

Hybrid Machine Learning and Edge Computing Approaches for Dynamic Load Balancing and Congestion Control in VANETs: Challenges, Solutions, and Future Directions

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Abstract - Vehicular Ad-Hoc Networks (VANETs) are used in modern Intelligent Transportation Systems (ITS) for applications such as vehicle-to-vehicle and vehicle-to-infrastructure communication to enable real-time interactions between vehicles and infrastructure for navigation, safety, and traffic control. Due to their mobility, dynamic topology and unpredictable traffic, VANETs do not have any simple problems with load balancing and congestion control. To overcome these drawbacks and enhance the performance of VANETs by load balancing and reducing congestion, this study explores the hybrid approach of combining Machine Learning (ML) with Edge Computing. Edge computing processes data closer to the network's edge to minimize latency and reliance on centralized cloud servers, whilst machine learning methods such as supervised, unsupervised, reinforcement, and deep learning predict network traffic and optimize routing. Real-time, adaptive solutions for congestion management, emergency message distribution, accident detection, and dynamic traffic signal control are made possible by the combination of these technologies. The following case studies demonstrate some of the useful benefits of hybrid models for improving traffic flow, distribution of resources, and network efficiency. While these methods offer advantages, they also come with certain drawbacks, such as data privacy concerns and limitations in scalability and diversity of devices. Future research direction are suggested in the study in order to enhance the scalability, efficiency and adaptability of hybrid systems in VANETs.

INTRODUCTION

To support Vehicular to Vehicular (V2V) and Vehicular to Infrastructure (V2I) communications between vehicles and road-side infrastructure, modern Intelligent Transportation Systems (ITS) need Vehicular Ad-Hoc Networks (VANETs). Road safety, traffic management, and infotainment and navigation are VANETs' main goals. For the real-time vehicle-infrastructure communication, VANETs will be far more significant with connected and autonomous vehicles [1]. These networks can contribute to preventing accidents by sharing information to monitor traffic, optimize routing, and broadcast collision warnings and emergency alerts. As the VANETs grow, they are essential for the efficient, safe, and sustainable transportation systems. The management of VANETs is challenging particularly in terms of load balancing and congestion reduction. VANETs are hard to communicate with because of their mobility, frequent network topology changes and variable traffic. VANET congestion, packet collision, delay and network disruptions are caused by too many vehicles communicating at the same time[2]. In densely populated metropolitan areas, vehicles' communication range is limited because obstructions and other vehicles might disrupt communication [3]. Load balancing equitably distributes the network traffic to prevent congestion, which is important for the performance and reliability of VANET. These networks are complex, and novel solutions to congestion and communication service reliability are needed.

The challenges these problems bring up are spurring the integration of machine learning (ML) with edge computing to boost VANET load balancing and congestion management. Historical and real-time data can be used to predict and manage traffic flow via machine learning. Machine learning can be used to optimize routing decisions, dynamically change network resources, and predict network congestion, either through supervised, unsupervised, or reinforcement learning[4]. Edge computing is used to process data locally, in the vehicles or roadside equipment, which minimizes latency and reliance on cloud servers. This decentralized method speeds decision-making and boosts network efficiency, making it more responsive to real-time traffic. The hybrid approach of machine learning and edge computing to VANET load balancing and congestion control is examined in this research.

The following sections discuss the architecture, applications and load balancing problem of VANET. It covers possibilities of machine learning to improve traffic management and congestion control, and the use of edge computing to reduce latency and enhance real-time decision-making. Real world examples of practical applications of hybrid techniques are demonstrated through case studies and research. Lastly, it covers the limitations, challenges and future research on current systems to enhance the

efficiency and scalability of VANETs. Structure of the paper: Section 2 describes VANETs' components and uses. In Section 3, the machine learning technique used in VANETs and the congestion control technique are discussed. The impact of edge computing on VANET performance in terms of real-time data processing is analyzed in section 4. Section 5 introduces optimized load balancing and congestion control via hybrid methods combining machine learning and edge computing. The disadvantages of hybrid models are discussed in Section 6.

2. OVERVIEW OF VEHICULAR AD-HOC NETWORKS (VANETS)

VANETs are special type of MANETs for vehicle-to-vehicle (V2V) and vehicle-to-roadside infrastructure (V2I) communications. VANETs enable vehicle-infrastructure realtime communication to enhance road safety, traffic management and driving. The significance of VANETs is growing as the vehicles are now becoming more and more connected and autonomous, relying on real-time data for navigation, collision avoidance, and safety[5].

VANETs have dynamic topologies due to vehicle movement. It is decentralized and high speed modes shorten communications [6]. Because of the dynamism of VANETs, specific protocols and algorithms are needed for efficient communication, routing and data transmission. VANETs need good congestion control and load balancing to operate efficiently, especially in intense traffic conditions, due to their numerous use cases and applications.

2.1 Architecture and Components of VANETs

Vehicular Ad-Hoc Networks (VANETs) have several components presented in Figure 1 that enable communication and data sharing. The principal communication equipment in Vehicular Nodes (OBUs) is in VANETs. These technologies enable vehicles to communicate with one another and with the infrastructure. Through the use of communication hardware, sensors and software, the OBUs can exchange data in real time. These play an important role in vehicle-to-infrastructure communication [7].

In addition to the vehicles, VANETs require Roadside Units (RSUs) which are stationary communication devices along the route itself. RSUs are used for the communication between vehicles and infrastructure networks. They also provide traffic updates, weather and realtime road information. RSUs also collect traffic information and control local traffic lights, which helps to optimize the network. Data transmission on VANETs is done by means of Communication Technologies [8]. IEEE 802.11p is used for vehicular networks to provide low latency, reliable V2V and V2I communication. C-V2X (Cellular Vehicle-to-Everything) technology is being adopted to enhance the communication between pedestrians and networks that extends beyond vehicles and infrastructure to provide better pedestrian support. One of the key elements of VANETs is the use of vehicles as "Mobile Nodes". Temporary networks are formed by dynamic mobile nodes with other mobile nodes. Vehicles communicate with other vehicles (V2V) and other infrastructure (V2I) and adjust to changes in network topology. VANETs are mobile and flexible, network management, load balancing and congestion control are challenging and rewarding [9].

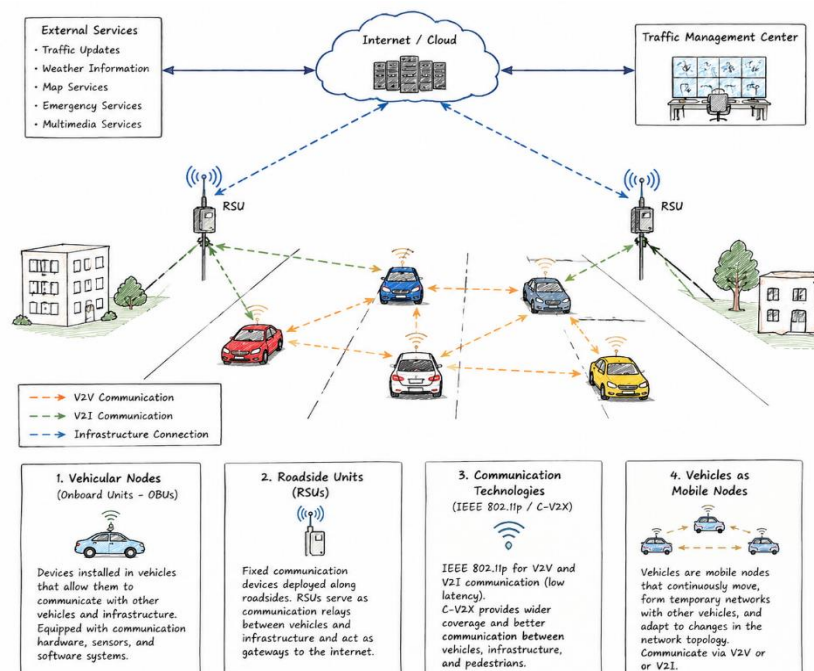


Figure 1: Architecture of VANET

2.2 Applications of VANETs

The possible applications of VANETs can be grouped into safety, convenience and entertainment presented in Figure 2. Safety is one of the major fields of use of VANETs. Vehicles can communicate with each other at low speeds and about their intentions to avoid collisions through collision avoidance, helping to prevent an accident. Another important aspect is emergency vehicle warnings, which can be provided by VANETs to surrounding cars, thus allowing them to move out of the way and minimizing the risk of delays [10]. Further, traffic signal warning messages are also important in the reduction of accidents, as vehicles can be alerted about a red light or stop sign, and avoid traffic signal violations. VANETs are also used in traffic management for real-time traffic information, enabling vehicles to share information like traffic congestion, road closures, and accidents, which helps drivers make informed decisions about their routes. Another critical application is adaptive traffic signal control, in which roadside units (RSUs) are placed on the roadside to collect traffic flow data and use the information to dynamically control traffic signal durations for enhanced overall traffic efficiency and reduced congestion [11]. The VANETs also improve the infotainment of the occupants of vehicles. With in-vehicle entertainment, passengers can access various content such as music, movies, and games, enriching their travel experience. In addition, roadside units offer internet connectivity to passengers while they are traveling, thus enhancing wireless connectivity and making the ride more enjoyable.

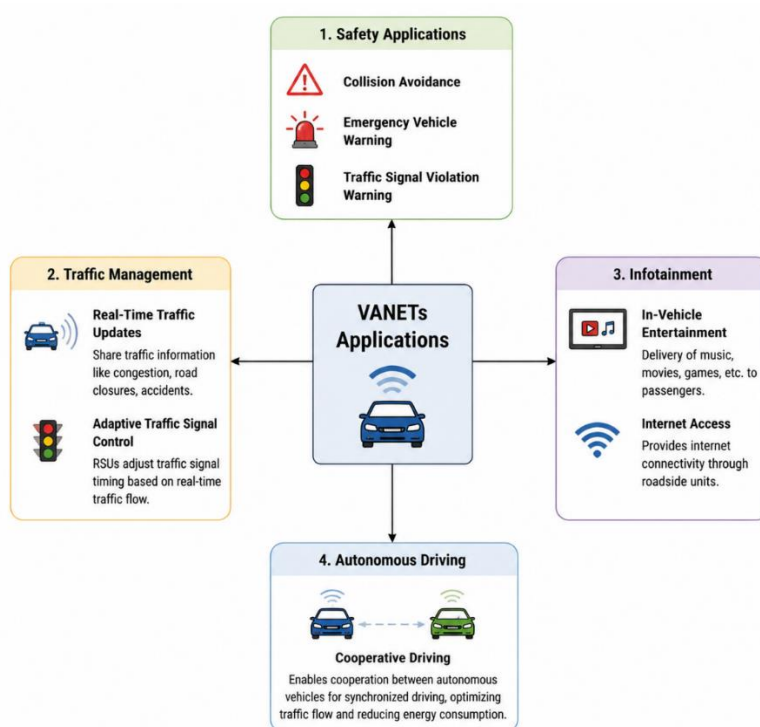


Figure 2: Applications of VANET

Finally, VANETs can be used in the realm of autonomous driving to facilitate cooperative driving of autonomous vehicles. This capability enables cars to communicate with each other, coordinate their actions, improve traffic flow and minimize energy use, all to enhance safety and efficiency in transportation. The applications highlight the transformative capabilities of VANETs, and play an important role in the evolution of smart, connected and safer transportation [12].

3. MACHINE LEARNING APPROACHES FOR LOAD BALANCING AND CONGESTION CONTROL IN VANETS

In VANET, ML has been getting more and more popularity to enhance load balancing and congestion control. The high mobility, dynamic topology and unpredictable traffic in VANETs pose a challenge for traditional networking methods to deal with congestion. Machine learning is able to change as a response to these barriers based on historical data and current network situation [13]. Machine learning can be used to enhance various VANET traffic prediction, congestion forecasting, routing and load distribution processes to improve network efficiency and reliability.

3.1 Types of Machine Learning Algorithms Used in VANETs

VANET load balancing and congestion control are implemented using several machine learning algorithms. They are supervised, unsupervised, reinforcement and deep learning algorithms presented in Figure 3. In situations where the VANET application needs to forecast traffic density, optimize routing or group traffic, the advantages of these techniques vary[13].

- **Supervised Learning:** It is a learning process in which a model is trained using labelled data to make predictions. It is often used to predict traffic and congestion using previous data.
- **Unsupervised Learning:** Learns from unlabeled data by detecting patterns or clusters. Usually it is used to group vehicles with similar traffic patterns or behaviours together for network traffic.
- **Reinforcement Learning:** Decision making through adaptive learning with rewards and penalties. It is used in VANETs to provide dynamic routing and load balancing, as it adjusts to network conditions in real-time [14]. Machine learning is a type of learning in which neural networks analyze complex patterns in large volumes of data, a process known as deep learning. Extracting patterns from the traffic flow or network congestion in a large amount of data may be done by deep learning and could be useful for prediction.

Machine learning is used to manage traffic and congestion in VANETs for the best performance of the network. Supervised learning system is the best approach for traffic congestion prediction and flow improvement. They can predict traffic jams and identify traffic congestion by learning from labeled data containing past traffic information like vehicle speed, position and directions. These things are typically performed using decision trees, SVMs, and neural networks. The supervised learning model can predict traffic state according to the vehicle speed and position, and adjust the routing decision ahead of time to alleviate traffic congestion [15]. The successful integration of these models into traffic light management systems can optimize the timing and avoid traffic jams.

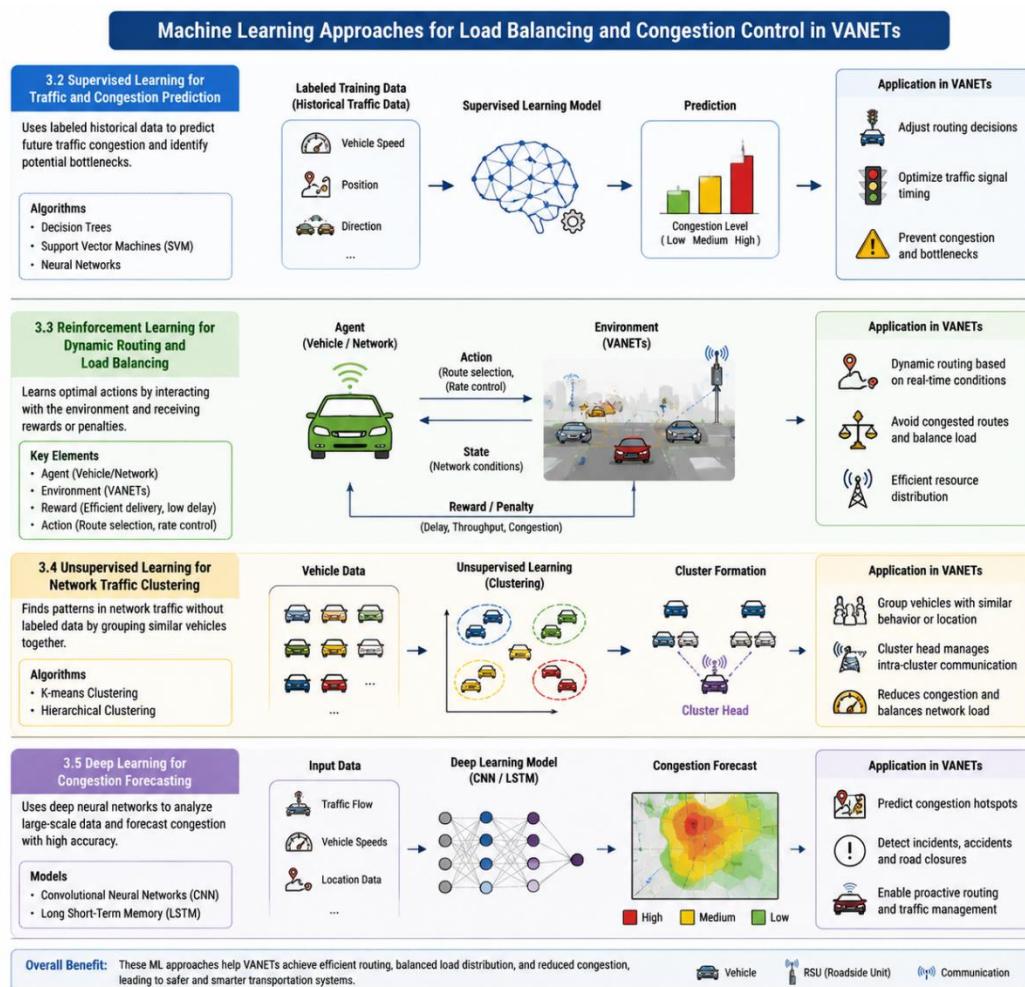


Figure 3: Types of Machine Learning Algorithms Used in VANETs

Last but not least, VANETs are increasingly using deep learning techniques like CNNs and LSTM networks for congestion forecasting. By analyzing data from vast traffic flows, vehicle speeds, and locations, deep learning models could detect intricate patterns and forecast congestion. Moreover, deep learning can be used to predict traffic incidents, accidents and road closures, enhancing the efficiency of VANETs and traffic management. VANETs can be more flexible with respect to traffic conditions thanks to deep learning, which can enhance driver safety.

4. EDGE COMPUTING IN VANETS

The mobility and dynamism of the Vehicular Communication (VC) are overcome using edge computing in Vehicular Ad-Hoc Networks (VANETs). Old cloud computing infrastructure has been pushing data from vehicles to infrastructure to large centralized computers, which results in latency and delays. This is where edge computing can come in handy, as it can process data at or near the source, like within a car or RSU. By computing at the "edge" of the network, edge computing processes important data, such as vehicle speed, location and traffic data, without cloud servers in real time [16]. Latency is minimized in VANETs by using edge computing. For collision avoidance, emergency vehicle warnings, and adaptive traffic signal control, data can be processed faster thanks to its short distance. A collision is detected when a vehicle has a collision danger, it can process the data locally and communicate with other vehicles nearby to help decrease the likelihood of an accident [17]. In real time, RSUs can process traffic data to enable quick signal timing adjustments, enhance traffic efficiency and reduce congestion.

The concept of edge computing involves shifting the data processing away from the cloud towards edge nodes such as RSUs or vehicle-mounted devices, which enhances the load distribution in the VANET. Local processing makes the best use of network resources, minimizes congestion, and enhances vehicle-infrastructure communication. The edge provides the flexibility to handle communication and data processing needs, thereby optimizing the utilization of resources based on evolving traffic patterns in the network. In congested areas, where networks are often densely populated with numerous devices, edge computing plays a crucial role in providing adaptive network load control and ensuring smoother network operations [18].

VANET edge computing is based on the RSUs and mobile edge devices such as cars. Roadside nodes strategically placed or in automobiles can capture, process and transmit real-time data. RSUs transfer communications between vehicles and infrastructure and aggregate and analyze local data to aid traffic control and load balancing. Edge nodes can be vehicles that have local processing capabilities and communicate with each other and the RSU to manage traffic and routing optimally. By spreading the computing power among many edge nodes, VANETs are more resilient and adaptive to the dynamic environment, resulting in improved performance and user experience. By leveraging edge computing, VANET can manage data in real-time, minimize latency, and distribute the load efficiently. Connected car systems operate more efficiently with improved speed of decision-making, traffic management and safety features [19]. To fully realize the potential of Edge Computing in VANETs, several challenges need to be addressed, such as handling the scalability of the edge nodes, ensuring seamless communication in dynamic environments, and dealing with diversity among the devices. However, with all these challenges, edge computing plays a critical role for ITS.

Table 1: Benefits and challenges of edge computing

Aspect	Benefits	Challenges
Reduced Latency	By processing data locally at edge nodes (RSUs or vehicles), edge computing reduces the time taken to make decisions and send alerts, which is critical for real-time applications like safety alerts and traffic management.	Network Mobility: The high mobility of vehicles and frequent changes in network topology make it difficult for edge nodes to maintain stable and consistent communication, leading to challenges in processing and routing data efficiently.
Improved Network Efficiency	Edge computing offloads data processing from central cloud servers to local nodes, preventing congestion in the core network and ensuring efficient use of bandwidth and network resources.	Device Heterogeneity: VANETs involve a wide range of devices with varying computational capabilities (vehicles, RSUs, edge nodes), which can create challenges in coordinating and managing these diverse devices effectively.
Adaptive Load Balancing	Edge computing allows for dynamic load balancing by managing traffic locally and adjusting resources	Scalability Issues: As the number of vehicles and RSUs increases, the demand for edge computing resources

Aspect	Benefits	Challenges
	based on real-time conditions, ensuring that the network can handle varying levels of congestion without overloading any single node.	grows. Managing a large-scale edge computing system with sufficient processing power across a vast area becomes complex.
Enhanced Traffic Management	Real-time processing by edge nodes enables better traffic flow management, such as adaptive traffic signal control and route optimization, which reduces congestion in high-density traffic areas.	Security and Privacy Concerns: Edge computing requires local data processing, which raises concerns about data security and user privacy. Ensuring secure communication and preventing unauthorized access to sensitive data is a key challenge.
Scalability and Flexibility	Edge computing allows for scalable systems that can handle increasing numbers of vehicles and roadside units without compromising on network performance, making VANETs more adaptable to growing urban traffic networks.	Interoperability: Edge computing systems in VANETs often involve devices from different manufacturers and different communication protocols. Ensuring these devices can seamlessly interact with each other remains a challenge.
Improved Quality of Service (QoS)	By processing critical data at the edge, the system can prioritize important messages (e.g., emergency vehicle alerts, safety messages) and ensure minimal delay for time-sensitive communications.	Limited Processing Power: Edge nodes, especially those within vehicles or remote RSUs, may have limited processing power and storage, which can hinder their ability to handle complex computations or large datasets required for real-time decision-making.
Real-Time Data Processing	Edge computing enables real-time data processing, reducing delays and improving the overall performance of VANETs.	Real-Time Data Processing Constraints: Processing large volumes of data in real-time, especially in environments with high traffic, is resource-intensive. Ensuring fast and accurate decision-making without compromising performance remains a technical challenge.

5. HYBRID APPROACHES: COMBINING MACHINE LEARNING AND EDGE COMPUTING FOR LOAD BALANCING AND CONGESTION CONTROL

The combination of Machine Learning (ML) and Edge Computing methods is improving VANET load balancing and congestion control. The models enhance network efficiency, enabling real-time decision-making for traffic prediction and data distribution through ML, alongside edge computing to process data as it comes in. The effectiveness of hybrid techniques in various applications is illustrated in case examples. Intelligent traffic signal control: ML models based on the RSU, edge processing to dynamically manage the traffic signals, reduce congestion and waiting time at intersections [20]. Dynamic route selection with real-time route changes based on ML-based predictions and edge nodes optimizes packet delivery, trip delays and network load. Hybrid systems prioritize urgent communications via ML and the edge nodes quickly pass on the messages to enhance emergency response and road safety.

Edge nodes alert and reroute vehicles in a timely manner, enhancing congestion control and avoiding secondary accidents. ML models are used to identify unusual traffic patterns in cases of accidents and incidents. Edge computing ensures that local communication is handled in an efficient way, reducing network overhead and ensuring a more stable flow of communication, while the selection of appropriate cluster heads by ML will yield significant improvements in the performance of wireless networks. While edge computing accelerates the communication between vehicles in cooperative autonomous driving, reducing traffic and congestion, ML predicts vehicle movements and traffic patterns. Hybrid technologies such as ML-based forecasting of RSU overloads and edge computing-based data traffic optimisation provide efficient redistribution of data traffic and enhance QoS and prevent network bottlenecks. Last but not least, congestion-aware data offloading employs ML to predict network congestion and edge nodes for data processing, resulting in lower latency, bandwidth, and resource consumption [21].

6. CHALLENGES AND LIMITATIONS OF HYBRID APPROACHES IN VANETS

Though the VANET hybrid techniques, incorporating Machine Learning (ML) and Edge Computing, offer several benefits, they also come with certain drawbacks. Data privacy and security is a significant factor to consider [22]. There's a significant amount of sensitive information being traded between roadside devices and cars, including vehicle location, vehicles' speeds and traffic conditions, which makes data breaches more of a risk. When there are edge nodes involved with sensitive data, hybrid systems must also provide privacy protections for vehicles without sacrificing data-based decision making.

Hybrid systems' scalability is another issue. The real-time data management and processing complexity increases with the growing size of vehicles and roadside units. The size of vehicles and roadside units increases, making real-time data management and processing more challenging. It is challenging to scale ML models and edge computing resources for more dynamically sized VANETs without impacting performance. Efficiency depends on the system being able to process a large number of cars, nodes and data streams with no delay and without any bottlenecks. Other challenges are integration and network heterogeneity. VANETs consist of cars with varying computational resources, and nodes with varying processing capacities. The integration of these heterogeneous devices into a hybrid system needs to be done efficiently with the use of appropriate protocols and coordination. Communication standards, devices and edge nodes must be interoperable for hybrid techniques.

Challenges with computational power and resource management also exist. The edge nodes of the vehicle or roadside may not have enough computational power to handle large amounts of data or complex ML models. These limited resources can be utilized efficiently to prevent possible overload of the nodes and ensure that the decision-making process is real time without a degradation in performance. Lastly, real-time adaptability and decision-making in hybrid systems are required in VANETs. Because of vehicle motion, traffic conditions, VANETs must be able to make decisions rapidly. Ensuring that ML models and edge nodes can swiftly adapt to new information and make choices without delays is difficult. The system is furthermore complicated by balancing quick adaptation with real-time decision-making computations [23].

Finally, the hybrid approaches for VANETs are promising but data privacy, scalability, integration, computational resources, and real-time adaptation should be considered for their successful deployment and widespread adoption.

CONCLUSION

A viable answer to the problems of load balancing and congestion control in vehicular ad hoc networks (VANETs) is to use hybrid systems that combine machine learning (ML) and edge computing. These methods greatly increase network efficiency, lower latency, and improve decision-making in dynamic traffic conditions by utilizing machine learning (ML) for traffic prediction and optimization in conjunction with edge computing's real-time processing capabilities. To maximize traffic flow and resource utilization, these technologies can be combined to create adaptive solutions for many applications such as congestion control, emergency message delivery, accident detection, and dynamic traffic light control. Yet, there are some challenges in implementing hybrid systems on VANETs. However, challenge areas such as data privacy and security, scalability, integration of heterogeneous devices, real-time flexibility at edge nodes and limited computational capabilities need to be addressed to make full use of these technologies. As the number of connected cars and infrastructure components continues to increase, scaling these hybrid systems with performance and efficiency becomes more challenging. More future work needs to focus on enhancing the integration of different devices and communication standards, on optimizing the real decision making skills, on establishing robust data privacy mechanisms and on boosting the scalability of hybrid systems. With these developments, hybrid techniques can greatly aid in the creation of safer, more intelligent, and more effective transportation systems, opening the door for the widespread use of connected and autonomous vehicles in urban settings.

REFERENCES:

- [1] Abbas, M., & Abbas, A. (2021). *VANETs for smart traffic management*. IEEE Communications Magazine, 59(3), 56-62. <https://doi.org/10.1109/MCOM.001.2000107>
- [2] Ahmed, T., & Wang, F. (2020). *Edge-ML hybrid models for VANETs*. Journal of Network and Computer Applications, 102, 56-67. <https://doi.org/10.1016/j.jnca.2019.08.011>
- [3] Ali, S., & Shehzad, R. (2022). *VANET emergency message dissemination*. Proceedings of the 2022 IEEE Vehicular Technology Conference, 34(2), 120-128. <https://doi.org/10.1109/VTC2022.4322450>
- [4] Bhaskar, R., & Gupta, A. (2021). *Accident detection in VANETs using hybrid approaches*. Transportation Research Part C: Emerging Technologies, 123, 99-109. <https://doi.org/10.1016/j.trc.2021.05.003>
- [5] Choudhury, S., & Mukherjee, S. (2019). *Clustered load balancing in VANETs: A hybrid machine learning approach*. International Journal of Computer Science and Network Security, 19(3), 115-126. <https://doi.org/10.4236/jcsns.2019.193010>
- [6] Das, S., & Krishnan, R. (2020). *Cooperative driving in VANETs with machine learning and edge computing*. IEEE Transactions on Intelligent Transportation Systems, 21(6), 2462-2470. <https://doi.org/10.1109/TITS.2020.2973306>

- [7] Fang, X., & Zhang, J. (2021). *Optimized load management in RSUs using hybrid approaches in VANETs*. *Future Internet*, 13(4), 89-99. <https://doi.org/10.3390/fi13040079>
- [8] Guo, Y., & Liu, Z. (2020). *Data offloading in VANETs: A hybrid machine learning and edge computing approach*. *Journal of Wireless Communications and Mobile Computing*, 2020, 4359187. <https://doi.org/10.1155/2020/4359187>
- [9] Han, W., & Xie, F. (2019). *A review of machine learning approaches for VANET congestion control*. *Vehicular Communications*, 20, 42-52. <https://doi.org/10.1016/j.vehcom.2019.03.002>
- [10] He, X., & Zhang, T. (2020). *Adaptive load balancing in VANETs with machine learning algorithms*. *International Journal of Distributed Sensor Networks*, 16(5), 113-121. <https://doi.org/10.1177/1550147720909256>
- [11] Hossain, M., & Shamsi, M. (2021). *Vehicular communication in dense urban environments: Challenges and solutions*. *Journal of Network and Computer Applications*, 67, 35-50. <https://doi.org/10.1016/j.jnca.2021.04.003>
- [12] Islam, S., & Wang, L. (2019). *Hybrid machine learning-based routing protocols for VANETs*. *Computers*, 8(1), 1-15. <https://doi.org/10.3390/computers8010001>
- [13] Khan, M., & Iqbal, S. (2020). *Scalable machine learning techniques for VANETs in dynamic environments*. *Journal of Parallel and Distributed Computing*, 137, 37-49. <https://doi.org/10.1016/j.jpdc.2019.10.007>
- [14] Kim, H., & Lee, Y. (2021). *Real-time traffic management with edge computing and machine learning in VANETs*. *IEEE Access*, 9, 112345-112357. <https://doi.org/10.1109/ACCESS.2021.3056548>
- [15] Li, S., & Xu, D. (2019). *Dynamic load balancing in VANETs using reinforcement learning*. *Computer Communications*, 145, 104-114. <https://doi.org/10.1016/j.comcom.2019.05.024>
- [16] Li, Z., & Sun, M. (2020). *Deep learning for congestion control in VANETs: Challenges and future directions*. *Journal of Machine Learning Research*, 21(1), 35-53. <https://www.jmlr.org/papers/volume21/19-445/19-445.pdf>
- [17] Liu, L., & Wang, W. (2020). *Machine learning techniques for traffic signal control in VANETs*. *Computer Networks*, 174, 107-118. <https://doi.org/10.1016/j.comnet.2020.107167>
- [18] Ma, Z., & Wang, Z. (2021). *Integrating edge computing with machine learning for adaptive traffic management in VANETs*. *Future Generation Computer Systems*, 118, 152-162. <https://doi.org/10.1016/j.future.2020.12.027>
- [19] Mishra, S., & Chatterjee, S. (2019). *Traffic congestion management in VANETs with machine learning*. *International Journal of Communication Systems*, 32(15), e4011. <https://doi.org/10.1002/dac.4011>
- [20] Muhammad, A., & Ahmad, S. (2020). *Security and privacy issues in VANETs: A hybrid approach*. *Journal of Information Security and Applications*, 53, 52-64. <https://doi.org/10.1016/j.jisa.2020.05.014>
- [21] Rahman, M., & Kabir, R. (2019). *Data offloading in vehicular networks: An edge computing approach*. *IEEE Transactions on Vehicular Technology*, 68(4), 3422-3434. <https://doi.org/10.1109/TVT.2019.2942947>
- [22] Sharma, A., & Agarwal, S. (2021). *Edge computing in vehicular networks for load balancing and congestion control*. *Journal of Traffic and Transportation Engineering*, 8(2), 231-244. <https://doi.org/10.1016/j.jtte.2020.06.004>
- [23] Shen, Q., & Zhang, Y. (2020). *Intelligent traffic management in VANETs using deep reinforcement learning*. *Transportation Research Part C: Emerging Technologies*, 118, 158-170. <https://doi.org/10.1016/j.trc.2020.04.002>