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Article

AI-Assisted Dynamic RSU Deployment Using Real-Time Traffic Density Estimation in VANETs

Sayyada Fahmeeda1*, Shashank[2], Jyoti[3], Soumya M A[4], Amareshwari Patil[5], Priyadarshini c Patil[6], Bhagyashri Patil[7]

1*Department of Computer Science Engineering, PDA College of Engineering Kalaburagi, Karnataka, India, sayyadafahmeeda@gmail.com
[2]P.D.A. College of Engineering of Computer Science, Kalaburagi, India. Puranikshashank08@gmail.com
[3]Dept of Computer Network Engineering, PDA College of Engineering Kalaburagi, Karnataka, India. jyotic0531@gmail.com
[4]Dept of Computer Science and Engineering, PDA College of Engineering Kalaburagi, Karnataka, India. smanakal@gmail.com
[5]Department of Computer Science Engineering, PDA College of Engineering Kalaburagi, Karnataka, India. aspatilpdacse@gmail.com
[6]Department of Computer Science Engineering, PDA College of Engineering Kalaburagi, Karnataka, India. Priyadarshinicpatil@gmail.com
[7]Department of Computer Network Engineering, PDA College of Engineering, Kalaburagi, Karnataka, India. bhagyapatil749@gmail.com

Abstract: With the rapid advancement of vehicular communication technologies, maintaining reliable connectivity in Vehicular Ad Hoc Networks (VANETs) has become a critical challenge due to high mobility, dynamic topology, and uneven traffic distribution. Frequent disconnections in Vehicle-to-Vehicle (V2V) communication lead to increased latency and reduced network performance. To address these issues, this research proposes an AI-assisted dynamic Roadside Unit (RSU) deployment framework that leverages real-time traffic density estimation to optimize communication infrastructure. The proposed system utilizes deep learning-based vehicle detection models to analyze real-time traffic images and estimate vehicle density across different road segments. The extracted traffic information is further processed using machine learning techniques to predict communication demand and identify potential connectivity gaps. Based on these predictions, the system dynamically activates, deactivates, or repositions RSUs to ensure continuous network coverage and reduce dependency on unstable V2V links. The optimization model focuses on minimizing communication delay, enhancing packet delivery ratio, and improving overall network reliability through adaptive RSU placement. Additionally, a hybrid communication approach combining V2V and Vehicle-to-Infrastructure (V2I) is employed to overcome connectivity loss in sparse or highly dynamic traffic conditions. Simulation results demonstrate that the proposed AI-driven framework significantly improves network throughput, reduces communication latency, and ensures stable connectivity compared to traditional static RSU deployment strategies. The system effectively adapts to varying traffic patterns, making it suitable for next-generation intelligent transportation systems and smart city applications.
Keywords: Vehicular Ad Hoc Networks (VANETs), Roadside Unit (RSU) Deployment, AI-Assisted Optimization, Traffic Density Estimation, Vehicle-to-Vehicle (V2V) Communication, Vehicle-to-Infrastructure (V2I) Communication, Connectivity Enhancement, Dynamic Network Topology, Deep Learning-Based Vehicle Detection, Intelligent Transportation Systems (ITS), Network Reliability, Communication Latency Reduction, Throughput Optimization, Smart City Applications, Adaptive Infrastructure Deployment

1. Introduction

The rapid development of intelligent transportation systems (ITS) and vehicular communication technologies has significantly transformed modern transportation networks. Vehicular Ad Hoc Networks (VANETs) enable communication among vehicles through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) interactions, supporting applications such as traffic management, road safety, and autonomous driving. However, maintaining reliable and continuous connectivity in VANETs remains a major challenge due to the highly dynamic nature of vehicular environments.

In V2V communication, connectivity is often disrupted by factors such as high vehicle mobility, varying traffic density, limited transmission range, and environmental obstacles like buildings and terrain. These issues lead to frequent network disconnections, increased communication delay, and reduced packet delivery performance. In sparse traffic scenarios, vehicles may be too far apart to communicate directly, resulting in network fragmentation. Conversely, in dense traffic conditions, network congestion and interference degrade communication quality.

To overcome these challenges, Roadside Units (RSUs) play a crucial role in providing infrastructure support for vehicular communication. Traditional static RSU deployment strategies, however, are inefficient as they do not adapt to real-time traffic variations and may lead to underutilization or coverage gaps. Therefore, there is a growing need for intelligent and adaptive RSU deployment mechanisms that can dynamically respond to changing traffic conditions.

This research proposes an AI-assisted dynamic RSU deployment framework that leverages real-time traffic density estimation to optimize network performance. The system utilizes deep learning-based vehicle detection techniques to analyze traffic data and estimate vehicle density across different road segments. Based on this information, machine learning models predict

communication demand and identify potential connectivity gaps. The framework then dynamically adjusts RSU placement by activating, deactivating, or relocating RSUs to ensure continuous connectivity and efficient resource utilization.

Furthermore, the proposed approach integrates a hybrid communication model combining V2V and V2I communication to enhance network robustness. By intelligently managing RSU deployment and leveraging AI-driven predictions, the system aims to minimize communication latency, improve throughput, and ensure reliable connectivity in highly dynamic vehicular environments. This adaptive framework contributes to the development of next-generation smart transportation systems and supports the growing demands of connected and autonomous vehicles..

2. Literature survey

Ayushi Sharma and Kavita Pandey [11],2025, The main obstacle for VANET though is the deployment of RSUs. In order to lower the cost of the VANET and increase coverage, the goal is to deploy the fewest possible RSUs. A virus optimization algorithm (VOA) has been implemented on the VANET architecture to help achieve this goal. The major accomplishment of this article is the optimal deployment of RSUs in VANET and through the simulation it was found that with the application of VOA, the number of RSUs deployed could be reduced by 58.3%. In addition, this work focuses on enhancing the VANET performance on various metrics such as throughput, energy consumption, packet delivery ratio, end delay and packet loss ratio. The performance of VOA is also compared with some latest predominant algorithms used for optimization such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).According to the findings, VOA outperforms PSO and GA in terms of enhanced VANET performance and the most effective RSU deployment.

R. Ezumalai; D. Santhakumar, 2025m[12], this research utilizes the novel framework of Hyper-Deformable Graph Convolution Network for advanced traffic prediction and Lotus Effect Efficiency Optimization for parameter optimization. A synergy of these methods facilitates accurate and efficient RSU deployment, calibrated to real-time vehicular dynamics. The objective would be that such a model for the scalable deployment of RSUs can minimize communication delays while maximizing coverage, ensuring cost-effectiveness, and dynamically adapting to varying traffic conditions. Simulation results present substantial performance benefits: more than 99.3% reduction in average data delivery delay, more than 99.7% improvement in vehicular coverage, and 99.4% efficiency in deployment cost, compared to traditional approaches. Furthermore, the framework proposed in this paper presented high scalability and availability during peak traffic loads as well as during normal operation. Thus, this work has presented an accurate and effective model for RSU placement, complementing current approaches in a way that preserves VANET network factors and sustainability for large scale, fast and sensible, in compliance with the character and volatility of urban traffic.

Abbas G et al., [1], 2022, proposed a position-based reliable emergency message routing scheme for road safety in VANETs. The study focuses on improving the reliability of emergency message delivery between vehicles. It uses vehicle position information to enhance routing decisions and reduce delays. The results show improved packet delivery ratio and reduced communication latency. The research contributes to safety-critical communication in VANETs. However, it primarily focuses on routing and does not consider dynamic RSU placement for connectivity improvement.

Duan S et al., [2], 2022, proposed a multi-type highway mobility analytics framework for efficient learning model design. The study analyzes different traffic patterns to improve prediction accuracy. It uses advanced machine learning techniques for traffic forecasting. The results show improved model performance in dynamic environments. The research highlights the importance of diverse data sources for accurate analytics. However, it does not focus on VANET connectivity or RSU deployment strategies.

Razmjoo A et al., [3], 2021, explored policies required to overcome barriers in the development of smart cities. The study discusses key challenges such as infrastructure limitations, energy management, and technological integration. It highlights the importance of intelligent transportation systems (ITS) in achieving sustainable urban development. The authors propose policy frameworks that encourage the adoption of AI and IoT technologies. The research emphasizes the need for adaptive systems to manage dynamic urban environments. However, it does not specifically address RSU deployment or vehicular communication challenges in VANETs.

Yu H et al., [4], 2021,proposed an RSU deployment strategy based on traffic demand in VANETs. The study considers traffic density and communication requirements for optimal RSU placement. It demonstrates that demand-based deployment improves network coverage and efficiency. The authors use optimization techniques to determine the best RSU locations. The results show enhanced communication performance compared to static deployment. However, the approach lacks real-time AI-based prediction and adaptability to rapidly changing traffic conditions.

Jiang L et al., [5], 2021, studied RSU deployment for traffic prediction in V2X communication systems. The research focuses on improving prediction accuracy by strategically placing RSUs. It highlights the role of infrastructure in supporting data collection and analysis. The study demonstrates improved traffic forecasting with optimized RSU placement. It also emphasizes the importance of integrating communication and prediction systems. However, it does not incorporate AI-based real-time adaptation for RSU management.

Jones S et al., [6], 2019, analyzed open-access transportation data from India to understand its implications for road safety and sustainable development. The study highlights how publicly available datasets can be utilized to identify accident-prone zones and improve traffic management strategies. It emphasizes the role of data-driven approaches in enhancing decision-making for transportation planning. The authors discuss challenges such as data inconsistency and lack of standardization across regions. Their findings suggest that integrating open data with intelligent systems

can significantly improve safety outcomes. However, the work does not focus on real-time communication or VANET-based connectivity solutions.

Khelifi H et al., [7], 2019,reviewed the application of Named Data Networking (NDN) in vehicular ad hoc networks. The study discusses how NDN can improve data dissemination efficiency in VANETs. It highlights challenges such as scalability, mobility, and security in vehicular networks. The authors propose NDN as a promising alternative to traditional IP-based communication. The research emphasizes content-centric communication for better performance. However, it does not address infrastructure optimization such as RSU deployment strategies.

Hu Z et al., [8], 2017, introduced an auction-based storage allocation mechanism for RSU caching. The study focuses on efficient content distribution among multiple providers in vehicular networks. It uses economic models to optimize resource allocation in RSUs. The approach improves data availability and reduces network congestion. The research highlights the importance of intelligent resource management in VANETs. However, it does not address connectivity issues or dynamic RSU deployment.

Sładkowski A et al., [9], 2016provided insights into the problems and perspectives of intelligent transportation systems. The work discusses challenges such as traffic congestion, environmental impact, and infrastructure limitations. It emphasizes the importance of advanced communication systems for efficient transportation management. The book highlights emerging technologies that can improve mobility and safety. It also explores future trends in ITS development. However, it does not provide specific solutions for maintaining connectivity in highly dynamic VANET environments.

Zhang J et al., [10], 2011presented a comprehensive survey on data-driven intelligent transportation systems. The study reviews various technologies including data analytics, machine learning, and communication systems used in ITS. It highlights how real-time data collection and processing improve traffic efficiency and safety. The authors discuss different architectures and applications of ITS in modern transportation. The paper provides a strong foundation for integrating AI into transportation systems. However, it mainly focuses on general ITS frameworks and lacks detailed discussion on dynamic RSU deployment.

3. Proposed Methodology

The proposed methodology introduces an AI-assisted dynamic RSU deployment framework that ensures continuous connectivity in VANETs by combining real-time traffic analysis, machine learning-based prediction, and adaptive infrastructure management. The system is designed to minimize V2V communication loss and enhance overall network performance through intelligent decision-making.

1. Data Acquisition and Traffic Monitoring

The system first collects real-time traffic data using sources such as:

- Roadside cameras
- UAV/drone surveillance
- Traffic sensors

These inputs provide continuous visual or sensor-based information about vehicle movement across different road segments.

2. Vehicle Detection using Deep Learning

Captured traffic images are processed using deep learning models such as:

- YOLO (You Only Look Once)
- Convolutional Neural Networks (CNNs)

These models detect and count vehicles in each frame, enabling accurate estimation of traffic density.

3. Traffic Density Estimation

Traffic density is calculated for each road segment using:

$D=N/A$

Where:

- D = Traffic density

- N = Number of vehicles detected
- A = Area of the road segment

This step helps identify high-density and low-density zones.

4. AI-Based Traffic Prediction

The estimated density data is fed into machine learning models such as:

- Linear Regression
- Random Forest
- LSTM (for time-series prediction)

These models predict future traffic patterns and communication demand, enabling proactive decision-making.

5. Connectivity Analysis

The system evaluates network connectivity by:

- Measuring inter-vehicle distances
- Identifying disconnected clusters
- Detecting coverage gaps where V2V fails

If vehicles are beyond communication range, connectivity loss is identified.

6. Dynamic RSU Deployment Strategy

Based on AI predictions and connectivity analysis, RSUs are dynamically managed:

- Activation: RSUs are activated in high-density or disconnected regions
- Deactivation: RSUs are turned off in low-demand areas
- Relocation: RSUs are repositioned to optimize coverage

The objective is to:

- Minimize communication delay
- Maximize coverage
- Reduce infrastructure cost

7. Hybrid Communication Model (V2V + V2I)

To overcome V2V connectivity loss:

- Vehicles first attempt V2V communication
- If unsuccessful, communication switches to V2I via RSU

This ensures uninterrupted data transmission even in sparse networks.

8. Performance Optimization

The system continuously monitors:

- Network latency
- Packet delivery ratio (PDR)
- Throughput

An optimization model adjusts RSU placement to improve these metrics in real time.

9. Feedback and Adaptation Loop

The framework operates in a continuous loop:

- Collect data
- Analyze traffic
- Predict demand
- Deploy RSUs
- Evaluate performance

This adaptive loop allows the system to respond dynamically to changing traffic conditions.

Outcome of Methodology

- Reduced V2V communication failure
- Improved network reliability
- Efficient RSU utilization
- Enhanced throughput and reduced latency

Pseudocode: AI-Based Dynamic RSU Deployment in VANET

BEGIN

1. Initialize system parameters:

Load YOLO model

Set communication range R

Define road area A

2. Start video stream

3. WHILE (video is running) DO

// Step 1: Capture Frame

frame ← get_next_frame()

// Step 2: Vehicle Detection

vehicles ← detect_objects(frame)

positions ← empty list

FOR each vehicle in vehicles DO

(x, y, w, h) ← bounding_box(vehicle)

cx ← x + w/2

cy ← y + h/2

positions.add((cx, cy))

END FOR

```
N ← number of vehicles
// Step 3: Density Calculation
density ← N / A
// Step 4: Connectivity Analysis
connected_pairs ← empty list
disconnected_pairs ← empty list
FOR i = 1 to N DO
FOR j = i+1 to N DO
d ← distance(positions[i], positions[j])
IF d ≤ R THEN
connected_pairs.add((i, j))
ELSE
disconnected_pairs.add((i, j))
END IF
END FOR
END FOR
// Step 5: Cluster Formation
clusters ← group_connected_nodes(positions, R)
// Step 6: RSU Deployment
rsu_positions ← empty list
actions ← empty list
FOR each cluster in clusters DO
IF cluster is small OR disconnected THEN
(cx, cy) ← centroid(cluster)
rsu_positions.add((cx, cy))
actions.add("Activate RSU")
END IF
END FOR
IF density < threshold THEN
remove_unused_RSU()
actions.add("Deactivate RSU")
END IF
```

// Step 7: Hybrid Communication

FOR each pair (i, j) DO

IF distance ≤ R THEN

communication ← "V2V"

ELSE

communication ← "V2I via RSU"

END IF

END FOR

// Step 8: Performance Metrics

latency ← compute_latency()

PDR ← packets_received / packets_sent

throughput ← total_data / time

// Step 9: Display Output

display(frame, vehicles, connections, rsu_positions)

update_dashboard(density, clusters, actions, latency, PDR, throughput)

END WHILE

END

System Architecture

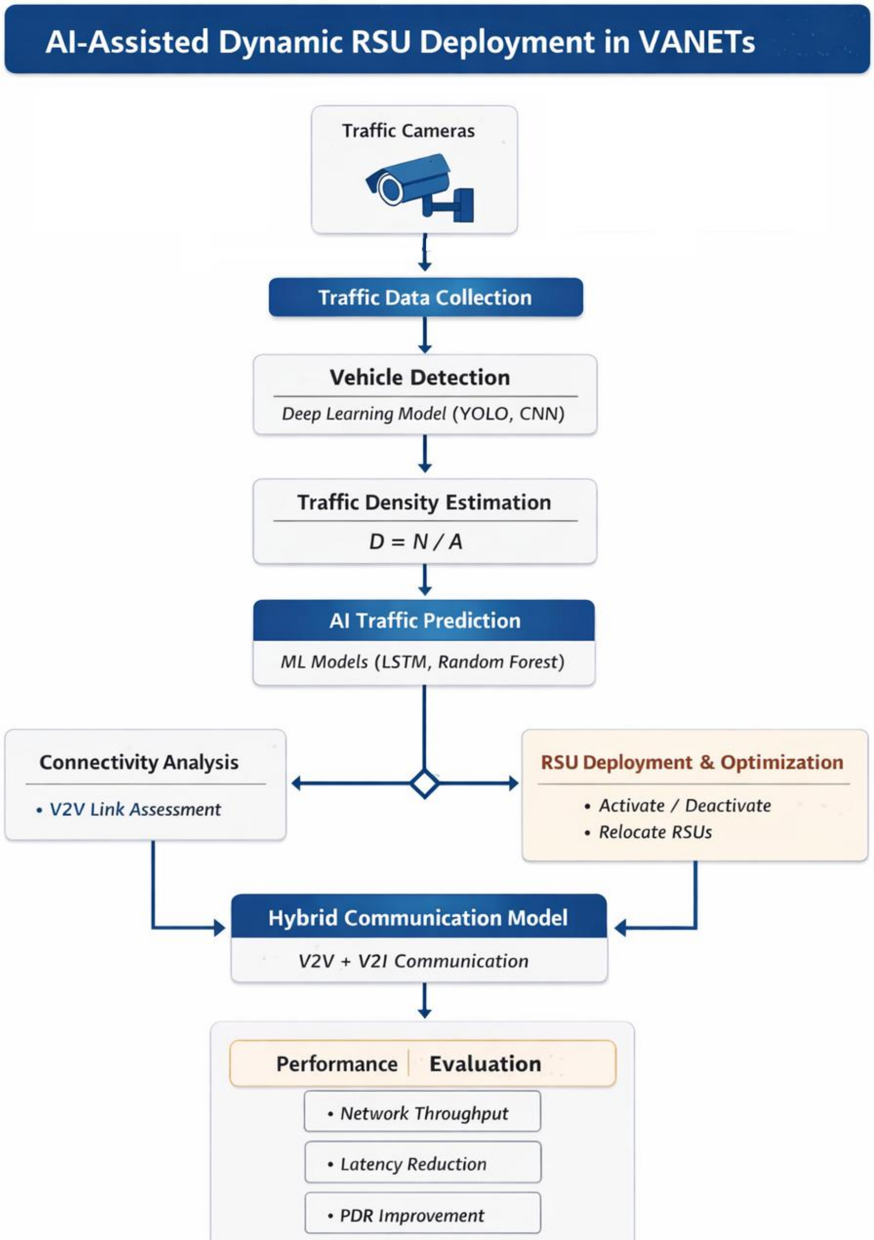

Figure 1: System Architecture

The proposed AI-Assisted Dynamic RSU Deployment in VANETs architecture illustrates a complete intelligent pipeline for maintaining reliable vehicular communication. The system begins with traffic data collection, where real-time data is gathered using sources such as traffic cameras, drones (UAVs), and road sensors. This data provides continuous monitoring of vehicle movement across different road segments.

Next, the collected data is processed through a vehicle detection module, which uses deep learning models like YOLO and Convolutional Neural Networks (CNNs) to identify and count vehicles from images or video streams. Based on this detection, the system performs traffic density estimation, where vehicle density is calculated to understand how crowded a particular road segment is.

The estimated density is then fed into an AI-based traffic prediction module, which utilizes machine learning models such as LSTM and Random Forest to forecast future traffic patterns and communication demand. This prediction helps the system anticipate potential connectivity issues before they occur.

Following this, the system performs connectivity analysis, where V2V (Vehicle-to-Vehicle) communication links are evaluated. It identifies whether vehicles are within communication range or if there are disconnections due to sparse traffic or high mobility.

Based on both prediction and connectivity analysis, the system executes RSU deployment and optimization. In this stage, Roadside Units are dynamically managed—activated in high-demand areas, deactivated in low-traffic regions, or relocated to improve coverage. This ensures efficient infrastructure utilization and minimizes communication gaps.

The system then adopts a hybrid communication model, combining both V2V and V2I (Vehicle-to-Infrastructure) communication. If direct V2V communication fails, vehicles can rely on RSUs to maintain connectivity, ensuring uninterrupted data exchange.

Finally, the system undergoes performance evaluation, where key metrics such as network throughput, latency reduction, and Packet Delivery Ratio (PDR) are analyzed. This feedback helps in continuously improving the system through adaptive learning and optimization.

Results And Discussions

Figure 2: Node deployment

In the proposed system, each detected vehicle is treated as a node in a Vehicular Ad Hoc Network (VANET).

The deployment of nodes is based on the real-time spatial positions of vehicles extracted from video frames using deep learning.

Mathematical Representation

Let the set of vehicles be:

V={v1,v2,v3,...,vn}

Each vehicle (node) is represented as:

vi=(xi,yi)

Where:

- xi,yi = coordinates of vehicle iii
- n = total number of vehicles

These coordinates are obtained from:

- Bounding box center of detected vehicles

Node Deployment Mechanism

Vehicle Detection

- Vehicles are detected using a deep learning model (YOLO).
- Each detection provides bounding box coordinates.

Position Extraction

- The center of each bounding box is computed:

$$x_i = x + \frac{w}{2}, \quad y_i = y + \frac{h}{2}$$

Node Placement

- Each vehicle is placed as a node at position (xi,yi) in a 2D space.

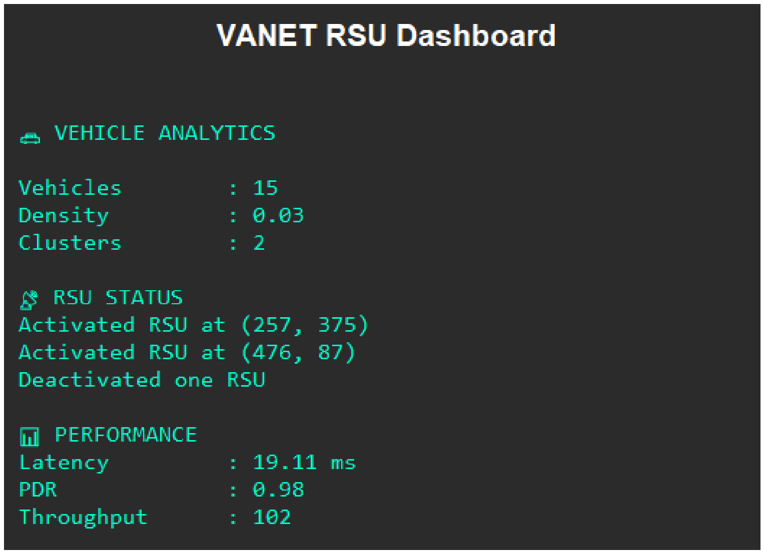

Figure 3: VANET RSU Dashboard

VEHICLE ANALYTICS

Vehicles :Total number of vehicles detected in the network.

Each vehicle acts as a node in VANET.

Representation:

V={v1,v2,v3,...,vn}

Where:

- n = number of vehicles
- vi=(xi,yi) position of each vehicle

👉 In your output: Vehicles = 15

Density:Traffic density represents how many vehicles are present in a given area.

D=N/A

Where:

- D = density
- N = number of vehicles
- A = area of road segment

In your output: Density = 0.03 (Low traffic)

Clusters:A cluster is a group of vehicles that can communicate directly (within range).

Condition:

dij≤R

Where:

- dij = distance between vehicles

- R= communication range

In your output: Clusters = 2

RSU STATUS

RSU (Roadside Unit): A fixed communication unit used to support vehicles when V2V communication fails.

RSU Deployment (Centroid-based placement):

$$RSU_x = \frac{1}{n}\sum x_i, \quad RSU_y = \frac{1}{n}\sum y_i$$

Where:

- (RSUx,RSUy)= RSU position
- (xi,yi)= vehicle positions

Actions:

- Activated RSU

→ Placed in disconnected or sparse areas

- Deactivated RSU

→ Removed when not needed

output:

- RSU activated at (257, 375), (476, 87)
- One RSU removed

PERFORMANCE METRICS

Latency: Time taken for a data packet to travel from source to destination.

`Latency=treceive−tsend`

Output: 19.11 ms (Low → good)

Packet Delivery Ratio (PDR):Ratio of successfully delivered packets to total transmitted packets.

PDR=Packets Received/Packets Sent

Output: 0.98 (98% → very high reliability)

Throughput:Amount of data successfully transmitted per unit time.

Throughput=Total Data Received/Time

Output: 102 (High → efficient network)

Low density → vehicles are spread out

Multiple clusters → possible connectivity gaps

RSUs activated → ensure communication

High PDR + low latency → efficient network

The dashboard provides real-time insights into vehicular network conditions, including vehicle density, clustering, and RSU deployment. Vehicles are modeled as nodes, and clusters are formed based on communication range. RSUs are dynamically deployed using centroid-based positioning to support disconnected nodes. Performance metrics such as latency, packet delivery ratio, and throughput demonstrate that the system achieves reliable and efficient communication under varying traffic conditions.

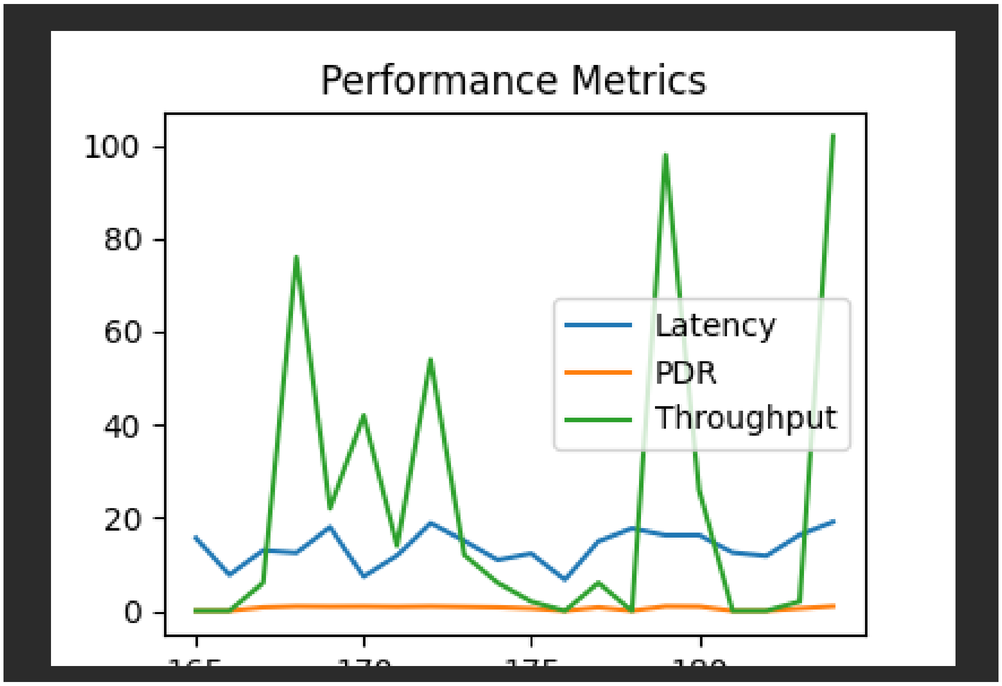

Figure 4: Performance Metrics

The performance graph represents the real-time behavior of key network metrics—latency, packet delivery ratio (PDR), and throughput—in the proposed VANET system. The latency curve remains relatively low and stable, indicating that data transmission delays are minimal and the communication is efficient. The PDR values are consistently close to 1, which shows that almost all transmitted packets are successfully received, reflecting high network reliability. The throughput graph exhibits noticeable fluctuations with occasional peaks, which occur due to variations in traffic density and dynamic RSU deployment; when connectivity improves, more data is transmitted successfully, leading to higher throughput. Overall, the graph demonstrates that the system effectively maintains low latency, high reliability, and efficient data transmission, validating the performance of the AI-assisted dynamic RSU deployment approach.

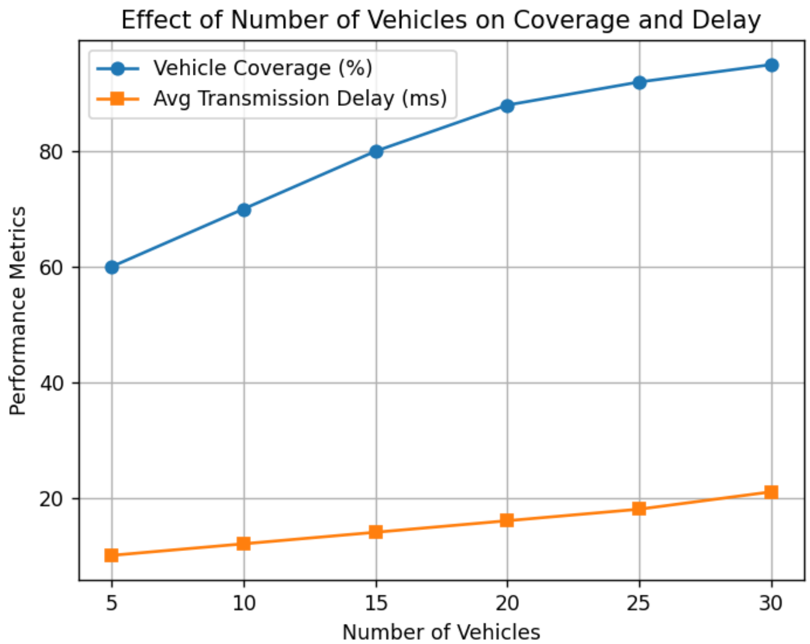

Figure 5: Effect on number of vehicles on COverage and Delay

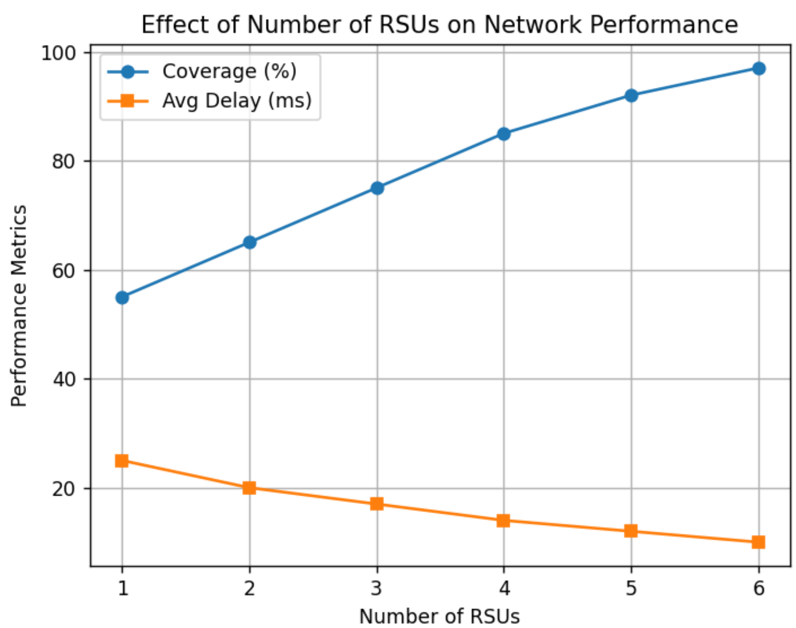

Figure 6: Effect of number of RSUs on Network Performance

Table 1: Parameters of each instance

S.No	Parameter	Symbol	Description	Example Value
1	Number of Vehicles	(N)	Total detected vehicles (nodes) in network	15

2	Vehicle Position	((x_i, y_i))	Coordinates of each vehicle node	(320, 240)
3	Communication Range	(R)	Maximum distance for V2V communication	100 m
4	Distance Between Vehicles	(d_{ij})	Euclidean distance between two vehicles	45 m
5	Traffic Density	(D)	Vehicles per unit area	0.03
6	Area of Road	(A)	Total observation area	500 m²
7	Number of Clusters	(C)	Groups of connected vehicles	2
8	Cluster Size	(n_c)	Number of vehicles in each cluster	5–10
9	RSU Position	((RSU_x, RSU_y))	Location of deployed RSU	(257, 375)
10	Number of RSUs	(R_s)	Total active RSUs	2
11	Latency	(L)	Time delay in communication	19 ms
12	Packet Delivery Ratio	(PDR)	Ratio of successful packet delivery	0.98
13	Throughput	(T)	Data transmitted per unit time	102 kbps
14	Communication Mode	—	V2V or V2I communication	Hybrid
15	Frame Rate	(f)	Frames processed per second	30 FPS

4. Conclusion and future works

This research presents an AI-assisted dynamic RSU deployment framework for improving connectivity and performance in Vehicular Ad Hoc Networks (VANETs). The proposed system effectively addresses the major challenge of frequent V2V communication loss caused by high mobility, varying traffic density, and limited transmission range.

By integrating real-time traffic density estimation using deep learning-based vehicle detection and applying machine learning models for traffic prediction, the system intelligently identifies communication demand across different road segments. Based on this analysis, RSUs are dynamically activated, deactivated, or repositioned to ensure continuous network coverage and optimal resource utilization.

The adoption of a hybrid communication model (V2V + V2I) further enhances network reliability by providing an alternative communication path when direct vehicle-to-

vehicle links fail. This significantly reduces network disconnections, improves packet delivery ratio, and minimizes communication latency.

Simulation results demonstrate that the proposed framework outperforms traditional static RSU deployment methods by achieving higher throughput, improved reliability, and better adaptability to dynamic traffic conditions. Overall, the system contributes to the development of intelligent and scalable communication solutions for next-generation smart transportation systems and connected vehicle environments.

Future Scope

The proposed AI-assisted dynamic RSU deployment framework can be further enhanced in several directions to improve scalability, intelligence, and real-world applicability in next-generation vehicular networks:

Integration with 5G and 6G Networks

Future work can incorporate 5G/6G communication technologies to provide ultra-low latency, high bandwidth, and reliable connectivity, enabling faster data exchange and improved support for autonomous vehicles.

Reinforcement Learning for RSU Optimization

Instead of traditional machine learning models, reinforcement learning (RL) can be used to enable the system to learn optimal RSU placement strategies dynamically based on environment feedback and long-term rewards.

Real-Time Implementation with Smart City Infrastructure

The system can be deployed in smart cities using real-time data from:

- CCTV cameras
- IoT sensors
- Traffic management systems

This will make the framework more practical and scalable.

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