International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 3, June 2024, pp. 3475∼3484
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i3.pp3475-3484

Enhancing routing efficiency in social internet of things: R-OPTICS and vEBT based congestion free model

Bhavya D.[1], D. S. Vinod[2], S. P. Shiva Prakash[2], Kirill Krinkin[3]
[1]Department of Computer Science and Engineering, Faculty of Engineering, PES College of Engineering, Mandya, India
[2]Department of Information Science and Engineering, Faculty of Engineering, JSS Science and Technology University, Mysuru, India
[3]School of Computer Science and Engineering, Constructor University, Bremen, Germany

Article Info

Article history:

Received Jun 30, 2023
Revised Oct 17, 2023
Accepted Jan 16, 2024

Keywords:

Congestion free routing
Relationship ordering points to identify the clustering structure
Routing efficiency
Social internet of things
van emde boas tree

ABSTRACT

The emergence of the social internet of things (SIoT) network has brought forth distinctive challenges, including node mobility and varying densities, leading to congestion and hampered network efficiency. To overcome these issues, a congestion-free routing model for SIoT is proposed. This model combines the relationship-ordering points to identify the clustering structure (R-OPTICS) algorithm for intelligent node clustering based on relationships and ordering, along with a van emde boas tree (vEBT) for efficient path selection. R-OPTICS enables effective network management by clustering nodes appropriately. The model's performance is evaluated using metrics such as Rand-Index (1.5765), Davies-Bouldin (-0.4305), and Silhouette Coefficient (1.71685) to assess average goodness values. vEBT identifies optimal paths between clusters, facilitating smart routing decisions. The primary objective of the model is to enhance network efficiency and alleviate congestion by intelligently routing data between clusters. Through extensive simulations, the proposed model outperforms existing routing methods, resulting in improved efficiency and congestion reduction. This congestion-free routing model presents a promising solution to address the unique challenges of SIoT networks, ensuring optimal performance and effective resource management.

Corresponding Author:

D. S. Vinod
Department of Information Science and Engineering, Faculty of Engineering, JSS Science and Technology University
Mysuru-570006, Karnataka, India
Email: dsvinod@jssstuniv.in

1. INTRODUCTION

Emergence of the social internet of things (SIoT) within the internet of things (IoT) has spurred the rapid development of smart objects, aligned with current trends. SIoT involves interconnections between smart objects established through various relationships [1], such as parental object relationship (POR), co-location object relationship (CLOR), ownership object relationship (OOR), social object relationship (SOR), and more. These connections utilize protocols like wireless fidelity (WiFi), Zigbee, Bluetooth, WiFi-Direct, and worldwide interoperability for microwave access (Wi-MAX), forming a network with both static and mobile nodes. The mobility of nodes enables unique features for identifying neighbouring nodes.

State of the art: The literature survey comprehensively reviews research in next-gen wireless networks (NWNs), IoT, and SIoT. Efficient routing is crucial for supporting delay-sensitive mobile applications in NWNs. Yao *et al.* [1] introduced a machine learning-based routing algorithm outperforming Bellman-Ford (BF) and Queue-Utilization BF (QUBF) in packet loss, throughput, and delay. Rad *et al.* [2] analyzed recent SIoT works, examining components, features, parameters, and challenges, proposing robust evaluation parameters. Jafarian *et al.* [3] focused on trust management, proposing a discriminative-aware trust management (DATM) system. Sharma *et al.* [4] explored IoT objectives, enablers for massive machine type communications (mMTC), and device learning techniques. In IoT, congestion management was addressed by Chowdhury *et al.* [5] with non-cooperative gaming for power-efficient congestion control (NGECC). Musaddiq *et al.* [6] introduced a Q-learning-based intelligent collision probability inference algorithm for optimal IoT network performance. Del-Valle-Soto *et al.* [7] contributed an energy model for wireless sensor networks (WSNs), accurately estimating energy consumption. Khelloufi *et al.* [8] explored social relationships among device owners to enhance service recommendations. Marche *et al.* [9] concentrated on object queries in SIoT for efficient application requests. Marietta *et al.* [10] discussed critical IoT issues, emphasizing optimal routing. Ganesh *et al.* [11] presented heterogeneous wireless sensor networks (HWSNs) and introduced protocols to enhance performance. Noureddine *et al.* [12] introduced a grid-based routing method for energy efficiency, validated through MATLAB simulations. Farag *et al.* [13] proposed a reinforcement-learning framework based on Q-learning for load balancing in RPL. Abid *et al.* [14] compared density-based spatial clustering of applications with noise (DBSCAN) and OPTICS for outlier detection, highlighting DBSCAN's superior performance. Meghana *et al.* [15] introduced methods to aggregate SIoT data, with decision tree and artificial neural network algorithms outperforming. In their work, Marche *et al.* [16] focused on trust management in IoT, addressing various trust attacks. Pancaroglu *et al.* [17] studied load balancing approaches in RPL. Samizadeh *et al.* [18] discussed the critical importance of IoT architecture and addressed challenges. In the context of IoT applications in the 6G era, Goswami *et al.* [19] highlighted the significance of energy-efficient routing for multi-access edge computing (MEC) in intelligent transportation systems (ITS) and introduced a hybrid DAI-SOM method to optimize energy consumption and intra-cluster communication. Devidas Mandaokar *et al.* [20] enhances DBSCAN with a partial probability function, boosting cluster accuracy and reducing computational overhead. Their swarm intelligence optimizes density-based algorithms for better merging, noise reduction, and core point value. Natarajan *et al.* [21] recommended an upgradable cross-layer routing protocol for cognitive radio (CR) network-based IoT to enhance routing efficiency and data transmission optimization in reconfigurable networks. Mohana *et al.* [22] presented classification, clustering and navigation simulator (CCNSim), a comprehensive SIoT simulator that incorporated basic network simulator features alongside advanced AI-based traffic analytics and visualization. Mohana *et al.* [23] proposed a feature selection method based on semantic rules and relationship artificial neural networks (R-ANN) to classify services in SIoT environments, achieving an accuracy rate of 89.62% for various services. Kaviani and Soltanaghaei *et al.* [24] introduced congestion and quality of service – aware routing protocol for low-power and lossy networks (QoS-Aware RPL) (CQARPL), a novel routing protocol for IoT that specifically addressed congestion control and quality of service (QoS) requirements. Yinan *et al.* [25] reiterated the importance of energy-efficient routing in IoT and introduced a hybrid DAI-SOM method to optimize energy consumption and intra-cluster communication. Finally, Ali *et al.* [26] underscored the significance of energy-efficient routing in WSNs supporting IoT applications and introduced a multipath routing approach that outperformed existing methods in terms of efficiency and resilience. The state-of-the-art work highlights the importance of efficient routing, load balancing, congestion control, trust management, and service recommendation in next-gen wireless networks, IoT, and SIoT, revealing the need for further research and development in these areas to overcome challenges and enhance the performance of these networks.

Problem in the SIoT network include congestion due to the increasing number of nodes, dynamic topology from node mobility causing frequent connection failures, and diverse communication protocols for various relationship types. Efficient routing models are crucial for seamless, congestion-free communication. Then, contribution to tackle the challenges posed in SIoT routing, we propose a model that combines two techniques: clustering using the relationship ordering points to identify the clustering structure (R-OPTICS) algorithm and finding the best path using a van emde boas tree (vEBT). The contributions of this work are highlighted as follows:

- Proposed a congestion-free routing model using clustering.
- Proposed a modified OPTICS algorithm using the relationship between devices as a metric for clustering.
- Proposed van Emde Boas vEBT algorithm for choosing congestion-free routing in the social internet of things.

2. RESEARCH METHOD

2.1. System model

Consider a SIoT network with a random number of objects connected through relationships in an environment represented by N_x. The SIoT system model S_M defined as a set of public and private objects that are randomly distributed and all are connected in a network N_x. The objects $O = 1, 2, ..., n$ in which each object is connected through a relationship R using object profiles O_P includes the protocols P with device types D_T, service S_R, and applications A_P. The similar features of objects create relationships among them. There are ten types of relationships $R = R1, R2, \ldots, R10$. SIoT provides services assuming objects have decentralized networks to provide services through nearby objects N_o in various locations L_C with a certain distance D. These objects are identified based on source object O_s to destination object O_d which helps to find the congestion-free path of a network using the clustering technique is as shown in (1). Hence the system model S_M is defined in (1),

$$S_M = \sum_{X=1}^{n} O(N_o, O_s, O_d) : N_x \rightarrow \forall(O, O_P, S_R, D, L_C, R, D_T, A_P) \tag{1}$$

2.1.1. Problem formulation

The model provides the congestion-free decision model C_{FD} while offering services S_R from applications A_P. Congestion avoidance in a network is achieved through clustering techniques. The clustering model C_L is used to train the network N_x, through the relationships R between the objects O from source s to destination d. Consider a cluster C_L having multiple paths p located at some distance d, to find the specific object with minimum distance path $Min(p)$ and maximum distance path $Max(p)$ for getting services from other objects in SIoT network is represented in 2.1.1., 2.1.1., and 2.1.1.. To find the congestion-free path, the objective function is defined as (2),

$$C_{FD} = \sum_{P=1}^{n} C_L(Max(p), Min(p)) \tag{2}$$

subjected to (3),

$$C_L = \{N_o, O_p, S_R, L_C, R, D_T, A_P\} \tag{3}$$

and,

$$Max(p) = (O_s, O_d) \quad Min(p) \rightarrow (O_s, O_d) \tag{4}$$

2.1.2. Problem solution

In (2), C_L is the clustering technique that uses the R-OPTICS technique to cluster the neighbour objects N_o using objects profiles O_p with respect to relationship R, based on protocols P, for service S_R of location L_C of given device type D_T in applications A_P. The R-OPTICS uses two parameters core distance objects C_D and reachability distance object R_D. The ϵ is the distance threshold and is calculated using (5).

$$C_D = Min(p)(O_s, O_d, \epsilon) \tag{5}$$

and

$$R_D = Max(p)(O_s, O_d, \epsilon) \tag{6}$$

Using (5) and (6) congestion can be avoided by navigating the path between the objects. Therefore, to navigate the objects by searching nearby connected objects using vEBT algorithm. The vEB tree is a data structure that supports fast query and update operations on a set of keys. The vEBT technique searches the objects in each cluster by representing clusters as trees and performing the operations namely insertion, deletion, find successor, and predecessor.

2.2. Proposed methodology design

The proposed model working procedure is as follows: first input the SIoT data, pre-process the data for normalizing the data values, then select the features of relationships between the objects, then analyze the reachability of objects in a density of SIoT environment using R-OPTICS technique in the data, then analyze the objects that are in multiple relationships and find the reachability nodes from source to destination objects in the environment. However, using the vEBT technique, find the path in the clusters of objects to analyze the maximum and minimum paths for the relationship between objects. Finally find the optimal path between the objects with multiple relationships in SIoT network. The design of proposed R-OPTICS-vEBT congestion free routing model is as shown in Figure 1.

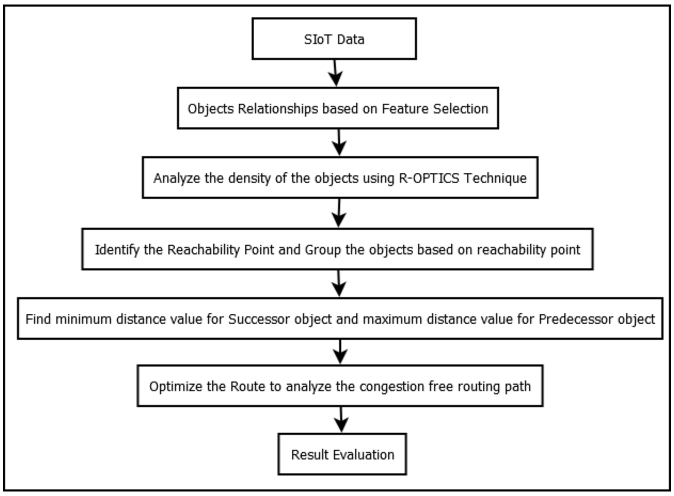

Figure 1. Proposed methodology design

2.3. Proposed algorithm

This section presents the proposed algorithm used to find the congestion-free path. The R-OPTICS algorithm operates through the following steps: Firstly, it computes the distance between every pair of data points within the dataset. Next, it determines the minimum points parameter (MinPts) and the radius parameter (Eps). For each data point, it calculates the density of its Eps-neighbourhood, which represents the count of data points within a distance of Eps from the given point. Additionally, it calculates the reachability distance for each data point, measuring the minimum distance to a core point within its Eps-neighbourhood. Finally, the algorithm generates a reachability plot that visualizes the reachability distance of each data point. By analysing the reachability plot, dense areas within the dataset can be identified. Algorithm 1 shows the detailed steps of the R-OPTICS algorithm.

Algorithm 1. R-OPTICS Algorithm

Data: Dataset D, Minimum Points ($MinPts$), Radius (Eps)
Result: Clustering Structure
Function ROPTICS(D, $MinPts$, Eps)**:**
  Compute pairwise distances between data points in D Initialize an empty list of core points
  for *each data point p in* D **do**
    Calculate the Eps-neighborhood $N_{\text{Eps}}(p)$ of p
    if $|N_{Eps}(p)| \geq MinPts$ **then**
      Mark p as a core point
    end
  end
  Initialize an empty list of reachability distances
  for *each data point p in* D **do**
    if *p is a core point* **then**
      Calculate the density of $N_{\text{Eps}}(p)$
      for *each data point q in* $N_{Eps}(p)$ **do**
        if *q is not processed* **then**
          Calculate the reachability distance $RD(q,p)$ of q to p Add $RD(q,p)$ to the list of reachability distances
        end
      end
      Mark p as processed
    end
  end
  Create a reachability plot using the list of reachability distances Analyze the reachability plot to identify dense areas and clusters

Further, the vEBT algorithm uses the devices clustered by using R-OPTICS algorithm and chooses a range of values for the distance information to be stored and then divide the range into two halves and store the distance information for each half in a separate vEB Tree, and continue dividing the range into halves until the range is small enough to be stored in a single vEBT. To find the distance between two nodes, traverse the vEBT hierarchy and retrieve the distance information stored at the appropriate level.

3. RESULTS AND DISCUSSION

3.1. Dataset description

The dataset consists of 16,216 devices, of which 14,600 are private objects and 1,616 are public devices. These devices were created in the city of Santander in Spain. Each object has various configurations such as device id, user id, device type, device brand, and device model. Additionally, the dataset includes the position of the adjacency matrix of the objects and the delay between them. The adjacency matrix contains various relationship types between objects such as POR, CLOR, SIOR, SOR, and SOR2. The dataset also includes randomly generated protocols such as ZigBee, Wi-Fi, blue-tooth low energy (BLE), and Wi-Fi-Direct for various types of devices, both private and public, and brands of equipment. The dataset has location variables, protocol types, and object relationships, which include properties such as protocol type, objects, locations, services [21], [22], [23] applications, device type, distance, and relationships.

3.2. Results

Figure 2 illustrates the simulation area where devices communicate, creating an environment for conducting experiments. The dataset in SIoT, all devices are multivariate which makes more density in the network present in different distributions [16], [20]. The dataset contains the various device types namely private devices and public devices and its distribution. The devices are connected with different protocol such as wifi, zigbee, and there are 10 types of relationships between the devices in a network. OPTICS is a density-based clustering method used to locate the structure of the clusters from which different types and densities of clusters can be extracted. For finding clusters of different densities in large, high-dimensional datasets, it is useful. It estimates the clusters and also estimates the noise points. The proposed model creates the order clusters of all different devices are shown in the Table 1.

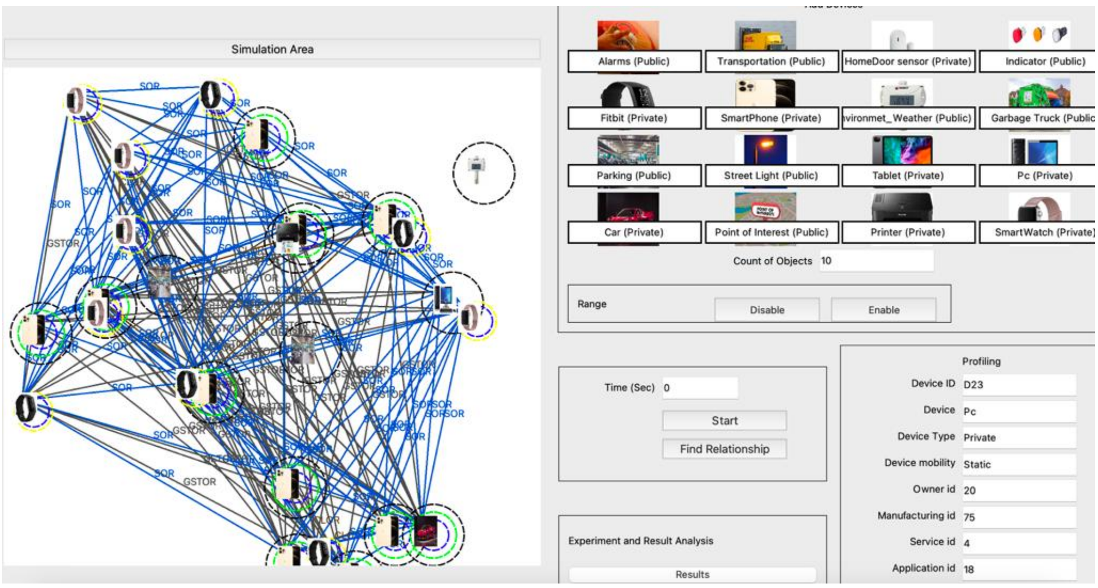

Figure 2. Simulation environment

Table 1 presents the training and testing samples of the SIoT dataset, along with the number of clusters obtained and a comparison with various results using OPTICS techniques. The performance metrics used include the Davies-Bouldin index, silhouette coefficient, and adjusted Rand index. The Davies-Bouldin index measures the ratio between cluster scatter and cluster separation, with a lower value indicating better clustering. However, in our dataset, we obtained higher values, indicating that the clusters are quite dense. The silhouette coefficient measures how well an object matches its own cluster compared to neighbouring clusters. The average number of clusters obtained is 1813, 1755, 1627, and 1483 for the 60:40, 70:30, 80-20, and 90:10 dataset ratios respectively in the SIoT dataset, as shown in Figure 3. In our dataset, the coefficient is predominantly influenced by neighbouring clusters. The adjusted Rand index yields positive values, indicating a high similarity between clusters. Figure 4 illustrates the reachability of devices in the network for a dataset ratio of 60:40 in the SIoT dataset of total vehicles ranging from 20,000 to 60,000, Figure 4(a) shows total vehicles of 20,000, Figure 4(b) depicts 30,000 total vehicles, later Figure 4(c) illustrates total vehicles of 50,000, and finally Figure 4(d) interprets total vehicle reachability of 60,000.

Table 1. SIoT dataset for Test in OPTICS cluster

Dataset Train : Test	Devices	clusters	Davies-Bouldin Index	Silhouette Coefficient	Adjusted Rand Index
90:10	10,000	376	1.61	-0.40	0.004
	25,000	848	1.33	-0.46	0.01
	50,000	1745	1.55	-0.46	1.66
	75,000	2630	1.62	-0.47	1.36
	100,000	3467	1.79	-0.48	1.86
80:20	10,000	376	1.61	-0.40	0.004
	25,000	848	1.33	-0.46	0.001
	50,000	1745	1.55	-0.46	1.66
	75,000	2630	1.62	-0.47	1.36
	100,000	3177	1.67	-0.47	-5.72
70:30	10,000	346	1.67	-0.39	0.001
	25,000	819	1.33	-0.41	6.51
	50,000	1659	1.71	-0.42	1.41
	75,000	2431	1.64	-0.44	7.85
	100,000	2882	1.65	-0.45	1.16
60:40	10,000	376	1.61	-0.40	0.004
	25,000	746	1.36	-0.37	4.9
	50,000	1482	1.61	-0.40	2.40
	75,000	2228	1.65	-0.40	6.5
	10,0000	2586	1.68	-0.42	1.29

The SIoT network's source and destination devices demonstrate a robust interdependence among diverse clusters. To pinpoint congestion-free routes within the SIoT, we employ the vEBT searching technique. OPTICS clusters fluctuate based on the total device samples in the environment, detailed in Table 1. It is noted that with an increase in clusters, noise escalates. Each cluster's performance is gauged by the minimum verified samples, assessed through connected objects' reachability. The vEBT method executes search steps for reaching cluster k in the SIoT network, enhancing navigability. Device connections signal a functional network, while their absence indicates a failed establishment. Nodes in cluster k are scrutinized to identify the optimal path for a congestion-free routing protocol. The vEBT path selection involves examining predecessor and successor nodes for similar protocols and relationships (1 for presence, 0 for absence). Path selection considers device profiling, factoring in positions, protocols, and relationships, ensuring a congestion-free, secure connection. Clustering aids in the vEBT-driven selection of the shortest path, securing connections in successive interactions between SIoT destination and source devices as illustrated in Figure 5. The proposed model's comprehensive performance is depicted in Figure 6.

3.3. Comparative study

Table 2 presents a comparative study of various routing techniques that integrate machine learning algorithms. The study undertook a comparative analysis between OPTICS and R-OPTICS, both density-based clustering techniques utilizing reachability links to cluster points, identifying clusters and outliers in the dataset. OPTICS with vEBT and R-OPTICS with vEBT were applied to an SIoT dataset, with the latter proposed as the model for evaluation. The metrics used for evaluation yielded average values: Rand-Index = 1.5765, Davies-Bouldin = -0.4305, and Silhouette-Coefficient = 1.71685. Notably, R-OPTICS with vEBT showcased superior performance over OPTICS with vEBT, particularly in terms of loglog(n) on-time reliability.

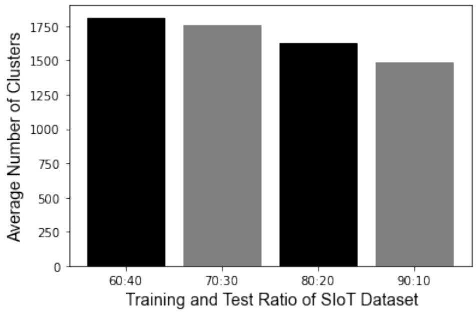

Figure 3. Average clusters formed in SIoT dataset for train and test ratio

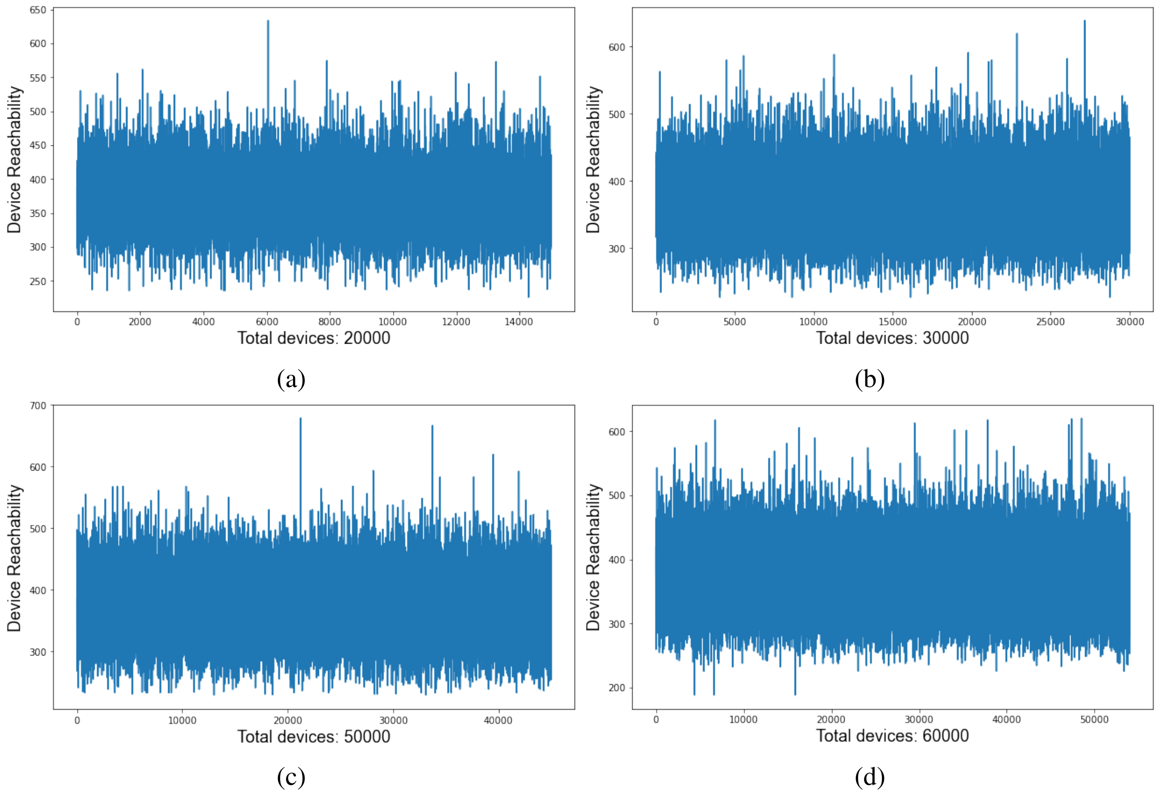

Figure 4. Reachability of various devices in SIoT dataset for train and test ratio 60:40: (a) 20,000 total vehicle, (b) 30,000 total vehicle, (c) 40,000 total vehicle, and (d) 60,000 total vehicle

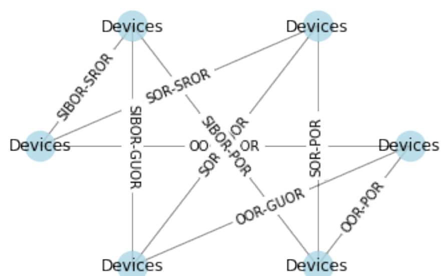

Figure 5. Congestion free path obtained in the proposed model using relationship between the devices

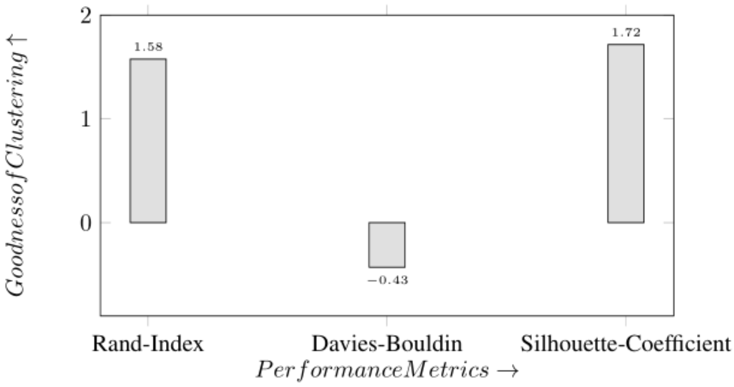

Figure 6. Performance metrics results of proposed model

Table 2. Performance comparison of touting techniques results

Models	Accuracy	Rand-Index	Davies-Bouldin	Silhouette-Coefficient
OPTICS	69%	-	-	-
Proposed Model R-OPTICS with vEBT	-	1.5765	- 0.4305	1.71685

4. CONCLUSION

The SIoT grapples with challenges related to routing path congestion and node mobility. As node numbers rise, congestion can hinder data flow efficiency between nodes. Node mobility introduces connection failures and impacts transmitting node energy consumption. Proposed solutions leverage machine learning, specifically comparing OPTICS and R-OPTICS clustering techniques integrated with the vEBT structure for SIoT dataset analysis. Results favor R-OPTICS with vEBT, exhibiting superior on-time reliability (loglog(n)) and outperforming OPTICS with vEBT across Rand-Index, Davies-Bouldin, and Silhouette-Coefficient metrics. Future research could expand to larger, diverse SIoT datasets for comprehensive validation and explore variations in the vEBT structure to enhance scalability and performance with larger datasets.

REFERENCES

[1] H. Yao, X. Yuan, P. Zhang, J. Wang, C. Jiang, and M. Guizani, "A machine learning approach of load balance routing to support next-generation wireless networks," in *2019 15th International Wireless Communications and Mobile Computing Conference (IWCMC)*, Jun. 2019, pp. 1317–1322, doi: 10.1109/IWCMC.2019.8766546.

[2] M. Malekshahi Rad, A. M. Rahmani, A. Sahafi, and N. Nasih Qader, "Social Internet of Things: vision, challenges, and trends," *Human-Centric Computing and Information Sciences*, vol. 10, no. 1, 2020, doi: 10.1186/s13673-020-00254-6.

[3] B. Jafarian, N. Yazdani, and M. Sayad Haghighi, "Discrimination-aware trust management for social internet of things," *Computer Networks*, vol. 178, 2020, doi: 10.1016/j.comnet.2020.107254.

[4] S. K. Sharma and X. Wang, "Toward massive machine type communications in ultra-dense cellular iot networks: current issues and machine learning-assisted solutions," *IEEE Communications Surveys and Tutorials*, vol. 22, no. 1, pp. 426–471, 2020, doi: 10.1109/COMST.2019.2916177.

[5] S. Chowdhury, A. Benslimane, and C. Giri, "Noncooperative gaming for energy-efficient congestion control in 6LoWPAN," *IEEE Internet of Things Journal*, vol. 7, no. 6, pp. 4777–4788, Jun. 2020, doi: 10.1109/JIOT.2020.2969272.

[6] A. Musaddiq, Z. Nain, Y. Ahmad Qadri, R. Ali, and S. W. Kim, "Reinforcement learning-enabled cross-layer optimization for low-power and lossy networks under heterogeneous traffic patterns," *Sensors*, vol. 20, no. 15, Jul. 2020, doi: 10.3390/s20154158.

[7] C. Del-Valle-Soto, C. Mex-Perera, J. A. Nolazco-Flores, R. Velázquez, and A. Rossa-Sierra, "Wireless sensor network energy model and its use in the optimization of routing protocols," *Energies*, vol. 13, no. 3, Feb. 2020, doi: 10.3390/en13030728.

[8] A. Khelloufi *et al.*, "A social-relationships-based service recommendation system for SIoT devices," *IEEE Internet of Things Journal*, vol. 8, no. 3, pp. 1859–1870, Feb. 2021, doi: 10.1109/JIOT.2020.3016659.

[9] C. Marche, L. Atzori, V. Pilloni, and M. Nitti, "How to exploit the social internet of things: query generation model and device profiles' dataset," *Computer Networks*, vol. 174, Jun. 2020, doi: 10.1016/j.comnet.2020.107248.

[10] J. Marietta and B. Chandra Mohan, "A review on routing in internet of things," *Wireless Personal Communications*, vol. 111, no. 1, pp. 209–233, Mar. 2020, doi: 10.1007/s11277-019-06853-6.
[11] G. Kavitha, P. Latchoumy, and A. Sonya, "An efficient traffic contention and control mechanism to improve QoS in heterogeneous wireless sensor networks," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 20, no. 2, pp. 968–975, Nov. 2020, doi: 10.11591/ijeecs.v20.i2.pp968-975.
[12] S. Noureddine, B. Khelifa, and B. Mohammed, "Approach to minimizing consumption of energy in wireless sensor networks," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 3, pp. 2551–2561, 2020, doi: 10.11591/ijece.v10i3.pp2551-2561.
[13] H. Farag and C. Stefanovic, "Congestion-aware routing in dynamic IoT networks: a reinforcement learning approach," *2021 IEEE Global Communications Conference, GLOBECOM*, 2021, doi: 10.1109/GLOBECOM46510.2021.9685191.
[14] A. Abid, S. El Khediri, and A. Kachouri, "Improved approaches for density-based outlier detection in wireless sensor networks," *Computing*, vol. 103, no. 10, pp. 2275–2292, Oct. 2021, doi: 10.1007/s00607-021-00939-5.
[15] J. Meghana, J. Hanumanthappa, and S. P. S. Prakash, "Performance comparison of machine learning algorithms for data aggregation in social internet of things," *Global Transitions Proceedings*, vol. 2, no. 2, pp. 212–219, Nov. 2021, doi: 10.1016/j.gltp.2021.08.032.
[16] C. Marche and M. Nitti, "Trust-related attacks and their detection: a trust management model for the social IoT," *IEEE Transactions on Network and Service Management*, vol. 18, no. 3, pp. 3297–3308, Sep. 2021, doi: 10.1109/TNSM.2020.3046906.
[17] D. Pancaroglu and S. Sen, "Load balancing for RPL-based internet of things: a review," *Ad Hoc Networks*, vol. 116, May 2021, doi: 10.1016/j.adhoc.2021.102491.
[18] T. Samizadeh Nikoui, A. M. Rahmani, A. Balador, and H. Haj Seyyed Javadi, "Internet of things architecture challenges: a systematic review," *International Journal of Communication Systems*, vol. 34, no. 4, Mar. 2021, doi: 10.1002/dac.4678.
[19] I. Das and S. Das, "Energy efficient cluster analysis for heterogeneous wireless sensor networks," *Wireless Personal Communications*, vol. 121, no. 1, pp. 337–352, Nov. 2021, doi: 10.1007/s11277-021-08638-2.
[20] R. Devidasmandaokar, "Extensive analysis of clustering algorithm for large datasets using density-based clustering and swarm intelligence," *Annals of the Romanian Society for Cell Biology 25*, vol. 25, no. 6, pp. 6368–6382, 2021.
[21] Y. Natarajan *et al.*, "An IoT and machine learning-based routing protocol for reconfigurable engineering application," *IET Communications*, vol. 16, no. 5, pp. 464–475, Mar. 2022, doi: 10.1049/cmu2.12266.
[22] S. D. Mohana, S. P. S. Prakash, and K. Krinkin, "Semantic rules for service discovery in social internet of things," in *Proceedings - 4th International Conference on Smart Systems and Inventive Technology*, pp. 119–124, 2022, doi: 10.1109/ICSSIT53264.2022.9716493.
[23] M. S. D., S. P. S. Prakash, and K. Krinkin, "Service oriented R-ANN knowledge model for social internet of things," *Big Data and Cognitive Computing*, vol. 6, no. 1, Mar. 2022, doi: 10.3390/bdcc6010032.
[24] F. Kaviani and M. Soltanaghaei, "CQARPL: congestion and QoS-aware RPL for IoT applications under heavy traffic," *The Journal of Supercomputing*, vol. 78, no. 14, pp. 16136–16166, Sep. 2022, doi: 10.1007/s11227-022-04488-2.
[25] P. Goswami *et al.*, "AI based energy efficient routing protocol for intelligent transportation system," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1670–1679, Feb. 2022, doi: 10.1109/TITS.2021.3107527.
[26] A. Ali *et al.*, "Enhanced fuzzy logic zone stable election protocol for cluster head election (E-FLZSEPFCH) and multipath routing in wireless sensor networks," *Ain Shams Engineering Journal*, vol. 15, no. 2, Feb. 2024, doi: 10.1016/j.asej.2023.102356.

BIOGRAPHIES OF AUTHORS

Bhavya D. received the B.Eng. degree in computer science and engineering from Visvesvaraya Technological University, Belagavi, Karnataka, India,in 2005 and M.Tech. degree in computer science and engineering from PES College of Engineering ,Mandya, Karnataka, India, in 2007 and i am pursuing my Ph.D. in JSSST University, Mysuru, Karnataka, India. My research intrests includes networking, machine learning and artificial intelligence. She can be contacted at email: bhavyadb@gmail.com.

D. S. Vinod holds a Bachelor's Degree in electronics and communications engineering and a Master's Degree in computer engineering from the University of Mysore, India. He further pursued his academic journey and successfully obtained a Ph.D. in computer science and engineering from VTU, Belgaum, India. His research interests include machine learning, intelligent systems, signal processing and medical image analysis. He has authored and co-authored papers in refereed journals and conferences. He has been recognized for his academic achievements and was awarded the UGC-DAAD short-term fellowship in Germany. Currently, he serves as a faculty member in the Department of Information Science and Engineering at JSS Science and Technology University, located in Mysore, Karnataka, India. He can be contacted at email: dsvinod@jssstuniv.in.

S. P. Shiva Prakash is working as Professor in the Department of Information Science and Engineering, JSS Science and Technology University (Formerly known as Sri Jayachamarajendra College of Engineering), Mysuru, Karnataka, India. He was awarded Ph.D in computer science degree in the area of wireless mesh networks in 2017 from University of Mysore, Mysuru Karnataka, India. He carried out post-doctoral research work at the Department of Software Engineering and Computer Applications, Saint Petersburg Electrotechnical University "LETI", Saint Petersburg, Russia. He has filed three Indian patents. He has published more than 25 research papers in various peer reviewed national, international conferences and journals. He can be contacted at email: shivasp@jssstuniv.in.

Kirill Krinkin currently serves as a researcher at JetBrains research and holds academic position as Adjunct Professor at Constructor University in Germany and he is also giving lectures at Neapolis University Pafos in Cyprus. He earned his Ph.D. in computer science and has dedicated over two decades to research and development in various fields including software engineering, operating systems, computer networks, autonomous mobile robots, and co-evolutionary intelligence engineering. Dr. Krinkin authored or co-authored over 100 technical papers. He is also a lecturer in mobile robotics at various universities. Since 2012, he has been organizing the joint advanced student school (JASS), an annual international project-driven initiative focusing on emerging technologies. Under his mentorship, student teams have twice won the artificial intelligence driving olympics challenge (AIDO) at the ICRA and NeurIPS conferences. He can be contacted at email: kirill@krinkin.com.