

AI-Assisted Dynamic RSU Deployment Using Real-Time Traffic Density Estimation in VANETs: A Comprehensive Survey

Shashank¹, Dr. Sayyada F²

¹ Student, Dept. Of computer science and engineering, PDA college of engineering, Kalaburagi, India.

² Associate Professor, Dept. Of computer science and engineering, PDA college of engineering, Kalaburagi, India.

ABSTRACT

Vehicular Ad Hoc Networks (VANETs) have become a cornerstone of Intelligent Transportation Systems (ITS), enabling real-time communication among vehicles, roadside infrastructure, and transportation management entities. Roadside Units (RSUs) play a critical role in supporting Vehicle-to-Infrastructure (V2I) communications, traffic monitoring, safety applications, and information dissemination. However, conventional static RSU deployment strategies often fail to accommodate rapidly changing traffic conditions, resulting in reduced coverage efficiency, increased communication delays, and inefficient utilization of infrastructure resources. To address these limitations, recent research has focused on integrating Artificial Intelligence (AI) techniques with real-time traffic density estimation to support dynamic and adaptive RSU deployment. This survey presents a comprehensive review of AI-assisted dynamic RSU deployment approaches in VANET environments. The study examines traffic density estimation methods, RSU deployment strategies, optimization algorithms, machine learning models, deep learning techniques, and emerging intelligent transportation frameworks. Furthermore, the survey categorizes existing literature according to deployment methodology, traffic prediction approach, and intelligence level while providing a comparative analysis of current solutions. Major research challenges including scalability, computational complexity, security, privacy, and infrastructure costs are discussed. Finally, future research directions involving reinforcement learning, federated learning, edge intelligence, digital twins, unmanned aerial vehicle-assisted RSUs, and 6G-enabled vehicular networks are highlighted. The survey aims to serve as a comprehensive reference for researchers and practitioners working toward the development of adaptive, intelligent, and efficient vehicular communication infrastructures.

Keywords: Vehicular Ad Hoc Networks, Roadside Units, Dynamic RSU Deployment, Traffic Density Estimation, Artificial Intelligence, Machine Learning, Intelligent Transportation Systems, V2X Communication, Smart Mobility.

1. Introduction

The rapid growth of urbanization, increasing vehicle ownership, and the rising demand for intelligent mobility services have significantly transformed modern transportation systems. Traditional traffic management approaches are often inadequate for handling dynamic traffic conditions, congestion, road safety concerns, and communication requirements in large-scale transportation networks. Consequently, Intelligent Transportation Systems (ITS) have emerged as an essential technological framework for improving transportation efficiency, road safety, and sustainable mobility through the integration of communication technologies, sensing devices, and data-driven decision-making mechanisms.

Data-driven transportation management has become a fundamental component of modern ITS. Zhang et al. (2011) highlighted the importance of intelligent transportation systems that leverage large-scale traffic data to support traffic prediction, congestion management, and infrastructure optimization. Similarly, Śladkowski and Pamuła (2016) emphasized that intelligent transportation infrastructures require continuous monitoring and adaptive management strategies to meet the increasing complexity of urban transportation environments. The growing availability of traffic data from connected vehicles, sensors, and transportation networks has further accelerated the development of smart mobility solutions and intelligent traffic control systems.

The concept of smart cities has also contributed significantly to the advancement of intelligent transportation infrastructures. Razmjoo et al. (2021) identified intelligent transportation as a critical component of sustainable smart city development and emphasized the need for efficient communication infrastructures capable of supporting real-time decision-making. Furthermore, open transportation datasets have provided valuable opportunities for traffic analysis and safety assessment. Jones et al. (2019) demonstrated how open-access traffic

and road safety data can be utilized to improve transportation planning and support sustainable development objectives.

Vehicular Ad Hoc Networks (VANETs) represent one of the most important enabling technologies within intelligent transportation systems. VANETs facilitate communication among vehicles and infrastructure components through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication mechanisms. These networks support numerous applications, including collision avoidance, traffic monitoring, route optimization, emergency message dissemination, and autonomous driving assistance. Khelifi et al. (2019) reviewed the evolution of VANET communication architectures and highlighted their role in supporting next-generation intelligent transportation services. Likewise, Abbas et al. (2022) demonstrated the importance of reliable communication frameworks in ensuring timely delivery of safety-critical messages within vehicular environments.

Among various infrastructure components within VANETs, Roadside Units (RSUs) play a crucial role in enhancing communication performance and network connectivity. RSUs are fixed communication devices deployed along roadways to facilitate information exchange between vehicles and transportation management systems. They act as gateways for data collection, traffic monitoring, content dissemination, and edge computing services. In addition, RSUs support intelligent transportation applications by extending network coverage and improving communication reliability in highly dynamic vehicular environments.

Despite their importance, the deployment of RSUs remains a challenging research problem. The installation and maintenance of RSUs involve significant financial investment, making optimal placement essential for maximizing network performance while minimizing deployment costs. Traditional RSU deployment approaches generally rely on static placement strategies based on geographical locations, intersections, or historical traffic observations. However, such approaches often fail to adapt to rapidly changing traffic patterns, resulting in inefficient infrastructure utilization and reduced communication performance.

Several researchers have proposed traffic-aware RSU deployment strategies to address these limitations. Yu et al. (2021) introduced a traffic-demand-based RSU deployment framework that considers vehicle density and communication requirements when determining deployment locations. Their findings demonstrated that incorporating traffic demand information can significantly improve network coverage and communication efficiency. Similarly, Jiang et al. (2021) investigated the deployment of V2X roadside units for traffic prediction and showed that strategically deployed RSUs can improve both traffic monitoring capabilities and predictive transportation analytics.

The increasing availability of real-time traffic data has encouraged the development of dynamic RSU deployment mechanisms capable of adapting to changing transportation conditions. Traffic density estimation has become a key enabling technology in this context. By accurately estimating current and future traffic conditions, transportation systems can dynamically allocate communication resources and optimize infrastructure utilization. Duan et al. (2022) demonstrated the effectiveness of highway mobility analytics and traffic prediction techniques for improving intelligent transportation decision-making processes. Their study highlighted the growing importance of predictive analytics in transportation infrastructure planning and management.

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and optimization algorithms have further expanded the possibilities for intelligent RSU deployment. AI-based approaches can analyze complex traffic patterns, predict future vehicle movements, and identify optimal deployment locations under dynamic traffic conditions. Emerging studies have explored the application of metaheuristic optimization techniques for RSU placement. For example, Sharma (2025) proposed a Virus Optimization Algorithm-based deployment framework that improved network coverage and communication performance by identifying optimal RSU locations. Similarly, Ezumalai and Santhakumar (2025) developed predictive traffic analysis algorithms for scalable RSU deployment and demonstrated the potential of intelligent traffic forecasting in enhancing deployment efficiency.

In addition to deployment optimization, RSUs are increasingly expected to support advanced services such as content caching, edge intelligence, and real-time data processing. Hu et al. (2017) investigated roadside unit caching mechanisms and demonstrated how intelligent resource allocation can improve content delivery performance within vehicular networks. These developments indicate a gradual transition from conventional communication infrastructure toward intelligent and adaptive roadside systems capable of supporting future connected and autonomous transportation ecosystems.

Although substantial progress has been achieved in traffic prediction, VANET communications, and RSU deployment optimization, existing research remains fragmented across multiple domains. Most studies focus either on traffic analytics, communication protocols, or deployment optimization independently. Furthermore, available survey articles often examine VANET architectures or intelligent transportation systems in general without specifically addressing the integration of artificial intelligence, traffic density estimation, and dynamic RSU deployment. Consequently, there is a need for a comprehensive review that consolidates existing knowledge and provides a unified perspective on AI-assisted dynamic RSU deployment strategies.

This survey aims to address this gap by systematically reviewing existing literature related to real-time traffic density estimation, intelligent RSU deployment, machine learning-based optimization, and emerging AI-driven transportation infrastructures. The survey further analyzes current research trends, identifies key challenges, and discusses future directions for developing adaptive and scalable vehicular communication systems. By providing a comprehensive overview of AI-assisted dynamic RSU deployment techniques, this study seeks to support researchers and practitioners working toward the realization of next-generation intelligent transportation networks.

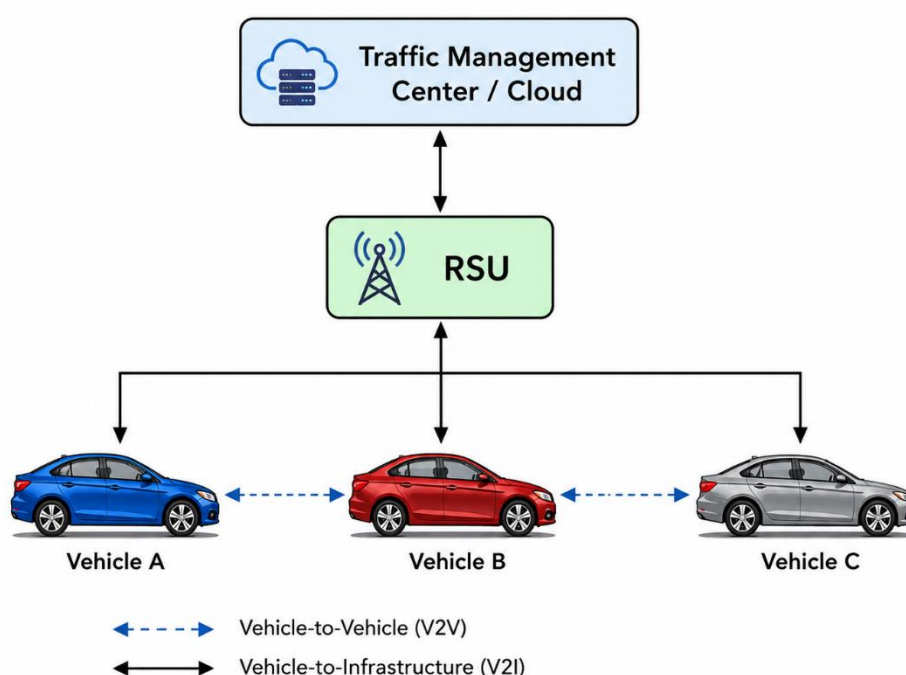


Figure 1. VANET Communication Architecture

2. Foundations of VANETs and RSU Deployment

Vehicular Ad Hoc Networks (VANETs) constitute the communication backbone of modern Intelligent Transportation Systems (ITS). By enabling seamless information exchange among vehicles, roadside infrastructure, and transportation management centers, VANETs support a wide range of applications including traffic management, accident prevention, emergency response, route optimization, and autonomous driving assistance. The effectiveness of these applications depends heavily on the availability of reliable communication infrastructure capable of supporting dynamic vehicular environments characterized by high mobility, rapidly changing topologies, and fluctuating traffic densities.

Unlike conventional wireless networks, VANETs operate in highly dynamic environments where vehicles continuously join and leave communication ranges. Consequently, maintaining stable communication links becomes a significant challenge. To address this issue, VANET architectures combine direct vehicle communications with infrastructure-assisted communication mechanisms. Among the infrastructure components, Roadside Units (RSUs) serve as critical elements that improve connectivity, extend network coverage, and facilitate communication between vehicles and centralized transportation systems.

2.1 VANET Communication Architecture

A typical VANET architecture consists of three major communication entities: vehicles, roadside infrastructure, and traffic management systems. Vehicles are equipped with onboard units capable of wireless communication, positioning, sensing, and data processing. These onboard units continuously exchange information regarding vehicle speed, location, traffic conditions, and road safety events.

Communication within VANETs is generally categorized into Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication modes. V2V communication enables direct information exchange among neighboring vehicles and is particularly useful for disseminating safety messages and collision warnings. However, V2V communication often suffers from limited communication ranges and intermittent connectivity, especially in sparse traffic conditions.

To overcome these limitations, V2I communication utilizes RSUs deployed along roadways to facilitate data transmission between vehicles and transportation management systems. RSUs act as intermediaries that collect information from vehicles, process traffic data, and disseminate relevant information to nearby nodes. According to Khelifi et al. (2019), infrastructure-assisted communication significantly improves network reliability and supports efficient content distribution within vehicular environments.

The emergence of Vehicle-to-Everything (V2X) communication has further expanded the capabilities of VANETs by enabling interactions among vehicles, infrastructure, cloud services, pedestrians, and intelligent transportation applications. This integrated communication framework provides the foundation for next-generation smart mobility ecosystems and connected transportation services.

2.2 Role of Roadside Units in VANETs

Roadside Units are fixed communication devices strategically installed along roads, intersections, highways, and urban transportation corridors. They serve as communication gateways that facilitate data exchange between mobile vehicles and transportation management infrastructures. The deployment of RSUs significantly enhances communication performance by reducing transmission interruptions and extending communication coverage beyond direct vehicle-to-vehicle interactions.

RSUs perform several essential functions within VANET environments. First, they collect traffic information from passing vehicles and forward the collected data to centralized traffic management systems for further analysis. This information includes vehicle speed, traffic density, congestion levels, accident reports, and environmental conditions.

Second, RSUs support information dissemination by broadcasting traffic alerts, safety warnings, route recommendations, and emergency notifications to nearby vehicles. Abbas et al. (2022) demonstrated that reliable infrastructure-assisted message dissemination can substantially improve the effectiveness of road safety applications by ensuring timely delivery of critical information.

Third, modern RSUs increasingly support edge computing capabilities. Instead of forwarding all collected information to remote cloud servers, RSUs can locally process data and execute intelligent decision-making algorithms. This capability reduces communication latency and enables real-time transportation management applications.

Furthermore, RSUs support content caching and resource allocation mechanisms that improve network efficiency. Hu et al. (2017) proposed an auction-based caching framework in which RSUs allocate storage resources among multiple content providers to enhance content delivery performance. Their findings highlight the evolving role of RSUs from simple communication relays to intelligent infrastructure nodes capable of supporting advanced vehicular services.

2.3 Conventional RSU Deployment Strategies

The performance of VANETs is highly dependent on the placement and density of deployed RSUs. Consequently, determining optimal deployment locations has become a major research area within intelligent transportation systems.

Traditional RSU deployment strategies typically rely on static placement approaches. In these approaches, RSUs are installed at predetermined locations such as intersections, traffic signals, toll plazas, highways, and major transportation hubs. The selection of deployment locations is generally based on historical traffic patterns, geographical characteristics, and infrastructure availability.

Static deployment approaches offer several advantages, including simplified network management, lower operational complexity, and predictable maintenance requirements. Because RSU locations remain fixed, transportation authorities can design communication infrastructures using well-established planning methodologies.

However, static deployment strategies also exhibit significant limitations. Traffic conditions often vary substantially across different times of the day, days of the week, and seasons of the year. Areas experiencing high traffic density during peak hours may become sparsely populated during off-peak periods. Consequently, fixed RSU deployments may provide excessive coverage in low-demand regions while simultaneously failing to support heavily congested areas.

Additionally, static deployment often results in inefficient utilization of communication resources because infrastructure remains active regardless of current traffic demand. This limitation becomes increasingly significant as transportation networks continue to grow in size and complexity.

2.4 Traffic-Aware RSU Deployment

Recognizing the limitations of static deployment, researchers have increasingly investigated traffic-aware deployment strategies that incorporate traffic characteristics into infrastructure planning decisions.

Traffic-aware deployment approaches seek to position RSUs in locations where communication demand is expected to be highest. By considering vehicle density, traffic flow patterns, road utilization levels, and communication requirements, these approaches aim to maximize coverage and network efficiency while minimizing deployment costs.

Yu et al. (2021) introduced a traffic-demand-based RSU deployment strategy for VANET environments. Their approach utilized traffic demand information to identify deployment locations capable of serving the largest number of vehicles. The results demonstrated significant improvements in communication coverage and network connectivity compared with conventional static deployment methods.

Similarly, Jiang et al. (2021) examined the deployment of V2X roadside units for traffic prediction applications. Their study emphasized the importance of strategically positioning RSUs in locations capable of capturing representative traffic information. By integrating deployment planning with traffic analytics, the proposed framework improved both communication performance and traffic monitoring capabilities.

These studies indicate that traffic-aware deployment strategies represent an important transition toward adaptive infrastructure management. However, most existing approaches still rely primarily on historical traffic information and may not fully address real-time traffic variations.

2.5 Emerging Need for AI-Assisted Deployment

Although traffic-aware deployment strategies have improved infrastructure planning, the increasing complexity of transportation systems presents new challenges that cannot be effectively addressed through conventional optimization techniques alone. Modern transportation networks generate massive volumes of heterogeneous data that require advanced analytical methods for effective interpretation.

Artificial Intelligence offers powerful tools for extracting meaningful insights from transportation data and supporting intelligent deployment decisions. Machine learning algorithms can identify hidden traffic patterns, predict future congestion levels, estimate communication demand, and recommend optimal deployment locations. Deep learning models can further enhance prediction accuracy by capturing complex nonlinear relationships within traffic datasets.

The integration of AI with dynamic RSU deployment enables transportation systems to transition from reactive infrastructure management toward proactive and predictive deployment frameworks. Instead of responding only after congestion occurs, AI-based systems can anticipate traffic fluctuations and adjust infrastructure allocation in advance.

Recent studies by Sharma (2025) and Ezumalai and Santhakumar (2025) demonstrate the growing potential of optimization algorithms and predictive traffic analytics for intelligent RSU deployment. Their findings suggest that AI-assisted approaches can significantly improve network performance, communication reliability, and infrastructure utilization compared with traditional deployment methodologies.

Consequently, the convergence of artificial intelligence, real-time traffic analytics, and adaptive infrastructure management represents one of the most promising research directions in contemporary VANET environments. The next section reviews traffic density estimation techniques that provide the foundation for intelligent and dynamic RSU deployment frameworks.

3. Traffic Density Estimation for Dynamic RSU Deployment

Traffic density estimation represents one of the most important enabling technologies for intelligent transportation systems and adaptive RSU deployment. The effectiveness of any dynamic deployment framework largely depends on its ability to accurately determine current and future traffic conditions. Since communication demand in VANETs is directly influenced by vehicle concentration, reliable traffic density estimation enables transportation systems to allocate infrastructure resources efficiently and maintain communication quality under varying traffic scenarios.

Traditional RSU deployment approaches generally relied on fixed traffic assumptions or historical traffic records. However, rapidly changing traffic patterns caused by accidents, weather conditions, road construction, public events, and daily commuting activities require more adaptive mechanisms capable of responding to real-time transportation dynamics. Consequently, traffic density estimation has become a fundamental component of modern intelligent deployment frameworks.

3.1 Data Sources for Traffic Density Estimation

The increasing digitization of transportation systems has generated vast amounts of traffic-related data from multiple sources. These datasets provide valuable information for understanding traffic behavior and predicting future mobility patterns.

One important source of transportation information is open-access traffic and road safety data. Jones et al. (2019) demonstrated how publicly available transportation datasets can be utilized to analyze road safety trends and support sustainable transportation planning. Such datasets often contain vehicle counts, accident records, traffic flow measurements, and infrastructure utilization statistics that can be used for traffic density modeling.

Modern transportation environments also generate data through connected vehicles equipped with onboard sensors, GPS devices, cameras, and communication modules. These vehicles continuously transmit information regarding location, speed, acceleration, direction, and traffic conditions. The integration of these data sources enables transportation systems to construct detailed representations of traffic behavior across large geographical regions.

Additional information may be obtained from traffic cameras, induction loop detectors, roadside sensors, cellular networks, and intelligent transportation infrastructures. The combination of multiple heterogeneous data sources improves estimation accuracy and enhances the reliability of traffic prediction models.

3.2 Data-Driven Traffic Analytics

The emergence of data-driven transportation systems has significantly transformed traffic monitoring and prediction methodologies. Rather than relying solely on mathematical traffic flow models, modern approaches utilize large-scale datasets to identify traffic patterns and generate predictive insights.

Zhang et al. (2011) emphasized the growing importance of data-driven intelligent transportation systems and highlighted the role of transportation analytics in supporting traffic management decisions. Their survey demonstrated that large-scale traffic datasets can reveal complex mobility patterns that are difficult to capture using conventional analytical models.

Data-driven traffic analytics generally involve four stages:

1. Data acquisition.
2. Data preprocessing.
3. Pattern extraction.
4. Predictive modeling.

These processes enable transportation systems to transform raw traffic observations into actionable information for infrastructure planning and deployment optimization.

3.3 Traffic Prediction and Mobility Analytics

While traffic density estimation provides information regarding current transportation conditions, effective RSU deployment often requires predictions of future traffic states. Predictive traffic analytics enables transportation systems to anticipate congestion patterns and proactively allocate communication resources.

Duan et al. (2022) investigated highway mobility analytics and demonstrated the effectiveness of predictive learning models for traffic forecasting applications. Their study revealed that mobility behavior exhibits recurring patterns that can be utilized to improve traffic prediction accuracy.

Predictive traffic analytics offers several advantages for dynamic RSU deployment:

- Anticipation of traffic congestion.
- Improved communication coverage.
- Better resource allocation.
- Reduced infrastructure underutilization.
- Enhanced network reliability.

The ability to forecast future traffic conditions is particularly valuable in urban environments where traffic density may change dramatically within short time intervals.

3.4 Traffic Prediction for RSU Deployment

The relationship between traffic prediction and RSU deployment has attracted increasing attention in recent years. Since communication demand generally follows vehicle density distributions, predicting future traffic conditions allows deployment algorithms to identify locations requiring additional infrastructure support.

Jiang et al. (2021) demonstrated that strategically deployed RSUs can significantly improve traffic prediction capabilities by providing continuous traffic observations from critical road segments. Their findings suggest that traffic prediction and RSU deployment should be considered jointly rather than as independent optimization problems.

Similarly, Yu et al. (2021) proposed a traffic-demand-oriented deployment strategy in which traffic patterns directly influence infrastructure placement decisions. Their results showed that incorporating traffic demand information improves network performance and communication coverage.

These studies collectively indicate that traffic prediction serves as a critical foundation for intelligent deployment frameworks.

Table 1. Summary of Traffic Density Estimation Studies

Study	Main Focus	Data Source	Contribution
Jones et al. (2019)	Road safety analytics	Open-access transportation data	Data-driven transportation insights
Zhang et al. (2011)	Data-driven ITS	Transportation datasets	Intelligent traffic analytics
Jiang et al. (2021)	Traffic prediction using RSUs	V2X traffic data	Traffic-aware deployment
Duan et al. (2022)	Highway mobility analytics	Highway traffic data	Predictive traffic modeling
Yu et al. (2021)	Traffic-demand-based deployment	Traffic density information	RSU placement optimization

4. AI-Assisted Dynamic RSU Deployment Techniques

The increasing availability of real-time traffic data, advancements in computational intelligence, and the growing complexity of vehicular communication networks have accelerated the adoption of Artificial Intelligence (AI) in RSU deployment optimization. Traditional deployment strategies are often unable to adapt efficiently to rapidly changing traffic conditions because they rely on predefined infrastructure planning and static optimization assumptions. In contrast, AI-assisted deployment approaches utilize data-driven learning, predictive analytics, and intelligent optimization mechanisms to dynamically determine optimal RSU locations according to current and anticipated communication demands.

The integration of AI with traffic density estimation enables transportation systems to continuously analyze traffic behavior, predict future mobility patterns, and proactively allocate communication resources. As a result, AI-assisted deployment frameworks have emerged as one of the most promising research directions for improving network coverage, communication reliability, infrastructure utilization, and transportation safety within VANET environments.

4.1 Classification of AI-Assisted RSU Deployment Approaches

Existing AI-based deployment methodologies can be broadly classified into four categories:

1. Optimization-Based Approaches
2. Machine Learning-Based Approaches
3. Deep Learning-Based Approaches
4. Predictive Traffic Analytics Approaches

Each category addresses RSU deployment from a different perspective while sharing the common objective of improving communication efficiency under dynamic traffic conditions.

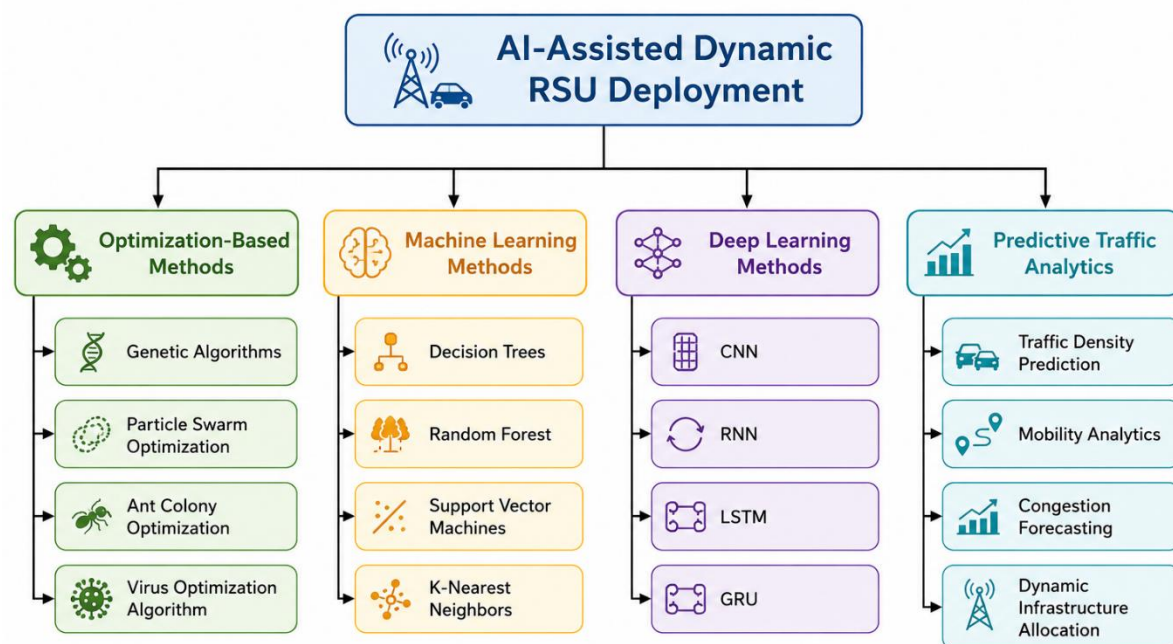


Figure 2. Taxonomy of AI-Assisted Dynamic RSU Deployment

4.2 Optimization-Based RSU Deployment

Optimization techniques represent some of the earliest intelligent approaches used for RSU placement. These methods formulate deployment as an optimization problem in which the objective is to maximize communication coverage, connectivity, packet delivery ratio, or network throughput while minimizing deployment costs.

Optimization-based deployment frameworks typically consider factors such as vehicle density, road topology, communication range, installation costs, and infrastructure constraints. By evaluating multiple deployment scenarios, these algorithms identify locations capable of providing the greatest communication benefits.

Metaheuristic optimization methods have become particularly attractive because RSU deployment is generally classified as a complex NP-hard optimization problem. Exact mathematical solutions often become computationally infeasible when transportation networks increase in scale and complexity. Consequently, heuristic and evolutionary algorithms are frequently employed to obtain near-optimal solutions within practical computational limits.

The primary advantages of optimization-based approaches include flexibility, scalability, and the ability to consider multiple deployment objectives simultaneously. However, their effectiveness often depends on the quality of traffic information available during the optimization process.

4.3 Virus Optimization Algorithm for RSU Deployment

Among recently proposed optimization approaches, the Virus Optimization Algorithm (VOA) has attracted attention as an effective mechanism for solving infrastructure placement problems within VANET environments.

Sharma (2025) proposed a Virus Optimization Algorithm-based framework designed to improve RSU deployment efficiency. Inspired by the propagation behavior of biological viruses, the algorithm explores multiple deployment configurations and iteratively identifies optimal infrastructure locations capable of maximizing communication coverage.

The proposed approach demonstrated improvements in:

- Coverage ratio.
- Vehicle connectivity.
- Communication reliability.
- Infrastructure utilization.

A notable advantage of the VOA approach is its ability to avoid premature convergence and effectively explore large solution spaces. This characteristic is particularly beneficial in urban transportation networks where deployment decisions are influenced by numerous interacting variables.

Despite these advantages, optimization-based approaches such as VOA may require significant computational resources when applied to large-scale metropolitan transportation systems. Furthermore, their performance is highly dependent on the accuracy of traffic demand information used during optimization.

4.4 Machine Learning-Based Deployment Approaches

Machine Learning (ML) techniques provide an alternative strategy for intelligent RSU deployment by learning deployment patterns directly from historical and real-time traffic data. Rather than relying exclusively on mathematical optimization models, ML algorithms identify relationships between traffic characteristics and infrastructure requirements through data-driven training processes.

Machine learning models can analyze:

- Vehicle density distributions.
- Traffic flow patterns.
- Road utilization characteristics.
- Temporal traffic variations.
- Communication demand fluctuations.

Based on these observations, trained models can recommend deployment locations likely to maximize network performance under future traffic conditions.

The integration of machine learning with VANET infrastructures offers several advantages. First, ML models can adapt to changing transportation environments through continuous learning. Second, they can capture complex nonlinear relationships that are difficult to represent using conventional analytical methods. Third, they can process large-scale traffic datasets generated by modern intelligent transportation systems.

As transportation data availability continues to increase, machine learning is expected to play an increasingly important role in adaptive infrastructure management and intelligent deployment planning.

4.5 Deep Learning and Traffic-Aware Deployment

Deep Learning (DL) has emerged as one of the most powerful technologies for traffic prediction and intelligent transportation analytics. Deep neural networks are capable of extracting complex patterns from high-dimensional traffic datasets and generating highly accurate predictions regarding future transportation conditions.

Traffic density estimation represents a critical component of dynamic deployment frameworks. Deep learning models can utilize historical traffic records, vehicle trajectories, sensor measurements, and mobility patterns to forecast future traffic density distributions. These predictions subsequently guide infrastructure allocation decisions.

Duan et al. (2022) demonstrated the effectiveness of highway mobility analytics in supporting predictive transportation applications. Their work illustrated how learning-based approaches can identify recurring traffic

patterns and improve forecasting accuracy. Such predictive capabilities are highly valuable for dynamic RSU deployment because infrastructure decisions can be made proactively rather than reactively.

Common deep learning architectures applied to traffic prediction include:

- Convolutional Neural Networks (CNNs).
- Recurrent Neural Networks (RNNs).
- Long Short-Term Memory Networks (LSTMs).
- Gated Recurrent Units (GRUs).

These models have shown considerable success in capturing temporal and spatial traffic dependencies that influence communication demand within VANET environments.

5. Comparative Analysis of Existing Studies

A comprehensive comparison of existing studies is essential for understanding the evolution of RSU deployment strategies and identifying the strengths and limitations of current research efforts. Over the last decade, research has progressed from conventional traffic monitoring and static infrastructure planning toward intelligent, traffic-aware, and AI-assisted deployment frameworks. This evolution has been driven by advancements in intelligent transportation systems, increased availability of transportation data, and growing demands for adaptive vehicular communication infrastructures.

The studies reviewed in this survey demonstrate that effective RSU deployment requires the integration of multiple disciplines, including vehicular networking, traffic engineering, artificial intelligence, optimization theory, and transportation analytics. While significant progress has been achieved, existing solutions differ substantially in terms of deployment objectives, optimization methodologies, traffic prediction capabilities, scalability, and practical applicability.

This section presents a comparative evaluation of the literature reviewed throughout the survey and identifies key research trends, strengths, limitations, and opportunities for future investigation.

5.1 Evolution of Research Trends

The development of intelligent RSU deployment research can be broadly divided into four major phases.

The first phase focused primarily on Intelligent Transportation Systems and data-driven transportation management. During this period, researchers investigated methods for collecting and analyzing transportation data to improve traffic monitoring and decision-making. Zhang et al. (2011) established an important foundation by highlighting the role of data-driven analytics in intelligent transportation systems, while Śladkowski and Pamuła (2016) discussed the broader challenges and opportunities associated with intelligent transportation infrastructures.

The second phase concentrated on VANET communication architectures and infrastructure support mechanisms. Research efforts focused on improving communication reliability, content dissemination, and routing performance within highly dynamic vehicular environments. Khelifi et al. (2019) provided a comprehensive review of vehicular networking architectures, whereas Abbas et al. (2022) proposed reliable routing mechanisms for emergency message dissemination in road safety applications.

The third phase introduced traffic-aware infrastructure planning. Researchers recognized that communication demand varies according to traffic density and mobility patterns. Consequently, studies such as Yu et al. (2021) and Jiang et al. (2021) investigated deployment strategies that incorporate traffic demand and traffic prediction information into infrastructure planning decisions.

The fourth and most recent phase focuses on AI-assisted deployment methodologies. Studies by Sharma (2025) and Ezumalai and Santhakumar (2025) illustrate the growing adoption of optimization algorithms and predictive

traffic analytics for intelligent deployment planning. This phase represents a transition toward adaptive and autonomous infrastructure management systems capable of responding dynamically to changing transportation conditions.

5.2 Comparative Analysis of Surveyed Studies

The reviewed studies can be categorized according to their primary research objectives, deployment methodologies, and contributions to intelligent transportation systems.

Table 3. Comparative Analysis of Existing Literature

Ref.	Year	Research Focus	Methodology	AI-Based	Traffic-Aware	Dynamic Deployment	Key Contribution
Zhang et al.	2011	Data-Driven ITS	Traffic Analytics	No	Partial	No	Foundation for intelligent transportation analytics
Ślaskowski and Pamuła	2016	ITS Infrastructure	Transportation Frameworks	No	No	No	ITS challenges and perspectives
Hu et al.	2017	RSU Resource Management	Caching Optimization	No	No	No	Intelligent RSU resource allocation
Jones et al.	2019	Transportation Data Analytics	Open Data Analysis	No	Yes	No	Traffic and safety data utilization
Khelifi et al.	2019	VANET Communication	Networking Frameworks	No	No	No	Vehicular communication architectures
Yu et al.	2021	RSU Deployment	Traffic Demand Analysis	Partial	Yes	Partial	Traffic-demand-based deployment
Jiang et al.	2021	Traffic Prediction	V2X Analytics	Partial	Yes	Partial	RSUs for traffic prediction
Razmjoo et al.	2021	Smart Cities	Policy Framework	No	Indirect	No	Smart transportation policies
Abbas et al.	2022	Emergency Routing	Position-Based Routing	No	Partial	No	Reliable safety communications
Duan et al.	2022	Mobility Analytics	Learning Models	Yes	Yes	No	Highway traffic prediction
Sharma	2025	RSU Optimization	Virus Optimization Algorithm	Yes	Yes	Yes	Intelligent RSU deployment
Ezumalai & Santhakumar	2025	Scalable Deployment	Predictive Analytics	Yes	Yes	Yes	Predictive traffic-aware deployment

The comparison reveals a clear progression from conventional transportation analytics toward intelligent deployment frameworks that integrate predictive traffic analysis and artificial intelligence.

5.3 Strengths of Existing Research

Several important strengths can be identified from the surveyed literature.

First, researchers have successfully demonstrated the importance of incorporating traffic information into deployment planning decisions. Studies by Yu et al. (2021) and Jiang et al. (2021) showed that traffic-aware deployment strategies significantly outperform purely static placement approaches.

Second, advancements in traffic analytics have improved the ability of transportation systems to estimate and predict traffic conditions. Data-driven approaches introduced by Zhang et al. (2011) and enhanced through mobility analytics by Duan et al. (2022) provide a strong foundation for intelligent infrastructure management.

Third, emerging AI-based approaches have demonstrated substantial improvements in deployment efficiency. Optimization techniques such as the Virus Optimization Algorithm proposed by Sharma (2025) illustrate the potential of computational intelligence for solving complex infrastructure placement problems.

Finally, recent predictive deployment frameworks indicate a growing shift toward proactive infrastructure management rather than reactive deployment decisions. This trend is expected to become increasingly important as transportation systems continue to evolve toward connected and autonomous mobility ecosystems.

5.4 Limitations of Existing Studies

Despite significant progress, several limitations remain evident within current research.

One common limitation is the reliance on simulation-based evaluation environments. Many proposed deployment algorithms have been tested primarily using synthetic traffic datasets or simulation platforms, making it difficult to assess their effectiveness under real-world transportation conditions.

Another limitation involves scalability. While numerous studies demonstrate promising results for small and medium-sized transportation networks, relatively few investigate deployment performance within large metropolitan regions containing thousands of vehicles and extensive road infrastructures.

Data dependency also remains a challenge. Machine learning and predictive deployment approaches often require large volumes of high-quality traffic data for effective training and operation. In many practical scenarios, such datasets may be unavailable or incomplete.

Furthermore, most existing studies focus on a single optimization objective such as coverage maximization or cost reduction. Real-world deployment problems typically involve multiple competing objectives including latency reduction, coverage enhancement, energy efficiency, infrastructure cost minimization, and communication reliability.

Finally, integration between traffic prediction systems and deployment optimization frameworks remains limited. Although many studies investigate traffic forecasting and infrastructure planning independently, relatively few provide fully integrated end-to-end deployment solutions.

5.5 Research Gap Identification

The comparative analysis reveals several significant research gaps that continue to hinder the development of fully intelligent deployment systems.

Gap 1: Limited Real-Time Adaptation

Many deployment strategies rely heavily on historical traffic information and fail to respond effectively to unexpected traffic fluctuations caused by accidents, weather conditions, or special events.

Gap 2: Insufficient AI Integration

Although artificial intelligence is increasingly used for traffic prediction, relatively few studies fully integrate AI-driven traffic forecasting with dynamic deployment optimization mechanisms.

Gap 3: Lack of Hybrid Deployment Frameworks

Current research often focuses on individual techniques such as optimization algorithms or machine learning models. Hybrid frameworks capable of combining multiple intelligent methodologies remain relatively unexplored.

Gap 4: Limited Edge Intelligence Support

The growing computational capabilities of RSUs provide opportunities for edge-based deployment decision-making. However, most existing studies continue to rely on centralized architectures.

Gap 5: Emerging Technologies Remain Underexplored

Technologies such as federated learning, digital twins, unmanned aerial vehicle-assisted RSUs, blockchain-enabled transportation systems, and 6G vehicular communications have received limited attention within deployment optimization research.

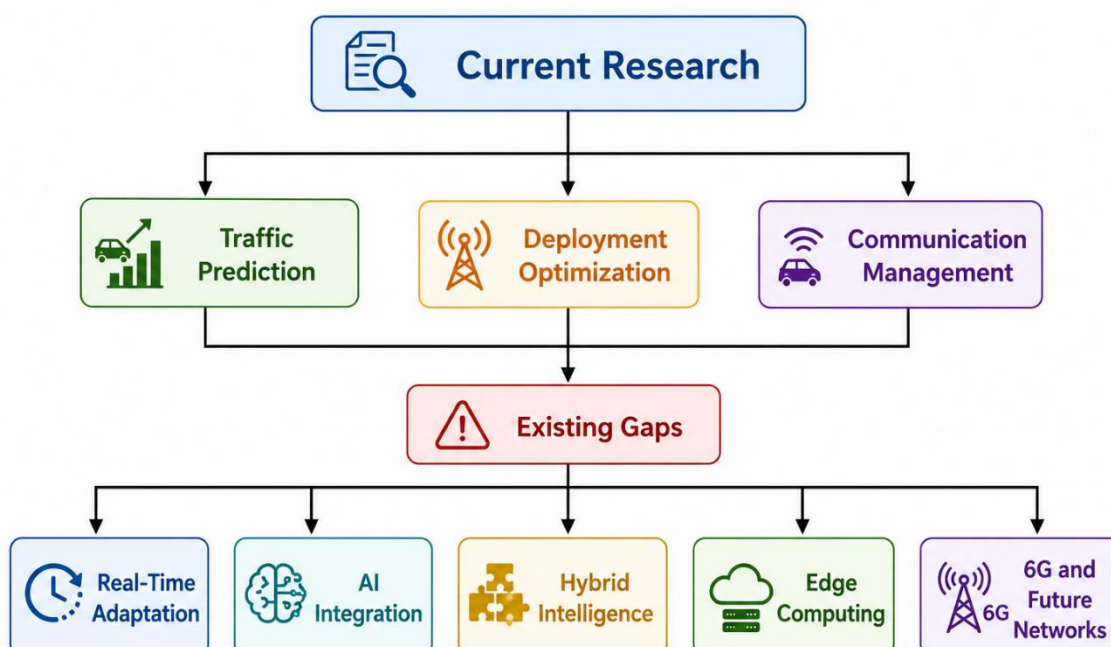


Figure 7. Research Gap Analysis

The comparative analysis demonstrates that AI-assisted dynamic RSU deployment remains an active and evolving research area. Although substantial progress has been achieved, significant opportunities remain for developing more adaptive, scalable, and intelligent deployment frameworks. The next section discusses the major challenges affecting current deployment systems and explores future research directions that may shape the next generation of intelligent vehicular communication infrastructures.

6. Conclusion

This survey presented a comprehensive review of AI-assisted dynamic RSU deployment strategies using real-time traffic density estimation in Vehicular Ad Hoc Networks (VANETs). The study examined the evolution of intelligent transportation systems, the role of roadside units in vehicular communications, traffic density estimation techniques, and recent advances in artificial intelligence-based deployment approaches. Existing literature indicates that traditional static deployment methods are increasingly inadequate for highly dynamic transportation environments, whereas traffic-aware and AI-driven deployment frameworks offer significant improvements in network coverage, connectivity, resource utilization, and communication reliability. The survey further highlighted the growing importance of machine learning, deep learning, predictive traffic analytics, and optimization algorithms in supporting intelligent infrastructure management. Through comparative analysis, several research gaps were identified, including limited real-time adaptability, scalability concerns, and insufficient integration between traffic prediction and deployment optimization. Overall, the findings demonstrate that AI-assisted dynamic RSU deployment represents a promising direction for future intelligent transportation systems and will play a critical role in supporting connected, autonomous, and next-generation vehicular communication networks.

7. Future Research Directions

Although significant progress has been achieved in traffic-aware and AI-assisted RSU deployment, several challenges remain unresolved. Future research should focus on developing adaptive deployment frameworks capable of responding to real-time traffic fluctuations while maintaining scalability and communication efficiency. Emerging technologies such as reinforcement learning, federated learning, edge computing, digital twins, and UAV-assisted mobile RSUs offer promising opportunities for enhancing deployment intelligence and reducing infrastructure costs. Furthermore, the integration of AI-driven traffic prediction with 6G-enabled vehicular communications and autonomous vehicle ecosystems is expected to transform next-generation transportation networks. Future studies should also emphasize real-world deployment validation, privacy-preserving data analytics, and hybrid optimization frameworks capable of simultaneously addressing coverage, latency, reliability, and cost constraints.

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