Smart Transportation System Using Machine Learning and IoT for EV Charging Stations Locator: A Review

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Abstract: The rapid and widespread adoption of Electric Vehicles (EVs) is virtually revolutionizing the transportation sector, thereby creating a growing demand for an efficient and highly accessible network of EV charging stations. A major challenge that arises during this pivotal transformation is the optimization of EV charging station (EVCS) locations to ensure widespread accessibility and effectively overcome the phenomenon of range anxiety among users. This review article comprehensively explores the innovative use of Machine Learning (ML) and the Internet of Things (IoT) in the ongoing advancement of smart transportation systems that can facilitate the optimal placement and locator services for EV charging stations. The review takes a close look at the numerous ML approaches that are currently being utilized, ranging from clustering algorithms, neural networks, and sophisticated optimization models, which are employed to predict and optimize the placement of EVCS based on various key factors such as traffic flow, power demand, geographic spread, and environmental conditions that may affect operations. The article further discusses the central role of IoT in facilitating real-time data gathering, effective communication, and ongoing monitoring, and its significant role in enhancing the user experience as well as the overall operational efficiency in the case of EV charging. Additionally, the article critically examines current methodologies, frameworks, and technologies being utilized, noting the various challenges, limitations, and future areas of focus in the development of a seamless and intelligent EV charging network that can meet emerging needs. Through the integration of both ML and IoT, this smart transportation strategy intends to effectively counter the challenges that currently hinder the adoption of EVs, hence making a substantive contribution to the broader goals of sustainable transportation as well as the critical mission of reducing carbon footprints across the globe.

Keywords: Smart Transportation, Machine Learning, IoT, EV Charging Locator, Sustainability

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1. Introduction

The global transport industry is undergoing a tremendous and revolutionary transformation today, which is being fueled by the enhanced and shared adoption of electric vehicles (EVs) around the world [1]. With different governments of the world adopting ambitious strategies to achieve climate objectives and also strive to reduce their dependence on fossil fuel, electric vehicles offer a promising and feasible solution to the conventional vehicles that are powered by internal combustion engines. In spite of the enormous and quick increase in the levels of uptake of EVs, there are new and rising challenges that emerge, especially in the provision of strong and effective charging centers that are required in order to satisfy the continuously growing demand by consumers [2]. One of the main challenges that have been reported, referred to as range anxiety, articulates the concern of customers who own electric vehicles; this anxiety is caused by the challenge that accompanies the identification and determination of a charging center exactly at the moment it is required. Conventional approaches that have been utilized for the discovery of charging centers, which are based on fixed geographical locations and heuristic planning tactics, are more likely to encounter challenges like urban congestion as well as challenges that are related to the unavailability of access in rural areas [3].

The worldwide transport sector is now in the midst of a gigantic and revolutionary change, led primarily by the mass-scale adoption and incorporation of electric transport (EV) technologies across the geographies of the world. With the widespread efforts being made by various nations in order to fulfill their climate commitments, coupled with their parallel efforts to de-carbonize transportation, electric vehicles are now becoming an extremely viable and sustainable solution to the traditional internal combustion engine vehicles that dominated the automobile sector for several decades [4]. While we are seeing a record-breaking surge in the adoption of EVs in recent years, this tremendous growth has created new challenges and issues as well, most prominently the issue of a strong and widespread charging facility required to support the explosive demand created by this revolution[5]. Among the most ubiquitous and acute issues that EV consumers are now confronted with is the issue of range anxiety, which is the outcome of anxiety and uncertainty regarding the availability of a charging station at the opportune moment when needed the most. The traditional methodologies and methodologies followed to deploy charging stations always result in inferior coverage, hence perpetuating the problem. Nevertheless with the advent of Machine Learning (ML) and the Internet of Things (IoT) into smart transport systems (STS), there lies a viable and novel solution that could prove to be an effective antidote to these chronic issues [6]. With the application of ML algorithms, it becomes possible to model real-time traffic flow, simulate user behavior, and make use of past histories of charging usage to detect the most optimal location of charging stations, all in real time. Similarly, IoT-based sensors could be utilized with great efficiency to track the utilization of charging stations continuously in real time, forecast the capacity of the grid, and dynamically track energy flow in real time, gaining great insights into the workings of this new infrastructure. With the integration of these new technologies, there can be a revolutionary shift to a smarter and more efficient system that can be implemented to identify charging stations strategically, ultimately leading to increased accessibility, reduced waiting times, and better energy management [7]. This review is an attempt to explore the pivotal role that ML and IoT can play in constructing and optimizing EV charging networks in the framework of smart transport systems. It will critically analyze the literature, identify loopholes in the existing methods, and suggest possible avenues of research that can potentially optimize and streamline the charging station network. Furthermore, fixed-point and heuristic-based planning techniques have a tendency to introduce a variety of complexities, such as urban traffic congestion and restricted access for rural area users, which need to be tackled through holistic approaches [8]. Figure 1 shows flow diagram for operations in charging station.

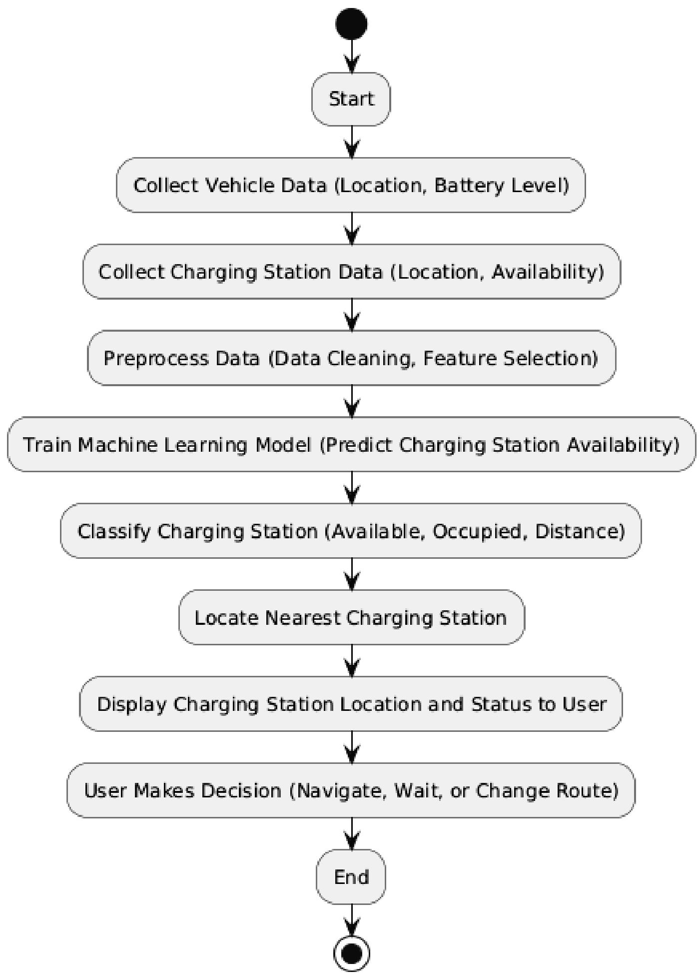

Figure 1: Flow diagram for operations in charging station

1.1. Uneven Distribution **of Charging Stations**

One of the largest challenges for the existing electric vehicle (EV) charging infrastructure is the uneven distribution of charging points. In urban centers, especially those located in economically developed areas, there is a high concentration of charging points that are highly concentrated [7], [9]. However, rural areas and low-density areas have low access to charging points, resulting in the unfortunate reality of "charging deserts" in more rural areas. This results in range anxiety for the owners of EVs in such under-served areas. Due to the low concentration of charging stations, individuals living in such rural areas are forced to make long trips just to get to a charging station within a reasonable distance. As a result, this condition makes the use and adoption of electric vehicles far less attractive. On the other hand, in high-density areas where there is high concentration of charging stations, there is the possibility of under-utilization or even over-crowding of charging stations, resulting in operational inefficiencies in the system as a whole.

1.2.Lack of Real-Time Data and Dynamic Decision-Making

Current EV charging networks are static and depend on stationary locations and utilization patterns to guide where new stations are to be added. Such networks do not include real-time information, which means that utilization of charging stations is wasted. Users tend to travel to a station only to discover that it is occupied or unavailable, whereas other stations can be underutilized, wasting operational costs. Lacking the ability to monitor usage patterns in real time, such systems cannot reallocate resources in response to present demand. This creates extended wait times at peak hours and lost opportunities to maximize station locations in response to evolving trends, e.g., traffic patterns changes, commuter patterns shifts, or seasonal changes. In addition, having current knowledge of station accessibility and charging speed would be able to lead the user to the closest available station, reducing crowding and maximizing efficiency [10].

1.3. Inefficient **Energy Management and Demand Prediction**

Energy management at EV charging stations is a big challenge. Most of the existing systems do not have sophisticated energy management tools that can efficiently distribute power across the network. For instance, most charging stations are dependent on the central grid without considering the availability of renewable energy sources, and this can cause grid overloads during peak hours. These inefficiencies not only drive operational costs higher but also harm the environment, as energy sources whose origin is fossil-based are likely to be utilized during these peak periods. In addition, demand forecasting is a matter of complexity. Although there are discernible patterns in charging demand, such as higher usage during morning and evening rush hours, several variables—such as unforeseen traffic, weather, or usage pattern shifts—significantly affect energy consumption. Without predictive software and real-time data, energy optimization and unnecessary stress relief on the grid are difficult, especially in areas with limited access to renewable energy sources [11].

1.4.High Installation and Operational Costs

The cost of building and running the electric vehicle charging stations is very, very high. Installing the charging stations involves a lot of investments, and these are not limited to buying properties but also include the preparation of the land itself, as well as the required electrical infrastructure that has to be installed to make them functional. These costs can be even higher if the charging stations are not well-placed. For example, if they are installed in low-demand areas, they might not be utilized sufficiently, leading to wasted resources. This condition not only renders the system less economically feasible but also limits the expansion of the charging network. Moreover, operational expenses include maintenance, energy consumption, and personnel, which can be quite high in low-traffic areas. If not optimized, charging stations in such less busy locations could become liabilities instead of useful assets. This inefficient resource deployment can dissuade investment and prevent expansion, making it more difficult to maintain pace with increasing demand [12].

1.5. Integration **with Transportation Systems and Smart Grids**

The lack of integration between charging stations, transport networks, and energy grids hinders the optimization of EV charging networks. Most charging stations are presently operating in isolation, without real-time knowledge of key factors such as traffic, grid load, or local energy demand. For example, during rush hours, traffic congestion may cause bottlenecks at charging stations, while energy consumption peaks may overload the grid, jeopardizing the infrastructure's reliability. Moreover, charging stations are also often not integrated with renewable power sources such as solar or wind, even though it is advantageous to incorporate them into a smart grid. Being out of synchronization with the electricity grid prevents effective utilization of renewable energy, incurring unnecessary costs and more emissions. In addition, the lack of proper integration is also to blame for severely restricting the use of sophisticated tools like predictive analytics and adaptive scheduling. These sophisticated technologies can greatly improve the overall station utilization, positively impact the stability of the power grid, and ultimately reduce operating costs related to energy management [13].

1.6.Scalability Issues in Large Urban Areas

All of the said issues are prevalent in different parts of the globe, but they are more crucial in megacities with dense population. Not only do cities struggle to support their infrastructure, but they struggle to plan for the fast-paced development of the EV charging infrastructure. Planning the existing infrastructure to meet the increasing demand for electric vehicles needs to be accomplished using smart decision-making tools that are capable of adjusting to short-term demands as well as long-term development trends. The majority of the current models used for the placement of charging stations are ineffective in urban centers, where traffic flows, user habits, and grid loads change frequently and at random. Added to this, the complexity of the systems makes it challenging to predict future energy demand accurately, and some locations remain underfunded while others are overcapitalized [14].

2. Related Research and Development

The focus of research pertaining to electric vehicle (EV) charging station optimisation has happened at an astonishing pace in recent years with studies attempting to capitalise on maximum efficiency, inclusivity, and scalability of the charging network. The optimization of dynamic charging networks and strategic positioning of optimal charging stations are actually the prime research areas of interest in this domain. The identification of these crucial parameters has been of prime concern and interest to various studies, all of which have invoked a range of advanced techniques and methodologies like Geographic Information Systems (GIS), optimization algorithms, machine learning (ML), and the Internet of Things (IoT) [15].

2.1. Methods for Charging Station Placement

Previously, location optimization of electric vehicle (EV) charging stations has utilized an incredibly broad variety of methodologies, ranging from not just Geographic Information Systems (GIS) but also other heuristic optimization methods. Although these methods can actually work in some instances, they are likely to fail in the context of managing the dynamic and real-time requirements of users as well as variability of users' behavior. Geographic Information Systems (GIS), in reality, have been widely utilized as a key tool for close inspection of geographic and spatial factors that have a crucial role to play in determining the most appropriate locations for the installation of charging stations. The models developed within GIS environments consider an extremely broad range of factors, ranging from population density considerations to the level of vehicle traffic as well as proximity to existing infrastructure. Utilization of the advantages of GIS, planners are capable of mapping and visualizing efficiently areas in which installation of charging stations would be most beneficial. For example, researchers have utilized GIS technology in order to recognize areas that attract high volumes of potential EV users but are inadequately served by existing charging facilities, thus enabling urban planners to make fact-based, informed decisions regarding the development of infrastructure. In the context of heuristic optimization, some of the early models utilized heuristic methods in order to determine potential locations based on pre-defined rules or discernible patterns. These models are highly reliant on static input, ranging from average traffic flow data, geographical boundaries, and demographic data, to identify potential locations for charging station installation. Although these models are marked by simplicity and ease of comprehension, they are plagued by the inability to include real-time data and effectively respond to changing conditions [16].

2.2. Machine Learning (ML) for Dynamic Optimization

Predictive Analytics and Demand Forecasting: Regression methods and decision trees are being increasingly used as ML algorithms to forecast demand for charging stations in the future. Based on historical data, user behavior, and traffic analysis, the algorithms are able to forecast ahead of time when and where the demand for charging stations is going to peak. With this type of information, the operators can strategically place stations along with optimizing energy distribution. Current research has outlined how ML can optimize the identification of high-traffic areas and peak hours to avoid swamping charging points. Reinforcement Learning for Adaptive Systems: More sophisticated is the use of reinforcement learning (RL), where an agent makes decisions and modifies its actions real-time based on feedback from the environment. For EV charging applications, RL-based models have been used for the identification of optimal station location for siting and dynamic assignment of energy resources. RL-based systems can automatically modify station availability based on traffic, weather, and user behavior. These systems have been developed to learn from the past and adapt to correct for unforeseen situations, like surprise peaks in take-up, as they continuously learn and improve from history. Clustering and Classification Methods: One other method applied extensively in ML is the implementation of clustering approaches like K-means and hierarchical clustering. They are used in classifying akin points, e.g., areas of high EV take-up or traffic areas, which makes their deployment in subsequent targeted stations easy. Additionally, ML classification methods like SVM and random forests categorize areas by parameters like the pattern of energy consumption or the pattern of behavior in an effort to facilitate strategic planning[17].

2.3. Integration of Internet of Things (IoT) for Real-Time Monitoring

IoT with EV charging stations has been a perennial popular research topic in the recent past. IoT-based sensors and devices allow real-time data acquisition and monitoring, significantly enhancing charging station management. Real-Time Monitoring and Data Acquisition: IoT-based sensors and smart meters can be used in charging stations to capture parameters such as station availability, charging rate, and energy consumed. The data is transmitted to central servers where they are processed, and based on the processing, usage patterns can be monitored, faults can be detected, and maintenance need can be forecasted. Real-time monitoring allows the stations to be used at their full capacity at all times with minimal downtime, thus enhancing the overall user experience. Smart Grid Integration: Smart grids are perhaps one of the brightest applications of IoT, where charging stations can be integrated with smart grids. Smart grids allow two-way communication between charging stations and the grid, and the stations can realize real-time load balancing and optimize energy utilization. Utilizing IoT sensors to monitor energy usage and energy demand in real time, the charging stations can optimize energy utilization automatically based on the grid condition to ensure optimal utilization of renewable energy sources and grid load reduction during peak usage[10], [12]. IoT can even be utilized to analyze user behavior, i.e., frequency of usage of a particular charging station and for how long. This can be utilized to optimize future charging station locations and optimize charging fee structures to maximize demand. Besides, IoT-based systems are capable of tracking traffic in real-time, which is needed in being capable of predicting when charging stations would be most demanded, particularly in places like shopping malls, airports, and urban business districts[18].

2.4. Blockchain for Security and Transparency

As electric vehicle (EV) charging infrastructures become more and more part of the larger Internet of Things (IoT) context and the envisioned future smart grid, a new set of challenges has arisen, namely the ones in the domains of data transparency, security, and transactional privacy. In resolving these critical issues, blockchain technology offers a highly effective solution, with a secure, transparent, and decentralized environment specifically tailored to managing transactions and enabling data exchanges. With respect to managing transactions, blockchain technology has the ability to manage the financial transactions involved in EV charging services efficiently. This new technology not only assures customers are charged reasonably and fairly based on their actual usage but also ensures that sensitive payment data is protected from possible breaches. Additionally, blockchain-based systems enable a micropayment model, where customers are charged exactly the amount of electricity they consume. This new approach eliminates the use of conventional subscription-based billing models and results in a higher level of automation in the billing process itself. With respect to data privacy and integrity, the decentralized nature built into blockchain ensures that critical information on the usage statistics of charging stations, the rates of electricity usage, and the behavior of users is made tamper-proof. This aspect is highly relevant as EV charging networks become more and more part of larger smart city infrastructures that handle sensitive and confidential data [19]. Blockchain technology offers an open and tamper-proof ledger, which can monitor data exchanges among different stakeholders in the network efficiently, thus ensuring individual privacy while preventing malicious behavior at the same time. In addition, blockchain technology-based smart contracts have the unique ability to automate much of the processes in the EV charging infrastructure, with the result of increasing efficiency and reliability across the system. For example, these particular kinds of contracts possess the ability to dynamically adjust and change prices based on real-time changes and fluctuations that happen in the supply or demand for electricity. They can also send and trigger repair requests for any equipment that has been found faulty and in need of repair. This mechanism not only increases and improves the efficiency of different administrative processes but also serves to optimize and improve the overall functionality and effectiveness of the charging network overall[20].

3. **Identified Gaps and Overlooked Aspects**

In the midst of the unparalleled and phenomenal developments that have been recorded in the optimization of electric vehicle (EV) charging stations' performance and efficiency, courtesy of the cutting-edge application of state-of-the-art technologies such as machine learning (ML), the Internet of Things (IoT), and other sophisticated instruments, it is important to report that there still exist numerous pivotal research gaps that have not yet been addressed in the current research work. Such gaps are crucial challenges and stumbling blocks that are hindering the successful establishment and deployment of an efficient, effective, and scalable network of electric vehicle charging stations, a network that is necessary to meet and contain the continuously increasing demand for electric vehicles in modern society [21]. In the coming sections of this book, we will clearly lay out and analyze some of the most critical areas where the current body of research has been missing or where pertinent elements have been glaringly missing, hence exposing the path to follow for further research and exploration [22].

3.1. Limited Integration of Real-Time Traffic and Energy Grid Data

One of the largest disadvantages of existing research on EV charging station optimization is the improper integration of real-time traffic and energy grid information. Most of the existing techniques rely on static models or historic data for the forecasting of charging station demand but are not sensitive to real-time traffic, weather, and behavior changes. For instance, road closure, accident, or traffic congestion can contribute substantially to the number of EV users who prefer to charge at specific stations. Nevertheless, most current models fail to integrate real-time traffic flow information dynamically, which can lead to inefficient and poor usage of stations. In addition, despite advancements in the use of IoT-powered smart grids for real-time energy consumption, there is still a deficiency in sophisticated integration of charging stations with grid-level energy forecasting. This creates inefficient use of energy, especially during peak usage hours when the grid comes under strain. In the absence of real-time feedback from the grid, charging stations do not modulate their energy intake properly, jeopardizing grid overloading and additional operational inefficiencies[8], [23].

3.2. Inadequate Consideration of User Behavior and Adaptability

One significant area lacking in existing research is the lack of proper focus on understanding and incorporating user behavior into the optimization process. Although some models have considered parameters such as traffic patterns and energy usage, few have successfully included user preferences and behaviors. For example, users prefer charging stations that are located near popular destinations like shopping malls, workplaces, or restaurants. In addition, factors such as charging time, ease of parking, and the nature of available charging options (e.g., fast charging vs. normal charging) can also influence user decisions considerably. Adaptive learning models, especially reinforcement learning (RL), are promising in modeling and predicting user behavior more accurately, but numerous studies have overlooked this significant aspect. Besides, the majority of models assume that all users have similar charging requirements and preferences, ignoring variables like gender, income, or social class. Such a non-personalization in optimization models may lead to an unbalanced coverage of charging stations that does not fully meet the disparate requirements of different groups of users. Furthermore, the ever-changing nature of user behavior—especially with varying demand during holidays, seasons, or events—necessitates ongoing adaptation. Existing models often struggle to capture these complexities in user behavior and do not adjust the charging infrastructure accordingly. For example, during major public events or holidays, the demand for charging stations can surge unexpectedly. Many current studies do not sufficiently explore how charging stations should respond to such sudden increases in demand [24].

3.3. Lack of Unified Frameworks Combining ML, IoT, and Blockchain

Though standalone studies have analyzed the application of ML, IoT, and blockchain technology for optimizing EV charging stations, there exists an evident need for the integration of all three technologies through the creation of unified frameworks. Predictive analytics and decision-making can be done with ML, IoT for real-time monitoring and data harvesting, and blockchain for transparent and secure transactions. Yet these technologies are employed individually, and their synergistic opportunities are far from being tapped [25].

One such research area that has great potential is the use of blockchain to secure, make transparent, and automate transactions between charging station operators and users. Blockchain can also enable dynamic pricing schemes that vary according to energy consumption patterns, demand, and supply. Yet, little research has been conducted on how IoT data can be combined with blockchain to provide finer control of energy distribution, station availability, and user charging history. A multi-technology, holistic approach can make the system work better by harnessing the capability of each technology and overcoming each technology's limitation. In addition, the intersection of these technologies may result in new solutions such as the establishment of decentralized autonomous systems for electricity distribution and charging station control. Nevertheless, this is an aspect that has been under-researched in current studies, especially in large-scale applications[26].

3.4. **Scalability and Generalization of Existing Models**

Though several studies have established the potential of ML and IoT to optimize the placement of the charging stations in small, controlled settings, few studies have considered the scalability of such models to large, complex city settings. Such models are predominantly calibrated for small areas of comparatively low charging station and user base. When such models are extended to large cities with higher populations and more complex transportation systems, the models fail because traffic, user behavior, and energy consumption heterogeneity is higher [27].

Scalability is particularly important in rapidly growing cities where the rate of adoption of EVs is on the rise. With growing demand for EVs, network optimization of charging stations will be an increasingly complex problem. Current models will not be best suited to accommodate such demand growth and can become a bottleneck as cities grow, based on hard-coded values. Furthermore, extrapolating such models to varied geographies and socio-economic settings challenges data availability, infrastructure, and user behavior and makes them even less scalable [28].

4. Conclusions

The rapid growth in the use of electric vehicles (EVs) demands development of efficient and sustainable charging infrastructure. In this paper, the use of machine learning (ML) and the Internet of Things (IoT) to optimize EV charging station location and management is proposed. Some of the most significant developments in this area are the use of predictive analytics, reinforcement learning, and real-time monitoring of data to optimize station efficiency and accessibility. Despite this, there are a few gaps in existing research, such as the limited utilization of real-time traffic and energy grid data, the lack of proper consideration of user behavior, and the lack of integrated frameworks that combine ML, IoT, and blockchain technologies.

The article discussed the need for scalable models that can be scaled up for big, complex cities and the importance of environmental and social impacts, such as equitable access to charging points and renewable energy. Future research needs to address sophisticated ML models, smart grid integration, blockchain for secure payment, and multi-disciplinary research. EV charging networks can be optimized for efficiency, flexibility, and social equity by adopting these technologies, making them capable of addressing the increasing demands of EV adoption and contributing to sustainability goals. The paper offers a vision for future development of smart transportation systems for EV charging.

References

1. Lalit N. Patil and Hrishikesh P. Khairnar, “Investigation of Human Safety Based on Pedestrian Perceptions Associated to Silent Nature of Electric Vehicle,” *Evergreen*, vol. 8, no. 2, pp. 280–289, Jun. 2021, doi: 10.5109/4480704.
2. E. Abotalebi, D. M. Scott, and M. R. Ferguson, “Can Canadian households benefit economically from purchasing battery electric vehicles?,” *Transportation Research Part D: Transport and Environment*, vol. 77, pp. 292–302, Dec. 2019, doi: 10.1016/j.trd.2019.10.014.
3. M. Adaikkappan and N. Sathiyamoorthy, “Modeling, state of charge estimation, and charging of lithium-ion battery in electric vehicle: A review,” *Intl J of Energy Research*, vol. 46, no. 3, pp. 2141–2165, Mar. 2022, doi: 10.1002/er.7339.
4. R. Aghapour, M. S. Sepasian, H. Arasteh, V. Vahidinasab, and J. P. Catalão, “Probabilistic planning of electric vehicles charging stations in an integrated electricity-transport system,” *Electric Power Systems Research*, vol. 189, p. 106698, 2020.
5. A. \Lebkowski, “Temperature, overcharge and short-circuit studies of batteries used in electric vehicles,” *Przeglad Elektrotechniczny*, vol. 1, no. 5, pp. 69–75, 2017.
6. D. Anadu, C. Mushagalusa, N. Alsbou, and A. S. A. Abuabed, “Internet of Things: Vehicle collision detection and avoidance in a VANET environment,” in *2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, Houston, TX: IEEE, May 2018, pp. 1–6. doi: 10.1109/I2MTC.2018.8409861.
7. M. U. Ali, A. Zafar, S. H. Nengroo, S. Hussain, M. Junaid Alvi, and H.-J. Kim, “Towards a smarter battery management system for electric vehicle applications: A critical review of lithium-ion battery state of charge estimation,” *Energies*, vol. 12, no. 3, p. 446, 2019.
8. M. Ashifuddin Mondal and Z. Rehena, “Intelligent Traffic Congestion Classification System using Artificial Neural Network,” in *Companion Proceedings of The 2019 World Wide Web Conference*, San Francisco USA: ACM, May 2019, pp. 110–116. doi: 10.1145/3308560.3317053.
9. M. H. Alkinani, W. Z. Khan, and Q. Arshad, “Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges,” *IEEE Access*, vol. 8, pp. 105008–105030, 2020, doi: 10.1109/ACCESS.2020.2999829.
10. Z. M. Ali, F. Jurado, F. H. Gandoman, and M. Ćalasan, “Advancements in battery thermal management for electric vehicles: Types, technologies, and control strategies including deep learning methods,” *Ain Shams Engineering Journal*, vol. 15, no. 9, p. 102908, Sep. 2024, doi: 10.1016/j.asej.2024.102908.
11. M. Åhman, “Government policy and the development of electric vehicles in Japan,” *Energy Policy*, vol. 34, no. 4, pp. 433–443, 2006.
12. M. Brandl *et al.*, “Batteries and battery management systems for electric vehicles,” in *2012 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, IEEE, 2012, pp. 971–976.
13. A. M. Bozorgi, M. Farasat, and A. Mahmoud, “A time and energy efficient routing algorithm for electric vehicles based on historical driving data,” *IEEE Transactions on Intelligent Vehicles*, vol. 2, no. 4, pp. 308–320, 2017.

14. Lalit N. Patil *et al.*, “An Experimental Investigation of Wear Particles Emission and Noise Level from Smart Braking System,” *Evergreen*, vol. 9, no. 3, pp. 711–720, Sep. 2022, doi: 10.5109/4843103.
15. L. M. Austmann, “Drivers of the electric vehicle market: A systematic literature review of empirical studies,” *Finance Research Letters*, p. 101846, Nov. 2020, doi: 10.1016/j.frl.2020.101846.
16. A. A. Ahmed, M. A. Nazzal, B. M. Darras, and I. M. Deiab, “Global warming potential, water footprint, and energy demand of shared autonomous electric vehicles incorporating circular economy practices,” *Sustainable Production and Consumption*, vol. 36, pp. 449–462, Mar. 2023, doi: 10.1016/j.spc.2023.02.001.
17. G. Z. de Rubens, “Who will buy electric vehicles after early adopters? Using machine learning to identify the electric vehicle mainstream market,” *Energy*, vol. 172, pp. 243–254, 2019.
18. S. Al-Youif, M. A. M. Ali, and M. N. Mohammed, “Alcohol detection for car locking system,” in *2018 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE)*, Penang: IEEE, Apr. 2018, pp. 230–233. doi: 10.1109/ISCAIE.2018.8405475.
19. N. Deepa *et al.*, “A survey on blockchain for big data: Approaches, opportunities, and future directions,” *Future Generation Computer Systems*, vol. 131, pp. 209–226, Jun. 2022, doi: 10.1016/j.future.2022.01.017.
20. K. M. Bin Hasan, M. Sajid, M. A. Lapina, M. Shahid, and K. Kotecha, “Blockchain technology meets 6 G wireless networks: A systematic survey,” *Alexandria Engineering Journal*, vol. 92, pp. 199–220, Apr. 2024, doi: 10.1016/j.aej.2024.02.031.
21. I. Ullah, D. Adhikari, X. Su, F. Palmieri, C. Wu, and C. Choi, “Integration of data science with the intelligent IoT (IIoT): current challenges and future perspectives,” *Digital Communications and Networks*, p. S2352864824000269, Mar. 2024, doi: 10.1016/j.dcan.2024.02.007.
22. M. Abramovici, C. E. Stroud, and J. M. Emmert, “Online BIST and BIST-based diagnosis of FPGA logic blocks,” *IEEE Trans. VLSI Syst.*, vol. 12, no. 12, pp. 1284–1294, Dec. 2004, doi: 10.1109/TVLSI.2004.837989.
23. H. K. Chaudhary, K. Saraswat, H. Yadav, H. Puri, A. R. Mishra, and S. S. Chauhan, “A Real Time Dynamic Approach for Management of Vehicle Generated Traffic,” vol. 10, no. 01, 2023.
24. M. Z. Ali, M. N. S. K. Shabbir, X. Liang, Y. Zhang, and T. Hu, “Machine learning-based fault diagnosis for single-and multi-faults in induction motors using measured stator currents and vibration signals,” *IEEE Transactions on Industry Applications*, vol. 55, no. 3, pp. 2378–2391, 2019.
25. S. M. Hosseini Bamakan and S. Banaeian Far, “Distributed and trustworthy digital twin platform based on blockchain and Web3 technologies,” *Cyber Security and Applications*, vol. 3, p. 100064, Dec. 2025, doi: 10.1016/j.csa.2024.100064.
26. F. V. Conte, “Battery and battery management for hybrid electric vehicles: a review,” *e & i Elektrotechnik und Informationstechnik*, vol. 123, no. 10, pp. 424–431, 2006.
27. P. Bellavista, R. D. Penna, L. Foschini, and D. Scotece, “Machine Learning for Predictive Diagnostics at the Edge: an IIoT Practical Example”.

28. S. Deshpande, “IIoT based framework for data communication and prediction using augmented reality for legacy machine artifacts,” *Manufacturing Letters*, 2023.