Journal of Theoretical and Applied Information Technology
31st May 2016. Vol.87. No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DECOMPOSING AND SOLVING CAPACITATED VEHICLE ROUTING PROBLEM (CVRP) USING TWO-STEP GENETIC ALGORITHM (TSGA)

[1]MUHAMMAD LUTHFI SHAHAB, [2]DARYONO BUDI UTOMO, [3]MOHAMMAD ISA IRAWAN
[1,2]Department of Mathematics, Institut Teknologi Sepuluh Nopember
E-mail: [1]shahab.luthfi@gmail.com, [2]daryono@matematika.its.ac.id, [3]mii@its.ac.id

ABSTRACT

Capacitated vehicle routing problem (CVRP) is one of the vehicle routing problem (VRP) that uses capacity restriction on the vehicles used. There are many methods have been studied to solve CVRP. To solve CVRP, it is possible to decompose CVRP into regions (sub problems) that can be solved independently. A two-step genetic algorithm (TSGA) is formulated in this paper. TSGA is used to decompose CVRP and then find the shortest route for each region using two different simple genetic algorithms. TSGA is then compared with genetic algorithm (GA). To compare these two algorithms, four instances is formed, those are P50, P75, P100, and P125. For each instance, fourteen different vehicle capacities is used. The results show that TSGA is better than GA in terms of computational time and distance except for some small vehicle capacities at P50 and P75.

Keywords: *Capacitated Vehicle Routing Problem (CVRP), Genetic Algorithm (GA), Decomposition, Two-Step Genetic Algorithm (TSGA)*

1. INTRODUCTION

Vehicle routing problem (VRP) is a hard combinatorial optimization problem with numerous industrial applications [1]. In the capacitated VRP (CVRP), all the customers correspond to deliveries and the demands are deterministic, known in advance, and may not be split. The vehicles are identical and based at a single central depot, and only the capacity restrictions for the vehicle are imposed. The objective is to minimize the total cost (i.e., a weighted function of the number of routes and their length or travel time) to serve all the customers [2]. CVRP is formally defined as an undirected graph $G = (V, E)$ where $V = \{v_0, v_1, \dots, v_n\}$ is a vertex set and $E = \{(v_i, v_j) | v_i, v_j \in V, i < j\}$ is an edge set. The depot is represented by vertex v_0, which uses m independent vehicles, with identical delivery capacity Q, to serve demands d_i from n customers, $i = 1, 2, \dots, n$, represented by set $\{v_1, \dots, v_n\}$. A non-negative distance matrix $C = (c_{ij})$ between customers v_i and v_j is defined on E. A solution for the CVRP would be a routes $R_1, R_2, \dots, R_m$ of V represent the routes of the vehicles, each route R_i that is $v_{i0} \to v_{i1} \to \cdots \to v_{ik+1}$, where $v_{ij} \in V$ and $v_{i0} = v_{ik+1} = v_0$, satisfying $\sum_{v_{ij} \in R_i} d_j \le Q$. The CVRP consists in determining a set of a maximum of m routes of minimum total distance, such that each route starts and ends at the depot, each customers is visited exactly once by exactly one vehicle, subject to the restriction that the total demand of any route does not exceed Q [1].

Because it is found to be widely applicable to many real world situations, it has been studied extensively [3][14]. While exact methods solve small problems quite efficiently, issues still exist for the larger problems. On the other hand, metaheuristic methods can find good solutions in less time. There are several metaheuristic methods that can be used, those are variable neighborhood search, stochastic local search, iterated local search, particle swarm optimization, simulated annealing, scatter search, differential evolution, simulated annealing, tabu search, and genetic algorithm [4].

To solve CVRP, it is possible to decompose CVRP into regions (sub problems) that can be solved independently [12]. Based on that, two-step genetic algorithm (TSGA) is formulated in this paper. TSGA is used to decompose CVRP and then find the shortest route for each region using two different simple genetic algorithms. TSGA will be formulated coherently and will be compared with GA to determine how well TSGA can be used to solve CVRP.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2. LITERATURE REVIEW

The success of genetic algorithms to solve problems such as traveling salesman problem (TSP) and vehicle routing problem with time windows (VRPTW), distribution of navy warship [5-6], flowshop scheduling [7] and the growth of GA such as genetic algorithm with artificial chromosome [7], automatic genetic algorithm clustering [8], two level genetic algorithm [9], parallel genetic algorithm [10], multi stage interactive genetic algorithm [11] shows that the use of genetic algorithms will give a good enough solution for CVRP if it is studied continously.

Genetic algorithm with artificial chromosome is proposed to solve flowshop scheduling problems. An artificial chromosome generating mechanism is designed to reserve patterns of genes in elite chromosomes and to find possible better solutions. The artificial chromosome generating mechanism is embedded in genetic algorithm [7].

A genetic algorithm based clustering method called automatic genetic clustering for unknown K (AGCUK). In the AGCUK algorithm, noising selection and division-absorption mutation are designed to keep a balance between selection pressure and population diversity. The Davies-Bouldin index is employed to measure the validity of clusters [8].

A two-level GA is proposed to solve an integrated multi-item supplier selection model [9]. The lifting path planning problem for terrain cranes in complex environments is studied in [10]. The crane lifting path planning is formulated as a multi-objective nonlinear integer optimization problem with implicit constraints. To solve that problem, a Master-Slave Parallel Genetic Algorithm is used.

Interactive genetic algorithm (IGA) can effectively solve the optimization problem. However, the challenge still remains for IGA to ameliorate user fatigue and reduce the noise in the process of evolution. To address the issue, a multi-stage interactive genetic algorithm (MS-IGA) is proposed [11], which divides the large population of the traditional interactive genetic algorithm (TIGA) into several stages according to different functional requirements. The proposed MS-IGA is then applied to the car console conceptual design system, to better capture the knowledge of users' personalized requirements and accomplish the product design. This is especially important in the field of complex product configuration design, such as in cars, personal computers, smart phones and the like.

3. GENETIC ALGORITHM (GA) FOR CVRP

Before we formulate TSGA, first we resume good enough GA that can be used to solve CVRP. The GA is formulated with the following characteristics:

- Chromosome representation which is used is a permutation of the customers. Each chromosome is unique and can only represents one CVRP solution. For example, if CVRP problem that is used consists of nine customers, one of the chromosomes that can be used is $v_1v_6v_8v_5v_3v_2v_7v_4v_9$. To change the chromosome into the desired solution, information about vehicle capacity and customers demand is used. Suppose that the capacity of the vehicle is 17 and demand from every customers v_i is i, $i = 1, \dots, 9$, then the first route is R_1, that is $v_0 \to v_1 \to v_6 \to v_8 \to v_0$, second route is R_2, that is $v_0 \to v_5 \to v_3 \to v_2 \to v_7 \to v_0$, and third route is R_3, that is $v_0 \to v_4 \to v_9 \to v_2$.
- Population size which is used is 100.
- Suppose that a chromosome represent routes R_i, $i = 1, \dots, n$, where R_i is $v_{i0} \to v_{i1} \to \cdots \to v_{ik_i+1}$ and $v_{i0} = v_{ik_i+1} = v_0$, then the fitness function that can be used is

$$\sum_{i=1}^{n}\sum_{j=1}^{k_i+1}\sqrt{(x_{i,j}-x_{i,j-1})^2+(y_{i,j}-y_{i,j-1})^2} \quad (1)$$

- Selection is done by selecting two random chromosomes.
- Crossover operator which is used is ordered crossover (OX) [3] with the crossover probability is 1. The example of how the OX works can be seen in Figure 1.

Parents

1	2	3	4	5	6	7	8	9
9	8	7	6	5	4	3	2	1

Child

					6	7	8	
9	5	4	3	2	6	7	8	1

Figure 1. Ordered Crossover (OX)

- Mutation operator which is used is exchange and inversion [3] with each operator mutation probability is 0.1. The example of how the

Journal of Theoretical and Applied Information Technology
31st May 2016. Vol.87. No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

exchange and inversion works can be seen in Figure 2 and Figure 3.

Parents

1	2	3	4	5	6	7	8	9

Child

1	2	3	4	8	6	7	5	9

Figure 2. Exchange

Parents

1	2	3	4	5	6	7	8	9

Child

1	2	6	5	4	3	7	8	9

Figure 3. Inversion

- Population replacement scheme which is used is elitism replacement with filtration and works as follows: both old population and new population are combined into a single population and sorted in a non-decreased order of their associated fitness value. The filtration strategy is used to identify identical individuals from the population. Then we choose half of the population. If the size of new population is smaller than the size of old population, we generate new individuals [1].
- Stopping condition which is used is fitness value is not improved after 2000 generations or 100000 generations is reached.

4. TWO-STEP GENETIC ALGORITHM (TSGA) FOR CVRP

TSGA works by combining two simple genetic algorithms that can be used to solve CVRP in a different way from the usual GA. GA are trying to solve CVRP directly, whereas TSGA will first decompose CVRP into regions that can be solved independently with TSGA1 (first genetic algorithm in TSGA) and then find the shortest route for each region with TSGA2 (second genetic algorithm in the TSGA). The regions which are formed from the decomposition performed by TSGA1 must meet the following characteristics:

- each region only requires one vehicle to serve any customers in the region. In other words, the total demand for the customers in each region does not exceed the vehicle capacity,
- customer locations in the region should be located near each other.

The first characteristic is taken because each route in CVRP solution must be served by a single vehicle. TSGA1 will try to meet this characteristic with consider vehicle capacity and customers demand. The second characteristic is taken so that CVRP solution that is formed will be good enough. TSGA1 will try to meet this characteristic with consider the slope of the line connecting the customer with the depot. In this case, the use of slope of the line based on the fact that if the slope between the two lines adjacent to each other, then the points that exist in the line will also be close enough.

Consider the example of a simple CVRP in Figure 4 where a large circle represents the depot and small circles represent the customers. From this example, one of which could be generated decomposition by TSGA1 can be seen in Figure 5.

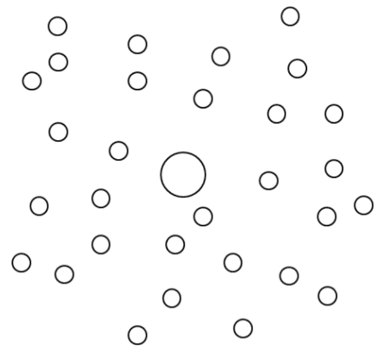

Figure 4. CVRP Example

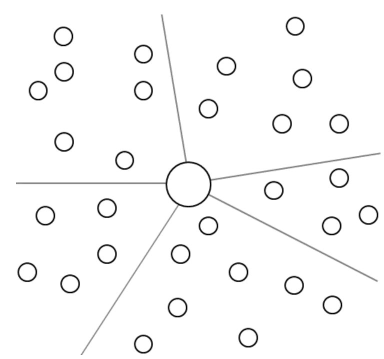

Figure 5. Decomposition Example by TSGA1

By doing decomposition, a solution for every region that is formed will be the solution of CVRP. Solution for every region that is formed is the shortest route which departs from the depot, and then connect each customers in the area, and then back again to the depot. Note that as each region formed from decomposition only needs one vehicle to serve all customers in the area, then information about customers demand can be eliminated so that the problem at each region can be called as a *traveling salesman problem* (TSP). For CVRP example in Figure 4 which has been decomposed as in Figure 5, the solution of which can be obtained by the TSGA2 can be seen in Figure 6.

Journal of Theoretical and Applied Information Technology
31st May 2016. Vol.87. No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

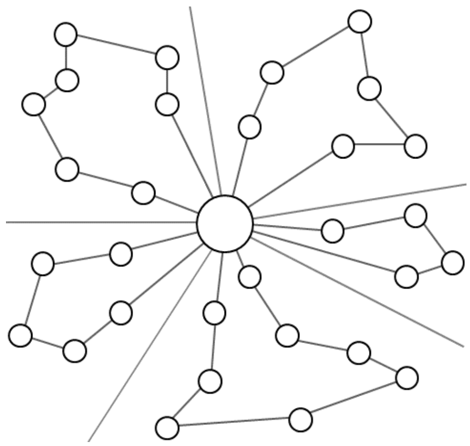

Figure 6. CVRP Solution Example by TSGA

4.1. TSGA1 for TSGA

Before TSGA1 can be used, every slope of the line must be calculated. Then slopes is sorted from the smallest to the largest. Once the slope is sorted, each customers from small slope to large slope is labeled by $v_1, v_2, \dots, v_n$, where n is number of customers in CVRP instances. TSGA1 is formulated with the following characteristics:

- Chromosome representation which is used is a binary representation. For example, if CVRP instance consist of 20 customers, one of the chromosomes that can be used is 00010000010010000000. That chromosome shows that CVRP is decomposed into three regions. Number of regions which is formed is equal to the number of digit 1. The first area is characterized by sub-chromosome 100000 which represents customers $v_4, v_5, \dots, v_9$. Second area is characterized by sub-chromosome 100 which represents customers v_{10}, v_{11}, v_{12}. Third area is characterized by sub- chromosome 10000000 and 000 which represents customers $v_1, v_2, v_3, v_{13}, v_{14}, \dots, v_{20}$.
- Population size which is used is 100.
- Suppose that a chromosome represent routes R_i, $i = 1, \dots, n$, where R_i is $v_{i0} \to v_{i1} \to \cdots \to v_{ik_i+1}$ and $v_{i0} = v_{ik_i+1} = v_0$, then the fitness function that be used is (7) defined as follows:

$$f_1 = |a - m| \tag{2}$$

$$f_2 = \max\left\{0, Q - \sum_{j=1}^{k_i} d_{ij}\right\} \tag{3}$$

$$f_3 = \left(x_{ij} - \frac{1}{k_i}\sum_{j=1}^{k_i} x_{ij}\right)^2 \tag{4}$$

$$f_4 = \left(y_{ij} - \frac{1}{k_i}\sum_{j=1}^{k_i} y_{ij}\right)^2 \tag{5}$$

$$f_5 = \sum_{j=1}^{k_i} \sqrt{f_3 + f_4} \tag{6}$$

$$10^6 f_1 + 10^3 \sum_{i=1}^{m} f_2 + \sum_{i=1}^{m} f_5 \tag{7}$$

where a is number of digit 1 in the chromosome, m is number of vehicle used.

- Selection is done by selecting two random chromosomes.
- Crossover operator which is used is 1-point crossover with the crossover probability is 1. The example of how the OX works can be seen in Figure 7.

Parents

1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0

Child

					1	1	1	1
0	0	0	0	0	1	1	1	1

Figure 7. 1-Point Crossover

- Mutation operator is done by selecting a random digit and then change the value. If selected value is 1, then changed to 0, and vice versa. Mutation probability is 0.5.
- Population replacement scheme which is used is elitism replacement with filtration.
- Stopping condition which is used is fitness value is not improved after 2000 generations or 100000 generations is reached.

4.2. TSGA2 for TSGA

TSGA2 is used to find shortest route of a regions formed by TSGA1. These routes are then combined to become CVRP solution. TSGA2 is formulated with the following characteristics:

- Chromosome representation which is used is a permutation of the customers. As an example,

Journal of Theoretical and Applied Information Technology
31st May 2016. Vol.87. No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

if customers in a region is $v_4, v_5, \dots, v_9$, then one of the chromosomes that can be used is $v_6 v_7 v_4 v_9 v_5 v_8$.

- Population size which is used is 100.
- Suppose that we have a chromosome $v_1 v_2 \dots v_n$, then the fitness function that can be used is

$$\sum_{i=1}^{n+1} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \qquad (8)$$

- Selection operator which is used is tournament selection and the size is 5.
- Crossover operator which is used is sequential constructive crossover (SCX) [13] with the crossover probability is 1.
- Mutation operator which is used is exchange with mutation probability is 0.2.
- Population replacement scheme which is used is elitism replacement with filtration.
  Stopping condition which is used is fitness value is not improved after $6 \times \frac{m}{p}$ generations (m is number of customers in the region and p is number of regions) or 1000 generations is reached.

5. RESULTS AND DISCUSSIONS

5.1. CVRP Instances

CVRP instances is created so that TSGA can be implemented to solve the instances. To be able to get well conclusion, four CVRP instances is created, those are P50, P75, P100, and P125. Abscissa, ordinate, and demand for each customer at the instances are selected randomly from a certain range.

Table 1. Abscissa, Ordinate, and Demand of P50

x	y	d	x	y	d	x	y	d	x	y	d
1	50	19	32	5	27	53	82	19	73	86	10
3	81	11	34	27	17	54	36	12	74	17	27
3	4	16	35	91	15	54	45	24	75	88	25
9	3	25	35	67	28	57	99	27	76	27	27
9	32	29	37	80	29	59	72	30	77	51	17
13	99	13	37	87	13	60	21	18	80	44	19
14	21	26	38	49	13	60	14	18	89	87	13
24	9	14	39	42	22	62	95	16	94	86	17
25	82	16	40	11	27	62	31	28	97	81	26
29	10	12	45	47	19	63	20	29	97	59	25
30	33	29	47	36	20	65	11	17	100	52	24
30	50	26	50	83	10	70	2	28			
32	52	18	51	94	24	70	30	26			

P50 consists of a depot and 50 customers that must be served. In this instance, the abscissa and ordinate of depot is 50, while the abscissa and ordinate of customers is between 0 and 100. Each customer has a demand, that is between 10 to 30. Abscissa, ordinate, and demand of each customer can be seen in Table 1.

Table 2. Abscissa, Ordinate, and Demand of P75

x	y	d	x	y	d	x	y	d	x	y	d
1	19	24	38	57	22	65	55	16	99	41	19
2	2	11	38	145	12	67	35	14	103	33	13
4	120	29	39	82	29	68	122	30	110	73	13
4	141	29	39	49	24	72	82	13	114	33	21
7	117	13	39	144	20	74	30	24	115	85	18
8	138	16	42	128	27	74	64	16	117	85	11
10	133	14	44	73	29	74	113	10	118	37	15
11	65	17	48	21	24	77	103	21	120	61	30
12	92	17	50	76	27	78	85	14	126	1	23
22	87	25	50	108	12	79	28	27	127	63	11
24	17	25	50	129	24	79	65	26	128	31	13
24	149	28	50	64	10	82	59	14	134	2	16
25	122	11	51	79	17	83	102	10	134	84	10
25	101	11	52	17	18	86	77	18	138	53	14
29	7	11	56	91	17	88	63	29	142	115	24
30	140	10	56	18	25	90	18	14	149	11	26
33	87	15	58	40	24	93	20	24	149	143	18
35	108	18	63	91	27	94	101	12	149	28	19
37	138	14	65	112	27	94	77	14			

Table 3. Abscissa, Ordinate, and Demand of P100

x	y	d	x	y	d	x	y	d	x	y	d
0	30	14	52	14	17	101	15	15	158	0	10
2	31	19	53	147	21	103	83	25	159	199	30
2	165	23	53	111	20	103	74	25	162	93	29
3	46	11	58	139	25	105	74	13	166	148	15
5	155	22	62	36	13	105	200	23	167	193	26
6	102	22	62	60	11	106	181	12	168	27	23
8	163	24	65	173	30	108	97	12	168	37	17
8	101	27	68	26	30	109	2	20	171	62	26
15	119	29	68	48	15	117	6	11	171	33	27
21	121	28	70	32	25	117	58	25	171	85	27
22	103	18	70	182	13	117	73	28	173	129	16
24	187	27	72	130	24	119	120	19	173	55	16
28	172	22	75	130	17	125	167	10	175	45	19
29	7	28	76	130	24	125	37	24	176	23	25
30	194	15	79	7	10	128	128	25	177	9	26
32	2	27	79	11	12	131	190	15	179	123	25
32	61	16	83	11	16	135	178	11	184	46	26
34	57	13	85	122	25	147	107	26	186	66	14
36	73	18	86	35	18	148	167	21	187	11	17
38	179	23	87	161	25	150	162	24	193	123	20
42	141	17	90	103	11	150	77	30	194	171	30
44	127	30	92	31	11	151	0	12	195	16	25
49	24	15	92	13	24	151	151	23	195	60	17
50	124	11	93	96	29	152	21	25	197	51	28
51	106	16	101	150	25	153	100	12	199	122	18

Journal of Theoretical and Applied Information Technology
31st May 2016. Vol.87. No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

P75 consists of a depot and 75 customers that must be d. In this instance, the abscissa and ordinate of depot is 75, while the abscissa and ordinate of customers is between 0 and 150. Each customer has a demand, that is between 10 to 30. Abscissa, ordinate, and demand of each customer can be seen in Table 2.

P100 consists of a depot and 100 customers that must be d. In this instance, the abscissa and ordinate of depot is 100, while the abscissa and ordinate of customers is between 0 and 200. Each customer has a demand, that is between 10 to 30. Abscissa, ordinate, and demand of each customer can be seen in Table 3.

P125 consists of a depot and 125 customers that must be d. In this instance, the abscissa and ordinate of depot is 125, while the abscissa and ordinate of customers is between 0 and 250. Each customer has a demand, that is between 10 to 30. Abscissa, ordinate, and demand of each customer can be seen in Table 4.

Table 4. Abscissa, Ordinate, and Demand of P125

x	y	d	x	y	d	x	y	d	x	y	d
4	152	15	52	81	16	112	136	12	197	187	28
4	12	20	52	60	21	112	19	23	199	47	30
5	179	24	52	149	17	115	236	17	200	148	22
8	225	18	56	102	29	117	35	25	204	179	13
9	6	10	61	71	29	124	195	19	205	6	19
10	246	15	63	77	15	129	7	19	211	124	21
10	135	28	65	32	11	132	48	19	215	138	11
14	78	22	67	246	15	135	83	18	216	77	24
14	119	11	67	238	28	136	153	23	217	66	29
15	103	22	72	140	14	143	139	13	217	28	20
16	34	13	73	177	11	144	126	16	218	237	13
17	119	11	76	74	23	147	112	11	219	140	29
19	139	25	77	19	10	152	44	30	221	116	22
20	192	11	83	184	20	154	237	14	221	212	28
22	85	29	86	124	16	155	212	18	221	120	28
27	7	30	86	96	29	159	19	30	228	209	10
30	142	17	87	233	25	159	111	26	228	181	19
31	240	10	87	97	25	161	220	22	229	25	21
32	240	15	87	127	27	162	24	16	231	52	20
32	246	14	88	153	13	164	108	22	234	142	12
33	217	10	89	1	15	167	180	24	235	197	16
38	226	16	93	174	15	170	150	29	235	132	14
41	165	16	93	182	16	174	0	16	241	237	25
43	108	30	94	233	13	175	198	13	241	177	30
43	106	22	94	145	29	178	18	24	243	166	24
43	165	18	95	30	17	178	114	14	244	77	22
45	194	19	96	14	28	183	4	16	244	83	11
47	112	26	99	147	15	190	132	13	247	155	23
48	74	29	102	108	26	190	167	22	247	242	30
49	230	15	103	15	21	194	38	21			
49	116	10	103	43	13	195	123	25			
51	201	23	107	132	28	197	33	24			

5.2. Comparison of TSGA and GA

Comparison of TSGA and GA can be done by using TSGA and GA to solve P50, P75, P100, and P125 which is created. For each instance, fourteen different vehicle capacities is used. Comparison between TSGA and GA will be seen in terms of distance and computational time needed to solve CVRP.

In term of distance, used $P = \frac{distance1 - distance2}{distance1} \times 100$ where $distance1$ is distance obtained by GA and $distance2$ is distance obtained by TSGA. This value show how well solution obtained by TSGA when is compared to solution obtained by GA. The results are computed after making 3 independent runs, and get the best distance from those runs. The comparison between TSGA and GA is showed in Table 5, Table 6, Table 7, and Table 8. The bold values in the table shows better value between TSGA and GA.

Table 5. Comparison of GA and TSGA for P50

Vehicle Capacity	GA		TSGA		P
	Distance	Time	Distance	Time	
77	**1459.428**	25	1591.732	**10**	-9.06
83	**1411.733**	31	1533.234	**10**	-8.60
90	**1319.670**	38	1429.179	**10**	-8.29
99	**1234.570**	24	1287.732	**7**	-4.30
109	**1205.129**	13	1247.899	**5**	-3.54
122	**1083.415**	29	1166.375	**6**	-7.65
139	**1015.836**	64	1059.293	**5**	-4.27
160	985.226	28	**915.086**	**4**	7.11
189	899.162	18	**863.571**	**3**	3.95
231	**801.136**	22	801.507	**3**	-0.04
297	788.582	44	**710.183**	**3**	9.94

Table 6. Comparison of GA and TSGA for P75

Vehicle Capacity	GA		TSGA		P
	Distance	Time	Distance	Time	
105	**2386.744**	85	2404.516	**9**	-0.74
113	**2309.077**	104	2401.982	**6**	-4.02
123	**2170.193**	65	2203.066	**9**	-1.51
135	**2053.659**	115	2068.197	**7**	-0.70
149	1961.569	55	**1885.894**	**5**	3.85
166	**1811.217**	136	1835.419	**6**	-1.33
188	1719.833	85	**1630.429**	**4**	5.19
217	1698.279	81	**1501.133**	**5**	11.6
257	1598.278	98	**1377.450**	**5**	13.8
314	1574.126	95	**1359.159**	**5**	13.6
404	1514.616	116	**1215.419**	**6**	19.7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

For P50, we use 77, 83, 90, 99, 109, 122, 139, 160, 189, 231, 297 as a vehicle capacity. If we use 77 as vehicle capacity, minimum number of vehicle that can be used is $\left\lceil \frac{1040}{77} \right\rceil = \lceil 13{,}507 \rceil = 14$ (where 1040 is total demand of all customers in P50). And if we use 297 as vehicle capacity, minimum number of vehicle that can be used is $\left\lceil \frac{1040}{297} \right\rceil = \lceil 3{,}502 \rceil = 4$. Similar reasons are used to choose the vehicle capacities for P75, P100, and P125.

Table 7. Comparison of GA and TSGA for P100

Vehicle Capacity	GA		TSGA		p
	Distance	Time	Distance	Time	
151	3951.525	123	**3664.148**	**10**	7,27
164	3622.753	153	**3428.708**	**11**	5,35
178	3588.194	125	**3119.468**	**9**	13,0
195	3454.294	166	**2958.256**	**5**	14,3
215	3287.016	293	**2726.513**	**6**	17,0
240	3060.496	231	**2604.126**	**5**	14,9
273	2717.931	171	**2463.602**	**6**	9,35
314	2829.297	256	**2216.962**	**7**	21,6
372	2742.865	164	**2094.614**	**8**	23,6
454	2638.619	148	**1939.120**	**13**	26,5
584	2458.270	232	**1814.500**	**17**	26,1

Table 8. Comparison of GA and TSGA for P125

Vehicle Capacity	GA		TSGA		p
	Distance	Time	Distance	Time	
183	5269.657	364	**4476.805**	**24**	15,0
198	5100.448	435	**4352.449**	**10**	14,6
215	4996.808	298	**4141.080**	**14**	17,1
235	4706.922	444	**3806.193**	**7**	19,1
260	4597.851	507	**3594.609**	**7**	21,8
291	4505.065	372	**3280.790**	**8**	27,1
330	4440.228	643	**3165.287**	**12**	28,7
380	4275.217	499	**3003.622**	**12**	29,7
449	4164.521	407	**2817.172**	**17**	32,3
549	3928.582	514	**2603.215**	**20**	33,7
706	3502.791	522	**2525.264**	**47**	27,9

Average computation time of TSGA for P50, P75, P100, and P125 does not exceed 20 seconds while the GA is in the range from 30 seconds to 400 seconds. So in terms of computational time, TSGA is better than AG.

6. CONCLUSIONS

Based on the results that has been presented, it can be concluded that TSGA can be used to solve CVRP in a different way from the AG. In terms of computational time, TSGA is better than GA. In terms of distance, TSGA is better than AG except for some small vehicle capacities at instances P50 and P75. Larger vehicle capacity will gives larger p value that means TSGA will be better if larger vehicle capacity is used.

REFERENCES:

[1] Nazif, H. and Lee, L.S.. 2012. "*Optimized Crossover Genetic Algorithm for Capacitated Vehicle Routing Problem*". Applied Mathematical Modelling 36, 2110-2117.

[2] Yucenur, G.N. and Demirel, N.C.. 2011. "*A New Geometric Shape-Based Genetic Clustering Algorithm for The Multi-Depot Vehicle Routing Problem*". Expert System with Applications 38, 11859-11865.

[3] Karakatic, S. and Podgorelec, V.. 2015. "*A Suvey of Genetic Algorithms for Solving Multi Depot Vehicle Routing Problem*". Applied Soft Computing 27, 519-532.

[4] Toth, P. and Vigo, D.. 2002. The Vehicle Routing Problem. Philadelpia: University City Science Center.

[5] Hozairi, Buda, K., Masroeri, and Irawan, M.I.. 2014. "*Implementation of Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for Multiobjective Optimization Problems on Distribution of Indonesian Navy Warship*". Journal of Theoretical and Applied Information Technology 64, 274-281.

[6] Santoso, P., Buda, K., Masroeri, Irawan, M.I., and Dinariyana. 2014. "*The Implementation of Binary Genetic Algorithm (BGA) for Optimizing the Task of Indonesian Navy Ship Patrols Related to The Security of Indonesia Seas*". Journal of Theoretical and Applied Information Technology 67, 247-253.

[7] Chang, P. C., Chen, S.H., Fan, C.Y., and Chan, C.L.. 2008. "*Genetic Algorithm Integrated with Artificial Chromosomes for Multi-Objective Flowshop Scheduling Problems*". Applied Mathematics and Computation 205, 550-561.

[8] Liu, Y., Wu, X., and Shen, Y.. 2011. "*Automatic Clustering Using Genetic Algorithms*". Applied Mathematics and Computation 218, 1267-1279.

[9] Aliabadi, D. E., Kaazemi, A., and Pourghannad, B.. 2013. "*A Two-Level GA to Solve an Integrated Multi-Item Supplier*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Selection Model". Applied Mathematics and Computation 219, 7600-7615.

[10] Cai, P., Cai, Y., Chandrasekaran, I., and Zheng, J.. 2016. "*Parallel Genetic Algorithm Based Automatic Path Planning for Crane Lifting in Complex Environments*". Automation in Constructioin 62, 133-147.

[11] Dou, R., Zong, C., and Nan G.. 2016. "*Multi-Stage Interactive Genetic Algorithm for Collaborative Product Customization*". Knowledge-Based Systems 2016, 43-54.

[12] Taillard, E. .1993.. "*Parallel Iterative Search Methods for Vehicle Routing Problem*". Network 23, 661-673.

[13] Ahmed, Z.H.. 2005. "*Genetic Algorithm for Travelling Salesman Problem using Sequential Constructive Crossover Operator*". International Journal of Biometrics & Bioinformatics 3, 96-105.

[14] Daryono B.U., Irawan M. Isa, dan M.L. Shahab. 2015. "*Algoritma Genetika Ganda (AGG) untuk Capacitated Vehicle Routing Problem (CVRP)".* Seminar Nasional Matematika dan Pendidikan Matematika UNY 2015