Experimental Results (2022), 3, e19, 1–11
doi:10.1017/exp.2022.19

COMPUTER SCIENCE
NOVEL-RESULT
SUPPLEMENTARY-RESULT

Distribution-based packet forwarding distance dissimilarity learning for topology characterizing in geographic routing

Gbadebo Oladeji-Atanda* and Dimane Mpoeleng

Botswana International University of Science and Technology, Palapye, Botswana
***Corresponding author:** Email: gbadebo.oladeji-atanda@studentmail.biust.ac.bw

(Received 26 April 2022; Revised 07 September 2022; Accepted 10 September 2022)

Abstract
We have previously shown that the geographic routing's *greedy packet forwarding distance* (PFD), in dissimilarity values of its *average* measures, characterizes a mobile ad hoc network's (MANET) topology by node size. In this article, we demonstrate a *distribution*-based analysis of the PFD measures that were generated by two representative greedy algorithms, namely GREEDY and ELLIPSOID. The result shows the potential of the distribution-based dissimilarity *learning* of the PFD in topology characterizing. Characterizing dynamic MANET topology supports context-aware performance optimization in position-based or geographic packet routing.

Key words: ad hoc networks; dissimilarity learning; geographic packet forwarding; position-based routing protocols; topology characterizing

Introduction

The position-based or geographic routing protocols generate the *greedy packet forwarding distance* (PFD) feature (Kao et al., 2005); which, based on dissimilarity indices, characterizes a mobile ad hoc network's (MANET) topology by node size (Kulin et al., 2021; Oladeji-Atanda & Mpoeleng, 2022). In multihop geographic routing, the *greedy* algorithm enables each intermediate network node to forward packets to a neighbor which is closer in Euclidean distance to a final destination (Kuruvila et al., 2004). Figure 1 illustrates a greedy forwarding at the node u, having transmission range r, which within its progress region would choose a neighbor, such as v, to be the next relay toward the destination d. The length measurement of the link between u and v thus forms the PFD. A node's next-relay choice is also determined by the geometric computation peculiarity of its greedy algorithm. For example, as depicted in Figure 1, the GREEDY algorithm implements the metric $\min\{|\overline{vd}|\}$ that chooses a neighbor having the minimum distance to the destination, whereas $\min\{|\overline{uv}|+|\overline{vd}|\}$ describes the ELLIPSOID metric (Kao et al., 2005). By employing the ELLIPSOID and the GREEDY geographic packet forwarding metrics, Oladeji-Atanda and Mpoeleng (2022) have shown that the dissimilarities in the *average* values of the greedy PFD aid in characterizing MANET topology by node size. In this article, we demonstrate the potential of the geographic routing's PFD *distribution*-based dissimilarity learning in MANET topology characterizing.

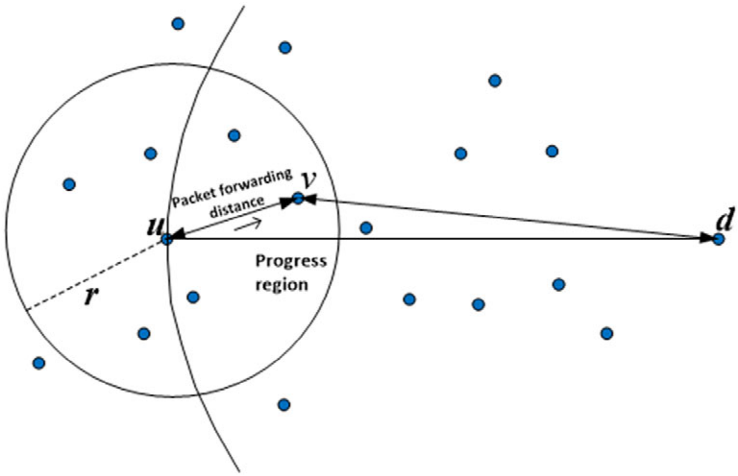

Figure 1. A greedy packet forwarding.

The characterizing of topologies supports context-aware packet routing performance optimization in dynamic MANETs, such as the vehicular ad hoc networks (VANETs) and flying ad hoc networks (FANETs), where node size varies significantly (Medina et al., 2008; Silva et al., 2019).

Dissimilarity learning and topology characterizing

The positionings and associated links between the nodes describe the topology of a network, which may be characterized based on the dissimilarity indices of the elements' statistical distribution. Cucka et al. (1997) showed that a network's underlying topology or graph type could be distinguished by an *exploration* agent, to determine the most optimal *exploitation* method in path-search tasks of repetitive nature. In their demonstration with Delaunay and random graph types, the arc or link length averages and histogram distribution patterns differentiate the two. Kolaczyk and Csárdi (2020) showed a similar mode of characterizing social networks by the distribution patterns of the node degrees or neighbor links. In Schieber et al. (2017), the network-distance and the node-distance distributions are incorporated into the definition of a dissimilarity metric $D(G, G\ )$ that quantifies graphs' fluid flow capacity. The dissimilarity approach entails distinguishing between similar entities through pairwise comparison of their defining *distance* measures (Costa et al., 2020; Riesen & Bunke, 2010).

Methods

The greedy PFD elements that we analyze are based on the data obtained from the simulation experiment described in Oladeji-Atanda and Mpoeleng (2022). The elements were generated using the NS-3 network simulator and the Greedy Perimeter Stateless Routing routing protocol, and based on a VANET environment of 30, 50, 70, 90, and 110 node sizes (Silva et al., 2019). Other simulation parameters are the network area: 1,100 m^2; nodal transmission range: 280 m; node speed: 0–15 m/s; simulation time: 200 s; and the packets type: 512 byte CBR/UDP. We illustrate greedy PFD distribution with the ELLIPSOID and GREEDY metrics due to their popularity in position-based routing protocol designs. We sort the metrics' PFD performance collections into classes based on arbitrarily determined length delimitations. We then produce frequency distributions of the PFD elements in each class. Finally, we show that the derived charts depict dissimilarities, which a learning method can ascertain, in characterizing a MANET's topology by node size.

Metrics of distance, classification, and dissimilarity indices

We specify metrics for the PFD element and its distribution classification. For two nodes u and v (Figure 1), the Euclidean distance between them in the two-dimensional plane is determined by

$$dist(u, v) = \sqrt{(u_x - v_x)^2 + (u_y - v_y)^2}. \tag{1}$$

Note that position-based routing can be evaluated or performed in 2D or 3D (Medina et al., 2008; Silva et al., 2019). For the neighbors of a node u represented by the set $N(u)t = \{v_1, \ldots, v_n\}t$ at time t, its set of edges or links is described by

$$E(u)t = \{e_{u,v_i}(t) \,|\, dist(u, v_i) \le r, \;\; i = 1, \ldots, |N(u)|\}. \tag{2}$$

Each link e_{u,v_i} has intrinsic values such as length, link duration, and so forth, associated with it. Our interest presently lies in the Euclidean "length" attribute of the greedy PFD, designated as d_{GF} (Oladeji-Atanda & Mpoeleng, 2022). Thus,

$$d_{GF}(e_{u,v_i}(t)) = dist(u, v_i)(t). \tag{3}$$

In a packet routing session, the collection of the PFD elements is representable as

$$D_{GF} = \{d_{GF_i}(t) \,|\, i = 1, 2, 3, \ldots, |D_{GF}|\} \tag{4}$$

For convenience, we do not continue showing the time t in our equations. Given a kth node size in a network, D_{GF}^{k} describes the relevant PFD collection, $1 \le k \le m$, where m is the environment's regular maximum. We can sort the elements in each D_{GF}^{k} into p subclasses based on the delimitations of the length l attribute. Let the set of the length delimitations be $\{l_1, l_2, \ldots, l_p\}$, $0 < l_1 < l_2 < \ldots < l_p$, and $l_p = r$ is the maximum nodal transmission range (Figure 1). Hence, we can sort the elements in each D_{GF}^{k} as follows:

$$D_{GF}^{k1} = \left\{d_{GF_i} \,|\, d_{GF_i} > 0 \bigwedge d_{GF_i} \le l_1\right\},$$

$$D_{GF}^{k2} = \left\{d_{GF_i} \,|\, d_{GF_i} > l_1 \bigwedge d_{GF_i} \le l_2\right\},$$

$$\vdots$$

$$D_{GF}^{kp} = \left\{d_{GF_i} \,|\, d_{GF_i} > l_{p-1} \bigwedge d_{GF_i} \le l_p\right\}. \tag{5}$$

We can then assign the number of PFD elements in each D_{GF}^{kj} $(j = 1, \ldots, p)$ to be the integer-valued occurrences count c^{kj}:

$$c^{k1} \leftarrow \left|D_{GF}^{k1}\right|,$$

$$c^{k2} \leftarrow \left|D_{GF}^{k2}\right|,$$

$$\vdots$$

$$c^{kp} \leftarrow \left|D_{GF}^{kp}\right|. \tag{6}$$

https://doi.org/10.1017/exp.2022.19 Published online by Cambridge University Press

Thus, for the chart representing the kth node size of a network, we may plot the x,y-coordinates (l_j, c^{kj}) to display the relevant distribution. The $c^{kj(ELLIPSOID)}$ and $c^{kj(GREEDY)}$ charts representing ELLIPSOID and GREEDY forwarding outcomes can be plotted accordingly. Finally, a dissimilarity-learning method can perform intra- and inter-chart comparisons to differentiate between network node sizes k and k':

$$Diss\left(D_{GF}^{k}, D_{GF}^{k'}\right) = x, \tag{7}$$

where the output, $x \geq 0$, indicates the dissimilarity index value. We do not explicate the metric $Diss(.)$ in this article, but we present distribution charts that illustrate the function in its expected outcomes. Example dissimilarity metrics and pattern recognition methods are described in Costa et al. (2020) and Schieber et al. (2017).

Results and discussion

As a result of our simulation experiment on neighbor choices of ELLIPSOID and GREEDY forwarding, we classify (as in equation (5)) the generated PFD elements by length delimitations of 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 120, 140, 160, 180, 200, 220, 240, 260, and 280 m. Then, we perform the occurrence count in each class (as in equation (6)) and plot the values as shown in Figures 2 and 3. Intra- and inter-chart comparisons show rich distinctions of the PFD frequency distributions for the ELLIPSOID and GREEDY forwarding methods. For instance, at the 110 node size, the ELLIPSOID's cumulative occurrence count below 150 m PFD length measure is about 28,000 out of about 34,000 total, an approximate of 82%, whereas that of GREEDY is about 4,000 out of about 25,000, an approximate of 16%. Furthermore, across all the node sizes (i.e., Figure 2a–e), the 100-m PFD cumulative values for ELLIPSOID steadily increase from 43 to 76%, whereas that of GREEDY decreases from 18 to 6%. Similar trends are observable for the 200-m PFD limit, and so on.

Figure 3 shows the charts of Figure 2a–e placed together. The ELLIPSOID charts show distinct hierarchies of the PFD distribution all through the 0–280 m classifications, whereas that of GREEDY is clear only from around 150 m upward. This implies that the ELLIPSOID's PFD is more sensitive to node size variations, which recommends it to solely provide dissimilarity indices in a topology characterizing scheme. In general, both methods' distinctive PFD outcomes are generalizable to other greedy metrics such as the Most Forward Routing and Compass Routing (Kao et al., 2005).

Conclusions

We have shown that a position-based or geographic routing protocol can perform dissimilarity learning of the greedy PFD distribution to characterize MANET topology by node size. The example next-relay neighbor choices of GREEDY and ELLIPSOID forwarding generated varied modes of the PFD, in length and proportion to network node size. The resultant *distribution*-based charts demonstrate an efficacious approach to PFD dissimilarity learning and topology characterizing. In dynamic environments, such as the VANET and the FANET, the characterizing of topologies is an aid in optimization tuning of a network's parameters (Kulin et al., 2021), like variable-range transmission or topology control (Medina et al., 2008). Our investigation on PFD distribution involved a MANET with a uniform node speed of 0–15 m/s, whereas it will be necessary to also study the effect of different mobility rates. Moreover, some *supervised learning* applications should be involved in verifying the efficacy of the distribution-based dissimilarity learning of the PFD in topology characterizing.

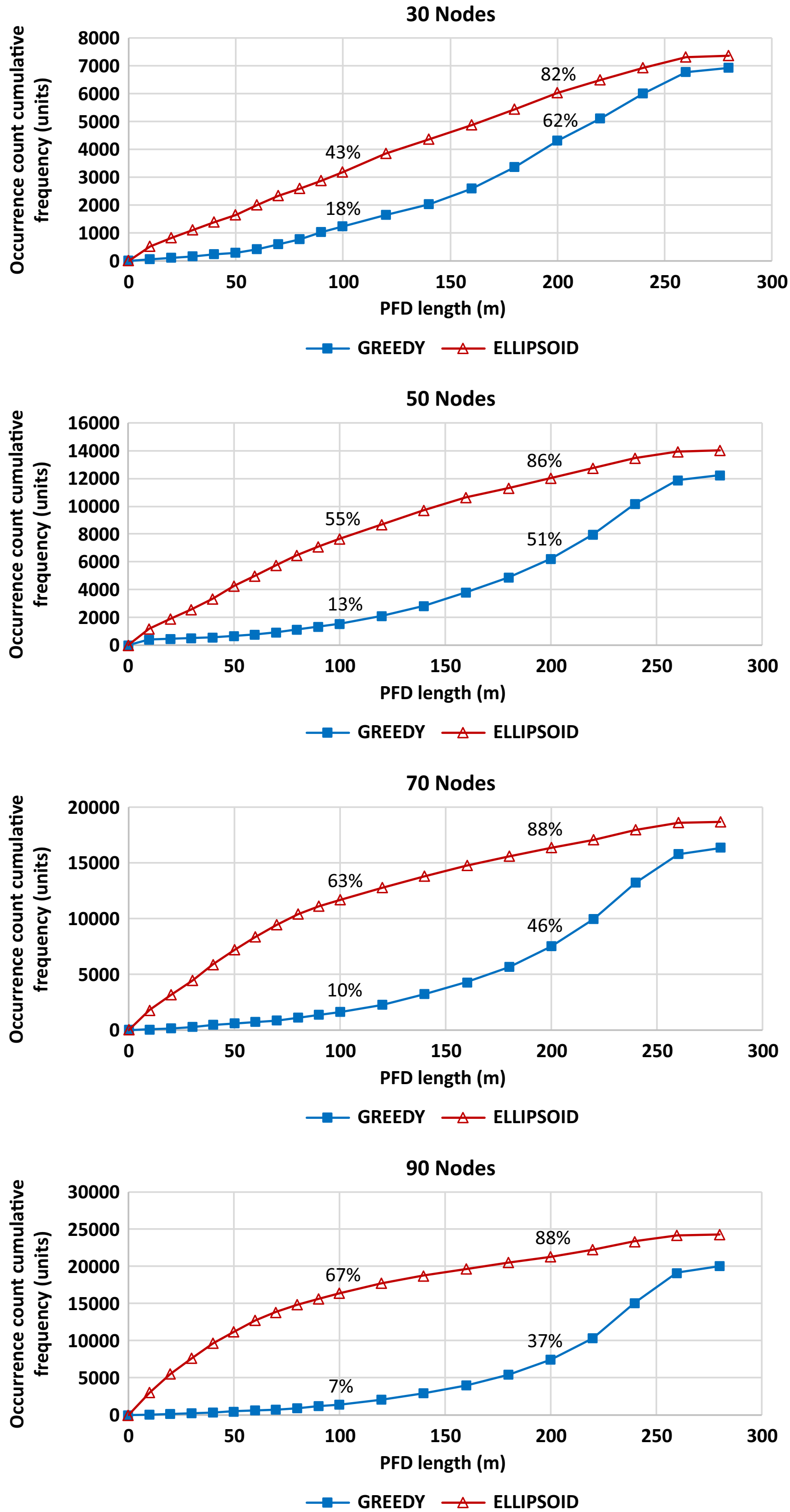

Figure 2. (a–e) PFD occurrence count cumulative frequency distributions.

https://doi.org/10.1017/exp.2022.19 Published online by Cambridge University Press

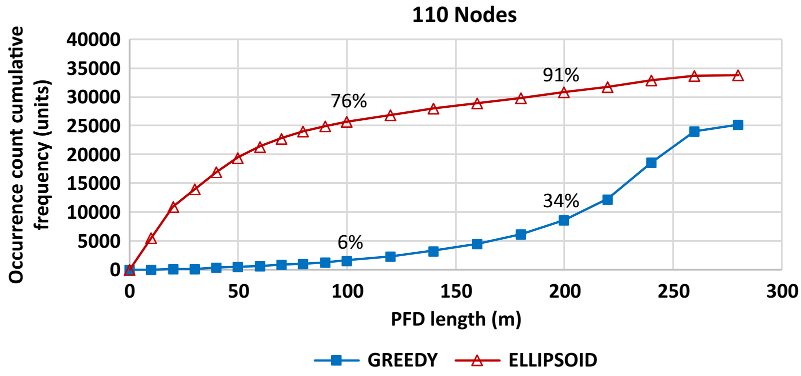

Figure 2. Continued.

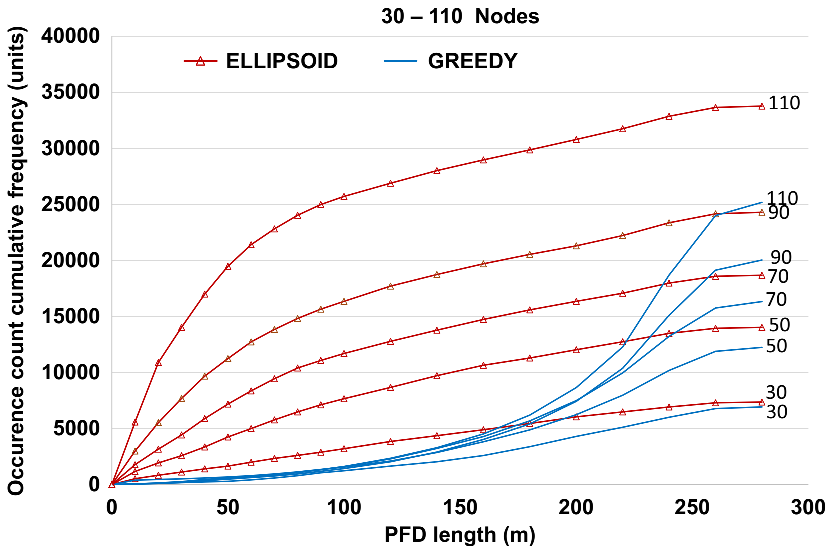

Figure 3. PFD occurrence count hierarchy of cumulative frequency distributions.

Data availability statement. The data used in this study was obtained from Silva et al. (2019) (https://github.com/CSVNetLab/PA-GPSR).

Funding statement. This work was supported in part by the Research Initiation Grant of the Botswana International University of Science and Technology, Project Code No. S00122.

Conflicts of interest. The authors declare that they have no conflict of interest.

Authorship contributions. G.O.-A. designed the study and wrote the article. D.M. supervised the study and the article writing.

References

Costa, Y. M. G., Bertolini, D., Britto, A. S., Cavalcanti, G. D. C., & Oliveira, L. E. S. (2020). The dissimilarity approach: A review. *Artificial Intelligence Review*, **53**, 2783–2808. https://doi.org/10.1007/s10462-019-09746-z

Cucka, P., Netanyahu, N. S., & Rosenfeld, A. (1997). Learning in navigation: Goal finding in graphs. In *Studies in pattern recognition* (Vol. **25**, pp. 39–56). World Scientific. https://doi.org/10.1142/9789812797728_0003

Kao, G. S.-C., Fevens, T., & Opatrny, J. (2005). Position-based routing on 3-D geometric graphs in mobile ad hoc networks. In *17th Canadian conference on computational geometry (CCCG'05)*, dblp computer science bibliography (Schloss Dagstuhl, Leibniz Centre for Informatics). (pp. 81–91. http://www.cccg.ca/proceedings/2005/ Accessed 25th January 2019.

Kolaczyk, E. D., & Csárdi, G. (2020). Descriptive analysis of network graph characteristics**.** In E. D.Kolaczyk & G.Csárdi (Eds.), *Statistical analysis of network data with R* (pp. 43–68). Springer International Publishing. https://doi.org/10.1007/978-3-030-44129-6_4

Kulin, M., Kazaz, T., De Poorter, E., & Moerman, I. (2021). A survey on machine learning-based performance improvement of wireless networks: PHY. *MAC and Network Layer Electronics*, **10**, 318. https://doi.org/10.3390/electronics10030318

Kuruvila, J., Nayak, A., & Stojmenovic, I. (2004). Hop count optimal position based packet routing algorithms for ad hoc wireless networks with a realistic physical layer. *2004 IEEE international conference on mobile ad-hoc and sensor systems (IEEE Cat. No.04EX975)*, IEEE. (pp. 398–405). https://doi.org/10.1109/MAHSS.2004.1392179

Medina, D., Hoffmann, F., Ayaz, S., & Rokitansky, C.-H. (2008). Topology characterization of high density airspace aeronautical ad hoc networks. *2008 5th IEEE international conference on mobile ad hoc and sensor systems*, IEEE. (pp. 295–304). https://doi.org/10.1109/MAHSS.2008.4660016

Oladeji-Atanda, G., & Mpoeleng, D. (2022). Topology characterizing using packet forwarding distance dissimilarity in multi-greedy geographic routing. *EAI Endorsed Transactions on Mobile Communications and Applications*, 6. **22**(20): e3, pp 1–10. https://eudl.eu/doi/10.4108/eai.11-1-2022.172815

Riesen, K., & Bunke, H. (2010). *Graph classification and clustering based on vector space embedding* (Vol. **77**). World Scientific. https://doi.org/10.1142/7731

Schieber, T. A., Carpi, L., Díaz-Guilera, A., Pardalos, P. M., Masoller, C., & Ravetti, M. G. (2017). Quantification of network structural dissimilarities. *Nature Communications*, **8**, 1–10. https://doi.org/10.1038/ncomms13928

Silva, A., Reza, N., & Oliveira, A. (2019). Improvement and performance evaluation of GPSR-based routing techniques for vehicular ad hoc networks. *IEEE Access*, **7**, 21722–21733. https://doi.org/10.1109/ACCESS.2019.2898776

Cite this article: Oladeji-Atanda G, Mpoeleng D (2022). Distribution-based packet forwarding distance dissimilarity learning for topology characterizing in geographic routing. *Experimental Results,* 3, e19, 1–11. https://doi.org/10.1017/exp.2022.19

Peer Reviews

Reviewing editor: Prof. Emanuele Frontoni

Minor revisions requested.

doi:10.1017/exp.2022.19.pr1

Review 1: Distribution-based packet forwarding distance dissimilarity-learning for topology characterizing in geographic routing

Reviewer: Dr. Weisheng Si

Date of review: 02 August 2022

Conflict of interest statement. Reviewer declares none.

Comment

Comments to the Author:

1. The experimental results are obvious intuitively. There seems no need to conduct such experiments. It's well known that Greedy favours long links and Ellipsoid favours short links.
2. The figures on cumulative frequencies show the same phenomena as the figures on separate frequencies. Only one set of figures will do.
3. The choice of words and the composition of sentences are poor. The English writing needs to be improved significantly.

Score Card

Presentation

3.0 /5

Is the article written in clear and proper English? (30%)	2/5
Is the data presented in the most useful manner? (40%)	3/5
Does the paper cite relevant and related articles appropriately? (30%)	4/5

Context

3.0 /5

Does the title suitably represent the article? (25%)	2/5
Does the abstract correctly embody the content of the article? (25%)	3/5
Does the introduction give appropriate context? (25%)	3/5
Is the objective of the experiment clearly defined? (25%)	4/5

Analysis

2.8 /5

Does the discussion adequately interpret the results presented? (40%)	3/5
Is the conclusion consistent with the results and discussion? (40%)	3/5
Are the limitations of the experiment as well as the contributions of the experiment clearly outlined? (20%)	2/5

https://doi.org/10.1017/exp.2022.19 Published online by Cambridge University Press

doi:10.1017/exp.2022.19.pr2

Review 2: Distribution-based packet forwarding distance dissimilarity-learning for topology characterizing in geographic routing

Reviewer: Dr. Paolo Sernani

Universita Politecnica delle Marche, Ancona, Italy, 60121

Date of review: 30 August 2022

Conflict of interest statement. Reviewer declares none

Comment

Comments to the Author: The paper analyzes the distribution of the Packet Forwarding Distance (PFD) for two geographic routing protocol (GREEDY and ELLIPSOID) when the number of nodes in the network varies.

Main comments:

1. The abstract is an introduction to the paper topic, i.e., topology characterizing, rather than a summary of the experiment and its results. I suggest rewriting the abstract to briefly describe the presented experiment.

2. The introduction section does not clearly state the experiment goal. Is it demonstrating or validating the hypothesis that the distribution of the greedy PFD is a dissimilarity-learning feature? Is it repeating an experiment that someone else did? I suggest explicitly writing the experiment goal in the introduction section.

Other comments:

3. The acronym MANET appears in the abstract without defining it as mobile ad hoc networks. Please write it in its extended form the first time it appears in the abstract.

4. There is no need to cite (Kao et al, 2005) for the definition of Euclidean distance (equation 1).

5. The figures appear grainy. I do not know which software the authors used to export the images; given that the figures are diagrams (Figure 1) and charts (Figures 2, 3, and 4), I suggest exporting them as vector graphics instead of raster. For example, I think you can export them as pdf files with embedded fonts instead of exporting the diagram and the charts as jpg or png.

Score Card

Presentation

4.0 /5

Is the article written in clear and proper English? (30%)	4/5
Is the data presented in the most useful manner? (40%)	4/5
Does the paper cite relevant and related articles appropriately? (30%)	4/5

Context

3.0 /5

Does the title suitably represent the article? (25%)	4/5
Does the abstract correctly embody the content of the article? (25%)	2/5

Does the introduction give appropriate context? (25%)	4/5
Is the objective of the experiment clearly defined? (25%)	2/5

Analysis

3.8 /5

Does the discussion adequately interpret the results presented? (40%)	4/5
Is the conclusion consistent with the results and discussion? (40%)	4/5
Are the limitations of the experiment as well as the contributions of the experiment clearly outlined? (20%)	3/5

https://doi.org/10.1017/exp.2022.19 Published online by Cambridge University Press