TELKOMNIKA Telecommunication, Computing, Electronics and Control
Vol. 19, No. 4, August 2021, pp. 1251~1259
ISSN: 1693-6930, accredited First Grade by Kemenristekdikti, Decree No: 21/E/KPT/2018
DOI: 10.12928/TELKOMNIKA.v19i4.18872

Sensitivity of shortest distance search in the ant colony algorithm with varying normalized distance formulas

Rahmad Syah, Mahyuddin K. M. Nasution, Erna Budhiarti Nababan, Syahril Efendi
Faculty of Computer Science and Information Technology, Universitas Sumatera Utara, Medan, Indonesia

Article Info

Article history:

Received Sep 14, 2020
Revised Mar 10, 2021
Accepted Mar 19, 2021

Keywords:

Ant colony
Normalized distance
Optimization
Searching

ABSTRACT

The ant colony algorithm is an algorithm adopted from the behavior of ants which naturally ants are able to find the shortest route on the way from the nest to places of food sources based on footprints on the track that has been passed. The ant colony algorithm helps a lot in solving several problems such as scheduling, traveling salesman problems (TSP) and vehicle routing problems (VRP). In addition, ant colony has been developed and has several variants. However, in its function to find the shortest distance is optimized by utilizing several normalized distance formulas with the data used in finding distances between merchants in the mercant ecosystem. Where in the test normalized distance is superior Hamming distance in finding the shortest distance of 0.2875, then followed by the same value, namely the normalized formula Manhattan distance and normalized Euclidean distance with a value of 0.4675 and without using the normalized distance formula or the original ant colony algorithm gets a value 0.6635. Given the sensitivity in distance search using merchant ecosystem data, the method works well on the ant colony Algorithm using normalized Hamming distance.

Corresponding Author:

Mahyuddin K. M. Nasution
Faculty of Computer Science and Information Technology
Universitas Sumatera Utara
Dr. Mansur St. No. 9 A Padang Bulan 20155, Medan, Indonesia
Email: mahyuddin@usu.ac.id

1. INTRODUCTION

Swarm Intelligence is an artificial neural network (ANN) technique based on collective behavior in decentralized and self-organizing systems [1], [2]. The system that utilizes Swarm Intelligence is usually a population consisting of members in the form of simple agents, who interact locally with fellow members, and also interact with the environment [3], [4]. Although in general there is no centralized control structure that conducts training data on how each individual acts and local interaction among members often leads to the emergence of global behaviors [5]. Ant colony is one of the techniques in swarm intelligence that is often found in literature [6]. Ant colony algorithm is suitable for solving combinatorial optimization problems such as scheduling, traveling salesman problems (TSP), vehicle routing problems (VRP) and others [7]-[9].

Ant colony algorithm has been developed in order to get optimization so that variations appear [10]. Ant algorithm variations starting from the first version are called ant system (AS), which is applied to TSP, elitist ant system (EAS), rank-based ant system (ASrank), min-max ant system (MMAS), ant colony system (ACS), approximate nondeterministic tree search (ANTS) and hyper-cube framework for ACO [11], [12]. Ant colony algorithm can be used in various disciplines, one of which is Abd-Allah *et al.* [13] ptimizing with ant colony in lightning hazard mitigation at more sensitive points in wind farms and getting results can contribute in designing the best place for wind farms and can increase capital on protection from lightning in certain areas. Meanwhile Sulaima *et al*. [14] adopted a load transfer strategy for manufacturing electricity consumers in connection with the consideration of setting ETOU tariffs by utilizing ant colony and resulting in the impact of reducing energy costs by 1% to 6% achieved during medium peak segmentation, while peak time segments contributed to cost reduction about 0.5% to 5% are congruent.

Jabbar *et al.* [15] conducted research on changing ACS so that it can group data and achieve results showing that by modifying ACS it outperformed the classic clustering algorithm in terms of minimum intra-distance and measurement results. Whereas Khan [16] conceals data in an image with ACO, where ACO is applied in measuring distance of data hiding and results in that complex region technique is an efficient and safe method of concealing data, producing high quality stego-image, very high PSNR and reasonable data hiding capacity.

In addition, Loubna *et al.* [17] conducted research on the optimization of ant colony for measuring low-pass state variable filters by drawing conclusions from the ant colony optimization technique for the optimal size of the state variable filter. The SPICE simulation confirms the validity of the proposed method. AS makes smaller total errors, AS and ACS provide fast convergence to optimal values and MMAS provides better convergence rates. Grari *et al.* [18] investigates the use of ant colony optimization in cryptanalysis of the simple advanced encryption standard (S-AES), uses known plaintext attacks and establishes important components of our algorithm such as heuristic values, fitness functions, and strategies to update pheromone pathways and produce S-AES cryptosystems explore minimum search space when compared to other techniques and only require two plaintext-ciphertext pairs.

There are algorithms that have the same function as ant colony, one of which is the Dijkstra algorithm [19]. Dramski [19] makes a comparison between the Dijkstra algorithm and ant colony in providing a navigation model and finding suboptimal routes in comparing between the two algorithms made. Dijkstra's algorithm provides better values for solving the shortest path route problem in a graph. Faster, guarantees optimality and has less computational complexity. It is important to let you know that only static situations are investigated while ant colony is the opposite. Meanwhile Santoso [20] analyzes the performance of the Dijkstra, A* and ant colony algorithms to find the optimal path on a map and produces research that the best ant colony is among the best.

From various studies that discuss ant colony algorithm, it is not found a discussion on distance by involving the distance formula in doing optimization. The use of the distance formula is to compare and find out the advantages and disadvantages of direct and indirect distance measurements [21]. In different algorithms Al-Khowarizmi *et al.* [22] performs optimal measurements on the simple evolving connectionist system (SECoS) method by replacing the normalized Hamming distance formula with normalized Manhattan distance and normalized Euclidean distance with optimal results in the replacement of normalized Hamming distance with normalized Euclidean distance proven by error when training is of little value. In addition, Lubis *et al.* [23] optimizes the k-nearest neighbor method by combining several distance formulas in the method and the results obtained by the Euclidean distance formula are more appropriate for use on k-nearest neighbor.

Wurdianarto *et al.* [24] also compares the Euclidean distance formula with Canberra distance in face recognition to produce a system calculation and get the results in the application that have been made accompanied by the results of the calculation of the level of similarity and processing time of each method. So, it is necessary to review the ant colony algorithm by measuring distance and finding the shortest distance with some normalized distance formula to find the optimal value. And in the future this paper can become the foundation of the process of big data and forecasting techniques in order to improve the process of intelligence and data science [25]-[27].

2. MATERIAL AND METHOD

2.1. Ant colony algorithm schema

Logically and mathematically the ants from the same origin, such as a nest, move independently through their respective paths to food as their destination. After they arrive at the destination point, these ants are analyzed one by one to find out the path and distance. Ants that cover the shortest distance are the winners and the path they take is determined as the shortest path [28]. Following are the stages of the ant algorithm in a graph.

In Figure 1 (a) shows ants who will travel to find a place where there is food, from X to Y. Ants will make random moves to the place of food with their respective paths. As in Figure 1 (b) ants walk in their respective lanes. After walking randomly based on their respective paths then the ants will meet again where the food is located in Figure 1 (c). When traveling through their respective paths, ants leave pheromones as a trail to be followed by other ants. In Figure 1 (d). The more ants and the closer the distance travelled, the more powerful the pheromones so that the other ants will follow the path. In the optimization of the ant algorithm, the process will be repeated in accordance with the specified maximum cycle.

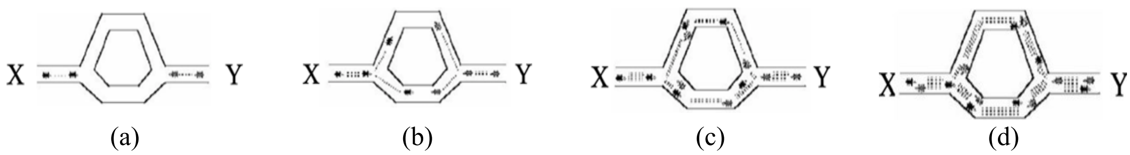

Figure 1. Ant trajectory scheme: (a) firstly, (b) secondly, (c) thirdly, and (d) fourthly

2.2. General architecture

The general architecture in this paper is shown in Figure 2. The steps in getting the closest distance using the ant colony algorithm by utilizing several normalized distance formulas:

a. Initialize the parameters of the ant colony algorithm:
   - Pheromone intensity (τij).
   - Ant cycle constant (V0).
   - The control constant intensity visibility (β), value β ≥ 0.
   - Pheromone control constant (α), value α ≥ 0.
   - Number of ants (n).
   - The pheromone evaporation constant (ρ) must be> 0 and <1.
   - Maximum number of cycles (NCmax).

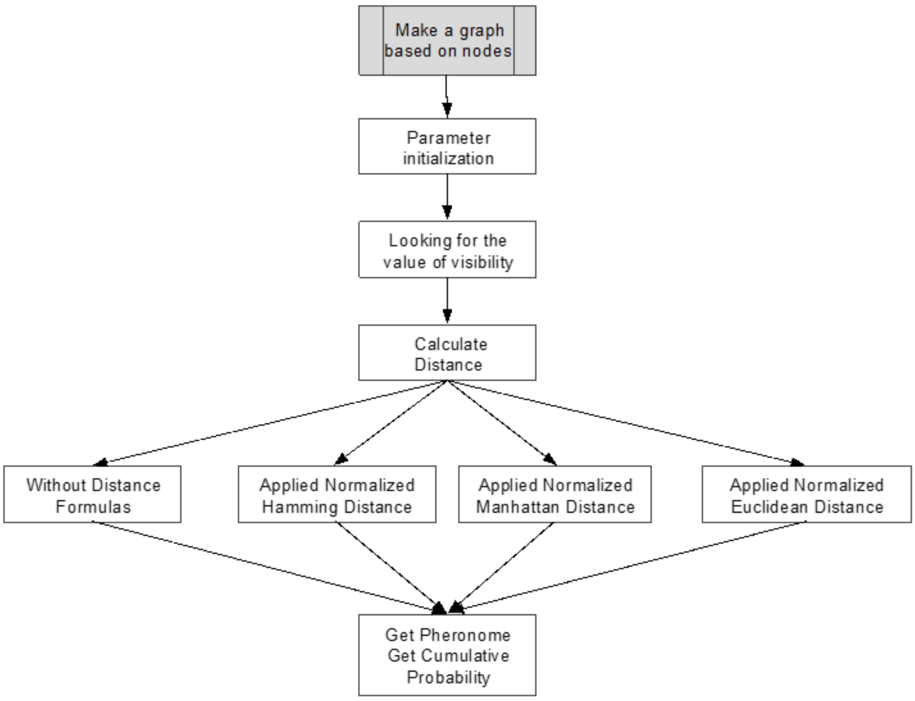

Figure 2. General architecture

b. Calculate visibility between nodes.
c. Calculate the distance between nodes and inverse visibility with as shown in (1).

$$n_{ij} = \frac{1}{D_{ij}} \tag{1}$$

d. Perform distance formula calculations with some normalized distance formula formulas.

e. If you have selected the destination node, the node is stored in a taboo list to declare that the node has been part of building a solution. After that the intensity of the pheromone on that side is changed using as shown in (2). Pheromone changes are called local pheromone changes. Transition rules again carried out until the destination node is reached.

$$\rho_{ij}^{k} = \{ \frac{\sigma ij^{\alpha} nij^{\beta}}{\sum_{uejk} \sigma ij^{\alpha} nij^{\beta}} \quad (2)$$

f. If the destination node has been reached, as well as getting the cumulative probability of the smallest value.

2.3. Sensitivity of shortest distance with normalized distance formulas

In this paper we will test the ant colony algorithm with several normalized distance formula formulas. The normalized Hamming distance formula is shown (3) [29]:

$$D_n = \frac{\sum_i^K |I_i - W_i|}{\sum_i^K |I_i + W_i|} \quad (3)$$

Besides using normalized Hamming distance, it was also tested with normalized Manhattan distance. The normalized Manhattan distance formula is shown in (4) [30]:

$$D_n = \sum_i^K \frac{|I_i - W_i|}{k} \quad (4)$$

Besides that, also tested normalized Euclidean distance. The normalized Euclidean distance formula is shown in (5) [31]:

$$D_n = \sqrt{\sum_i^K \frac{|I_i - W_i|^2}{k}} \quad (5)$$

where:
K is number of input nodes
I is initial node value
W is value of the destination node
In conducting distance searches using merchant ecosystem data, several distance equations are used to obtain sensitivity values.

3. RESULTS AND DISCUSSION

This paper collects data and materials as needed, so that when conducting research runs smoothly. The data used in this paper is the merchant ecosystem, which consists of 3 things that rank the highest in the hierarchy, namely variant, identity and neighborhood. Furthermore, in variants, identity and neighborhood are regrouped based on objects that are connected to each other in order to communicate appropriate information. Within the group variant it is reproduced based on multi channels to find similarities between objects. In separating the existing patterns in the literature according to various levels of coverage and levels of abstraction to reduce the problem of overlapping patterns so that in calculating the existing patterns, a precise search algorithm is needed, namely ant colony. The merchant ecosystem that will be calculated using ant colony is shown in Figure 3.

Graphical images aim to provide a framework for something as an approach. Generally, the framework uses a tree graph. A graph consists of a collection of points A = $\{a_i$|i =, i…., n$\}$ 6 = $\emptyset$ and a collection of lines written B = $\{ b_j$| j = 0…, m$\}$. Meanwhile, the sub-graph tree contains roots, branches and leaves. The root is one point $a_1 \in$ a. Branches are the distinct points of a_1, namely a_i, i = 2, 3, …, n. but there is a line a_j that connects each to a_l, so that the degree of the root is determined by the number of lines formed on it, just as a branch that has the degree of each branch is determined by the other branches. The lowest degree of the root or branch is d (a_1) = 1, thus the degree of the root or branch is d $(a_l) \leq 1$. While the leaf is the end point that is connected to the branch or root but has the degree d (a_i) = 1. In general, the ratio between points and lines in a tree is that for n points there will be n − 1 lines [32].

Ant colony algorithm calculation consists of the probability in determining the journey to be taken in some time. In this paper choose 7 points or nodes to be compared if using several normalized distance formulas. Based on the data obtained from the search results with the help of a pointer tool, the distance can be arranged from each point/node shown in Table 1.

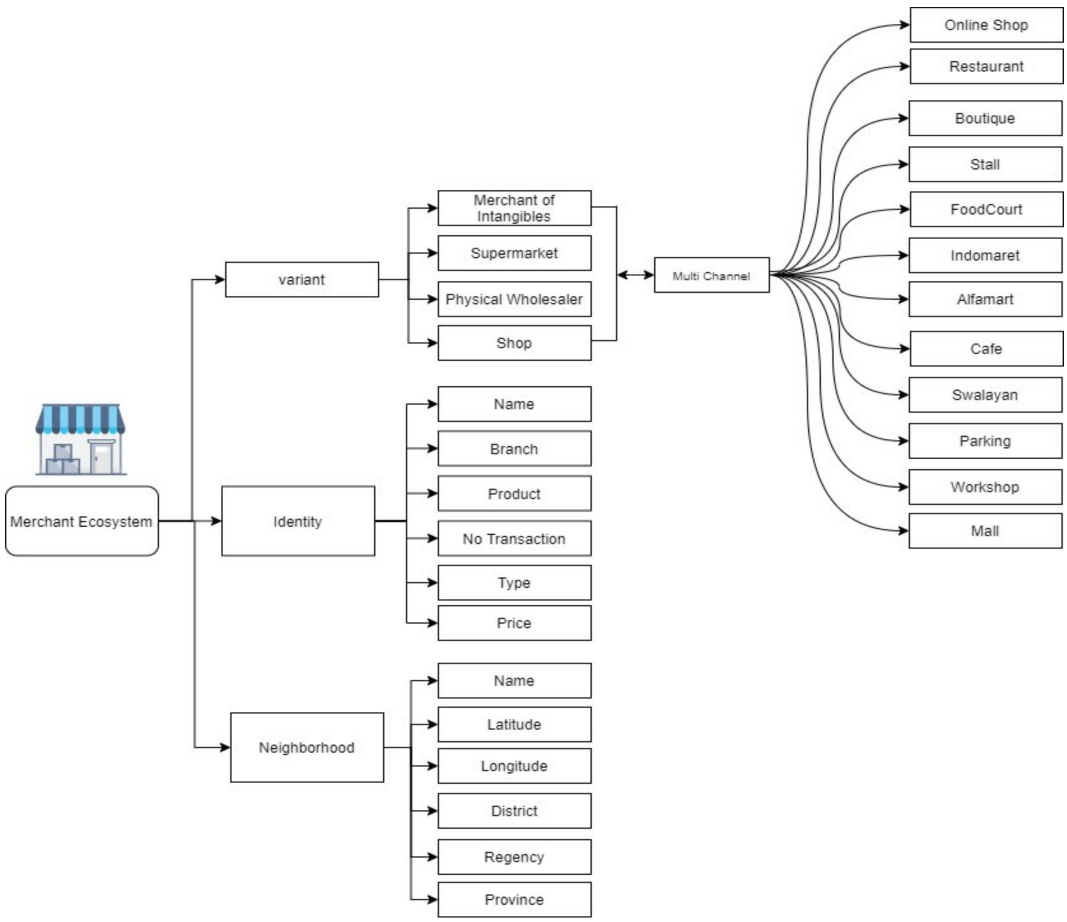

Figure 3. Merchant ecosystem

Table 1. Node of distance

Node (N)	1	2	3	4	5	6	7
1	0	6.2	8.9	27.8	24.7	21.7	1.8
2	6.2	0	4.5	21.5	21	15.4	8
3	8.9	4.5	0	25.5	27.2	19.5	9.7
4	27.8	21.5	25.5	0	38.4	5.7	30.5
5	24.7	21	27.2	38.4	0	31.7	26.5
6	21.7	15.4	19.5	5.7	31.7	0	23.1
7	1.8	8	9.7	30.5	26.5	23.1	0

Next is using the ant colony algorithm to get the shortest (optimal) distance. The first step taken is initializing the price of the algorithm parameters, the parameters used are: $\alpha = 1, \beta = 1, \rho = 0.1, n = 7$. The steps in using the ant colony algorithm are:
- Choose a starting point, which is N1.
- N1 has a path in N2, N3, N4, N5, N6, and N7, then the minimum or smallest distance is taken so that the chosen one is N7 so that the first path is obtained N1 → N7.
- Do the same with the second step which starts from the selected point N7. N7 has pathways in N2, N3, N4, N5, and N6. Furthermore, the minimum or smallest distance is taken so that the chosen one is N4 so that the second path is obtained N1 → N7 → N6.
- Do the same with the third step which starts from the selected point N6. N6 has pathways in N2, N3, N4, and N5. Next take the minimum distance or the smallest so that the chosen one is N3 so that the third path is obtained N1 → N7 → N6 → N2.
- Do the same with the fourth step which starts from the selected point N2. N2 has lines on N3, N4, and N5. Next take the minimum or smallest distance so that the chosen one is V2 so that the fourth path is obtained N1 → N7 → N6 → N2 → N4.

- Do the same with the fifth step which starts from the selected point N4. N4 has a path at N3, and N5. Next take the minimum or smallest distance so that the chosen one is N3 so that the fourth path is obtained N1 → N7 → N6 → N2 → N4 → N3.

Furthermore, because there is no longer a point, the last point is N5 so that the path N1 → N7 → N6 → N2 → N4 → N3 → N5 is obtained. But in this paper the calculation still raises the problem of whether to return to the crew node or not. If taken from the initial node, the value of τ_{ij} or initial feronom is as follows:

$$\tau_{ij} = \tau_0 = \frac{7}{91.1} = 0.077$$

If it does not return to the initial node then:

$$\tau_{ij} = \frac{7}{76.6} = 0.091$$

This value is based on the nodes in Table 1. However, in order to get the optimal distance in this paper, the feronom value returned to the initial node is 0.077.

The second step is to find the value of visibility between nodes by using as shown in (1). Where is the distance between known points. $D_{ij}$is the distance value calculated based on the ant colony algorithm. But in this paper the calculation of the distance value will be analyzed using the normalized distance formula in accordance as shown in (3) (4) (5). So, in more detail based on Table 2:

Based on the normalized Hamming distance formula according to as shown in (3) the inverse visibility is in accordance with Table 3. Besides that, an analysis is also performed based on the normalized Manhattan distance formula in accordance as shown in (4), the inverse visibility is in accordance with Table 4. And in this paper an analysis is also performed based on the normalized Euclidean distance formula in accordance as shown in (5) then the inverse visibility is in accordance with Table 5.

Table 2. Visibility of inverses between nodes without the normalized distance formula

Node	1	2	3	4	5	6	7
1	0	0.1613	0.1124	0.036	0.0405	0.0461	0.5556
2	0.1613	0	0.2222	0.0465	0.0476	0.0649	0.125
3	0.1124	0.2222	0	0.0392	0.0368	0.0513	0.1031
4	0.036	0.0465	0.0392	0	0.026	0.1754	0.0328
5	0.0405	0.0476	0.0368	0.026	0	0.0315	0.0377
6	0.0461	0.0649	0.0513	0.1754	0.0315	0	0.0433
7	0.5556	0.125	0.1031	0.0328	0.0377	0.0433	0

Table 3. Inverse visibility between nodes with the normalized Hamming distance formula

Node	1	2	3	4	5	6	7
1	0	1	0.1788	0.515	0.059	0.0647	0.8468
2	1	0	1	0.6538	0.0118	0.1538	0.3162
3	0.1788	1	0	1	0.0323	0.1649	0.3356
4	0.515	0.6538	1	0	1	0.7415	0.6851
5	0.059	0.0118	0.0323	1	0	1	0.0893
6	0.0647	0.1538	0.1649	0.7415	1	0	1
7	0.8468	0.3162	0.3356	0.6851	0.0893	1	0

Table 4. Inverse visibility between nodes with the normalized Manhattan distance formula

Node	1	2	3	4	5	6	7
1	0	0.8857	0.3857	2.7	0.4429	0.42857	2.84286
2	0.8857	0	0.6429	2.4286	0.0714	0.8	1.05714
3	0.3857	0.6429	0	3.6429	0.2429	1.1	1.4
4	2.7	2.4286	3.6429	0	5.4857	4.67143	3.54286
5	0.4429	0.0714	0.2429	5.4857	0	4.52857	0.74286
6	0.4286	0.8	1.1	4.6714	4.5286	0	3.3
7	2.8429	1.0571	1.4	3.5429	0.7429	3.3	0

Table 5. Visibility of inverses between nodes with the normalized Euclidean distance formula

Node	1	2	3	4	5	6	7
1	0	2.3434	1.0205	7.1435	1.1717	1.13389	7.52149
2	2.3434	0	1.7008	6.4254	0.189	2.1166	2.79694
3	1.0205	1.7008	0	9.6381	0.6425	2.91033	3.70405
4	7.1435	6.4254	9.6381	0	14.514	12.3594	9.37352
5	1.1717	0.189	0.6425	14.514	0	11.9815	1.96542
6	1.1339	2.1166	2.9103	12.359	11.981	0	8.73098
7	7.5215	2.7969	3.7041	9.3735	1.9654	8.73098	0

The ant journey continues until all the points have been visited and form a path. Following is the calculation of the probability for the 1st cycle (NC=1), 1st ant (n1) and Tabu list=V1. So based on the calculations, the ant probability value from N1 to another node is based on (2) and the results are shown in Table 6. The results of the end of the journey of the ant algorithm is to get the value of cumulative probability and the next system based on the decisions made. From table 6 it can be seen that the smallest probability value using the normalized Hamming distance formula is 0.2875, followed by the same value, namely the normalized Manhattan distance and normalized Euclidean distance formula with a value of 0.4675 and without using the normalized distance formula or the ant colony algorithm the original got a value of 0.6635.

From these results prove that the optimization by using the normalized distance formula which in this case is more superior, namely the normalized Hamming distance formula, then followed by normalized Manhattan distance and normalized Euclidean distance get the same value in the cumulative probability calculation. But the application of the normalized distance formula adds to the algorithm's performance because the data received has to normalize data with a range of 0 to 1. So, in the future it is necessary to test the distance formula with another normalized distance formula. And if using big data, it also requires an optimal technique to run the algorithm.

Table 6. Probability of ants to 1 from the initial node and back to the initial node

Tabu	Ant Colony Distance	Normalized Hamming Distance	Normalized Manhattan Distance	Normalized Euclidean Distance
V1	0	0	0	0
V2	0.2354	0.1429	0.0401	0.0401
V3	0.0525	0.0736	0.1221	0.1221
V4	0.0189	0.0243	0.1402	0.1402
V5	0.0242	0.0031	0.0223	0.0223
V6	0.3325	0.0437	0.1429	0.1429
Cumulative Probability	0.6635	0.2875	0.4675	0.4675

4. CONCLUSION

Finally, this paper discusses optimization in finding the closest distance in the ant colony algorithm by utilizing several normalized distance formulas in determining calculations with the merchant ecosystem distance running well using the ant colony algorithm. It is clear that there is an optimal value using the normalized distance formula. The most optimal value is to apply the normalized Hamming distance formula with a probability value of 0.2875, followed by the same value normalized formula Manhattan distance and normalized Euclidean distance with a value of 0.4675 and without using the normalized distance formula or the original ant colony algorithm gets value of 0.6635. Given the sensitivity in distance search using merchant ecosystem data, the method works well on the ant colony algorithm using normalized Hamming distance.

ACKNOWLEDGEMENTS

The author would like to thank the Research Institute Doctoral Program of Universitas Sumatera Utara for supporting the dissemination of this research.

REFERENCES

[1] Z. Zhang, K. Long, J. Wang, and F. Dressler, "On Swarm Intelligence Inspired Self-Organized Networking: Its Bionic Mechanisms, Designing Principles and Optimization Approaches," *IEEE Commun. Surv. Tutorials*, vol. 16, no. 1, pp. 513-537, 2014, doi: 10.1109/SURV.2013.062613.00014.

[2] B. A. Garro and R. A. Vázquez, "Designing Artificial Neural Networks Using Particle Swarm Optimization Algorithms," *Comput. Intell. Neurosci.*, vol. 2015, 2015, doi: 10.1155/2015/369298.

[3] X. Qian and X. Zhong, "Optimal individualized multimedia tourism route planning based on ant colony algorithms and large data hidden mining," *Multimed. Tools Appl.*, vol. 78, no. 15, pp. 22099-22108, Aug. 2019, doi: 10.1007/s11042-019-7537-0.

[4] M. Brambilla, E. Ferrante, M. Birattari, and M. Dorigo, "Swarm robotics: a review from the swarm engineering perspective," *Swarm Intell.*, vol. 7, no. 1, pp. 1-41, Mar. 2013, doi: 10.1007/s11721-012-0075-2.

[5] D. P. F. Cruz, R. D. Maia, and L. N. De Castro, "A critical discussion into the core of swarm intelligence algorithms," *Evol. Intell.*, vol. 12, no. 4, pp. 189-200, Jun. 2019, doi: 10.1007/s12065-019-00209-6.

[6] S. Mirjalili, J. Song Dong, and A. Lewis, "Ant Colony Optimizer: Theory, Literature Review, and Application in AUV Path Planning," *Nature-Inspired Optimizers: Theories, Literature Reviews and Applications*," pp. 7-21, Jan. 2020, doi: 10.1007/978-3-030-12127-3_2.

[7] V. M. Joy and S. Krishnakumar, "Optimal design of adaptive power scheduling using modified ant colony optimization algorithm," *International Journal of Electrical and Computer Engineering*, vol. 10, no. 1, pp. 738-745, Feb. 2020, doi: 10.11591/ijece.v10i1.pp738-745.

[8] M. Mazlan, M. Makhtar, A. F. K. Ahmad Khairi, and M. A. Mohamed, "University course timetabling model using ant colony optimization algorithm approach," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 13, no. 1, pp. 72-76, Jan. 2019, doi: 10.11591/ijeecs.v13.i1.pp72-76.

[9] Y. Siyamtining Tyas and W. Prijodiprodjo, "Best Route Search Application with Ant Colony Optimization (ACO) Method (in Indonesian: Aplikasi Pencarian Rute Terbaik dengan Metode Ant Colony Optimazation (ACO))," *IJCCS Indonesian J. Comput. Cybern. Syst.*, vol. 7, no. 1, p. 55, 2013, doi: 10.22146/ijccs.3052.

[10] C. Blum, "Ant colony optimization: Introduction and recent trends," *Phys. Life Rev.*, vol. 2, no. 4, pp. 353-373, Dec. 2005, doi: https://doi.org/10.1016/j.plrev.2005.10.001.

[11] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization," *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28-39, 2006, doi: 10.1109/MCI.2006.329691.

[12] L. F. de Mingo López, N. Gómez Blas, and C. Morales Lucas, "Ant colony systems optimization applied to BNF grammars rule derivation (ACORD algorithm)," *Soft Comput.*, vol. 24, no. 3, pp. 3141-3154, 2020, doi: 10.1007/s00500-020-04670-9.

[13] M. A. Abd-Allah, A. Said, and M. N. Ali, "Mitigation of lightning hazards at the more sensitive points in wind farms using Ant-Colony Optimization technique," *J. Electr. Eng.*, vol. 5, no. 2, pp. 113-122, Jun. 2016, doi: 10.11591/eei.v5i2.618.

[14] M. F. Sulaima, N. Y. Dahlan, M. H. Isa, M. N. Othman, Z. M. Yasin, and H. A. Kasdirin, "ETOU electricity tariff for manufacturing load shifting strategy using ACO algorithm," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 1, pp. 21-29, Mar. 2019, doi: 10.11591/eei.v8i1.1438.

[15] A. M. Jabbar, K. R. Ku-Mahamud, and R. Sagban, "An improved ACS algorithm for data clustering," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 17, no. 3, pp. 1506-1515, Mar. 2020, doi: 10.11591/ijeecs.v17.i3.pp1506-1515.

[16] S. Khan, "Ant colony optimization (ACO) based data hiding in image complex region," *Int. J. Electr. Comput. Eng.*, vol. 8, no. 1, pp. 379-389, 2018, doi: 10.11591/ijece.v8i1.pp379-389.

[17] K. Loubna, B. Bachir, and Z. Izeddine, "Ant colony optimization for optimal low-pass state variable filter sizing," *International Journal of Electrical and Computer Engineering*, vol. 8, no. 1, pp. 227-235, Feb. 2018, doi: 10.11591/ijece.v8i1.pp227-235.

[18] H. Grari, A. Azouaoui, and K. Zine-Dine, "A cryptanalytic attack of simplified-AES using ant colony optimization," *International Journal of Electrical and Computer Engineering*, vol. 9, no. 5, pp. 4287-4295, Oct. 2019, doi: 10.11591/ijece.v9i5.pp4287-4295.

[19] M. Dramski, "A comparison between Dijkstra algorithm and simplified ant colony optimization in navigation," *Zesz. Nauk./Akad. Morska w Szczecinie*, vol. 144, pp. 149-160, Feb. 2017, doi: 10.1016/j.jclepro.2016.12.084.

[20] Santoso L. W., "Performance Analysis of Dijkstra, A* and Ant Algorithm for Finding Optimal Path Case Study: Surabaya City Map," Scientific Repository, 2010.

[21] C. E. Tudor-Locke and A. M. Myers, "Challenges and Opportunities for Measuring Physical Activity in Sedentary Adults," *Sport. Med.*, vol. 31, no. 2, pp. 91-100, Mar. 2001, doi: 10.2165/00007256-200131020-00002.

[22] A. Al-Khowarizmi, O. S. Sitompul, S. Suherman, and E. B. Nababan, "Measuring the Accuracy of Simple Evolving Connectionist System with Varying Distance Formulas," *Journal of Physics: Conference Series*, 2017, doi: 10.1088/1742-6596/930/1/012004.

[23] A. R. Lubis, M. Lubis, and A.- Khowarizmi, "Optimization of distance formula in K-Nearest Neighbor method," *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 1, pp. 326-338, Feb. 2020, doi: 10.11591/eei.v9i1.1464.

[24] S. Wurdianarto, S. R. Wurdianarto, S. Novianto, and U. Rosyidah, "Comparison of Euclidean Distance and Canberra Distance in Face Recognition (in Bahasa: Perbandingan Euclidean Distance Dengan Canberra Distance Pada Face Recognition)," *Techno. Com.*, vol. 13, no. 1, pp. 31-37, 2014, doi: 10.33633/tc.v13i1.539.

[25] A. R. Lubis, S. Prayudani, M. Lubis, and Al-Khowarizmi, "Decision making in the tea leaves diseases detection using mamdani fuzzy inference method," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 12, no. 3, pp. 1273-1281, Dec. 2018, doi: 10.11591/ijeecs.v12.i3.pp1273-1281.

[26] A. R. Lubis, M. Lubis, Al-Khowarizmi, and D. Listriani, "Big Data Forecasting Applied Nearest Neighbor Method," *International Conference on Sustainable Engineering and Creative Computing (ICSECC),* 2019, doi: 10.1109/ICSECC.2019.8907010.

[27] Al-Khowarizmi, I. R. Nasution, M. Lubis, and A. R. Lubis, "The effect of a secos in crude palm oil forecasting to improve business intelligence," *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 4, pp. 1604-1611, Aug. 2020, doi: 10.11591/eei.v9i4.2388.

[28] M. Dorigo and C. Blum, “Ant colony optimization theory: A survey,” *Theor. Comput. Sci.*, vol. 344, no. 2-3, pp. 243-278, 2005, doi: 10.1016/j.tcs.2005.05.020.
[29] R. F. Rahmat, A. Rizki, A. F. Alharthi, and R. Budiarto, “Big data forecasting using evolving multi-layer perceptron,” *2016 4th Saudi Int. Conf. Inf. Technol.,* Nov. 2016, doi: 10.1109/KACSTIT.2016.7756069.
[30] M. F. Ahmad Fauzi, “Optimal Discrete Wavelet Frames Features for Texture-Based Image Retrieval Applications BT-Visual Informatics,” *Bridging Research and Practice*,” 2009.
[31] Muhathir, R. Muliono, N. Khairina, M. K. Harahap, and S. M. Putri, “Analysis Discrete Hartley Transform for the recognition of female voice based on voice register in singing techniques,” *J. Phys. Conf. Ser.*, vol. 1361, no. 1, Nov. 2019, doi: 10.1088/1742-6596/1361/1/012039.
[32] R. Syah, M. Elveny, M. K. M. Nasution, and G. W. Weber, “Enhanced knowledge acceleration estimator optimally with mars to business metrics in merchant ecosystem,” *4rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM)*, 2020, pp. 1-6, doi: 10.1109/ELTICOM50775.2020.9230487.

BIOGRAPHIES OF AUTHORS

Rahmad Syah, from Doctoral Program of Universitas Sumatera Utara (USU), Medan Indonesia. Magister Program of Informatics, University of Sumatera Utara (USU). Bachelor degree from the Indonesian Computer University (UNIKOM) Bandung. Research Fields of study in Modelling and Computational System, Artificial Intelligence, Information Systems, Business Intelligence and Analytics (BI&A), Data Science.

Prof. Drs. Mahyuddin K. M. Nasution, M. IT, Ph. D., Professor from Universitas Sumatera Utara, Medan Indonesia. Mahyuddin (K. M. Nasution) was born in the village of Teluk Pulai Dalam, Labuhan Batu Regency, North Sumatera Province. Worked as a Lecturer at the University of Sumatera Utara (USU), fields: Mathematics, Computer and Information Technology. Education: Drs. Mathematics (USU Medan, 1992); MIT, Computers and Information Technology (UKM Malaysia, 2003); Ph. D in Information Science (Malaysian UKM). Research Fields: Artificial Intelligence, Social Network, Uncertainty, Data Modeling and Management, Data Science.

Dr. Erna Budhiarti Nababan, M. IT, Associate Professor from Universitas Sumatera Utara (USU). MIT, Computers Industry (UKM Malaysia, 2005); PhD in Sistem Science and Management (Malaysian UKM, 2010). Worked as a Lecturer at the University of Sumatera Utara (USU) Medan. Research Fields: Artificial Intelligence, Genetic Algorithm, Information Technology, Data Science, Machine Learning.

Dr. Syahril Efendi, M. IT, Associate Professor from Universitas Sumatera Utara, Medan Indonesia. MIT, Computers Science (UKM Malaysia, 1998). Department of Mathematics, Universitas Sumatera Utara (USU, 2013). Worked as a Lecturer at the University of Sumatera Utara (USU) Medan. Research Fields: Stochastic Programming and Data modelling, Operation Research, Mathematics.