Optimization of Waste Transportation Routes using Multi-objective Non-dominated Sorting Genetic Algorithm II (MNSGA-II) in the Eastern and Southern Regions of Bandung City, Indonesia

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Abstract. Ensuring high-quality and effective urban waste management has been an important priority to achieve sustainable and environmental-friendly cities and communities mandated by Sustainable Development Goals (SDGs). The massively growing population in urban regions of developing countries, such as Bandung City, Indonesia, leads to the increasing volume of daily goods consumption and households waste production. The waste transportation route is one of the main determining factors for the cost of waste management. In this paper, we introduce the Multi-objective Non-dominated Sorting Genetic Algorithm II (MNSGA-II) to solve the waste transportation route optimization problem in the Eastern and Southern Regions of Bandung City, Indonesia. Compared to the existing traditional evolutionary algorithms, MNSGA-II offers three major important benefits: efficient computational complexity, no requirement of sharing parameters, and a non-elitism mechanism. Algorithm parameters include the number of generations, mutation rate, and crossover rate. Our extensive experiments suggest the best solution resulted in 14 routes with a total distance of 152,63 km. Further, our proposed route optimization is potentially beneficial to support the improvement of the sustainable waste management service system at Bandung City.

1. Introduction

Urban waste management has been one of the fundamental global issues, especially in developing countries, such as Indonesia. Population growth and improvement in living standards have led to an increase in the volume of waste. According to Waste Management Law of Indonesia No. 18 of 2008, waste management is defined as an integrated activity of waste reduction, disposal, and handling which should be conducted in a comprehensive, systematic, and sustainable manner. Among other metropolitan areas in Indonesia, Bandung City has been facing critical challenges in maintaining sustainable waste management. The significantly increasing number of populations in Bandung City has implications in the growing volume of households and industries consumption and urban waste production activities. The waste transportation route is known as one of the determining factors for the cost of waste management. Hence, it is necessarily required to optimize the process of collecting the waste throughout the city areas.

The increasing volume of daily waste production in Bandung City is quite fast. The average amount of waste transported to the Final Processing Site (*Tempat Pemrosesan Akhir* - TPA) is 1400-

1500 tons/day. Waste management in Bandung is carried out by a specially formed organization, namely *Perusahaan Daerah* (PD) *Kebersihan*. The task of the organization is to transport waste from a Temporary Shelter (*Tempat Penampungan Sementara* - TPS) to a TPA. Transportation of waste in the city of Bandung is divided into 4 (four) operational areas with the number of TPS, namely Western Bandung with 42 units of TPS locations, 35 units of Eastern Bandung, 38 units of Southern Bandung, and 39 units of Southern Bandung. TPA is located in the village of Sarimukti, Western Bandung. Due to the distance between TPA Sarimukti from the city center, which is about 45 km, the Gedebage Intermediate Transfer Facility (*Stasiun Peralihan Antara* - SPA) was chosen as the starting point as well as the endpoint of the waste transportation route.

The problem of collecting waste from TPS to SPA can be considered as an instance of the Vehicle Routing Problem (VRP). One major type of VRP is known as the Capacitated Vehicle Routing Problem (CVRP). CVRP is a VRP model with vehicle capacity constraints. CVRP can design a route to collect waste with the minimum cumulative traveling distance, served by the minimum number of available vehicles with respect to the specific constraints, such as the capacity of vehicles [1].

The waste collecting route must be effective and efficient so that the most optimal collecting route is obtained. Optimization is carried out by considering aspects of distance, the amount of waste piled up at the TPS, and the capacity of the waste trucks. An optimization problem that has several objective functions is called multi-objective optimization. Multi-objective algorithm finding a solution that is close to Pareto optimality [2].

In this study, there are two objectives to be achieved. The objectives are to minimize the total traveled distance by waste trucks and the number of waste trucks used. The route starts from the SPA. Each TPS is only served once by one truck. The total capacity carried on a trip does not exceed the maximum capacity of the truck. Each route returns to the SPA. One of the algorithms that are quite well known to get the optimal solution is the Multi-objective Non-dominated Sorting Genetic Algorithm II (MNSGA-II). The MNSGA-II is one of the evolutionary algorithms developed by Kalyanmoy Deb. This algorithm will store the optimal solution by sorting based on the Pareto front and comparing the solutions between each generation [3].

Extensive studies have been conducted to investigate the effectiveness of MNSGA-II optimization in multiple different objectives. For instance, in the application of the MNSGA-II in stock portfolio optimization [4], MNSGA-II improves the aimed performance with adaptive mutation operators in the case of stock mutual fund portfolios [5]. Other examples include the contribution of waste transportation to the optimization of waste management in the Bandung City [6] as well as optimizing the waste transportation route in the Yogyakarta City using a hybrid genetic algorithm [7]. In this study, we aim to propose the use of the MNSGA-II algorithm to find the optimal route for waste transportation in the Southern Bandung and Eastern Bandung regions. The main contribution of this study is expected to support the Bandung City government in solving the distribution problem of waste transportation, especially the Eastern Bandung and Southern Bandung region.

2. Material and Methods

This study uses data available in the Open Data of Bandung City and BPS-Statistics of Bandung Municipality. The data used is data on the location of TPS contains the name of the TPS, coordinate (latitude and longitude), the amount of waste entering each TPA (± m^3≥/day), and the number of operational vehicles/trucks for waste management with a capacity of 10 m^3. Based on data obtained from BPS in 2018, the number of trucks is 64, and the capacity is 10 m^3. The list of TPS for the Eastern Bandung and Southern Bandung region is described in Table 1.

Table 1. List of TPS

TPS ID	TPS	Amount of waste generated in TPS (m^3/day)
TT05	Cicukang	0.3
TT06	Bojong Awi	0.5
TT08	Gading Regensi	3
TT13	Cipadung Rw 08	1.5
TT15	Cempaka Arum	7.71
TT16	Rancabolang	2.56
TT17	Derwati	7.57
TT19	Bandung Inten	1.5
TT20	Cipagalo	9.29
TT21	Cijaura Girang	1.5
TT25	Suka Asih	3
TT28	Cigending	8
TT29	Ujung Berung Indah	1.71
TT30	Cinambo Indah	1.14
TT31	Golf	7.43
TT32	Panyileukan	6.29
TT33	Pangaritan	7
TT35	Polda Jabar	1.5
TS01	Kosambi	9.08
TS03	Gedung Pakuan	1.78
TS05	Bi Braga	8
TS10	Tarumatex	1.5
TS15	Pln Sukarno Hatta	9.1
TS24	Pt. Delami	6
TS25	Lp Kb. Waru	1
TS27	Cibangkong Rw 11	3.84
TS29	Maleer Rw 05	4.21
TS30	Maleer Rw 06	3
TS34	Pasar Moden Batununggal	1.5
TS35	Len Lipi	1.4
TS37	Jakapurwa	5.8

2.1. Captivated Vehicle Routing Problem

The problem of collecting waste from TPS to SPA is a problem that regulates the distribution of resources with limited vehicles and truck capacity. The parameters are the number of TPS, the capacity of the waste trucks, and the total distance from TPS to another TPS [8].

2.2. Haversine Distance

The haversine formula is a method to measure the angular distance between two points located on a sphere, such as a ball, from their respective coordinates on the surface of the sphere, i.e., the longitudes and latitudes. The distances are calculated according to this formula [9].

$$d=2r.\arcsin\left(\left(\sin^2\left(\frac{\text{latt1-latt2}}{2}\right)+\cos(\text{latt1})\cos(\text{latt2})\sin^2\left(\frac{\text{long1-long2}}{2}\right)\right)^{1/2}\right) \tag{1}$$

where *d* is distance, *latt* is latitude, *long* is longitude, *R* is the Earth radius (radius = 6,371km).

2.3. Multi-objective Optimization

In single-objective optimization, the solution is easier to find because the search space is well defined. But if there is more than one objective, there is a set of possible solutions. Multi-objective optimization is an objective optimization problem which consist of two or more functions. Multi-objective optimization can be defined in equation [10]:

$$\text{minimize}[f_1(x),f_2(x),\ldots,f_k(x)] \tag{2}$$

where *k* is the total objective function; *x* is the vector of decision variables.

In this study, the function that will be optimized is the total distance of the waste collecting route and the number of the truck.

2.4. Dominance Test

In a multi-objective optimization problem, the best solution is determined by dominance. X_1 dominates X_2 if the solution X_1 is better than X_2 in all the outcomes of the objective function or at least one objective function. A non-dominated solution set is defined as a set of all the possible solutions that are not dominated by any solution from the available solution set. The collection of the non-dominated solution set is called the Pareto-Optimal set. The boundary that is defined by the set of all points mapped from the Pareto-Optimal set is known as the Pareto-optimal Front [11]. Hence, all Pareto-Optimal members set are considered as the best optimal solutions according to the existing objective functions.

2.5. Multi-objective Non-dominated Sorting Genetic Algorithm (MNSGA-II)

Genetic algorithm, a metaheuristic algorithm and a member of evolutionary algorithms class, has been widely used as an optimization scheme in numerous human daily activities and operations. Metaheuristic algorithms are known for their effectiveness to optimize the objective function of diverse machine learning tasks, including clustering [18-21], classification, regression, etc.

Individuals in the initialized population are sorted according to the non-domination solution on each front. The first front is formed based on non-dominant groups in the initial population, while the next front will be dominated by individuals on the previous front and so on [4]. Individuals also use crowded distance as a parameter to measure the distance from other individuals. In addition, the crowding process on each individual also helps in exploring the search space and maintaining population diversity [12]. Flowchart of the Multi-objective Non-dominated Sorting Genetic Algorithm II (MNSGA-II) is illustrated in Figure 1.

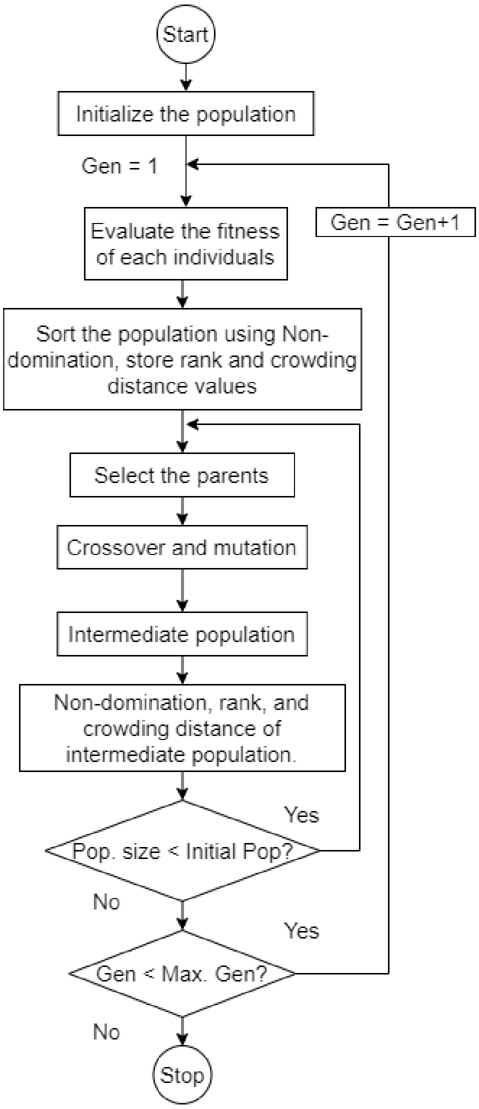

Figure 1. Flowchart of MNSGA-II

2.6. Non-dominated Sorting

Non-dominated sorting is used to sort the solutions in the population according to dominance. The sorting algorithm can be seen in Table 2.

Table 2. Pseudocode of MNSGA-II for Waste Transportation Route Optimization

```
Multi-objective Non-dominated Sorting Genetic Algorithm II

Step 1: for each p in the population P, do
        a) Initialize Sp=∅, which will contain all individuals dominated by
           p.
        b) for each q in p, do
           -  If p dominates q then add q to the set of solutions dominated
              by p. Sp = Sp U{q}.
           -  If q dominates p then np = np + a1
        c) If np=0 i.e., no individual dominates p so that p is the first
           front and then individual p is given rank 1. Update the first
           front by adding p to the first front, namely F1 = F1U{p}.
Step 2: Initialize the front counter.
Step 3: Performed on the I-front when Fi≠0
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Multi-objective Non-dominated Sorting Genetic Algorithm II
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a) Q=∅ is the storage for the members of the next front.
b) for each p in the Fi front, do
   - Each q that is in Sp (Sp contains all the individuals
     dominated by p.
   - nq= nq-1, individual subtraction q.
   - If nq = 0, no individuals on the next front dominate q.
     Consequently, change qrank = i+1 and update Q by adding
     individual.
c) Add count front by 1.
d) The change Q to the next front so that Fi = Q
```

2.7. Crowding Distance
Crowding distance reflects the density of surrounding individuals from other individuals in the same population. When the rankings of the two non-dominant solutions are different, the solutions with the lower rank will be chosen. When two solutions fall within the same Pareto boundary, the solution with the larger crowding distance will be chosen [13].

2.8. Binary Tournament Selection
The selection process uses the binary tournament selection method. When forming parents, two solutions are chosen randomly in the population then their rank values are compared. The best solution is the solution that has a lower rank. If the rank values are the same, then the best solution is the solution that has the largest crowding distance [14].

2.9. Crossover
The crossover process can produce new offspring. The first thing to do is determine the initial random value. The random value is compared with the crossover probability value. If the random value is less than the probability value, the crossover process begins. The result generates a new offspring based on a cross with a certain part of parents [15].

2.10. Mutation
The mutation process is replacing a gene in an individual by exchanging genes that have been chosen at random [15]. The mutation process is carried out on each gene with a predetermined mutation rate. The mutation rate value determines the number of genes selected for mutation and produces new offspring [16].

3. Result and Evaluation
Bandung City consists of 30 districts with a total of TPS. Figure 2 shows that the operational areas of waste collection in Bandung City are Western Bandung, Eastern Bandung, Southern Bandung, and Northern Bandung. In this study, the authors took two regions to be analyzed. The selected regions are Eastern Bandung and Southern Bandung. The amount of waste transported to the TPA is not always the same as the number of existing landfills. The reason is that the waste transportation system is not optimal, so there are still piles of waste that are not collect every day.

Figure 2. Map of Waste Collection Operational Areas in Bandung [17]**.**

In modeling the selected area, it is necessary to know the location of the latitude and longitude coordinates. The distance between two points on the coordinates is calculated using the Haversine formula. Generating the initial population requires initializing the genetic algorithm parameters first.

The MNSGA-II parameters used (300) population size, (100) generation, (0,9) crossover rate, and (0,2) mutation rate. Later we will be evaluating the comparison of crossover rate and mutation rate to the fitness value. The fitness value is calculated using the DEAP library in the python programming language. The formation of offspring through a selection process using the mutation, tournament selection, and crossover mechanisms.

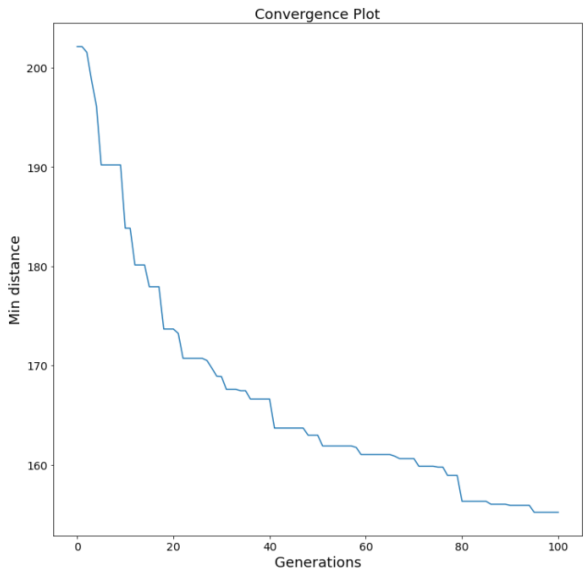

Figure 3. MNSGA-II Convergence Plot (100)

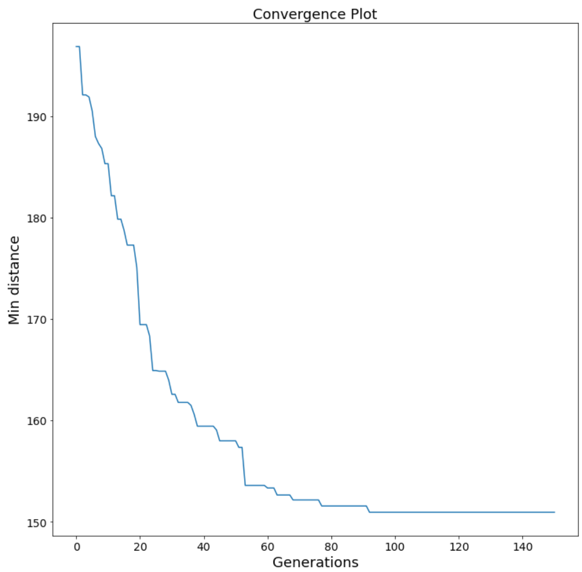

Figure 4. MNSGA-II Convergence Plot (150)

The total distance in the first generation is in the range of 210 km. Furthermore, the graph decreased to 160 km but still did not converge, so the author added more generations. The graph is shown in Figure 3. The distance from generation to generation is monitored and recorded in a convergence plot as depicted in Figure 4. From this plot, it can be clearly visualized that the minimum distance to converge to the optimum between one generation and the next generation is about 150 km.

The trial of the combination of both mutation and crossover rates aims to find out the most optimal combination. The crossover rate and mutation rate values used are between 0 to 1. Each generation has experimented with five times, and the average distance value is calculated. The test results show in Figure 5. In conclusion, the best combination of mutation rate and crossover rate is 0.3:0.7. The optimal solution obtained results in a total distance of 152,63 km.

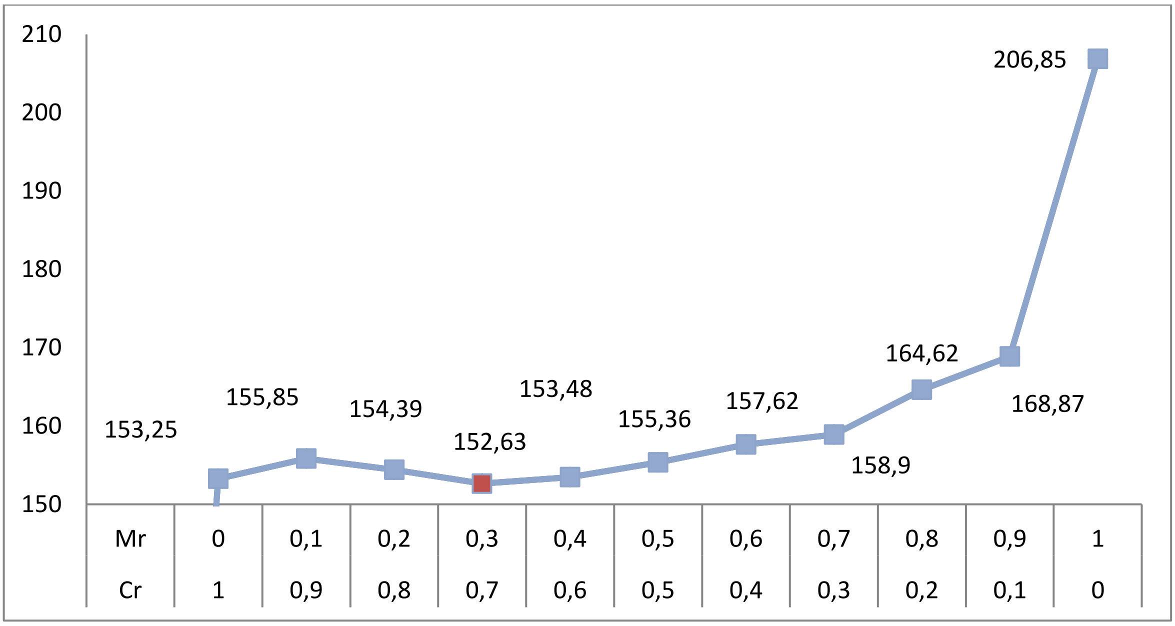

Figure 5. Comparison of Crossover Rate and Mutation Rate

The route plot generated is presented in Figure 6. Each node represents the TPS ID, while each edge denotes the generated route of trucks during waste collection throughout the city. X and Y coordinates represent the real coordinate of each TPS in terms of longitudes and latitudes respectively. Different edge color illustrates different assigned truck for each particular route.

Waste collection by one truck in one cycle starting from the SPA to the first TPS and another TPS until it reaches truck capacity. The optimal route arrangement obtained is 0 – 3 – 27 – 22 – 25 – 7 – 8 – 20 – 21 – 28 – 26 – 30 – 29 – 17 – 4 – 14 – 13 – 12 – 15 – 1 – 6 – 31 – 10 – 23 – 9 – 16 – 11 – 2 – 19 – 24 – 5 – 1 8 – 0 with a total distance of 152,63 km and 14 sub-routes. Complete details regarding the sub-routes are described in Table 3.

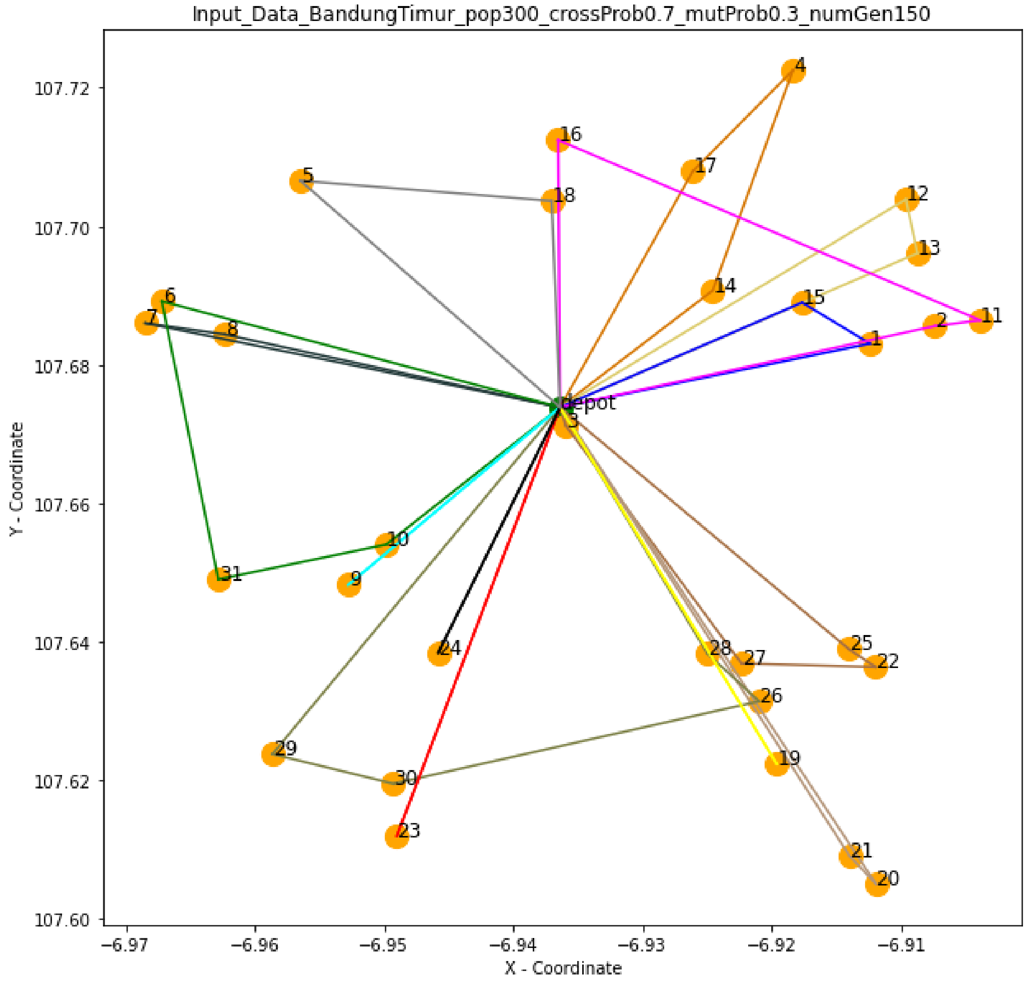

Figure 6. Optimal Route of Waste Transportation for Eastern Bandung and Southern Bandung Region.

The optimal route found by the MNSGA-II algorithm is described in table 3. For instance, the first truck start from SPA to Gading Regensi, then proceed to pick the produced waste at Maleer Rw 05. Tarumatex is set to be the next destination of garbage collection before the truck heading to Lp Kb. Waru and finalizes its trajectory at SPA. Among fourteen trucks, different routes are being allocated regardless the number of visiting point during waste collection process.

Table 3. Optimal Route

Truck	Route
1	SPA - Gading Regensi - Maleer Rw 05 - Tarumatex - Lp Kb. Waru – SPA
2	SPA - Derwati - Bandung Inten - SPA
3	SPA - Gedung Pakuan – Bi Braga – SPA
4	SPA - Maleer Rw 06 - Cibangkong Rw 11 - Len Lipi - Batununggal Indah - SPA
5	SPA - Pangaritan – Cipadung Rw 08 – Cinambo Indah – SPA
6	SPA - Ujung Berung Indah - Cigending - SPA
7	SPA - Golf - Cicukang – SPA

Truck	Route
8	SPA - Rancabolang - Jakapurwa - Cijaura Girang – SPA
9	SPA –Pln Sukarno Hatta – SPA
10	SPA - Cipagolo – SPA
11	SPA - Panyileukan - Suka Asih – Bojong Awi - SPA
12	SPA - Kosambi - SPA
13	SPA - Pt. Delami- SPA
14	SPA – Cempaka Arum – Polda Jabar - SPA

4. Conclusion

Based on the experimental evaluation at Eastern and Southern regions of Bandung City, we can conclude that the proposed use of Multi-objective Non-dominated Sorting Genetic Algorithm II (MNSGA-II) is able to find the optimal route solutions for modeling waste transportation activities managed by the local government institution, namely *PD Kebersihan*. The best achieved solution resulted in 14 routes with a total distance of 152,63 km. The results of this study are potentially beneficial in providing the supporting information to improve the service quality of the waste collecting system in the Eastern and Southern regions of Bandung city as well as to be implemented in other metropolitan areas of Indonesia.

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