** pickup **and** delivery, **split-loads**, vessel capacity, **and time**

window constraints (VRPSDPSLTW) optimization problem. Employing GA with parameters 1000

25**generations, 0.9 crossover probability, and 0.2 mutation probability**

, vessel capacity utilization significantly rose to 80.93%, a remarkable 21.23% enhancement from the prior 59.7%. GA innovatively devised routes, yielding superior capacity utilization while considering empty container loads. Notably, the GA solution adeptly managed port visits, split-loads, time, and vessel capacity for POL to POD trips. Average trip duration was approximately 35 days, aligning closely with the 31-day target. Achieving a 100% sales target validated GA's efficacy. Future research can explore multi-objective GA for conflicting goals and address real-world factors like stochastic voyage time and time-dependent demand. Recommendations To enhance the GA's performance in the

12**future research, the following** suggestions **can be considered**: ? Modify **the**

Control Engineering, 9, 61-72. https://doi.org/10.1080/21642583.2020.1863276. Karakatič, S., 2021. Optimizing nonlinear charging times of electric vehicle routing with genetic algorithm. Expert Systems with Applications, 164, 114039. https://doi.org/10.1016/j.eswa.2020.114039. Liu, S., Huang, W., Ma, H., 2009. An effective genetic algorithm for the fleet size and mix vehicle routing problems. Transportation Research Part E: Logistics and Transportation Review, 45, 434-445. https://doi.org/10.1016/j.tre.2008.10.003. Visutarrom, T., Chiang, T., 2019. An evolutionary algorithm with heuristic longest cycle crossover for solving the capacitated vehicle routing problem. In IEEE Congress on Evolutionary Computation (CEC), 2019 (pp. 673-680). https://doi.org/10.1109/CEC.2019.8789946. Toth, P., Vigo, D., 2002. The vehicle routing problem. SIAM. http://dx.doi.org/10.1137/1.9780898718515 Ho, W., Ho, G. T. S., Ji, P., Lau, H. C. W., 2008. A hybrid genetic algorithm for the multi-depot vehicle routing problem. Engineering Applications of Artificial Intelligence, 21, 548-557. https://doi.org/10.1016/j.engappai.2007.06.001. Wang, Y., Ma, X., Lao, Y., Wang, Y., Mao, H., 2013. Vehicle routing problem simultaneous deliveries and pickups with split loads and time windows. Transportation Research Record Journal of the Transportation Research Board, 2378, 120-128. doi:10.3141/2378-13.