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PAPER

Traffic Management Based on Cloud and MEC Architecture with Evolutionary Approaches towards AI: A Review

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ABSTRACT

This review paper explores the significance of machine learning (ML), deep learning (DL), reinforcement learning (RL), and deep reinforcement learning (DRL) techniques in improving traffic management based on cloud and mobile edge computing (MEC) architectures. The key findings and contributions of this review highlight the potential of these techniques for transforming traffic management systems through data-driven decision-making, adaptive control, and optimization. The challenges identified in this field include data availability and quality, scalability and computational requirements, privacy and security concerns, and ethical considerations. In conclusion, ML, DL, RL, and DRL techniques, in conjunction with cloud and MEC architectures, have significant implications for improving traffic management. Their ability to process and analyse large-scale and real-time traffic data enables improved traffic flow, reduced congestion, enhanced energy efficiency, and enhanced overall transportation system performance.

KEYWORDS

machine learning (ML), deep learning (DL), reinforcement learning (RL), traffic management, cloud computing, mobile edge computing (MEC), scalability, energy efficiency, privacy, security

1 INTRODUCTION

The increasing number of vehicles is one of the challenges of the modern age in developing traffic management systems. Traffic management refers to the efficient distribution and control of network traffic, ensuring optimal performance and resource utilization. The use of cloud computing and mobile edge computing (MEC) has led to the development of several data-intensive applications [1]. The number of connected devices has grown exponentially. While traditional approaches to traffic management struggle to cope with the dynamic nature of traffic models, technologies such as machine learning (ML), deep learning (DL), reinforcement learning (RL), and deep reinforcement learning (DRL) are commonly employed to solve this problem.

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This issue becomes even more critical in cloud architectures, as their resources are shared and virtualised, resulting in congestion and a lack of quality of service (QoS). Other authors [2] have demonstrated the evidence for this, as they developed QoS-aware scheduling in a cloud infrastructure that allows different types of traffic to be scheduled based on their QoS demands. Moreover, with MEC included in cloud architectures, this need becomes even more pressing. The main strengths of MEC lie in the distribution of computing and storage facilities on the network's fringe and the reduction of latency for real-time applications. Therefore, in this context, most traffic management regulations need to be strict, as more traffic circulates between users and their nearest edge servers [3].

Over the past few years, several emerging techniques based on artificial intelligence (AI) have significantly influenced traffic management. ML, DL, and RL have opened up new opportunities for managing traffic by considering existing flows, possible scenarios, and complex solutions. Many studies have demonstrated the potential of these techniques in traffic management. For example, Li et al. [4] demonstrated the effectiveness of DL in traffic prediction and pre-emptive maintenance. Another example is from Tang et al. [5], who focused on the advantages of RL in intelligent traffic signal control. These examples illustrate how ML and DL techniques enable efficient traffic analysis and prediction, while RL helps control traffic in real-time, minimizing delays and increasing traffic efficiency. While, as already mentioned in the Corina Chen [6], DL-based traffic flow prediction has evidence for traffic management systems based on hospital characteristics, reinforcement learning, as shown in Mendonca and Pereira [7], has significantly affected traffic signal control adjusting to real-time changes. Combining such AI techniques will ensure efficient traffic management, allowing normal flow, reducing stagnation, and improving operation in general.

The objectives of this paper are:

1. To review and summarize the existing literature on the utilization of ML, DL, RL, and DRL in traffic management systems based on cloud and MEC architecture.
2. To evaluate the benefits and drawbacks of ML, DL, RL, and DRL techniques in the context of traffic management, considering factors such as traffic flow optimization, congestion prediction, dynamic route planning, and intelligent traffic signal control.
3. To identify key challenges and potential study directions for the integration of ML, DL, RL, and DRL in traffic management systems based on cloud and MEC architecture. Some of the considerations are data privacy concerns, the accessibility level of real-time processing options, scaling options, and energy consumption strategies.

The purpose of this review is to encourage readers and stakeholders to explore the potential benefits of new technologies in traffic management. The primary audience refers to both studied and practitioners. Specifically, the current paper consists of the following sections: The literature on the benefits of clod and MEC architectures in traffic management is reviewed in Section 2. The literature on available ML strategies with regards to traffic predictions and forecasts, resource management, anomaly detections, and network securities is presented in Section 3. Section 4 focuses on DL strategies in traffic analysis, pattern recognition, and congestion detection. Strategies relevant to AI applications in traffic control, traffic light smartening, and route planning for diversions are described in Sections 5–6. The potential proposal for DRL-based RL functioning is suggested in Section 7, a comprehensive net of discussions is presented in their respective Section 8, and the future proposed improvements are presented in Section 9.

2 CLOUD AND MEC ARCHITECTURE FOR TRAFFIC MANAGEMENT

Cloud computing is a prevalent area that offers scalability, flexibility, and low-cost advantages. In the review of Wang et al. [8], cloud-based traffic management systems have all the infrastructure to handle large-scale data processing, real-time data analytics, and intelligent decision-making. However, it has some limitations, such as network latency, bandwidth constraints, and data privacy issues [9]. For better traffic management, the emergence of MEC was introduced. MEC decentralizes computing and storage functions at the network's edge. It allows real-time data processing and low-latency communication to be done, which is essential for traffic applications due to their time-bound nature [10]. Also, it provides more resource efficiency, less network congestion, and the support of emerging technologies such as the Internet of Things (IoT) for traffic data. Bellavista et al. [11] proposed a solution that addressed the challenge of MEC integration within a multi-access edge computing framework. The combination of edge-powered in-network processing (eINP) and software-defined networking (SDN) is their primary technological solution. Figure 1 presents a model for application-aware network traffic management in an industrial MEC-integrated environment that was based on the work.

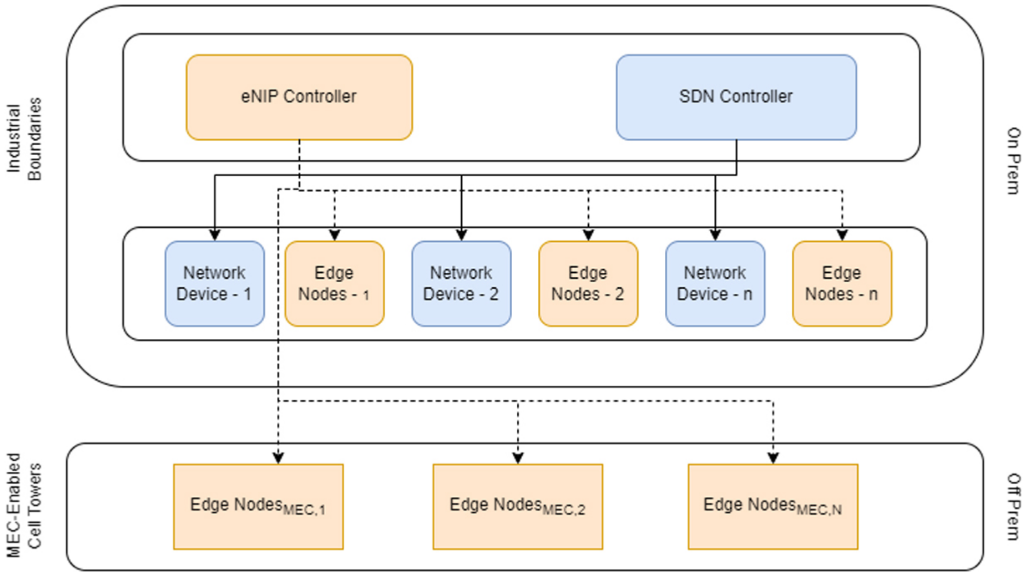

Fig. 1. Application-aware network traffic management

Source: Author.

Cloud architectures are optimized for large-scale data processing and resource-intensive tasks. In contrast, MECs are preferred for low-latency communications and real-time interactions that are elucidated by their proximity to users and traffic sources. By merging the architecture of MEC and cloud computing, an optimal combination can be realized for a hybrid distributed traffic management system [12].

3 MACHINE LEARNING FOR TRAFFIC MANAGEMENT

Machine learning techniques have become valuable tools for solving multiple challenges concerning management, in particular traffic. When using large amounts of data and analysing them to identify patterns and relationships, ML ensures accurate and timely traffic prediction demonstration, proper congestion evaluation, handling incidents, and controlling in an intelligent manner. Regression techniques have gained popularity in the field of traffic management, with these classification measures serving as traffic flow prediction and travel time indication. Some studied, e.g., Ma et al. [13], describe how support vector regression (SVR) per se or in combination with a convolutional neural network can be used to predict traffic flow. Classification techniques are involved when identifying incidents and recognizing traffic signs. Other studies, for instance, Rahmani et al. [14], use deep-learning-based classification methods to check the images from the camera for the effect or the incident. Considering the clustering techniques used for traffic pattern elaboration and anomaly detection, K-means clustering is applied to determine the different types of vasculature regimes in urban areas [15]. Rules association is also dedicated to traffic management, e.g., for identifying different columns. Reinforcement learning is used for optimizing traffic signal control [16, 17].

3.1 Traffic prediction and forecasting

Precise and accurate prediction and forecasting of traffic are essential to ensuring economic traffic management. Several ML algorithms and models have been adopted to capture complex traffic patterns and dynamics, as shown in Table 1. As much as the techniques aim to achieve these results, they also encounter various challenges as they practice.

Table 1. ML techniques in traffic prediction and forecasting

Authors and Year	Purpose	Proposed Solution	Performance	Challenges
Zhao et al. (2022) [18]	Short Term Traffic Flow Prediction	Hybrid ML approach of time-varying filtering-empirical mode decomposition (TVF-EMD) and local mean decomposition (LMD)	Prediction with improved with 33.3% when compared with TVF-EMD-based method.	Identifying optimal model combination
Velez-Serrano et al. (2021) [19]	Spatio-Temporal Traffic Flow Prediction	Convolutional residual neural networks	Improved accuracy and capability with 18.22% (mean absolute percentage error)	Use of encoder–decoders or Attention mechanisms could improve the model
Yin et al. (2021) [20]	Traffic flow forecasting during special events	Deep Residual Spatio-Temporal Long Short-Term Memory (LSTM) (DRST-LSTM)	Enhanced accuracy and ability to handle complex event-related traffic patterns	Handling irregular patterns during special events, capturing spatio-temporal dependencies
Wang et al. (2021) [21]	Traffic flow prediction with pedestrian information	Attention-based Graph Convolutional LSTM (AGC-LSTM)	Improved accuracy and consideration of pedestrian influence on traffic flow	Incorporating pedestrian flow data, handling heterogeneous data sources
Zhang et al (2023) [22]	Network traffic prediction	Convolutional Block Attention Module (CBAM) Spatio-Temporal Convolution Network-Transformer (CSTCN), for time-series prediction	CSTCN-Transformer reduced the mean square error by 65.16%, and mean average error of prediction by 51.36%	The proposed model collected data every 10 minutes. This can be improved so that the model can be used for real-time traffic prediction. The integration of different approaches in the model can lead to higher complexity that can slow the training.

(Continued)

Table 1. ML techniques in traffic prediction and forecasting *(Continued)*

Authors and Year	Purpose	Proposed Solution	Performance	Challenges
Agrawal et al. (2024) [23]	Predict and recommend TMIs (traffic management initiatives) at an airport based on current weather and airport conditions	Supervised learning techniques: Logistic Regression, K-Nearest Neighbor, Random Forest, XGBoost, LSTM networks	Random Forest and XGBoost can predict if a TMI is needed but struggle with specific program type; LSTM networks perform better in predicting program type based on historical data sequences	Difficulty in predicting specific TMI program type with Random Forest and XGBoost algorithms, need advanced modeling techniques and architectures for future predictions
Jin, Zhang, & Liu (2024) [24]	Predict TMIs at airports based on current conditions	Supervised learning models: Logistic Regression, K-Nearest Neighbor (KNN), Random Forest, XGBoost, LSTM, Hybrid LS-SVM with PSO and GA	Good prediction accuracy over 90%, lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) compared to other models, increased EC (5%); stable and accurate in traffic flow prediction	Sensitivity of model parameters, optimization of parameters needed
Obaid et al. (2024) [25]	Predict incident durations and evaluate impact on roadway network	Feature optimization (FO) using feature engineering (FE) and feature selection (FS) techniques with multivariate linear regression, decision trees, support vector regressors, KNN regression, ensembles, and artificial neural networks	Successful reduction in feature count without performance loss; FE techniques like log-normal transformation, min-max normalization, and principal component analysis (PCA) improve accuracy across all models	Data modeling challenges like complex correlations, skewed data, heteroscedasticity, and outliers; need effective feature optimization techniques

3.2 Traffic optimization and resource allocation

Machine learning techniques are essential in ensuring the streamlined flow of traffic and efficient allocation of resources in traffic management systems. Several ML-based procedures have emerged aiming to curb traffic and congestion. One such notable application is traffic signal control, where reinforcement learning has proven to be effective. El-Tantawy et al. [17] have demonstrated the effectiveness that RL-based signals can have in ensuring traffic delays are removed. The system can maintain illumination duration and thus smooth the traffic without resultant setbacks. Additionally, the techniques are essential in resource prediction. Several authors have indicated that ML-based urban traffic predictions are engaging, and Chen et al. [6] found that deep learning algorithms are useful. Other clustering-based techniques have been suggested to identify areas and provide statistics based on the level of congestion [26]. The algorithms depend on K-mean clustering. Classification algorithms are also utilized for real-time incident identification, aiding in the detection of incidents and accidents [14].

Jiang et al. [27] stressed the necessity of accurate traffic prediction for resource management efficiency. The presented review thoroughly describes several ML techniques, including neural networks and reinforcement learning models, outlining their advantages and disadvantages. Guerra-Gómez et al. [28] studied resource management for Cloud Radio Access Network (C-RAN) systems with machine learning-based traffic forecasting methods. The studied proposed a forecast model supported by long-short-term memory neural networks, which provided accurate predictions of demand loading in the future. They verified this approach with multiple simulations and showed that their optimization approach allowed for better resource management and a decrease in latency in C-RAN systems. The authors emphasized the potential of ML to improve traffic forecasting in the C-RAN system and, subsequently, resource optimization. Jooloudari et al. [29] closely examined the artificial intelligence methods of resource allocation optimization. Through an extensive review of relevant study works, these authors characterize the main benefits and challenges of this optimization approach.

For instance, Hazarika et al. [30] presented a new approach to a dynamic traffic light system that utilized self-learning algorithms and vision-based techniques, which could adjust traffic signals dynamically based on current traffic density, improve inter-junction communication for prioritization, and establish green traffic corridors for emergencies, ensuring that delays are minimized and traffic flow remains optimized in urban environments. Another example is an investigation of the problems associated with increased data traffic flow management in cloud computing environments performed by Sekwatlakwatla and Malele [31]. The professionals showed that sufficient resource allocation was essential in this case. The study included the use of autoregressive integrated moving average, Monte Carlo, and extreme gradient boosting regression to work with traffic flow data in an organizational cloud computing environment. The use of the Monte Carlo method with 84% prediction accuracy showed that it was more efficient than autoregressive integrated moving average (ARIMA) and XGBoost methods and that it could be used to enhance the prediction accuracy in traffic flow. This study works as a platform for future studies that will rely on ML algorithms, hourly observations, and resource allocation optimized for specific industries.

3.3 Anomaly detection and network security

The term “anomaly detection” refers to the process of identifying any patterns or events that differ significantly from what is normal or expected. This review will state the importance of ML in detecting abnormal patterns and its importance to network security. A significant number of studies [32, 33] explore how the importance of ML techniques has been expanded in the fields of anomaly detection and network security. ML is an automated process that can analyse large volumes of data, detect abnormalities in real-time, and assist in identifying abnormal activities that can lead to security failure. The primary function of ML in anomaly detection is that it allows a learning system that can be adapted to changing trends and evolving threats [34].

Many attack activities are emerging each day; traditional rule-based approaches and signature-based systems are insufficient to prevent and protect from known attack vectors only, and they are not conceptual for developing newly emerging attacks. In contrast, ML algorithms can continuously learn and update their models to recognize novel attack patterns and adapt their detection capabilities accordingly. Therefore, ML algorithms are more reliable and efficient than these traditional algorithms, and ML also identifies anomalies in large networks more accurately and effectively than traditional methods [35]. Because multiple network parameters are considered, ML can detect complex attacks which are unnoticed by traditional method. Such ML algorithms can discover subtle modulations in traffic patterns, user accounts, or alarms based on unauthorized use of these accounts, which means security breaches [36].

Machine learning algorithms integrated with network security systems result in advanced intrusion detection systems that can monitor network traffic system log information and user systems to detect dangerous action in real-time [37]. These methods can help network administrators identify possible threats and reduce the risks of information theft and system crashes due to a lack of security. ML also helps data workers remove false positives and false negatives and advance systems for use [38]. However, it is important to note that ML-based anomaly detection systems are not flawless. They may encounter challenges such as data imbalance, evasion attacks, or adversarial examples. Therefore, further study and development are required to enhance the robustness and effectiveness of these systems [39].

To summarize, ML techniques have revolutionized the fields of anomaly detection and network security. The ability of ML algorithms to detect abnormal patterns and protect networks from security threats is invaluable. By leveraging the power of ML, network administrators can enhance their security posture, strengthen their defence mechanisms, and effectively respond to potential cyberattacks. Continued study and development in this area holds great promise for the future of network security.

4 DEEP LEARNING FOR TRAFFIC MANAGEMENT

Deep learning is a subfield of ML that involves the training of artificial neural networks with multiple layers of interconnected nodes, also known as deep neural networks. These networks are designed to mimic the structure and functionality of the human brain. In the context of traffic management systems, deep learning algorithms can be used to analyse large amounts of data on traffic flows, the state of roads, and other similar variables. DL can be used to predict accurately and help traffic management systems, in case of accidents, optimize the flow and misallocation of highway patrol duties for greater efficiency.

Deep learning provides a number of unique characteristics that distinguish it from conventional ML systems and are particularly suited to traffic management. First, DL algorithms are capable of extracting and identifying features from input raw data, eliminating the need to manually extract features. Second, DL models can manage high-dimensional data; for example, many traffic images or sensor data are transmitted in thousands of dimensions [40]. Finally, DL models are excellent at identifying non-linear connections in data. Traditional ML systems are frequently based on linear assumptions or tolerant shallow models. This is inadequate for capturing complex relationships. At the same time, DL models can automatically identify more intricate nonlinear relationships, producing better DL traffic management models.

4.1 Traffic analysis and pattern recognition

Due to its capacity to identify traffic patterns and learn features relevant to traffic management, DL significantly contributes to effective traffic management. DL techniques presented in the traffic management sector, such as traffic flow predictions, congestion detection, and anomaly detection, have been very effective. By using specific models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which effectively capture spatial and temporal dependencies in traffic data with high accuracy, meaningful features can be extracted from raw traffic to easily predict and identify patterns [41]. For example, a CNN can recognize spatial patterns seen from various images captured by surveillance cameras depicting traffic behaviour, whereas an RNN has an added advantage due to the distinctive temporal dependency modelling traffic flow data. These models would help urban planners and transportation authorities understand traffic patterns, such as what the patterns of congestion look such as and where the high congestion hotspots will most likely occur. The beneficiaries will then allocate resources appropriately and ascertain traffic signal timings to conduct proactive measures to reduce congestion.

Table 2 highlights a comparison of DL techniques utilized in traffic prediction, analysis, and forecasting, outlining their objectives, suggested solutions, and encountered challenges.

Table 2. DL techniques used in traffic prediction, safety, and analysis

Authors	Purpose	Proposed Solution	Performance	Challenges
Najafi Moghaddam Gilani, et al. (2021) [40]	Urban traffic accident analysis and prediction	Logit and machine learning-based pattern recognition models	Accurate accident analysis and prediction, with accuracy prediction power of 89.17%. The ML model has higher prediction accuracy (98.9%) than the logit model.	Handling class imbalance in accident datasets
Yao & Ye (2020) [41]	Freeway traffic safety and prediction	Image recognition and Naive Bayes algorithm	Average prediction error is 13.8%. Accuracy of vehicle matching model based on Naive Bayes is 82.7%	Data availability and quality, real-time processing limitations
Jin, Sun, & Hu (2023) [42]	Highway vehicle detection using pattern recognition	Pattern recognition and deep learning	Enhanced vehicle detection accuracy	Robustness to diverse environmental and traffic conditions
Zhang, et al. (2021) [43]	Bus trajectory analysis for traffic insight	Deep learning-based detection of anomalous patterns, and offline detection approach (OFF-ATPD)	Accurate traffic insight analysis. Anomaly detection performance by OFF-ATPD is 100% detection rates.	Anomaly detection for diverse and evolving traffic patterns
Cui & Zhao (2023) [44]	Dynamic traffic pattern recognition and prediction	Deep learning-based dynamic pattern recognition	Improved prediction accuracy	Dynamic traffic patterns, real-time analysis complexity
Ismaeel, et al. (2023) [45]	Traffic pattern classification in smart cities	Deep recurrent neural network for pattern classification	Effective traffic pattern classification	Handling diverse traffic patterns and fluctuations in smart cities
Moumen et al. (2024) [46]	Optimize traffic flow prediction and energy efficiency in urban transportation	Deep learning approach using Gated Recurrent Unit (GRU) to analyze traffic patterns at multiple intersections simultaneously, integrating data fusion techniques	Real-time accurate traffic flow predictions lead to improved traffic management and reduced fuel consumption, aiding in energy efficiency and sustainability	Complexity of urban traffic networks, accuracy of predictions with distributed system approach, integration of data from various sources

4.2 Deep learning for traffic prediction and congestion detection

Deep learning techniques, such as CNNs and RNNs, have proven to be highly effective in predicting traffic patterns and detecting congestion accurately. This section will delve into how DL, along with other techniques such as deep belief networks (DBNs), radial basis function networks (RBFNs), graph neural networks (GNNs), and variational autoencoders (VAEs), are utilized in traffic prediction and congestion detection tasks.

Traffic prediction. Deep learning techniques have also significantly contributed to traffic prediction by learning complex patterns and dependencies in the traffic data. CNNs have particularly attracted great interest due to their capability of extracting spatial features from traffic images, which enable high recognition of traffic objects, congestion, and flow characteristics. For instance, a CNN based model presented by Yin et al. [47] was used to predict traffic flow from traffic camera data, and the results enhanced the accuracy of the prediction.

Recurrent neural networks, in addition to variants such as long short-term memory (LSTM) and gated recurrent units (GRUs), have an advantage in learning temporal dependence in traffic data. Due to their success in traffic prediction, they have been applied to counter similar issues. Kashyap et al. [48] presented a study in which a survey on traffic flow prediction using LSTM was carried out, showing the model can learn long-term dependence and provide good predictions. As specified by the author, the DL models use multiple layers to get all features from raw inputs. Generative models such as DBNs, which have a great ability to learn hierarchical representation, have also been used in traffic prediction. The model can learn the spatial information in an input feature and provide reasonable results. Through the combination of DBNs and other DL models, the programs have similar performance [49].

Congestion detection. Deep learning techniques are essential for accurate traffic congestion detection. CNNs have been used to identify congestion-related features through traffic camera pictures. Vehicles' density and abnormal traffic cues used by CNNs have proven to be effective in determining congested areas. For example, Zhang et al. [50] applied CNNs to analyze camera images' spatial-temporal cues to detect traffic congestion and estimate travel times. In this paper, a deep-learning method named ST-ResNet is designed to predict the inflow and outflow of crowd flows in all regions of the city. The model can accurately forecast both the inflow and outflow of crowds. The present paper approaches the problem with specific techniques to analyse spatio-temporal data in a unique way that explores its characteristics. For this, they utilized a residual neural network framework to characterize the temporal closeness, period, and trend features of crowd traffic [50]. The results showed that the prediction was achieved in 18.56 seconds.

Radial basis function networks are models that approximate nonlinear relationships, which are critical in traffic prediction and congestion detection. These models create complex traffic patterns by linking input values to target values. By identifying extensive and complicated patterns, RBFNs help to accurately detect congestion and predict traffic [51]. GNNs have also facilitated remarkable performance in traffic prediction. GNNs are models specifically designed to handle graph-structured data, such as traffic. They learn relational information characterizing the traffic nodes, providing accurate traffic patterns. GNNs have outperformed several ML algorithms in traffic flow estimation in situations where traffic data can be represented as a graph [52]. In a study [52], the studied developed a novel model for real-time traffic-speed estimation using deep graph neural networks (DGNNs) and GNNs and named the model STGGAN. The study found the prediction accuracy to be 96.67% for the PeMSD4 database and 98.75% for the PeMSD8 database. VAEs are generative models used in traffic prediction. These models are designed to learn the underlying probability distribution of the traffic data. This information is crucial in developing reasonable future prediction and prediction uncertainty estimation [53]. In a study [53], the studied proposed an unsupervised generative neural network for traffic data imputation using VAE and found that their model achieved the lowest imputation errors.

5 REINFORCEMENT LEARNING FOR TRAFFIC MANAGEMENT

Reinforcement learning is a subset of ML that focuses on system control. The concept of RL involves an agent perceiving the environment through its states, taking actions, and receiving immediate rewards based on those actions. This allows the agent to learn control policies and maximize long-term objectives through 'trial and error' learning. RL has been proposed as a promising technique to enhance the traffic management system. Using RL methods can optimize the traffic signal control process and minimize congestion during transit. In this review, the implications of using RL for changing the traffic signal and controlling the traffic flow are reviewed. This section discusses the employment of RL in dynamic route planning and traffic diversion.

5.1 RL in traffic signal control

In traffic management, the traffic signal is the most important control parameter at the intersection. RL provides a framework for learning optimal control policies without the need for explicit knowledge of traffic system dynamics [54]. The RL agent interacts with the environment and receives rewards or punishments based on the action done. Studies have shown that RL can effectively be applied to the traffic signal of the signalized control of the intersection. Wang et al. [55] used the RL method to optimize the traffic signals for the intersection. The RL agent was set to look at the traffic status and minimize the average waiting time and network congestion. The study showed an improvement in the traffic system as compared to the previous methods using dynamic programming, where the proposed data-driven model showed an improvement of 3.9% better than the existing adaptive control system.

Furthermore, deep Q-networks (DQNs) have been utilized to control traffic signals. DQNs are neural networks that have been utilized to approximate the state-action value function and design an optimal signal timing policy. The DQNs can be done using historical information that the agent learns from the traffic data, making them suitable for the job. Punia et al. [56] showed remarkable performance on the traffic system applied to the DQNs. Agents using the DQNs optimized their policies and minimized travel time and network. Another notable RL algorithm in traffic signal control is proximal policy optimization (PPO). PPO considers and optimizes the policy to guide signal control. The approach was used by Wei et al. [57] and showed improvements in road network performance. The RL agent learned to adjust the timing based on traffic conditions, aiming to minimize average waiting times or congestion in the network. The results showed significant improvements in traffic flow and reduced congestion compared to traditional fixed-timing approaches.

5.2 RL for dynamic route planning

Dynamic route planning is the act of continuously rerouting vehicles based on dynamic, real-time traffic conditions, bottleneck events, and levels of traffic on segments of the road network. In this context, reinforcement learning is a suitable framework to learn optimal navigation policies without any prior knowledge of the dynamics of the traffic system in question. The RL agents learn the optimal routing by interacting with the environment, which provides feedback to the agent as a reward or a penalty based on the route decision. Several works apply RL to dynamic route planning. For instance, Ahmadi and Allan [58] applied RL to real-time traffic management systems. In this case, the RL agent leverages historical traffic data to plan routes. The learning agent adaptively routes vehicles based on the traffic congestion observed by the agent, traffic incidents, and anticipated traffic in the near future. The algorithm resulted in shorter overall travel times by 31.5% during rush hours.

Another work used RL techniques, DQNs, to develop and train an agent that reroutes vehicles in real-time based on traffic. The RL algorithm replaced traffic lanes affected by high traffic congestion, optimized travel time, and reduced travel time. The study [59] proposed a DQN-based approach for dynamic route planning that effectively rerouted vehicles in response to changing congestion levels, resulting in reduced travel times and improved traffic flow. In addition to traditional RL algorithms, PPO have shown promising results in dynamic route planning. The work by Silva, Alaeddini, and Najafirad [60] demonstrated the effectiveness of PPO in adaptive traffic diversion, achieving enhanced traffic flow and reduced travel times. The studied developed a model based on RL with

PPO for assessing the complexity of the shortest path query in spatio-temporal graphs. They divided the spatio-temporal graph into two components, static and dynamic sub-graph. They used PPO to develop an action policy that helps with the selection of local optimal actions in the Markov process. This provides the shortest path. The study obtained an efficiency of 75% greater than the existing solutions.

6 DEEP REINFORCEMENT LEARNING FOR TRAFFIC MANAGEMENT

Due to its potential benefits for traffic management in terms of optimizing traffic flow patterns, reducing congestion, and enhancing overall transportation efficiency, DRL has become one of the most powerful techniques. DRL applies DL and RL to traffic flow dynamics to create artificially intelligent agents capable of making decisions based on environmental feedback. Table 3 provides a comprehensive comparison of the DRL techniques utilized in traffic prediction, analysis, and forecasting, outlining their respective objectives, proposed solutions, and encountered challenges.

Table 3. DRL techniques used in traffic optimization

Authors	Purpose	Proposed Solution	Performance	Challenges
Calvo and Dusparic (2018) [61]	Traffic lights control optimization	Heterogeneous Multi-Agent DRL for Traffic Lights Control by using Independent Deep Q-Network (IDQN). The study uses Dueling Double Deep Q-Networks (DDDQNs) to train each individual agent	Improved traffic flow, reduced waiting times. The proposed approach gives higher rewards outperforming ERM by around 45% for low traffic loads.	Scalability to large-scale traffic networks; lack of results for high traffic loads
Hussain, Wang and Jiahua (2020) [62]	Traffic light optimization with V2X communication	Multi-Agent DRL and Vehicle to everything (V2X) Communication. The solution analyses rewards to enable multi-agents in controlling the duration of traffic lights.	Enhanced traffic flow, reduced congestion, optimized traffic signals, and deduced average waiting cars to 41.5%.	Integration of V2X communication in traffic management
Li et al. (2024) [63]	Interactive merging strategy optimization in mixed traffic	Nash Double Q-based Multi-Agent DRL for Interactive Merging Strategy. One agent predicts and analyses the behaviour of mainline vehicles; and other agent finds the optimal merging actions of ramp vehicles.	Improved merging efficiency, reduced collisions	Handling diverse merging scenarios and traffic conditions
Wu et al. (2021) [64]	Resource allocation for V2Es communications	Multi-Agent DRL for Resource Allocation in Vehicular Networks. Proposed solution uses resource of edge nodes in the proximity, thereby timely processing emergency information	Efficient resource allocation for V2Es communications. The proposed system can learn the scheduling policy more efficiently, resulting in an average reduction of service latency by over 10%.	Scalability to large-scale vehicular networks
Gong (2020) [65]	Adaptive signal control for traffic safety and efficiency	Decentralized network-level Adaptive Signal Control System (ATSC) based on multi-agent DRL	Improved traffic safety and efficiency; travel time reduction. It reduced average daily delay by 25.93%; and average daily crash risk by 8.89%	Integration with real-time traffic data and system validation
Fernández Sánchez (2021) [66]	Optimization of traffic signaling and speed advisory	DRL for Joint Optimization of Traffic Signaling and Vehicle Speed Advisory	Enhanced coordination between signaling and advisory	Addressing variability in traffic conditions and vehicle response

7 CHALLENGES AND LIMITATIONS

Although traffic management can be transformative, there are numerous challenges and limitations that need to be addressed in order to create more efficient systems. The first is the issue of congestion. As Batiebo et al. [67] argue, conventional traffic management systems are still unable to deal with the ever-increasing traffic volume; they manifest bottlenecks and delays. Additionally, these systems are unable to cope with a second issue related to congestion, i.e., its dynamic nature. Indeed, congestion is rarely static. Over the course of the day, during rush hours and the off-peak period, on weekdays and weekends, and in a broad range of other conditions, demand and congestion fluctuate [68]. This necessitates an entirely different system capable of rapid adjustment to the changing conditions. Thirdly, there is a lack of accurate real-time data. Traditional control methods, such as cameras and sensors, are not reliable enough to ensure the timely traffic data needed for effective governance. One serious obstacle is the high integration and privacy capacity of this process. The fact is that algorithms using deep learning require a huge amount of data for effective operation, as well as a set of applications to train them. However, given the difficulties in monitoring routes and detecting congestion in the flow of this difficulty, it cannot be decrypted.

Indeed, DL algorithms require enormous amounts of data for effective operation. However, due to the complications related to route observations or the identification of congestion in the flow, this barrier is insurmountable. The fact that the data is only real-time, further complicates the issue, as this process necessitates constant data access. Moreover, another barrier to learning is the lack of labelled data [69]. Numerous algorithms require labelled training data to teach, and there may not be sufficient or accurate data available, rendering learning impossible and the level of the whole system's complexity exceedingly high.

Furthermore, interoperability and integration present challenges. Different stakeholders, including transportation agencies, service providers, and travellers, use diverse systems that often lack interoperability, hindering effective collaboration and coordination [70]. The integration of traffic management solutions with emerging technologies, such as IoT and data analytics, also faces challenges related to standardization and compatibility.

8 FUTURE PROSPECTS AND DIRECTIONS

Based on the challenges encountered above, the integration of ML, DL, RL, and DRL with the cloud and MEC has contributed majorly to the advancements and improvements in the traffic management system. Despite how far the technology has progressed, there are quite a few challenges that will need to be addressed later. Future developments should, therefore, consider the existing challenges in addressing the future possibilities of the traffic system.

1. Enhanced Data Acquisition and Management: Future study should focus on developing more efficient and robust data acquisition and management techniques. Improved data collection methods, including advanced sensors, connected vehicles, and Internet of Things (IoT) devices, can provide real-time and high-quality data.
2. Scalable Algorithms and Architectures: To address scalability challenges, future directions should explore developing scalable ML, DL, RL, and DRL algorithms

that can handle the increasing complexity of large-scale traffic networks. This includes the development of distributed computing architectures, edge computing solutions, and parallel processing techniques.

3. Privacy-Preserving and Secure Solutions: As traffic management systems rely heavily on sensitive and personal data, future study must focus on privacy-preserving and secure solutions. Novel techniques, such as differential privacy, secure federated learning, and secure multi-party computation, can help protect individual privacy while leveraging the power of ML, DL, RL, and DRL algorithms.
4. Explainability and Transparency: To overcome the black-box nature of ML, DL, RL, and DRL models, future directions should emphasize developing explainable and interpretable algorithms for traffic management. Explainability is crucial for building user trust and ensuring accountability in decision-making processes.
5. Integration with Emerging Technologies: The integration of ML, DL, RL, and DRL with emerging technologies opens new avenues for improving traffic management. Future study should explore the integration of these techniques with connected and autonomous vehicles, smart infrastructure, and vehicular ad-hoc networks (VANETs).

9 CONCLUSION

This review paper aimed to explore the potential of utilizing ML, DL, RL, and DRL techniques through cloud and MEC frameworks to enhance traffic management. The main outcomes and findings of this review emphasized the possibility of revolutionizing traffic management practices through the utilization of data-driven decision making, adaptive control, and optimization. Applying ML, DL, RL, and DRL methods makes it feasible to analyse and process decentralized data in real-time. Moreover, by utilizing cloud and MEC frameworks, these are scalable and allow distributed computing across the network, ensuring decentralized operational decision-making in real-time. Overall, this results in improved traffic flow, congestion avoidance, energy stream optimization, and better transportation system operation. The review also outlined several challenges and restrictions that should be resolved to ensure the benefits of ML, DL, RL, and DRL and hence empower traffic planning through the utilization of the mentioned methods. It is expected to be solved by improved mechanisms of data acquisition and consolidation, scalable algorithms and cloud infrastructures, privacy protection, and comprehensive decision-making.

This review also contributes to understanding the potential prospects in the field. These include enhanced data acquisition and management, scalable algorithms and architectures, privacy-preserving and secure solutions, explainability and transparency, integration with emerging technologies, sustainable and green traffic management, and human-centric approaches. These directions offer tremendous potential for further advancements in traffic management practices and will contribute to achieving safer, more efficient, and more environmentally friendly transportation systems.

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