



# Simulated annealing algorithm for solving the capacitated vehicle routing problem: a case study of pharmaceutical distribution



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## ARTICLE INFORMATION

Article history:

Received: May 09, 2020

Revised: June 15, 2020

Accepted: July 17, 2020

Keywords:

VRP

Nearest neighbour

Simulated annealing

Heuristic method

## A B S T R A C T

This study aims to find a set of vehicles routes with the minimum total transportation time for pharmaceutical distribution at PT. XYZ in West Jakarta. The problem is modeled as the capacitated vehicle routing problem (CVRP). The CVRP is known as an NP-Hard problem. Therefore, a simulated annealing (SA) heuristic is proposed. First, the proposed SA performance is compared with the performance of the algorithm from previous studies to solve CVRP. It is shown that the proposed SA is useful in solving CVRP benchmark instances. Then, the SA algorithm is compared to a commonly used heuristic known as the nearest neighbourhood heuristics for the case study dataset. The results show that the simulated Annealing and the nearest neighbour algorithm is performing well based on the percentage differences between each algorithm with the optimal solution are 0.03% and 5.50%, respectively. Thus, the simulated annealing algorithm provides a better result compared to the nearest neighbour algorithm. Furthermore, the proposed simulated annealing algorithm can find the solution as same as the exact method quite consistently. This study has shown that the simulated annealing algorithm provides an excellent solution quality for the problem.

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## 1. INTRODUCTION

It is known that in logistics the most important factor besides meet customer satisfaction is minimizing the cost that commonly associated with traveled distance by the vehicles [1]. A common problem in transportation is to find

the optimal route by determining which route will be used that incurred the least transportation cost. The problem is commonly addressed as the Vehicle Routing Problem (VRP) [2]. VRP is a well-known class of combinatorial optimization problems proposed in the late 1950s [3].

VRP has many applications in real-life situations, especially in the distribution of goods and in supply chain management. Vehicle Routing Problem (VRP) aims at designing a set of minimum cost routes starting from and ending at a single depot. Each route can be visited once, so the total demand of the customers in each route does not exceed the vehicle capacity.

The situation might be a little bit different from the distribution of a non-perishable product, such as in the pharmaceutical industry. In the pharmaceutical industry, the entire distribution process is crucial and may need more attention [4]. In many cases, pharmaceutical products are urgently needed to recover everyone who is sick, and it is required to be fulfilled immediately [5]. Pharmaceutical products often require high caution when being transported, especially for liquid products. The distribution of these types of products usually is time-critical [6]. It can be mentioned explicitly that pharmaceutical distribution demands short delivery times [7]. Thus, vehicle routing and scheduling problems become more challenging for distributors.

The case study of vehicle routing problems in the pharmaceutical industry has developed in recent years. The first related research is the application of genetic algorithms to solve routing problems in pharmaceutical warehouses involving 200 pharmacies in three different cities [8]. The next research seeks to overcome consistency problems in vehicle routing problems in pharmaceutical cases by applying mathematical models that take into account service level agreements such as time windows and release dates [4]. Further is the application of the simulated annealing algorithm in a variant of the weighted vehicle routing problem to design distribution routes in high theft risk areas. Simulated Annealing is also shown to be performed well in various types of location-allocation and vehicle routing variants [9], [10]. The model aims to minimize transportation and cargo theft costs [11]. Last but not least research in the field of pharmaceutical distribution that introduces Disrupted Vehicle Routing problems with Soft Time Windows since. The model tries to increase response to efficient delivery to dynamic demands. The method used is a neighbourhood search such as a large neighbourhood search (LNS) and a neighbourhood search variable (VNS) based on a hybrid approach in the optimization of vehicle routes [12].

Although this research has the same focus as some of the studies mentioned above namely pharmaceutical products. The perspective of pharmaceutical products considered in this study is not a very sensitive or perishable type of product. However, we consider to minimize the total delivery duration. We proposed heuristic approaches to generate VRP results. To solve the VRP problem, this study used the nearest neighbour and simulated annealing algorithms. The two algorithms then compared to see the performance of both algorithms in determining optimal results. Therefore, the purpose of this research is to apply methods to solve problems in a practical situation, such as pharmaceutical distribution. The experimental results then show which method can generate the most efficient solution.

The distribution problem in PT. XYZ is considered as a Vehicle Routing Problem (VRP) that aims for optimizing the delivery of goods, choosing the best route, which reduces travel time. This research focuses on pharmaceutical products. The perspective of pharmaceutical products considered in this study is not a very sensitive or perishable type of product. However, we consider to minimize the total delivery duration. We proposed heuristic approaches to generate VRP results. To solve the VRP problem, this study used the nearest neighbour and simulated annealing algorithms. The two algorithms then compared to see the performance of both algorithms in determining optimal results. Therefore, the purpose of this research is to apply methods to solve problems in a practical situation, such as pharmaceutical distribution. The experimental results then show which method can generate the most efficient solution.

## 2. RESEARCH METHODS

### 2.1 Assumptions and problem definitions

To simplify the modeling process several assumptions are stated as follows.

1. Market share of PT. XYZ is assumed by 24% of the population in West Jakarta.
2. The amount of pharmacy demand is derived from the total population in each district.
3. Drug distribution conducted once a week.
4. Drug distribution is carried out using a motorcycle.
5. Demand in the number of boxes, one box is assumed to meet the demand of approximately

- 100 people.
- 6. The vehicle carrying capacity is four boxes.
- 7. The vehicles used are eight motorbikes.
- 8. The number of nodes is 11, with one depot.

### 2.2 Capacitated vehicle routing problem (CVRP)

The mathematical formulation of CVRP, including the inputs, decision variables, and constraints are described as follows.

#### Inputs

- $N$  Set of nodes where  $\{1..n\}$  are customers and 0 is a depot
- $c_{ij}$  Travel time from node  $i$  to  $j$  where  $(i, j) \in N$
- $K$  Number of vehicles
- $Cap$  Vehicle capacity
- $d_i$  The demand of customers  $i$  where  $i \in N$

#### Decision Variables

- $X_{ij} = \begin{cases} 1 & \text{One if node arcs } (i, j) \text{ is appears in the optimal tour} \\ 0 & \text{Otherwise zero} \end{cases}$
- $u_i, u_j$  Variables that being used to apply the sub tour elimination

#### Minimize

$$\sum_{i \in N} \sum_{j \in N} c_{ij} X_{ij} \tag{1}$$

#### Subject to:

$$\sum_{i \in N; i \neq j} X_{ij} = 1 \quad \forall j \in N \setminus \{0\} \tag{2}$$

$$\sum_{j \in N; i \neq j} X_{ij} = 1 \quad \forall i \in N \setminus \{0\} \tag{3}$$

$$\sum_{j \in N \setminus \{0\}} X_{0j} \leq K \tag{4}$$

$$u_j - u_i + Cap * X_{ij} \leq Cap - d_i \quad \begin{matrix} i \neq j; \forall j \in N \setminus \{0\}; \\ \forall i \in N \setminus \{0\}; \end{matrix} \tag{5}$$

$$d_i \leq u_l \leq Cap \quad \forall i \in N \setminus \{0\} \tag{6}$$

$$u_i \geq 0; u_j \geq 0 \quad \forall i \in N, \forall j \in N \tag{7}$$

The objective function in (1) is to find the total minimum travel time. Each vehicle will return to the depot after serving the consumer. The decision variable used is  $X_{ij}$ ; it equals to one indicates vehicle  $k$  is moving from location  $i$  to  $j$ , otherwise zero. Constraints (2) and (3) ensure one node is visited only once. Constraint (4) limits the maximum number of routes to  $K$ , the number of vehicles. Constraints (5) and (6) ensure together that the vehicle capacity is not exceeded. Constraints (7) is the sub-tour elimination constraint that determines the route formed is the Hamiltonian path.

### 2.3 Simulated annealing (SA) procedure

The Simulated Annealing (SA) method is developed from an analogy in the cooling process of liquid metal to form crystals, which is known as annealing process [13]. Annealing is a metallurgical technique that uses the science of scheduling the cooling process to produce efficiencies in the optimal use of energy to produce metals [14]. Kirkpatrick, et al. [15] explain the working principle of SA is that at high temperatures liquid molecules have high energy levels so that they are relatively easy to move towards other molecules. If the temperature is lowered, the molecules will arrange themselves to look for configurations or arrangements with lower energy levels. By slowly lowering the temperature, the molecules are allowed to self-regulate so that a stationary or stable state is obtained with a minimum energy level. The gradual decrease in temperature is called the annealing process, which is used to solve the VRP problem so that an optimal solution will be obtained.

The implementation of SA for VRP is as follows. First, the proposed SA starts with a random initial  $X$ . Then, the initial parameter is set along with note the current best solution  $X_{best}$  is equal to the initial solution  $X$ . The following process is to find a better solution using neighbourhood move such as swap, insert, and reverse. The probability of choosing each neighbourhood is treated equal which is one third for each. If the new solution  $Y$  is better than current solution  $X$ , then replace  $X$  with  $Y$ . Otherwise, a small probability of accepting a worse solution is

calculated based on the value of  $\exp(-d/T)$ . The value of  $d$  is the difference of the objective between solution Y and X. While  $T$  is the current temperature. If the solution is better than the best-found solution  $X_{best}$  then replaces the  $X_{best}$ . The iteration is conducted for liter times. After that, a temperature decrease is conducted based on alpha. The algorithm is terminated after the current temperature  $T$  is less than the final temperature  $T_f$ . The algorithm flowchart can be seen in Fig. 2.

The solution is represented by the permutation of n customers (1, 2,..., n), and Ndummy zeros. The Ndummy zeros are used to randomly terminated the route to explore the solution space better. Routes can also be terminated based on capacity constraints. The number of Ndummy is calculated as  $\text{ceil}(\frac{\sum_{i=1}^n d_i}{\text{Cap}})$ , where  $d_i$  is the demand of customer  $i$  and cap as the capacity of the vehicle while ceil is a round-up function. The illustration of the solution representation can be found in Fig. 1.

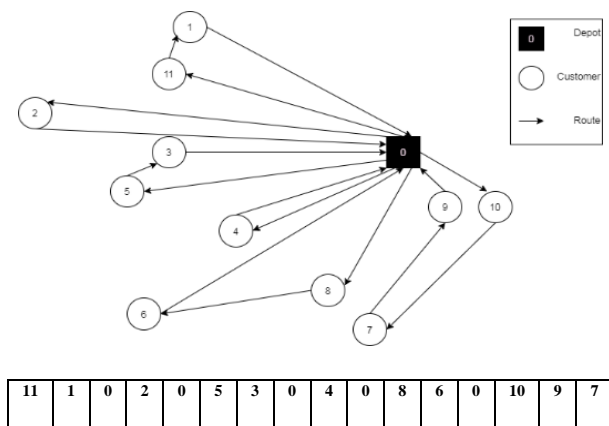


Fig.1. Solution representation

2.4 Nearest neighbour (NN)

The nearest neighbour algorithm uses a very simple rule to determine or generate a routing decision [16]. By applying the rule of always visiting the nearest node, this algorithm can produce a good VRP solution [17]. The nearest neighbour works as follows. For each route, an unserved customer is selected based on the nearest distance to the last inserted node starting from the depot. A route is terminated if no unserved node can be added without violating the capacity constraint. After a route is terminated, the route generation process starts again from the depot and continues until all customers are served.

The step by step of the algorithm is described in a flowchart in Fig. 3.

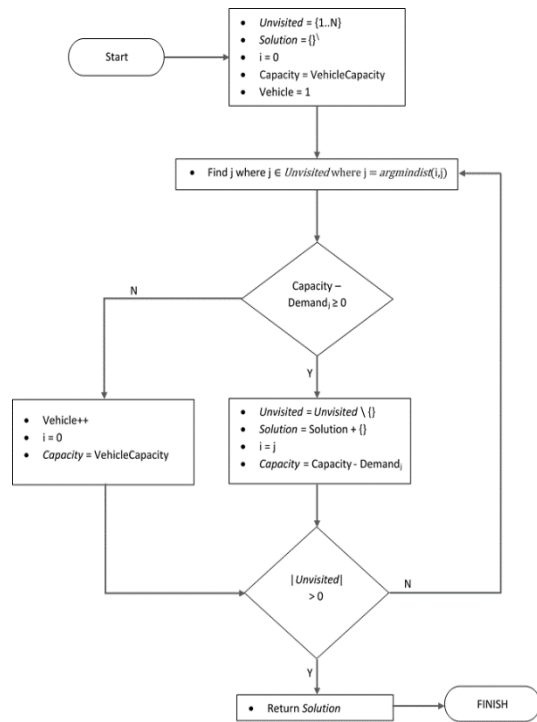


Fig. 2. Flowchart nearest neighbour algorithm

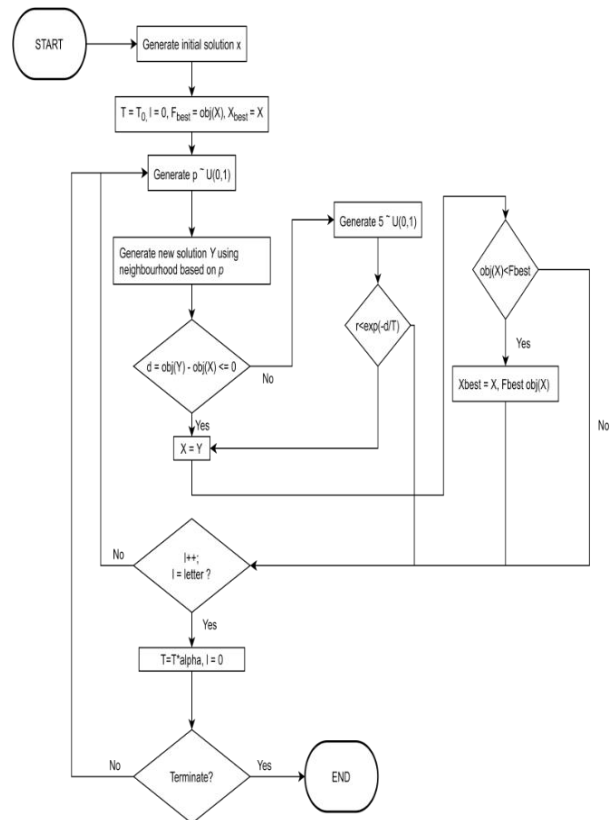


Fig. 3. Flowchart simulated annealing algorithm

## 2.5 Data collection and analysis

This study uses the Google Maps API to collect the average time to distribution and Google MyMaps application to depict the location of each pharmacy owned by PT. XYZ in West Jakarta, as illustrated in Fig. 4.



Fig. 4. Area customer and distribution center

PT. XYZ is a company that produces various types of drugs. In this case, we assumed that the distribution of drugs was carried out from the factory to each distribution center in each region. After that, each DC distributes drugs to each pharmacy in the region. For the West Jakarta, we assume that DC is located in one of PT.XYZ's pharmacies located in Jl. Podomodo Avenue Tanjung Duren Selatan, West Jakarta. Therefore, the nodes are consist of one depot and 11 pharmacy retail as a customer. List of customers and depots from PT. XYZ in West Jakarta can be seen in Table 1.

The demand data of each pharmacy is obtained based on the population in West Jakarta. It is assumed that the market share of PT. XYZ is 24%. That demand is aggregated in yearly, and then it is derived to daily demand. Based on the results of the literature that we get based on the results of the questionnaire on the thesis results it was found that the average person came to the pharmacy was 18.87% per day [18]. We assumed that drug delivery is done with a frequency of delivery once a week. So to get demand in a week, we multiply the demand per day by the number of days in a week. Because of PT. XYZ delivers in a box, we convert the demand from units into boxes. One box can meet the demands of 100 people.

There is the data demand for each pharmacy in West Jakarta can be seen in Table 1.

Table 1. List of customers and depot

No	Address	Demand
0	Jl. Podomoro Avenue (DC)	0
1	Komplek Ruko Mutiara Taman Palem	2
2	Jl. Citra Garden VII	4
3	Jl. H. Nimin III	2
4	Jl. Meruya Ilir Raya	4
5	Ruko Taman Semanan Indah	2
6	Jl. Murni Kec. Joglo	2
7	Sukabumi Selatan	2
8	Jl. Raya Pos Pengumben	2
9	Jl. Let. Jend. S. Parman	1
10	Jl. Aipda K.S. Tubun Raya	1
11	Jl. Utama Raya	2
1	Komplek Ruko Mutiara Taman Palem	2
2	Jl. Citra Garden VII	4
3	Jl. H. Nimin III	2
4	Jl. Meruya Ilir Raya	4
5	Ruko Taman Semanan Indah	2
6	Jl. Murni Kec. Joglo	2
7	Sukabumi Selatan	2
8	Jl. Raya Pos Pengumben	2
9	Jl. Let. Jend. S. Parman	1
10	Jl. Aipda K.S. Tubun Raya	1
11	Jl. Utama Raya	2

To distribution of the drugs, PT. XYZ has 8 vehicles to serve the distribution of the West Jakarta area. The vehicle is in the form of a capacity of 4 boxes. The type of motorcycle used is Revo110FI.

In carrying out the distribution of drugs the travel time must be considered. Jakarta is a city that has a very high intensity of traffic. In collecting data the length of travel time from the depot to the pharmacy for the objective function of this study considers three scenarios. Where the scenario is the time of delivery in the morning, in the afternoon, and in the evening.

## 3. RESULTS AND DISCUSSION

The computational experiments were implemented using AMPL with Gurobi solver and Microsoft Visual Studio C# 2019. It is performed on a computer with specifications encompassing Intel (R) Core (TM) i7 at 3.60 GHz, 8 Gb of RAM, and running on a 64-bit platform under Windows 10 Operating System. The parameter settings procedure provides an analysis on the parameters being used for SA algorithm. Then, the performance of the proposed SA algorithm with



previous algorithms on CVRP instances is conducted. Finally, the numerical experiments are conducted to provide a comparison between the performance of AMPL, nearest neighbourhood, and simulated Annealing on the case study dataset of PT. XYZ in Jakarta.

### 3.1 Parameter settings

The proposed SA uses four parameters: Iter, T<sub>0</sub>, T<sub>f</sub>, and Alpha. Iter denotes the number of iterations that the search proceeds at for a particular temperature, while T<sub>0</sub> represents the initial temperature, and T<sub>f</sub> represents the final temperature below which the SA procedure is stopped. Finally, alpha is the coefficient controlling the cooling schedule.

This study is using a one-factor-at-a-time (OFAT) procedure for the parameter tuning that is shown effective to choose the parameter for metaheuristics [19]. The OFAT procedure sets one parameter sequentially at a time. For example, as shown in figure 5a, three parameters of Iter were observed, meanwhile, the other parameters were fixed at the same number. The experiment has shown that parameter with Iter is equal 100\*N provide the best objective function with acceptable computational time. Therefore, the selected parameter for Iter is 100\*N. Meanwhile, when observing T<sub>0</sub>, the result has shown that the objective value of all three parameters was not much different. Therefore, computational time was used as the tie-breaker that ends up choosing T<sub>0</sub> is equals to 10. The rest of the parameters were using the same principle. After parameter tuning, it is decided that the parameter used for the experiments T<sub>0</sub> = 10, T<sub>f</sub> = 0.01, Iter = 100\*N, and alpha = 0.9. The analysis of the impact of each SA parameter on the objective function and computational time is shown in Fig. 5.

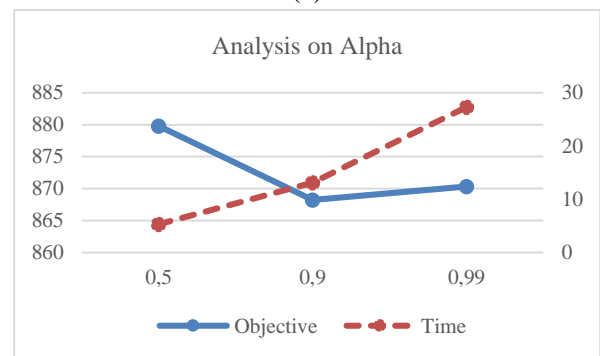
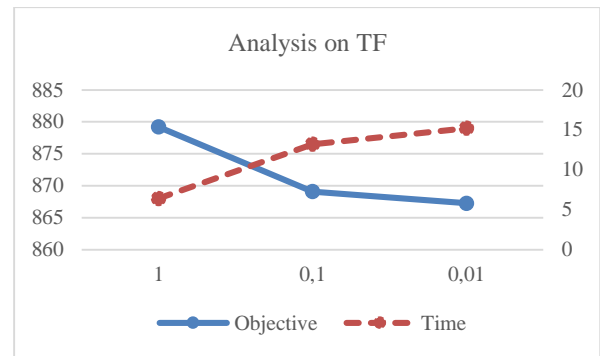
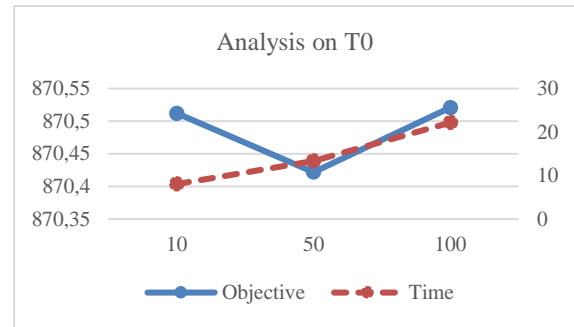
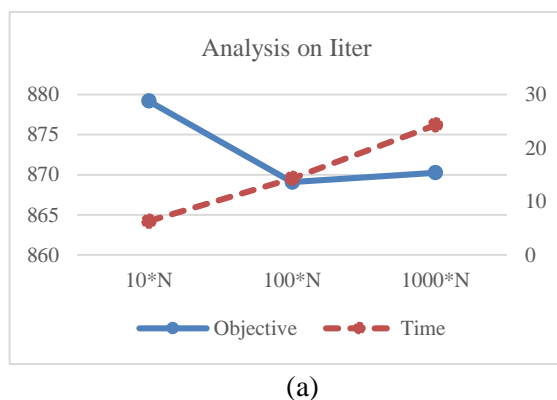


Fig. 5. Analysis on impact of SA parameters

### 3.2 Benchmark instances

In order to check the performance of the proposed SA algorithm, it is necessary to compare it with other metaheuristics for benchmarking purposes. The proposed SA is solving a problem that is treated as a capacitated vehicle routing problem. Therefore the first numerical experiment was conducted on benchmark instances consists of datasets for CVRP proposed by Augerat et al., [20] (datasets A, B, and P). The best-known solution is from various metaheuristics that previously been used to solve the instances [21].

The second computational experiments consider the real-time condition that might have different delivery time due to traffic. We conduct the experiment on three different time settings.

This setting can represent the real-case study when the route is generated just in time before the delivery process is being conducted. For example, a route for delivery tasks that are delivered at 7 am is normally generated 10-15 minutes before the delivery time. Therefore, this study considers three delivery scenario which is morning, mid-day, and afternoon. The average result of three instances can represent the delivery result during three different traffic schemes

In this study, three scenarios were considered. The first scenario is the distribution of drugs in the morning, scenario two in the mid-day, and scenario three in the afternoon. In the morning, the data is acquired at 07:00 am. At noon the data is collected at 01:00 pm. While in the afternoon, the data is collected at 05:00 pm.

### 3.3 The comparison results on the CVRP benchmark problems

Table 2 shows the experimental results for the first benchmark problem set in terms of the best objective function found and the average computational time. The experiment is set for over ten replications. As shown in Table 2, SA has an average percentage difference with the best-known solution (BKS) of 1.61%.

**Table 2.** The comparison between simulated annealing with a previous best-known solution for CVRP

Instance	BKS	SA			Diff (%)
		Best	Avg.	Std. Dev.	
An33k5	661	669	670.6	4.5	1.20
An46k7	914	915	953.22	30.93	0.11
An60k9	1354	1372	1400.8	12.91	1.31
Bn35k5	955	958	962.21	5.67	0.31
Bn45k5	751	752	770.9	66.42	0.13
Bn68k9	1272	1290	1300.27	7.73	1.40
Bn78k10	1221	1238	1247.57	15.56	1.37
En30k3	534	580	651.17	30.82	7.93
En51k5	521	526	535.43	12.16	0.95
En76k7	682	700	717.3	27.94	2.57
Fn72k4	237	240	243.8	27.95	1.25
Fn135k7	1162	1210	1243.13	14.48	3.97
Mn101k10	820	824	839.93	12.71	0.49
Mn121k7	1034	1037	1040.23	7.08	0.29
Pn76k4	593	604	629.57	35.29	1.82
Pn101k4	681	686	701.2	13.14	0.73
Avg.	837	850.06	869.21	20.33	1.61

The average best known solution out of ten runs, average solution, and standard deviation are 850.06, 869.21, and 20.33, respectively. This solution are obtained with average computational time are 16.3s. These results indicate that SA

performs well on the benchmark instances and it gives confidence so that the proposed SA can be used further in the experiments.

### 3.4 The comparison between simulated annealing and nearest neighbour algorithm

In this study, we make a comparison between two heuristic methods compared to the exact method. Table 3 shows the comparison results between the exact result using AMPL, simulated annealing algorithm and the nearest neighbour algorithm. The Simulated Annealing is an approximation method, so we experiment on ten runs. Table 3 reports the results regarding the average, best objective, and standard deviation of objective value for each scenario in the experiment using SA.

**Table 3.** The comparison between simulated annealing and nearest neighbour

Inst.	AMPL	NN	SA			Diff1	Diff2
			Avg	Best	Std		
1	340.5	398.5	340.5	340.5	0.00	0.00%	14.55%
2	302	305	302.3	302	0.95	0.10%	0.98%
3	365.5	369	365.85	365.5	1.11	0.10%	0.95%
Avg						0.06%	5.50%

The results showed that the objective of each scenario using the nearest neighbour is 398.5 minutes, 305 minutes, and 369 minutes for scenario one, two, and three. Meanwhile, The average results using the simulated annealing algorithm are 340.5 minutes, 302.02 minutes, and 365.85 minutes for scenario one, two, and three. The average computational time needed (in seconds) by each approach can be seen in Table 4.

**Table 4.** The computational time

Scenario	AMPL	NN	SA
1	0.078	0.029	0.625
2	0.109	0.014	0.640
3	0.063	0.016	0.641

The column Diff1 shows the percentage difference between the result from the simulated annealing algorithm and the exact method using AMPL. Meanwhile, Diff2 shows the percentage difference between the result from the nearest neighbour algorithm and the exact method using AMPL. The average percentage difference for SA and NN results is 0.03% and 5.50%, respectively. The results indicate that SA performs better than

NN. However, further investigation needs to be done to see how the SA perform on larger size instances such as instances with a number of nodes more than 100.

Furthermore, the computational results considered in all three scenarios can give the decision-maker consideration on the traffic of each time phase during a day. The results indicate that morning and afternoon delivery is the peak traffic hour for the customer served by PT. XYZ. In addition, we can see that the average computational time is less than one second. Therefore, for the current size of the problem, the proposed algorithm is possible to be used just in time before the departure of the vehicles. However, we did not include the detailed route travelled by the vehicle in the report. Interested reader may contact the author independently.

#### 4. CONCLUSION

This study utilizes simulated Annealing and the nearest neighbourhood algorithm for solving capacitated vehicle routing problems in a study case of the pharmaceutical distribution of PT. XYZ located in West Jakarta. Data obtained by using the Google Maps API and Google MyMaps to determine the distribution of customers and the estimated length of distribution time needed to distribute drugs. The first experiment is conducted to show the effectiveness of the proposed SA to solve benchmark CVRP. It is shown that the proposed SA is performing effectively with the average percentage difference with the previously best-known solution is 1.61%. Then, the experiment considers three scenarios, where the first scenario is product distribution in the morning, the second scenario at noon, and the last scenario in the afternoon. Computational experiments are conducted to compare the performance between the exact solution approach, the nearest neighbourhood, and a simulated annealing algorithm. The results show that the simulated annealing algorithm performs better than the nearest neighbour algorithm. It can be seen from the percentage difference result with the optimal solution for the simulated annealing algorithm is 0.03% while the nearest neighbour algorithm is 5.50%. Therefore, for these instances, the SA algorithm can be used to solve the pharmaceutical distribution problems of PT effectively. XYZ.

Despite the success of SA implementation in

this study, there are many sophisticated metaheuristics algorithms being developed recently. Further research can address this development of metaheuristics algorithms to improve the result further. Moreover, the consideration of traffic might be more represented in a more complex model such as vehicle routing problems with time-dependent travel time.

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