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Addressing Global Sustainability Challenges in Business and Industry through Technology, Governance and Culture

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Application of Genetic Algorithm in Containerships Network Design Problem

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Abstract - **This paper studies the application of genetic algorithm (GA) for heterogeneous vehicle routing problem with time windows (HVRPTW) that considers fixed costs. Typical application of this VRP variant can be found in network design problem for containerships and an example from Indonesian archipelago is used as a case study. The GA is extended from the principles of effective GA published in the literature and its performance is compared to that of LP optimization using branch-and-bound. Two approaches in population initialization are tested but no differences found. However, on reaching optimality, the GA can point out the optimal or less than one percent optimal solution ten times faster than the B&B.**

Keywords - **Genetic algorithm, vehicle routing, network design**

I. INTRODUCTION

Vehicle routing problem (VRP) was first formulated under the name “The Truck Dispatching Problem” in 1959 [1]. It generalizes the NP-Hard Traveling Salesman Problem (TSP) and consequently all of its other variants are also NP-Hard [2]. The VRP variants can involve any or combination of these factors: time constraints, backhauls, modes of deliveries (with pick-ups or split), stochastic nature of some elements such as demand size or travel time, site-dependent problem, multiple objectives, etc. The list goes on as the model continues adopting rich real-world examples. The VRP literature is also massive as evidenced by its annual exponential growth at 6.09% between 1956 and 2005 [3].

Given the complexity, it becomes increasingly common nowadays for researchers to turn their attention to heuristics and metaheuristics for solving the VRP. Tabu search (TS) stands out as the most effective metaheuristic for VRP as argued in [4]. However, a simple but effective genetic algorithm (GA) was formulated and proposed in [5] and the author showed that the algorithm was able to outperform most published TS heuristics on some well-known benchmark instances. This GA was later extended to cater heterogeneous and limited number of vehicles in [6]. A separate work that deals with heterogeneous VRP but with unlimited number of vehicles appeared in [7]. Although the models studied in these papers are already complex with the inclusion of heterogeneous vehicles and time windows, fixed costs are not assumed and the heterogeneity of the vehicles comes only from capacities and speeds (translated in variable costs). Omitting the fixed costs may not be critical in land-based logistics, however, in maritime logistics, the cost of idling a ship is very large owing to its fixed cost, thus ignoring it in evaluation could lead to erroneous conclusion.

The subset between maritime logistics and VRP is a much smaller domain than each of the parent theme. One example is the use of VRP with list-based threshold acceptance (LBTA) metaheuristic to solve a coastal freight shipping problem with 13 nodes (ports) and 25 arcs (sea links) [8]. Filtered further with GA as the solution methodology, only a few can be mentioned. An example is the application of GA in routing a fleet of homogeneous vessels by considering repositioning of empty containers [9]. In this study, the authors compared the solution found by GA with the optimal solution found by brute force approach and showed that their GA always found the best solution. However, computation time is not benchmarked against other optimization methods (e.g., MILP), thus it is not possible to evaluate the overall efficiency of their GA. The authors later suggest that in general the computation should terminate at most at the 100th generation. Another example is the use of GA for VRP with time windows and pick-ups and deliveries (VRPTWPD). Soft time deadlines are imposed (penalty cost is incurred if a deadline is not met) rather than strict deadlines, and homogeneous vessels with capacity of 100 small containers and average speeds of 12 knots are employed for a real problem in the Aegean Archipelago [10]. The authors used similar methods of chromosome construction (permutation of *n* nodes without trip delimiters) and crossover operator (order crossover), but differ in mutation operator (simple gene swapping versus local search) as used in [5] and [6]. Last, containership routing using GA in an 18-port hub-and-spoke network problem is studied in [11]. Two types of heterogeneous vessels (1,500 and 8,000 TEU) are considered. Since hub-and-spoke environment is different from the classical VRP, one-point crossover followed by rearrangement to ensure validity of the chromosome is adopted. The algorithm is validated using the Civil Aeronautics Board data set which is widely used in hub-and-spoke network problems.

The above review indicates scarcity of VRP studies using GA, particularly in maritime logistics that demands specific variants of VRP. The closest are [6] and [10] but both did not include fixed costs as important parameter. The aim of this paper is to fill this gap by showing a case example from a perspective of a liner shipping company operating in Indonesian archipelago.

II. METHODOLOGY

A. *Data Generation*

The case study is built according to the following scenario. A liner shipping company operates in domestic seas serving twelve ports (excluding the depot port) with a distance range of 63–2282 nautical miles (nm). The company owns nine heterogeneous feeder vessels with capacities ranging between 400 and 800 TEU (twenty-foot equivalent unit) and speeds of 13–17 knots. The port Jakarta has a large demand that cannot be served in one shipment of containers by any of the available vessel, thus the demand of this port is divided into two batches and a dummy city at the same coordinate is created to assume roughly half of the demand. This dummy city adds another port-of-call thus brings the total number of ports to thirteen. The layout of the cities is shown in Figure 1.

Fig. 1. Geographical layout of the case study.

The costs data are extrapolated from those of larger ships in [12], without inflation adjustment. The bunker costs in [12] are estimated from the speed of 19 knots. A cubical constant is obtained from the relationship of speed and cost which is then used to estimate bunker costs of the other speeds.

The maximum due dates that serve as upper time windows in each port are seven days to correspond with typical weekly liner service. This will allow a vessel to visit more than just one port in a trip. The port demands follow [13] and 4.5% is assumed as the market share of the company, converted to weekly figures. The number is then used as the mean of uniform distribution to generate data sets. The demands also affect berthing times: a constant of eight hours plus a fixed 40-container-per-hour unloading times in all ports are assumed for these figures, except in home base port Surabaya where only eight hours of service time is assumed.

The distances, data sets of demand, due dates, and vessels' particulars can be accessed in the following URL: http://ti.ubaya.ac.id/index.php/component/content/article/24-dosen/224-ga-for-hvrptwf.html

B. *Mathematical Model for HVRPTWF*

The effectiveness of GA developed in this paper will be evaluated by comparing the results with those obtained from linear programming optimization using branch-and-bound solver. The LP model for heterogeneous vehicle routing problem with time windows and fixed cost (HVRPTWF) is extended from VRPTW [14] and the problem can be stated as: given a fleet of heterogeneous vehicles differing in capacities, speeds, and both fixed and variable costs, determine a set of vehicle trips to minimize total costs, such that: (1) each vehicle starts from and ends at the depot, (2) each customer is visited exactly only once within a predetermined time frame, and (3) total demand in each trip does not exceed the vehicle capacity.

The following are definitions of sets, parameters and variables, and the model formulation.

$\mathcal{V}$	Set of vessels, indexed by v
$\mathcal{A}$	Set of arcs (i, j) denoting a flow from port i to port j
$\mathcal{N}$	Set of all ports $\mathcal{N}=\{0, 1, \ldots, N\}$; $\{0\}$ is depot port
$\mathcal{C}$	Set of ports-of-call, or $\mathcal{N}\setminus\{0\}$
f^v	Weekly fixed cost of vessel v
$c_{i,j}^v$	Bunker cost of vessel v if it sails from port i to port j
$t_{i,j}^v$	Sailing time of vessel v if it sails from port i to port j
C^v	Capacity of vessel v
D_i	Total demand at port i
T_i	Due date at port i
p_i	Service time at port i
M	A large constant
$x_{i,j}^v$	Binary variables for vessel v in arc (i,j); $x_{i,j}^v = 1$ if the vessel traverses arc (i,j) and $x_{i,j}^v = 0$ otherwise
s_i^v	Time window for vessel v at port i

$$\text{Minimize} \sum_{v\in\mathcal{V}} \sum_{i,j\in\mathcal{A}} x_{i,j}^v . c_{i,j}^v + \sum_{v\in\mathcal{V}} \sum_{j\in\mathcal{A}} f^v . x_{0,j}^v \qquad (1)$$

Subject to:

$$\sum_{v\in\mathcal{V}} \sum_{i,j\in\mathcal{A}} x_{i,j}^v . C^v \geq D_i \qquad \forall\, i \in \mathcal{C} \qquad (2)$$

$$\sum_{i\in\mathcal{C}} D_i \sum_{j\in\mathcal{N}} x_{i,j}^v \leq C^v \qquad \forall\, v \in \mathcal{V} \qquad (3)$$

$$\sum_{i\in\mathcal{N}} x_{i,k}^v - \sum_{j\in\mathcal{N}} x_{k,j}^v = 0 \qquad \forall\, k \in \mathcal{C};\ v \in \mathcal{V} \qquad (4)$$

$$x_{i,i}^v = 0 \qquad \forall\, i \in \mathcal{N};\ v \in \mathcal{V} \qquad (5)$$

$$\sum_{j\in\mathcal{C}} x_{0,j}^v \leq 1 \qquad \forall\, v \in \mathcal{V} \qquad (6)$$

$$s_i^v \leq T_i \qquad \forall\, i \in \mathcal{C};\ v \in \mathcal{V} \qquad (7)$$

$$s_i^v + t_{i,j}^v + p_i - M(1 - x_{i,j}^v) \leq s_j^v \qquad \forall\, i \in \mathcal{N}; j \in \mathcal{C};\ v \in \mathcal{V} \qquad (8)$$

$$x_{i,j}^v \in \{0, 1\} \qquad \forall\, i,j \in \mathcal{A};\ v \in \mathcal{V} \qquad (9)$$

$$s_0^v = 0 \qquad \forall\, v \in \mathcal{V} \qquad (10)$$

$$s_i^v \geq 0 \qquad \forall\, i \in \mathcal{N};\ v \in \mathcal{V} \qquad (11)$$

The above formulation is explained as follows. The objective function (1) minimizes total cost. Constraints (2)–(3) guarantee that demands are fulfilled without violating vessel capacity. Constraints (4) are the flow balancing equations. Constraints (5) prevent a vessel from looping in the same node. Constraints (6) regulate a vessel to take only one tour. Constraints (7)–(8) are the time windows formulation with M being a large constant such that when $x_{i,j}^{v} = 0$, the constraints will become redundant. This formulation allows sub-tour breaking constraints to be non-existent. Finally, constraints (9)–(11) are the nature of decision variables involved. Note that since $x_{i,j}^{v}$ are binary and s_i^v are continuous, the model is a mixed integer linear programming problem.

C. Genetic Algorithm for HVRPTWF

The GA for HVRPTWF is developed based on [5] and [6]. In [5], a tour-splitting procedure called *Split* is introduced with a purpose to partition a chromosome m into T feasible trips, subject to available constraints such as vehicle capacity and time windows. For problems with heterogeneous vehicles, the splitting becomes more complex and necessitates a dynamic programming approach [6]. *Split* is optimal for VRP but can lead to infeasibility for HVRP.

An important point to highlight between the GA for VRP and HVRP concerns the use of heuristics for some chromosomes in the initial population construction. In [5], the author used Clarke-Wright savings, Mole-Jameson sequential insertion, and Gillett-Miller sweep algorithms to build the first three chromosomes, but in the absence of reliable heuristics for HVRP, randomly generated chromosomes improved by *Split* were used instead in [6]. A promising development was later shown in [15] where the author proposed two simple heuristics for HVRP called *load* and *ray* heuristics that could possibly help the GA engine in HVRP cases.

Both in the initial construction and during the runs, the population is managed in such a way that all members are unique and no identical members (clones) can exist in the same generation. This is achieved by controlling a parameter called the *dispersal value* (*DV*) that serves as a threshold for accepting new population members. A new chromosome C is accepted if it is *spaced*, i.e., it has a fitness-value gap larger than the *DV* (12).

C Newly generated chromosome
p_t Chromosome number t in the population
S Number of population

$$|F(C) - F(p_t)| > DV \qquad t = 1..S \tag{12}$$

Mutation operator using local search is triggered at a certain probability after a successful reproduction of a new chromosome. The operator works by scanning $O(n^2)$ neighborhoods of n cities and $O(k^2)$ neighborhoods of k vehicles, and performs swapping of cities or vehicles via a number of moves (Fig. 2). Each time a chromosome is improved by one move, the iteration restarts from the first move. LS_2 is used in this paper and the series of steps therein (M2-1 to M2-4) is executed in each step of LS_1 (M1-1, M1-2, etc.). Therefore, the complexity of LS_2 is $O(n^2k^2)$. The combined population management and local-search mutation operator described above is a form of a memetic algorithm, producing a hybridized GA.

LS_1: u and v are nodes in different trips; x is the successor of u, y is the successor of v
M1-1. Relocate u to a different trip,
M1-2. Swap u and v,
M1-3. Replace $(u; x)$ and $(v; y)$ by $(u; y)$ and $(v; x)$,
M1-4. Replace $(u; x)$ and $(v; y)$ by $(u; v)$ and $(x; y)$.

$LS_2 = LS_1$ + the following:
F is the set of free vehicles; T_1 and T_2 are two different trips
M2-1. The two trips exchange their vehicles,
M2-2. T_1 gives its vehicle to T_2 and takes one in F,
M2-3. T_2 gives its vehicle to T_1 and takes one in F,
M2-4. Both T_1 and T_2 exchange their current vehicle with a free one.

Fig. 2. Local search mutation.

The preceding tenets of effectively-proven GA are incorporated in the proposed algorithm. First, *Split* is used throughout the algorithm with added feasibility test on time windows. Despite its simplicity, this procedure was not tested in [5] and [6]. Therefore, its addition in this paper will enrich the analysis on the algorithm's complexity. Second, two heuristics as proposed in [15] are used in the initial population construction phase. These first two parts are the novelty of our GA. Third, population management using dispersal value and mutation using local search (memetic algorithm) are developed as in [6]. In our experiments, the *DV* parameter is set equal to 1 and the probability for mutation is 30%.

The pseudo-code of the GA is given in Fig. 3. After reading the input data (line 1), three initial chromosomes are generated and enhanced in certain ways (lines 2–4). We will compare the use of heuristics (as in Fig. 3) and fully randomized chromosomes enhanced with LS_2 and *Split* (replace lines 2–3 with line 4). The rest of the chromosomes are constructed in lines 5–15, maintaining the *Split*-partition feasibility and *spaced* criterion as regulated by (12). Line 16 sorts the population based on cost in an ascending order, i.e., the best chromosome ranks first in the population.

The main algorithm runs in lines 17–40, looping for *maxIter* iterations. Two parents are selected by binary tournament followed by a crossover using order-crossover (OX) operator. *Split* is then called to form feasible trips. Infeasible splitting can occur at this stage that will prompt repeat of the process. These are executed in lines 18–23. Successful generated chromosome is mutated with a probability *probMut*, followed by *Split* and LS_2 (lines 24–29). In lines 30–33, *spaced* requirement is overridden and the new chromosome is accepted if it has a smaller cost than that of the best chromosome. In lines 34–38, *spaced* criterion is again checked to see if the new chromosome can be accepted. The new chromosome will replace one of the old chromosomes, randomly selected in the worse lower-half of population. The rationale of this approach is to retain good chromosomes in the upper-half of population while advancing the search.

Three data sets are generated and run with Lingo 11 for the LP optimization and Matlab R2100b for the GA, both on an Intel i5-2430M processor running at 2.4 GHz and 4 MB of RAM on Windows 7 Ultimate.

```
read input data;
initialize population #1 with load heuristic; LS2; Split;
initialize population #2 with ray heuristic; LS2; Split;
initialize population #3 with random permutation; LS2; Split;
ctrPop = 4;
while ctrPop <= popSize
  issplit = false; isspaced = false;
  while not(issplit) and not(isspaced)
    generate new chromosome C by random permutation; Split;
    if F(C) ≠ ∞, issplit = true; end
    if |F(C) – F(pt)| > DV, isspaced = true; end
  end %while
  accept new chromosome;
  ctrPop = ctrPop + 1;
end %while
sort the population ascending based on fitness values;
for i = 1:maxIter
  issplit = false;
  while not(issplit)
    select two parents by binary tournament;
    apply OX operator and randomly select one child; Split;
    if F(C) ≠ ∞, issplit = true; end
  end %while
  if U[0, 1] < probMut
    run mutation with LS2; Split; M = mutated chromosome;
    if F(M) < F(p1)
      C = M;
    end %if
  end %if
  if F(C) < F(p1)
    accept new/mutated chromosome;
    replace one chromosome in the lower half;
    count productive iteration;
  elseif |F(C) – F(pt)| > DV
    accept new/mutated chromosome;
    replace one chromosome in the lower half;
    count productive iteration; count unimproved iteration;
  end %if
  sort the population ascending based on fitness values;
end %for
```

Fig. 3. Pseudo code for the proposed GA.

III. RESULTS

Table 1 shows the experiment results from three data sets. Since GA is sensitive to random values generated in random permutation during chromosome construction and mutation, each data set was run for ten times, controlled by 'rng' function in Matlab so the results are traceable.

In the first data set, 200 iterations (generations) of GA were able to obtain optimal objective value in much shorter time (about one-tenth) than the time used by B&B. This performance got worse in the other two data sets, so the number of iterations was doubled to 400 because GA's run time is less than half of B&B's run time in 200 iterations. In each data set, we compared the performance of two initial population constructed using: 1) heuristics (as suggested in [15]), and 2) purely randomized chromosomes enhanced by *Split* and *LS* mutation. The ability of GA to reach the optimal point in data set 2 and 3 could not match that in data set 1, despite the added iterations. However, the gap between the optimal value from B&B and the less-optimal solution from GA is less than 1%, with faster computation time on the latter.

TABLE I
EXPERIMENT RESULTS

	Data set 1 (200 it.)		Data set 2 (400 it.)		Data set 3 (400 it.)	
	Heu	Rnd	Heu	Rnd	Heu	Rnd
Run time (mins)						
a. Average	20.29	20.94	32.88	33.85	32.82	32.67
b. Min	19.16	19.93	31.44	32.11	30.86	31.12
c. Max	22.46	24.41	34.44	36.57	34.74	34.77
B&B		202.45		48.73		332.63
Reach optimal	10/10	10/10	8/10	6/10	7/10	8/10
Worst gap (%)	0	0	0.0015	0.0015	0.76	0.76
# of iterations						
a. Average	79	79	246	199	114	226
b. Min	11	4	40	1	24	100
c. Max	191	142	394	384	224	363

As to the comparison between heuristics and random approach in the initial population construction phase, contrary to [15], the results in Table 1 do not exhibit firm conclusions with respect to each approach. Faster run time differs from one data set to another, favoring the heuristics in data set 1 and 2, but yielding otherwise in data set 3, although these differences are statistically insignificant. The same goes with the number of times the GA reaches optimality and the average number of iterations needed to reach that point. In fact, the random approach on some occasions could reach that point in as low as less than five generations (data set 1 and 2), but was outperformed by the heuristics in data set 3.

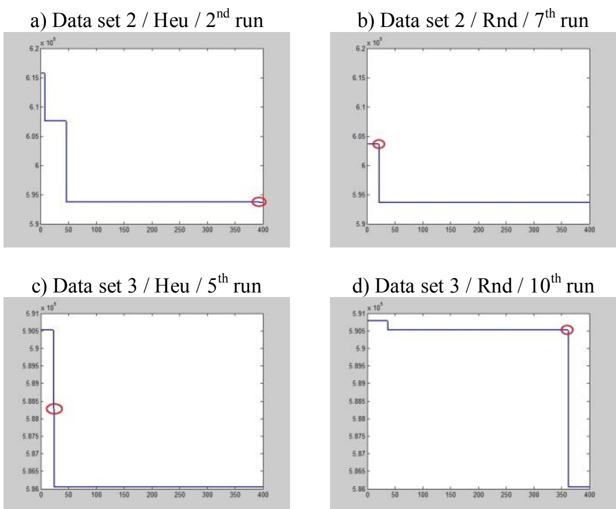

Fig. 4. Examples of GA runs.

Fig. 4 displays few examples of charted GA runs. The upper row shows chart results of data set 2 with heuristics approach on the left and random approach on the right. After 400 iterations, the heuristics approach reached optimality as late as at the 394th iteration (marked with red circle), whereas the random approach did it at the 46th iteration on those particular instances. The lower row, on the other hand, shows contrasting pictures where the heuristics reached optimal point faster at the 24th iteration compared to random approach that did so near the end of the 363th iteration. This indicates that the GA performance largely depends on the number of iterations, outweighing other factors such as methods in population initialization or operators in crossover and mutation. It also suggests that if a criterion is added to stop the runs if the fitness value does not improve after a number of generations (as in Fig. 4b and 4c), the GA run time can be reduced and shows further superiority than the B&B, with the worst gap still maintained.

IV. DISCUSSION

A further look on the results from data set 3 reveals important findings. The optimal routing is shown in Table 2a (ordered by the vessel number) with a total cost of US$586,051, and the routing of the second-best solution is shown in Table 2b with a total cost of US$590,531 (note the 0.76% gap between these two figures). To jump from the second-best to the optimal solution, three moves are required in the local search, but the fitness value has to be sacrificed in the first two moves. These three moves are explained in Table 3: the first move swaps vessel 5 and vessel 7 in their respective tour, worsen the fitness from 590,531 to 590,598; the second move swaps Ptk in vessel 6 with Btm in vessel 7, again worsen the fitness from 590,598 to 593,676; lastly, vessel 6 takes the free vessel 1 and improve the fitness to 586,051, above the initial fitness value. The order of these three moves has to be executed exactly as above; any other sequence will result in an infeasible solution. For example, after move 1, vessel 6 cannot immediately take the free vessel 1 because, although cheaper, vessel 1 has a smaller capacity and cannot serve all demands from the cities in its tour. The same infeasibility will occur if the second and third moves described in the first scenario are attempted first.

TABLE II
THE ROUTING RESULTS OF DATA SET 3

a) Optimal	b) Second best
1: **Sby→Kdi→Amb→Sby**	1: Not used
2: **Sby→Jk2→Btm→Sby**	2: **Sby→Kdi→Amb→Sby**
3: Not used	3: **Sby→Bpn→Smr→Tar→Sby**
4: Not used	4: Not used
5: **Sby→Mks→Bit→Sby**	5: **Sby→Btm→Mdn→Sby**
6: **Sby→Bpn→Smr→Tar→Sby**	6: **Sby→Jk2→Ptk→Sby**
7: **Sby→Ptk→Mdn→Sby**	7: **Sby→Mks→Bit→Sby**
8: **Sby→Bjm→Jk2**	8: **Sby→Bjm→Jk1**
9: Not used	9: Not used
Cost: US$586,051	Cost: US$590,531

TABLE III
ANALYSIS OF THE LOCAL SEARCH IN DATA SET 3

Move required	Results
1. Swap vessel 5 with vessel 7	
5: Sby→Btm→Mdn→Sby	5: Sby→Mks→Bit→Sby
7: Sby→Mks→Bit→Sby	7: Sby→Btm→Mdn→Sby
Cost: US$**590,531**	Cost: US$**590,538**
2. Swap Ptk with Btm	
6: Sby→Jk2→Ptk→Sby	6: Sby→Jk2→Btm→Sby
7: Sby→Btm→Mdn→Sby	7: Sby→Ptk→Mdn→Sby
Cost: US$**590,538**	Cost: US$**593,676**
3. Swap vessel 6 with vessel 1	
1: Not used	1: Sby→Jk2→Btm→Sby
6: Sby→Jk2→Btm→Sby	6: Not used
Cost: US$**593,676**	Cost: US$**586,051**

From this analysis, it can be said that the less-optimal solution is a local optimum and the best solution cannot be found from this point by a local search that explores only its neighboring space for improved solutions. A one-step-back-two-steps-forward approach is a potential avenue for further testing, but two-steps-back-three-steps-forward as shown in this case will increase the level of complexity and reduce the advantage of GA. Nevertheless, this finding marks an area deserving further investigation.

V. CONCLUSION

This paper studies the application of GA in VRPTW that considers heterogeneous vehicles differing in speeds, capacities, and both fixed and variable costs. Previous similar studies are oriented for problems with hundreds of cities but ignore the fixed cost of the vehicles. In maritime logistics, fixed cost is a major part in the cost structure given the high capital cost of vessels, thus it cannot be neglected in calculation. Although problems in maritime logistics typically deal with 20–50 ports (cities), including fixed cost in the model adds as much complexity as in the problems with hundreds of cities without fixed cost. The algorithm is tested on a case study of the Indonesian archipelago with a scope on containerships network design problem.

The proposed GA is built based on the principles of effective GA from published literature, particularly on the method of constructing trips from chromosome and the local-search mutation operator. The investigation is carried out on the impact of using some heuristics in initializing few population members and by comparing the effectiveness of the GA against the results from LP optimization using branch-and-bound. Three data sets were generated in this study and the GA was run for ten times on each scenario.

The experiment results show that the GA can reach the optimal point ten times faster than the B&B on certain data sets. On cases where it fails, the gap to the less-optimal solution found by the GA is very small or less than 1%. In data set 2, it is even barely significant at 0.0015%. The GA is therefore very suited for this type of problem, i.e., a variant of heterogeneous VRPTW that considers the fixed costs. Its application can be found in maritime logistics such as containerships network design problem and an example is showcased in this paper.

V. FUTURE RESEARCH

Many elements in the GA can still be explored to enhance its effectiveness. One aspect identified from this study is regarding the local-search mutation that has difficulty escaping from local optima. A simpler bit-wise mutation could possibly be more efficient with a close performance. Also, three unstructured (randomized) data sets used here could not confirm the obtained solutions since these solutions vary on different aspects. More data sets are required thus the agenda for further studies are still a vast exploration ground.

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