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Systematic review of the impacts of electric vehicles on evolving transportation systems

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Abstract

Electric vehicles (EVs) promise significant advancements, including high energy efficiency and the facilitation of grid-stabilizing technologies such as vehicle-to-grid. However, their increased adoption introduces challenges such as elevated congestion, compromised safety, and grid instability. These challenges stem from differences in acceleration and deceleration patterns between EVs and internal combustion engine vehicles (ICEVs), mismatches between charging station demand and grid supply, and potential cyberattacks on the communications of EVs with charging stations and local grids. To address these issues, novel mathematical and machine-learning models have been developed. These models incorporate both simulated and real-world traffic flow data, charging station distribution and utilization data, and in-vehicle energy management and driver assistance data. The outcomes include optimally planned routes for EVs to destinations and charging stations, stabilized power distribution systems during peak hours, enhanced security in EV-station-grid communication, more energy-efficient storage systems, and reduced range anxiety for EV drivers. This paper systematically reviews the emerging impacts of EVs on evolving transportation systems, highlighting the latest developments in these areas and identifying potential directions for future research. By reviewing these specific challenges and solutions, this paper aims to contribute to the development of more efficient and sustainable electrified transportation systems.

Keywords: Electric vehicle; Traffic congestion; Charging infrastructure; Traffic flow model; Machine learning

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Introduction

Electric vehicles (EVs) are gaining market share over internal combustion engine vehicles (ICEVs) due to their higher energy efficiency, superior energy conversion, regenerative braking technology, and the ability to support grid-stabilizing technologies like Vehicle-to-Grid (V2G)[1−3]. The transition from ICEVs to EVs influences driver behavior and route choices[4,5], thereby impacting transportation systems. The differences in acceleration and deceleration patterns between EVs and ICEVs raise concerns regarding congestion and safety[6]. Furthermore, integrating EVs into smart grids *via* V2G technology[1] presents additional challenges, such as its impact on urban mobility. This paper examines recent advancements in these areas, with a particular focus on mathematical and machine learning models, and identifies critical gaps and future research directions.

The increasing presence of EVs on roads not only directly impacts traffic patterns but also interacts with smart grids, introducing potential cyber vulnerabilities due to extensive communication technology use. Research indicates that EVs, whether alone or in conjunction with ICEVs during morning commutes, can cause traffic congestion[2]. One study found that a 15% and 30% increase in EV usage led to an 8.7% and 12.1% annual rise in waiting periods[7], respectively, highlighting the congestion impact of EVs on traditional traffic systems. However, other studies have proposed potential solutions. For instance, separating traffic flows and implementing optimal tolling could reduce the additional congestion caused by the growing market penetration rate (MPR) of EVs[2]. Additionally, a traffic control model incorporating traffic lights and a flow model based on total time spent has been implemented to identify congested areas, ensuring smoother traffic flow, minimizing energy consumption, and reducing emissions[8]. The adoption of micro-mobility options for shorter trips has also been suggested. A case study in Seattle (USA) estimated that replacing a significant portion of short car trips with micro-mobility options could reduce traffic congestion by up to 18%[9].

Beyond normal commuting conditions, areas near EV charging stations are prone to traffic congestion due to factors such as the availability of parking slots, charging plugs, and charging rates[7]. Hence, the positioning, sizing, and coordination of charging stations play crucial roles in mitigating the induced congestion, which can spill over to adjacent road networks. This issue is considered as a multi-dimensional optimization problem[10] and was addressed using queueing theory to determine the optimal number of charging outlets needed to minimize wait times and optimize station utilization. Compared to concurrent models, the proposed scheme demonstrated a notable 40% increase in customer satisfaction and a 45% improvement in charging station utilization. A study using queuing theory with an M/M/C model for fast charging stations (FCS) indicated potential improvements, showing a 40% increase in EV user satisfaction and a 45% boost in FCS utilization through optimized allocation and sizing[10]. Additionally, integrating EVs into smart grids, especially those incorporating renewable energy sources (RES), can alter charging patterns, thereby influencing overall traffic flow by potentially changing when and where EVs are on the move. Since EVs spend most of their time being idle, they can fulfill surges in energy demand during peak hours through V2G technology, potentially reducing congestion near charging stations by encouraging charging during off-peak hours through lower electricity rates and through earning by plugging in the vehicles[11−13]. However, the increasing integration of EVs into smart grids also raises cybersecurity concerns. These concerns are substantiated by potential attacks on the growing connections between EVs, charging infrastructures, and smart grids[14−16].

Traffic flow models are crucial for understanding the effects of increasing EV market penetration and for finding solutions to address these effects. Recent models have focused on the unique driving behaviors of EVs compared to traditional ICEVs. For example, the micro-traffic model proposed by Xu et al.[17] considered the distinct acceleration and braking patterns of EVs in both free-flow and stop-and-go traffic. Compared to behavioral models, it provided additional insights into vehicle energy consumption in complex and congested scenarios. To direct EVs to their destinations or appropriate charging stations and thereby manage traffic congestion, route planning can serve as an effective solution. For instance, Sebai et al.[18] proposed a scheme for planning EV routes that accounts for dynamic traffic phenomena, road topologies, and charging station locations. This scheme provided predictive flow identification based on previous trajectory data to plot energy-efficient maps. The algorithm was tested in real-world scenarios and demonstrated efficiency in planning optimal routes for EVs.

In addition, Yang et al.[19] proposed a microscopic model to simulate the impacts of charging station location on traffic flow and charging load, subsequently developing a joint planning model that integrates real-world traffic network data with power distribution planning to balance traffic assignment and reduce congestion. Other studies have examined the impact of EVs on pedestrian safety, finding that they have a higher risk of collisions due to their quiet operation — 31.5% higher in one study[20] and up to 30% higher in noisy environments and 10% higher in quieter ones in another[21]. This suggests that adding alert sounds to EVs may improve pedestrian awareness[22].

While traditional analytical and optimization methods have improved traffic efficiency, recent studies use machine learning (ML) to better plan EV routing and charging. For example, Jin et al.[23] used a Deep-Q Network (DQN) in a deep reinforcement learning framework to optimize route planning in dynamic environments. Another study combined Gaussian processes with optimization techniques to predict where to place charging infrastructure[24]. ML-based schemes for managing charging demand can also help reduce peak hour congestion by encouraging off-peak charging[25,26]. Additionally, accurately estimating an EV's state-of-charge (*SoC*) is important for predicting its range; Praveena & Manoj[27] developed a neural network model to improve *SoC* prediction accuracy.

Limited reviews on the impacts of EVs have primarily focused on addressing challenges such as range anxiety, grid stabilization, and driver safety through innovative technologies like smart sizing and allocation of charging infrastructure, predictive *SoC*, and V2G[28−30]. The present study complements existing literature in the following ways:

• This paper systematically reviews the impacts of EVs on various aspects of the evolving transportation system, including travel behavior, traffic congestion, routing, and charging planning, cybersecurity, among others, with an overarching representation shown in Fig. 1.

• It provides a thorough summary and analysis of the latest research advancements in traffic flow models, EV-grid inte gration, transportation safety and security, and experimental data collection, considering the growing presence of EVs on the roads.

• By reviewing the current state of the field and identifying promising future research directions, this study aims to inspire new insights into mitigating the potential adverse impacts of widespread EV adoption and enhancing the efficiency and reliability of future transportation systems.

Impacts of EVs on evolving traffic flow

As the MPR of EVs increases, their impacts on traffic flow, charging infrastructure, grid stability, and associated cybersecurity concerns are becoming more pronounced[7,10,14−16,31]. Figure 2 provides an overview of the impacts of EVs in comparison with ICEVs, while the subsequent subsections elaborate on these impacts, highlighting future research directions to enhance the efficacy of existing technologies where necessary. Table 1 familiarizes the readers with the list of important acronyms that will be used throughout the subsequent discussions, and Table 2 summarizes the relevant studies that discuss the impacts of EVs on emerging traffic flow.

Impacts of EVs on microscopic and macroscopic traffic flow

Microscopic and macroscopic traffic flows exhibit distinct characteristics. Microscopic flow examines individual vehicle behavior, whereas macroscopic flow considers overall traffic dynamics. EVs significantly impact traffic flows at both the microscopic and macroscopic levels due to their unique acceleration and deceleration patterns compared to ICEVs. EVs typically accelerate faster from a stop, affecting stop-and-go traffic dynamics. Although ICEVs are slower initially, they tend to accelerate quickly to match EV speeds, potentially disrupting the flow in mixed traffic scenarios[6]. Fernandes et al.[32] investigated the environmental and traffic performance implications of integrating shared, electric, and automated vehicles into the transportation system. The study developed a simplified model to estimate CO_2 and NO_X emissions at both individual and system levels. It concluded that, in the context of an increasing MPR of EVs, these vehicles are notably more efficient at lower speeds compared to higher speeds. Additionally, EVs have been shown to be energy-efficient due to regenerative braking and optimized part-load operation in congested urban conditions, achieving up to 13% energy savings compared to ICEVs[33]. The study also indicates that EVs experience greater gains from congestion reduction compared to ICEVs, further demonstrating their potential for improved efficiency in evolving traffic scenarios.

In addition, Wang et al.[2] used a microscopic energy consumption model to assess the impacts of increased EV MPR on traffic congestion, considering the variable exit flow rate of a morning commute model. They concluded that congestion is

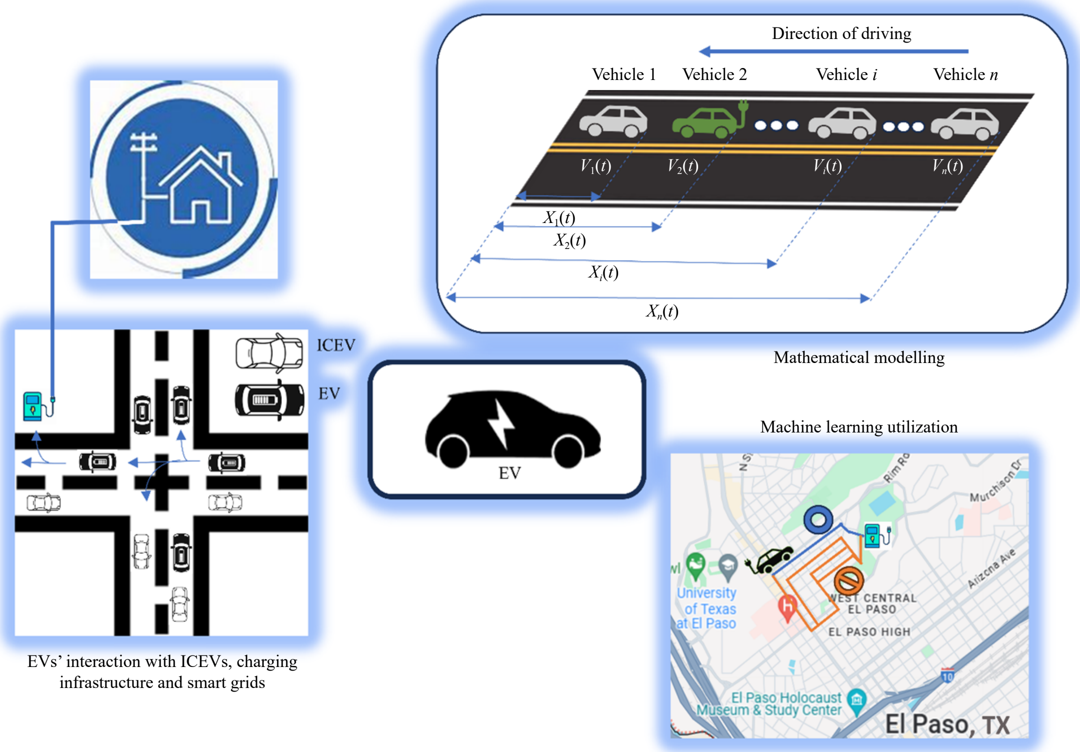

Fig. 1 The increasing adoption of EVs can pose challenges on the existing transportation network. These stem from discrepancies in acceleration/deceleration patterns of EVs and ICEVs, disparities between charging station demands and grid supplies, or even from the cybersecurity of EVs' internal communication and external communication with charging stations and local grids. The figure on the left shows possible decision-making points of EVs while being part of a smart grid network. The figure on the top right illustrates a car-following scenario involving EVs based on mathematical modeling. The figure on the bottom right demonstrates a hypothetical case of ML application in determining the optimal route to a charging station.

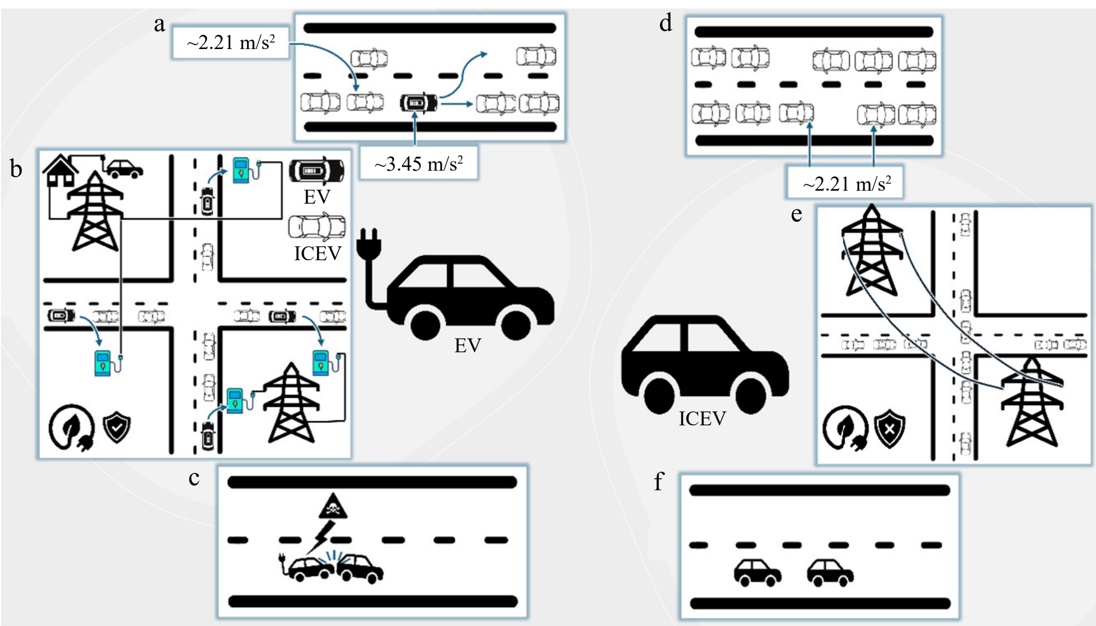

Fig. 2 Illustration of the comparative impacts that EVs and ICEVs have on the transportation system. (a) shows two hypothetical values for the accelerations of EVs and ICEVs. The higher acceleration value of EVs enables them to quickly catch up with the vehicle in front during stop-and-go traffic, facilitating traffic smoothing. In contrast, ICEVs, with their comparatively slower acceleration, take longer to catch up (d), leading to ripple effects in traffic wave propagation. (b) illustrates how EVs, through their integration into smart grids and optimal allocation of charging stations, may impact the equilibrium distribution of vehicles on the road (compared to (e)). The leaf connected to an electric plug symbol indicates that this approach is environmentally friendly by accommodating renewable energy sources and reducing carbon emissions. While EVs offer certain benefits to the transportation system, they may be more vulnerable to cyber threats, such as CAN bus attacks and false data injection attacks, compared to ICEVs (c) and (f), which requires additional safety precautions.

Table 1. List of acronyms.

Acronym	Full form
QoE	Quality-of-Experience
SoC	State-of-Charge
SoH	State-of-Health
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
CAN	Controller Area Network
DQN	Deep-Q-Network
DRL	Deep Reinforcement Learning
EV	Electric Vehicle
FCS	Fast Charging Station
GCN	Graph Convolutional Network
GPS	Global Positioning System
ICEV	Internal Combustion Engine Vehicle
MDP	Markov Decision Process
ML	Machine Learning
MPR	Market Penetration Rate
PDS	Power Distribution System
RES	Renewable Energy Source
RL	Reinforcement Learning
V2G	Vehicle-to-Grid

inevitable in mixed or all-EV scenarios. However, a staggered arrival time for EVs and ICEVs can mitigate this, modeled by parameters like the extra congestion period (ECP) and total extra congestion delay (TECD). Both ECP and TECD are eliminated at MPR values of approximately 0.718 and 0.836, respectively. Moreover, an optimal toll paradigm, ensuring both EVs and ICEVs spend the same trip time, can eliminate congestion[2]. In mixed traffic scenarios, Zhang et al.[31] employed an improved cellular automaton model, considering the unique acceleration and deceleration patterns of EVs and ICEVs. This model handled mixed traffic better than previous models, showing that increased EV penetration reduces congestion and improves safety near critical density. However, at high EV penetration rates, congestion fluctuates, and traffic safety decreases compared to homogeneous traffic.

EV-grid integration: potential impacts on traffic patterns

This subsection discusses how the interplay between power systems and EVs can impact the entire transportation network. An overview of the main ideas is illustrated in Fig. 3. The integration of EVs and smart grids significantly affects traffic dynamics by altering charging patterns and road availability[34]. Increased EV adoption places additional demand on local grids, leading to instability, particularly during peak hours like early evening. This can cause congestion near charging stations, spilling over to adjacent roads and intersections, affecting overall traffic flow[35]. Some additional studies have assessed the impact of large-scale EV integration on grid stability and traffic congestion[35−38]. For example, Tang & Wang[35] concluded that increased EV charging demand leads to higher congestion levels and nodal voltage deviation, particularly during evening peaks, which are 160% higher than morning peaks. Congestion near charging stations may persist even with V2G due to uneven station distribution or off-peak charging demand.

However, the proper integration of EVs with smart grids can help mitigate these issues. Acting as mobile energy storage systems, EVs can store renewable energy and supply it to the grid during peak hours, thereby alleviating extra demand[12]. V2G technology, supported by predictive control mechanisms, further curtails grid instability[11]. Tang & Wang[35] suggested nodal time-of-use and traffic congestion pricing to dynamically shift EV loads, altering charging and driving behaviors. Similarly, the dynamic pricing methodology proposed by Zhou et al.[34] can alter the charging trends of EV drivers through hourly forecasts of traffic flow and RES generated energies while suggesting optimal routes to various charging stations. This paradigm is also claimed to be efficient in reducing traffic congestion to some degree during both peak and off-peak hours. Complementing these studies, Zhang et al.[31] demonstrated that increasing the MPR of EVs and adopting V2G technology significantly improves grid and EV reliability, especially when MPR ranges from 20% to 60%. In addition, Chen et al.[36] treated the charging network as a cyber-physical system while

Table 2. Impacts of EVs, EV-grid integration, and their cybersecurity on transportation systems.

Study	Impact/concern presented	Solution proposed (in case of negative impacts)
Zare et al.[6]	The differences in acceleration/deceleration patterns between EVs and ICEVs in stop-and-go traffic lead to disruptions[6].	Proposed the EVM car-following model to better assess the EV-ACC behavior in those traffic scenarios, creating future research opportunities to mitigate the disruption[6].
Wang et al.[2], Zhang et al.[31]	Whether in a mixed EV or all-EV scenario, congestion during morning commuting persists[2].	Staggering the arrival times of EVs, or implementing an optimal tolling paradigm, can help alleviate or eliminate congestion[2].
	Fluctuations in congestion and degradation of traffic safety occurs only at higher EV MPRs[31].	Increased EV penetration reduces congestion and improves safety at critical density levels[31].
Zhou et al.[8]	The integration of EVs and smart grids significantly affects traffic dynamics by altering charging patterns and road availability[8].	Dynamic pricing based on hourly forecasts of traffic flow and RES generated energy can reduce traffic congestion during both peak and off-peak hours[34].
Mishra et al.[11], Rizvi et al.[12], Tang & Wang[35], Chen et al.[36]	Increased EV charging demand leads to higher congestion levels and nodal voltage deviations[35]. Congestion near charging stations may persist even with V2G due to uneven station distribution or off-peak charging demand[35].	Nodal time-of-use pricing and traffic congestion pricing can be used to dynamically shift EV loads[35]. EVs can act as mobile energy storage for RES and supply energy to the grid during peak hours, thereby alleviating excess demand[12]. EV charging can facilitate load balancing by transferring energy among power grids[36]. Large-scale V2G adoption can promote off-peak charging and peak-hour discharging, potentially alleviating congestion by altering the availability of cars on the road[11].
Avatefipour et al.[39], Acharya et al.[40], Dey & Khanra[41], Gunduz & Das[45]	CAN bus attacks[39] can cause accidents; false data injection attacks can manipulate vital information such as battery health or charging status[40,41,45].	ML model for CAN bus anomaly detection[39]. Algorithms combining system dynamics knowledge with measurements[41].

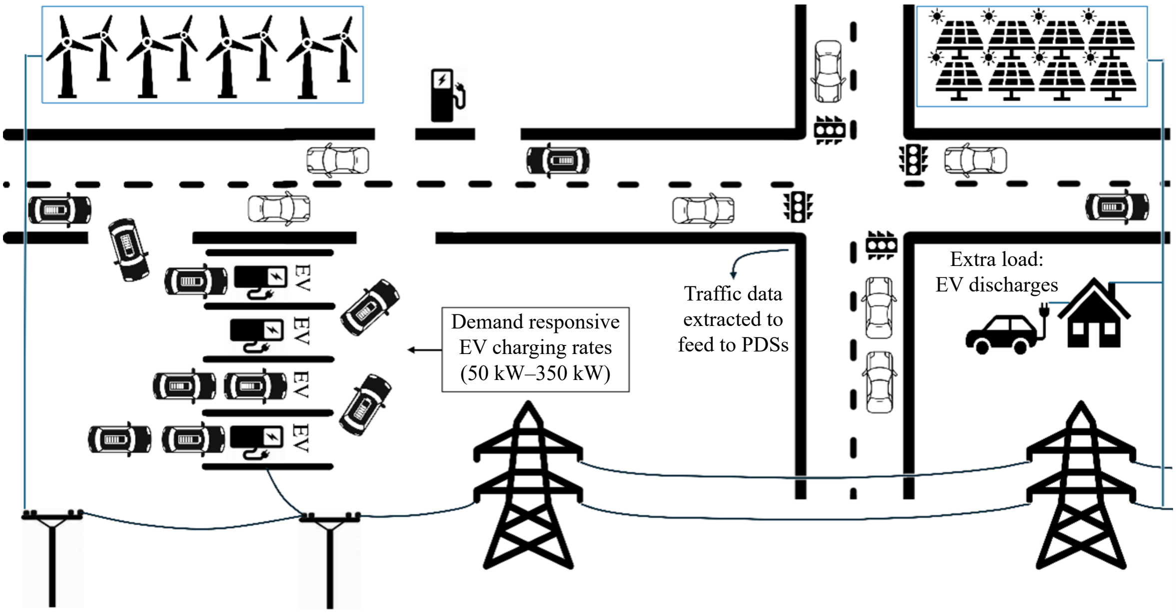

Fig. 3 Illustration of the interactions between power systems and transportation networks, with a primary focus on EVs. Acting as mobile energy storage devices, EV integration into power grids can accommodate the uncertainty of renewable energy sources (RES) such as solar and wind. This stored energy can be fed back to the power grid during peak energy demands through V2G technology, thereby facilitating grid stability. Additionally, charging stations can contribute to grid stability by regulating the charging rates of EVs in a demand-responsive manner. Furthermore, integrating traffic network data with power distribution network data can optimize FCS allocation and route planning, as well as dynamically adjust charging schedules to reduce congestion.

coupling it to the transportation network and smart grid. Then, an algorithm was proposed to schedule EV charging in a way that would balance the load across unbalanced power grids by transferring energy between them. Additionally, widespread V2G adoption is expected to alter EV charging behavior, promoting off-peak charging to reduce utility costs and discharging during peak hours, potentially earning revenue and alleviating peak-hour congestion[11].

Cybersecurity concerns

EVs, like other vehicles, use controller area network (CAN) bus structures for internal communication[39]. Their integration into charging infrastructure and smart grids necessitates frequent data exchanges, posing cybersecurity threats at various data points within these communications[40−42]. This section discusses the vulnerabilities inherent in these systems, the potential impacts of cyberattacks on traffic flow, and explores viable solutions to mitigate these risks.

Security vulnerabilities and impacts on traffic flow

The internal communication among electronic components within an EV, similar to other vehicles, is facilitated by a CAN bus. However, the CAN bus protocol lacks message authentication, making it vulnerable to malicious actors. Attackers accessing the CAN bus can alter data to manipulate or disable EV functionalities, potentially causing accidents or sudden changes in driving behavior, significantly impacting traffic flow, especially with high EV density[39]. Additionally, EVs integrated into smart grids exchange data with charging stations and local grids using protocols like ISO 15118 for station-to-vehicle communication[43] and SCADA (supervisory control and data acquisition) for station-to-grid monitoring[44]. These communications expose EVs to information disclosure and tampering during charging. Cyberattacks, such as false data injection, can manipulate vital information like battery health or charging status[40,41,45]. This can result in grid instability, unexpected charging delays, or stops, causing congestion near the charging stations as other EVs wait in line.

Potential solutions

The vulnerabilities discussed above underscore the need for robust security measures to protect EVs and ensure smooth traffic flow. Some exemplary approaches include:

CAN bus security

The ML model developed by Avatefipour et al.[39] is capable of detecting anomalies in the CAN bus, potentially identifying and preventing cyberattacks. The authors also developed a bat algorithm to optimize the ML model's efficiency and performance, ultimately ensuring better security.

Charging station security

The risk assessment framework proposed by Shirvani et al.[42] can address cybersecurity concerns at charging stations through utilizing personalized criteria and the STRIDE (spoofing, tampering, repudiation, information disclosure, denial of service, the elevation of privilege) threat model to evaluate vulnerabilities.

Smart grid security

The STRIDE threat model[40] can also be used to assess security weaknesses in smart grid components and communication protocols, ensuring standardization across the EV ecosystem.

Data security

Blockchain technology[46,47] can secure EV charging data exchanges between charging stations and smart grids, making tampering difficult through timestamped and hashed data lists.

Attack detection

The dynamic attack detection algoriths developed by Dey & Khanra[41] overcome the limitations in existing static attack detection algorithms by combining system dynamics knowledge and measurements.

Traffic flow models for EVs: adapting to a new era

As the MPR of EVs continues to rise[2], and given their unique driving patterns within mixed traffic environments[6], there is an urgent necessity for the development of new traffic flow models that address the issues and concerns posed by the increasing presence of EVs on the roads. To this need, researchers are actively developing novel models and adapting existing models to accommodate the new traffic dynamics introduced by EVs[6,10,17–19,48]. The following subsections discuss the models in detail, and before diving into the associated future research directions, Table 3 summarizes the main ideas of these models.

Strengths and limitations of existing traffic flow models for EVs

Despite significant contributions from researchers in accurately modeling EV-induced traffic dynamics and providing measures to mitigate the concerning impacts of the increasing MPR of EVs, substantial opportunities for improvement and adaptation remain. The following are some promising traffic flow models, along with their major strengths and limitations.

EV behavioral model[17]

This study introduces a detailed traffic flow model for EVs, taking into account their unique acceleration and deceleration patterns. This approach is important for better understanding how EVs behave in traffic, especially in congested situations where their distinct characteristics are most noticeable. Although the model shows good performance in heavy traffic, it behaves similarly to simpler models in free-flowing traffic. This similarity suggests that a simpler model might be just as effective in these conditions, which could be worth investigating.

EV route planning with real-time traffic prediction[18]

This study improves existing traffic flow models by using real-time data (like incidents and congestion) and road features (such as slopes) to optimize routes. Although it considers real-time data and factors affecting individual EVs, it does not account for how EVs interact with overall traffic. Including other factors like driver behavior, different vehicle types, and weather conditions could provide a more complete picture of EV traffic dynamics.

Bi-level dynamic charging scheduling model[48]

This study suggests a combined approach to manage both traffic flow and power grid stability. By using real-time traffic data to optimize EV charging schedules, it aims to efficiently manage charging loads and reduce wait times. The focus is on day-ahead power system scheduling, but integrating real-time power grid dynamics could make the model more effective. Since the study uses a hypothetical system, validating it with real-world data would make the findings stronger.

Optimal FCS allocation and sizing model[10]

This study aims to optimize the placement of FCS to maximize EV user satisfaction and station utilization. It uses a queuing algorithm to determine the best FCS size, reducing user wait times. However, the model does not include traffic flow data, limiting its ability to assess how FCS placement and queuing affect overall traffic patterns.

Traffic-aware joint planning model for FCS[19]

This study improves on previous work by integrating traffic network data into a combined planning model for power

Table 3. Traffic flow models to address emerging questions and concerns related to EVs.

Study	Model	Main ideas
Xu et al.[17]	EV Behavioral Model	To consider the unique acceleration and deceleration patterns of EVs to better understand their behavior in congested traffic.
Sebai et al.[18]	EV Route Planning with Real-Time Traffic Prediction	To use real-time data, such as incidents and congestion, along with road features like slopes, to optimize routes for EVs.
Li et al.[48]	By-Level Dynamic Charging Scheduling Model	To utilize real-time traffic data and day-ahead power system scheduling to optimize EV charging schedules, thereby efficiently managing charging loads and reducing wait times.
Guler[10], Yang et al.[19]	Optimal FCS Allocation and Sizing Model[10]	To use a queueing algorithm to determine the optimal FCS size that maximizes EV user satisfaction and station utilization while reducing user wait times[10].
	Traffic-Aware Joint Planning Model for FCS[19]	To improve on the study by Guler[10] by integrating traffic network data into a combined planning model for PDS and FCS to efficiently balance traffic flow and reduce congestion[19].
Liu et al.[20], Karaaslan et al.[21]	Pedestrian Traffic Safety Models[20,21]	Liu et al.[20] used a logistic regression model to analyze factors such as pedestrian traffic and road type, finding that EVs, due to their quiet operation, are 31.5% more likely to collide with pedestrians or cyclists.
		Karaaslan et al.[21], using a simulation model, concluded that EVs are at a 30% higher risk of colliding with pedestrians in noisy environments and a 10% higher risk in quieter environments, compared to ICEVs.
Zare et al.[6]	Electric Vehicle Model	To better assess the EV-ACC behavior in stop-and-go traffic and ultimately to mitigate the disruptions using these vehicles.
Ozkan et al.[51]	Green Wave Control Model	To anticipate road traffic, regulate vehicle speed within a predetermined range, and ultimately reduce energy usage while extending the range of EVs.
He et al.[52]	Real-Time Traffic Prediction Model	To consider the impacts of lane changing on the evolution of traffic states to optimally control the speeds of EV eco-driving to maximize energy efficiency.
Li et al.[53]	Communication-Efficient Distributed Pricing Model[53]	To account for uncertainties in RES while simultaneously distributing power and pricing, and managing traffic flow assignments[53]
Čičić & Canudas-De-Wit[54]	EV Virtual Power Line Model[54]	To dynamically adjust charging prices and rates at charging stations based on the concept of virtual power lines for EVs[54].
Li et al.[55]	Reliability Evaluation Model	To accurately describe the spatiotemporal characteristics of PDS that incorporate microgrids to facilitate the integration of EVs into vehicle-sharing networks.

distribution systems (PDS), and FCS. The method helps balance traffic flow and reduce congestion. It also tests the results using real data from two systems, making the model more relevant to real-world situations. However, it doesn't account for the effects of new technologies like V2G on EV charging patterns, which could limit its effectiveness in infrastructure that uses such technology.

***Pedestrian traffic safety models*[20,21]**

These studies examine how adopting EVs affects pedestrian safety using different models. For example, one study used a logistic regression model to analyze factors like pedestrian traffic and road type[20], finding that EVs are 31.5% more likely to collide with pedestrians or cyclists, possibly because they are quieter. Another study used simulations to show that EVs have a higher risk of pedestrian collisions compared to ICEVs[21] — 30% higher in noisy environments and 10% higher in quieter ones. However, the crash data in the first study is from 2011 to 2018, which may not reflect recent trends in EV adoption. Additionally, neither study considers different types of EVs, which might have different noise levels and safety features.

Adapting models to account for emerging EVs

In the microscopic traffic simulation model presented in a previous study[17], particular focus was placed on the unique acceleration and deceleration patterns exhibited by EVs. This is a useful approach as it enhances the understanding of EV behavior within traffic networks, especially in congested scenarios where these distinctive characteristics have significant implications[17]. With the increasing presence of EVs on roadways, the potential impact of advanced driver assistance systems (ADAS) such as ACC on traffic flow dynamics becomes more pronounced. This underscores the necessity for models that not only account for EV-specific traits but also anticipate future ADAS adoption trends. Zare et al.[6] developed an EVM that strides toward addressing these needs by capturing the unique behavioral patterns of EVs compared to ICEVs. Beyond car-following behaviors and ADAS influences, maximizing the efficiency of EVs is critical for optimizing traffic flow as their penetration rates grow. Technologies such as regenerative braking are integral to EV efficiency enhancements. For instance, Ziadia et al.[49] focused on strategies that optimize energy recovery while considering driver comfort. Unlike conventional approaches that solely aim to maximize energy capture, this study integrated naturalistic regeneration performance aligned with driver behavior preferences. By employing machine learning techniques to predict braking patterns and optimize deceleration profiles, the approach enhances efficiency while maintaining user acceptance. This underscores the significance of incorporating driver-centric strategies alongside traffic flow modeling to effectively enhance the overall efficiency and integration of EVs in complex traffic scenarios.

Other innovative measures to enhance the efficiency of EVs in mixed traffic scenarios include energy-efficient route choices. For example, Deshpande et al.[50] proposed a model that employs real-time data from traffic lights to guide surrounding traffic along the most energy-efficient trajectories. This approach can reduce energy consumption and mitigate range anxiety in EVs. Similarly, Ozkan et al.[51] developed a green wave control strategy, which anticipates road traffic and regulates vehicle speed within a predetermined speed frame. This technique can lead to significant energy savings and ensure an extended range for EVs. In addition, lane-changing behavior was incorporated into a standard traffic flow model to enhance traffic prediction, thereby enabling more efficient eco-driving controls for EVs[52].

In addition, as the MPR of EVs continues to increase, there is a growing need for integrating RES into smart grids to manage rising energy demand and to alleviate congestion near charging stations. To address this, Li et al.[53] proposed a data-driven optimization model that simultaneously distributes power and pricing while managing traffic flow assignments. This model also accounts for uncertainties in renewable energy generation through a robust optimization framework. Additional innovative technologies for regulating the grid and shifting power transmission include virtually controlled power plants and power lines. For instance, Čičić & Canudas-De-Wit[54] utilized a similar technique and proposed an EV virtual power lines concept to dynamically adjust charging prices and rates at charging stations. This approach can modify charging patterns and reduce peak demand periods, thereby alleviating congestion near charging stations. Finally, leveraging the potential of EVs in vehicle-sharing networks, Li et al.[55] integrated an improved charging load model with the Gauss-Markov mobility model to accurately describe the spatiotemporal characteristics of PDS incorporating microgrids. This integration can enhance the efficiency of charging load transfer throughout the network, further reducing peak demand periods.

Future research directions

While the studies mentioned above have made important contributions to modeling and managing emerging traffic flow in the context of EVs, there remain ample opportunities for further improvement and future research. For instance, the EV behavioral model[17] demonstrates the effectiveness of microscopic traffic flow models by considering unique EV acceleration and deceleration patterns. However, the added complexity of these models may not be necessary under free-flow conditions. Future research could explore simpler models that achieve similar performance under free-flow traffic while maintaining a detailed approach for congested scenarios. It is crucial that the models developed are not oversimplified. For example, the one proposed by Zare et al.[6] only covers ACC; future studies should consider incorporating more ADAS. Additionally, this model was tested only on a simulated string of EVs equipped with ACC. Further research should investigate the model's performance in more realistic scenarios, considering interactions with non-ACC vehicles, lane changes, and merging conditions[56].

On the other hand, studies such as the one carried out by Li et al.[48] highlight the potential of combining traffic flow and power grid models. However, this approach relies on day-ahead power system scheduling, which may not sufficiently capture the evolving dynamics of the real grid. Future research could focus on integrating real-time power grid data for more flexible and responsive charging scheduling optimization. Considering the potential of integrating traffic flow data with grid and charging infrastructure data, Yang et al.[19] developed an effective approach to incorporate traffic flow information into an integrated model for PDS and FCS planning. This approach ensures smoother traffic flow while planning for the necessary infrastructure. This study paves the way for exploring innovative technologies such as V2G systems to create a more balanced EV-PDS-FCS ecosystem.

Future research could also explore how the proposed route planning algorithm by Sebai et al.[18] can be further expanded to incorporate real-time charging station availability information for more efficient route optimization. Additionally, the route planning process could consider individual driver preferences, such as preferred driving styles or charging priorities, to add an extra layer of sophistication. While Guler[10] proposed an approach for optimal FCS allocation and sizing, it could be enhanced by using the methodologies developed by Yang et al.[19] and incorporating microscopic information such as individual driving patterns.

In addition, Ziadia et al.[49] proposed a novel regenerative braking strategy to improve the overall efficiency of EVs. However, it is also important to explore the integration of driver-centric strategies like regenerative braking into existing traffic flow models for greater efficiency improvements. A similar approach was proposed by Deshpande et al.[50] to enhance EV efficiency in mixed traffic scenarios. However, this study did not consider battery models and state-of-health (*SoH*) estimation in the eco-driving algorithm to maximize battery efficiency. Similarly, the energy savings scheme of Ozkan et al.[51] could be further extended by incorporating a battery management system, and its robustness could be examined across more diverse scenarios.

Finally, there are numerous opportunities for grid-level optimization to facilitate the integration of EVs and RES into smart grids while minimizing adverse impacts. Although Li et al.[53] incorporated a distributed pricing strategy to enhance demand-supply management and optimize traffic flow assignments, their approach could benefit from considering the optimal placement of charging stations to minimize congestion and maximize utilization. Li et al.[55] also made significant efforts to understand the impact of EV sharing on distribution networks with microgrids. However, it would be beneficial to explore the potential of implementing dynamic pricing strategies for shared EVs to optimize charging behavior and reduce peak load on the grids. In comparison to these studies, the EV virtual power lines concept with its dynamic charging rates and pricing options, as presented by Čičić & Canudas-De-Wit[54], shows considerable promise. A potential improvement would be to incorporate traffic management strategies to optimize EV routing and charging based on dynamic grid conditions. Further enhancements could be achieved by examining how dynamic pricing and incentives affect EV driver behavior and charging patterns, thus facilitating the optimization of grid utilization.

Machine learning applications for optimizing EV integration into transportation networks

With the rise in EV adoption within traffic networks, there is a concurrent increase in the generation of real-time traffic flow data[2,23], presenting a unique opportunity to optimize the increasingly diverse traffic environment. ML models provide a robust framework to leverage this data either independently or in conjunction with mathematical models[23–25,57]. In this section, we explore the successful applications of ML in addressing several critical challenges in evolving transportation systems involving EVs: optimizing route planning for EVs, managing demand at charging stations, efficiently managing energy use alleviating range anxiety, and integrating automation for smoother traffic flow. Finally, Table 4 provides a summary of the key implementations of the ML models discussed in the following three subsections.

Optimal route planning for EVs

Complementary to traditional methods, ML can take into account factors such as real-time traffic conditions, availability of charging stations, and driver preferences when planning routes. For instance, Basso et al.[58] introduced an ML-based approach to address the EV routing problem. Their method employs a Bayesian model to predict energy consumption

Table 4. Machine learning applications for optimizing EV integration into transportation networks.

Study	ML model used	Purpose of the model used
Basso et al.[58,59]	Bayesian Model[58]	To predict energy consumption variations across different route choices, enabling the most efficient selection of routes that offer lower energy consumption and increased reliability[58].
	Safe Reinforcement Learning (SRL)[59]	To solve the dynamic stochastic EV routing problem through offline learning of stochastic customer requests and energy consumption, allowing for predictive and safe online route planning that minimizes energy usage and prevents battery depletion[59].
Lin et al.[60]	Deep Reinforcement Learning (DRL)	To solve the EV routing problem with time windows for commercial EV fleets.
Jin et al.[23]	Deep Q-Network (DQN)	To effectively handle large-scale complex traffic network data and to facilitate the application of Markov decision processes in route planning problems.
Li et al.[63]	Graph Convolutional Network (GCN)	To predict charging demand and optimize charger placement and resource allocation strategies while taking into account the market the market penetration of EVs.
Zhang et al.[64]	Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Artificial Neural Network (ANN)	To facilitate charging infrastructure planning and scheduling through urban charging load forecasting, considering trip patterns and network characteristics.
Mohammad et al.[61], Golsefidi et al.[24], Abdalrahman & Zhuang[66], Chen et al.[67]	Convolutional long short-term memory (ConvLSTM), Bidirectional ConvLSTM, and Gaussian Process Regression (GPR)	To capture spatio-temporal features in energy demand data from charging stations across cities and to predictively expand EV charging infrastructure.
Praveena et al.[27]	Artificial Neural Network (ANN)	To accurately predict an EV's *SoC*[27].
Yang et al.[69]		To estimate *SoH* using data directly extracted from EV batteries[69].
Chaoui et al.[68]	Deep Reinforcement Learning (DRL)	To optimize battery health in EVs by strategically managing the *SoC* of multiple energy storage devices to extend battery lifespan.

variations across different route choices, enabling more efficient selection of routes with lower energy consumption and increased reliability. In a subsequent study, they applied safe reinforcement learning (RL) to solve the dynamic stochastic EV routing problem (DS-EVRP)[59]. This approach incorporates offline learning of stochastic customer requests and energy consumption through Monte Carlo simulations, allowing for predictive and safe online route planning that minimizes energy usage and prevents battery depletion. The effectiveness of this approach is demonstrated through realistic traffic simulations, highlighting its potential to enhance the efficiency and reliability of EV operations. Prior to Basso et al.[59], a DRL framework was developed by Lin et al.[60] to solve the EV routing problem with time windows (EVRPTW) in commercial EV fleets. Their framework incorporates an attention model, utilizing a pointer network and graph embedding layer to formulate a stochastic policy. Training is conducted using policy gradient with rollout baseline, resulting in significant improvements in solving large-scale EVRPTW instances compared to existing methods. Given the complexity of traffic networks and the volume of data they generate, a route planning approach was proposed by Jin et al.[23] using DQN, a DRL algorithm, to dynamically manage MDP in such environments. This approach aims to optimize route planning while effectively handling the vast amounts of data originating from traffic networks.

Demand response management for charging infrastructure

Building on route planning, this section focuses on how ML can enhance the optimization of charging infrastructure by predicting EV demand based on traffic flow patterns and enabling flexible charging schedules. For example, Mohammad et al.[61] evaluated the Quality-of-Experience (*QoE*) for public EV charging stations, which effectively assesses user satisfaction and optimizes station utilization. Such metrics can serve as inputs to ML models trained on recent real-world datasets to forecast long-term charging station loads[62]. Li et al.[63] proposed a market-based approach for optimal EV charger planning using a multi-relation graph convolutional network (GCN) to predict charging demand and optimize charger placement and resource allocation strategies. Zhang et al.[64] developed an ML model for urban charging load forecasting, incorporating trip patterns and network characteristics to optimize charging infrastructure planning and scheduling. Orzechowski et al.[65] introduced a method for medium-term EV charging demand forecasting, integrating weather conditions and forecasting demand for multiple stations and the entire network. Mohammad et al.[61] proposed convolutional long short-term memory (ConvLSTM) and bidirectional ConvLSTM models to capture spatio-temporal features in energy demand data from charging stations across cities. Mejdi et al.[25] presented an online grid-level model predictive control system for predicting EV charging demand and mitigating grid impacts. Palaniyappan & Vinopraba[26] explored ML models for short-term electricity consumption forecasting and dynamic pricing to manage peak demand. Other studies underscore the potential to integrate spatiotemporal data like traffic flow patterns into ML models for improved demand forecasting and optimized charging strategies[24,66,67]. Finally, to address the escalating charging demand due to the increasing MPR of EVs, Golsefidi et al.[24] integrated Gaussian processes with optimization techniques to predictively expand EV charging infrastructure.

Energy management and range anxiety mitigation

ML also plays a vital role in estimating the remaining stored energy and managing EV battery usage during planned routes, thereby mitigating range anxiety during travel. Alongside accurately estimating the state-of-charge (*SoC*), maintaining satisfactory battery *SoH* is essential for ensuring long-term EV performance and addressing range anxiety concerns. For instance, Praveena & Manoj[27] proposed a hybrid *SoC* estimation model for EVs that integrates machine learning with mathematical modeling. This neural network-based *SoC* estimation model enhances accuracy in predicting an EV's *SoC*, a critical factor for estimating its driving range. Meanwhile, Chaoi et al.[68] introduced a DRL approach for optimizing battery health in EVs by strategically managing the *SoC* of multiple energy storage devices to extend battery lifespan. Additionally, Yang et al.[69] developed a neural network-based method for *SoH* estimation using data directly extracted from EV batteries. Furthermore, Yang et al.[70] devised an ML-based *SoH* estimation model tailored for real-world EVs, which considers changes in ohmic internal resistance as a key indicator of *SoH* degradation, thereby offering reliable *SoH* assessment and driving range prediction.

In addition to accurately identifying the *SoC* and *SoH* of EV batteries using ML models, research has investigated their connection with range anxiety among EV users, which significantly impacts EV-induced congestion. For instance, Wang et al.[71] demonstrated that in-vehicle information systems that display the remaining EV range adjusted by *SoH* can substantially alleviate drivers' range anxiety compared to systems lacking this information. Akasapu & Singh[72] further explored the role of in-vehicle information in mitigating range anxiety by proposing a method that utilizes current *SoC* to suggest optimal driving speeds, thereby maximizing travel distance. Beyond examining the effects of *SoC* and *SoH* on range anxiety, studies have explored alternative approaches to address this concern. For example, Chakraborty et al.[73] introduced the peer-to-peer car charging (P2C2) concept, enabling charging while in motion to reduce reliance on fixed charging stations. Song & Hu[74] focused on understanding driver behavior by employing an ensemble learning model to identify at what battery level EV drivers typically recharge their vehicles. The model integrates factors such as traffic conditions, charging station availability, and spatiotemporal information of charging events. Furthermore, Zhang et al.[75] suggested that faster charging could potentially alleviate anxiety by increasing *SoC*, although this effect is influenced by variables such as temperature and charging station availability. Hence, investigating the underlying relationships between anxiety and charging decisions remains a critical area for further research.

Collection and utilization of real-world EV data

As EVs become more prevalent in our transportation network, concerns regarding their effects on traffic flow are increasingly being discussed. An effective way to examine the realistic impacts of EVs is by leveraging real-world data, which can be fed into appropriate mathematical and machine learning models to understand how these models will perform in EV-integrated traffic. To this end, multiple studies have been conducted to develop EV data collection methods, supporting further research utilizing data from real-world experiments.

Different approaches have been developed for EV data collection. For instance, Ziryawulawo et al.[76] proposed a method that utilized an in-vehicle device to collect data from the CAN or local interconnect network (LIN) bus and wirelessly store that data in an EV driving database through general packet radio service (GPRS) and the internet. Analysis of this database provided insights into driving patterns, driving cycles, and control strategies of EVs in real-world traffic scenarios. A more recent study[77] leveraged the global navigation satellite system (GNSS), GPRS, and other auxiliary sensors to collect in-vehicle diagnostic data. This system, with its real-world data on EV driving patterns, including acceleration, braking, and speed profiles, is useful for refining traffic flow models, leading to more accurate traffic simulations and predictions. Additionally, the system can identify congestion points or areas of high EV concentration, providing insights into optimizing traffic signal timings and suggesting alternative routes.

Range anxiety and charging infrastructure remain critical barriers to widespread EV adoption. To address these challenges, significant efforts have been made to understand and optimize EV usage patterns. For example, Ping et al.[78] proposed a real-time microscopic EV driving data collection method. This method considered microscopic driving phenomena such as instantaneous speed and acceleration, and EV states such as battery *SoC*. The resulting model showed significant improvements in assessing energy consumption during deceleration, with slight uplifts during acceleration and cruising. Zhuang et al.[79] complemented these efforts by collecting data from a systematic driving setup and developed a methodology for constructing representative urban driving cycles, providing a foundation for accurate energy consumption modeling. Additionally, Svendsen et al.[80] collected energy consumption data from 201 actual trips of an EV. This data was then mapped against the actual speed profiles of the EV to gain insights into how driving behavior impacts battery drainage. To further improve EV efficiency and range, Zhang & Yao[81] focused on collecting voltage information from individual lithium-ion battery cells, gathered through a sensing layer within the battery pack. The data was then transmitted *via* the CAN bus to the central control unit to facilitate monitoring the health and balance of individual battery cells.

Despite the rapid increase in EV adoption, there is a lack of training datasets for developing ML models. Zhao et al.[82] introduced physical rationality in data augmentation to expand driving trip datasets, thereby facilitating data-driven approaches. The study demonstrated that synthesizing trip patterns with rational physical context leads to promising improvements in energy consumption predictions. To address the charging infrastructure challenge, previous studies[83,84] have integrated driving data with charging profiles. Specifically, Lee & Wu[83] conducted a three-year study across eight European countries, monitoring the charging and driving patterns of EVs on a monthly basis. This data is useful for determining the appropriate locations and quantities of charging stations for future deployment. Yang & Zhang[84] employed a stochastic modeling approach to generate synthetic EV driving and charging profiles using real-world global positioning system (GPS) data. This approach captures the uncertainty in EV behavior and facilitates analyses of aggregated power demand and charging station optimization.

To accurately assess the impacts of large-scale EV adoption, Ma et al.[85] analyzed real-world data from over 40 private EVs in Beijing (China). The study examined factors such as charging habits, trip distances, and energy consumption to facilitate the strategic placement of charging stations and assist in managing the impact of broader EV adoption on electricity grids. Another study conducted in Shanghai (China), a city with one of the highest numbers of EVs, provided further insights into the real-world driving behavior of EVs[86]. The experimental data revealed charging patterns with a peak around 9:00 PM and a preference for urban charging spots. These insights are valuable for optimizing the placement of charging infrastructure.

In addition to the optimal allocation of charging stations, optimal route planning plays a significant role in mitigating EV-induced congestion. Brady & O'Mahony[87] presented a model integrated with real-world data for energy-efficient route planning for EVs. By predicting energy consumption on various roads and prioritizing low-energy paths, the model offers a potential solution for optimizing traffic flow. The integration of real-world data enhances the model's accuracy, making it a promising tool for future EV route optimization and congestion mitigation.

Apart from optimal routing, range anxiety is another major concern for large-scale EV adoption[88,89]. De Cauwer et al.[90] utilized real-world driving data from electric taxis to develop a more precise energy consumption prediction model using ML. The results significantly improve prediction accuracy over traditional approaches, paving the way for optimized battery sizing, energy-efficient route planning, and improved charging infrastructure operation. Motivated by both charging infrastructure limitations and range anxiety, Pevec et al.[91] used real-world traffic data to develop a more precise link-level energy consumption model for EVs, advancing EV adoption through applications such as eco-routing systems.

Conclusions and recommendations

Based on a review of the literature concerning the emerging impacts of EVs on evolving traffic flow, as well as the existing mathematical and ML models aimed at assessing and mitigating these impacts, it is evident that the widespread adoption of EVs will pose challenges for transportation systems with emerging cyber-physical characteristics. However, with methodological and technological advancements, it is possible to mitigate EV-induced congestion, stabilize grid systems during peak hours, and address associated cybersecurity concerns.

There is significant potential for dynamic electricity usage pricing and V2G technology to encourage off-peak charging, thereby mitigating both congestion near charging stations and grid instability during peak hours. Further improvements in traffic conditions can be achieved through the integration of real-time EV data into traffic management systems and the development of advanced demand response strategies for EVs. Additionally, ML applications have the potential to address cybersecurity concerns related to EVs' internal communication and their external communication with charging stations and local grids, thereby preventing undesired charging delays and grid instabilities. Overall, there are extensive opportunities for both mathematical and ML models to address various EV-related concerns, including route planning, demand management, resource allocation, and the personalization of driver assistance systems.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Ahmed S, Wang S; data collection: Ahmed S; analysis and interpretation of results: Ahmed S, Wang S; draft manuscript preparation: Ahmed S, Wang S. Both authors reviewed the results and approved the final version of the manuscript.

Data availability

Any data necessary for further understanding of the paper will be provided upon reasonable request by the reader.

Conflict of interest

The authors declare that they have no conflict of interest.

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