Empirical study of MOPSO and NSGA II comparison in multi-objective location routing problem incorporating the service level of delivery

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Abstract

Logistics optimization in empirical cases is essential, especially in designing an effective and efficient last-mile delivery in developing countries. Yogyakarta, a city located in the central-south part of Java Island, also faces complexity in the last-mile delivery problem, mainly due to heavy traffic, which can cause the product to be delivered not in time, hence reducing the service level. On the other hand, the location routing problem is a model that can assist in determining the proper location of the distribution center and minimizing the delivery cost. However, finding the solution needs an efficient and effective algorithm, particularly for large instances. This study compares the performance of two metaheuristics commonly used, i.e. Multi-objective Particle Swarm Optimization (MOPSO) and Non-dominated Sorting Genetic Algorithm (NSGA) II, to be applied in the empirical research of delivery problems in Yogyakarta city. The objective is to minimize the delivery cost and maximize the service level of delivery in specific time windows. The comparison between the two is based on five indicators, namely Number of Pareto Front Solutions (NPS), Computational Time (CT), Spacing Metrics (SM), Generational Distance (GD), and Diversity Metrics (DM). Based on these five indicators, NSGA II indicates a better performance because it excels in four aspects: NPS, CT, SM, and GD. Meanwhile, MOPSO is only better in the DM indicator.

Keywords
Location routing problem, service level, time windows, multi-objective Particle Swarm Optimization (MOPSO), Non-dominated Sorting Genetic Algorithm (NSGA) II

1. Introduction

Logistics costs are one of the most significant contributors to the company's activities. According to Ballou (1997), logistics costs range from 4-30% in the activities of a business. Hence, it is essential to make an optimal logistics design to minimize logistics costs. One of the challenges faced in logistics is how to design an effective and efficient last-mile delivery design. According to Gavaers *et.al* (2014), last-mile delivery is the process of distributing goods from the last distribution point to a predetermined location point. Last-mile delivery is very important to optimize because it is an activity that requires a lot of cost and time (Dolan, 2018). The importance of last-mile delivery was also conveyed by Goh et.al (2001) who said that the percentage of last-mile delivery cost is about 53% of the total logistics cost. Therefore, implementing last-mile delivery that is effective and efficient is very important, especially in developing countries. This is based on the Logistic Performance Index (LPI) described by the World Bank annually. From the LPI indicator, it can be concluded that developing countries tend to still lag far behind developed countries. Therefore, it is very important to design a good logistic distribution. One way that can be done to optimize logistic distribution is to determine the location of facilities and routes simultaneously.

The approach that can be done to optimize logistic design includes optimization with Travelling Salesman Problem (TSP) and Vehicle Routing Problem (VRP). For both models, the best vehicle route can be obtained by involving various considerations. However, the use of such an approach may cause the design obtained to be sub-optimal. It can be due to the determining factors of location that are not necessarily optimal. LRP is an approach that can solve the problem of determining the location of facilities and vehicle routes simultaneously (Prodhon and Prins, 2014). With LRP, the optimization process will not get stuck in the sub-optimal solution resulting from the determination of the location of facilities and vehicle routes separately.

The way to do last-mile delivery can be in the form of pickup by consumers, shared reception boxes, own reception boxes, and attended reception (Kamarainen et al., 2001). Pick up by consumers is a service in the form of opening a retailer where consumers will come directly to buy their needs. Shared reception boxes make delivery addressed to a locker shared by the customer. By owning reception boxes, delivery is done in lockers located at the location of each customer. Furthermore, attended reception is a delivery that the customer directly receives at his home. Based on the way last-mile delivery has been described by (Kamarainen et al., 2001) previously, the case was raised here using a pickup system by consumers.

In the last mile delivery application, there are considerations used to determine the solution to be taken. Among these considerations are the total costs incurred for the distribution process, the emissions caused by the goods distribution process, the limitations related to the delivery time to the customer, or the service level of the distribution process. Based on previous research, usually, the cost is one of the objectives that want to be achieved in addition to other objectives. In addition to costs, this study also considers aspects of service level and time windows. Both things are considered because service level is one of the determinants of the competitive level of a company (Xiao and Yang, 2008). The better the level of service level provided by the company to the customer, the greater the level of customer satisfaction and can make loyal customers. However, there will be a trade-off between the service level and the total cost that will be issued, so it is necessary to find the optimal point between the two (Chen et al., 2020). Based on the description, the model that will be used to solve the problem is Multi-Objective Location Routing Problem With Time Windows (MLRPTW), taking into account the minimization of costs and maximization of service level.

Research on MLRPTW to minimize costs and maximize service levels is still being developed. Dharmika (2019) conducted the study using the goal programming exact method for small-scale cases. But that method is not good enough to be used in large-scale instances. Celine (2020) developed a model of Dharmika (2019) using Non-Dominated Sorting Genetic Algorithm (NSGA-II) method for large-scale cases. She obtained a good solution, but it is not yet certain that the solution obtained is the optimal solution. Therefore, finding a better solution can try using other metaheuristic methods and then make a comparison. In comparing the performance of metaheuristic methods, they must be applied in the same case. This is as explained by Sorensen (2015) that the performance of metaheuristic methods can not be compared in theory but should be directly applied to particular cases. The method that will be used in this study is Multi-Objective Particle Swarm Optimization (MOPSO). MOPSO was chosen because it has been widely applied in various fields, providing a good enough solution and producing high-quality pareto fronts (Liu and Kachitvichyanukul, 2015). In addition, according to Castro et al. (2009), MOPSO was able to provide a good solution despite the poor start of conditions.

Thus the case that will be optimized in this study is the last-mile delivery of the distribution of staple commodities such as sugar, rice, and cooking oil in the Special Region of Yogyakarta (DIY). This large scale distribution activity involves 9 Distribution Center (DC) candidates, 86 retailers, and three different types of vehicles. Location Routing Problem (LRP) model is used to model the problem. Furthermore, this study will compare MOPSO method performance with NSGA II to determine which method is better to apply to MLRPTW by considering the minimization of cost and maximization of service level.

2. Literature Review

Location routing problem (LRP) is an approach that can solve the problem of determining the location of facilities and vehicle routes simultaneously (Prodhon and Prins, 2014). LRP can attract the attention of researchers because it can combine facility location problems (FLP) and vehicle routing problems (VRP). The implementation of the LRP model has been widely done in various fields, including parcel delivery by Bruns et al. (2000) and Wasner and Zapfel (2004), Telecom network design by Billionnet et al. (2005), medical by Pourreza (2018), and environment Toro et al. (2017). In general, most LRP models are applied to make cost minimization as one of the objectives functions besides the other objectives to be achieved (Nagy and Salhi, 2006).

In addition to discussing costs, research on time windows is also widely done on LRP. In general, the application of time windows is used to determine the level of customer satisfaction of the model created. Some previous research also applies time windows, namely Bagherinejad (2015), which discusses the importance of distributing perishable products in time windows. Then Wang et al. (2019) used time windows to minimize the number of depot costs, vehicle fixed costs, and total travel costs of the routes. Furthermore, Zhang (2020) implemented time windows to reduce logistics costs and minimize environmental pollution due to vehicle emissions.

Research on service levels in LRP is also increasingly conducted. This is because the achievement of a good level of service can increase revenue for the long term with the formation of loyal customers. Some of the LRP research considers service level, like Chen (2019), who applies service level in bike station model. Service level is used to optimize bike station location and travel route for bicycle users. In addition, there is Wang (2013) applies service level to minimize total customer waiting time. Therefore, there is generally a service level used as the second objective function in addition to the cost aspect.

To solve complex problems with large amounts of data, metaheuristic methods can be used. The metaheuristic method is a method that can solve optimization problems with the process of approach or search for optimal solutions based on certain conditions or procedures (Hussain et al. 2019). By using the metaheuristic method, a good enough solution can be produced even though there is no guarantee of the discovery of an optimal solution, or in other words, the solution can be near-optimal. However, the use of metaheuristic methods can save time because computing time will be faster. Thus, metaheuristic methods are very suitable to be applied in complex cases with large amounts of data.

The application of metaheuristic methods on LRP models has been widely done. This is because of an increasingly complex model with various restrictions and data applied. The following are the use of metaheuristic methods in LRP, namely hybrid simulated annealing (SA) and ant colony optimization (ACO) implemented by Bouhafs et al. (2006). Bouhafs et al. (2006) determine the facilities to be opened using SA and determine the route to be traversed using the ACO. Then, Prins et al. (2006) use randomized extended Clarke and Wright algorithm (RECWA) to form an initial solution. Then, in making a decision, Prins et al. (2006) using the memetic algorithm with population management (MA| PM). Hussain et al. (2019) concluded that the particle swarm optimization (PSO) method is the most commonly used method regarding the application of metaheuristic methods.

PSO is one of the metaheuristic methods widely applied in various fields. Referring to Hussain et al. (2019), PSO is widely applied because of its ease and effectiveness when applied to science and industry. The applicative nature of PSO was also conveyed by Marinaki (2017) through surveys conducted related to vehicle routing problems (VRP) and PSO. From the survey covering 100 papers, it can be concluded that PSO can provide excellent solutions in various variants of VRP (Marinaki, 2017). One type of PSO is multi-objective particle swarm optimization (MOPSO). MOPSO is a modification of the PSO to solve the multi-objective optimization problem (MOOP). MOPSO was once applied to MLRP cases by Liu and Kachitvichyanukul (2015) with pareto based. Liu and Kachitvichyanukul (2015) concluded that MOPSO has better pareto front quality than NSGA II. Later, Castro et.al. (2009) has also applied MOPSO to vehicle routing problems with time windows (VRPTW). Based on the analysis results, Castro et al. (2009) concluded that MOPSO could produce a good solution, although it begins a very bad infeasible solution.

Research on MLRP to minimize total cost and maximize service level continues to be conducted. First, MLRP research was conducted by Dharmika (2019) who designed the problem model using the goal programming exact method and solved it with LINGO 18.0 software. The resulting model was tested in a small-scale case consisting of 4 distribution center (DC) candidates, eight retailer points, and three different vehicles. Then, the model initiated by Dharmika (2019) was developed by Celine (2020). Celine (2020) uses the metaheuristic non dominated sorting genetic algorithm (NSGA II) method for more complex cases on a large scale. This research will compare metaheuristic method performance in completing the multi-objective location routing problem with time windows (MLRPTW) model in Dharmika's research (2019). The method to be compared is the NSGA II used by Celine (2020) with MOPSO. Comparisons are made to find out which methods perform better in the case raised. The case that will be resolved is the determination of the location of the distribution center retailer as in Maruti (2017). Maruti (2017) determined the location of the distribution center (DC) for the distribution of staple commodities in DIY using data in Pradana (2015) and Iswari (2015). Thus, this study will compare MOPSO and NSGA II performance implemented in Matlab software to solve the distribution of staple commodities in DIY.

3. Problem Description and Mathematical Formulation

The model used to solve the case in this study is the Location Routing Problem (LRP) which combines the problem of distribution of staple commodities and retailer routes as well as the determination of distribution center (DC) locations in the Special Region of Yogyakarta (DIY). The types of goods considered are sugar, rice, and oil. For staple commodities that will be distributed to retailers previously imported from the central building in West Java. Then, before sending the goods to an existing retailer, the goods will be stored first on a DC in DIY. The case to be optimized has a limit with the number of retailers analyzed 86 retailers, 9 candidates of DC, and 3 types of vehicles used with different capacities and specifications.

3.1 Assumptions

1. Each retailer's request must be fulfilled by one DC using one route.
2. There is at least 1 DC opened to serve retailers.
3. Each route starts and ends on the same DC.
4. The total demand for each route does not exceed the capacity of the vehicle used.

5. Acceptance of demand needs for each retailer is attempted within the time windows so it can reach the condition of on-time delivery (OTD).

3.2 Notations

Parameters :

D	= set of potential DC candidate locations, $d \in$ D
I	= set of retailer, $i \in$ I
K	= set of vehicle types, $k \in$ K
U_{ik}	= auxiliary variable for subtour elimination
g_d	= investment costs of candidate location selection DC d
f_k	= fixed cost of vehicle use k
VC_k	= variable cost of vehicle k per unit distance
D_j	= customer request at retailer j
Q_k	= capacity of vehicle type k
dis_{ij}	= matrix distance from node i to j
t_{ijk}	= matrix time from node i to j with vehicle k
S_i	= service time at retailer i
$Start_{dk}$	= departure time vehicle k in DC d
End_{dk}	= return time vehicle k in DC d
$[A_i, B_i]$	= time windows at retailer i
T_i	= arrival time at retailer i
$[Open_d, Close_d]$	= open and close time DC d
N	= number of retailer
WT	= working time

Decision Variables :

$$Xijk = \begin{cases} 1, & \text{if the vehicle k passes through the arc } (i,j) \in \ I \ \cup J \\ 0, & \text{otherwise} \end{cases}$$

$$Yd = \begin{cases} 1, & \text{if } DC\ d\ \in\ D\ is\ opened \\ 0, & \text{otherwise} \end{cases}$$

$$OTDi = \begin{cases} 1, & \text{if on time delivery at retailer } i\ \in I \\ 0, & \text{otherwise} \end{cases}$$

$$Vk = \begin{cases} 1, & \text{if vehicle } k\ \in K \text{ is used} \\ 0, & \text{otherwise} \end{cases}$$

$$Zijk = \begin{cases} 1, & \text{if } retailer\ j\ \in I \text{ is served by } DC\ i\ \in D \text{ with vehicle } k \in K \\ 0, & \text{otherwise} \end{cases}$$

3.3 Mathematical Formulation

Objective Function :

1. Minimization total cost

$$Min\ Total\ Cost(TC) = \sum_{d \in D} g_d\, Y_d + \sum_{k \in K} f_k\, V_k + \sum_{i,j\ \in\ D \cup I} \sum_{k \in K} X_{ijk} dis_{ij}\, VC_k \tag{1}$$

2. Maximization service level

$$Max\ Service\ Level\ (SL) = \frac{OTD_i}{N} \tag{2}$$

Constraints :

$$\sum_{k \in K} \sum_{i \in D \cup I} X_{ijk} = 1\,, \quad \forall\, j \in I \tag{3}$$

$$\sum_{i \in D} \sum_{j \in I} X_{ijk} \leq 1\,, \quad \forall\, k \in K \tag{4}$$

$$\sum_{d\in D} Y_d \geq 1 \tag{5}$$

$$\sum_{j\in D\cup I} X_{ijk} = \sum_{j\in D\cup I} X_{jik} \quad \forall\, k \in K, i \in D \cup I \tag{6}$$

$$\sum_{j\in I}\sum_{i\in D\cup I} D_j X_{ijk} \leq Q_k V_k\,, \quad \forall\, k \in K \tag{7}$$

$$U_{ik} + U_{jk} + NX_{ijk} \leq N - 1, \quad \forall\, i, j \in I, k \in K \tag{8}$$

$$\sum_{i\in I} X_{ijk} + \sum_{i\in D} X_{ijk} \leq 1 + Z_{ijk}, \quad \forall\ i \in D, j \in I, k \in K \tag{9}$$

$$Y_d \geq X_{ijk}, \qquad \forall\ d, i \in D, j \in I, k \in K \tag{10}$$

$$T_i \geq A_i, \qquad \forall\ i \in I \tag{11}$$

$$T_i + S_i \leq B_i + (WT - B_i) \times (1 - OTD_i), \qquad \forall\ i \in I \tag{12}$$

$$Start_{dk} \geq Open_d, \qquad \forall\ d \in D, k \in K \tag{13}$$

$$End_{dk} \leq Close_d, \qquad \forall\ d \in D, k \in K \tag{14}$$

$$-M\big(1 - X_{ijk}\big) - \big(T_j - T_i - S_i - t_{ijk}\big) \leq 0, \quad \forall\ i \in I, j \in J, k \in K \tag{15}$$

$$M\big(1 - X_{ijk}\big) - \big(T_j - T_i - S_i - t_{ijk}\big) \geq 0, \quad \forall\ i \in I, j \in J, k \in K \tag{16}$$

$$-M\big(1 - X_{ijk}\big) - \big(T_j - Start_{dk} - t_{ijk}\big) \leq 0, \quad \forall\ i, d \in D, j \in J, k \in K \tag{17}$$

$$M\big(1 - X_{ijk}\big) - \big(T_j - Start_{dk} - t_{ijk}\big) \geq 0, \quad \forall\ i, d \in D, j \in J, k \in K \tag{18}$$

$$-M\big(1 - X_{ijk}\big) - \big(End_{dk} - T_{ik} - S_i - t_{ijk}\big) \leq 0, \quad \forall\ i, d \in D, j \in J, k \in K \tag{19}$$

$$M\big(1 - X_{ijk}\big) - \big(End_{dk} - T_{ik} - S_i - t_{ijk}\big) \leq 0, \quad \forall\ i, d \in D, j \in J, k \in K \tag{20}$$

$$X_{ijk} = \{0,1\}, \quad \forall\ i \in I, j \in J, k \in K \tag{21}$$

$$Y_d = \{0,1\}, \quad \forall\ d \in D \tag{22}$$

$$OTD_i = \{0,1\}, \quad \forall\ i \in I \tag{23}$$

$$V_k = \{0,1\}, \quad \forall\ \ k \in K \tag{24}$$

$$Z_{ijk} = \{0,1\}, \quad \forall\ i \in I, j \in J, k \in K \tag{25}$$

$$U_{ik} \geq 0, \quad \forall\ i \in I, k \in K \tag{26}$$

$$T_{ik} \geq 0, \quad \forall\ i \in I, k \in K \tag{27}$$

$$Start_{dk} \geq 0, \quad \forall\ d \in D, k \in K \tag{28}$$

$$End_{dk} \geq 0, \;\; \forall \; d \in D, k \in K \tag{29}$$

Equation (1) is the first objective function: minimizing the total cost consisting of 3 components as its constituent. The three components of the cost are dc fixed cost, vehicle fixed cost, and transportation variable cost. The total cost of DC investment is indicated by the total multiplication between *gd* and *Yd*. *gd* is an investment fee incurred for the opening of DC *d* and *Yd* candidates are variables of decisions of selected DC *d* candidates. The fixed cost of using the vehicle is the total multiplication between the *fk* which is the fixed cost of the vehicle for each shipment and *Vk* which is the variable decision of the type of vehicle *k* used for delivery. The variable cost of transportation is the cost for each shipment made which is described with the total multiplication between *Xijk, disij*, and *VCk*. *Xijk* is a decision variable that describes the route from node *i* to *j* using vehicle *k*. As for d*isij* describes the distance between node *i* to *j*. Further, *VCk* is a component of the cost incurred by the vehicle *k* every delivery made.

Equation (2) describes the second objective function which is service level maximization. The category of service level that wants to achieve is on-time delivery for each delivery at a retailer. The on-time delivery happens if the delivery at a retailer is in the time windows range for that retailer. The service level will be measured using the punctuality indicator as described by Rafele (2004). With the punctuality indicator, a comparison between on-time delivery and the number of deliveries or retailers served will be calculated.

Constraint (3) shows that each retailer visited once. Constraint (4) describes the routes passed once by vehicles. Constraint (5) describes minimal there is 1 DC opened. Constraint (6) describes flow conservation constraints. Constraint (7) indicates the total demand delivered by the vehicle does not exceed its capacity. Constraint (8) describes sub tour elimination constraints. Constraint (9) explains that the retailer is attached to the DC if there is a route. Constraint (10) gives the limitation that the vehicle only departs from the opened DC. Constraint (11) ensures the vehicle arrival time for each retailer must be more or equal to the earliest time windows of the retailer. Constraint (12) explains delivery for retailers is on-time delivery if the service process is in the range of time windows. Constraint (13) ensures that the vehicle departs from DC after DC is opened. Constraint (14) ensures that the vehicle is returned to the DC before the DC close time. Constraints (15-20) are used to determine the arrival, departure, and return times of vehicles on a route. Constraint (21-29) indicates the decision variables and nonnegativity constraint.

4. Solution Approach

4.1 NSGA II

NSGA II is the development of the NSGA that was first introduced by Deb et al. (2002). NSGA II is one of the most popular methods used by researchers, especially to solve multi-objective optimization problems. This is because the use of NSGA-II can provide more efficient computational results, using elitism and crowded distance comparisons that can maintain diversity without adding certain parameters (Coello et al., 2001).

The following are the NSGA II stages :

1. Initiate the population
   Random population initiation will be used to determine the D.C. candidate chosen, the route to visit the retailers, the type of vehicle used, and departure time. The number of populations to be initiated will depend on the specified number of population parameters.
2. Calculate the objective function
   After the initiation of the population is completed, calculate the fitness for each of these populations. In this study, fitness is calculated in the form of total cost and service level.
3. Perform non dominated sorting and calculate crowding distance
   At this stage, dominance is determined for all populations. Populations that are increasingly not dominated by other populations will have a smaller front value. The value of the front that has been formed will be the basis of decision making where the priority of the solution taken is the first front. In addition to determining dominance, populations on the same front will be sorted by crowding distance.
4. Perform selection parent
   Tournament selection will be used for selection process. Parent selection at this stage is done by considering the value of fitness or rank front and crowding distance
5. Execute crossover
   Crossbreeding of the parent is performed to form offspring. The crossover mechanism to be used is the crossover cycle.

6. Execute mutation
   Modifications to those populations aim to form the possibility of a better population. The mutation method to be used is swap mutation.
7. Replacement
   At this stage, the formation of a new population consists of a combination of the initial population and the population formed from the results of crossover and mutation. Then the new population will be calculated its objective function and determined dominance until it gets the next generation and will end when it reaches stopping criteria.

4.2 MOPSO

MOPSO is a modification of the PSO to solve multi-objective problems. Implementing MOPSO requires some adjustments from the PSO to be applied. The adjustment that needs to be done is creating a global repository to determine the leader to be used as Gbest. In addition to creating the global repository, another thing that needs to be customized is the selection of a leader. In PSO leader can be determined by directly comparing the value of the objective function and then assigning the best particle as Gbest. However, that mechanism cannot be applied to MOPSO because the objective functions that are to be achieved are more than 1 and these functions may be also contradictory. To deal with this, Govindan et al. (2014) explained that two ways can be done in the selection of MOPSO leader are as follows:

1. Geographically based system (Grids)
   This strategy is based on a population of hyper-cubes that divide the search space that has been explored. Then, the leader selected here is a solution on the grid with the least number of grid members.
2. Crowding Distance (CD)
   This strategy chooses leaders based on crowding distance. Thus, the leader is a solution that has the highest CD value.

Based on the explanation of both strategies, this study will use the *grids strategy.* Referring to Coello *et al.* (2004), the MOPSO stages are as follows.

1. Initiate particle
   Population initiation is done randomly for each particle.
2. Initiate speed of particle
   Initiating the speed of the entire particle is equal to 0.
3. Calculate fitness for each particle
   Calculate fitness for each particle that has been raised in accordance with the goal to be achieved.
4. Input particle position to repository
   Input the position of each non dominated particle into the repository
5. Create hypercubes from the search space
   Create hypercubes from the search process that has been done and determine the location of particle coordinates based on the value of the objective function.
6. Initiate memory of each particle
   Inisasi memory particle by Pbest and Gbest. Pbest is the best solution ever achieved by a particle and Gbest is the best solution ever achieved by all particles. Gbest or leader on MOPSO is taken from the repository using grids strategy. After each repository member has their own grid value, then the roulette wheel mechanism will be performed to determine the leader.
7. Update position and speed of each particle
   Update the position and speed of particle based on Pbest and Gbest. Speed update is a major change that will be applied to a particle.
   Mathematical model of speed update is as follows:

$$vi(t) = vi(t\text{-}1) + p_1 \, C_1 \times (p_{best} - x_i(t - 1)) + p_1 \, C_1 \times (REP(h) - x_i(t - 1)) \tag{30}$$

where :

$v_i(t)$	= Speed on iteration *i*
$v_i(t\text{-}1)$	= Speed on iteration *i-1*
p_1, p_2	= Random variable between [0,1]
C_1, C_2	= Constant of learning factor
P_{best}	= Pbest
$REP(h)$	= Leader
$x_i(t\text{-}1)$	= Position on iteration *i-1*

Meanwhile, the mathematical model of position update is as follows:

$$x_i(t) = x_i(t-1) + v_i(t) \tag{31}$$

where :

$x_i(t)$ = Position on iteration i

8. Perform mutation process
   Mutation is a process of changing the composition of solutions in the hope of finding a better solution.
9. Keep particle in search space
   Keeping particles in search space can be done by adjusting the position and speed of the particle to stay within its limits.
10. Update repository and particle representation in hypercubes
    Repository updates are done due to a limit on the number of particles that can be accommodated in the repository. Initially, all non-dominated particles will be inserted into the repository. After that, particles dominated by other particles will be removed from the repository.
11. Update memory of each particle
    Update the memory of particle is done by considering P_{best} and leader based on iterations that have been done before.
12. Conduct iteration until it reaches stopping criteria.

4.3 Solution Representation

The particle and chromosome representation in this study consists of 3 strings. The first string is a route that includes DC and retailers. The second string is the type of vehicle selected for each route. The third-string is the vehicle departure time for each route. By using NSGA II, route determination can be done by randomly selecting routes for all retailers. However, this cannot be done for MOPSO, because MOPSO is basically used to solve continuous problems. Therefore, the adjustment made is to apply the priority list mechanism as described by Liu and Kachitvichyanukul (2015). An illustration of the chromosome/particle representation and priority list mechanism can be seen in Figure 1.

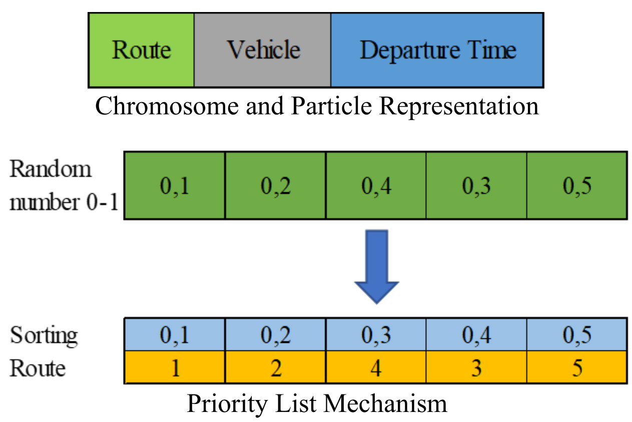

Figure 1. chromosome/particle representation and priority list mechanism

5. Computational Results

The resulting solution uses the posterior method on multi-objective optimization problems (MOOP). By using the method, the decision-maker will give the preferred solution preference after running is done. Thus, from the results of running in the form of non-dominated solutions (NDS), decision-makers will choose one of the solutions that will be applied based on their preferences and circumstances.

5.1 Algorithm Parameters

Before using both methods to solve the problem, it will be determined the parameters first. The parameters used for running MOPSO method refers to Liu and Kachitvichyanukul (2015) who also solve multi-objective location routing problem with the same scale. The details of the values of each parameter are Number of particles (*NoP*) = 150, Number of Iteration = 1200, inertia weight (ω) reduced linearly from 0.9 to 0.4, personal learning (*c1*) = 1, global learning (*c2*) = 1, Number of Member Repository (*NRep*) = 100. In addition, this study also used parameter values from Coello *et al.* (2004) namely mutation rate = 0.5 and Total Adaptive Grid as much as 30 to 50.

The parameters used for NSGA II are as used by Celine (2020), consisting of pop size (*Np*) = 150, crossover rate (*Pc*) = 0.9, mutation rate (*Pm*) = 0.1, and stopping criteria in the form of maximum iteration of 1200 times. The running result of each experiment produced a different non-dominated solution or first front so that the pareto front graph and the resulting solution set are different.

5.2 Data Set

The data used includes :

1. Distribution center and retailer coordinates
2. Demand of each retailer
3. Capacity and specifications of the vehicle used
4. Investment costs of distribution center based on location
5. The fixed cost of using the vehicle includes the investment cost of the vehicle and the driver.
6. Variable transportation costs per unit distance
7. Time windows and service time of each retailer
8. Distribution center’s opening and closing times

5.3 Solution

To find the solution, each method will be run five times with the parameters that have been defined before. Here is the comparison of the resulting solutions.

Pareto front :

For comparing the resulting pareto front, the running pareto front results are displayed for the first try on each method. Figure 2. shows the pareto front for MOPSO and Figure 3. for NSGA II. Based on both pareto, it can be seen that pareto NSGA II more uniform than MOPSO that tends to be random and accumulate.

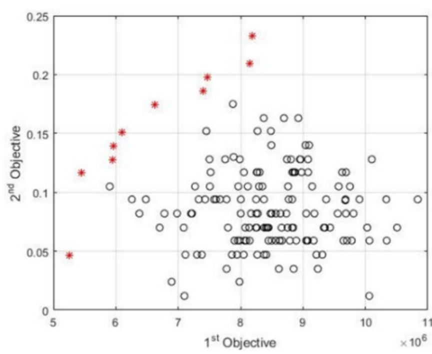

Figure 2. Pareto front MOPSO

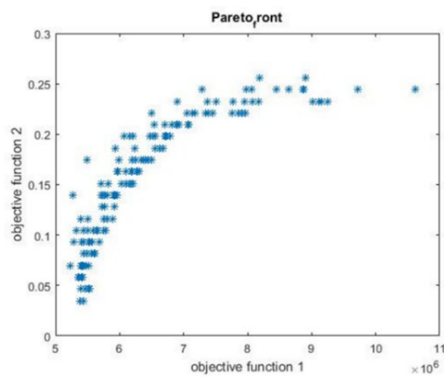

Figure 3. Pareto front NSGA II

Objective Function :

Based on the results of running on both methods using posterior principles, the decision-maker will choose several solutions. As an illustration of the resulting objective function, in Table 1 shows the resulting solution in experiment 1 on each method MOPSO and NSGA II.

Table. 1 Objective Function of Solution

NDS	MOPSO		NSGA II	
	Objective Function 1	Objective Function 2	Objective Function 1	Objective Function 2
1	5.450.218	11,63%	8183620	25,58%
2	8.185.618	23,26%	7292106	24,42%
3	5.954.159	13,95%	5930571	18,60%
4	7.395.028	18,60%	6494436	22,09%
5	7.472.639	19,77%	6900266	23,26%
6	6.092.326	15,12%	5270052	13,95%
7	5.253.802	4,65%	5232962	6,98%
8	6.626.195	17,44%	6069356	19,77%
9	8.146.739	20,93%	5492977	17,44%
10	5.944.533	12,79%		

5.4 Comparison Metrics

Comparison Metrics are used to compare performance between two methods. Five comparison indicators will be used to evaluate the performance of the method in multi-objective cases, with respect to the number of pareto front solution (NPS), computational time (CT), Spacing Metrics (SM), Diversity Metrics (DM), and Generational Distance (GD).

1. *The Number of Pareto Front Solutions* (NPS)

NPS describes the number of non-dominated solutions that can be achieved by a method or algorithm. The more NPS produced, the more solutions decision makers can consider, the better the performance of the method.

2. *Computational Time* (CT)

CT describes the length of time it takes to find a set of solutions. The less time it takes, the better the performance of an algorithm or method.

3. *Spacing Metrics* (SM)

SM describes how pareto points are distributed in search space. The lower the SM value, the pareto points will tend to be distributed uniformly. SM is calculated with reference to Rabbani *et. al* (2018).

4. *Generational Distance* (GD)

GD is used to see the convergence of an algorithm. The smaller the GD value, the better the performance of an algorithm. GD is calculated with reference to Veldhuizen and Lamont (1999)

5. *Diversity Metrics* (DM)

DM is used to distinguish the deployment of solution sets. The greater the value of DM, the wider the solution distribution so that more search space is explored. DM is calculated with reference to Rabbani *et. al* (2018).

5.5 Results of The Comparison

Based on these five comparison metrics, it will be calculated for each MOPSO and NSGA II method. Comparison metrics can be seen in Table 2. From the results of the calculation, it can be interpreted as follows:

1. The average number of NDS produced by NSGA II is more than MOPSO so in the NDS aspect, NSGA II is better. This is because the more NPS, the more options for decision makers.
2. Based on CT indicators, it can be concluded that NSGA II is better than MOPSO. This is because the smaller the CT, the faster the computing time will be.
3. Based on the SM indicator, it can be concluded that NSGA II is better than MOPSO. This is because the distance between NSGA II solutions on the pareto front is more uniform than MOPSO.
4. Based on the DM indicator, it can be concluded that MOPSO is better than NSGA II. This is because the spread of MOPSO solutions is more diverse so the search space that has been explored more widely.
5. Based on the GD indicator, it can be concluded that NSGA II is better than MOPSO. The solution in NSGA II is more convergent than MOPSO, because the average distance between optimal pareto with other solutions closer.
6. Overall NSGA II performed better than MOPSO in this case, as NSGA II was better in 4 indicators while MOPSO was only 1.

Table. 2 Comparison Metrics

Trial	MOPSO					NSGA II				
	NDS	CT	GD	SM	DM	NDS	CT	GD	SM	DM
1	10	1438,6374	66095	156006	22090,9	9	595,62214	28368,1	85188,4	18444,3
2	9	1418,94349	34123,9	23187,9	21638,1	12	1014,842	20330,5	29064,8	21973,4
3	9	1394,60678	34123,9	23187,9	21638,1	12	592,2534	20330,5	29064,8	21973,4
4	5	1412,18552	171216	34758,7	21178,6	12	613,68322	20330,5	29064,8	21973,4
5	9	1419,01209	34123,9	23187,9	21638,1	12	596,50878	20330,5	29064,8	21973,4
Average	8,4	1416,67705	67936,5	52065,8	21636,7	11,4	682,58191	21938,1	40289,5	21267,6

6. Conclusion

This study has successfully applied and compared the performance of MOPSO and NSGA II methods in distributing staple commodities in DIY. The model used is a multi-objective location routing problem with time windows. The objective functions cover cost minimization and service level maximization. From the results of both methods, a set of solutions consisting of dc location, the vehicle used, route to be passed by the vehicle, departure and return time of the vehicle, and the objective function value of the decision taken. Because the model is multi-objective, the solution is represented in the form of a pareto front where the decision-maker can decide on the set of solutions in the pareto front. The range of objective functions of the first set of solutions is 5,200,000 to 8,200,000 for both MOPSO and NSGA II. Then the second objective function range is in the range of 4.65% to 23.26% for MOPSO and 6.98% to 25.58% for NSGA II.

There are five performance metrics used to compare MOPSO and NSGA II performance. The five performance metrics indicators are the number of pareto front solutions (NPS), computational time (CT), spacing metric (SM), generational distance (GD), and Diversity Metrics (DM). The comparison is done by calculating the five aspects for each method and then calculate the average for each indicator. Based on the performance metric calculation, NSGA II has better performance than MOPSO for 4 indicators, namely NPS, CT, SM, and GD. However, for the DM aspect, MOPSO is still better. Thus, the overall method that gives better performance in the case of this study is NSGA II.

The future research that can be done is model development to produce a better distribution process. The development of the model can be a modification to the service level formula used because the formula tends to be very strict and allows to produce a low service level. In addition to service level modifications, further research considerations can be used to use other metaheuristic methods to obtain a better set of solutions. Other suggestions for further research can be a sensitivity test to the parameters to be used, considering dc capacity, and applying a set covering problem.

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