National Journal of Antennas and Propagation
RESEARCH ARTICLE
National Journal of Antennas and Propagation, ISSN: 2582-2659 Vol. 7, No. 2, 2025 (pp. 175-186)
WWW.ANTENNAJOURNAL.COM

A Two-Phase Clustering Framework for Adaptive Load Balancing in Vehicular Networks using OPTICS and K-Medoid algorithms

Mohammed F. Alomari[1]*, Jaafar S. Alrubaye[2], Abdul Hadi M. Alaidi[3], Haider Th. Salim Alrikabi[4]
[1]Department of Computer Technical Engineering, Imam Alkadhim University College, Baghdad, Iraq.
[2]Department of Computer Science, College of Education for Pure Sciences, University of Wasit, Wasit, Iraq.
[3]Department of Computer Science, College of Computer Science and Information Technology, University of Wasit, Wasit, Iraq.
[4]Department of Electrical Engineering, College of Engineering, University of Wasit, Wasit, Iraq.

KEYWORDS:

OPTICS Algorithm.
Vehicular Networks,
Mobility-Aware Networking,
Communication,
Handoff Performance

ARTICLE HISTORY:

Received 11.09.2025
Revised 22.09.2025
Accepted 01.10.2025

DOI:
https://doi.org/10.31838/NJAP/07.02.24

Abstract

Vehicular Ad Hoc Networks (VANETs) form a cornerstone of intelligent transportation systems; however, high vehicle mobility and overlapping base station (BS) coverage often lead to inefficiency and frequent handoffs. This paper presents a two-phase adaptive load-balancing framework that integrates OPTICS clustering with K-Medoid refinement to dynamically redistribute vehicles between neighboring BSs. In the first phase, OPTICS identifies high-density regions to enable efficient cluster formation. In the second phase, K-Medoid reassigns vehicles across adjacent BSs with uneven loads, ensuring balanced traffic without modifying the underlying network structure. Simulation results demonstrate that the proposed method enhances throughput, reduces handoff latency, and decreases load imbalance by more than 30% compared with conventional clustering techniques. Unlike existing resource-centric approaches, this framework offers a lightweight, scalable, and infrastructure-independent solution suitable for dense urban VANET environments.

Authors' e-mail: mohamed.fadhil@iku.edu.iq; jsadiq@uowasit.edu.iq; alaidi@uowasit.edu.iq; hdhiyab@uowasit.edu.iq

Authors' Orcid: 0000-0002-8268-2978; 0009-0006-2731-4271; 0000-0001-9120-708X; 0000-0002-5201-2084

How to cite this article: Alomari M.F, et al., A Two-Phase Clustering Framework for Adaptive Load Balancing in Vehicular Networks using OPTICS and K-Medoid algorithms, National Journal of Antennas and Propagation, Vol. 7, No. 2, 2025 (pp. 175-186).

Introduction

Vehicular ad hoc networks (VANETs) have garnered significant attention within intelligent transportation systems as they enable efficient communication between vehicles and roadside infrastructure, such as base stations (BSs). However, one of the key challenges in VANETs is effective bandwidth management when vehicles travel across the coverage areas of neighboring BSs. Load balancing among various BSs is crucial in densely populated regions to reduce traffic congestion, maintain continuous communication, and optimize spectrum utilization.[1,2] Two widely used clustering algorithms for dynamically organizing vehicular nodes based on their position and density are K-Medoid, which enhances network load distribution, and OPTICS (Ordering Points to Identify the Clustering Structure). Communication hotspots where BSs may become overloaded can be detected by using OPTICS to identify high-density vehicle clusters.[3] In contrast, the conventional K-Medoid algorithm[4,5] provides a robust clustering mechanism that minimizes communication costs and improves network stability, particularly in dynamic environments, by employing actual data points as cluster centers.[6,48] A common approach to this challenge involves integrating intelligent load-balancing techniques with traditional cellular systems.[7,8] However, spectrum reuse policies often

prevent BSs from effectively coordinating inter-BS handovers, limiting network adaptability.[9,10] By dynamically redistributing vehicles between overloaded and underloaded BSs, network managers can efficiently balance traffic loads without altering the allocated spectrum, thereby optimizing overall resource utilization.[11] The resulting improvements in connectivity and communication reliability significantly enhance VANET performance and Quality of Service (QoS).[10]

Using two-phase clustering techniques, this work investigates how to dynamically adjust the load across neighboring base stations (BSs). The proposed method focuses on real-time cluster formation to manage reassignment and handover concentration efficiently. Because VANETs are inherently dynamic, the proposed solution ensures scalability and supports adaptive network configuration through the use of integrated clustering algorithms.

Reference[12,35] suggest a round-robin load-balancing method that evenly distributes workloads among available BSs, disregarding real-time traffic load and vehicle density. Despite its simplicity and wide adoption, this approach often struggles to accommodate dynamic variations in traffic density and BS load fluctuations. In a different study,[13] authors propose threshold-driven techniques that switch connections between BSs based on predefined load thresholds. Once a BS exceeds its threshold, incoming vehicles are rerouted to neighboring BSs. However, this method fails to respond effectively to continuous fluctuations in vehicular density. In reference,[14] the authors introduce a clustering approach based on signal strength and distance metrics, assigning vehicles to BSs with the strongest signal. This technique often results in unbalanced load distribution, particularly in high-density environments.

The clustering method suggested by references[15] and [39] groups vehicles according to their positions; however, it is less effective in highly dynamic vehicular environments because it does not account for individual BS loads or dynamically adjust clusters in real time. In addition, the authors of references[16,17] introduced a fuzzy logic–based approach similar to that of reference,[14] which bases load-balancing decisions on a predefined set of fuzzy rules. Although these strategies are more adaptive than strictly threshold-based techniques, they still depend on static rule sets that may not effectively capture rapid network changes. To balance loads, methods proposed in references[18-20] predict future vehicle positions while considering mobility; however, these approaches often require high processing power and complex mobility models. The present paper proposes a new two-phase clustering approach that employs OPTICS in Phase 1 and K-Medoid in Phase 2, together with group optimization, to balance loads among adjacent BSs in a serviced VANET area. The problem and proposed scenario can be defined as follows: in dense VANET environments, neighboring BSs are often restricted from sharing the same frequency continuum, which leads to inefficient bandwidth utilization. Therefore, in the first phase, the Ordering Points to Identify the Clustering Structure (OPTICS) algorithm identifies high-load areas by automatically grouping vehicles within each BS's coverage region according to their density. In the second phase, using medoid distances and mobility predictions, the K-Medoid algorithm refines the assignment of vehicles to less-loaded BSs by restructuring dense vehicle clusters located in the overlapping areas of adjacent BSs. Moreover, a load-transfer strategy—considered a third step—is triggered after the restructuring stage (i.e., after Phases 1 and 2). This strategy defines a vehicle-to-BS assignment mechanism that accounts for group density and load variation between BSs (e.g., set load differential). If the load variation has not decreased (i.e., if $l_{variation}\gamma$ is not achieved), the regrouping area is expanded to include additional clusters by a factor of (2^n), and the process is repeated within the overlap region between congested and uncongested BSs. This study's contributions are as follows:

- A novel integration of OPTICS (for density-based clustering) and K-Medoid (for inter-BS load balancing), specifically designed for dynamic VANET environments.
- A framework that operates without modifying the communication field, thereby reducing coordination overhead between BSs.
- Enhanced mobility management: by accounting for vehicle density and proximity, the approach reduces handoff delay and improves quality of service under high-mobility conditions.
- High scalability: the proposed method adapts effectively to varying traffic densities and network topologies, making it suitable for large-scale urban deployments.
- Extensive simulation results demonstrate significant improvements in throughput, handoff latency, and load-balancing efficiency compared with baseline clustering strategies.

Regardless of the broad RF range available, only a few frequency bands are efficiently utilized due to constraints such as propagation characteristics, penetration loss, path loss, and device compatibility. Therefore, designing a dynamic and efficient system for 5G, 6G, and

beyond is essential to achieve high spectral and energy efficiency.[21] The summarized contributions in this study primarily address load balancing and efficient handoff control in VANETs, emphasizing their innovative applications and practical benefits. Accordingly, the proposed method integrates OPTICS and K-Medoid to dynamically balance loads between BSs without modifying the cellular spectrum. In contrast, conventional techniques typically rely on static or semi-dynamic mechanisms that fail to effectively handle real-time traffic variations, leading to poor load distribution and increased handoff failure rates.[14] Unlike previous studies, this paper focuses exclusively on multiband-capable load balancing using OPTICS and K-Medoid, demonstrating superior handoff performance and throughput in smart city environments.

Related Work

Several research studies have examined load-balancing and handover management challenges in VANETs. These works primarily focus on clustering and bandwidth optimization to mitigate the effects of high vehicular mobility and network density in urban environments. The following section reviews some of the most relevant strategies.

Clustering has been widely applied in VANETs to optimize and manage dynamic node movement.[15] A DGVS algorithm based on mobility patterns and spatial density was proposed in,[16] which reduces the overhead of frequent handoffs and alleviates network congestion in dense vehicular networks by facilitating efficient handovers between BSs. However, studies on spectrum reuse have also been conducted to further enhance VANET communication.[22,23] The authors in reference [24] proposed a cognitive radio–based scheme for dynamic spectrum sharing, in which BSs allocate channels based on demand from neighboring nodes. Although this method improves bandwidth utilization, its implementation is limited due to restrictions on frequency reuse in VANET regions managed by multiple BSs. The study in reference [25] examined a system that combines clustering with handover control to manage bandwidth handovers between BSs. While this approach reduces handover delay, it does so at the cost of modifying the cellular spectrum, which is incompatible with the constraints of VANET environments.[24]

In vehicular networks, effective handover management plays a crucial role in reducing latency and preventing large-scale connection drops. An adaptive handover algorithm based on vehicle velocity and the load on neighboring BSs was proposed in reference [27]. Although this method efficiently distributes the load among BSs, it does not incorporate clustering, resulting in inefficiencies in networks with high user density. In reference[28], the authors integrated fuzzy logic with handover management to predict vehicle movement and allocate spectrum resources more efficiently. While this approach reduces handover latency, it also faces challenges due to its dependence on access to cellular resources. When multiple BSs are located in close proximity, existing research offers a comprehensive overview of equilibrium distribution and clustering techniques in VANETs. An advanced strategy for mitigating congestion in VANETs focuses on minimizing load-balancing issues by using K-Means in conjunction with load balancers. This method facilitates communication between roadside units (RSUs) and moving vehicles to prevent excessive congestion and maintain a balanced network load. In real-world scenarios where BSs are positioned close to one another, the clustering algorithm enhances communication efficiency by dynamically adjusting centroids based on vehicle position and speed.[5]

A novel method for improving cluster organization in VANETs leverages the Whale Optimization Algorithm (WOA). This technique reduces the number of clusters while extending the network's operational lifespan, thereby enhancing overall performance. It achieves this by optimizing parameters such as the number of cluster heads and the load-balancing factor, which together improve network efficiency in scenarios where multiple BSs are required.[15] Another innovative strategy involves the use of multi-agent systems to strengthen clustering in 5G-enabled VANETs. This approach employs lightweight authentication and load-balancing mechanisms to boost network performance and is particularly effective when vehicle nodes can seamlessly switch between nearby BSs while distributing traffic load.[18] By comparing various cluster-based routing algorithms in VANETs, studies have demonstrated that bio-inspired and graph-based techniques significantly enhance load balancing and reduce network congestion. Multi-agent clustering and WOACNET (Whale Optimization Algorithm for Clustering in VANETs) outperform conventional methods in terms of transmission efficiency[19] and cluster lifetime.[29,44] Table 1 provides an overview of recent advancements in load-balancing techniques that incorporate clustering, including multi-agent systems and whale optimization. These methods optimize load distribution among neighboring BSs while adhering to spectrum reuse constraints—an essential consideration in densely populated urban VANET environments.

Table 1: Comparison of Related Work

Approach	Clustering type	Load balancing Method	Optimization technique	compatibility	Network congestion reduction	Reference
Density-based Clustering Algorithm	Density-based	Partial	Basic	Yes	Medium	[1]
Mobility-aware Clustering	Mobility-aware	Partial	Basic	Yes	Medium	[2]
Cognitive Radio-based	None	Yes	Basic	No	High	[3]
Joint Handover	None	Yes	Advanced	No	High	[4]
Adaptive Handover Algorithm	None	Yes	Advanced	Yes	High	[5]
Fuzzy Logic Handover Management	None	No	Advanced	No	Medium	[13]
WOA-based Clustering	Whale Optimization Algorithm	Yes	Advanced (Bio-inspired)	Yes	High	[22]
Multi-agent Clustering for 5G-VANETs	Multi-agent-based	Yes	Advanced	Yes	High	[23]
K-Medoid with Load Balancer	K-Medoid	Yes	Advanced	Yes	High	[19]
Proposed Method	OPTICS&k-Medoid (two phases Clustering)	Yes	Advanced	Yes	High	-

METHODOLOGY

Despite providing valuable insights into handover control and clustering, none of these studies fully address the limitations imposed by neighboring BSs in VANETs.[28] The proposed approach in this work leverages two OPTICS algorithms to efficiently manage load balancing and handover without altering the cellular spectrum. By dynamically forming vehicle groups based on density, the method ensures seamless load balancing while maintaining network stability and adherence to VANET design constraints.

We introduce a hybrid clustering method that employs two distinct techniques in two phases: OPTICS[47] and K-Medoid clustering.[31,32] This approach effectively addresses the challenge of load balancing across adjacent BSs in VANET environments, similar to other methods proposed in references.[30,33,34,36,37,46]

System model

In the proposed method, multiple base stations (BSs) are utilized, ensuring that no adjacent BSs operate on the same frequency range. When the VANET area is clustered, the network load is then estimated. Each BS can assess the load within its coverage area by identifying densely populated regions (i.e., clusters), and the traffic between neighboring BSs is determined using this information (see Figure 1). To alleviate congestion in heavily loaded areas, clusters that form within the high-density overlap regions between adjacent BSs are prioritized for restructuring. These clusters are subdivided into smaller groups when they are located between BSs with differing loads, allowing the smaller subgroups to be handed over to the neighboring low-load BSs. Consequently, a portion of the load from the heavily loaded BSs is redistributed to adjacent BSs with lighter loads.[38]

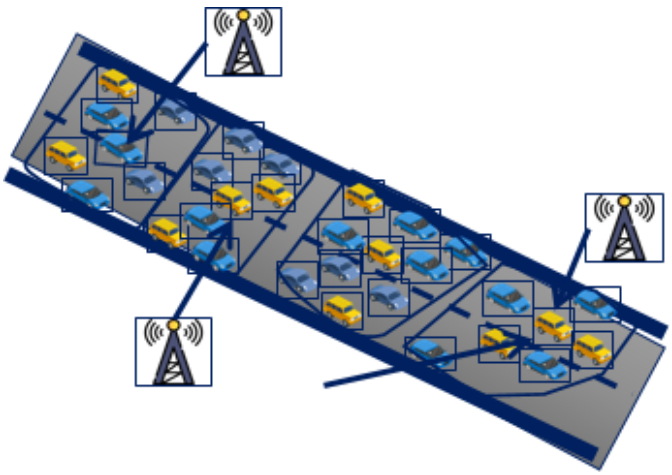

Fig. 1: Two Base Stations (BS1 and BS2) next to each other in a VANET. BS2 (low load) and BS1 (high load)

OPTICS is employed in the first stage of the proposed approach.[45] This algorithm forms clusters of vehicles that are spatially close by grouping them within a BS's coverage area according to their density and proximity. The primary advantage of OPTICS lies in its ability to autonomously detect clusters of varying sizes and shapes, even in highly dynamic environments such as VANETs, where vehicle density and mobility patterns frequently change.[40] OPTICS operates based on a specified neighborhood radius and a minimum number of vehicles required within that radius to form a cluster. Densely populated regions that do not meet the minimum criteria are classified as noise or outliers, while areas containing a sufficient number of vehicles constitute valid clusters.

In the OPTICS algorithm, nodes (points) are classified as core points, border points, or outliers based on their reachability and density connectivity.

The operation of OPTICS is outlined as follows: in its initial phase, Algorithm 1 identifies clusters of vehicles using spatial density as the key criterion through the application of the OPTICS method.

Within Stage 1, the algorithm first refines the clusters, where the K-Medoid algorithm selects representative vehicles (medoids) from the density-based clusters. This selection ensures that the vehicle occupying the most central position within each cluster is chosen, thereby minimizing the total intra-cluster distance between vehicles. In the subsequent step of the same stage, these medoids act as representative vehicles for their respective clusters, and load-balancing decisions are made based on their proximity to neighboring BSs. The algorithm evaluates each medoid's distance from its serving BS as well as from adjacent BSs to determine optimal load distribution.

In Stage 2, several clusters are positioned adjacent to one another and are associated with neighboring BSs. If a medoid is located closer to an adjacent BS, or if the serving BS becomes overloaded, the load is redistributed by restructuring the selected clusters using the K-Medoid algorithm. The number of clusters generated in this stage depends on the value of the parameter *k*, where the number of selected clusters is represented as 2^n (an equal number of clusters from each BS).

The advantage of combining K-Medoid with OPTICS lies in K-Medoid's effectiveness at fine-tuning clusters produced by the density-based algorithm, as it is less sensitive to noise and outliers. Because actual vehicles serve as medoids, the technique ensures smoother handovers and reduces communication overhead. Phase 2 of Algorithm 2 represents the second stage of refinement, in which the medoid vehicle is selected and connected to the nearest BS.

Algorithm 1: OPTICS (Phase 1)

1. **Inputs:**
   - 1.1. Dataset: D (points to be grouped)
   - 1.2. MinPts: Minimum number of points to form a core
   - 1.3. eps: Maximum neighborhood radius (can be very large if not known)
2. **Outputs**:
   - 2.1. Reachability distances and core distances for each point
   - 2.2. Ordered list of points (optics order)
3. **Initialization:**
   - 3.1. Mark all points in D as unprocessed.
   - 3.2. Initialize an empty list Order to store the ordering of points.
4. **Core Distance Calculation:**
   - 4.1. For each point pp, calculate the core distance:
     - 4.1.1. Find pp's MinPts nearest neighbors.
     - 4.1.2. If there are fewer than MinPts neighbors within eps, set Core Distance(p)=Undefined Core Distance(p)=Undefined.
     - 4.1.3. Otherwise, set Core Distance(p)=Distance to MinPts-th neighbor(p)
5. **Process Each Point:**
   - 5.1. Select an unprocessed point p, mark it as processed, and add it to Order.
   - 5.2. If p has a defined core distance:
     - 5.2.1. Place p's neighbors in a priority queue, ordered by their reachability distance:
       - 5.2.1.1. Reachability Distance (p, q) =max (Core Distance(p), Distance (p, q))
     - 5.2.2. Update the reachability distance for all neighbors of p.
6. **Expand Cluster:**
   - 6.1. Continue processing points from the priority queue, updating their reachability distances and adding them to Order, until the queue is empty.
7. **Repeat:**
   - 7.1. Repeat steps 3–4 until all points in D are processed.
8. **Output:**
   - 8.1. The ordered list Order, with reachability distances, can be used to extract groups.

- Combined Clustering Approach (Third phase)
  An effective load-balancing solution for vehicular environments can be achieved by combining the two

Algorithm 2: Refinement groups by K-medoid grouping

1. **Input:** Dataset D, number of groups K
2. **Output**: K groups with their medoids
3. Initialize K medoid randomly selected from D
4. Repeat until convergence:
   a. Assign each point P in D to the nearest medoid based on distance (e.g., Manhattan or Euclidean)
   b. For each group C:
      i Find the medoid M that minimizes the total distance to other points in C:
      $M = arg_{min}$ (sum (distance (M, P) for P in C))
   c. Update the medoid of each group with the new M found
   d. If no change in medoids, stop

Return the final groups and medoids

grouping algorithms (OPTICS and K-Medoid). The steps of the combination stage are outlined as follows:

- **Dynamic Cluster Formation**: By forming groups that dynamically adjust to vehicle density, the OPTICS algorithm captures changes in traffic patterns in real time. This ensures that the load can be distributed effectively without requiring modifications to the cellular network.
- **Optimal Constellation Assignment**: To balance the load, K-Medoid first selects two neighboring groups that are between low- and high-load BSs. These groups are then restructured and refined by K-Medoid. For the output groups, K-Medoid finds the best representative vehicle (medoid) for redistributing the groups between BSs to achieve load balancing.
- **Scale Reuse**: As the proposed approach only considers group formation and load balancing, without modification, it guarantees conformance with the current BS setup. This is crucial in VANET environments where several BSs may share bandwidth over overlapping coverage regions.

- Handover and Load Balancing Process
  - **Cluster Identification: Within each BS's coverage area, groups are identified using OPTICS grouping.**
  - **Refinement**: For every group, K-medoid chooses medoids as representative nodes.
  - **Load Balancing Decision**: Some groups within the restructured area can be reassigned from one BS to another to balance traffic, depending on the medoids' proximity to neighboring BSs and the current load on each BS.
  - **Handover Execution**: Once some of the vehicles are reassigned to a nearby BS, the handover process is carried out smoothly, ensuring continuous communication and optimal load distribution.
  - Performance Benefits
    - **Reduced Handover Delays**: The number of handovers is minimized through group-based load balancing, as only vehicles that need reassignment are transferred.
    - **Scalability**: Scalability is ensured by the dual-grouping approach, which can adapt to both low- and high-density traffic conditions without requiring major modifications to the network infrastructure.
    - **Energy Efficiency**: The technique enhances the network's overall energy efficiency by reducing the signaling overhead caused by frequent handovers.[42]

Algorithm 3 combines two phases: to reduce the load difference between high- and low-load BSs, the vehicle nodes are first grouped using OPTICS, and the groups between the high-load and low-load BSs are then reconstructed into *k* groups and redistributed.

By effectively identifying congested areas, this technique assists in dynamically distributing the load among BSs without requiring range adjustments, as frequency ranges are reused by different areas (e.g., BSs) and such adjustments can cause interference. Additionally, it performs well across various vehicle densities and automatically adapts to changes in network topology. **Error! Reference source not found.** shows that two adjacent BSs have a load difference greater than γ (a value determined by the user in the core network).

Experimental Results

Illustrative Example

Problem and Solution Explanation

We focus on a portion of the VANET where, as in the problem under consideration, two adjacent BSs (BS2 and BS3) manage vehicle traffic. Due to vehicle mobility, BS2 becomes overloaded, leading to inefficient bandwidth utilization and increased handoff delays, while BS3 remains underutilized.

Given:

- **BS_2**: Initially serves 545 vehicles.
- **BS_3**: Initially serves 168 vehicles.
- **Load imbalance(γ)**: refers to imbalance in the load, and redistributing the vehicles is the aim.
- To refine and redistribute the vehicle groups, OPTICS is used for vehicle grouping in the first phase and K-Medoid in the second.

Algorithm 3 K-Medoid and OPTICS combined for load redistribution.

Input:
D - Dataset of nodes with their positions and load information
BS_{high} - Overloaded Base Station
BS_{low} - Lowest Load Base Station
ε - Radius for OPTICS
MinPts - Minimum points for density grouping
K - Desired number of groups for redistribution
Output:
Re-grouped nodes assigned between
Initialize:
a. Identify border nodes between BS_{high} and BS_{low} based on signal strength and coverage overlap.
b. Set $cluster_{id}$ = 0
OPTICS Phase (Initial Clustering):
a. For each node P in the border nodes set:
    i. If P is visited, skip to the next node
    ii. Mark P as visited
    iii. Retrieve neighbors N within radius ε
    iv. If |N| < MinPts:
        - Mark P as noise (not part of any group)
    v. Else:
        - Increment $cluster_{id}$
        - Expand the group using reachable nodes as per OPTICS steps
K-Medoid Re-grouping Phase (Redistribution of Border Clusters):
a. Identify groups formed in the OPTICS phase that are located near the boundary between BS_{high} and BS_{low}.
b. Select 2^k groups adjacent to (overloaded) and (lowest load) ($2^k/2$ groups from BS_{high} and $2^k/2$ groups from BS_{low}).
Re-group Adjustment:
a. Merge nodes from selected groups into a temporary dataset set.
b. Apply K-Medoid to the temporary dataset to form *K* groups:
    i. Initialize K-medoids randomly from the temporary dataset
        - n=1
        - For *k* from n to ∞
        - if difference between BS_{high} (overloaded) and BS_{low} (lowest load) ≥ β *n* = *n*+1
        - Else
        - End
    iii. Assign each node to the nearest medoid
    iv. For each group C:
        - Update medoid *M* to minimize total dissimilarity within the group
    v. If the medoids do not change, stop
Load Redistribution:
a. Distribute the K groups based on their new medoid positions:
    i. Assign groups closer to BS_{low} to be managed by BS_{low}.
    ii. Assign groups closer to BS_{high} to be managed by BS_{high}.
b. Rebalance load to minimize overloading of BS_{high}.
Output the new group assignments and the updated load distribution between BS_{high} and BS_{low}.

Parameters

- OPTICS Parameters:
  - **Epsilon (ϵ)**: Neighborhood radius = 50 meters.
  - **MinPts**: Minimum points to form a group = 11.
- K-Medoid Parameters:
  - Number of groups = k.
  - **Distance function**: Euclidean distance between vehicles.

Implementation steps

- Step 1: Initial Load Imbalance:
  - There are 545 vehicles served by BS_2, and 168 vehicles by BS_3.
  - Redistributing the load between the two BSs in an even manner is the aim.
    The Load imbalance is calculated in the below equation:

$$Load\ \text{Im}balance = \frac{|545-168|}{545+168} \times 100$$
$$= \frac{377}{713} \times 100 = 52.87\%$$

  - The system identifies that **BS_2** is overloaded by 52.87% compared to **BS_3**.
- Step 2: Density-Based Clustering (OPTICS):
  - Using **OPTICS** with ϵ = 50 meters and MinPts = 11, vehicles are grouped based on their proximity to each other.
  - Vehicles that are near to one another group together.
  - For load balancing, densely populated areas close to where BS_1 and BS_2 overlap.
    Clusters are created according to how close together Vehicles as shown in Figure 1, and in the center, overlapping groups form, indicating locations where vehicles can be moved to balance the load.
- Step 3: Load Balancing:
  In the overlapping region, **K-Medoid** grouping is applied to further refine groups and by restructuring and generating new groups, some of groups will be reassigned to the least-loaded BS if it is the closest BS.
  - **Medoids** (central vehicles) are selected in each group.

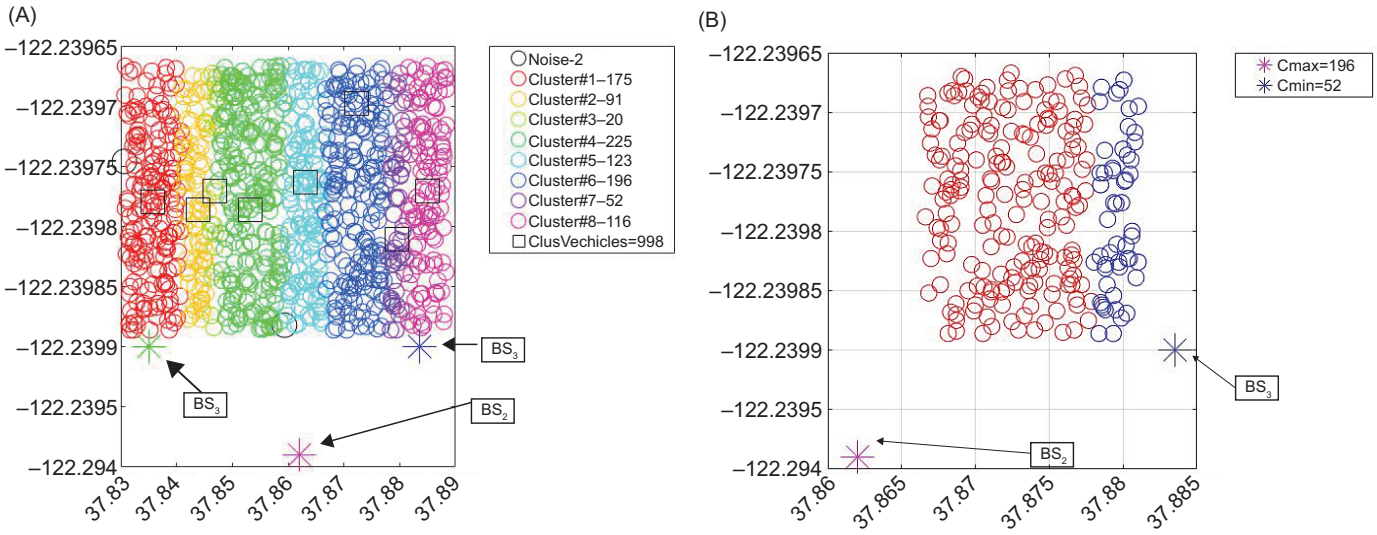

Fig. 2: (A) Two adjacent imbalance BSs(BS2 and BS3), squares are medoids of groups, (B) Ovelap area (selected groups) to be re grouped for achieve load balancing.

- groups closest to the medoid of BS_2 (means high load) are reassigned to balance the load.

- Real Values for K-Medoid:
  - From the 248 vehicles in the overlap region, 114 vehicles are reassigned from BS_2 to BS_3.
  - The new load distribution:
  - BS_2: 545−114=431 vehicles.
  - BS_3: 168+114=282 vehicles.
- Step 4: Final Load Balancing:
  As shown in Figure 4, and after applying **K-Medoid**, the load is balanced between **BS2** and **BS3**.
  - The final load on BS_2 and BS_3 are 431, and 282 vehicles, respectively.
  - **Load imbalance**:

$$\text{Final load imbalance} = \frac{|431-282|}{431+282}\times 100 = 20.8\%$$

So, if the γ = 25%, the final load imbalance will be satisfied, when:

$$\text{load imbalance} < \beta$$

- Load Redistribution:
  - The redistribution of the vehicles in the overlapping region using K-Medoid grouping (shown in Figure 3(a)) is depicted in Figure 4.
  - **Squares**: Medoids selected for each group.
  - Some of vehicles reassigned from BS_2 to BS_3 to balance the load (e., g vehicles of group#6).

Solution Summary

- **Problem**: BS_2 was overloaded with 545 vehicles, while **BS3** was underutilized with 168 vehicles, leading to a 52.87% load imbalance.

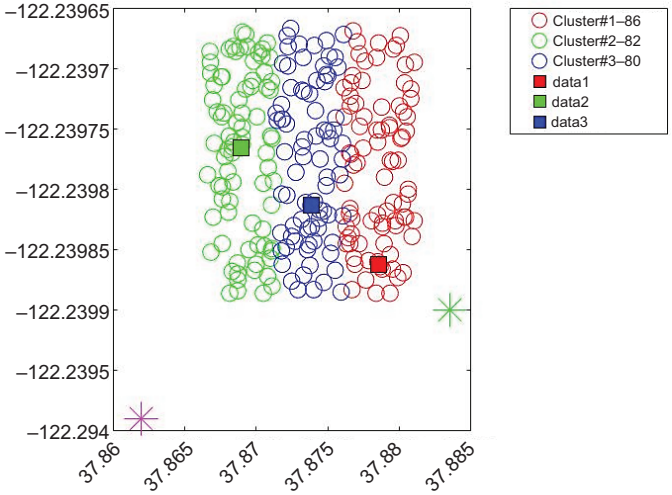

Fig. 3: After applying restructuring stage on overlap groups between high and low load BSs

- **Solution**: Vehicles were reassigned from BS_2 to BS_3 using OPTICS and K-Medoid grouping. The load was balanced between the two BSs through restructuring in the middle leads of the groups.
- **Result**: Handoff delays were decreased, and overall network efficiency increased when the load imbalance was brought down to 20.8%.

Simulation Results

We demonstrated the effectiveness of the proposed two-phase grouping method through simulations conducted on synthetic data. The initial load distribution revealed a *B* load imbalance between two adjacent BSs in the VANET area. To simulate the load-balancing scenario, we used a combination of OPTICS and K-Medoid to

implement the proposed method and obtain meaningful results. The simulation setup included three cellular BSs, an epsilon value of 50 meters, a minimum point value of 6, a BS load threshold of ≥85%, and 250 simulation runs. The model assumed a 25% ß load difference between adjacent BSs for ≥1000 vehicles within the proposed VANET area.

1. **Dataset Simulation**: Given that we have a real VANET dataset, the simulated vehicle traffic conditions were matched to datasets from the Next Generation Simulation (NGSIM) program, which include a variety of real-world highway scenarios.[42] Different sections of the dataset were selected, where vehicles are distributed across a two-dimensional space with multiple BSs managing overlapping zones. These NGSIM dataset sections were scaled to one thousand meters.
2. **Step-by-Step Simulation**:
   - **Phase 1:** In the designated areas, the proposed algorithm monitors the load of each BS. If a BS reaches the maximum threshold () and a load imbalance is detected in overlapping BS regions, the proposed algorithm is triggered. OPTICS then begins clustering by grouping vehicles according to their density.
   - **Phase 2:** Central vehicles (medoids) are selected for the clusters created by OPTICS to refine them further. The algorithm then recalculates the load distribution and, if necessary, performs load balancing while considering the varying loads between the two BSs.

The implementation outline can be explained as the following:

- **Select dataset** representing vehicle locations and simulate the BSs' load.
- **Perform OPTICS** to identify groups in both BS areas.
- **Apply K-Medoid grouping:** The groups located in the middle of the overlapping region are refined using K-Medoid clustering. The number of groups, based on the parameter *k*, between the low-load and high-load BSs is then selected for restructuring, where *k* is equal to or greater than two (edge groups between and). The value of *k* is increased incrementally until the optimal level of load balancing is achieved. Each generated group is refined and connected to the closest BS. This step divides the large border group, along with adjacent groups connected to high-load and low-load BSs, into smaller groups that are redistributed between the adjacent BSs, resulting in the transfer of some load from the high-load BSs to the low-load BSs.
- **Measure load balancing impact** Calculate the final load balance following handovers and redistribute the vehicles to gauge the impact of load balancing.

The following metric are used to compare the proposed and traditional methods:

Load Distribution Imbalance

This indicator shows how effectively the load is distributed among nearby BSs.

- **Metric**: The percentage that separates the two BSs' loads.
- **Comparison**: The suggested two-phase grouping in contrast to... a conventional method[42] (e.g., round-robin load balancing or static threshold-based methods).

Let:

- L_{BS_1} be the number of vehicles served by BS_1.
- L_{BS_2} be the number of vehicles served by BS_2.

The load imbalance percentage is calculated as:

$$\text{Load Imbalance} = \frac{\left|L_{BS_1} - L_{BS_2}\right|}{L_{BS_1} + L_{BS_2}} \times 100 \quad (1)$$

A lower imbalance indicates better load distribution is shown in Figure 4.

Handoff Latency

- Handoff latency is critical in VANETs due to the high mobility of vehicles.
- **Metric**: The average time taken for vehicles to hand off between BSs.
- **Comparison**: Proposed grouping-based handoff mechanism vs. traditional methods are shown in Figure 5.

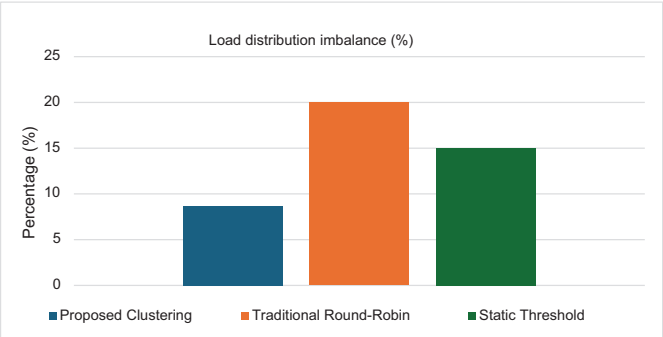

Fig. 4: Comparison of proposed method against traditional methods for load distribution imbalance

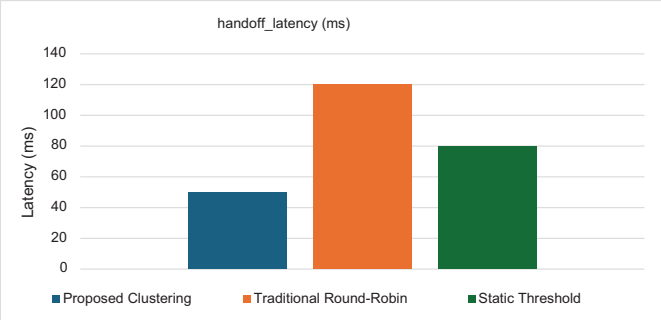

Fig. 5: Proposed grouping-based handoff mechanism vs. traditional methods

Let:

- $T_{handoff}$ be the handoff latency in milliseconds.
- T_{init} be the time to initiate the handoff.
- T_{comp} be the time to complete the connection with the new BS.

The total handoff latency is:

$$T_{handoff} = T_{init} + T_{comp} \quad (2)$$

Network Throughput

- The effectiveness of the load balancing scheme is reflected in the overall network throughput.
- **Metric**: following load balancing, the average network throughput.
- **Comparison**: Proposed method vs. traditional approaches,[17] shown in Figure 6.

Let:

- T_{total} be the total data transmitted in Mbps.
- $N_{vechicles}$ be the total number of vehicles served by the BSs.

The average network throughput is:

$$\text{Throughput} = \frac{T_{total}}{N_{vehicles}} \quad (3)$$

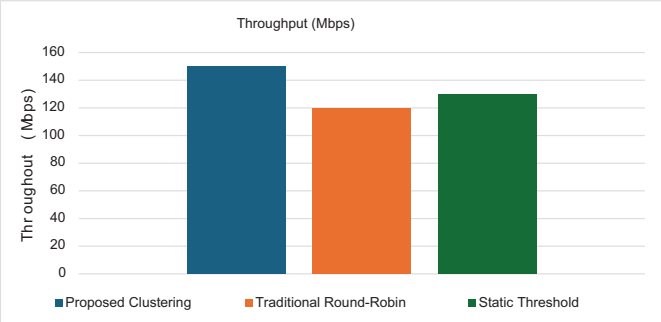

Fig. 6: Comparison of proposed method against traditional methods for throughput

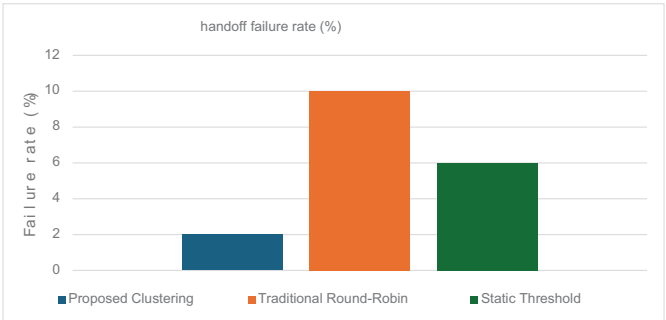

Fig. 7: Comparison of proposed method against traditional method for handoff failure rate

Handoff Failure Rate

- This indicator shows how frequently handoffs fail because of uneven loads or ineffective handoff procedures.
- **Metric**: Percentage of handoff attempts that fail.
- **Comparison**: Two-phase grouping method vs. traditional load balancing methods,[22] as it is shown in Figure 7.

Let:

- $N_{failures}$ be the number of failed handoff attempts.
- $N_{attempts}$ be the total number of handoff attempts.

The handoff failure rate is:

$$\text{Failure Rate} = \frac{N_{failures}}{N_{attempts}} \times 100 \quad (4)$$

Conclusion

We present a novel two-phase grouping strategy in this study that can be applied in vehicular network environments to achieve load balancing between neighboring BSs. To enable potential load redistribution, densely populated areas were identified in the first phase using the OPTICS algorithm, which grouped vehicles based on spatial density. The second phase refined vehicle assignments to BSs with the goal of balancing the load by applying K-Medoid clustering in the overlapping regions between adjacent BSs. The proposed approach is particularly effective in scenarios where frequency reuse is limited, as it does not require inter-BS range coordination. To address the continuous mobility of vehicles, future work will focus on integrating mobility prediction into the load-balancing algorithm to improve the robustness and efficiency of the handoff process. Furthermore, exploring additional clustering techniques such as self-organizing maps (SOMs) or hierarchical clustering may further optimize load balancing in more complex

environments. Reassigning frequency ranges produced a more evenly distributed load, reducing load disparities by at least 17.5% and significantly improving overall load distribution without requiring BSs to coordinate frequency use or reallocate bandwidth. Future research will also focus on integrating aerial platforms with AI for wireless optimization, including a detailed analysis of energy constraints, scalability considerations, and the behavior of AI models (e.g., graph-based optimization and reinforcement learning) in collaborative drone and IoT (FANET) systems for enhancing real-time smart city applications.

References

1. Wang Y, Chen H. K-medoid clustering approach for VANET performance optimization. IEEE Access. 2023;11:1–10.
2. Ahmed M, Khan S, Li X, Patel R, Kim J, Zhao Y, et al. Dynamic spectrum reuse with load balancing strategies in VANETs. In: Proceedings of the International Conference on Vehicular Networks. 2024.
3. Hajihosseinlou M, Maghsoudi A, Ghezelbash R. A comparative study of OPTICS, GMM, and K-means clustering for geochemical anomaly detection in catchment basins. Geochemistry. 2024;84(2):126094.
4. Lee H, Jung S, Lim J. Performance evaluation of round-robin scheduling in vehicular ad hoc networks. IEEE Trans Veh Technol. 2019;68(7):6376–87.
5. Haider SE, Khan MF, Saeed Y. Adaptive load balancing for mitigating congestion in VANETs. Computers. 2024;13(8):194. https://doi.org/10.3390/computers13080194
6. Zhao J, Liu Y, Wang T, Chen R, Kumar S, Li P, et al. Cluster-based resource selection for 5G V2X. In: IEEE Vehicular Technology Conference. 2019. https://doi.org/10.1109/VTCSpring.2019.8746637
7. Liu H, Zhao J, Wang X, Zhang L, Li Y, Chen P, et al. Clustering-based load balancing in VANETs with spectrum reuse. Wirel Commun Mob Comput. 2020;2020:8897452. https://doi.org/10.1155/2020/8897452
8. Murshedi TA, Almuttairi R, Satar R, Al-sultany G, Almhanna M, Al-Turaihi F, et al. Optimizing cloud operations using ant colony load balancing for sustainable computing. Int J Intell Eng Syst. 2024;17(5). https://doi.org/10.22266/ijies2024.1031.23
9. Alkhafaji AR, Al-Turaihi FSS. Traffic-aware QoS in SDN/NFV-5G networks with multi-layer slicing. In: 2022 8th International Conference on Contemporary Information Technology and Mathematics (ICCITM). 2022.
10. Patel S, Kumar R, Lee J, Zhang H, Gomez F, Li Y, et al. Resource management in VANETs: clustering and load balancing. IEEE Commun Surv Tutorials. 2023.
11. Alomari MF, Mahmoud MA, Yusoff YB, Gharaei N, Abdalla RA, Gunasekaran SS. Data encryption-enabled cloud cost optimization and energy efficiency for border security. IEEE Access. 2023;11:104126–104141. https://doi.org/10.1109/ACCESS.2023.3317883
12. Lee H, Jung S, Lim J. Performance evaluation of round-robin scheduling in vehicular ad hoc networks. IEEE Trans Veh Technol. 2019;68(7):6376–87. https://doi.org/10.1109/TVT.2019.2915561
13. Ahmed A, Rahim R, Kim K. Threshold-based handoff for adaptive load balancing in mobile networks. J Netw Comput Appl. 2017;94:89–98. https://doi.org/10.1016/j.jnca.2017.06.009
14. Wong PW, Chin LM, Goh MC. Signal strength-driven clustering for efficient VANET handoff management. Wirel Netw. 2020;26(2):423–33. https://doi.org/10.1007/s11276-018-1887-2
15. Husnain G, Anwar S. Whale optimization-based intelligent clustering for VANETs (WOACNET). PLoS One. 2021;16(4):e0250271. https://doi.org/10.1371/journal.pone.0250271
16. Park J, Park H, Lee Y. Fuzzy logic load balancing in vehicular networks. IEEE Access. 2020;8:30849–60. https://doi.org/10.1109/ACCESS.2020.2972705
17. Wu P, Feng X. Fuzzy logic approach for load balancing in VANETs. IEEE Access. 2022;10:23356–66. https://doi.org/10.1109/ACCESS.2022.3153472
18. Zheng Y, Wu Y, Xu Z, Lin X. Cluster-on-demand algorithm with load balancing for VANET. In: Hsu CH, Wang S, Zhou A, Shawkat A, editors. Internet of vehicles – technologies and services. Lecture Notes in Computer Science. Vol. 10036. Cham: Springer; 2016. p. 105–18. https://doi.org/10.1007/978-3-319-51969-2_10
19. Roy R, Suganthan T. Machine learning-driven cluster-based routing in VANETs. Neurocomputing. 2022;344:151–9. https://doi.org/10.1016/j.neucom.2021.11.001
20. Wang B, Xiao L. Machine learning-based clustering for load balancing in VANETs. IEEE Trans Veh Technol. 2022;71(5):4152–63. https://doi.org/10.1109/TVT.2022.3148735
21. Alomari M, Alrubaye J, Alaidi AH, Alrikabi H. Energy-aware collaborative routing protocol using bio-inspired algorithms for heterogeneous wireless sensor networks. J Adv Inf Technol. 2025;16(5):696–709. https://doi.org/10.12720/jait.16.5.696-709
22. Liu H, Zhao J, Wang X, Zhang L, Li Y, Chen P, et al. Clustering-based load balancing in VANETs with spectrum reuse. Wirel Commun Mob Comput. 2020;2020:8897452. https://doi.org/10.1155/2020/8897452
23. Alsharif M, Kim J, Park J, Kang S, Ahmed A, Song H, et al. Density-based clustering for dynamic load balancing in vehicular networks. IEEE Trans Veh Technol. 2018;67(3):1972–85. https://doi.org/10.1109/TVT.2017.2779838
24. Chen Z, Li X, Zhang Y, Wang H, Zhao L, Xu M, et al. Mobility-aware clustering for VANET load balancing. J Commun Netw. 2019;21(5):499–510. https://doi.org/10.1109/JCN.2019.000059
25. Zhou L, Zhang J, Wang Y, Chen X, Li P, Zhao Q, et al. Adaptive handover optimization in VANETs. IEEE Commun Lett. 2018;22(7):1456–9. https://doi.org/10.1109/LCOMM.2018.2828655
26. Fan Z, Liu Y, Chen W, Zhang H, Li X, Wang J, et al. Cooperative load balancing in vehicular networks. IEEE Trans Mob Comput. 2020;19(6):1342–55. https://doi.org/10.1109/TMC.2019.2903903
27. Cicioğlu M. Fuzzy logic handover management in small cell networks. In: 2021 29th Signal Processing and Communications Applications Conference (SIU). 2021. p. 1–4. https://doi.org/10.1109/SIU53274.2021.9477934
28. Al-Hchaimi AJ, Alaidi AH, Muhsen YR, Alomari MF, Sulaiman NB, Romdhini MU, et al. Optimizing energy

and QoS in VANETs through approximate computation on heterogeneous MPSoC. In: 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA); 2024. https://doi.org/10.1109/eSmarTA62850.2024.10638904
29. Alomari MF, Mahmoud MA, Ramli R. Energy efficiency of dynamic clustering in heterogeneous WSN environments: a systematic review. Electronics. 2022;11(18):2837. https://doi.org/10.3390/electronics11182837
30. Ramchurn R. Advancing autonomous vehicle technology: embedded systems prototyping and validation. SCCTS J Embedded Syst Des Appl. 2025;2(2):56–64.
31. Alrubaye JS, Ghahfarokhi BS. Geo-based resource allocation for joint clustered V2I and V2V communication. IEEE Access. 2023;11:82601–12. https://doi.org/10.1109/ACCESS.2023.3300294
32. Gupta S, Garg RK. Comparative study of clustering algorithms for load balancing in VANETs. Int J Comput Netw Commun. 2021;12(4):55–69. https://doi.org/10.5121/ijcnc.2021.12404
33. Zhu C, Li S, Zhang Z. Adaptive clustering algorithm for VANET-based Internet of Vehicles. Mob Netw Appl. 2021;26(3):1087–1101. https://doi.org/10.1007/s11036-020-01697-z
34. Hamdi M, Amar H, Chaabouni R. Hybrid genetic algorithm for load balancing in VANETs. J Netw Comput Appl. 2021;99:65–75. https://doi.org/10.1016/j.jnca.2021.05.006
35. Zakaria R, Zaki FM. Vehicular ad-hoc networks (VANETs) for enhancing road safety and efficiency. Prog Electron Commun Eng. 2024;2(1):27–38. https://doi.org/10.31838/PECE/02.01.03
36. Gupta S, Pahwa P. Hybrid PSO-ACO clustering algorithm for VANET load balancing. Wirel Netw. 2022;28:345–56. https://doi.org/10.1007/s11276-021-02841-4
37. Al-Turaihi FS, Al-Raweshidy HS. Super adaptive routing protocol for MANETs. In: Arai K, Kapoor S, Bhatia R, editors. Intelligent computing: proceedings of the 2018 computing conference. Vol. 2. Cham: Springer; 2019. p. 834–48. https://doi.org/10.1007/978-3-030-22871-2_59
38. Zhao Y, Hu T, Lin J. Density-aware load balancing in VANETs under dynamic traffic conditions. IEEE Access. 2021;9:12978–89. https://doi.org/10.1109/ACCESS.2021.3051584
39. Sindhu S. RFID-based asset tracking system using beam-steerable antennas for enhanced range and accuracy. Natl J RF Circuits Wirel Syst. 2024;1(1):28–38.
40. Colyar J, Halkias J. US highway dataset. Federal Highway Administration (FHWA); 2007.
41. Alomari MF, Alaidi AH, Alrikabi H, Almohammed OA, Abdulsattar NH, Mahdi SS, et al. Optimizing cloud storage costs: introducing the pre-evaluation-based cost optimization (PECSCO) mechanism. In: 4th International Conference of Science and Information Technology in Smart Administration (ICSINTESA). IEEE; 2024. https://doi.org/10.1007/978-3-031-75091-5_5
42. Shafiq M, Raza A. Load balancing perspective on clustering in VANETs. IEEE Trans Mob Comput. 2023;22(4):1967–82. https://doi.org/10.1109/TMC.2021.3136784
43. Al-Hchaimi AAJ, Alaidi AH, Alrikabi H, Alomari MF, Sulaiman NB, Romdhini MU, et al. Energy and QoS optimization in VANETs using approximate computation on heterogeneous MPSoCs. In: 2024 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA). IEEE; 2024. https://doi.org/10.1109/eSmarTA62850.2024.10638904
44. Alomari MF, Alsammak ILH, Rasool SM. Lifetime enhancement of mobile nodes in WSNs using routing algorithms. Technology. 2021.
45. Li X, Yang M. Fuzzy logic-based clustering for VANET load management. IEEE Trans Veh Technol. 2023;72(2):457–68. https://doi.org/10.1109/TVT.2022.3225098
46. Kaur J, Gupta S. Optimizing VANET clustering using PSO-based algorithms. IEEE Trans Intell Transp Syst. 2021;22(11):3638–51. https://doi.org/10.1109/TITS.2020.3021464
47. Quy NM, Chehri A, Quy VK, Nguyen TP, Tran QT, Pham VH, et al. Multi-agent clustering algorithm for VANETs in 5G networks. Wirel Netw. 2024. https://doi.org/10.1007/s11276-023-03627-8
48. James A, Elizabeth C, Henry W, Rose I. Energy-efficient communication protocols for long-range IoT sensor networks. J Wirel Sens Netw IoT. 2025;2(1):62–8.