JurnalMantik
Volume 3 Number 4, February 2020, pp. 611-618 E-ISSN 2685-4236
https://iocscience.org/ejournal/index.php/mantik/index

Simulation Of Traveling Salesman Problem For Distribution Of Fruits In Bogor City With Simulated Annealing Method

Ali Khumaidi[1], Ridwan Raafi'udin[2], Indra Permana Solihin[3]

[1,2,3]Teknik Informatika,
Universitas Krisnadwipayana, Jl. Kampus Unkris, Jatiwaringin, Bekasi, Indonesia
[2,3] Universitas Pembangunan Nasional Veteran Jakarta, Jl. Rs. Fatmawati, Pondok Labu, Jakarta Selatan, DKI Jakarta, Indonesia

E-mail: alikhumaidi@unkris.ac.id, raafiudin@upnvj.ac.id, indrapermanasolihin@upnvj.ac.id

ARTICLE INFO

Article history:
Received: 25/01/2020
Revised: 01/ 02/2020
Accepted: 13/02/2020

***Keywords**:*
Traveling Salesman Problem, TSP, Simulated Annealing, Fruit Distribution, Iteration

ABSTRACT

Traveling Salesman Problem (TSP) is a problem of finding the shortest distance when a salesman visits a number of cities, provided that each city is visited exactly once and then returns to the initial city. TSP simulations for fruit distribution in Bogor city with each location having x and y coordinates as distances. The TSP used is a symmetrical TSP whose distance from city a to b has the same distance as city b to a. To solve and find solutions to problems using the Simulated Annealing (SA) Algorithm. The working principle is that at high temperatures metal liquid particles have a high energy level so it is relatively easy to move against other particles. Then as the temperature drops the particle slowly adjusts itself to form a configuration so that a stable state with a minimum energy level is obtained. This minimum energy is the shortest distance. Based on experiments that have been done using SA Algorithm on the TSP problem, the results show that the number of iterations that produce the optimal solution depends on the number of simulated locations. The more simulated location points, a large number of iterations are needed.

1. Introduction

Problems with the delivery of fruit and vegetables to market traders often occur due to late acceptance. In addition, other problems are due to time and cost efficiency so that accuracy is needed in determining the path or the shortest route between places. Because there are problems in determining the efficiency of time and cost in determining the path or the shortest route, it is necessary to find a solution to overcome them. With the problem of distribution, we want to do a simulation to determine the path or route of fruit and vegetable distribution distribution that aims to find out which distribution channels provide the shortest route so as to provide minimal costs.

Samana, et al (2015) have conducted research on simulations with this annealing method. The simulated problem is Traveling Salesman Problem (TSP), to check the availability of spare parts [1]. In the case of the TSP, looking for the shortest route and obtaining the optimal time and cost by simulating the shortest distance [2][3]. Research on the optimization of the distribution of goods based on route and capacity using the simulated annealing method [4][5]. In this research an optimization application is made to distribute goods by considering the route of travel. Simulated annealing is also used for production scheduling[6] and course scheduling[7]. So the Simulated Annealing method can be used in various cases. Thus, we want to implement the system in the process of distributing fruit in Bogor City so as to minimize distribution channels.

Accredited "Rank 4"(Sinta 4), DIKTI, No. 36/E/KPT/2019, December 13th 2019.

JurnalMantik
Volume 3 Number 4, February 2020, pp. 611-618 E-ISSN 2685-4236
https://iocscience.org/ejournal/index.php/mantik/index

2. Theory

2.1 Traveling Salesman Problem

TSP is a combinatorial optimization problem. Mathematical problems about TSP were brought up in 1800 by Irish mathematician Willian Rowan Hamilton and English mathematician Thomas Penyngton [8]. TSP is a collection of cities and travel costs (or distances) given between each pair of cities used to find the best way to visit all cities and return to the starting point in an effort to minimize the cost or distance of travel [9]. Traveling Salesman Problem (TSP) is a problem in determining the shortest path that can pass through all points and only once. For example, for 3 points, there are two paths, namely A-B-C-A or A-C-B-A which are the opposite directions of A-B-C-A or for 4 points, there are 3 paths namely A-B-C-D-A, A-D-B-C-A or A-D-C-B-A and 3 opposite directions.

For a number of lanes with very large dots, it takes a lot of time to complete. If tested manually it is not possible to try all the possible paths, but choose the best possible solution from the existing path. So to solve this case a simulated annealing method is needed [10]. In the Traveling Salesman Problem (TSP), the goal achieved is the route with the shortest distance, and the limit is that all cities must be traversed and each city only traveled once. Means State is defined as a possible path and written with S = [1, N]
So, the state in a TSP is a set of point numbers from 1 to N and there are no equal numbers.

2.2 Simulated Annealing

The solution to an optimization problem using Simulated Annealing is inspired by the physical process, namely the cooling of a metal called annealing. The annealing process can be defined as a slow drop in temperature of an object that has been previously heated to a state where the object reaches a freezing point or in other words freezes the freezing point. The principle works that is a high temperature solid liquid particles have a high energy level so it is relatively easy to move against other particles, then when the temperature is lowered the particles will arrange themselves to find a stable arrangement with a minimum energy level. Here is a table of analogies between the annealing process in metal cooling and annealing in optimization problems.

The simulated annealing algorithm was first introduced by Metropolis At Al. in 1959. The simulated annealing algorithm is an algorithm that sometimes moves towards solutions with high costs or solutions that are no better in the hope that this movement can exclude the state from the local minimum point [11]. The ability to accept a bad solution at a certain time is what distinguishes annealing algorithm from other algorithms. Acceptance of the solution to the situation is based on a probabilistic method developed by Kirkpatrick At. Al in 1983, namely the acceptance of a new solution based on a certain probability to find the global minimum value of a function that has a minimum local value.

Simulated Annealing on the TSP is used to trace and search for every possible route, then get the shortest route. The Simulated Annealing model for solving the TSP is a state model built to express possible routes and definitions of energy expressed by the total distance traveled [12].

In Simulated Annealing, the process of reducing the temperature needs to be considered. In the initial iteration the temperature needs to be high so that the random search process has a wide range. As the iteration increases, the temperature continues to fall but may not reach zero. So with Simulated Annealing, objective functions which are getting smaller or decreasing are obtained. In Simulated Annealing, “temperature” is a factor that functions as a controlling factor for the model being accepted or rejected. When the temperature value is high, the chances of the model to be accepted are greater, but when the temperature decreases or is of little value, many models are rejected. Temperature is the formation of a substance used as a control function in Simulated Annealing.

Annealing simulation uses the Boltzman distribution principle. Annealing simulation can only be accepted if the possibility is

$$P = e^{-\frac{\Delta E}{KT}}$$

Where ΔE is the difference between initial energy and final energy, K is the Boltzman constants (0 and 1) and T is temperature.

From the above function, if at ΔE the final energy (E_1) is greater than the initial energy (E_2) then E_1 is received as a new point solution. In the SA algorithm, there are special steps to get out of the optimum

Accredited “Rank 4”(Sinta 4), DIKTI, No. 36/E/KPT/2019, December 13th 2019.

JurnalMantik
Volume 3 Number 4, February 2020, pp. 611-618 E-ISSN 2685-4236
https://iocscience.org/ejournal/index.php/mantik/index

local solution. That step is the reception of an initial energy point (E_1) with the probability $e^{-\frac{\Delta E}{KT}}$ even though the value of the function at this point is no better than the previous point. This is done with the hope that in the next step a point with a better function value will be reached [7].

Some things that need to be considered in the implementation of Simulated Annealing, namely:

1. State: defined as a combination of the value of possible settlement of the route taken to pass through all cities until returning to the city of origin on the condition that each city must be passed once. State is defined as S = (x1, x2, x3, ..., xn).
2. Energy: defined as how much the minimum objective function of a state combination. In the case of TSP, energy is defined as the distance that must be traveled on a path that is expressed as a sequence of city numbers to pass. Energy can be expressed by the equation:

$$E = \sum_{i=1}^{n} d$$

Where E is energy and d is the distance of cities to s (i) and s (i + s). Whereas distance (d) is stated by:

$$d = \sqrt{(s_x(i) - s_x(i+1))^2 + (s_y(i) - s_y(i+1))^2}$$

3. Temperature: defined as a control value that makes a random state move up or not. Like the analogy with thermal events, ions move freely at high temperatures, and their movements become more limited when the temperature drops.
4. Process State Update: in this process, the state will be received simulated this annealing with probability:

$$P = e^{-\frac{\Delta E}{KT}}$$

Simulated Annealing (SA) algorithm in general for all optimization problem solving are:

a) Generate the initial state S0 obtained by generating random numbers on the computer and there should not be twin numbers.
b) Calculate Energy E0 at the beginning of S0
c) Update State S with the update rules according to the problem becomes Si
d) Calculate Energy Ei
e) Generate random numbers p = [0,1]
f) If p <exp (-ΔE / T), the state is accepted; otherwise, the state is rejected. With Energy E for the TSP problem is defined as follows:

$$E = \sum_{i=1}^{M-1} |x(s_{i+1}) - x(s_i)| + |x(s_1) - x(s_M)|$$

where

E	: The energy function after iteration
x (si)	: Position from the i point
x (si) - x (sj) |	: Distance from the i point to the j point
M	: Number of points visited.

g) Lower T (temperature) with the cooling schedule function. For cases of TSP, the cooling schedule function used

$$T_i = T_0\left(\frac{T_n}{T_0}\right)^{\frac{i}{N}}$$

where

T_i	: Cooling Schedule Temperature from i
T_0	: Initial Temperature
T_n	: Cooling Schedule Temperature
N	: Number of Iterations
i	: i-iteration

Accredited "Rank 4"(Sinta 4), DIKTI, No. 36/E/KPT/2019, December 13th 2019.

JurnalMantik
Volume 3 Number 4, February 2020, pp. 611-618 E-ISSN 2685-4236
https://iocscience.org/ejournal/index.php/mantik/index

h) Repeat the third step until it reaches the stop criteria.

The algorithm of simulated annealing is based on the Metropolis algorithm which is used to get a good configuration. The advantage of simulated annealing compared to other methods is its ability to avoid local optimal traps. The algorithm is a random search algorithm, but not only accepts an objective value that always goes down, but sometimes receives an objective value that goes up.

3. Reseach Method

In this section a Simulated Annealing (SA) algorithm for the TSP problem will be applied at 22 locations of fruit and vegetable customers in Bogor City. The data used in the form of coordinates with the following data:

TABLE 1
LOCATION COORDINATE DATA

Location Number	Coordinate (x)	Coordinate (y)
1	3,002556	45,846117
2	0,644905	44,896839
3	1,380989	43,470961
4	1,376579	43,662010
5	5,337151	43,327276
6	7,265252	43,745404
7	1,650154	47,385427
8	1,430427	48,197310
9	2,414787	48,953260
10	3,090447	50,612962
11	5,013054	47,370547
12	4,793327	44,990153
13	2,447746	44,966838
14	1,750115	47,980822
15	4,134148	49,323421
16	7,506950	48,580332
17	1,233757	45,865246
18	4,047255	48,370925
19	0,103163	49,532415
20	1,495348	49,667704
21	4,494615	48,447500
22	0,457140	46,373545

Based on the SA algorithm the steps in the SA method can be made as follows:

Accredited "Rank 4"(Sinta 4), DIKTI, No. 36/E/KPT/2019, December 13th 2019.

JurnalMantik
Volume 3 Number 4, February 2020, pp. 611-618 E-ISSN 2685-4236
https://iocscience.org/ejournal/index.php/mantik/index

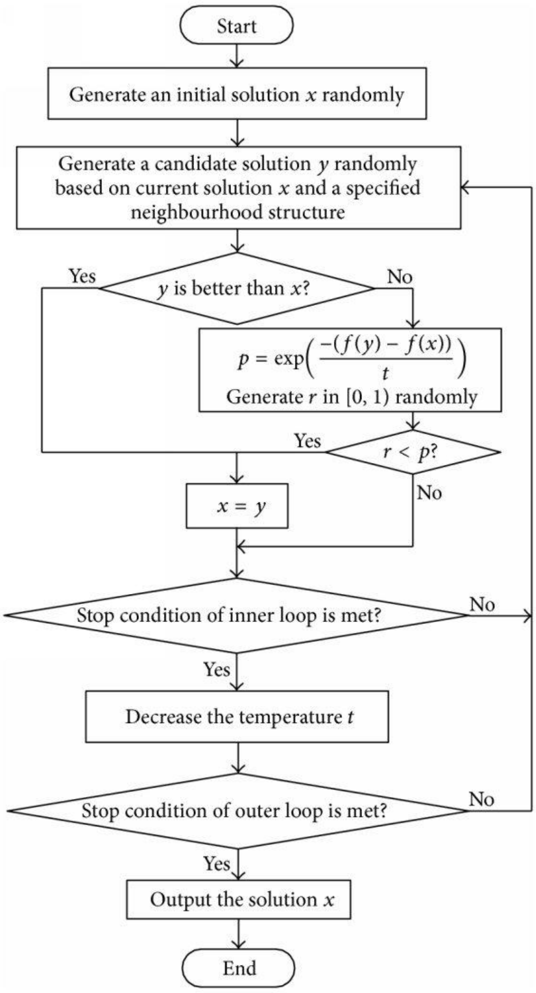

Figure 2. Flowchart of Simulated Annealing Method[10]

Stages of simulated annealing algorithm with a 10 location case:

a) Revive the initial state S0 obtained by generating random numbers on the computer and there should not be multiple numbers.
Applied to the example with 10 coordinate points in table 2 numbers 1 through 10
Obtained initial state along 28.459728603126003 Km.

b) Calculate Energy E0 at the beginning of S0
The distance that has been passed on a path that states the order of the city number traversed.
Obtained the energy value of: 25.151696358872837 Km

c) Update State S with the update rules according to the problem being Si
Thus, S1 was re-determined as = 25.151696358872837 Km, this is because the new solution can be accepted (the new state is better than the previous state)

d) Calculate Energy E1
The calculation of energy with the next state produces E1 of 26.625758887223228 Km, thus the solution is rejected because the new state is no better than the previous state, then it will look for new solutions at the 5th and 6th stages.

e) Generate random numbers p = [0,1]
Because the results of the generation of random numbers (R) <p, then the solution is accepted that is 26.625758887223228 Km

JurnalMantik
Volume 3 Number 4, February 2020, pp. 611-618 E-ISSN 2685-4236
https://iocscience.org/ejournal/index.php/mantik/index

f) Calculate Energy E2
Calculation of energy with the next state produces E2 of 25.151696358872833 Km, the solution is accepted.

g) Lower T (temperature) with the cooling schedule function.
T1 = T0 - 0.0001 or 0.5 - 0.0001 = 0.4999

h) Repeat the third step until it reaches the stop criteria.
In this case the optimum state is obtained at the 200th iteration with the following results: 24,034263695271754 Km

4. Result

The application of Simulated Annealing in the case of TSP, will be simulated at locations that must be visited, in one trip displaying visualization at each iteration until it reaches its optimum position, in this case the shortest circumferential route. In each simulation the same input parameters are given, such as: Cooling Schedule (Tn = 0.0001), and iteration (N = 1000).

Following are the outputs for the 4 location points with outputs including: initial state of simulation, final state of simulation and energy reduction.

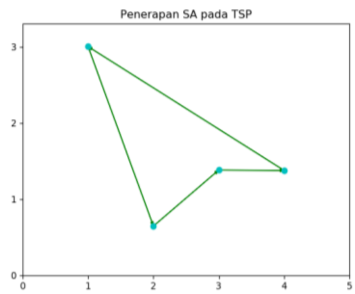

Figure 2. Initial State Iteration

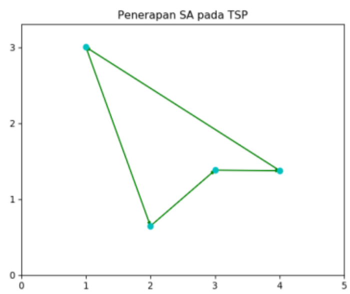

Figure 3. Final State Iteration

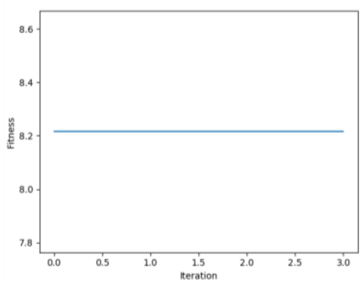

Figure 4. Energy reduction

Following are the outputs for the 10 location points with outputs including: initial state of simulation, final state of simulation and energy reduction.

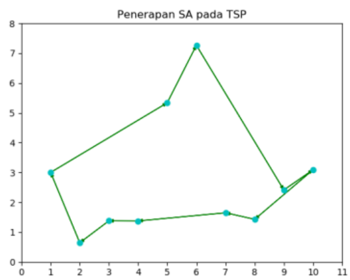

Figure 5. Initial State Iteration

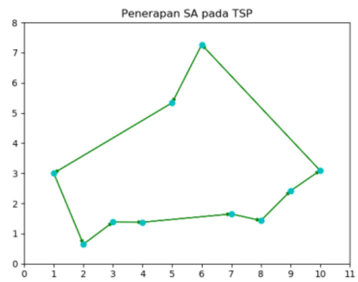

Figure 6. Final State Iteration

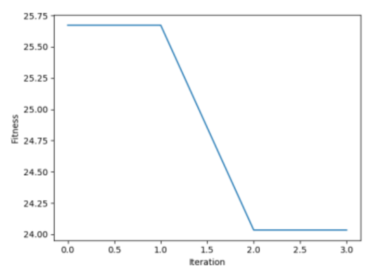

Figure 7. Energy reduction

Final state obtained distance: 24.034263695271754 Km and decreased distance after optimized: 6.38%

Following are the outputs for the 22 location points with outputs including: initial state of simulation, final state of simulation and energy reduction.

Accredited "Rank 4"(Sinta 4), DIKTI, No. 36/E/KPT/2019, December 13th 2019.

JurnalMantik
Volume 3 Number 4, February 2020, pp. 611-618 E-ISSN 2685-4236
https://iocscience.org/ejournal/index.php/mantik/index

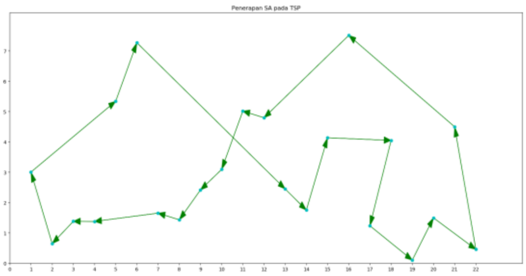

Figure 8. Initial State Iteration

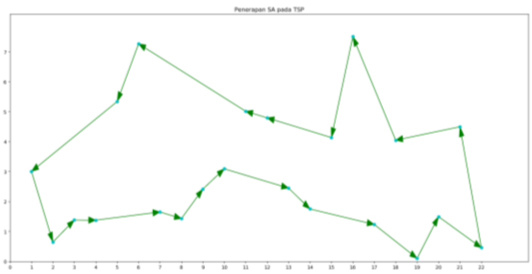

Figure 9. Final State Iteration

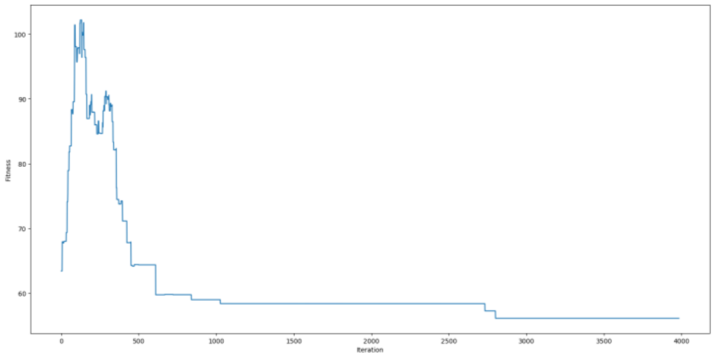

Figure 10. Energy reduction

Final state obtained distance: 56.134938628085166 Km and decrease distance after optimized: 7.72%

5. Conclusion

For cases 4 and 10 location points it is enough to do 1000 iterations the optimal results are obtained while for the case of 22 locations doing 100000 new iterations the optimal results are obtained. Can be seen from the graph of energy reduction for each location point where for 4 location points it is enough to do with 1 iteration. Whereas for 10 locations, 200 iterations are needed. In the case of 22 points, 1000 iterations have not resulted in an optimal final state, it can be seen from the final display of the simulation, where there are still many crossing routes. Apart from that, the energy decrease graph doesn't look stationary. The iteration needed to achieve optimal conditions for the 22-point case is 2800 iterations. This is indicated by the tendency of the graph after iteration above 2800 tends to be stationary (flat). The number of iterations that produce optimal conditions / solutions depends on the number of simulated location points. The more simulated location points, a large number of iterations are needed. Simulation results from 4, 10, and 22 location points show that the optimal travel route is by taking the outermost route and there are no crossing routes.

6. References

[1] E. Samana, B. Prihandono, and E. N. Intisari, "Aplikasi Simulated Annealing Untuk Menyelesaikan Travelling Salesman Problem,", Buletin Ilmiah Mat. Stat. dan Terapannya (Bimaster) Volume 03, No. 1, pp. 25 – 32, 2015.

[2] Citra Nur Alpianty and J. Dharma Lesmono, "Penerapan Algoritma Simulated Annealing Untuk Menyelesaikan Asymmetric Travelling Salesman Problem," in *Seminar Nasional Matematika Vol.13*, 2018, pp. 63–69.

[3] A. Meitrilova, F. M. Puspita, and Yahdin, "Implementasi Travelling Salesman Problem (Tsp) Dengan Algoritma Genetika Dan Simulated Annealing Pada Pendistribusian Pupuk Pt. Austindo Nusantara Jaya," Sriwijaya

Accredited "Rank 4"(Sinta 4), DIKTI, No. 36/E/KPT/2019, December 13th 2019.

University, 2017.
[4] R. Hidayati, I. Guntoro, and S. Junianti, “Penggunaan Metode Simulated Annealing Untuk Penyelesaian Travelling Salesman Problem,” 2019.
[5] Jose Rizal, “Optimasi Pada Traveling Salesman Problem (TSP) dengan Pendekatan Simulasi Annealing,” *J. Gradien*, vol. 3, no. 2, pp. 286–290, 2007.
[6] M. Hamdani Azmi and C. Farela Mada Tantrika, “Penjadwalan Produksi Rokok Untuk Meminimalkan Maximum Tardiness MenggunakanAlgoritma Simulated Annealing,” *J. Rekayasa Dan Manaj. Sist. Ind.*, vol. 3, no. 2, pp. 353–362, 2015.
[7] Dany Purno Yuwono, “Penerapan Simulated Annealing Untuk Penjadwalan Matakuliah Di Jurusan Teknik Elektro Universitas Negeri Malang,” Universitas Negeri Malang, 2014.
[8] S. Vats and N. Bakshi, “Review Paper on Genetic Algorithm and Simulated Annealing for solving Travelling Salesman Problem,” *Int. J. Innov. Res. Technol.*, vol. 5, no. 3, pp. 272–275, 2018.
[9] Fatmawati, Bayu Prihandono, and Evi Noviani, “PenyelesaianTravelling Salesman ProblemDenganMetodeTabuSearch.,” *Bul. Mat. Stat. dan Ter.*, vol. 4, no. 1, pp. 17–24, 2015.
[10] L. Wang, M. L. R. Cai, and Y. Zhong, “Enhanced List-Based Simulated Annealing Algorithm for Large-Scale Traveling Salesman Problem,” *IEEE Xplore Digit. Libr.*, pp. 144366–144380, 2019.
[11] ChangYing Wang, Min Lin, YiWen Zhong, and Hui Zhang, “Solving travelling salesman problem using multiagent simulated annealing algorithm with instance-based sampling,” *Int. J. Comput. Sci. Math.*, vol. 6, no. 4, 2015.
[12] Hüsamettin Bayram and Ramazan Şahin, “A New Simulated Annealing Approach for Travelling Salesman Problem,” *Math. Comput. Appl.* , vol. 18, no. 3, pp. 313–322, 2013.