Extreme Learning Machines and van Emde Boas Tree-based Congestion-Free Model for Social Internet of Things

Bhavya D, D. S. Vinod, S. P. Shiva Prakash, and Kirill Krinkin

Abstract—**In the dynamic landscape of the Internet of Things (IoT), the emergence of Social IoT (SIoT) is propelled by rapid technological advancements. SIoT interconnects devices through various protocols such as WiFi, Zigbee, Bluetooth, and WIFI-MAX, contributing to its application in diverse domains including smart homes, smart cities, and smart hospitals. As the proliferation of connected devices introduces challenges like congestion and interruptions, especially in mobile networks, the role of Machine Learning (ML) and classification algorithms becomes pivotal in enhancing routing efficiency. Additionally, swarm intelligence techniques are employed for optimal communication path selection. In response to these challenges, a novel congestion-free routing model is introduced, leveraging an Extreme Learning Machine (ELM) and a van Emde Boas Tree (vEBT). These techniques classify devices based on their relationships within SIoT networks, with swarm-optimizing communication paths. The model's performance is rigorously evaluated using error rate metrics such as mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and adjusted R^2 error. The results of the evaluation highlight the effectiveness and accuracy of the proposed approach in addressing the complexities of SIoT networks, with MSE recorded at 0.027, RMSE at 0.164, MAE at 0.123, and an adjusted R^2 value of 0.893. These outcomes demonstrate the model's capability to mitigate congestion and interruptions while enhancing routing efficiency in SIoT environments.**

Index Terms—**vEBT, ELM, SIoT, Swarm, Network.**

I. INTRODUCTION

The world has warmly welcomed fast and secure Internet domains, thanks to the advancements in IoT technologies. The concept of the Internet of Things (IoT) has evolved into what we now call the Social Internet of Things (SIoT), where objects form different types of relationships with each other. SIoT encompasses ten distinct relationship types, including Parental Object Relationship (POR), Co-Location Object Relationship (CLOR), Ownership Object Relationship (OOR), Guardian Object Relationship (GROR), Social Object Relationship (SOR), Guest Object Relationship (GUOR), Sibling Object Relationship (SIOR), Stranger Object Relation (STOR), Service Object Relationship (SEOR) and Co-Work Object Relationship (CWOR). In SIoT applications, communication relies on various routing protocols like WiFi, Zigbee, Bluetooth, and WIFI MAX. These protocols facilitate the exchange of SIoT technologies and enable seamless communication among nearby objects. The primary objectives of these communication routing protocols include sharing knowledge, exchanging services between request and response objects, as well as ensuring efficient and reliable information sharing. SIoT technology finds its applications in various domains such as smart cities, smart homes, smart hospitals, and many others. These applications make use of the connectivity and service-sharing capabilities provided by communication routing protocols to enhance their functionality and offer valuable services.

Machine learning (ML) plays a crucial role in efficiently managing data selection within an SIoT network. Through classification methods, ML aids in organizing data, encompassing the identification of prevalent protocols utilized by objects and their grouping based on relational patterns. Notwithstanding its utility, congestion remains a persistent challenge within SIoT routing paths due to several factors. These encompass the continuous proliferation of networked objects, the dynamic movement of some while others remain static. Consequently, challenges emerge from the abundance of relationships at a single object, scarcity of relationships in certain objects, as well as the high density of relationships within certain objects, compounded by the clustering of a maximum number of objects in specific locations, each offering singular services.

To address congestion, ML techniques are necessary. Moreover, for efficient service sharing, objects must detect nearby objects in their vicinity. This can be achieved through a Swarm-Intelligence-based approach, which helps determine optimal routing paths within the SIoT network. Hence to tackle these challenges is the implementation of a congestion-free routing model, utilizing the ELM-vEBT-based method. This innovative method involves classifying service-providing objects according to their relationships and utilizing swarm techniques to select the most optimal delivery paths. Specifically, ELM (Extreme Learning Machine) will be utilized as a classification tool, featuring randomly assigned hidden nodes within the network. Additionally, the vEBT (van Emde Boas Tree) will be used to determine the quality and likelihood of feasible links, ultimately leading to the most efficient routing paths. This work offers advancements in the field with various key contributions:

- **Innovative Integration of Techniques:** A new approach in managing congestion and improving routing, in Social Internet of Things (SIoT) involves combining

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Extreme Learning Machine (ELMs) and variable length Edge Based Trees (vEBT).

- **Efficient Node Allocation (ELM):** This method utilizes the unpredictability of hidden nodes, within ELM to achieve accurate classification without requiring continuous fine tuning adjustments.
- **Effective Link Assessment (vEBT):** Utilizing vEBT enhances the evaluation of link quality and helps pinpoint potential congestion areas to aid in selecting the best path efficiently.

The structure of this work is comprised of several sections: II discusses related works, III focuses on the problem statement of the work, IV presents the system model along with problem formulation and the proposed problem solution, V outlines the proposed model design and methodology, VI details the algorithms used, VII highlights the results, and finally, VIII wraps up with the conclusion of the study.

II. Literature Survey

To improve the way people and computers interact and foster strong connections in the constantly evolving world of IoT systems, researchers are examining the realm of social IoT. This field of research covers the following areas:

In their study, Shailendra Rathore et al.[1] developed a spammer detection system using a bagging approach with ELMs. Through aggregating multiple ELMs, their system showed success in identifying spammers on social networking sites. Based on a study by Haipeng Yao et al. [2], load-balancing routing in Next-generation Wireless Networks (NWNs) relies on machine learning methods, particularly utilizing the network topology's adjacency matrix through Principal Component Analysis (PCA). This information is then used to train a neural network to anticipate the network queue's status, resulting in efficient content transmission and a superior user experience. The comparative study conducted by DS Vinod et al. [3] on a healthcare dataset, using machine learning models in R, suggests that Naive Bayes is the preferred choice due to its advantages in both time and space complexities. In their study, Xia Hui and colleagues [4] delved into cooperative intelligence and human-like social behaviors to create a more socially aware approach to semantic service discovery called the SLSA mechanism. By implementing a dual-modular-ordering stack strategy, their proposed knowledge index update procedure significantly improves search efficiency. Additionally, fuzzy logic is utilized to determine the correlation degree for device ranking.

In their study, Xiong Luo et al. [5] explored the potential of using a weighted extreme learning machine (ELM) with distribution optimization for predicting user behavior in social networks. ELM, a type of single-layer feedforward network (SLFN), has garnered significant attention from researchers for its efficient training and generalization capabilities. Through experiments conducted on imbalanced social network data, their weighted ELM - known as ODW-ELM - showed promising results in handling both binary and multi-class classification tasks. The IoT is rapidly growing, offering new opportunities and challenges. Jeretta Horn Nord et al. [6] study review shows IoT literature, establishes a theoretical framework, and uncovers key areas and challenges in IoT development, guiding future research and initiatives. IoT, a promising paradigm, introduces new challenges to networks. RPL, the routing protocol for low-power and lossy networks, is discussed in Kharrufa et al. [7], with an evaluation of its applications and related research. Comparative aspects and future directions are also explored. Mozhgan et al. [8] review the Social Internet of Things (SIoT), examining its components, features, parameters, and challenges. Articles from 2011 to December 2019 are evaluated, revealing varying evaluation parameters across SIoT elements. It notes Eclipse's high usage (28%) in simulations, with SWIM at 13%.

In a notable study by Besat Jafarian et al. [9], a solution was devised to address the issue of trust management in service provisioning for the SIoT. This involved the development of a discriminative-aware trust management (DATM) data mining model that compares current service requests with previous queries from other raters. Item ratings were utilized in this approach for effective evaluation. SK Sharma et al. [10] address challenges posed by massive machinetype communication (mMTC) devices in 5G and beyond networks. Key issues include quality of service, dynamic traffic, signaling overhead, and congestion. The paper highlights solutions, focusing on IoT standards, transmission scheduling, and the application of Q-learning and machine learning in ultra-dense networks. J. Marietta et al. [11] addresses IoT challenges, including security, scalability, and performance. They review routing protocols in wired, wireless, and sensor IoT environments, discuss issues and classifications, and analyze existing routing methods. Hanane Lamaazi et al. [12] explore objective functions (OF) in RPL routing for low-power and lossy networks (LLNs). It surveys existing OFs based on various metrics, assesses their strengths and weaknesses, classifies the metrics, and conducts a comparative analysis. The study provides insights for LLNs research and future work to enhance RPL in this context.

In another recent research endeavor, Srijit Chowdhury et al. (2020) [13] delved into critical concerns surrounding the use of IPV6 over low-power and lossy wireless personal area networks (6LoWPAN). These concerns include high packet loss, reduced throughput, and increased energy consumption. To tackle this, the researchers proposed a noncooperative game theory-based approach known as noncooperative gaming for energy-efficient congestion control (NGECC). This method calculates optimal data transfer rates for all source nodes (leaf nodes) to prevent congestion. In their work, Arslan Musaddiq et al.[14] address challenges faced by sensor devices in terms of energy and computational limitations. To enhance sensor node performance, the authors propose a QL-based approach for predicting collision probabilities using channel collision likelihood and network layer ranking, aided by a cumulative reward function. Carolina Del-Valle-Soto et al. [15] also tackle energy optimization in wireless sensor networks with their research. The authors specifically examine the energy consumption of the Multi-Parent Hierarchical (MPH) routing protocol and compare it to five other commonly used sensor network routing protocols. In their study, Amar Khelloufi et al. [16] explore the potential of SIoT in addressing network discovery, navigability, and service composition challenges. Their system leverages social relationships between device owners to deliver personalized service recommendations. Results from experiments demonstrate that considering user social interactions in service suggestions significantly improves the accuracy and diversity of services in the IoT environment. Meanwhile, Claudio Marche et al. [17] focused on the development of a Query Generation Model that utilizes the Social Internet of Things. The proposed model classifies all available devices according to FIWARE Data Models, making the dataset readily transferrable across different platforms.

Hossam Farag and Edomir Stefanovi [18] conducted a study on the load balancing issue in RPL networks, which negatively impacts packet delivery and network performance during high-traffic-load scenarios. To address this issue, they proposed a reinforcement-learning framework that utilizes Q-learning. Aymen Abid et al. [19] explored the use of density-based outlier detection in wireless sensor networks, specifically focusing on the DBSCAN proposal. Their study found that this method is more accurate and comprehensive than existing techniques used in WSNs. Further, Rajendra DevidasMandaokar and Shailesh Jaloree [20] also investigated cluster accuracy and processing overhead in the DBSCAN method, proposing an improved version that incorporates swarm intelligence algorithms. This resulted in more efficient and accurate density-based outlier detection in WSNs. J Meghana et al. [21] explore objective functions (OF) in RPL routing for low-power and lossy networks (LLNs). It surveys existing OFs based on various metrics, assesses their strengths and weaknesses, classifies the metrics, and conducts a comparative analysis. The study provides insights for LLNs research and future work to enhance RPL in this context.

In a recent study, Claudio Marche and Michele Nitti [22] introduced a trust management framework for the Social Internet of Things (IoT) that effectively thwarts all reported attacks. Through simulations, the proposed model was able to successfully isolate almost all malicious nodes within the network. However, it requires a higher number of transactions to reach convergence. Tina et al. [23] address the significance of IoT architecture in various domains and the challenges it faces, including interoperability, security, energy constraints, and more. It offers a systematic mapping survey and a technical taxonomy for these challenges, providing a structured overview of research trends. The classification model serves as a guide for future work in IoT architecture. Doruk et al. [24] highlight the significance of Low-Power and Lossy networks within the IoT ecosystem, focusing on the Routing Protocol for Low-Power and Lossy Networks (RPL). Despite RPL's acceptance, areas like load balancing need improvement. The study reviews various approaches proposed for load balancing in RPL, assesses their strengths and weaknesses, and suggests future directions for addressing this issue. Stan et al. [25] propose a scalable solution to predict and alleviate urban traffic congestion using range query data structures. Validated in a Brooklyn, New York traffic simulation, it significantly reduces congestion and enhances efficiency. This innovative approach holds promise for urban traffic management. Yuvaraj Natarajan et al. [26] proposes an upgradable cross-layer CR-IoT routing protocol for efficient data transmission. It utilizes a distributed controller for load balancing, sensing, and machine-learning path construction, considering metrics like energy efficiency, capacity, and interference. Experiments confirm its robustness and scalability.

The Semantic Rules for Service Discovery in Social IoT were developed by Mohana S. D. et al. [27]. The model establishes a connection between users and items to facilitate effective service discovery. This is achieved through the use of an intelligent object model that takes into account the contextual and semantic interactions between users and objects. For the services to be discovered effectively, such a model is crucial. In their groundbreaking research on online social networks, Zhang et al. [28] introduced the ELM-WalkNet. This cutting-edge mechanism leverages a two-hop trust calculation methodology, enabling accurate assessment of trust levels between members. The ELM-WalkNet operates iteratively, utilizing the ELM-NeuralWalk technique to continuously update the OSN based on the calculated trust values. This approach yields comprehensive multi-hop trust evaluations among users, revolutionizing the way trust is measured and utilized in online social networks. X Yuan et al. [29] introduce an extended ELM algorithm to predict satellite communication attenuation due to weather, improving satellite routing. IoT sensors collect weather data, which the model uses for category predictions, enhancing data link selection in space–air–ground integrated networks (SAGINs). Mohana S D et al. [30] address SIoT challenges through a feature selection method guided by semantic rules and relationship artificial neural networks (R-ANN). R-ANN accurately classifies SIoT services, achieving 89.62% accuracy for services like weather, air quality, parking, light status, and people presence. F. Kaviani and M. Soltanaghaei [31] introduced the Congestion and QoS-Aware RPL for IoT Applications (CQARPL) protocol, which stands out for its ability to select parents based on multiple metrics and consider path conditions to the root. This latest routing protocol effectively addresses the unique routing requirements of IoT networks characterized by low power and frequent packet loss.

As illustrated in Table I, recent studies have explored various methods and techniques for congestion-free routing and prediction in smart environments."

III. Problem Statement

In the dynamic environment of SIoT, the presence of static and mobile objects creates a complex network of interconnected nodes. However, due to potential congestion, establishing connections between these objects may prove challenging. This can lead to route queueing delays, packet loss, or even the inability to form new connections. Moreover, the mobility of objects can result in delays and information loss, hindering effective data collection from responding objects. The constantly changing relationships between objects can also cause the blocking of new connections in the SIoT network. Therefore, a thorough examination of routing is necessary to understand the relationship dynamics and how it impacts the availability of multiple paths. Consequently, studying the behaviors of objects becomes crucial in understanding the parameters involved in establishing efficient connections between objects in the SIoT.

TABLE I: State of the Art.

Authors & Year	Methods or Techniques	Review
Ioan Stan et al. (2021) [30]	Query data structures (K-ary Interval Tree and K-ary Entry Point Tree)	The experiments examined innovative data structures, emulating 10,000 vehicles to swiftly access traffic information and generate congestion-free routes in urban traffic prediction.
Xueguang Yuan et al. (2022) [31]	Space–air–ground integrated networks (SAGINs) and Extreme learning machine (ELM).	SAGINs employ ELM for predicting communication attenuation from rainy weather, then use extended ELM to forecast blockages due to weather.
Mohana SD et al. (2022) [32]	r-ann knowledge model	Social objects are distinct, transferable, and share information among people and objects in smart environments, like smart homes and cities.

IV. System Model

The system model S_M in SIoT has a set of public and private objects: $O_{i,j}$ where O = 1,2,3,n numbers that are connected to a randomly distributed network N_x. Every object is connected through a relationship of R where R= $R_1, R_2, ...R_{10}$ in ten types of relationships as described in SIoT. The relationship between the objects is represented using object profile relationships O_P. The similar features of object communication are C_M for applications A_P for services, where A_P= 1,2,3...n, for various services S_R, where S_R = 1,2,3...n, between objects. The information between the objects is O_I based on the user profile O_P. Since the objects $O_{i,j}$ are distributed randomly in the network to provide services, S_R for relationships, R creates the congestion, C_G, while offering services. Analyze the objects' relationships and services, S_M.

$$S_M = \sum_{1}^{n} O_{i,j}(C_M, O_I) : N_x, \ \forall (R, C_G, S_R, A_P) \quad (1)$$

A. Problem Formulation

From the system model equation 1, it is to define knowledge model K_M in objects $O_{i,j}$ to, provides services S_R in relationships R, creates the congestion C_G, while offering services S_R. To avoid congestion, we need to analyze the objects by classifying the available routes using the Congestion Free Route model CFR. Let the classification model C_L be used to train the network N_x, through the relationships R between the objects $O_{i,j}$. Consider the classes and optimize P_O the path for services in objects of SIoT. These objects $O_{i,j}$ communicate the objects profiles O_P to provide the services S_R in an application A_P. Hence, the objective function can be defined as

$$K_M = \sum_{i,j}^{n,m} Optimize(CFR : (O_{i,j}, O_P, S_R, R, N_x) \quad (2)$$

subjected to,

$$O_P, R = C_G$$

and

$$S_R, N_x, O_{i,j} = P_O$$

congestion

$$C_G = C_L$$

Where C_G is used to avoid the congestion in the model and P_O is used to optimize the path in the SIoT.

B. Proposed Solution

The objective function in equation 2 is to learn the congestion-free route CFR model

$$CFR = P_m(K_M : C_L, P_O) \quad (3)$$

Here, C_L is to classify the objects $O_{i,j}$ using object profiles O_P concerning relationship R. The ELM is the best-used random hidden layer to learn the network, and weights of W of hidden nodes are usually learned in a single step. Learning is essential to the linear model. The model is shown in equation 4.

$$C_L = f(O_P(R)) + b \quad (4)$$

Where O_P is an object profile having weights W, the output of hidden nodes produces the output weight W, and it is equal to the matrix H as is shown in the equation 5.

$$W = H * T \quad (5)$$

The classification model provides the ten relationship class objects $O_{i,j}$ to obtain the services needed to identify the best path in the classes using the vEBT techniques. vEBT optimizes the path by its binary tree with a fixed height determined by the maximum number of elements it can store, it has two key attributes min() and max() selecting edges in the network N_x of the Optimization model. An optimization model is shown in 6

$$P_O = P(A, E_G, P) \quad (6)$$

Where, optimize the path P_O is directly proportional to the probability of P finding edge selection E_G and update the path using objects $O_{i,j}$ of SIoT.

The van Emde Boas Tree approach in ELM is to define relationship parameters enhancing with types of protocols and ensemble the relationship parameters like distance from source to destination, and give node preference based on the energy of protocols to establish links between nodes. After classifying the nodes, estimate the likelihood of the distribution of a function using the ELM algorithm. The vEBT algorithm for classification using Pi, μ, and $\sum$ equations are represented in the equations 7, 8 and 9.

$$\Pi = \frac{N_k}{T_k} \quad (7)$$

$$\mu = \frac{1}{N_k} \sum_i r_{ik} N_R \tag{8}$$

$$\sum = \frac{1}{N_k} \sum_i r_{ik} N_R - {\mu_k}^T (N_R - \mu_k) \tag{9}$$

where N_k - Number of nodes in a classes, T_k - Total number of nodes in a network.

The van Emde Boas tree approach stores a set of node protocols belonging to 1 to (N_R -1) nodes and finds many protocols link in $O(log\ logN_R)$, including navigation to the next or to the previous node protocols link of the network. This navigation tests whether the node belongs to a similar protocol and then adds it to the network path. Insertion and removal during this process identify the minimum and maximum hops to similar protocols. In addition, it requires the random access memory for indexing the nodes in an array parametrized by N_x. It stores the maximum and minimum nodes explicitly. For $N_x = 1$ there can be only two nodes, so the implication is trivial. For $N_x > 1$, the nodes other than the minimum and maximum are stored in the array N_x which are stored in an array of size k. A key N_x is stored in an indexed array with values of N_x. For efficient performance of the next routing path that serves an indexed array path for the congestion-free shortest path to the node.

The obtained results of ELM-vEBT is measured using performance metrics (PM) accuracy, precision and recall are shown in the equations 10, 11 and 12 respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

V. Proposed Congestion Free Routing (CFR) Model Design and Methodology

The proposed CFR model design used to categorize the services based on relationships to responses of the requested object is explained in this section. The ELM classification model displayed in figure 1 is applied to the SIoT dataset to categorize the associations. ELMs are feed-forward neural networks with a single layer of hidden nodes for classification and feature learning. The weights linking to the inputs of the hidden nodes do not need to be tuned to account for the parameters of hidden nodes. For non-linear transforms, these hidden nodes are random projections that can be assigned at random and are never updated. Equation 4 displays the output weights of hidden nodes that are learning a linear model.

The methodology followed to classify the service based on the relationships is shown in figure 2. The Extreme Learning Machine (ELM) method uses a three-layer architecture as its foundation. Data from the input layer is supplied into nodes that represent various features in the first layer. The links between the input and the hidden layer are then given random weights. The output of each hidden neuron is then produced by the hidden layer by performing a nonlinear transformation on the input data. Based on the intended labels from the training data, the third layer, known as the output layer, chooses the weights connecting the hidden layer to the final output. Importantly, this weight calculation requires the efficient solution of a linear system of equations, which can be done by applying techniques like least squares. The vEBT is a dynamic set of integers that is maintained using this specialized data structure, which supports operations like insertion, deletion, minimum, maximum, successor, and predecessor searches that are effective and time-saving. By recursively breaking up the range of integers into smaller clusters and preserving summary and cluster structures, the vEB tree can perform operations quickly. Van Emde Boas tree highlights include effective minimum and maximum queries in O(1) time. O (log M) is an efficient predecessor and successor query, where M is the largest integer in the tree, an efficient operation for inserting and deleting data in O (log M). The vEB tree's implementation is relatively complex, especially for wider ranges, which is its fundamental flaw. When quick integer operations are necessary and the range of the numbers is not too wide, it is most useful.

VI. Algorithm

The ELM-eVBT (Extreme Learning Machine - enhanced vEB Tree) algorithm 1 is designed for efficient congestion management and optimized routing in Social Internet of Things (SIoT) networks. SIoT networks consist of interconnected devices that collect and share data in social settings. Congestion management is crucial in SIoT networks to ensure efficient data transmission and prevent network overload. The algorithm begins by taking input features, including device identifiers (W_{ID}), device relationships ($O_{i,j}$), device types (O_T), device brands (O_B), device proximity (D), service requirements (S_R), application preferences (A_P), device location (L), and device popularity (O_P). These features provide information about the devices and their interactions in the network. Next, the algorithm iterates over each feature, randomly assigning input weights (W_i) and biases (b_i) to initialize the hidden layers of the ELM model. The hidden layer outputs are calculated using a linear model, and the output weights are determined to optimize the routing paths. During the initialization phase, the algorithm checks for the insertion of node protocols into the set. If node insertion is required, it continues the process; otherwise, it exits the loop. After initializing the weights and biases, the algorithm proceeds to initialize a predefined number of paths (P). It then enters a loop to generate solutions, compare paths found by different ants, and update pheromone levels. This process is repeated until optimal paths are found to minimize congestion and optimize routing in the SIoT network.

The ELM-eVBT algorithm combines the efficiency of Extreme Learning Machines (ELM) with the enhanced routing capabilities of the van Emde Boas Tree (vEBT) to manage congestion and optimize routing in SIoT networks effectively. By leveraging machine learning techniques and efficient routing algorithms, the ELM-eVBT algorithm ensures efficient data transmission and improved network performance in SIoT environments.

VII. Results and Discussion

A. Dataset

The benchmark dataset consists of a total of 16216 devices having 14600 private objects and 1616 public devices in the city of Santander in Spain. The object profiles include

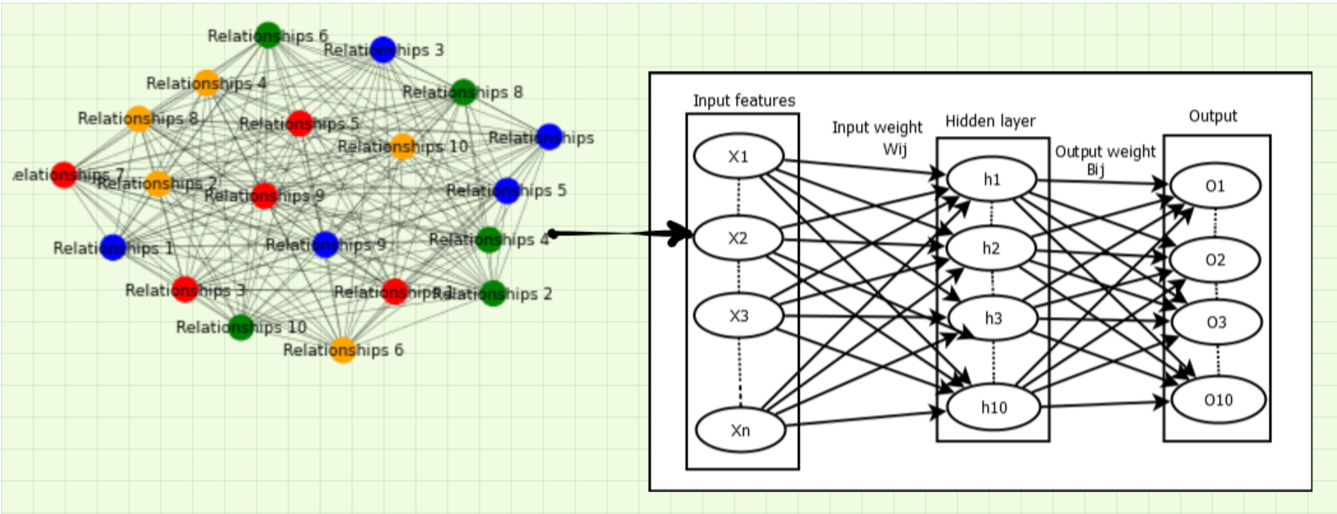


Fig. 1: ELM Model.

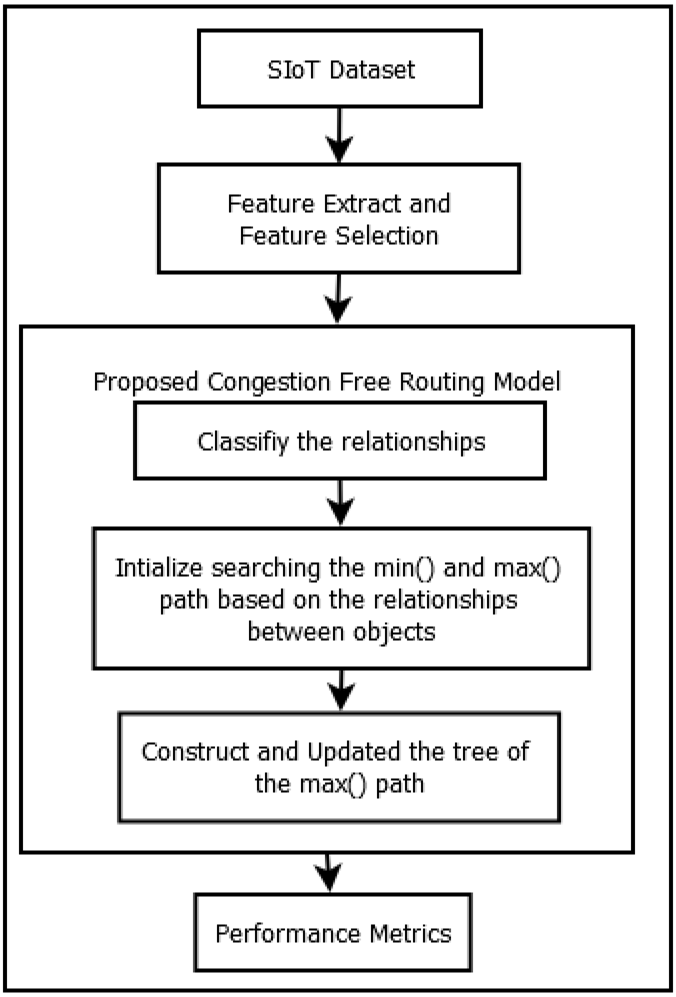


Fig. 2: Proposed Congestion-Free Routing Model.

Algorithm 1: ELM-eVBT Algorithm

Input: Features X: W_{ID},$O_{i,j}$, O_{ID},O_B, D, O_P, O_T, L, S_R, A_P, R

Output: P_M, C_L

Read input features X

$i = 1, 2, 3...N$;

while *Randomly assign input weight W_i, bias b_i* **do**

  Calculate the hidden layer output from the equation 4 ;

  Calculate the output weight W from the equation 5;

  if *insert nodes protocols to the set* **then**

  else

    exit;

  end

end

Initialize the k number of paths P;

while *Paths P_k* **do**

  Generate Solution from equation 7 ;

  Paths found by different ants are compared from equation 8 ;

  Paths value by pheromone Update from equation 9 ;

end

namely, object id O_{ID}, user id U_{ID}, object type O_T, object brand O_B, and Object models O_M. It consists of an adjacency matrix with the location of the objects and timings between the objects. In adjacency, the matrix provides the relationship types between the objects. The dataset has the attributes of protocols type P_T, Object type O_T, user id U_{ID}, number of meetings N_M and object location O_L [1], [2]. Hence, the work focuses on considering these parameters to experiment with a congestion-free routing model in SIoT. The dataset preparation includes owner ID W_{ID}, object O, object ID O_{ID}, object brands O_B, distance D, protocols O_P, Object types O_T, locations L, servicesS_R, applications A_P, and relationships R all these are attributes shown in the figure. Relationships between the devices are shown in the figures.

B. Results

Within the SIoT dataset, all devices exhibit multivariate characteristics, leading to increased network density across various distributions [23], [24]. This dataset encompasses diverse device types, including both private and public devices, each with its respective distribution. Devices are interconnected using various protocols such as Wi-Fi, Zigbee, among others. Additionally, there exist 10 distinct types of relationships between devices within the network, as depicted in Figure 3, each with its corresponding distribution pattern.

ELM employs a method known as Extreme Learning Clustering (ELC), which is tailored to identify cluster structures within datasets. ELC, integrated into ELM for clustering purposes, facilitates the extraction of clusters with varying types and densities from large, high-dimensional datasets. This technique estimates clusters while also identifying noise points, assigning higher probabilities to noise points and lower probabilities to dissimilar points. Initialization of hidden layer weights can be performed randomly or by utilizing a predefined distribution for feature extraction, as illustrated in Figure 4.

The proposed model creates the order clusters of all different devices to introduce non-linearity for density-based clustering that is shown in table II.

TABLE II: Performance Metrics of SIoT dataset in ELM.

Dataset Train : Test	Devices	Mean Square Error	Root Mean Square Error	Mean Absolute Error	Adjusted R^2 Error
90:10	10000	8.96	2.99	2.54	0.13
	25000	11.31	3.36	2.78	0.36
	50000	8.37	2.89	2.50	0.01
	75000	8.35	2.89	2.51	0.01
	100000	8.40	2.89	2.50	0.01
80:20	10000	8.31	2.88	2.50	0.01
	25000	8.85	2.97	2.57	0.06
	50000	8.70	2.95	2.53	0.05
	75000	8.44	2.90	2.52	0.01
	100000	8.70	2.94	2.52	0.05
70:30	10000	10.24	3.20	2.68	0.26
	25000	10.15	3.18	2.69	-0.22
	50000	8.41	2.90	2.50	0.02
	75000	10.80	2.90	2.52	0.01
	100000	9.88	3.14	2.65	-0.19
60:40	10000	8.44	2.90	2.50	0.04
	25000	10.22	3.19	2.68	0.24
	50000	11.31	3.36	2.78	0.36
	75000	10.22	3.19	2.69	0.22
	100000	9.82	3.13	2.64	0.19

Table II presents various training and testing samples from the SIoT dataset, alongside the corresponding number of clusters. These clusters are compared with results obtained using Extreme Learning Machine (ELM) techniques, and evaluated across multiple performance metrics including Mean Square Error, Root Mean Square Error, Mean Absolute Error, and Adjusted R^2 Error. However, in the SIoT dataset, observed higher values, indicating denser clusters. Additionally, the Silhouette Coefficient, typically indicating good cluster fit and poor fit to neighboring clusters, seems to depend heavily on neighboring clusters in our dataset. The Adjusted Rand Index yields positive values, as depicted in Figure 5, highlighting distinctions between clusters with significant similarities. Moreover, Figure 6 illustrates the relationships within these clusters.

Therefore, the reachability of devices on networks for various services in relationships are measured in the training and testing ratios of databases as shown in Figures 7.

The source and destination devices are highly dependent on various clusters. Therefore, the vEBT searching technique is used to identify the congestion-free path in SIoT. The clusters are varied for the total number of samples between the various devices present in an environment as shown in Table II. It is also observed that noise is increased due to the increase in clusters. The performance of each cluster is based on minimal samples that are verified using the reachability of the connected objects.

TABLE III: Sample data of SIoT in a vEBT based routing path selection.

Frelation Device Locations	Connections	Predecessor	Successor
A[0]	True	0	1
A[1]	True	0	1
A[2]	True	0	1
A[3]	True	0	1
A[4]	True	0	0
A[5]	True	0	1
A[6]	True	0	1
A[7]	True	1	2
A[8]	True	1	2
A[9]	True	1	2
A[10]	True	1	2
A[11]	True	1	2
A[12]	True	2	3
A[13]	True	2	3
A[14]	True	2	3

Using the vEBT technique, search steps persistently gather nodes into clusters denoted by k within the SIoT network to facilitate network navigability. A true device connection indicates network presence, while a false connection signifies a failed attempt at network establishment. Furthermore, the nodes within cluster k are scrutinized to determine the shortest congestion-free route via a routing protocol. The path selection mechanism in vEBT dictates that when a similar protocol and device connection exist, the predecessor and successor of the connected node should be identified. The predecessor, representing the preceding node, and the successor, representing the subsequent node, are assessed. A value of 1 signifies the presence of the same protocol, whereas 0 denotes its absence. Consequently, path selection is tailored based on device profiling, including node positions and protocol relationships. Thus, the clustering approach ensures the selection of a congestion-free shortest path, enhancing connection security when employing the vEBT technique. The outcomes, depicting successive interactions between destination and source devices in SIoT interactions, are tabulated in Table III.

Generally, the search devices prioritize the smallest value for storage in the minimum path, while the largest value is allocated to the maximum path, as illustrated in Figure 8. This ensures the recursive progression of the search, incorporating corresponding devices when necessary. The tree-based searching technique involves inserting finds to search for preceding empty locations and determining both the minimum and maximum length of the device's path. Deletion of the smallest device path is executed based on the device's current position for maximum device path length. Similarly, the minimum length path of the device is deleted based on the device's previous path to its current position. In vEBT, a queue device operates as a queue with a priority function, forming the foundation of the priority queue. The

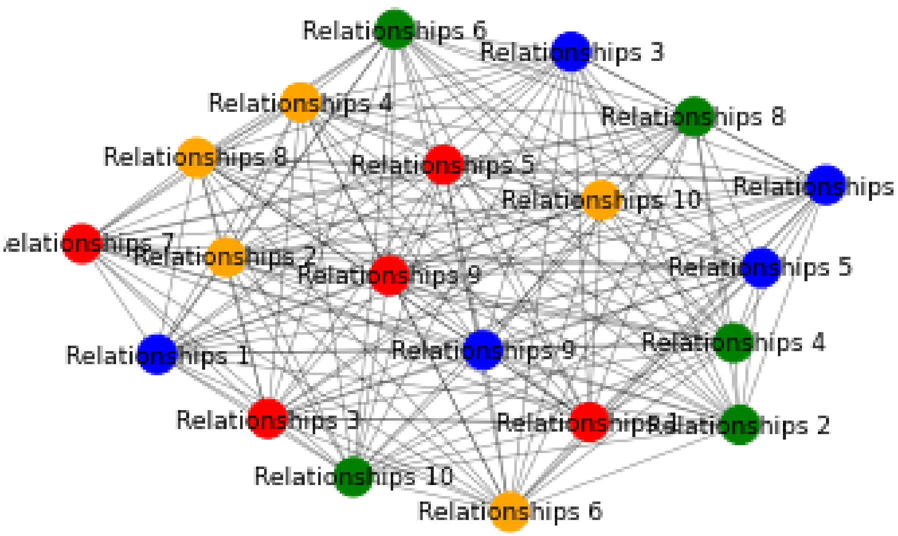


Fig. 3: Sample Network of Devices in Relationships

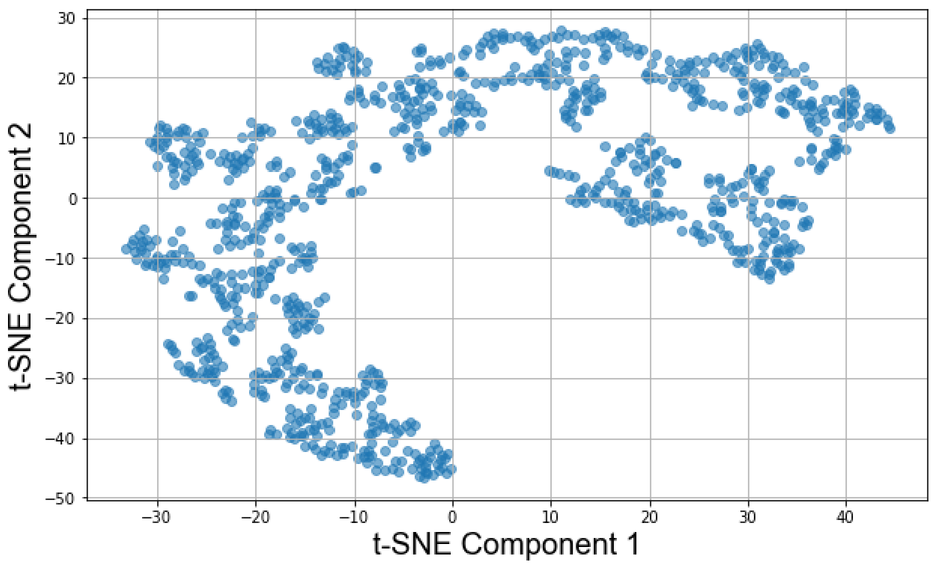


Fig. 4: Random Distribution of Devices in Relationships

heap organizes devices in a specific order, with each item in the queue possessing a distinct priority. The dequeue order influences priority, thereby influencing model performance. The performance evaluation of the model is conducted using metrics such as Mean Square Error, Root Mean Square Error, Mean Absolute Error, and Adjusted R^2 Error on the SIoT dataset, with training and testing ratios set at 60:40, 70:30, 80:20, and 90:10, respectively, as depicted in Figure 9.

C. Result Analysis

In a network where nodes experience both static and mobile characteristics of objects, congestion can lead to queuing delays and the blocking of new connections. This congestion arises due to the presence of connections or relationships between objects within the network. To address these issues, an analysis is conducted by considering multiple path parameters between objects to better understand the relationships that exist among them, even when there is congestion. The analysis focuses on individual objects and their relationships in the context of providing various services. In this process, a dataset specific to the Social Internet of Things (SIoT) is used, consisting of training and testing samples. The goal is to determine the maximum number of objects for achieving an optimal ratio between cluster scatter and cluster separation. A lower value in this ratio indicates better clustering, implying that clusters are well-defined and separated from each other.

However, having clusters that are too thick can lead to high similarity within each cluster, making it difficult to distinguish objects from neighboring clusters. This dependency on neighboring clusters can result in positive values, indicating that objects have similarities with objects in other clusters as well. Therefore the quality of optimization with routing and without routing for cumulative congestion under several requests is shown in the figure 10. These insights are for

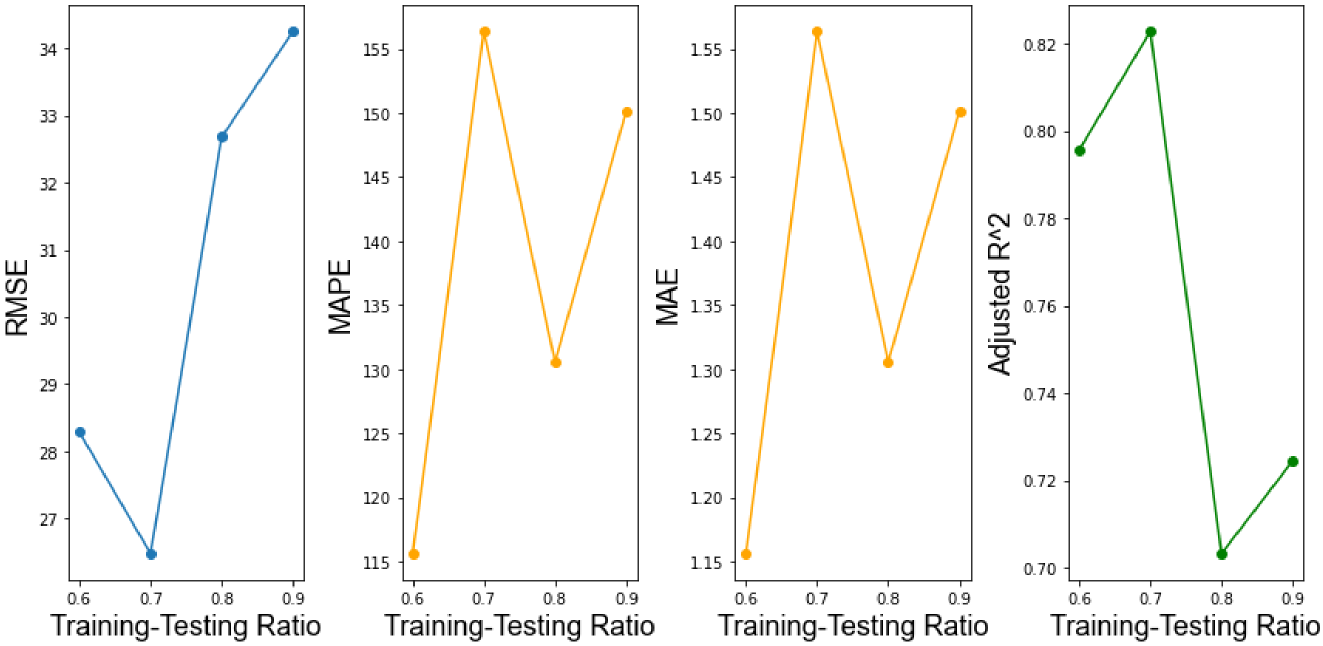


Fig. 5: Performance metrics results for training and testing ratios of 60:40, 70:30, 80:20, and 90:10. All axis labels, legends, and annotations have been enlarged for clarity. Distinct colors and patterns are used for each item, and in-figure pointers with descriptions identify the corresponding lines/bars.

the quality of clustering and the level of similarity among objects in the dataset under various conditions.

VIII. Conclusion

The research presented advocates for the utilization of a diverse range of services for both private and public activities involving devices. It introduces several key contributions, including an innovative integration of Extreme Learning Machine (ELM) and van Emde Boas Tree (vEBT) techniques aimed at efficiently managing congestion and optimizing routing within Social Internet of Things (SIoT) networks. This integration offers a unique approach to addressing network challenges. Additionally, the research highlights the efficiency of Node Allocation through ELM, which leverages the randomness of hidden nodes to achieve accurate classification without iterative adjustments. Furthermore, it underscores the effectiveness of Link Assessment using vEBT, enabling quick link quality assessment and identification of potential congestion points, thereby facilitating optimal path selection. The suggested model demonstrates significant improvement in service performance, as evidenced by metrics such as Mean Squared Error (MSE) of 9.39, Root Mean Squared Error (RMSE) of 3.032, Mean Absolute Error (MAE) of 2.582, and an R-Square value of 0.327. These results, derived from the congestion-free model, underscore the predictive capabilities of the proposed approach in forecasting long-term inventory trends, thereby contributing to the advancement of SIoT network management strategies.

References

[1] R. Shailendra, K. Arun and P. Jong, "A Novel Framework for Internet of Knowledge Protection in Social Networking Services," *Journal of computational science*, vol. 26, 2017.

[2] H. Yao, X. Yuan, P. Zhang, J. Wang, C. Jiang and M. Guizani, "A Machine Learning Approach of Load Balance Routing to Support NextGeneration Wireless Networks," *15th International Wireless Communications and Mobile Computing Conference (IWCMC)*, pp. 1317-1322, 2019.

[3] D S. Vinod, D Bhavya and S P. Shiva Prakash, "A Comparative Analysis of Machine Learning Algorithms For Healthcare Device Data of Social IoT," *Conference of Open Innovations Association, FRUCT*, no. 25, pp. 428-433, 2019.

[4] H. Xia, C. Q. Hu, F. Xiao, X. Cheng, Z. K. Pan, "An efficient social-like semantic-aware service discovery mechanism for large-scale Internet of Things," *Journal of Computer Networks*, vol. 152, pp. 210-220, 2019.

[5] X. Luo, C. Jiang, W. Wang, Y. Xu, J. H. Wang, & W. Zhao, "User behavior prediction in social networks using weighted extreme learning machine with distribution optimization," *Journal of Future Generation Computer Systems*, vol. 93, pp. 1023-1035, 2019.

[6] Jeretta Horn Nord, Alex Koohang, Joanna Paliszkiewicz, "The Internet of Things: Review and theoretical framework," *In Journal of Expert Systems with Applications*, vol. 133, pp. 97-108, 2019.

[7] H. Kharrufa, H. A.'A. AlKashoash and A. H. Kemp,"RPL-Based Routing Protocols in IoT Applications: A Review," *In Journal of IEEE Sensors*, vol. 19, no. 15, pp. 5952-5967, 1 Aug, 2019.

[8] Malekshahi Rad M, Rahmani A M, Sahafi A, Nooruldeen Nasih Qader,"Social Internet of Things: vision, challenges, and trends," *In Journal of Humancentric Computing and Information Sciences*, vol. 10, no. 52, 2020.

[9] B. Jafarian, N. Yazdani and M. S. Haghighi, "Discriminationaware trust management for social Internet of Things," *In Journal of Computer Networks*, vol. 178, Sep. 2020.

[10] S. K. Sharma and X. Wang, "Toward massive machine type communications in ultradense cellular iot networks Current issues and machine learningassisted solutions," *In Journal of IEEE Communications Survey & Tutorials*, vol. 22, no. 1, pp. 426-471, 2020.

[11] Marietta J, Chandra Mohan B, "Review on Routing in Internet of Things," *In Journal of Wireless Personal Communication*, vol. 111, pp. 209–233, 2020.

[12] Hanane Lamaazi, Nabil Benamar, "A comprehensive survey on enhancements and limitations of the RPL protocol A focus on the objective function," *In Journal of Ad Hoc Networks*, vol. 96, 2020.

[13] S. Chowdhury, A. Benslimane and C. Giri, "Non-cooperative gaming for energy−efficient congestion control in 6Lowpan," *In Journal of IEEE Internet of Things*, vol. 7, no. 6, pp. 4777-4788, Jun. 2020.

[14] A. Musaddiq, Z. Nain, Y. Ahmad Qadri, R. Ali, and S. W. Kim, "Reinforcement LearningEnabled CrossLayer Optimization for LowPower

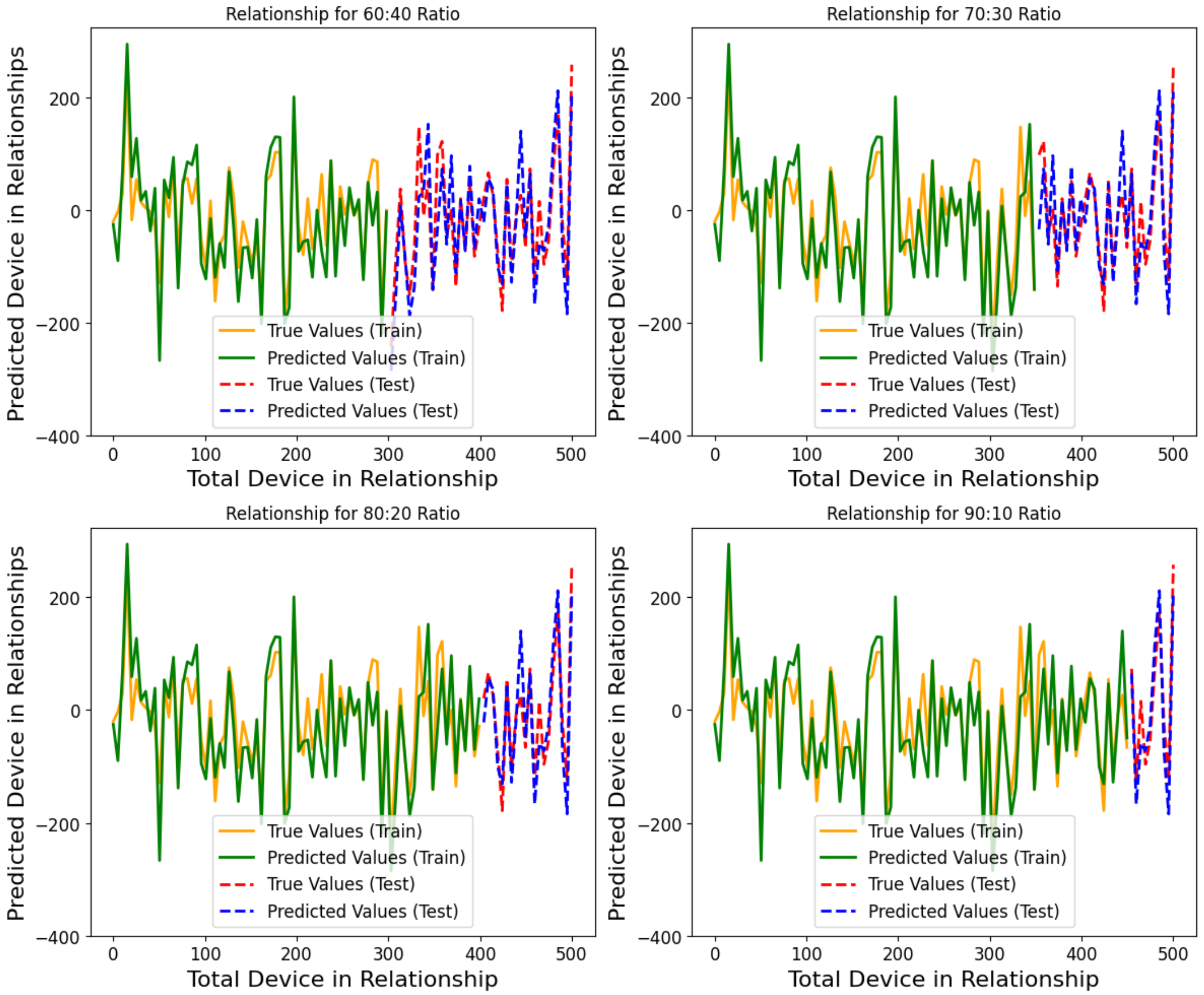


Fig. 6: Relationships established for training and testing ratios of 60:40, 70:30, 80:20, and 90:10 in (a), (b), (c), and (d) respectively.

and Lossy Networks under Heterogeneous Traffic Patterns," *In Journal of Sensors*, vol. 20, no. 15, p. 4158, July. 2020.

[15] C. DelValleSoto, C. MexPerera, J. A. NolazcoFlores, R. Velázquez, and A. RossaSierra, "Wireless Sensor Network Energy Model and Its Use in the Optimization of Routing Protocols," *In Journal of Energies*, vol. 13, no. 3, p. 728, Feb. 2020.

[16] Khelloufi Amar, Huansheng Ning, Sahraoui Dhelim, Tie Qiu, Jianhua Ma, Runhe Huang, and Luigi Atzori. "A socialrelationshipsbased service recommendation system for SIoT devices," *In Journal of IEEE Internet of Things*, vol. 8, no. 3, pp. 1859-1870, 2020.

[17] Claudio Marche, Luigi Atzori, Virginia Pilloni, and Michele Nitti. "How to exploit the social Internet of Things: Query generation model and device profiles' dataset," *In Journal of Computer Networks*, vol. 174, 2020.

[18] H. Farag and Č. Stefanovič, "CongestionAware Routing in Dynamic IoT Networks A Reinforcement Learning Approach," *In Conference of 2021 IEEE Global Communications (GLOBECOM)*, pp. 1-6, 2021.

[19] Aymen Abid, Salim El Khediri, and Abdennaceur Kachouri. "Improved approaches for density-based outlier detection in wireless sensor networks," *In Journal of Computing*, vol. 103, no. 10, pp. 2275-2292, 2021.

[20] Rajendra Devidas Mandaokar, Shailesh Jaloree, "Extensive Analysis of Clustering Algorithm for Large Datasets Using Density-Based Clustering and Swarm Intelligence," *In Journal of Annals of RSCB*, vol. 25, no. 6, pp. 6368–6382, May 2021.

[21] J. Meghana, J. Hanumanthappa, and SP Shiva Prakash. "Performance comparison of machine learning algorithms for data aggregation in social internet of things," *In Proceedings of Global Transitions*, vol. 2, no. 2, pp. 212-219, 2021.

[22] C. Marche and M. Nitti, "Trust-Related Attacks and Their Detection: A Trust Management Model for the Social IoT," *In Journal of IEEE Transactions on Network and Service Management*, vol. 18, no. 3, pp. 3297-3308, Sept. 2021.

[23] Samizadeh Nikoui T, Rahmani A M, Balador A, Haj Seyyed Javadi H, "Internet of Things architecture challenges: A systematic review," *In Journal of International Journal of Communication Systems*, vol. 34, no. 4, 2021.

[24] Doruk Pancaroglu, Sevil Sen, "Load balancing for RPLbased Internet of Things A review," *In Journal of Ad Hoc Networks*, vol. 116, 2021.

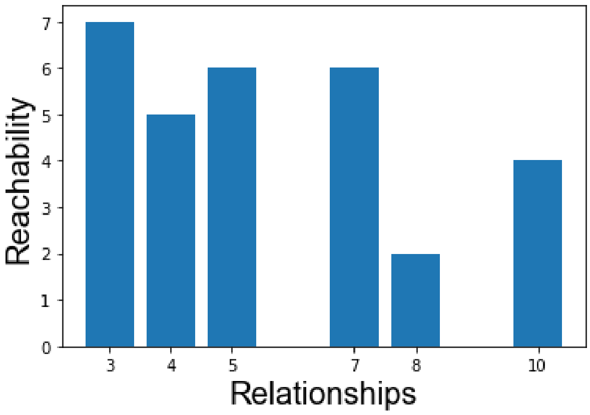
[25] Stan I, Suciu V, & Potolea R, "Scalable data model for traffic congestion avoidance in a vehicle to cloud infrastructure," *In Journal of Sensors*, 21(15), 5074, 2021.

[26] Yuvaraj Natarajan, Kannan Srihari, Gaurav Dhiman, Selvaraj Chandragandhi, Mehdi Gheisari, Yang Liu, ChengChi Lee, Krishna Kant Singh, Kusum Yadav, Hadeel Fahad Alharbi, "An IoT and machine learning-based routing protocol for reconfigurable engineering application," *In Journal of IET Communications*, vol. 16, no. 5, pp. 464-475, 2022.

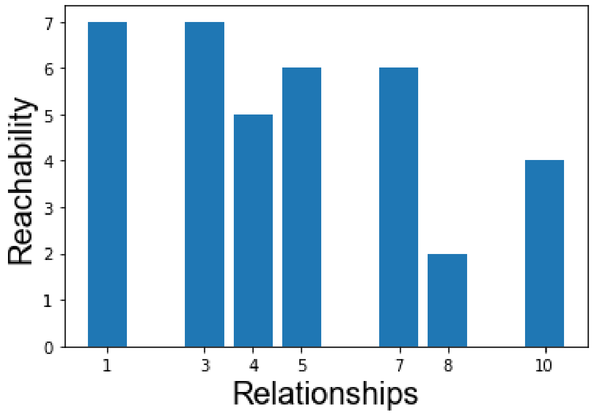
[27] Mohana S. D., SP Shiva Prakash, and Kirill Krinkin, "Semantic Rules for Service Discovery in Social Internet of Things," *In 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, pp. 119-124, 2022.

[28] Zhang S. S., Tong X. R., & Wang S. G., "ELMNeuralWalk trust evaluation for online social networks," *In International Journal of Bio-Inspired Computation*, vol. 19, no. 4, pp. 199-209, 2022.

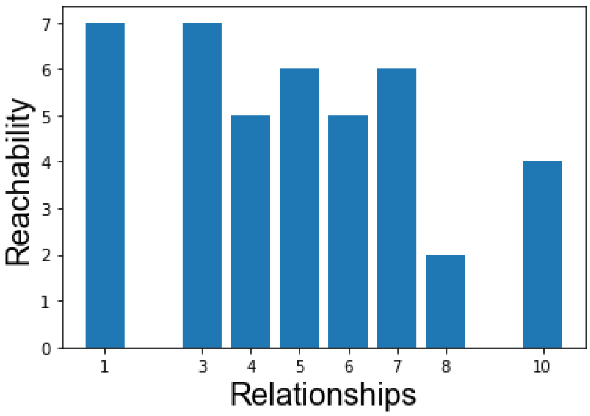
[29] Yuan X., Liu J., Du H., Zhang Y., Li F., & Kadoch M, "Machine



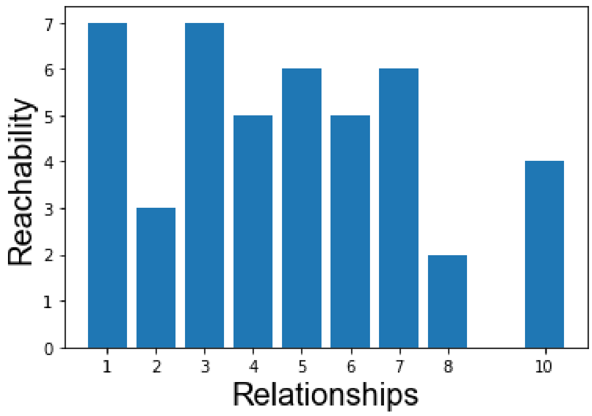
(a) Reachability with 60:40 ratio.



(b) Reachability with 70:30 ratio.



(c) Reachability with 80:20 ratio.



(d) Reachability with 90:10 ratio.

Fig. 7: Reachability of devices in SIoT training and testing ratios.

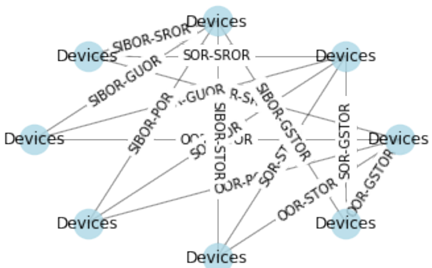


Fig. 8: Sample Congestion-free path Relationship between the devices

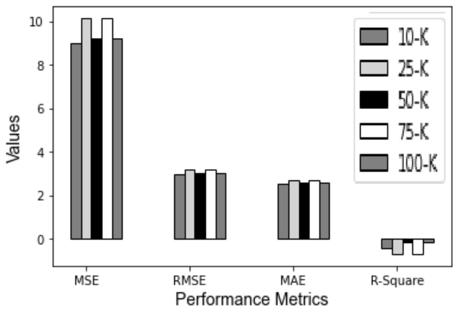


Fig. 9: Performance metric results

learningbased satellite routing for SAGIN IoT networks," *In International Journal of Electronics*, vol. 11, no. 6, p. 862, 2022.

[30] SD Mohana, SP Shiva Prakash, and Kirill Krinkin, "Service Oriented RANN Knowledge Model for Social Internet of Things," *In International Journal of Big Data and Cognitive Computing*, vol. 6, no. 1, p.32, 2022.

[31] Farzaneh Kaviani and Mohammadreza Soltanaghaei, "CQARPL: Congestion and QoS-aware RPL for IoT applications under heavy traffic," *In Journal of Supercomputing*, vol. 14, no. 78, pp. 16136–16166, Sep 2022.

[32] SD, Mohana, SP Shiva Prakash, and Kirill Krinkin. "Service oriented r-ann knowledge model for social internet of things." Big Data and Cognitive Computing 6.1 (2022): 32.

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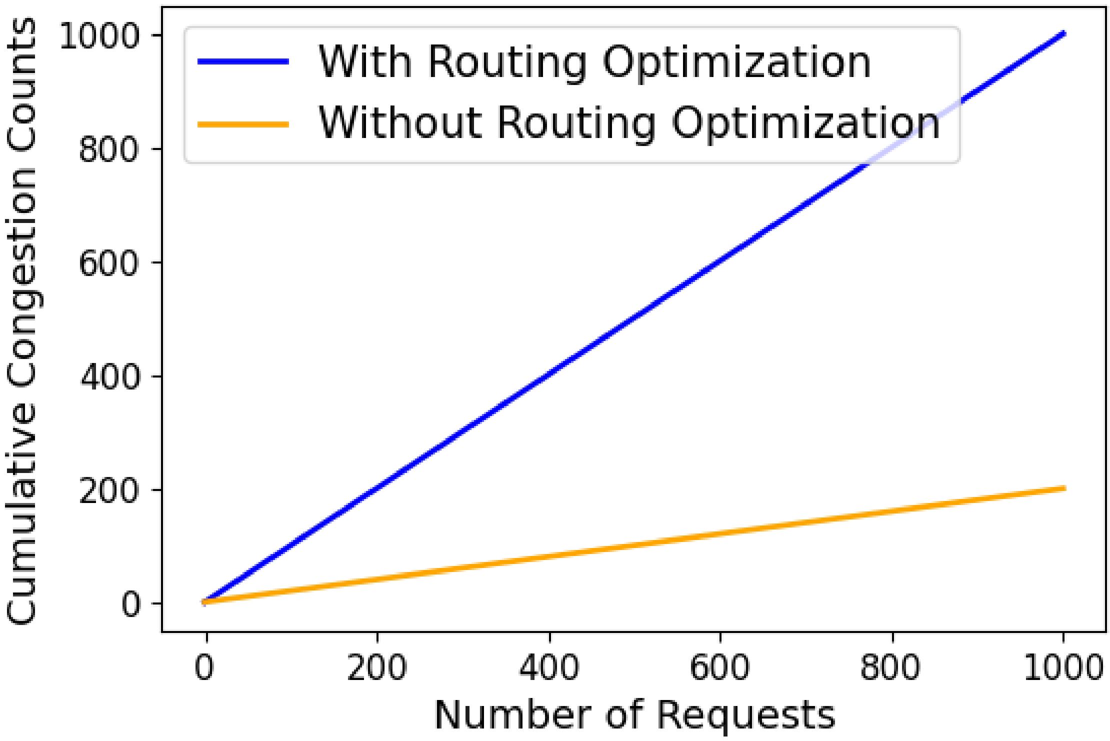

Fig. 10: The quality of optimization for cumulative congestion under the number of requests.

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