Energy Reports 13 (2025) 2958–2996

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Review article

Energy transition towards electric vehicle technology: Recent advancements

Muhammad Ali Ijaz Malik [a,*], Md Abul Kalam [a,*], Adeel Ikram [b,c], Sadaf Zeeshan [d], Syed Qasim Raza Zahidi [c]

[a] School of Civil and Environmental Engineering, FEIT, University of Technology, Sydney, NSW 2007, Australia
[b] Faculty of Engineering, Chungnam National University, Daejeon, Republic of Korea
[c] Department of Mechanical Engineering, Superior University, Lahore, Pakistan
[d] Department of Mechanical Engineering, University of Central Punjab, Lahore, Pakistan

ARTICLE INFO

Keywords:
Electric vehicles
Sustainable development goals
Carbon footprint
Lifecycle assessment

ABSTRACT

Electric vehicles (EVs) have emerged as a potential solution to address the ecological issues posed by conventional internal combustion engine vehicles. The current study entails a comprehensive overview of the advancements and challenges in EV technology, focusing on key areas of development, including battery technology, environmental impact, charging infrastructure, and vehicle design. The current study begins by summarizing the significant improvements in battery energy density, cost reduction, and durability, which have contributed to the growing popularity of EVs. Evaluating developments in battery chemistry, energy density, and affordability, the study emphasizes how vital batteries are to determining the range and efficiency of electric vehicles. Focusing on deploying fast-charging networks and wireless charging technologies highlights the lack of technological advancements in the current charging infrastructure. Maximizing EV performance and range encompasses advancements in lightweight materials, aerodynamic improvements, and the integration of advanced driver-assistance systems. Environmental factors play a major role in this assessment since reducing air pollution and greenhouse gas emissions drives the switch to EVs. In this study, the life cycle of EVs is compared to that of conventional vehicles, and the possibility of EVs reducing the transportation sector's overall carbon footprint will contribute to net zero carbon emissions. In conclusion, this comprehensive review of recent developments and trends in EV technology, such as solid-state batteries, driverless EVs, and the contribution of tax breaks to EV adoption. To conclude, this thorough analysis is an invaluable resource for scholars, decision-makers, and industry participants who seek to comprehend the condition of EV technology today, its obstacles, and its potential to transform sustainable transportation completely.

1. Introduction

The abrupt depletion of natural resources is an alarming situation across the globe. The swift upsurge in global population and industrialization are the two primary root causes of resource depletion. The global population is expanding at an alarming rate of 83.1 million per year, primarily due to consuming natural sources (Malik et al., 2023a). The transportation industry mainly consists of internal combustion engine vehicles (ICEVs), which consume around 30 % of the world's energy. Moreover, these ICEVs are responsible for 17 % of greenhouse gases (GHGs), which may have damaged the biosphere (Malik et al., 2023b; Usman et al., 2023a). Global trends are shifting towards EVs instead of ICEVs due to environmental sustainability and energy conservation. A sustainable future is being ushered in by the continuous improvements in electric vehicles (EVs), which are now essential to attaining the Sustainable Development Goals (SDGs) in line with the United Nations Vision 2030. According to the most recent statistics (Thakur et al., 2020), the transport sector accounted for about two-thirds of the world's oil consumption, recorded at 1.9 million barrels per day. The worldwide EV market was worth USD 129,671 million in 2020. It is anticipated to have increased to USD 359,854 million by the end of 2025, growing at a 15.69 % year (Zhang et al., 2020). It demonstrates the potential of the EV industry, which is increasing day

* Corresponding authors.
E-mail addresses: muhammadaliijaz.malik@student.uts.edu.au (M.A.I. Malik), mdabul.kalam@uts.edu.au (M.A. Kalam), adeel.ikram@superior.edu.pk, dr.adeelikram@gmail.com (A. Ikram), sadaf.zeeshan@ucp.edu.pk (S. Zeeshan), syed.qasim.raza007@gmail.com (S.Q. Raza Zahidi).

https://doi.org/10.1016/j.egyr.2025.02.029
Received 12 November 2024; Received in revised form 24 December 2024; Accepted 16 February 2025
Available online 28 February 2025

Nomenclature

AC	Alternating current
ADAS	Autonomous driving assistance system
ADB	Aggressive driving behavior
AES	Auxiliary energy system
AI	Artificial intelligence
APS	Announced pledges scenario
AWARE	Agency and the available water remaining per area
AWS	Amazon web services
AMC	Aluminum matrix composite
ANN	Artificial neural network
AR	Augmented reality
BEV	Battery electric vehicle
BTMS	Battery thermal management systems
BLDC	Brushless direct current
CAD	Computer-aided design
CO_2	Carbon dioxide
CO	Carbon monoxide
CMC	Ceramic matrix composites
CFD	Computational fluid dynamics
DERs	Distributed energy resources
DD	Driver distribution
DF	Driver fatigue
DFD	Driver fatigue detection
DGs	Distributed generators
DNN	Deep neural network
DRL	Deep reinforcement learning
DT	Digital twin
EKF	Extended kalman filter
EMI	Electromagnetic interface
EMS	Energy management systems
EOL	End of life
EPA	Environmental Protection Agency
EV	Electric vehicle
FCEV	Fuel cell electric vehicle
FEM	Finite element method
FLC	Fuzzy logic controllers
FWD	Four-wheel drive
GA	Genetic algorithm
GHGs	Greenhouse gas emissions
GPS	Global positioning system
HEVs	Hybrid electric vehicles
HIDB	Human driver inattentive behavior
ICE	Internal combustion engine
IEA	International Energy Agency
IMs	Induction motors
IoT	Internet of things
LED	Light emitting diode
LiDAR	Light detection and ranging
LIB	Lithium-ion battery
LCA	Lifecycle assessment
LSTM	Long short term memory
MES	Multi-energy system
MIP	Mixed integer programming
MPC	Model predictive control
NOx	Oxides of nitrogen
NIOC	Neural inverse optimal control
NIR	Near infra-red
PCA	Principal component analysis
PEVs	Plug-in electric vehicles
PHEVs	Plug-in hybrid electric vehicles
PID	Proportional integral derivative
PM	Particulate matter
PMSM	Permanent magnet synchronous system
PSO	Particle swarm optimization
REEVs	Range-extended electric vehicles
RBS	Regenerative braking system
RSUs	Roadside units
RL	Reinforcement learning
SAE	Society of automotive engineers
SDGs	Sustainable development goals
STEPS	Stated Policies Scenario
SWOT	Strengths, weaknesses, opportunities and threats
SRM	Switch reluctance machine
SO_2	Oxides of sulphur
SoC	State of charge
VOCs	Volatile organic compounds
TRACI	Tool for the reduction and assessment of chemicals and other environmental impacts
VANET	Vehicular ad hoc network
VR	Virtual reality
V2G	Vehicle to grid

by day. Environmental Protection Agency (EPA) research states that worldwide GHG emissions from industrial processes and fossil fuels are mainly caused by carbon dioxide (CO_2). This accounts for approximately 65 % of all GHG emissions worldwide. Furthermore, a report from the World Business Council for Sustainable Development projects that the number of light-duty vehicles will rise to 1.3 billion by 2030 and 2 billion by 2050 (Verma et al., 2022). The abrupt increase in the automotive results in the loss of non-renewable energy sources, urban air pollution, and global climate change.

These concerns have forced manufacturers and researchers to implement new technology in the automotive sector. With the merging of many technologies, including EVs, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and fuel-cell electric vehicles (FCEVs) have become the utmost option for automobiles. EVs provide benefits over ICEVs, such as zero tailpipe emissions, lower maintenance requirements, increased powertrain efficiency, and reduced urban air pollution (Hawkins et al., 2013). Global GHGs emissions have decreased due to the transportation industry using electric energy rather than fossil fuels like petrol, diesel, and petrol. Potential reductions in GHGs emissions are around 90 % for EVs, 25 % for HEVs, and 50–80 % for PHEVs (Tagliaferri et al., 2016). In the realm of EV applications, energy storage plays a pivotal role by overseeing and regulating the intricate flow of energy. Selecting suitable energy storage devices involves considering many factors, including energy density, power density, cycle efficiency, self-charging and discharging attributes, and their operational lifespan. Notably, the utilization of heavy metals in battery manufacturing and the composition of the electricity mix used for charging are critical facets of the holistic life cycle of EVs. Moreover, EVs are experiencing rapid global market growth; they concurrently confront various technological challenges in their development. Consequently, a comprehensive analysis of the environmental implications tied to the distinct phases of EVs, encompassing vehicle manufacturing, the fuel cycle, usage, and recycling, is essential to understand their ecological footprint comprehensively.

Comparing EVs to ICEVs, the emission intensities of CO_2, oxides of nitrogen (NO_X), and volatile organic compounds (VOCs) are lower in EVs. However, it releases more oxides of sulfur (SO_2) and particulate matter (PM) than ICEVs. It is important to note that this difference should close as the move towards greener energy sources gathers steam. Compared to ICEV, one battery electric vehicle (BEV) may reduce CO_2

emissions by an impressive 6.2 metric tons. It can also reduce volatile organic compounds (VOCs) by 9.7 kg and NO_X by 2.2 kg. However, it does contribute to an increase in PM emissions by 4.0 kg and SO_2 emissions by 28.5 kg. PHEVs are also environmentally favorable compared to ICEVs. One PHEV reduces 1.4 metric tons of CO_2, 6.7 kg of VOCs, and 1.2 kg of NO_X. Yet, it is essential to acknowledge that PHEVs increase PM emissions by 1.9 kg and SO_2 emissions by 14.2 kg compared to their traditional ICEV counterparts (Yang et al., 2021a). Meanwhile, it has been observed that emissions such as CO_2, NO_X, VOCs, and SO_2 are anticipated to improve as electricity becomes cleaner, particularly with the increased integration of renewable energy sources. However, reducing PM emissions is expected to diminish. Fig. 1(a) displays the global warming potential of three vehicle types (ICEV, HEV and PEV). The production phase of all three vehicles contributes less towards global warming. However, the user phase contributes more towards global warming. The HEV and PEV contribute 14 and 41.4 % less to global warming than ICEV. The battery production for BEV contributes 4215 GWP (kg CO_2 eq). Fig. 1(b) compares the global warming potential of three vehicle types (ICEV, HEV and PEV) based on lifetime distance traveled. Initially, BEV contributes more towards global warming than ICEV and HEV. Still, as electric vehicles travel in a lifetime, their contribution towards global warming starts decreasing compared to ICEV.

Fig. 2 compares global average medium-car lifecycle emissions by powertrain in the Stated Policies Scenario (STEPS) and Announced Pledges Scenario (APS) between 2023 and 2035. Switching to EVs already offers significant reductions on a lifecycle basis, encompassing both production and well-to-wheel emissions. Over 15 years, a medium-sized BEV emits roughly half the lifecycle emissions of a similar ICEV. As the energy grid becomes greener, these emissions savings increase. For vehicles purchased in 2035, an ICEV will emit about 2.5–3 times more than a BEV, with a lifetime carbon footprint of approximately 38 t CO_2-eq for ICEVs versus 15 t CO_2-eq for BEVs. Decarbonizing the power grid is essential to maximize the environmental benefits of BEVs. Between 2023 and 2035, well-to-tank emissions for BEVs could drop by 55–75 % due to cleaner electricity, with battery production emissions reducing by about 10 %. Although larger vehicles generally produce more emissions, electric SUVs still offer significantly lower lifecycle emissions than ICE SUVs about 60 % lower. PHEVs produce 30–35 % fewer emissions than ICEVs, with higher savings achievable if more distance is traveled on electric power. PHEVs purchased in 2023 are estimated to produce 30 % fewer emissions than ICEVs over their lifetimes, with this gap increasing to 35 % for 2035 purchases due to grid decarbonization. The analysis assumes a utility factor of 40 % for electric travel; however, real-world data shows this is often much lower, with CO_2 emissions from PHEVs averaging 3.5 times higher than laboratory values. This discrepancy is partly because PHEVs are not charged and used in full electric mode as frequently as expected. Increasing charging frequency and battery use could further reduce emissions, though enforcing such practices remains challenging.

EVs have rapidly become a focal point of technological innovation aimed at mitigating fossil fuel consumption and addressing the adverse environmental effects of vehicular traffic, including regional smog, ground-level ozone, and climate change. Growing public awareness of global warming and the demand for clean energy sources has been a driving force behind the development of the EV market. EVs have emerged as the most promising mode of transportation, primarily due to their cost-effectiveness, high speeds, and energy-efficient battery technologies. To mitigate CO_2 emissions, it is advisable to strategically locate the production of materials and the manufacturing of power batteries for EVs in regions with high utilization of renewable energy. Additionally, upgrading biomass power plants, known for emitting higher levels of air pollutants like PM and SO_2, is recommended to minimize indirect emissions from EVs. Recognizing the challenges posed by entrenched energy mixes in regions heavily reliant on fossil fuels, short-term changes may be impractical. Decision-makers should prioritize adopting energy-efficient vehicles, including hybrid electric vehicles, in such areas. While these initiatives contribute significantly, it is essential to acknowledge limitations, such as the national average-level assessment of the total life cycle emissions of both EVs and ICEVs, without considering regional variations. Much research has been conducted on biofuels to reduce greenhouse gases, but they still contribute to global warming. Table 1 compares distinct conventional fuels that emit exhaust emissions, but EVs are mainly responsible for zero tailpipe emissions.

Table 2 reviews the literature related to the performance parameters of EVs. The performance parameters are mainly related to battery, vehicle performance, thermal, operational, and environmental parameters. The battery performance primarily comprises battery capacity, energy storage, state of charge, depth of charge, battery lifetime, charging time and charging efficiency. The vehicle performance parameters are related to driving range, acceleration time, top speed, torque, power output, and efficiency in terms of energy consumption per distance (kWh/100 km). The operational parameters linked with EV performance are mainly aerodynamic efficiency, regenerative braking efficiency, chassis design, and vehicle weight. The environmental parameters are mainly linked with battery recycling and lifecycle assessment. Thermal management includes the efficiency of cooling systems for optimal motor and battery temperatures. The detailed investigation of thermal parameters is presented in Table 7.

The increasing demand for EVs is directly proportional to the annual energy consumption. It is reported that the annual energy consumption of EVs ranges from 500 to 4350 kWh, which may increase to 300 TWh by 2030 (Barman et al., 2023). The network charging systems from renewable energy are the potential solution to reduce the burden on power grids. In this regard, Austin Energy (Energy, 2024) and EV Go: fast charging (Charging, 2024) are doing a tremendous job in providing charging facilities to EV consumers. Austin Energy uses wind as a renewable energy source and provides a 50 % discount on Level 2 chargers, a 1500 USD discount on DC fast chargers, a 4000 USD discount on Level 2 chargers and a 700 USD discount on Level 1 chargers. Likewise, EV Go: Fast Charging uses solar and wind as renewable energy sources and EV consumers can get a federal tax credit of up to 7500 USD.

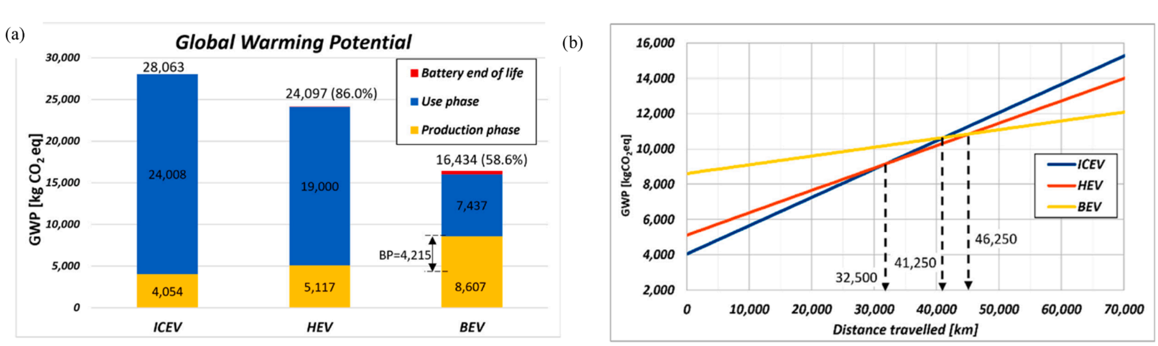

Fig. 1. Global warming potential of three vehicle types: (a) based on entire lifetime, (b) based on distance traveled (km) (Pipitone et al., 2021).

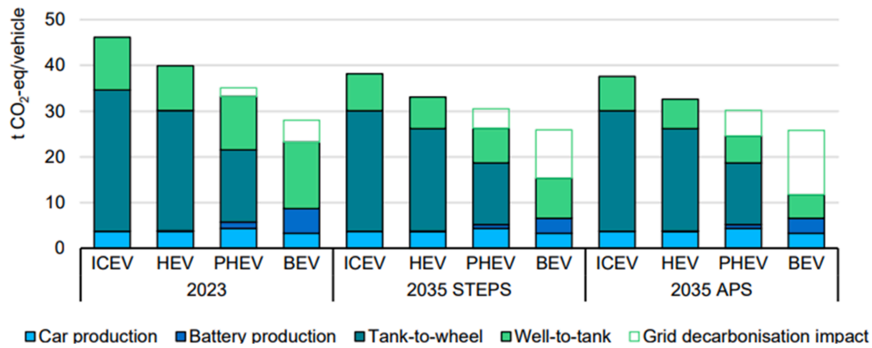

Fig. 2. Comparison of global average medium-car lifecycle emissions by powertrain in the Stated Policies and Announced Pledges Scenarios, 2023–2035 (Agency, 2024a).

Table 1
Exhaust emissions from conventional fuels.

Fuel type	Exhaust emissions	Impact
Diesel	Carbon monoxide (CO)	Fatigue, Heart issues, Hypoxia
Gasoline	Carbon dioxide (CO_2)	bone demineralization, headache, Dizziness, and kidney's calcification
Biodiesel/Ethanol	Hydrocarbons (HC) Volatile Organic Compounds (VOCs)	Cancer and respiratory issues
Compressed natural gas (CNG)	Nitrogen oxides (NOx)	Lung and respiratory issues

Lithium (Li)-ion batteries are frequently used in EVs with a specific energy of 250–300 Wh/kg, and battery packs cost up to 156 USD/kWh. The specific energy of Li-ion batteries can be enhanced by using metallic lithium anodes instead of graphite anodes. The energy density of metallic lithium anode and graphite anode is 3860 mAh/g and 372 mAh/g, respectively. This means that the energy density of metallic lithium anodes is 10 times higher than that of graphite anodes (Gnanavendan et al., 2024). Another approach to reducing energy consumption is the application of lightweight materials like aluminum alloys, carbon fiber-reinforced polymers, magnesium alloys, high-strength steel, composites and thermoplastics. These lightweight materials increase energy efficiency, and ultimately, the battery range will be increased (Burd et al., 2021). EV manufacturers are fascinating consumers through their auto-pilot feature, which provides full autonomy in driving. Tesla is leading in marketing their fully autonomous vehicles by incorporating the adaptive cruise control, navigation, and neural network-driven vision system, which can replace expensive light detection and ranging (LiDAR) systems (Jatavallabha, 2024).

Path transfer methods for EVs are crucial for optimizing operational efficiency, enhancing travel time, and ensuring energy conservation. One approach, traffic-aware dynamic routing, continuously monitors real-time traffic data, including congestion, road conditions, and accidents, to reroute vehicles along less congested paths. This method reduces travel time and energy consumption while improving battery efficiency. Various studies support its effectiveness: a vehicular ad hoc network (VANET) has been proposed to integrate real-time EV charging services by considering charging station status and urban traffic conditions (Bautista et al., 2019). The A* algorithm has also been employed to derive optimal EV routes based on real-time data (Sebai et al., 2022). Cooperative information-sharing approaches between vehicles and roadside units (RSUs) also enhance path planning by reducing communication costs through shortest-path-based relays (Regragui and Moussa, 2023). Further research addresses route planning in dynamic networks with stochastic link travel times that minimize total energy consumption and travel time (Zhou and Wang, 2019). Moreover, a dynamic traffic network model incorporating real-time traffic and grid information has already been developed to improve EV navigation and charging strategies (Qiang et al., 2020). Battery state-aware routing is another innovative approach, which adjusts the route based on the EV's state of charge (SoC). When battery levels are low, this method ensures the vehicle can reach a charging station without running out of power, increasing the EV's range and mitigating the risk of stranding. Research into this method also highlights the importance of energy management that accounts for the health of onboard lithium-ion battery systems (Huang et al., 2022).

Charging station-aware routing integrates the locations and statuses of charging stations into the routing algorithm. This ensures EVs can access charging stations promptly, factoring in capacity, availability, and charging speed to prevent unnecessary detours. Studies on this topic include the development of a dynamic stochastic simulation model for EV fast-charging stations, which reduced average wait time by 26 %, increased charging station revenue by 5.8 %, and enhanced social welfare by 2.7 % (Yang et al., 2021b). Another study proposed a real-time server-based forecasting application leveraging IoT technology to manage charging station scheduling and provide economic, low-wait-time recommendations (Savari et al., 2020). Research into coordinated charging scheduling further optimized charging operations by minimizing total charging time for a given set of vehicles using a mathematical model that incorporates real-time traffic conditions and travel distances (An et al., 2023). Multi-objective dynamic routing evaluates travel time, energy consumption, and safety factors to identify optimal EV routes. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) effectively balance competing objectives. Studies demonstrate the effectiveness of GA in optimizing EV routing (Alolaiwy et al., 2023). In contrast, context-aware routing algorithms in a multi-agent system have shown a 5.6 % improvement in urban cleaning operations and an 18.5 % improvement in vehicle charging (Jelen et al., 2022). Furthermore, a multi-objective charging and discharging scheduling strategy based on improved PSO has been proposed to enhance EV operations (Fang et al., 2021). Predictive routing leverages historical and real-time data to forecast traffic and environmental conditions, enabling preemptive route adjustments. This method minimizes delays and optimizes travel time by predicting potential traffic issues. Research combining EV health monitoring with range prediction and route planning offered a holistic solution to enhance the EV ownership experience (Jayaram et al., 2024). Additionally, an artificial intelligence-based energy consumption prediction model using long short-term memory (LSTM) has been proposed to optimize EV charging planning, addressing energy consumption challenges effectively. These advancements collectively contribute to developing efficient, intelligent EV routing systems (Sebai et al., 2022).

Table 3 presents various studies on energy management systems (EMS) integrated with Vehicle-to-Grid (V2G) technologies and their associated optimization techniques. It summarizes the optimization

Table 2
Review of the literature investigating performance parameters of EVs.

Authors	Performance parameters of EVs
	Battery performance
Olabi et al (Olabi et al., 2023).	They investigated the different types of batteries based on their lifecycle, energy density, efficiency, working voltage, operating temperature and self-discharge as follows: 1. Lithium-ion battery for 1000 lifecycles with an energy density of 200 Wh/kg, up to 99 % efficiency, 4–5.3 V, −20°C to 60°C operating temperature, and self-discharge up to 44 %. 2. Nickel- Iron battery for 2000 lifecycles with an energy density of 100 Wh/kg, up to 91 % efficiency, up to 1.7 V, 40°C operating temperature, and self-discharge up to 30 %. 3. Lead acid battery for 200 lifecycles with an energy density of 30–50 Wh/kg, 75–80 % efficiency, 12–42 V, −25°C operating temperature and self-discharge up to 5–10 %. 4. Nickel metal hydride battery for 500–800 lifecycles with an energy density of 40–110 Wh/kg, 70–90 % efficiency, 6–9.78 V, 15–35°C operating temperature and self-discharge up to −20–45 %. 5. Nickel-cadmium battery for 2000–2500 lifecycles, with an energy density of 50–75 Wh/kg, 75–85 % efficiency, 1.2–1.45 V, 10–40°C operating temperature, and self-discharge up to 10 %.
	Vehicle performance
Ancuta et al (Ancuta et al., 2024).	They simulated the performance of EVs based on autonomy. They obtained a maximum motor speed of 12720 rpm, maximum acceleration of 1.694 m/s^2, state of charge of 95.95 %, total energy consumption of 14.49 kWh/100 km and autonomy of 512 km.
Rezaei et al (Rezaei et al., 2021).	They used n- n-hexadecane phase change material (PCM) to investigate its impact on energy consumption, depth of discharge, and vehicle mileage at ambient temperature (O°C). The energy consumption for a conventional EV heat exchanger is 1.99 kW, and 1.79 kW for an EV with PCM heat exchange. The depth of charge for an EV with a traditional exchanger of heat was 8.27 % and 7.44 % for an EV with a PCM heat exchanger. The vehicle mileage was 116.77 km and 129.76 for EVs with conventional and PCM heat exchangers, respectively.
	Thermal parameters
Fan et al (Fan et al., 2019a).	They investigated the impact of forced air convection on the performance of a 3.5 Ah lithium-ion battery at 0.5, 1 and 2 C. They observed maximum 6, 14, and 29°C temperatures at 0.5 C, 1 C, and 2 C, respectively.
Hussain et al (Hussain et al., 2016).	They investigated the performance of lithium-ion batteries by observing their maximum temperature of 45°C when nickel foam paraffin wax is used as a phase change material.
	Operational parameters
Lee et al (Lee et al., 2023).	They observed an increase of 30 Nm in torque due to the regenerative braking system.
Kaluva et al (Kaluva et al., 2020).	The results for dynamic autonomous road transit displayed a reduction of up to 23 % in average drag coefficient and energy savings of up to 10 % for the EV platoon.
	Environmental Parameters
Pipitone et al (Pipitone et al., 2021).	They conducted a lifecycle assessment of electric vehicles and found that the global warming potential of electric vehicles is 41.4 % lower than that of conventional ICEVs.
Gutsch and Leker (Gutsch and Leker, 2024)	For the recycling of lithium-ion batteries, the global warming potential is 4.0–5.8 $kgCO_2eq\ kWh^{-1}$, compared to 64.5 $kgCO_2eq$ for fresh cell production.

method, application, outcomes, advantages, and challenges faced in each case. The optimization techniques mainly include mixed integer programming (MIP), genetic algorithms (GA), fuzzy logic, and deep reinforcement learning (DRL). The applications range from managing energy exchange in photovoltaic (PV) systems to reducing operational costs in V2G power grids and optimizing energy scheduling in microgrids. The main findings indicate improvements in energy efficiency, cost reductions, and enhanced local energy utilization. For instance, some studies report a 54 % reduction in total energy costs (Sorour et al., 2022), a reduction in costs of up to 16 (Torkan et al., 2022) to 19 % (Yavuz and Kivanç, 2024) or increased energy self-sufficiency (Salari et al., 2024). However, common challenges include high computational demands, reliance on accurate forecasts, and system complexity. The literature review indicates the need for fine-tuning and customization to ensure optimal performance, particularly in large-scale applications.

Table 3 outlines various optimization techniques employed in energy management systems (EMS) integrated with Vehicle-to-Grid (V2G) technologies, focusing on enhancing energy efficiency and reducing operational costs. Mixed-integer programming (MIP) is a mathematical optimization approach used to address problems involving discrete and continuous variables, enabling the minimization of grid dependency and the reduction of energy costs in photovoltaic (PV)-battery systems (Sorour et al., 2022). A, inspired by the principles of natural selection, optimize the balance between energy demand and supply in V2G-integrated power grids, aiming to reduce operational costs (Torkan et al., 2022; Rudbari et al., 2024). The Fuzzy Logic-Based Charge and Discharge Management System, coupled with Artificial Neural Networks (ANN) and PSO, was employed to manage the charge/discharge processes of EV batteries, ensuring high energy efficiency despite varying conditions (Nouri et al., 2024). Deep Reinforcement Learning (DRL), a machine learning technique that utilizes trial and error to optimize decision-making, was applied to manage energy exchanges and pricing within peer-to-peer energy trading systems (Yavuz and Kivanç, 2024). Furthermore, Reinforcement Learning (RL) was utilized to coordinate energy demand and optimize the operation of smart microgrid elements, including EVs, PV systems, and storage units (Almughram et al., 2023). Moreover, Fuzzy Q-Learning, a hybrid method combining fuzzy logic and Q-learning, was used to optimize the scheduling of PEV charging and discharging, effectively reducing electricity market prices and enhancing microgrid efficiency (Salari et al., 2024). Additionally, Dynamic Programming was applied to optimize multi-stage decision--making processes, particularly in the charging and discharging of EVs, while addressing the intermittency of PV generation and balancing grid demand (Salvatti et al., 2020). Lastly, Game Theory is utilized to manage energy exchange among households, electricity retailers, and EVs, optimizing charging and discharging patterns to achieve a 28%-45% reduction in household energy budgets while reducing the carbon footprint (Javadi and Baghramian, 2024). These techniques collectively aim to improve energy management, reduce costs, and enhance the efficiency of energy systems involving V2G technologies.

Integrating EVs and distributed energy resources (DERs) into distribution networks is a pivotal focus for modern power systems. With the accelerating adoption of EVs and advancements in renewable energy technologies, their incorporation must address grid stability, energy optimization, and environmental sustainability challenges. Vehicle-to-grid (V2G) technology, when coupled with energy management systems (EMS), has emerged as a promising solution for achieving these objectives (Alsharif et al., 2021). V2G facilitates bidirectional energy flow between EVs and the grid, transforming EVs into distributed energy storage units. This capability supports load balancing, voltage regulation, and renewable energy integration while providing economic benefits like cost savings and revenue opportunities for EV owners. However, significant challenges persist, including battery degradation, cybersecurity vulnerabilities, and the necessity for robust regulatory frameworks (Noel et al., 2019). Artificial intelligence (AI) plays a transformative role in optimizing the integration of EVs and Distributed Energy Resources. AI techniques, including machine learning, reinforcement learning, and heuristic algorithms, enable real-time decision-making, predictive analytics, and load forecasting (Antonopoulos et al., 2020). Multi-objective optimization models, supported by AI, balance trade-offs among technical, economic, and environmental goals.

Table 3
Comprehensive review of optimization techniques in electric vehicle performance.

Author/ year	Optimization Technique	Application in EMS with V2G	Outcome	Advantages	Challenges/Limitations
Sorour et al. (2022) (Sorour et al., 2022)	Mixed-Integer Programming (MIP)	Energy exchange for PV-battery systems and two days-ahead forecasts to minimize grid dependency.	Cuts total energy costs by up to 54 % and energy bills by 46 %. Reduces absolute net energy exchange with the grid by up to 194 %.	Achieves efficient energy flow scheduling Increases local solar energy utilization, reducing grid reliance.	Computationally intensive for large-scale applications. Performance is forecast-dependent, making accuracy critical.
Rudbari et al. (2024) (Rudbari et al., 2024)	Genetic Algorithm (GA)	Balancing energy demand and supply in V2G-integrated power grids.	Lowers operational costs of the energy management system		Requires fine-tuning to avoid premature convergence. Requires significant computational resources for large-scale problems
Nouri et al. (2024) (Nouri et al., 2024)	Fuzzy Logic-Based Charge and Discharge Management System with ANN and PSO	Charging/ discharging process of electric vehicle (EV) batteries integrated with renewable energy sources	The system achieves a constant energy efficiency of 97 % under different conditions	Demonstrates excellent resistance to changes in irradiance and load variations Allows EVs to support energy-balancing activities	Adds complexity to the system design and implementation may require extensive customization and tuning
Torkan et al. (2022) (Torkan et al., 2022)	Genetic Algorithm (GA)	Optimize the scheduling of energy generation and consumption in microgrids	16 % Reduction in Reservation Costs	Demonstrates reduced operation, reservation, startup costs and decreased pollution levels.	Require substantial resources for large-scale implementations.
Yavuz et al. (2024) (Yavuz and Kivanç, 2024)	Deep Reinforcement Learning	Manage energy exchange and pricing in Peer-to-Peer (P2P) energy trading systems involving multiple Electric Vehicles (EVs) and technologies (V2H, V2L, V2G).	Proposed EMS reduces overall energy costs by 19.18%, Self-Sufficiency Ratio (SSR) increases by 9.39 %	Optimizes energy exchanges, cost-effective, and better utilization of locally generated energy	Significant computational resources and extensive training to optimize decision-making are required
Almughram et al. (2023) (Almughram et al., 2023)	Reinforcement Learning (RL)	Managing energy demand and coordinating smart microgrid elements, including (EVs), (PV) and microgrid storage.	proposed RL-HCPV algorithm can minimize the reliance on grid prices by 38 % on sunny days and 24 % on cloudy days;	Cost Reduction Efficient Energy Management	Computational Complexity Dependence on V2H and Storage
Salari et al. (2024) (Salari et al., 2024)	Fuzzy Q-Learning	Efficient integration and scheduling of plug-in electric vehicle (PEV) charging and discharging	The system reduces electricity market prices by 15 %. The system reduces dependence on the EPG by 30 %.	Peak Load Reduction Cost Reduction Enhanced Microgrid Efficiency	Complexity in Multi-Agent Coordination increase computational complexity
Qiu et al. (2022) (Qiu et al., 2022)	Reinforcement Learning	Coordinating the charging, discharging, and routing of electric vehicles (EVs) within a power-transportation network	Contributes to reducing carbon intensity by optimizing the integration of EVs and renewable energy Improved System Resilience	Reinforcement learning enhances the system's resilience	High Computational Requirements Privacy Concerns
Shulei Zhang (2023) (Zhang et al., 2023a)	Reinforcement Learning	Manage the charging and discharging of EVs while optimizing the overall profit of the microgrid	Maximize the microgrid's profit by efficiently scheduling EV charging and discharging, ensuring demand is met	Profit Maximization Reduced Dimensionality	Dynamic Demand Computational Complexity
Salvatti et al. (2020) (Salvatti et al., 2020)	Dynamic Programming	Optimize the charging (G2V) or discharging (V2G) of EVs while also addressing the intermittency of PV generation and balancing demand from the grid.	Efficient energy use, reduced peak grid demand, and enhanced microgrid efficiency	Grid Dependence Reduction Improved Efficiency	Complexity in User Preferences fluctuating nature of solar power generation introduces uncertainties
Javadi et al. (2024) (Javadi and Baghramian, 2024)	Game Theory	Manage the energy exchange between households, electricity retailers (ER), and EVs, optimizing charging and discharging patterns	Save 28–45 % of their energy budget by optimizing EV charging/discharging, reducing the carbon footprint of households	Cost Reduction Profit Maximization reducing overall demand on the grid	Leading to suboptimal solutions can be complex and may require significant computational resources

These models provide actionable insights for renewable energy utilization, grid stability, and user-centric charging schedules. Additionally, game theory-based approaches facilitate cooperation among stakeholders such as grid operators, EV owners, and energy providers, enhancing the potential of V2G systems (Antonopoulos et al., 2020). Integrating V2G technology with EMS significantly improves the operational efficiency of distribution networks. EMS ensures real-time monitoring and control of energy flows, while V2G offers flexibility through energy storage and dispatch. This synergy enables dynamic scheduling, demand response programs, and optimization of renewable energy use. AI-driven predictive analytics address uncertainties in EV charging behavior and renewable energy generation, ensuring the scalability and resilience of the grid, especially in regions with high EV penetration (Al Badawi and Nashwan, 2024).

The adoption of smart charging systems is vital for the efficient integration of EVs into distribution networks. Smart chargers with bidirectional power flow capabilities support controlled vehicle-to-home charging, easing grid stress and enhancing renewable energy storage. Modernization efforts, such as advanced metering infrastructure (AMI) and microgrids, further facilitate the management of EV loads (Dhara et al., 2022). Pairing EV charging stations with on-site solar panels or stationary batteries optimizes clean energy usage. AI-driven models for forecasting EV charging demand and optimizing grid operations have proven crucial. Incorporating distributed generators (DGs), including solar panels and wind turbines, complements the benefits of V2G and EMS. Optimal placement and sizing of DGs through multi-objective optimization models improve energy efficiency, reduce emissions, and enhance grid reliability. Approaches such as centralized, decentralized, and hybrid coordination models address network constraints and uncertainties in energy generation. Table 4 comprehensively compares centralized, decentralized, and hybrid coordination models for distributed generators (DGs), focusing on their descriptions, advantages, challenges, and typical applications. Centralized coordination relies on a central controller to optimize resources and ensure efficient operation but demands robust communication infrastructure and is prone to single-point failures. Decentralized systems, characterized by the autonomy of individual DGs, offer higher resilience and scalability, though they may suffer from inefficiencies and limited optimization. Hybrid coordination combines the strengths of both approaches, achieving a balance between global optimization and local autonomy while addressing single-point vulnerabilities. This model, however, introduces added complexity in design and implementation. Choosing a coordination model depends on specific system requirements, scale, and infrastructure capabilities.

The control systems used in Energy Management Systems (EMS) are pivotal in optimizing the efficiency and performance of complex systems, especially in applications such as electric vehicles (EVs), smart grids, and renewable energy integration. Table 5 compares various control systems with unique strengths and limitations. Model Predictive Control (MPC) is a widely employed control strategy, particularly in dynamic environments where future conditions must be predicted and optimized. MPC offers high efficiency and the ability to adapt to changing conditions, making it suitable for energy management in EVs, battery optimization, and smart grids (Ishaque et al., 2021; Beşkardeş et al., 2024; Jafari Kaleybar et al., 2022; Siddula, 2024; Ta et al., 2022). However, the significant computational demands of MPC, particularly in real-time optimization, pose a challenge to its implementation in systems with limited resources. MPC's moderate to slow transient response may also hinder its application in scenarios requiring immediate control actions. Despite these limitations, MPC remains highly valuable in scenarios where long-term optimization and handling of constraints are essential. MPC optimizes control inputs by solving a finite horizon optimization problem at each time step. The control action is computed by solving Eq. (1):

$$\Sigma_k^{N-1} = [y(k) - y_r(k)]^T \cdot Q[y(k) - y_r(k)] + u(k)^T R u(k) \tag{1}$$

where y(k) is the output at time step k and y_r (k) is the reference trajectory, u(k) is the control input and Q and R are weighting matrices for the outputs and inputs.

In contrast, Fuzzy Logic Controllers (FLCs) provide a simpler and more flexible approach, especially in systems with uncertain or imprecise data. FLCs offer fast execution and moderate to high efficiency, making them ideal for systems without well-defined dynamics (Behera and Dev Choudhury, 2021; Konijeti and Murugan Lakshmi, 2024; Katuri and Gorantla, 2021; Mohanty and Mohanty, 2024; Millo et al., 2023; Kalaivani and Joice, 2024). The primary drawback of FLCs lies in their dependence on rule definitions, which may require fine-tuning to achieve optimal performance. While FLCs can handle uncertainties effectively, they may struggle with highly dynamic or nonlinear systems, which limits their applicability in more complex EMS scenarios. The control signal for FLCs is mentioned by Eq. (2)

$$u(t) = \sum_{i=1}^{N} \mu_i \quad (e(t).\Delta u_i \tag{2}$$

Where e(t) is the error signal, μ_i e(t) is the degree of membership for the error in the fuzzy set, Δu_i is the fuzzy control action for each rule, and N is the number of fuzzy rules.

PID controllers, known for their simplicity and fast response times, are widely used in well-understood systems where computational efficiency is crucial. Although they are easy to implement and provide good performance in straightforward tasks, PID controllers are limited in their ability to handle complex or nonlinear systems (Afzal et al., 2023; Min et al., 2022; Yavasoglu et al., 2020; Liu et al., 2024; Ganesh and Xu, 2022; Xu et al., 2020). As a result, their application in modern EMS may be restricted to simpler control problems or in conjunction with other techniques to address more sophisticated requirements. The control signal u(t) is given by Eq. (3)

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \quad \frac{d \quad e(t)}{dt} \tag{3}$$

where e(t) is the error signal (difference between desired setpoint and actual output), K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain.

Deep Neural Network-Based Controllers (DNN) are gaining attention due to their ability to learn from large datasets and adapt to complex, nonlinear system behaviors. The control action can be represented by Eq. (4):

$$u(t) = f(w^T x(t) + \beta) \tag{4}$$

where w is the vector of weights, x(t) is the input vector, β is the bias term, f is the activation function, and u(t) is the control output.

This high adaptability makes DNNs suitable for applications such as EV charging optimization, microgrid energy distribution, and renewable energy integration, where traditional control methods may fall short (Wang et al., 2024a; Lin et al., 2024; He et al., 2024; Jouda et al., 2024). However, the high computational requirements and slow transient response of DNN-based controllers present challenges, particularly in real-time systems. Furthermore, the need for extensive training data can make their deployment resource-intensive and time-consuming. Similarly, as a decision-making paradigm, Reinforcement Learning (RL) excels in learning optimal strategies through interaction with the environment. Its continuous improvement makes it well-suited for dynamic and uncertain environments, such as demand-response in smart grids or vehicle-to-grid systems (Lü et al., 2022; González-Rivera et al.,

Table 4
Summary of coordination models for distributed generators in EV applications.

Coordination Model	Applications	Advantages	Challenges	Reference Studies
Centralized	Smart grids, large microgrids, and urban power systems.	Global optimization of resources. Simplified integration with the main grid.Rapid fault response.	Requires a robust communication network. Vulnerable to single-point failures and cyber-attacks.Scalability challenges.	(Stennikov et al., 2022; Ahmadi et al., 2021; Diaz et al., 2016)
Decentralized	Rural microgrids, off-grid systems, standalone systems.	Higher resilience due to autonomy. Scalable for large networks.Reduced dependency on central systems.	Limited optimization potential.Coordination issues among DGs.May result in inefficiencies.	(Lemeski et al., 2022; Wang et al., 2018; Zhang and Wei, 2020; Li et al., 2021)
Hybrid	Community grids, renewable energy clusters, industrial microgrids.	Balances optimization and resilience. Mitigates single-point failures. Flexible for varying scales.	Complexity in design and implementation. Requires robust communication and coordination strategies.	(Saldarriaga-Zuluaga et al., 2021; Shukla et al., 2024; Najafi et al., 2022)

Table 5
Comparison of EMS Controllers for EVs.

Study Reference	Control system	Computation Time	Transient Response	Efficiency	Complexity	Advantages	Disadvantages
(Ishaque et al., 2021; Beşkardeş et al., 2024; Jafari Kaleybar et al., 2022; Siddula, 2024; Ta et al., 2022)	Model Predictive Control (MPC)	Medium to Large	Moderate to Slow	High	High	Optimizes for future conditions, adaptable to dynamic environments	High computational demands and require real-time optimization
(Behera and Dev Choudhury, 2021; Konijeti and Murugan Lakshmi, 2024; Katuri and Gorantla, 2021; Mohanty and Mohanty, 2024; Millo et al., 2023; Kalaivani and Joice, 2024)	Fuzzy Logic Controller (FLC)	Medium	Fast	Moderate to High	Medium	Handles uncertainties well, simple tuning, fast execution	Performance depends on rule definition, may require fine-tuning
(Afzal et al., 2023; Min et al., 2022; Yavasoglu et al., 2020; Liu et al., 2024; Ganesh and Xu, 2022; Xu et al., 2020)	PID Controller	Small	Fast	Moderate	Low	Simple, fast, easy to implement, well-understood in control systems	Limited for complex systems, may not handle nonlinearities well
(Wang et al., 2024a; Lin et al., 2024; He et al., 2024; Jouda et al., 2024)	Deep Neural Network-Based Controller	Large	Slow	High	Very High	High adaptability learns from data patterns, effective for complex systems	High computational requirements demand extensive training data
(Lü et al., 2022; González-Rivera et al., 2021; Jia et al., 2022; Pereira et al., 2020; Nguyen et al., 2022; Ali et al., 2023; Hassanzadeh and Rahmani, 2022)	Reinforcement Learning (RL)	Large	Slow to Moderate	Very High	Very High	Can learn optimal strategies, improves with experience	High computational demands, training time required, complexity in real-time

2021; Jia et al., 2022; Pereira et al., 2020; Nguyen et al., 2022; Ali et al., 2023; Hassanzadeh and Rahmani, 2022). RL, however, faces significant challenges in real-time applications due to its high computational demands and lengthy training times. The complexity involved in implementing RL models can also hinder their practical use in certain EMS applications that require immediate responses. Considering these observations, hybrid control approaches appear to be a promising solution for future EMS applications. By combining Model Predictive Control (MPC) with Deep Learning or Reinforcement Learning (RL), it is possible to leverage the strengths of each method. For example, MPC can be employed for short-term prediction and optimization, while deep learning or RL can be used for long-term strategy development and adaptation. Such hybrid models can balance real-time decision-making with the adaptability and optimization required for more complex systems. Controllers like PID and FLC will remain relevant for simpler, real-time applications due to their simplicity and fast execution times. However, integrating Deep Learning and Reinforcement Learning offers significant potential for more complex EMS systems, especially those involving EVs, smart grids, and renewable energy. Despite the computational challenges, the long-term benefits of these advanced control strategies make them promise for future EMS development.

An adequate control system can potentially sort out the drag issues in EVs. MPC uses a model of the vehicle and its environment to predict and optimize future vehicle states. This allows drag reduction by optimizing the vehicle's speed, acceleration, and braking strategy over a defined horizon. For instance, MPC can predict the optimal speed profile for the vehicle to minimize air drag, especially at highway speeds, by adjusting acceleration and deceleration in response to road characteristics, vehicle load, and external weather conditions (Liu et al., 2017). By solving an optimization problem at each time step, MPC ensures that the vehicle operates most efficiently, reducing energy loss caused by drag. Furthermore, FLCs are particularly effective when dealing with uncertainty and imprecision, such as fluctuating road conditions or wind resistance. They can smooth out driving patterns and reduce abrupt or decelerations, contributing to drag (Tang and Ahmad, 2024). The fuzzy logic controller would adjust the vehicle's behavior in real time based on inputs such as road incline, wind speed, and traffic conditions. These adjustments help avoid sudden accelerations, reducing energy losses from drag and making the vehicle more comfortable.

Neural Network-Based Controllers can process large amounts of real-time data, such as weather conditions, terrain, and wind patterns, to dynamically predict and adjust for drag. Over time, these controllers learn how to minimize energy loss due to drag more effectively by optimizing speed profiles and vehicle behavior across various conditions (Achermann et al., 2024.). Reinforcement Learning (RL) is well-suited for continuous optimization. It learns optimal policies through trial and error, adjusting driving behavior to minimize drag-induced energy consumption. Over time, RL controllers can significantly reduce drag by learning which driving strategies (such as maintaining a constant speed or anticipating uphill gradients) (Wang et al., 2024b). Reducing energy loss from drag relies on selecting a controller capable of adapting to real-time dynamic conditions that influence drag. Key factors include vehicle speed, as higher speeds result in greater drag forces, and optimizing speed profiles can substantially reduce energy consumption. Terrain also plays a crucial role, with uphill and downhill gradients affecting the energy required to overcome drag forces, and an effective controller can adjust energy usage based on these variations.

Additionally, external conditions such as wind speed, direction, temperature, and road surface type alter the drag forces acting on the vehicle, and a well-designed controller can dynamically adjust to these changing factors to minimize energy loss. It is the least energy loss due to air resistance and rolling friction. Hence, manufacturers and researchers can select or hybridize controllers that effectively minimize drag-related energy losses by understanding the strengths of various techniques, such as MPC's predictive optimization, FLC's adaptability to uncertain conditions, and Learning-Based Controllers' continuous improvement.

The distinction between global and local effects is crucial, particularly for air pollutants like PM and SO_2. Consequently, future research could delve into high-resolution local analyses of the effects of EVs and ICEVs, identifying regions with heavier emissions and pollution. This information can then inform the design of targeted local policies. The originality of the current study is in its comprehensive approach to analyze EVs' performance. The previous studies are mainly concentrated on isolated aspects related to EVs. However, the current study integrates all the primary factors affecting EV performance, like the recent technological advancements in efficient electric motors, regenerative braking, advanced driver-assistance systems, battery thermal management, aerodynamics, lightweight materials, charging architecture, tribological analysis and digital twin technology. It provides deep insight into economic and market feasibility, along with the sustainability of EVs through life cycle assessment (LCA) and emission protocols. The policy implications section features governmental influences on the EV market, while a SWOT analysis presents a balanced outlook of EV strengths, weaknesses, opportunities and challenges. Finally, the current review article addresses technical challenges and entails prospects, organizing a comprehensive overview of electric vehicles' future potential and current state. Fig. 3 shows the critical aspects of the current study, which are individually combined to form a complete study.

2. Recent technological evolution of EVs

The current section includes recent advances in regenerative braking systems, design and aerodynamics of EVs, efficient electric motors, development in lightweight materials, integration of advanced driver-assistance systems (ADAS) to optimize EV performance and range, battery thermal management system (BTMS), charging system architecture, digital twin in EVs and tribological analysis between conventional and electric vehicles.

2.1. Advances in regenerative braking systems

A regenerative braking mechanism incorporated within EVs represents a technological innovation that facilitates recuperating and preserving energy that would otherwise dissipate as heat during deceleration. This system is meticulously engineered to enhance the overall efficiency of EVs and extend their operational range by repurposing a portion of the energy initially expended for acceleration. In recent times, notable progress has been achieved in the realm of regenerative braking system technology, including developments such as single-pedal control-based regenerative braking for electric vehicles, the application of Neural Inverse Optimal Control to Regenerative Braking Systems, optimizations in the Switched Reluctance Generator Drive System, and the pursuit of an ideal distribution of braking force for Regenerative Braking Systems.

Ma and Sun (Ma and Sun, 2020) attempted to resolve the issue of EV range anxiety through compact four-wheel drive (FWD). They applied the concept of the ideal distribution of braking force to improve the regenerative braking system. This improved energy recovery approach is then thoroughly validated by numerical simulations applied to an already-existing vehicle system model. These simulations include a variety of scenarios with both constant and fluctuating braking force levels. Notably, the model can recover brake energy at a remarkable rate of around 29 % under moderate braking force and nearly 79 % under low braking force. These simulation results confirm that the suggested energy recovery technique is useful for enabling regenerative braking under various braking circumstances while maintaining the critical requirements of stability and braking efficiency. A regenerative braking control system designed for single-pedal operation was presented by Li et al. (Li et al., 2023). to address driver operating issues and increase the driving range of electric commercial vehicles. First, a tiered architecture for the one-pedal control system was painstakingly designed, including levels for understanding the driver's intention and computing the necessary torque. Once the driver's intentions were ascertained, a logical threshold technique found the best braking pattern. Then, a fuzzy theory was used using road gradient, braking force, and vehicle speed as input parameters and calculating the ratio coefficient of braking force as the output parameter. An optimal distribution curve served as the base of the design of this hybrid regenerative braking system. The simulation findings demonstrate a significant improvement in effective braking and brake energy recovery rates, with increases of 3.5 % and 20.3 %, respectively, credited to the suggested approach.

The plan was then rigorously validated using extensive simulations, and an experiment using a car followed steadily. In the later trial, the single-pedal regenerative braking control approach produced an average optimization rate of 4.33 % and a maximum optimization rate of 5.81 % for energy consumption. Adopting this strategy efficiently limits energy consumption, thus boosting the economic viability of single-pedal EVs. A Neural Inverse Optimal Control (NIOC) system specifically designed for the regenerative braking system used in electric vehicles (EVs) was developed by Hernandez et al. (Ruz-Hernandez et al., 2022). A Neural Inverse Optimal Control (NIOC) system specifically designed for the regenerative braking system used in electric vehicles (EVs) was developed by Hernandez et al. (Ancuta et al., 2024). An auxiliary energy system (AES), a main energy system (MES), and a storage unit comprise this regenerative system. The main goal of the latter, which comprises a buck-boost converter and a supercapacitor, is

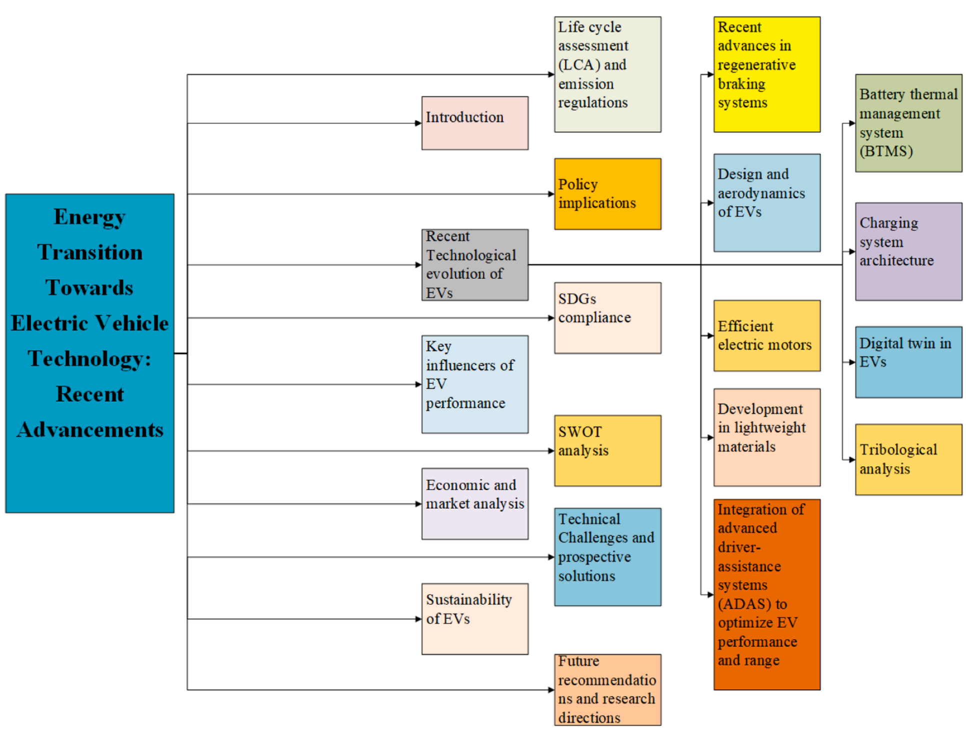

Fig. 3. Components of the current study.

to recover energy produced during braking that the MES cannot hold onto and use it again during the acceleration phase. To precisely estimate the dynamic behavior of the buck-boost converter, a neural identifier was trained using an extended Kalman filter (EKF) during the building of the NIOC. The NIOC controls the dynamics of voltage and current in the AES. The EV's propulsion system comprises a DC motor for evaluation, and a PID controller regulates its speed to track the reference source when regenerative braking is used accurately. The simulation results demonstrate how well the suggested control system tracks time-varying references for the voltage and current dynamics of the AES, which are monitored at the buck-boost converter. Moreover, the control design of the supercapacitor ensures smooth transitions between the charging and discharging phases. Furthermore, the suggested control method clearly improves the efficiency and overall performance of the EV's energy storage system while the regenerative braking system is engaged. The mean squared error is computed and contrasted with a traditional PID controller to verify this improvement further.

Lan et al. (Lan et al., 2022). presented an innovative six-phase switched reluctance machine (SRM), introducing a misaligned segmental rotor by 15 degrees. This design innovation results in a one-layer, 2D structure with a notably shortened flux path. In the suggested SRM, intentional misalignment successfully reduces torque ripple. Compared to a typical SRM, the torque ripple dramatically decreases by 54.9 % at an operating speed of 1500 rpm. Notably, this achievement is facilitated by the concurrent excitation of two phases, further enhanced by applying an optimization method that aligns the phase with maximum torque to the zero-torque position of the adjacent phase. The design and performance of this SRM are rigorously evaluated using the finite element method (FEM), which also encompasses simulations of a liquid cooling system. The analysis includes both static and dynamic torque waveforms. SiC MOSFETs are used in dynamic simulations, and a dual-loop control system is constructed on a DSP platform. The novel SRM's prototype is then produced and put through experimental validation, showing a notable decrease in torque ripple throughout a range of speed ranges compared to traditional SRMs. An excellent current controller is envisioned as part of the future research agenda to produce smoother waveforms and further reduce torque ripple. Efforts are also being made to resolve issues about electromagnetic interference (EMI) and thoroughly assess the converter cost and efficiency of the suggested SRMs compared to interior permanent magnet machines. In addition, although the longer copper length in the SRM design has advantages, it also creates worries about higher copper losses.

2.2. Design and aerodynamics of EVs

The aerodynamics and design of EVs significantly influence this technology's performance and efficiency. Aerodynamics has a big influence on an electric vehicle's range. Efficiency is increased when air resistance is decreased by improved aerodynamic design. An EV's overall efficiency increases, and its energy consumption decreases for an aerodynamically streamlined design. The longevity of an EV's battery is also directly impacted by aerodynamics and efficient vehicle design. Because of its design, the car faces less resistance, so the battery doesn't have to work as hard, reducing wear and extending its life. Optimizing aerodynamics can also increase the effectiveness of regenerative braking. Regenerative braking systems enhance a vehicle's efficiency by recovering more energy during deceleration when the vehicle encounters less resistance. Aerodynamics and efficient design can assist cut down on energy usage, reducing the time needed for charging. Faster charging times improve the use and convenience of EVs, which is why they are critical to the adoption of EVs. The driving experience may be significantly impacted by aerodynamics and design. Well-designed EVs entice buyers because there is less wind noise during a smooth and quiet ride.

EV manufacturers may stand out in the severe competition and draw in more business through aesthetic and aerodynamic design. Enhanced aerodynamics can help EVs emit fewer greenhouse gases. The total environmental effect of producing and using EVs can be decreased when propulsion requires less energy. EV safety may also be enhanced via aerodynamics and effective design. They improve the vehicle's overall safety by guaranteeing stability at high speeds and on different types of roads. Advanced computational fluid dynamics (CFD) modeling has been used by Afianto et al. (Afianto et al., 2022). to improve the design of an electric hatchback and increase the range of EVs. They used experimental data to evaluate their modeling, and the simulation outcome closely matched the experimental results, with a divergence of just 4.36 %, indicating a respectable degree of agreement. The electric hatchback's optimized design ultimately included the addition of rear fins, a rear spoiler, a front splitter, and a rear diffuser. This comprehensive redesign greatly lowered the hatchback's drag coefficient, which greatly improved safety and stability, especially at higher speeds and made the car easier to handle. Notably, this optimization conferred a notable 10 % reduction in the drag coefficient of the electric hatchback, ultimately enhancing its aerodynamic performance and, consequently, the operational range of electric vehicles. Furthermore, it is worth highlighting that adding a front splitter, when assessed individually, resulted in only a marginal improvement of 1.17 %. In stark contrast, the rear diffuser alone engendered a substantial 11.18 % enhancement. Concurrently, the lift coefficient was drastically diminished by 73 %, thus offering a substantial boost in stability and accounting for enhanced safety measures, particularly when operating the vehicle at high velocities.

Budiprasojo and Firmansyah (Budiprasojo and Firmansyah, 2022) have inferred that flow separation is the root cause behind the disparities in pressure and velocity observed between the upper and lower regions of a vehicle's body. The lower section exhibits lower pressure and higher velocity than the surrounding atmosphere, owing to its quasi-vacuum nature and reduced resistance. This phenomenon results in a suction effect that facilitates the swift influx of air. Their work also highlights a fundamental principle: the drag force is directly proportional to the square of the velocity. Consequently, heightened drag force corresponds to increased resistance on the vehicle, ultimately leading to higher fuel consumption. Notably, the drag coefficient identified in this study stands at approximately 0.318. It is worth mentioning that the reduction in the coefficient of drag achieved through varying flow steam velocities amounts to 2.48 %. Atkinson-cycle engines have gained substantial traction in hybrid electric vehicles (HEVs) due to their commendable fuel-saving performance. Modern iterations of Atkinson engines predominantly leverage Variable Valve Timing (VVT) technology. The architecture of Range-Extended Electric Vehicles (REEVs) empowers Atkinson engines to consistently operate within high-efficiency zones, which is advantageous for downsizing the engine. In the realm of future engine designs, the adoption of the Otto-Atkinson cycle could hold promise for enhancing power density (Wang et al., 2022a).

2.3. Efficient electric motors

In EVs, the propulsion system consists only of the electric motor or an internal combustion engine that works with it. In the literature, EVs that use electricity from the battery as the energy source are called pure electric vehicles (PEVs) or battery electric vehicles (BEVs). In contrast, vehicles that use different energy sources in addition to the battery are called hybrid electric vehicles (HEVs). These vehicles use a flywheel or capacitor and the battery as the energy source. A fuel cell electric vehicle (FCEV) also falls in the category of EVs. Electric motors are undoubtedly the most critical part of the propulsion systems of EVs. The motors must actuate under bad conditions, where the humidity rises to 85 % and the ambient temperature is between −40–135 °C. Other challenging factors are the high driving duty cycle, higher torque density, and wide constant power range (Yılmaz and Özdemir, 2021).

DC motors are the most common motors now a days. They have permanent magnets in the stator and brushes in the rotor to supply power to the stator. The advantage of these electric machines is that they provide high torque at low speeds. On the other hand, these motors are large, inefficient, and have losses caused by brushes. Maintenance requirements and related costs of brushes are additional disadvantages of these motors. Also, the DC motor's regenerative breaking capacity is highly limited (Cao et al., 2019). The current state of AC motors, developments in power electronics, and control systems have left DC motors behind their colleagues. However, DC motors are rarely seen in modern EVs. Unlike DC motors, permanent magnets are in the rotor in brushless direct current (BLDC) motors. The DC source supply is converted to alternating current (AC) via the inverter and provided to the stator. Since there is no winding in the rotor, there are no copper losses, making BLDC motors more efficient than induction motors. In addition, BLDC motors are lighter, smaller, reliable, and have more torque density (Aliasand and Josh, 2020). Nonetheless, the duration of the constant power range proves to be rather limited, with a concurrent reduction in torque values as the velocity escalates. Utilizing a permanent magnet configuration in these motors contributes to elevated manufacturing costs, compounded by the susceptibility of the magnets to thermal degradation. Nevertheless, there should be augmentation in the winding components; the potential arises for enhancing both the speed range and the comprehensive efficiency of these motor systems (Khamari et al., 2023).

Asynchronous motors are the widely used motors in EVs due to their high dynamic performance and basic characteristics (Saha and Mukherjee, 2023). Although the constant power range of the induction motors (IMs) can be extended by 4–5 times the base speed, the high speed and constant power range operation are limited due to the pulling torque (Chandrakar et al., 2021). The main disadvantages of IMs are decreasing efficiency at low speeds and decreasing power at high speeds (Mohammad and Jaber, 2022). Their main advantage is that they do not produce much noise and vibration compared to other electric machines. In addition, production costs are relatively low, and the ability to work in severe conditions is high. However, PMSM, which offers high torque density, efficiency, and low rotor losses, is in line with IM's throne (Rind et al., 2017), described in the next subsection. In the automotive market, Tesla is the most prominent brand that incorporates IMs in their vehicles. Selective models from Chevrolet, Chrysler, and Renault also integrate IMs into their drive systems.

Permanent magnet synchronous motors (PMSMs) contain permanent magnets in the rotor and 3-phase AC windings in the stator. Rare-earth neodymium magnets are often used in high-performance PMSMs. If AC with sinusoidal waveform feeds the permanent magnet terminals, these motors are called PMSM, while trapezoidal waveform feeds these motors are called BLDC motors. Although the hardware structures of both motor types are the same, the control strategy differs in the software part due to different control algorithms and communication modes. BLDC motors use trapezoidal commutation with simpler control techniques, while PMSMs use sinusoidal commutation with vector control. It is mentioned that PMSMs are a threat to IMs. Permanent magnet synchronous motors (PMSMs) are characterized by their remarkable attributes, including elevated torque and power density, exceptional controllability, substantial torque output within compact dimensions, reduced weight, and a compact footprint. These qualities render them particularly well-suited for in-wheel direct drive applications. Nonetheless, it is essential to acknowledge that the constant power operation of PMSMs is constrained by limited high-speed ranges, primarily due to the constraints imposed by permanent magnets, which limit the magnetic field's expansion. Furthermore, the scarcity of rare-earth magnets and their associated high costs present significant barriers to the widespread adoption of PMSMs in the affordable electric vehicle (EV) market. Notable examples of automotive brands incorporating PMSMs in their vehicles include Nissan Tino, Honda Insight, and Toyota Prius. Switched reluctance motors (SRMs) have attracted great attention from researchers in recent years in high dynamic performance required applications. SRMs have salient poles or teeth in the stator and rotor. These stator/rotor pole number combinations are important when applying the motor. The most important characteristics of SRMs compared to IM and PMSMs are that they are more reliable, have high tolerance in high temperatures, have a high-speed range, and are suitable for gearless operation (Pindoriya et al., 2018). The constant power range can be increased by 6–7 times the base speed. Although SRMs have lower than maximum efficiency compared to PMSMs, they have considerable efficiency over a wide speed and torque range compared to other electric machines. The disadvantages of these motors are noise, complex design, and control structure (Pindoriya et al., 2018). Table 6 shows the comparison of different motors based on performance rating.

2.4. Developments in lightweight materials

The advancement of composite materials that are lightweight, flame-resistant, and cost-effective offers the potential to replace the current materials used in EVs, thereby reducing the overall cost of these vehicles. The market for EV battery housing was estimated to be worth \$0.87 billion globally in 2020 and is expected to grow to \$4.47 billion by 2025 (Mohanty et al., 2023). By 2025, 1167.3 thousand tons of battery housing materials are anticipated to be needed (Mohanty et al., 2023). According to reports, EVs' life cycle costs might vary from \$0.49 to \$0.52 per km (Bekel and Pauliuk, 2019). However, some reports indicate a lower life cycle cost of \$0.25 per km (Petrauskienė et al., 2021). To enable a smooth transition to the burgeoning EV industry without jeopardizing current automotive sector investments, maximizing the utilization of existing automotive and industrial facilities and investments, even in the face of significant investments in EV technology. Moreover, EV technology offers cost advantages to vehicle owners, including reduced electricity bills and annual maintenance expenses. A study by Carlstedt et al (Carlstedt and Asp, 2020). compared the Tesla Model S and BMW i3, highlighting the potential for significant weight savings in vehicles while maintaining drive range performance. Alternatively, introducing structural batteries can maintain vehicle weight, resulting in a 70 % increase in the driving range for lightweight EVs.

Composite materials, including EVs, play a significant role in the automotive industry. They are used to reduce weight, improve fuel efficiency, enhance safety, and increase overall performance. A lightweight composite material incorporating carbon fibers in a polymer matrix is called carbon fiber-reinforced polymer (CFRP) (Pandey et al., 2022). It is frequently used for interior components, chassis elements, and body panels on EVs. CFRP increases structural stiffness and reduces

Table 6
Comparison of performance of different motors in terms of performance rating (Ahmed, 2022).

Parameters	IM	SRM	BLDC	PMSM
Efficiency	18	18	13	16
Cost	3	4	3	3
Speed	15	19	15	17
Power Density	8	8	9	10
Controllability	17	16	15	15
Maximum Speed	15	19	15	17
Noise	3	3	4	4
Applications	2003 Honda Civic Hybrid	2000 Holden Commodore	1997 Toyota Prius XW10	2012 Toyota Yaris Hybrid
	2012 Ford Focus Electric		2011 Renault Fluence Z.E	2014 Honda Accord PHEV
	2012 Tesla Model S			2015 Porsche 918 Spyder

weight. Similar to CFRP, glass fiber reinforced polymer (GFRP) (Liu et al., 2023) substitutes glass fibers for carbon fibers. It is utilized in EVs for parts like bumpers, interior trim pieces, and some structural parts that don't need the exceptionally high strength of carbon fiber. Aluminum alloys reinforced with ceramic fibers or particles are called aluminum matrix composites (AMCs) (Elumalai et al., 2020). They are utilized in EVs for several parts, including suspension parts, braking rotors, and structural parts. AMCs provide a nice mix of stiffness, strength, and lightweight. Glass or carbon fibers strengthen a polymer matrix in thermoplastic composites (Liu et al., 2023). They are employed in EVs for a variety of external and interior parts as well as battery casings. Thermoplastic composites are recyclable and easy to process. Natural fiber composites (Mohanty et al., 2023) are fibers in a polymer matrix that come from sustainable sources, such as flax, hemp, or sisal. They are utilized in EVs' interior parts, such as upholstery and door panels. They provide weight loss and environmental advantages. EV bumpers, fenders, and external panels are made of reinforced polymers (Wazeer et al., 2022) including fiberglass and carbon-reinforced plastics. They are cost-effective and have strong impact resistance. Composite materials can benefit from adding carbon nanotube composites (Fantuzzi et al., 2021) to improve mechanical attributes like conductivity and thermal stability. They are occasionally used in EVs for parts like lightweight structural components and battery casings.

Epoxy resin composites (Wang et al., 2022b) are utilized in electric vehicles (EVs) for several purposes, including high strength-to-weight ratio components, lightweight structural parts, and electrical insulation. Ceramic fibers are incorporated in a ceramic matrix comprising ceramic matrix composites (CMCs) (Behera et al., 2020). They are utilized in various high-temperature EV applications, such as thermal insulation and braking discs. The choice of composite material in an EV depends on factors like cost, weight reduction goals, performance requirements, and manufacturing processes. Manufacturers often use a combination of these materials to optimize the EV's overall performance and efficiency while meeting safety and cost constraints. The lithium, cobalt, nickel, and graphite market for EVs will grow 26 times, 6 times, 12 times, and 9 times, respectively, between 2021 and 2050 to fulfill the net-zero emissions objectives (Niri et al., 2024). Meeting this need will provide a variety of obstacles, including the global need to accept new investments and technological advancements without creating conflicts between competing agendas. The global and regional concerns about the effectiveness of transport decarbonization have been driven by the uncertainties around a sustainable supply of battery materials, the complexities of environmental, social, and governance issues, and the geopolitical conflicts along the battery value chain.

2.5. Advanced driver-assistance systems: EV performance and range optimization

Suganthi et al. (Suganthi et al., 2023). have examined various parameters within the In-Vehicle system. This evaluation encompasses speed, distance traveled, idle time, and fuel efficiency. It involves a comprehensive analysis of the electronic control unit, which, through modules that govern braking, powertrain, transmission, suspension, and battery management, aids in forecasting driving conditions in diverse terrains. Furthermore, it can recommend tailored driving modes to enhance advanced driver assistance systems. These functionalities are executed with the support of the vehicle-to-infrastructure protocol, which acquires data via gateway nodes, subsequently presenting it in an IoT data framework. The research focuses on analyzing and visualizing factors influencing drivers' experience in modern vehicles, which are closely linked to the IoT cloud platform. Customized driving modes and enhancements are developed through computational analytics, culminating in implementing over-the-air updates to upgrade the embedded vehicle system for improved drivability. All these operations are orchestrated through a pivotal element of this study, namely, the cloud server.

Balan et al. (Balan et al., 2022). proposed a driver identification system that leverages a deep driver classification model, employing a deep neural network (DNN) combined with feature reduction techniques, specifically random forest (RF) and principal component analysis (PCA). The current system is intended to improve and automate key processes, such as the functioning of the braking system. They simulated a real-time cost-effective driver assistance program using task models, investigating several situations and determining if task scheduling was feasible before deploying electric cars (EVs). Comparing the new driver assistance program to the ones now available, multiple key benefits exist, including fewer accidents and increased driver safety. The PCA-DNN model showed an accuracy of 95.55 %, while the RF-DNN model produced an excellent accuracy rate of 97.05 %. By comparison, an accuracy rate of about 92 % was attained by the artificial neural network (ANN) that utilized PCA and RF. Currently, driving trajectories are created using machine learning techniques, namely reinforcement learning (Cai et al., 2020). These trajectories consider longitudinal acceleration and lateral lane-changing maneuvers (Yang et al., 2023). These trajectories consider many elements, including vehicle cooperation during lane selection in a multi-lane traffic situation (Liu et al., 2021), longitudinal acceleration and lateral lane-changing maneuvers (Yang et al., 2023). Even though much research has been done to forecast how cars would behave, there is still a significant gap in modeling neighboring vehicle behaviors. Machine learning and deep learning algorithms are two of the most promising data-driven approaches to solving this difficulty in advanced driver assistance systems (ADAS). Human driver inattentive driving behavior (HIDB) has been thoroughly classified by Alkinani et al. (Alkinani et al., 2020). HIDB is divided into two main domains: driver distraction (DD) and driver tiredness (DF) or sleepiness (DFD). Additionally, they explore the causes and effects of aggressive driving behavior (ADB), another dangerous human driving behavior. ADB includes a broad range of risky and aggressive driving behaviors that frequently cause catastrophic accidents. These aberrant human driving behaviors, including DD, DFD, and ADB, are influenced by various factors, including driver experience or inexperience, age, gender, and health conditions. However, it is worth noting that this paper does not encompass an in-depth exploration of the impacts of these factors on the deterioration of a human driver's driving skills and performance. Following an introduction to deep learning and its associated algorithms, the authors thoroughly examine the most recent deep learning-based systems, algorithms, and techniques designed to detect driver distraction, fatigue/drowsiness, and aggressiveness in human drivers. They aim to comprehensively understand HIDB detection by offering a detailed comparative analysis of this domain's recent techniques.

Zhang et al. (Zhang et al., 2023b). conducted a comparative analysis of conventional phosphor-converted near-infrared light-emitting diodes (NIR pc-LEDs) and near-infrared persistent phosphor-converted LEDs (NIR ppc-LEDs). The findings indicate that NIR ppc-LEDs can be employed in traditional systems and emerging technologies within intelligent security, driverless vehicle technology, and virtual reality. However, it's worth noting that there has not been extensive research on NIR ppc-LEDs. In this context, the researchers introduced a novel NIR ppc-LED featuring specially prepared SrAl12O19: Fe3þ, Mg2þ, Ti4þ NIR persistent phosphors. Unlike pc-LEDs, the new ppc-LED demonstrated a remarkable ability to sense a full spectrum of light, particularly in response to photo-stimulated adjustments in lattice defects. Moreover, when employed as a smart sensing LED in a digital NIR imaging system, it allowed the conversion of optical feedback into a digital signal through a self-regulated transition from visible to NIR operation. These findings suggest that the designed ppc-LED, with its full-spectrum sensing capabilities, significantly boosts the sensitivity of digital NIR imaging. This is particularly relevant in the context of low-light digital NIR imaging, which has recently gained substantial attention in advanced driver assistance systems and VR/AR technology. Fig. 4 displays the progressive enhancement of ADAS capabilities, highlighting

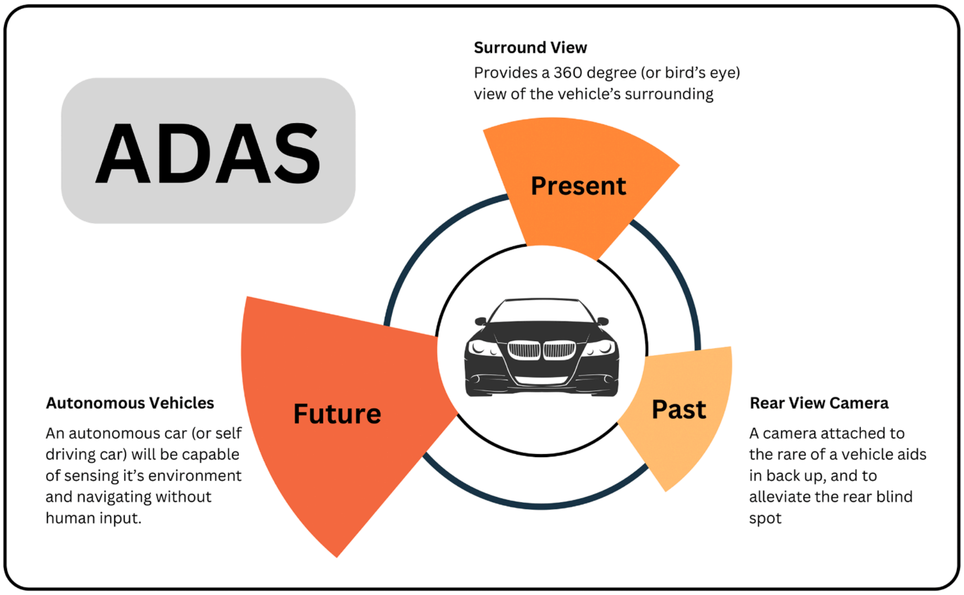

Fig. 4. Comparison of Autonomous Driving Assistance Systems: Evolution from Past Technologies, Current Innovations, and Future Advancements.

key milestones and projected developments in sensor integration, decision-making algorithms, and user interaction.

2.6. Battery thermal management system (BTMS)

The operating temperature range of a lithium-ion battery in an electric vehicle is between 15°C and 35°C. A battery thermal management system is essential for studying the temperatures of batteries in EVs (Tete et al., 2021). The range of working temperature of battery systems is the main area of focus for automotive researchers. Appropriate and efficient cooling techniques can boost battery thermal efficiency, lower the negative effects of high battery cell surface temperatures, increase EV safety, and lengthen battery life. Various BTMS technologies are used, such as heat pipe cooling, direct and indirect liquid cooling, and forced and natural air-cooling methods. It was discovered that the air-cooled battery BTMS has good qualities, including a reliable, easy-to-use design and lower heat capacity. It is used in low-capacity batteries due to the air's poor thermal efficiency, and because of this, forced air-cooled battery transfer modules BTMS are used at high charging and discharging rates. In these modules, air circulates via internal battery pack channels to achieve the best possible cooling. One of the most promising cooling solutions is liquid-cooled BTMS, which requires careful design considerations of the sealing cover of the battery to prevent leaks. The system's weight is a key concern, and cooling performance can be increased by integrating metal plates. Because of higher heat conductivity, liquefied metals, nano-fluids, and boiling liquids are considered the most appropriate for battery cooling systems.

Developing hybrid cooling by combining microchannel-based cooling with fins, nanofluids, and PCM would greatly enhance battery performance at high charging and discharging rates. Upgrading the current cooling medium with future enhanced cooling systems is important to effectively dissipate huge heat created by the operation of the battery at high temperatures and fast charging modes. Another method for improving the efficiency of current air-cooled BTMSs is to use evaporative cooling. This cutting-edge technique uses the specific and latent heat of the evaporative fluid, which has significantly higher cooling effectiveness, to absorb the heat collected in the battery system through coolant droplets. Saw et al. (2018) A mist cooling technique was used to study the BTMS. The authors used a combination of two-phase tiny mist droplets generated through an ultrasonic generator to cool the target at a high temperature during the experiment. As the droplets moved downstream, they evaporated and took up heat from the surrounding air. Mist cooling removed more heat than dry air systems (10035 J kg^{-1} K^{-1}). This is because mist has a higher heat capacity (41813 J kg^{-1} K^{-1}). Findings indicated that the air/mist mixture of 3 % was sufficient to keep the surface temperature of the battery below 40°C. It was determined that mist cooling can do so due to better cooling capacity and lower cost. Due to the low thermal conductivity of coolant, liquid-cooled battery thermal storage modules cannot be used in developing high-end cooling systems for EVs that require fast charging and operate at high temperatures.

Researchers are looking to improve the performance of liquid-cooled BTMSs by dispersing high thermal conductive nanoparticles in the coolant. Mondal et al. (Burban et al., 2013). studied the effect of utilizing Al_2O_3 nanoparticles scattered across a water-based coolant on the battery's thermal performance. Compared to the baseline situation, it was observed that an increase in the concentration of nanoparticles in the coolant lowered the maximum temperature of the cell module. For improved battery pack thermal performance, nanoparticles with higher thermal conductivity and specific heat capacity must be researched in the future. Future research should concentrate on creating new technologies that will enable waste heat radiated via the battery module to be recovered and used properly to improve the thermal performance and overall efficiency of the BTMS. Table 7 compares several battery pack cooling methods that use liquid heat pipes and air cooling. It compiles the different cooling methods researched for Li-ion battery packs while considering the battery's design variable, which includes the battery's layout and liquid flow arrangement.

Numerous researchers also considered the importance of cell spacing, fan operation, and air duct inlet and outlet angles as design variables. The distinct chemical makeup of the Li-ion battery systems examined in every study has been emphasized. The primary goal of the BTMS design is to minimize the temperature problem, as well as the maximum cell temperature (T_{max}) and highest difference in cell temperature (ΔT_{max}) that the battery pack can achieve. Most researchers who have studied different BTMS for Li-ion batteries have concurred that air-cooling BTMSs are straightforward to use, inexpensive, and have readily available coolant. Since air has a low heat removal coefficient, most air-cooling systems focus on the optimization of layouts and other parameters of operation. However, this cooling method cannot handle a battery's rising temperature or energy efficiency. T_{max} and ΔT_{max} are greatly impacted by the forced liquid cooling method used by the BTMS.

Table 7
Distinct battery thermal management system characteristics.

Sr. #	Cooling Systems	Used Heat Transfer Fluid or Coolant	Type of Battery and Capacity	Battery loads	T_{max} (∘C)	ΔT_{max} (∘C)	Ambient Temperature (∘C)
Air-based BTMS							
1	Forced Air Cooling System (Yang et al., 2015)	Air	3.3 Ah 26,650 LFP Cylinder shaped battery	2 C	34.55	0.93	25
2	Pin fin heat removal sink + Air cooling system (Mohammadian, 2015)	Air	15 Ah prismatic 8 cells Battery Pack	2 C	35.2	< 5	27.15
3	Parallel airflow system (Saw et al., 2016)	Air	16 Ah pack with 24 pieces of 38,120 commercial type (LFP) cells	40 A (5 C), 24 A (3 C), 8 A (1 C)	33.2 at 3 C	1.5	30
4	Air cooling with Embedded metal foam system (Mohammadian and Zhang, 2015)	Air	Battery pack with 8 15 Ah prismatic cells	1 C	43.43	-	27
5	Parallel air cooled BTMS system (Hong et al., 2018)	Air	Prismatic type Li-ion batteries	5 C	51.85	3.7	27
6	Forced Air-cooled system (Fan et al., 2019b)	Air	3.5 Ah lithium-ion 18,650 battery type	0.5 C, 1 C, 2 C	6, 14, 29 at 0.5 C, 1 C, 2 C respectively.	3, 7, 16 at 0.5 C, 1 C, 2 C	30
7	Air-cooled (Zhao et al., 2015)	Air	3 LIBs (2.5 Ah, 18,650; 3.2 Ah, 26,650; 10 Ah, 42,110)	50 A (5 C)	27.15	< 5	27.15
8	Forced Air-cooled (Xie et al., 2017)	Air	10 Prismatic LIBs cells	20 A	34.45	4.47	25
9	Forced air cooled (Z-type flow structure) (Chen et al., 2019a)	Air	Prismatic-type LIB cells	5 C	58.9	*2*	26
10	Double silica cooling plate with copper mesh (Li et al., 2019a)	Air	16 Ah Lithium-polymer batteries	1 C, 3 C, and 5 C	49.76 at 5 C	0.53	30.5
PCM based BTMS							
1	Paraffin + EG matrix (Lin et al., 2015)	PCM Cooling	40 Ah commercial-type rectangular $LiFePO_4$ battery (100 ×32 ×180) mm	1 C and 2 C	24.4 (1 C), 27.7 (2 C)	2 (1 C), 3.8 (2 C)	15
2	PCM/Al foam (Khateeb et al., 2005)	PCM Cooling	Eighteen 18,650, 2.2 Ah Li-ion cells	C/1, C/2, C/3 and C/5	22, 9, 6, 3	2.5	25
3	Nickel foam-paraffin wax (Hussain and Chao, 2016)	PCM Cooling	Commercial Type 18,650 Li-ion batteries with cells of 3.4 A h	2 C	45	0.8	25
4	n-octadecane (Javani et al., 2014a)	PCM Cooling	Prismatic type LIB cell	2 C	35.28	3.38	21
5	Paraffin wax with Al Foam and Al Fins (Khateeb et al., 2004)	PCM Cooling	12 Ah 18,650 type Li-ion cells	2.4 C	25 (Temp. rise)	-	40
6	n-octadecane wax (Javani et al., 2014b)	PCM Cooling	4 Prismatic-type Li-ion battery cells	3 C	30.7	1.2	21
7	Paraffin + Carbon fibers (Samimi et al., 2016)	PCM Cooling	Cylindrical battery simulator having (14.5 dia & 50.5 mm length)	-	52.5	1.1	25
8	RPCM, T-PCM 920 (Duan, 2010)	PCM Cooling	Electric heaters as simulated battery types	-	< 65	8	25
9	Pure paraffin type (PCM1), EG 20 % + paraffin 80 % (PCM2), EG 3 % + epoxy 47 % + paraffin 50 % (PCM3) (Wang et al., 2017a)	PCM Cooling	18,650-type LIBs	1 C, 3 C and 5 C	38.46 (1 C), 45.33 (3 C) and 51.73 (5 C)	< 3	-
10	Paraffin/EG (Ling et al., 2014)	PCM Cooling	Electric heater as simulated battery	-	< 60	< 2	25
Water Based BTMS							
1	Compact Liquid Cooled system (Basu et al., 2016)	Water	Li-NCA/C 18,650 cell types	0.9 C (15.6 A) and 0.6 C (10.4 A)	27 (0.9 C), 28 (1.8 C) and 30.54 (2.7 C)	< 5	23.45
2	Liquid-cooled (water pipe) (Li et al., 2018)	Water	Commercial type 2 Ah Li-ion 18,650 battery	0.5 C, 1 C and 3 C	31.8 (0.5 C), 38.5 (1 C) and 56.2 (3 C)	1.6 (0.5 C), 3.5 (1 C) and 29.5 (3 C)	25.5
3	Liquid cooled (thermal silica plates) (Wang et al., 2017b)	Water	20 Ah Prismatic type LiFePO4 battery	3 C, 5 C	39.1 (3 C), 47.1 (5 C)	2.5	30
4	Liquid cooled plate (Chen et al., 2019b)	Water	8Ah lithium-ion soft-pack battery type	1 C	34.6	0.35	25.15
5	Liquid cooled with mini channel cold plate (Huo et al., 2015)	Water	7 Ah Rectangular type LIB pack	5 C	58.4	9.02	25
6	Liquid cooled (Copper tubes-based silicon cold plate) (Li et al., 2019b)	Water	20 Ah Rectangular LiFePO4 battery pack	5 C	41.92	1.78	30
7	Liquid cooled (rectangular channels and cold (Jiaqiang et al., 2018)	Water	-	0.5 C, 1 C, 2 C and 3 C	34.7 (3 C)	7 (3 C)	27
8	Mini-channel liquid cooled cylinder type (Zhao and Li, 2015)	Water	42,110 cylindrical type $LiFePO_4$ battery	5 C	< 39	< 12	25
9	Liquid cooled using Aluminum mini-channel cold plate (Tang et al., 2019)	Water	50Ah lithium iron phosphate battery (rectangular type)	2 C and 3 C	26.6 (2 C, 1200 S), 29.9 (3 C, 200 s)	6 (2 C, 1200 S), 9 (3 C, 200 s)	20
10	Liquid Cooled (mini-channel tubes) (Lan et al., 2016)	Water	55 Ah single prismatic type battery	1 C, 1.5 C and 2 C	27.81 (1 C) and 27.9 (1.5 C)	0.8 (1 C) and 0.9	27

Similarly, research on indirect liquid-cooled BTMS was mostly concerned with enhancing the cooling liquid's heat transfer coefficient, channel shape, and system architecture. The typical issue with forced air and liquid cooling BTMS systems is the addition of pumps, valves, blowers, cooling ducts, and channels. These parts add extra weight to the system and consume extra space. Heating pipes are key to cooling systems.

For electric vehicles (EVs), Alkawak et al. (AlKawak et al., 2024).] presented a hybrid energy management method that used a hybrid energy storage system (HESS), which combines a battery and supercapacitor. Namib Beetle Optimization (NBO) and Quantum Neural Networks (QNN) were combined in the suggested method, known as NBO-QNN, to maximize battery life and minimize power consumption. While the QNN anticipated and controlled the power supply to satisfy load needs, the NBO controlled the voltage and current. The NBO-QNN approach, which was implemented in MATLAB, demonstrated better energy management, decreased system stress, and increased battery lifespan when compared to other techniques, including the Cooperation Search Algorithm (CSA), Latent Semantic Analysis (LSA), and Grasshopper Optimization Algorithm (GOA). A novel Sustainable Power Management System for Light Electric Vehicles (LEVs) was presented by Punyavathi et al. (Punyavathi et al., 2024). It integrated machine learning-enhanced management with a hybrid energy storage solution (HESS). Reliance on conventional batteries was decreased by the system's effective integration of renewable energy sources like solar panels and supercapacitors. The suggested control method maintained accurate voltage regulation of the DC bus while optimizing power distribution across the battery, supercapacitor, and PV sources. This research provides scalable solutions for enhanced electric mobility, paving the road for more environmentally friendly and effective LEVs. The cooling techniques and power ratings that are essential for the durability and best performance of electric vehicle motors were investigated by Raj et al. (Raj et al., 2024). They examined many cooling techniques like liquid, hybrid, and air cooling and assessed how well they worked to control the heat produced by running motors. The study also examined how power ratings affect motor performance, highlighting the necessity of carefully choosing cooling techniques and power ratings to maximize longevity and efficiency. These observations provide manufacturers and designers of electric vehicles with useful direction for creating motors that satisfy contemporary transportation needs while promoting sustainability.

A hybrid strategy known as STO-IWGAN was presented by Viji et al. (Viji et al., 2024). to enhance fuel cell electric vehicle (FCEV) energy management. Utilizing an improved Wasserstein Generative Adversarial Network (IWGAN) in conjunction with Siberian Tiger Optimization (STO), the technique boosts overall vehicle performance, lowers fuel consumption, and increases energy efficiency. Using MATLAB, the STO-IWGAN method's evaluation reveals that it performs much better than heap-based optimization, particle swarm optimization, and wild horse optimization. It achieves an efficiency of 95 %, compared to the other methods' 85 %, 75 %, and 65 % efficiencies. Furthermore, the thermal performance of heat pipe systems depends on the choice of a suitable working fluid and a good connection between the heat pipe and the battery pack. The data from Table 7 indicates that most of the discussed Li-ion battery cooling solutions have constraints regarding high battery power or higher energy storage density applications. Therefore, the extreme heat management difficulties brought about by EV's super-fast charging, and the continued improvement of battery energy density should be addressed by future BTMS. The air-cooled system is easy to operate, safe, and appropriate for various battery types. Its design is straightforward. Nevertheless, the air has little heat conductivity, a lower heat capacity value, and less ability to regulate temperature.

Other limitations of active thermal management systems are higher power consumption, cost, and decreased vehicle comfort. Therefore, air-cooled systems are acceptable without additional power for cars with little battery capacity and shorter operation times. For refrigerant direct BTMS, choosing the appropriate refrigerant, enhancing its performance, addressing overheating, and enhancing its fire safety features is imperative. The direct refrigerant BTMS uses flow control systems and temperature control systems. The electric vehicle sector extensively uses liquid cooling systems, which are incredibly effective cooling techniques. The sealing layer should be configured during design to stop liquid leaks. Optimizing the microchannel configuration can enhance cooling efficacy while circumventing intricate configurations and excessive packing. Current research focuses primarily on ways to lower the peak temperature of battery packs. In the future, research should be done to lower the temperature differential between battery cells. Furthermore, boiling liquids, liquid metals, and nano-fluids have steadily benefited liquid-cooled systems because of their high thermal conductivity.

The primary development trend for PCM-based BTMS is minimizing power consumption and increasing thermal conductivity when combined with other active BTMS. Future PCM-HP hybrid BTMS development and design should focus on the sensible distribution of active-passive management, reduction in energy usage in thermal management systems, and increase the hybrid type BTMS's utilization. The cylindrical battery's exterior surface has a modest contact area. There will be a significant temperature gradient with a high-temperature value at the hot spot within the battery. This will happen if there is a cooling system on the exterior, which decreases performance and hastens the battery's aging. This is due to the addition of heat pipes inside the cylinder-shaped battery, which significantly lessens the size of the hot spot and reduces the temperature gradient. Prismatic lithium-ion batteries, on the other hand, offer better thermal performance and a greater contact area.

The majority of PCM-based BTMS research uses cylindrical batteries. In the future, surface cooling technology development can focus on PCM-based prismatic thermal management systems of batteries. When the new BTMSs are compared with older ones, it is discovered that the latest BTMS is an optimization of the old BTMS as a foundation. The new BTMS is more practical, has a more compact design, and performs better for cooling. The energy density in batteries is gradually rising with the increasing demands for electric vehicle batteries, making the need for BTMS more critical. Fig. 5 compares conventional and modern cooling techniques based on their advantages, disadvantages, and development phases.

The structure of the battery and arrangement of liquid flow comprises the design variable of the battery, which is used to describe different cooling approaches investigated for Li-ion battery packs in Table 7. Numerous researchers also considered the importance of cell spacing, fan operation, and air duct inlet and outlet angles as design variables. The distinct chemical makeup of the Li-ion battery systems examined in each study has been emphasized. The primary goal of the BTMS design is to minimize the maximum cell temperature (T_{max}) and reduce the value of the maximum cell temperature difference (ΔT_{max}) that the battery pack can achieve. Table 7 indicates that most of the discussed Li-ion battery cooling solutions have constraints regarding high battery power or energy storage density applications. Thus, the super-fast charging method used in EVs and the continued increase in battery energy density might present significant hurdles for future BTMS regarding heat control. A key component of a successful battery cooling system is the appropriate coolant choices. The most widely used and traditional cooling media are air and water, which are only available in the form of commercial fluids for EVs or other HEVs. The most researched coolants are water and a combination of water and ethylene glycol; new coolants for liquid cooling can also be found. The base fluid's thermal conductivity increases when nanoparticles are added, but the cooling efficiency does not increase much. It is possible to create and test appropriate nanoparticles for cooling. Although materials for battery cooling systems are being extensively researched, their constraints prevent them from being used in real-world EV or HEV

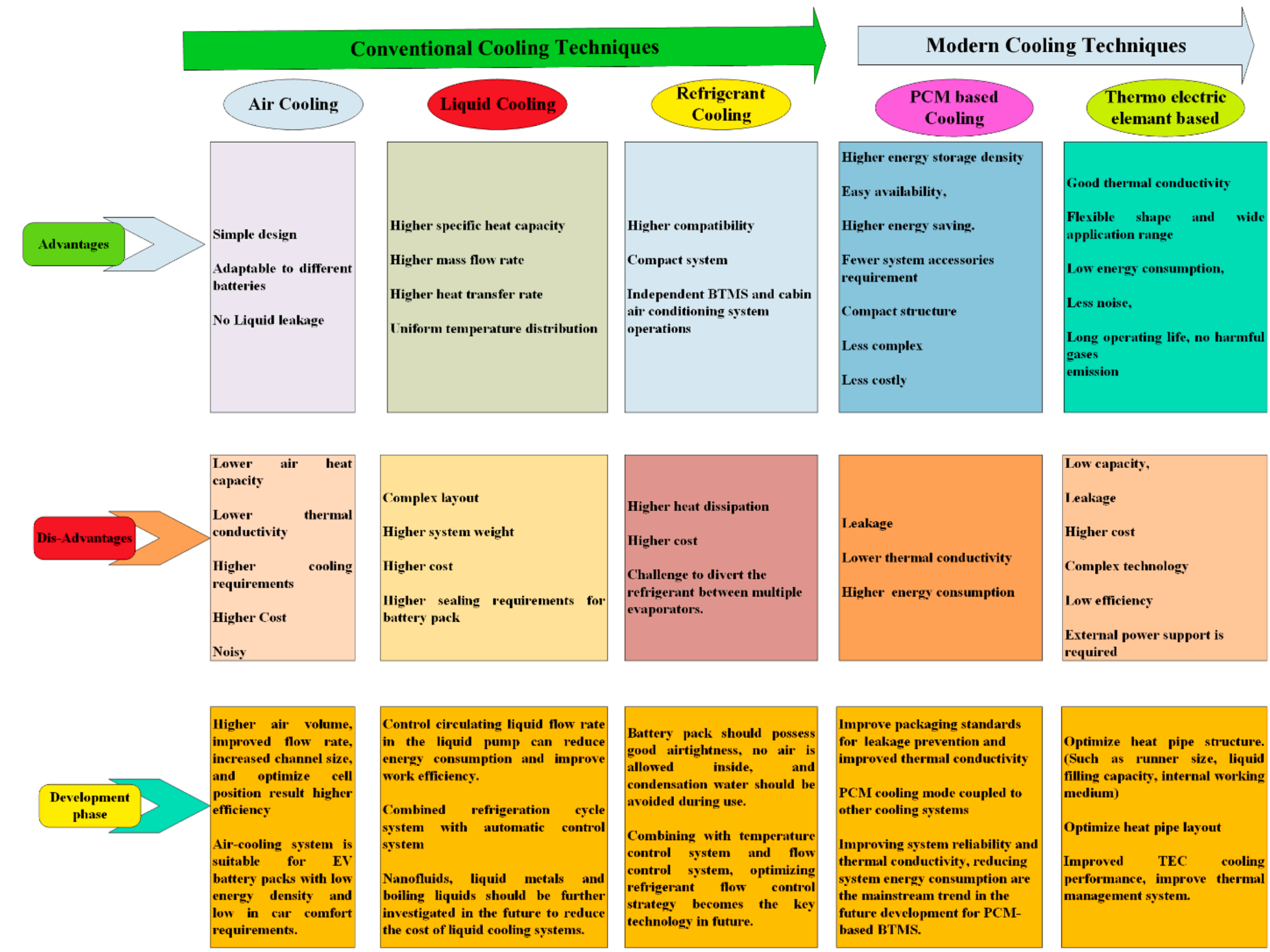

Fig. 5. Comparison of conventional and modern cooling techniques.

applications. The challenges associated with integrating PCM into automotive applications have not yet been investigated. The room for improvement is very broad for better PCM thermal conductivity, and it is possible to create composite PCMs. The coolants for HP cooling that are most frequently researched include acetone and water. For the same, different fluids can be recognized.

2.7. Charging system architecture

EVs provide many advantages compared to conventional engines, including reduced fuel cost and maintenance, reduced levels of noise, and high efficiency. The short-distance range and everyday commute on EVs are serious concerns; however, even though the number of EVs on the road is growing, there is still a shortage of infrastructure to charge them. To address this issue, a widespread and reasonably priced charging system analogous to the infrastructure currently in place for gasoline-powered recharging is needed. Several automakers are establishing DC fast charging stations even though AC charging stations are less expensive to install than fast charging stations in DC because these stations have a larger power capacity and can fully charge EV batteries faster (Lim et al., 2022). Additionally, the EV consumer's needs are considered when selecting the sorts of stations for charging. Having a voltage output value of 120 V or 220 V AC, charging stations of Level 1 are categorized as sluggish. A complete charge of an EV battery takes between 10 and 12 h. In domestic outlets, a charging station of Level 1 is used with a range of 0–10 km. The standard J1772–2 connector is used for connecting EV ports to charging stations. The estimated cost of a charging station with Level 1 is between $400 and $900 USD (Savari et al., 2023). The EV battery takes longer to charge than other battery types despite the installation cost being much lower (Mohammed et al., 2024). Level 2 (sometimes called accelerated) charging stations were created to shorten the charging time and address the issues encountered by level 1 (slow) charging stations.

Both public and private spaces are intended for Level 2 charging stations. The EV's battery takes four to six hours to charge fully. Level 2 charging station installation costs can range from $400 to $6500, while residential unit installation costs are $2150 (Savari et al., 2023). Charging stations of Level 2 on the AC side use the standard connector SAEJ1772. These charging stations require less time than other slow charging stations. For a 50 km range, the charging station of level 2 is selected. For a range of 100–200 kilometers, a DC rapid charging station is the preferred option. A thorough analysis of the technological issues and current developments with EV fast-charging stations is done. Three charging stations have been examined, considering installation costs, charging times, and power output. Level 1, Level 2 and Level 3 stations take up to 11 h, 3 h and 30 min, respectively, to fully charge an EV battery. The cost of installation of a DC-fast charger station ranges between USD 30,000–160,000 (Deb et al., 2021). DC fast-charging facilities have very expensive operating costs. A detailed analysis is conducted on several DC fast-charger models, considering power level, voltage output values and current output, charging time, peak efficiency, volume and weight. Power factor deterioration and harmonics are common problems with AC/DC charging converters. To address these issues and enhance the likelihood of greater EV penetration, an AC/DC power converter analysis is conducted to study the number of control switches, input current harmonics, and filters' needs. According to research, the Vienna rectifier (Rajendran et al., 2021a) has the highest power density of all AC/DC converters at 12 kW/dm^3, making it an efficient converter architecture for the AC/DC conversion in charging stations. THD has an input current of less than 5 %. Vienna rectifier's numerous conversion benefits make it an excellent choice for use at fast-charging stations. It can also be applied to high-power uses. In addition, a detailed examination of isolated and non-isolated converters for use in EV charging stations is done.

An isolated converter is more dependable than a non-isolated converter in ensuring adequate insulation between the grid and battery for AC/DC conversion for charging EVs. The Dual Active Bridge converter (Nguyen et al., 2023), is the most efficient electric car charging station converter. It has smaller filter component sizes, increased efficiency, and a greater power density. Several international standards are developed to standardize safe charging practices, power quality, charging station protocols, and the proper means of communication between EVs and charging stations to guarantee that EVs are recognized globally. The International Electrochemical Commission (IEC) and the Society of Automotive Engineers (SAE) are largely acknowledged as global standards for electric cars. IEC standards provide general requirements for the battery swap system, DC-off board power supply system, AC/DC conductive power supply, and communication system for EVs. It has also produced several standards for vehicle inlets, automobile connections, socket outlets, and plugs for EV charging systems. Furthermore, the IEC standard has covered the requirements for power transfer systems with magnetic fields for the WPT application. IEC and ISO have also developed standards for EV vehicle-to-grid communication interface systems. Conversely, SAE has produced global guidelines for digital communication, power quality specifications, safety standards for batteries and charging stations, communication, and technical reports for vehicle battery recycling, and EVSE system test protocols. High-power bidirectional converters are developed by wide band-gap technologies including gallium nitride (GaN) and silicon carbide (SiC), which bid fast charging and discharging times for electric vehicle batteries and better thermal performance (Prajapati and Balamurugan, 2023).

The isolation converters for Si, SiC, and GaN are compared in terms of their weight, efficiency, and volume. Compared to Si device-based isolation converters, it demonstrates that isolation converters based on GaN have a 53 % reduction in volume, a 79 % weight reduction, and a 170 % gain in power density with a 500 % increased specific power (Su, 2018). With the help of these devices, EV chargers based on Si can have a better power density, which could positively affect applications down the road. Many companies, including Samsung Electronics, ABB Schweiz., Porsche, Ford Global Technologies., Honda Motors and Texas Instruments, are researching EV charging stations in detail and have filed patents on a variety of topics and subsystems, such as power converters, wireless communication, cybersecurity protections, precooling systems for batteries, and charging systems based on renewable energy. Furthermore, studies on various intelligent EV charging and discharging methods are being conducted; these studies may be applied to developing a renewable energy-based smart grid infrastructure. To determine the fleet size, number of trips per vehicle, and charging station requirements, Zhang et al. (Zhang et al., 2024). used agent-based simulations to study the deployment of Shared Autonomous Electric Vehicles (SAEVs) in 374 US small and medium-sized urban districts. The findings demonstrated notable regional variations in SAEV operations and established a connection between these variances and traffic patterns and road networks. According to the study, Level 3 chargers are more effective than Level 2 charges and can accommodate more journeys per car with fewer stations.

These insights are valuable for policymakers and urban planners in optimizing SAEV fleet performance and advancing sustainable urban transportation. Zeng et al. (Zeng et al., 2024). presented a new approach to optimizing charging station locations for intercity highway networks, considering electric vehicles with varying driving ranges that require multiple charges on long trips. The study modeled driver behavior, accounting for route, trip, and mode choices based on vehicle range limitations, and formulated the problem as a mixed integer linear programming model to maximize travel efficiency within a limited budget. A branch-and-bound algorithm and a more efficient neighborhood search heuristic were developed to solve the problem, with the latter proving significantly faster while often achieving optimal solutions in computational tests on synthetic and real-world networks. Nasab et al. (Nasab et al., 2024). explored the charging management of electric vehicles (EVs) in the presence of renewable energy resources, developing a radial distribution network model in two scenarios. The first scenario focused on distributed generation without considering EVs, while the second included the impact of EVs. Using a 54-bus network and real data from US highways, the study applied clustering and Capiola's probability distribution methods for accurate vehicle load forecasting. Over a five-year horizon, the results showed that incorporating EVs and distributed generation improves network performance and reduces equipment costs. However, adding 10,000 uncontrolled EVs increases energy shortfalls, though equipment costs rise by only 5 %. By 2030, the US is expected to require between 13 and 30 million EV chargers for light-duty cars. The accompanying investment may exceed the $24 billion stated investments by up to $97 billion cumulatively through 2030. In the upcoming years, these investments could outpace those made in conventional vehicles as EV stock rises. The average charger-to-vehicle ratio in the United States in 2030 is expected to be 0.8, with a range of 0.5–1.2 in the analyzed studies. Most studies suggest accelerating and simplifying permitting and policy supports, such as EV-ready building requirements, to encourage timely and sufficient infrastructure for charging. The development of the charging infrastructure will also move much more quickly with more public funding and private sector investments made through creative business models (Yang et al., 2024a). Fig. 6 shows the country-wise data related to the fast charger proportions. Charging ratios also illustrate the differing priorities of governments regarding slow versus fast charging. Although New Zealand has the most vehicles per charger, it is ahead of countries such as Australia and Thailand when considering charging capacity per EV. This can be attributed to New Zealand prioritizing fast public chargers over slow, resulting in the highest proportion of fast chargers to slow chargers globally, standing at 75 %. Similarly, the next highest proportions globally are observed in South Africa, China, and Norway, with 53 %, 44 % and 41 %, respectively. At the other end of this spectrum lie countries such as Brazil, the Netherlands and Korea, which have installed more slow public chargers, with the share of fast public chargers representing 0.1 %, 4 % and 10 %, respectively.

2.8. Digital twin in EVs

Digital Twin (DT) is specified as 'an integrated multi-physics, multiscale, probabilistic simulation of a complex product, serving the purpose of replicating the lifecycle of its real-world counterpart (Bhatti et al., 2021). The primary goal of this technology is to function as a comprehensive representation of a physical entity in the digital realm. It's worth noting that it's occasionally confused with IoT or Computer-Aided Design (CAD). However, it fundamentally diverges from these concepts. IoT is primarily associated with physical implementation, while CAD is concerned solely with a standalone digital representation. Digital twin technology, on the other hand, distinguishes itself by emphasizing the two-way interconnection between the virtual and physical representations (Tao et al., 2019). This presents several inherent advantages, as the physical product can dynamically adjust its real-time performance in response to feedback generated by the digital twin. Conversely, this integration enables the simulation to mirror the real-world state of the physical entity accurately. To achieve a genuine

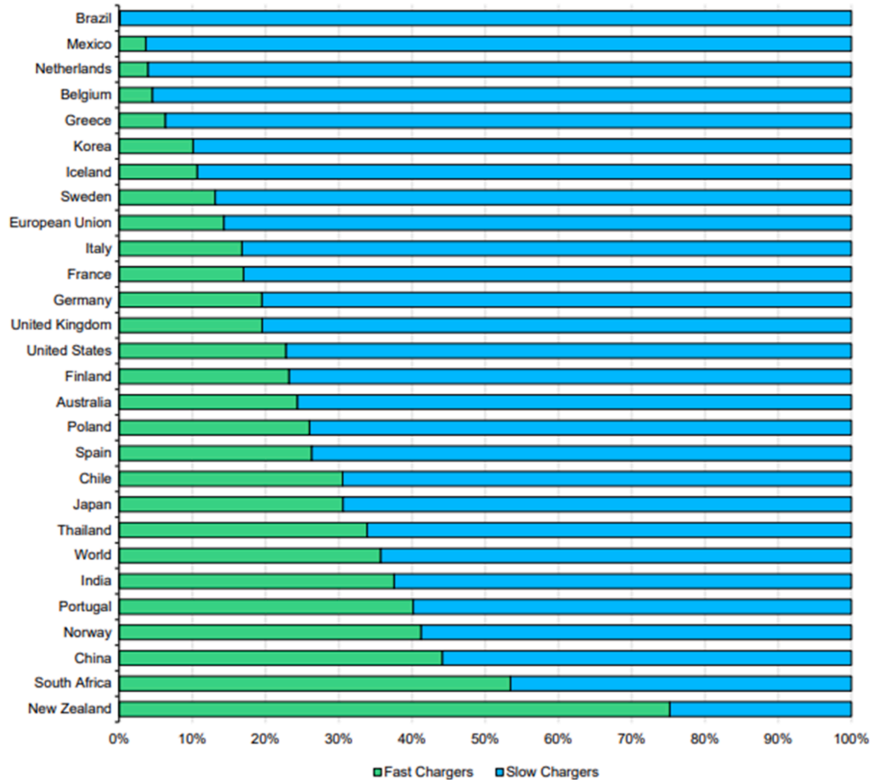

Fig. 6. IEA analysis on country-wise fast chargers proportion in 2023 (Agency, 2024a).

cyber-physical system, the digital twin must maintain a dynamically interconnected relationship with the physical model, which can be realized through real-time sensor data. In this process, the machine's environment must also be dynamically replicated in the digital realm, encompassing all relevant parameters influencing its operation (Yang et al., 2017). The real-time, two-way data interaction inherent in the

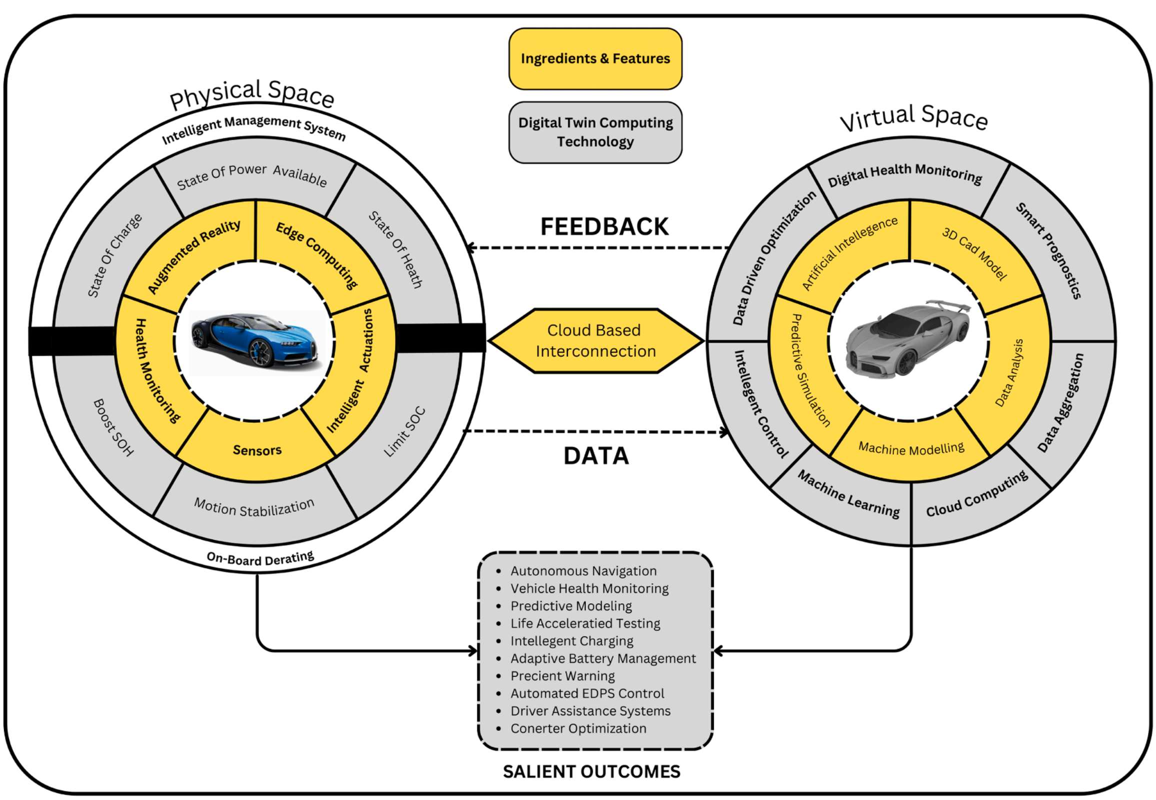

Fig. 7. Digital Twin Ecosystem.

digital twin ensures its benefits of exceptional accuracy, immediate responsiveness, and expandability (Zhang et al., 2021a). Fig. 7 displays the components of the digital twin ecosystem in the case of EVs. The physical area of an electric vehicle (EV) is digitally reproduced in a virtual environment inside an ecosystem of digital twins. Often called the "digital twin," this virtual representation is a realistic and dynamic three-dimensional replica or simulation of the actual EV and its immediate environment. The following are some significant features of an EV's physical area in a digital twin:

- A thorough 3D representation of the EV's exterior and interior is included in the digital twin. This covers the vehicle's dimensions, body panels, wheels, chassis, and other external components. Instrumentation, displays, controls, and seating might be found within.
- The digital twin includes all the electric vehicle's systems and parts, including the battery pack, power electronics, wiring, sensors, and electric motor. Every part has a digital representation and can be tracked and replicated.
- The digital twin precisely replicates the placements of the sensors and cameras on the real EV. Sensor fusion and the virtual environment's visualization of the data from these sensors depend on this.
- The digital twin could contain the car's immediate surroundings and the actual vehicle. The road, other cars, pedestrians, traffic signs, and traffic lights can all be examples. A precise depiction of the environment is essential to simulate real-world driving situations.
- It frequently uses modeling based on physics to create a digital twin that is as lifelike as feasible. This indicates that the vehicle's and its parts' behavior is modeled using physical concepts such as energy consumption, friction, and aerodynamics.
- Real-time data from the physical EV is continually integrated into the digital counterpart. The battery state of charge (SoC), motor temperature, sensor readings, GPS position, and vehicle speed are some examples of this data. Within the virtual environment, monitoring and analysis are made possible by this real-time data.
- The digital twin tests and mimics a variety of situations. It can, for instance, assess the effectiveness of advanced driver assistance systems (ADAS) or mimic the effects of changing driving behavior on energy usage.
- Predictive analytics may also be performed using the digital twin by merging real-time and historical data. For instance, patterns and present conditions can forecast how much driving range is left.
- A useful tool for diagnosis and maintenance is the digital twin. By mimicking the behavior of the real EV and comparing it to anticipated performance, it can detect problems with the actual vehicle. This can cut down on downtime and help with predictive maintenance.
- In certain instances, the infotainment and user interface of the car may also be part of the digital twin. This makes it possible to test and modify the user experience.

The latency and bandwidth consumption can be reduced by processing data closer to the source using edge computing capabilities. Create feedback loops allowing real-time optimizations and changes between the virtual and physical domains. Use AI models to forecast future occurrences or enhance operations using data from virtual and physical domains. Predictive maintenance, resource optimization, and anomaly detection are other artificial intelligence applications (AI). Cloud computing systems, such as AWS, Azure, and Google Cloud, host virtual spaces and process data. Use elastic and scalable cloud resources to manage different workloads. To collect real-time data, a network of sensors and Internet of Things devices must be set up in physical space. In addition to tracking temperature, humidity, and air quality, sensors may also track the state of assets, machine performance, and other factors. All things considered, an electric vehicle's digital twin offers a thorough and precise depiction of the vehicle's physical area and its interactions with the surroundings. It is an effective tool that can be used to create, test, optimize, and monitor electric vehicles (EVs), leading to better efficiency, performance, and user experience.

Digital twins in electric vehicles (EVs) have a bright future. As technology develops and the automotive sector continues to shift towards electrification and autonomy, it is anticipated to change in several ways. Future advances and trends for digital twins in electric vehicles (EVs) include the following:

- EVs' digital twin will have finer-grained physical and environmental modeling, making them even more realistic and detailed. Users and engineers can have a more immersive experience using high-fidelity rendering and simulation technologies.
- Digital twins will be continually updated by real-time data from sensors and IoT devices on EVs, allowing for more precise monitoring and predictive analytics. As circumstances change, digital twins will adjust to maximize efficiency and security.
- Digital twins will use more machine learning algorithms to enhance their capacity for energy management, autonomous driving, and predictive maintenance. Digital twins powered by AI will improve user and manufacturer decision-making.
- Digital twins will greatly aid in developing and testing autonomous EVs. Robust testing of self-driving algorithms and scenarios will be possible thanks to advanced simulations, which will lessen the need for lengthy testing in real-world settings.
- By modeling and predicting battery behavior with sophisticated algorithms, digital twins will maximize battery performance and longevity. Predicting deterioration, streamlining charging schedules, and improving thermal control are all part of this.
- Accurate predictive maintenance capabilities will increase, decreasing maintenance expenses and downtime. Digital twins will track component deterioration, allowing for proactive replacement prior to breakdowns.
- Digital twins will offer highly customized user experiences, which can adjust to each driver's unique habits and preferences. Interfaces for augmented reality (AR) might be included in the cabin to improve communication between the driver and passengers.
- By reducing emissions, increasing sustainable habits, and optimizing energy use, digital twins will help make driving more environmentally friendly. EV owners will get immediate feedback on how environmentally beneficial their driving is.
- Stakeholders and automakers will work together more often on cloud-based digital twin platforms. This will allow industrial data to be developed, shared, and integrated seamlessly.
- It will be crucial to guarantee the privacy and security of data inside digital twins. Strong cybersecurity defenses will fend off any attacks and weaknesses.
- Fleet management and mobility services will be heavily reliant on digital twins, enabling operators to track and optimize whole fleets of electric cars.
- Automakers' use of digital twins will aid in their adherence to changing safety, data privacy, and emissions laws.
- EV manufacturers will use digital twins to monitor and report on their cars' energy efficiency and emissions reductions.

The future of digital twin applications in EVs is knotted with the broader trends in automotive technology, comprising autonomous driving, electrification, sustainability and connectivity. As these technologies advance, digital twins will become increasingly sophisticated tools for designing, testing, operating, and maintaining EVs, ultimately leading to more efficient and sustainable transportation solutions.

2.9. Tribological analysis

Recent developments in novel materials, lubricants, and design alterations can potentially mitigate energy losses by 18–40 %. These losses primarily stem from friction and wear. Such improvements could lead to a noteworthy reduction, equating to 8.7 % of the global energy consumption and 1.4 % of the gross national product (GNP). One can discern the advantages of electric cars when assessing energy usage and frictional losses in battery-powered electric passenger vehicles, as their overall energy consumption tends to be approximately 3.4 times lower on average compared to traditional combustion engine vehicles. Furthermore, considering electric cars powered by renewable energy sources, they exhibit significantly lower CO_2 emissions, approximately 4.5 times less than their combustion engine counterparts. Due to friction in the energy production process, energy losses may be reduced by more than 60 % by switching from fossil fuels to renewable energy sources (Holmberg and Erdemir, 2019). Battery electric vehicles (BEVs) exhibit a fundamental difference from ICEVs by substituting the conventional combustion engine with an electric motor. Additionally, BEVs streamline the mechanical transmission system, incorporate elements for storing, charging, and controlling electricity, and employ brake energy recovery systems. This shift to an electric powertrain yields enhanced efficiency, primarily owing to reduced thermal losses and diminished friction—the latter benefit results from the absence of reciprocating components and the utilization of elevated pressures. The global potential for yearly energy, cost, and CO_2 emission reductions following eight years of widespread, sophisticated tribology integration is a prospect of significance (Holmberg and Erdemir, 2019). The prospective economic benefits in the United Kingdom arising from adopting advanced tribology in machinery and equipment equate to a staggering transformation. Specifically, the 515 million UK pounds from 1966 would be revalued to an impressive 9,000 million UK pounds in the context of 2017 (Holmberg and Erdemir, 2019).

Thermal inefficiencies and reduced friction, attributed to the absence

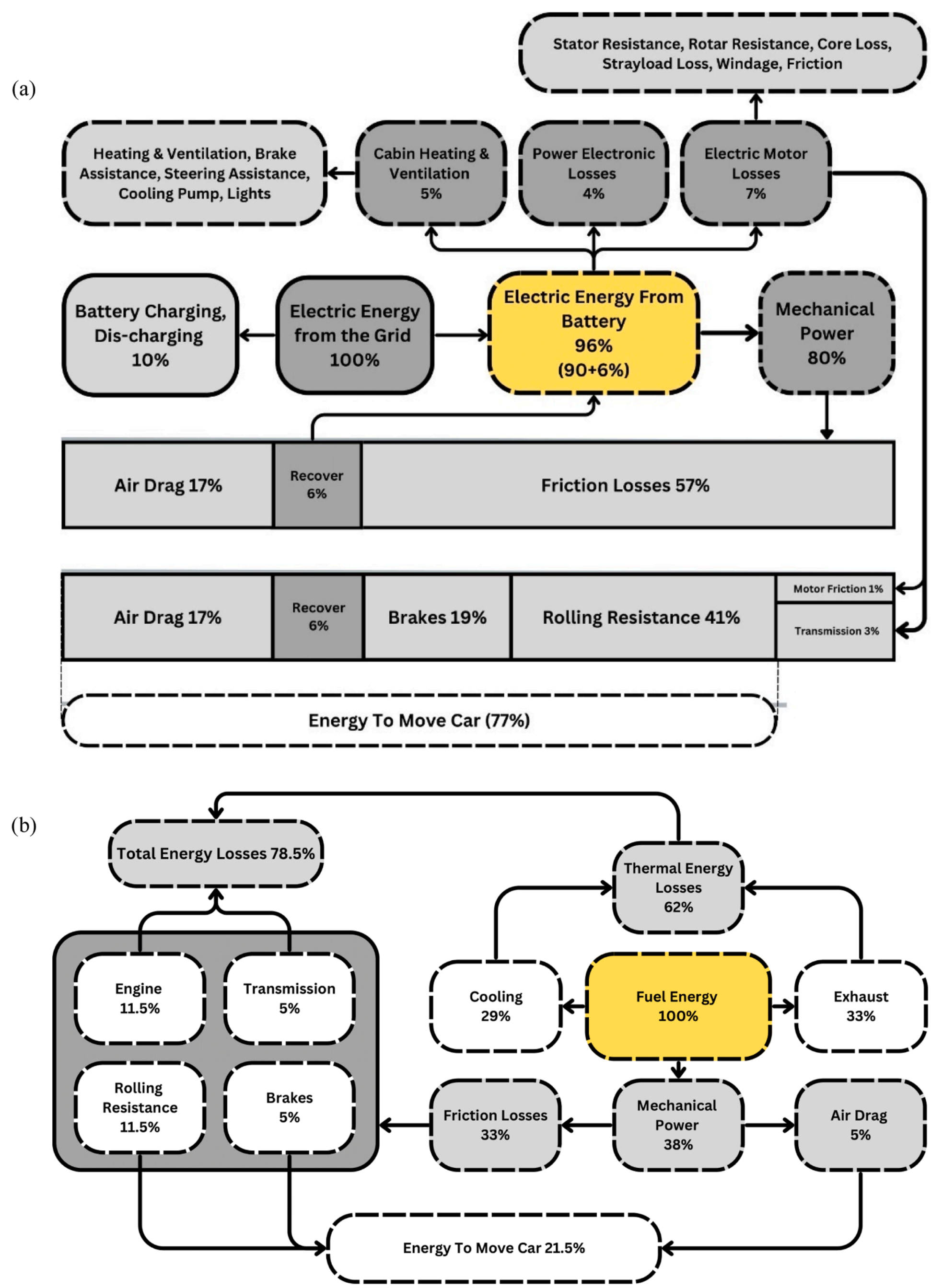

Fig. 8. Comparison between (a) EVs and (b) ICE based on Tribological analysis.

of reciprocating components and the application of high pressures, play pivotal roles in this context. The energy breakdown of an electric passenger automobile that derives its electricity from the grid is shown in Fig. 8. The global average electric car for the study is a 2017 mid-sized plug-in electric passenger vehicle. This automobile weighs 1500 kg, has a 75-kW electric motor, a simplified one-step mechanical gearbox, lithium-ion batteries, and an average power usage of 18 kWh per 100 km. It can go 13,000 km annually (Ke et al., 2017). The same characteristics used in the ICE passenger vehicle calculations previously described characterize the driving circumstances. These parameters involve maintaining an average speed of 60 km/h and encompassing a spectrum of global road conditions, encompassing highways, urban roads, and unpaved dirt roads (Holmberg et al., 2012).

In this context, the electric power is sourced entirely from the grid (100 %), and the reclaimed energy harnessed from the braking system (6 %) is allocated for charging the vehicle's battery. It's worth noting that this battery is specified as a lithium-based one, and it incurs an energy loss of 10 % during both the charging and discharging processes (Holmberg and Erdemir, 2019). Approximately 5 % of the total energy allocation is dedicated to functions such as heating, cabin ventilation, cooling, steering and braking assistance, the operation of cooling pumps, and lighting. It's worth noting that, unlike ICEVs, no surplus heat or elevated motor temperature can be harnessed for cabin heating in EVs. Additionally, the electric motor in an electric car loses 7 % of its energy, and the power electronics lose 4 % of it. Windage, friction, core and stray load losses, stator and rotor resistance, and other variables contribute to these losses (Holmberg and Erdemir, 2019). As a result, 80 percent of the excess energy initially taken from the grid and recovered energy may be used to generate mechanical power (Tie and Tan, 2013). The energy used to reduce friction makes up 57 % of the energy drawn from the grid. Of this percentage, 41 % goes towards overcoming rolling resistance, while the remaining 19 % is accounted for by inertia throughout the acceleration and deceleration stages. But it's vital to remember that the electric motor's function as a brake generator recovers 7 % of this energy. Consequently, the net loss for acceleration and braking is effectively reduced to 12 %. Nevertheless, the recuperated energy diminishes by 6 % due to losses incurred during the battery's charging and discharging cycles.

Further energy losses manifest as 3 % within the transmission system, with an additional 1 % attributed to friction within the electric motor (Holmberg and Erdemir, 2019). As depicted in Fig. 8, around 77 % of the total energy is dedicated to propelling the vehicle, leaving the remaining 23 % allocated to overcoming other energy losses. This energy expenditure for moving the vehicle is employed to overcome the wheels' aerodynamic drag, rolling resistance, and the energy needed for acceleration, which is the process by which electrochemical energy is transformed into kinetic energy. The energy recovered during braking is equivalent to the energy of inertia used during accelerating. Even with thermal energy losses, regenerative braking converts kinetic energy back to electrochemical energy. This is shown in Fig. 8, in the second column from the left, where an extra 6 % energy intake results in a total of 106 % energy consumption by the vehicle. It's crucial to remember that the electric automobile is a 2017 model, and the internal combustion engine (ICE) car is the global average for 2010. Around 77 % energy efficiency of the electric automobile is 3.6 times better than that of the ICE car, which has an energy efficiency of only 21.5 %.

Friction losses inside the vehicle, excluding braking and tire rolling friction, make up 16.5 % of the total for an ICE automobile but are substantially lower at 6 % for an electric vehicle. Assuming that both cars were produced in 2017 to provide a fair comparison. This required changing the combustion engine car's fuel usage to 7 liters per 100 km to reflect the present circumstances. Moreover, the electric vehicle's large battery was believed to add 200 kg to its overall weight. For the same experimental conditions, a 100-kilometer drive requires 7 liters of gasoline, or 230 MJ, for the combustion engine vehicle. Of this, 180 MJ is accounted for by energy losses in the engine, transmission, and control systems; the remaining 50 MJ is related to aerodynamic drag, rolling resistance, and braking (Fig. 8). However, electric automobiles use 18 kWh of power, or 65 MJ, for the same distance, with 15 MJ going towards energy losses. Due to its additional weight, the electric automobile has more rolling resistance, yet because of its energy recovery system, it has fewer brake losses. To move both cars 100 km at a time, they need about 50 MJ (Björnsson and Karlsson, 2016; Jungmeier et al., 2015). A thorough lifecycle study is conducted to comprehend energy efficiency and the ensuing CO_2 emissions by comparing EVs with ICEVs. In addition to the usage phase, which covered energy consumption "from tank-to-wheels" during vehicle operation, this evaluation also included the processes related to fuel and electricity production "from well-to-tank," as well as the entire vehicle lifecycle, which covered maintenance and manufacturing up until the point of recycling "from cradle-to-grave." (Holmberg and Erdemir, 2019). It can be concluded that CO_2 emissions from ICEVs are equivalent to 224 g per kilometer (Ke et al., 2017; Baptista et al., 2013). Out of the total emissions amounting to 224 g, 31 g stem from the vehicle's lifecycle stages, encompassing manufacturing, maintenance, and recycling, 30 g arise from the fuel production stage, and 163 g result from the actual driving phase. The vehicle manufacturing phase emissions are notably higher for the electric car, totaling 48 g per kilometer. However, once the electric car is in operation, it produces no emissions. It's crucial to highlight that the overall CO_2 emissions of the electric car are heavily reliant on the energy source used for electricity generation, as demonstrated in Fig. 8, illustrating the breakdown of energy usage in a battery electric passenger car with grid-to-wheel calculations (Edenhofer et al., 2011).

The emissions stemming from electricity generation vary significantly based on the energy source. When coal is employed, the emissions amount to 180 g per kilometer, whereas oil-based generation results in 151 g per kilometer. Using natural gas as an energy source reduces emissions to 84 g per kilometer. However, the most environmentally friendly sources are solar photovoltaics and geothermal energy, with emissions as low as 8 g per kilometer. The most ecologically sound electricity generation methods, yielding the lowest emissions, fall within the range of 1–3 g per kilometer, and these sources include biomass, nuclear, wind, hydro, and concentrated solar power (Hernandez et al., 2017). In the case of EVs, the emissions would amount to 108 g of CO_2 per kilometer when powered by electricity generated from a European energy mix (Holmberg and Erdemir, 2019). The transition from fossil fuels to renewable energy sources is poised to influence the global energy consumption required to overcome friction significantly. This is attributed to the shift in technology and methodologies within the energy production sector. Notably, renewable energy sources, such as solar photovoltaics, wind, geothermal, and concentrated solar power, do not involve large machinery and transportation systems during their production phase. Consequently, their energy expenditure due to friction is markedly lower. The frictional losses are projected to be most pronounced in coal production, accounting for up to 35 %, particularly when considering coal mining. For oil production, the figure stands at 20 %, while it is 15 % for gas, 10 % for biomass, hydro, and nuclear, 5 % for wind and geothermal, and nearly negligible for solar energy. A transition from fossil fuels to renewable energy sources holds the potential to decrease the proportion of global friction losses within energy production. Presently, friction losses constitute 20 % of the energy production landscape. On a shorter-term horizon, by 2035, this proportion could decline to 13 %, and on a longer-term trajectory by 2050, it might reduce further to 8 %. As it stands, approximately 81 % of global energy production relies on fossil energy sources (coal, oil, gas), 17.5 % is derived from heavy renewables (biomass, hydro, nuclear), and 1.5 % is sourced from light renewables (solar, geothermal, wind). We anticipate transitioning to a more balanced distribution in our short-term calculations: 40 % from fossil sources and 30 % from renewables. Looking further ahead to the long term, the projection assumes a distribution of 10 %, 40 %, and 50 % for fossil sources, heavy renewables, and light renewables, respectively (Holmberg and Erdemir, 2019).

3. Key influencers on EV performance

Temperature is the key parameter that influences EV energy consumption. However, the fundamental energy consumption model for EVs fails to accurately represent the real-time, dynamic changes in energy consumption as the vehicle operates. Consequently, the next critical step involves continuously updating and optimizing the electric vehicle's energy consumption model in response to changing conditions. During the test drive on public roads, various power-consuming features unrelated to driving were deactivated when unnecessary, such as seat heating, air conditioning, and audio features. The data was collected through a cloud-based monitoring platform, which included information like time, vehicle speed, state of charge (SoC), instantaneous battery voltage and current output, accelerator pedal position, maximum battery pack temperature, minimum battery pack temperature, and more. Hu et al. (Hu et al., 2024). analyzed the performance of RL-based EMS in Fuel Cell Electric Vehicles (FCEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) across four aspects: algorithm choice, hyperparameters and reward function, perception and decision granularity. Findings revealed that Off-policy algorithms provide more fuel-efficient solutions, while improved perception and decision granularity enhance the balance between battery power and fuel consumption.

The study also showed that, although a high initial SoC during training leads to better performance, building a reward function based on instantaneous SoC change might be dangerous and can violate SoC constraints. A reward function based on total SoC fluctuation was suggested as a safer substitute. Enhancing the multi-step battery state-of-charge (SoC) prediction in electric cars was the major goal of Hong et al. (Hong et al., 2024). This is because SoC safety and precise estimation of the remaining driving range depend on this. The scientists created a brand-new hybrid neural network by fusing Long Short-Term Memory (LSTM) and Gate Recurrent Unit (GRU) models. By reducing input parameter dimensionality and comparing the performance of LSTM-GRU with other models, the study demonstrated the effectiveness and accuracy of the proposed method. Validated with real-world vehicle data across different seasons, the method achieved high accuracy, particularly in summer, with minimal error margins. This approach shows promise for future applications in real-world vehicle battery SoC prediction. EVs performance is influenced by a variety of factors, which can be categorized into several key areas:

- Battery technology includes battery size, battery chemistry, and state of charge. The size of the battery pack affects the range an EV can achieve on a single charge. A larger capacity generally results in a longer range. Different battery chemistries (e.g., lithium-ion, solid-state) have varying energy densities, charge/discharge rates, and lifespans, which impact performance. The level of charge in the battery affects an EV's performance. As the battery depletes, the power output may decrease.
- Electric motors play a key role in the effective performance of EVs. They include motor efficiency and power rating. The efficiency of the electric motor impacts overall performance. More efficient motors convert a higher percentage of electrical energy into kinetic energy. The power rating of the motor determines the acceleration and top speed of the EV.
- The vehicle weight and design are the third important parameter. Heavier EVs typically have reduced performance, including acceleration and energy efficiency. A streamlined design reduces air resistance, improving efficiency and range. Tire choice affects grip, rolling resistance, and handling.
- Charging Infrastructure includes charging speed and charging network density. The availability of fast-charging stations can significantly impact convenience and long-distance travel capability. The density of charging infrastructure affects the ease of finding a charging point when needed.

Extreme cold or hot weather can affect battery performance and range. EVs often have thermal management systems to mitigate this. Using air conditioning or heating can drain the battery and affect the range. Driving Conditions and style also affect EV performance. Hilly or mountainous terrain can affect range and performance. Aggressive driving, such as rapid acceleration and high-speed driving, can reduce efficiency and range. The efficiency and effectiveness of regenerative braking systems can vary between EV models. Regular maintenance, including tire rotation, brake system inspection, and battery health checks, can help maintain optimal performance. Over time, EV batteries degrade, resulting in reduced capacity and range. Proper battery management and cooling systems can mitigate this. The quality of components and manufacturing processes can affect reliability and long-term performance. The placement of the battery pack and other components can impact handling and balance. Table 8 summarizes the role of digital twins in electric vehicle technology and the methods to implement this technology.

4. Economic and market analysis

In 2018, EVs constituted about 4.40 % of the total 28.08 million automobiles sold in China, a significantly higher proportion compared to the United States (slightly over 2 %) and Europe (approximately 3 %) (Xiong et al., 2020). Table 9 compares ICE and EVs based on cost analysis. However, Table 10 compares different models of EV battery usage, capacity, charging, range, and prices.

The market for EVs has grown rapidly; by 2022, sales will have surpassed 10 million (Khaleel et al., 2024). Around 14 % of all newly purchased cars were electric, up from approximately 9 % in 2021 to less than 5 % in 2020 (Khaleel et al., 2024). This remarkable growth was particularly evident in three key markets. With over half of all-electric cars sold globally and almost 60 % of global sales of electric cars, China remains the leader. China's sales target for new energy vehicles by 2025 has already been surpassed. More than one in five electric cars were sold in Europe in 2022, the second-largest market, where sales of electric cars rose by more than 15 %. Sales of electric cars increased by 55 % in 2022 in the United States, the third-largest market, to reach a sales share of 8 % (G. E. O, 2023). The cutoff year, 2010, is grounded in the evolution of EVs during this timeframe and is intended to capture the most recent research developments. It is worth noting that the era commonly referred to as the "golden age" of EVs began after the introduction of the Nissan Leaf and Chevrolet Volt models in 2010. These pioneering models, launched that year, marked the turning point, with sales escalating from approximately 50,000 units in 2011 to a remarkable 315,000 units by 2014 (Moawad et al., 2016). According to the International Energy Agency, the global EV outlook for 2021 shows the projections for EV sales from 2020 to 2030. The EVs will contribute 39.9 million USD to the automotive market through their sale. Fig. 9 compares the differences in EV sales during 2020 and 2030, categorized by different countries.

4.1. Circular economy

The circular economy is a regenerative system that minimizes waste and maximizes resource efficiency by extending product lifecycles through reuse, refurbishment, remanufacturing, and recycling. In EVs, the circular economy is pivotal in promoting sustainability and reducing environmental impacts. Manufacturing EVs involves using various materials, including metals, plastics, and rare earth elements. A circular economy approach in EV manufacturing prioritizes the recovery and recycling of these materials. By implementing efficient recycling processes, manufacturers can reclaim metals from end-of-life vehicles and reintegrate them into the production cycle, reducing the need for virgin

Table 8
Role of digital twin technology in EVs.

Author/Reference	Methodology	Role of Digital Twin Technology
Zhang et al (Zhang et al., 2021b).	Modeling, EV energy research, real data optimization and energy consumption predictions.	Replication and updating EV models via digital twinning for better optimization and forecasting.
Weihan Li et al (Li et al., 2020).	Estimation of SoH and SoC by using cloud Computing and the Thevenin model.	Battery replication in virtual space and cloud integration to improve computing efficiency, data storing capacity and BMS reliability.
Sergiy Korotunov et al (Sergiy Korotunov and Okhmak, 2020).	V2G AND G2V strategy with Genetic Algorithm Scheduling.	Optimal smart grid designing by genetic algorithm-based corrections. Evaluation of EV charging impact on grid and its impact reduction.
Mohsen Ebadpour et al (Ebadpour et al., 2023).	Digital Twin EDS with robust controls and précised sensor stability in Metaverse transport.	Metaverse optimization of replicated EDS for virtual testing and enhanced stability.
X. Qu et al (Qu et al., 2024).	Lithium Ion Battery (HI Based LSTM) Digital Twin.	Actual battery capability evaluation. Dynamic health computing and virtual charge profile degradation.
L. Merkle et al (Merkle et al., 2019).	Simulation of high voltage LI BMS by unified modeling language meta model.	Precise progression of system from manufacturing to functioning stage for BMS-based prognosis.
Heng Li et al (Heng Li et al., 2023).	BMS Digital twin using former data, BPNN regressions, optimization of WOA and fault detection techniques.	BMS replication for fault detection, analysis & optimizing the performance of EV's.
Y. Peng et al (Peng et al., 2019).	ANN and support vector machine (Kalman Filter).	Battery packs DT analyze SoH, SoC and RUI by remote sensing links through learning models.
H. Shikata (Shikata et al., 2019)	3D vehicle engine rendering, ECU positioning, and charge control and automatic network parking.	Electrical and mechanical dynamic subsystem integration for modeling and optimization of an automatic EV charging model.
Vandana et al (Vandana and Ketan Panigrahi, 2021).	Framework of DT batteries for fault detection, performance optimization and future integration.	Digital Twin technology enhances the performance, fault detection, lifecycle and recycling.
R. Ramachandran (Ramachandran, 2018)	SoC analysis using RLS algorithm and least square static battery model.	EV battery system realistic model to analyze battery parameters when linked independently and physically.

Table 9
Comparison between ICE and EVs based on cost analysis.

Nature of vehicle/ Type of costs	EVs	ICEs
Purchasing	Higher	Lower
Operating	Lower	Higher
Environmental	Lower	Higher
Resale	Lower	Higher
Fuel/Charging	Lower	Higher
Maintenance	Lower	Higher
Disposal	Lower	Higher
Total Cost of Ownership	Lower	Higher

materials and minimizing environmental impact. In the EV sector, using sustainable manufacturing techniques is essential to advancing a circular economy. The circular economy based on EV production and applications is explained in Fig. 10. This entails minimizing waste generated during production, employing renewable energy sources, and consuming less water and energy. Automakers are also looking at employing recycled and bio-based components in the manufacturing process to improve sustainability further. To ensure that valuable materials are recovered and reused, manufacturers are working with recycling firms and legislators to create standardized procedures for handling and processing electric vehicles (EVs) at the end of their useful lives. For EVs to thrive in a circular economy, industry cooperation and governmental regulations are essential. Manufacturers are encouraged to implement circular economy ideas by regulations requiring recycling and resource recovery and incentives for sustainable operations. To find creative solutions and build a sustainable environment for EVs, stakeholders, automakers, suppliers, recycling firms, and researchers must work together. Encouraging ethical consumption and educating consumers about the advantages of a circular economy are equally crucial. Increasing customer awareness of the value of recycling, how to properly dispose of batteries, and how their purchases affect the environment might encourage the EV sector to develop more environmentally friendly goods and procedures.

5. Sustainability of EVs

Electric vehicles' (EVs') sustainability depends on several interrelated elements. From the standpoint of the power grid, the widespread use of EVs necessitates a strong and resilient system that can manage higher electrical loads; to maximize environmental advantages, the grid should ideally be powered by renewable energy sources. Environmentally speaking, EVs provide notable reductions in tailpipe emissions, which help to improve air quality and cut greenhouse gas emissions. Nevertheless, there are still issues with the sustainability of EVs' whole lifespan, which includes the manufacture and disposal of batteries. Economically, while EVs offer long-term savings through lower operating costs and reduced dependence on fossil fuels, the initial investment and the need for extensive charging infrastructure pose significant economic considerations. The overall sustainability of EVs depends on the continuous integration of cleaner energy, advancements in battery technology, and supportive economic policies. Fig. 11 displays the impact of electric vehicles on power grids, the environment and the economy.

5.1. Economic impact

Economic measurements include, in general, market share/sales, profit and net present value analysis, and revenue generation/reduction. Zhao et al. (Balan et al., 2022). found that offering regulation services for electric trucks might result in a sizable additional revenue of around \$20,000–\$50,000 compared to conventional vehicles. In certain places, like New York ISO, where regulatory services prices are comparatively higher, the lifetime vehicle-to-grid income might reach up to \$60,000. This could result in a sizable profit. Noel and McCormack (Noel and McCormack, 2014) provided a cost-benefit study comparing vehicle-to-grid electric school buses to conventional school buses in the USA, which indicated a net present value reduction of about \$6070 per seat. They calculated that if the district moved to vehicle-to-grid-based school buses, the net current savings would be greater than \$38 million. After examining how policy instruments have affected EV sales and market share, Rietman and Lieven (Rietmann and Lieven, 2019) concluded that policy measures favorably influenced the EV market share. Jenn et al (Jenn et al., 2015). also examined a situation of reduced tax revenue, which demonstrated how the high adoption trend of EVs in the United States would lower the use of gasoline and, in turn, reduce the revenue of the transportation sector.

Table 10
Latest EV models comparison based on battery usage, capacity, charging, range and prices (Database, 2024).

Sr #	Appearance	EV Model	Car Type	Price in USD	Drive Range (km)	Top Speed (km/h)	Efficiency (Wh/km)	Battery Capacity (kWh)	Battery Usage (kWh)	Duration for a full charge	
										Level 2 AC Charging	DC Fast Charging
1		Tesla Model Y	SUV	54130	350	217	164	60	57.5	6 h 15 mins for 11 kW	25 mins for 170 kW
2		Hyndai IONIQ 6 Long Range 2WD	Sedan	53650	495	185	149	77.4	74	8 h for 11 kW	16 mins for 233 kW
3		Audi Q4 Sportback e-tron 40	SUV	50995	425	160	180	82	76.6	8 h 15 mins for 11 kW	27 mins for 143 kW
4		Kia EV6 Long Range 2WD	SUV	42600	410	185	180	77.4	74	8 h for 11 kW	16 mins for 233 kW
5		Volkswagen ID.4 Pro	SUV	44,875	410	160	188	82	77	8 h 15 mins for 11 kW	27 mins for 143 kW
6		Ford Mustang Mach E GT	SUV	74,540	425	200	214	98.7	91	9 h 45 mins for 11 kW	47 mins for 107 kW
7		Mercedes EQS SUV 500 4MATIC	SUV	181,050	490	210	221	120	108.4	11 h 45 mins for 11 kW	32 mins for 207 kW
9		BMW i4 M50	Sedan	68,700	450	225	179	83.9	80.7	8 h 45 mins for 11 kW	27 mins for 207 kW
10		Nissan Leaf e+	Hatchback	28,140	340	157	174	62	59	10 h 45 mins for 6.6 kW	59 mins for 46 kW

(continued on next page)

Table 10 (*continued*)

Sr #	Appearance	EV Model	Car Type	Price in USD	Drive Range (km)	Top Speed (km/h)	Efficiency (Wh/km)	Battery Capacity (kWh)	Battery Usage (kWh)	Duration for a full charge	
										Level 2 AC Charging	DC Fast Charging
11		Porsche Taycan Turbo S	Sedan	209000	430	260	195	93.4	83.7	9 h for 11 kW	17 mins for 268 kW
12		BYD ATTO 3	SUV	47,500	330	160	183	62	60.5	6 h, 30 min for 11 kW	37 min for 89 kW
13		Tesla Model 3	Sedan	44130	415	201	139	60	57.5	6 h, 15 min for 11 kW	25 min for 170 kW

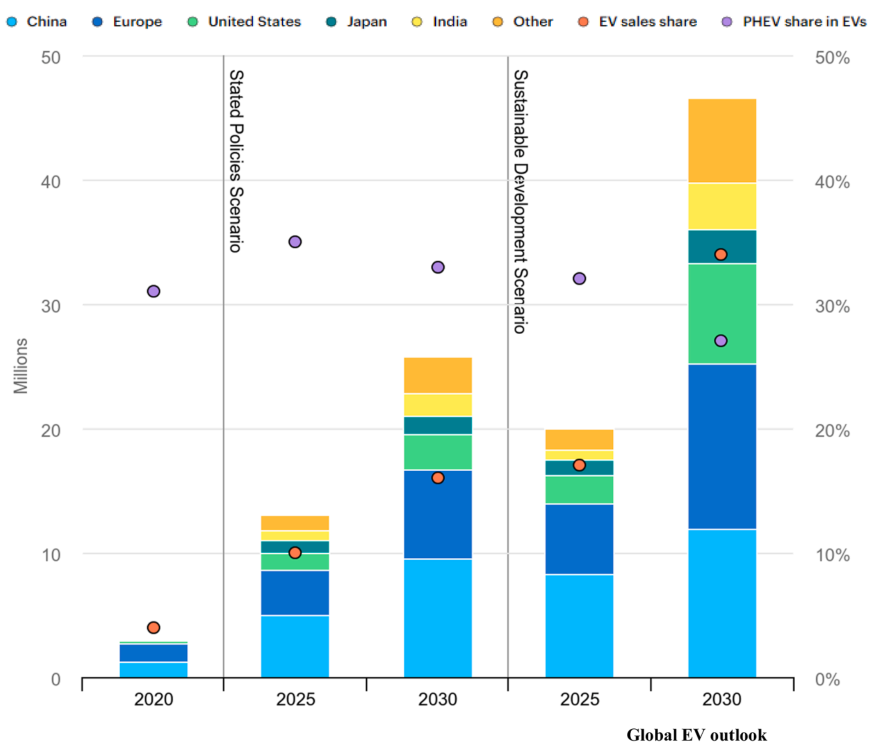

Fig. 9. Distinct Automotive Market Share Comparison between 2020 and 2030 (Agency, 2024b).

5.2. Environmental impact

"Environmental impact" refers to the overall energy generation and usage lifecycle, including greenhouse gas emissions, carbon footprint, and water footprint. Zhao et al. (Zhao et al., 2016). discovered that providing vehicle-to-grid regulation services for electric trucks might result in a large decrease in GHG emissions (to around 300 tons of CO_2) compared to a traditional diesel engine truck, in addition to the financial benefits. However, the total lifespan emissions of an electric vehicle are almost the same as those of a conventional truck due to the greenhouse gas emissions generated during the power generation and gearbox stages. Nations such as South Korea, which import most of their oil via sea transportation, Choi and Song (Choi and Song, 2018) investigated the well-to-wheel GHG emissions of BEVs. Based on statistical comparisons, driving BEV results in emissions of approximately 90–110 g CO_2 equivalents per kilometer lower than those of an ordinary vehicle of the same type. It is mainly made possible by the nearly minimal greenhouse gas emissions produced during nuclear energy generation. In all 50 states in the US, Onat et al.'s study (Onat et al., 2015) examined the energy and carbon footprints of conventional, hybrid, and electric vehicles. In 24 states, EVs are the least carbon-intensive alternative based on current electricity generation, while the most efficient option in 45

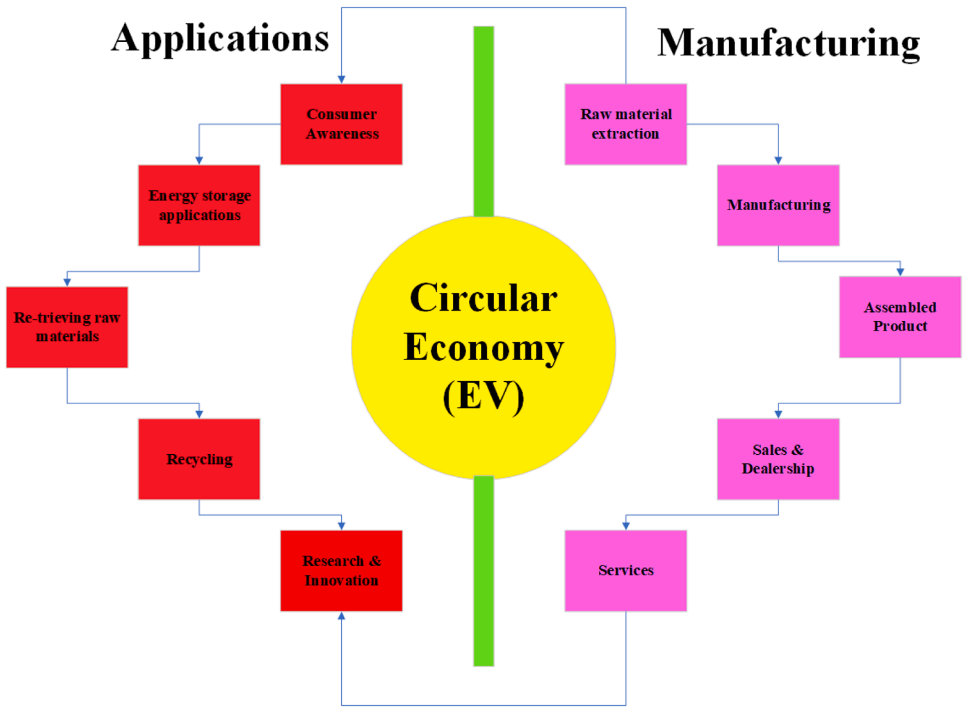

Fig. 10. Circular economy dependent on EV manufacturing and application.

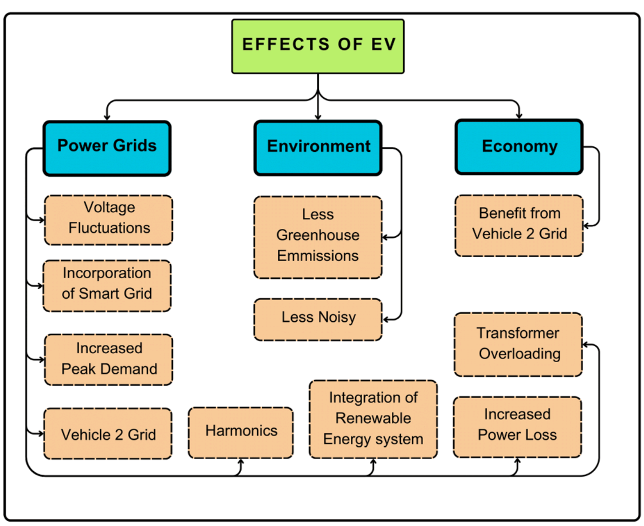

Fig. 11. Impact of Electric Vehicles on Power Grids, Environment, and Economy.

states is hybrid electric vehicles. Onat et al. (Pandey et al., 2022). investigated the well-to-wheel water footprint of EVs compared to conventional vehicles in the United States. According to the research, in the worst case, a BEV can use water up to 70 times more as compared to a conventional car; on the other hand, a BEV that uses power from solar charging would use the least water and could even cut its water footprint up to 97 %.

5.3. Social impact

Modernizing technologies, the shift to electric vehicles offers numerous prospects for automakers. In addition to automakers, technological advancements and job opportunities across many industries could also assist energy and service providers. To determine the influence of the development of EVs, Onat et al. (Onat et al., 2015). examined the lifespan for the ideal deployment of the latest energy vehicles in the United States. Socioeconomic metrics, such as maximizing employment in various scenarios, were examined for this. Karaaslan demonstrated the significance of the safety of pedestrians when EVs are moving versus conventional vehicles (Karaaslan et al., 2018). Comparing EVs to conventional vehicles, their results showed that EVs have a 10 % higher safety risk for pedestrian traffic accidents at low ambient sound levels and a 30 % higher risk for pedestrian traffic accidents at high ambient sound levels.

5.4. Mediating variables

The relationship map's mediating variables are essential components that affect a wide range of factors that ultimately affect EV adoption. Adnan et al (Adnan et al., 2018)., for example, examined how Malaysian consumers behaved when adopting PHEVs and found that adoption intention and environmental concern were mediated by attitude toward adoption, behavioral control, and moral standards. On the other hand, subjective norms did not mediate between the intention of adoption and environmental concerns. According to He et al (Wazeer et al., 2022)., perceived financial benefits and perceived risk partially moderate the relationship between individual innovativeness and intention to buy an EV. Similarly, the perceived cost partially mediates between the intention to buy an EV and environmental concerns. Schuitema et al. (2013) studied that there is a partial mediation link between the instrumental attributes and the desire to adopt a BEV. In contrast, symbolic and hedonic attributes mediate the relationship between instrument attributes and the intention to adopt a PHEV as a secondary automobile. The enjoyment of driving is the hedonic characteristic here and owning and operating an electric vehicle is the symbolic quality. White and Sintov (White and Sintov, 2017) concluded that considering EVs as social innovators and ecological symbols could somewhat mediate the association between the intention to adopt EVs and concern for climate change. In addition to environmental concerns, other antecedent variables studied for the mediation effect include psychological traits, design of vehicles, performance metrics, and cultural values. The purchase intention or adoption intention is the only dependent variable that is employed, and neither the consequence factors nor the influence of variables on EV adoption were examined in any of the research. Three main categories of mediating variables were employed to comprehend the mediation effect on EV purchase intention. (i) Personality traits, (ii) symbolic qualities, (iii) perceived qualities.

5.5. Moderating variables

Numerous academics have examined the relevance of moderating variables in connection maps. For instance, he and Zhan (He et al., 2018) examine external cost distinguished price and complexity as a moderation factor in the relationship between the intention of adopting EVs and personal norms. They discovered that distinguished complexity had a nonlinear effect between them, while the price was adversely modulating the relationship of the personal norm with the intention of EV adoption. Adnan et al. (Adnan et al., 2017). performed an experiment-based investigation to forecast Malaysian users' EV adoption behavior. According to the study, there was a positive value in moderating the effect of environmental concern on the connection between customer purchase intention and actual electric vehicle uptake. He and colleagues (He et al., 2018) investigated the role that gender plays in moderating personality and buying intention.

According to their research, men are more likely than women to have a favorable impact on purchase intention due to their inventiveness. In conclusion, women are less inclined to buy EVs because of their lower usefulness. Men, on the other hand, are more likely to purchase an EV because of its advantages. Notably, concern for the environment and hyperbolic discounting positively influence the relationship between purchase intention and actual adoption. Additionally, environmental concerns were examined as a moderating factor in addition to an independent variable. Most of the antecedent variables researched for moderation analysis relate to psychological traits. The most researched moderating variable that affects EV buying intention is gender. Factors connected to psychological traits are the second most researched moderating variables behind gender. No studies examined the moderating effect on the consequence variables included in the sample literature.

5.6. Socio-demographic variables

Previous research has examined sociodemographic traits to differentiate adopters from non-adopters. In several instances, the degree of significance for these variables has shifted due to factors such as national circumstances, cultural norms, and geographic location. The overview of the research found that several sociodemographic characteristics, like a higher level of education, membership in a group with higher income, younger age, and middle age group, are important for EV adoption. Factors connected to psychological traits are the second most highly researched moderating variable behind gender. No studies examined the moderating effect on the consequence variables included in the sample literature. Different regions have varying characteristics of these socio-demographical variables, which must be measured adequately to foster EV diffusion. The comprehensive homological network of all variables in the sustainability of EVs is shown in Fig. 12.

6. Life cycle assessment (LCA) and emission regulations

The International Organization for Standardization (ISO) acknowledges ISO 14040 and ISO 14044 as widely accepted standards for

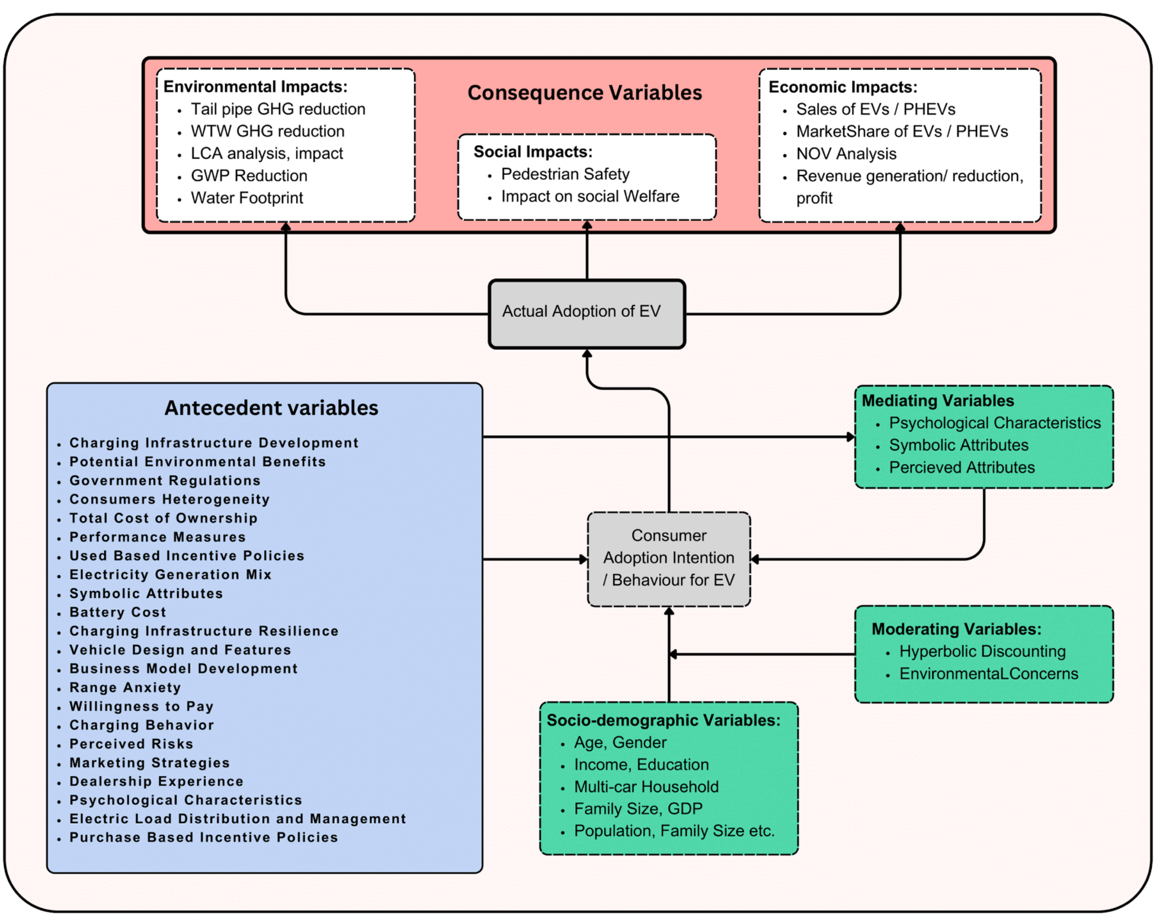

Fig. 12. Sustainable EVs roadmap.

conducting life cycle assessment (LCA). These standards provide a quantitative method for evaluating the environmental impact of a given product or system throughout its entire lifecycle, from the extraction of raw materials to the recycling or disposal of the system. Generally, LCA can be divided into four main phases: 1. Goal and Scope Definition, 2. Inventory Analysis, 3. Impact Assessment, and 4. Interpretation. The Goal and Scope Definition phases ensure that LCA is conducted for a specific functional unit within a predetermined system boundary and over a defined analysis period. The extent of these system boundaries can vary, depending on the product or service under analysis, ranging from comprehensive to more specific boundaries based on the specific needs of the assessment (Finnveden et al., 2009). Given the intricate nature of contemporary supply chains, the extensive scope of system boundaries aids in identifying the processes that have the most significant environmental impact. The system boundary sets the parameters for which processes should be encompassed within the LCA analysis, contingent upon the assumptions made in the initial phase, the intended application, and the established cut-off criteria. The functional unit establishes the benchmarks to which input and output can be correlated, enabling a meaningful comparison between two fundamentally different systems (Verma et al., 2022).

The duration of the analysis period significantly impacts LCA results, as energy consumption within the process varies over time. The credibility of LCA results is also contingent upon the quality of the data utilized. During the inventory analysis phase, the examination quantifies the energy and materials consumed or generated at various points along the supply chain. This phase comprises three key steps: first, the creation of a flowchart outlining raw materials, manufacturing processes, transportation, usage, and waste management; second, the collection of data concerning material inputs, products, by-products, and solid waste, as well as air and water emissions; and finally, the calculation of their relationships with the functional unit. After the inventory analysis, the impact assessment computes the overall environmental impact. This process includes evaluating factors such as eutrophication in freshwater, marine, and terrestrial environments, human toxicity levels, ozone depletion, land transformation, and climate change. Specific indicators, like the equivalent mass of CO_2, are chosen for each impact category, especially for reporting climate change effects. Various characterization models, such as the Tool for the Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) developed by the US Environmental Protection Agency and the available water remaining per area (AWARE) method used in Open LCA, are employed in this phase. The interpretation stage represents the final step in the systematic approach to comprehending assessment results. The assessment results are summarized and evaluated in this phase, and conclusions are drawn based on the LCA analysis. It serves to establish a level of confidence in the results and communicate them transparently and accurately.

Yang et al. (Yang et al., 2024b). conducted a life cycle assessment of the secondary use and physical recycling of lithium-ion batteries retired from electric vehicles in China. They developed various battery assessment scenarios based on the progression of battery recycling in the country. The results indicated that secondary use outperformed full-component physical, pyrometallurgical, and hydrometallurgical recycling methods. Shang et al. (Shang et al., 2024). conducted a life cycle assessment to examine the atmospheric environmental impact of widespread adoption of electric vehicles (EVs) in China. They created a detailed model to compare air pollutants and greenhouse gas emissions between EVs and internal combustion engine vehicles (ICEVs). The study found that EVs reduce lifecycle emissions of CO_2 by 12 %, NOx by 69 %, and VOCs by 9 % compared to ICEVs. However, the main obstacles to further emission reductions with EVs lie in producing raw materials and components, especially lithium batteries. By 2025, under a low-carbon EV policy, extensive EV production and sales could result in lifecycle emission reductions of 3.55 million tons of CO_2, 36,289 tons of NOx, and 4315 tons of VOCs. During the driving phase, EVs are projected to contribute 495 %, 124 %, and 253 % to the total lifecycle emission reductions (Shang et al., 2024).

The LCA of ICEVs and EVs involves evaluating their environmental impact throughout their life cycle, from raw material extraction to manufacturing, operation, and eventual disposal. Here are some key differences between IC engines and EVs in terms of their LCA:

- ICEVs rely on fossil fuels (gasoline or diesel) for energy, which involves extracting, processing, and transporting these fuels, contributing to greenhouse gas emissions. However, EVs are typically powered by electricity, which can come from various sources, including fossil fuels, renewable energy (such as solar or wind), or a mix of both.
- The environmental impact of EVs largely depends on the source of their electricity. Manufacturing an ICEV involves producing the engine, transmission, exhaust system, and other components. This process can be resource-intensive and result in emissions.
- EVs have batteries, electric motors, and power electronics as key components. Batteries, particularly LIBs, can have a big environmental impact during manufacture. However, improvements in this area come from battery technology and recycling advances. When in use, ICEVs release greenhouse gases and other pollutants. Driving conditions and engine technology impact their efficiency. When fueled by renewable energy or low-emission electrical sources, EVs are cleaner than ICEVs since they don't emit any tailpipe emissions while in use.
- Energy losses may occur from the intricate gearbox arrangement used by ICEVs to get power to the wheels. Electric motors, the more straightforward power transmission mechanism in EVs, have the potential to be more efficient and reduce energy loss. Because internal combustion engines are more complicated, ICEVs often need frequent maintenance, such as oil changes, filter replacements, and exhaust system repairs.
- EVs often require less maintenance since they have fewer moving parts. However, how long their electric and battery systems last may affect their total environmental performance. Because hazardous items like lead-acid batteries and engine fluids are disposed of during ICEV disposal, there may be environmental problems. An important environmental factor to address is the recycling and disposal of EV batteries. Negative effects can be reduced with appropriate recycling and disposal techniques.

In summary, the ecological impact of EVs and ICEVs varies across their life cycles. Energy sources, manufacturing processes, operation, and end-of-life considerations influence it. Generally, EVs tend to have a lower environmental impact during operation, especially when powered by clean energy sources. Still, their batteries and manufacturing processes can pose environmental challenges that need to be addressed through ongoing improvements in technology and recycling methods. Fig. 13 compares the life cycles of both ICEVs and EVs.

The fact that these fuels' emissions come with significant environmental dangers, such as global warming, is one of their main drawbacks (Usman et al., 2023b). According to the Energy Information Administration, there will be a 56 % increase in the world's energy use in 2040 compared to 2010 (Malik et al., 2022). The main issue is the depletion of fossil resources due to increased fuel usage, stringent pollution standards, and rising fuel costs, which highlights the importance of environmentally beneficial alternative fuels (Ijaz Malik et al., 2023). Furthermore, new processes highlighting cold start contribution will be added to the stricter emissions standards centered on further reductions in NOx and particle restrictions under future regulations, such as Euro 7 in the European region and the United States LEV IV/Tier 4. Modern Euro 6d vehicles comply with the regulations of NOx emissions more consistently as compared to the laboratory limits (Senecal and Leach, 2019).

Europe has established the strictest CO_2 tailpipe emission standards, calling for a reduction of 37.5 % by the end of this decade, with a target

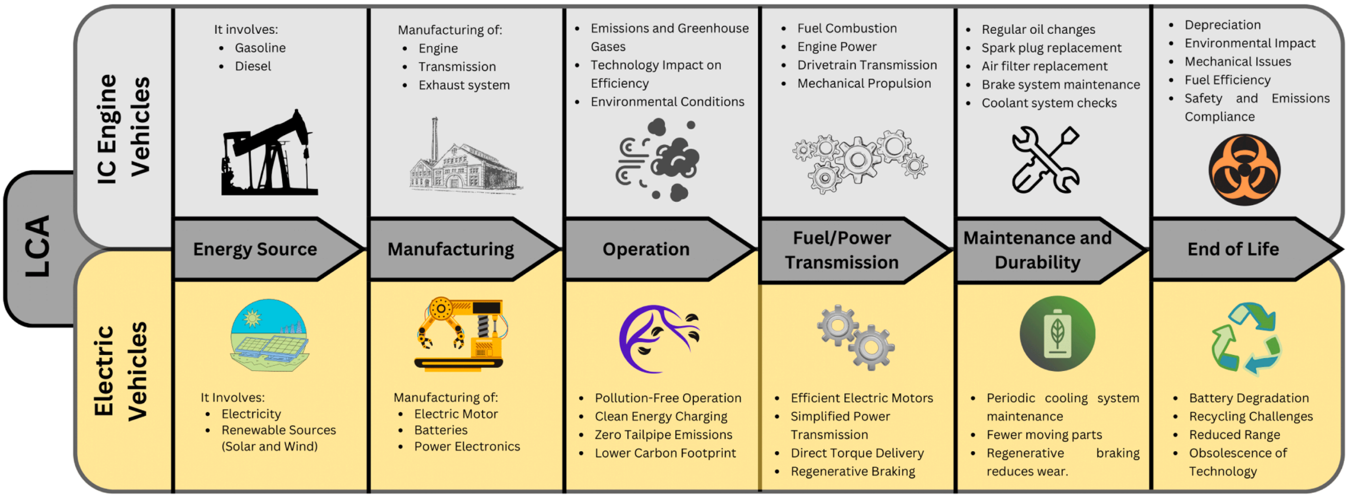

Fig. 13. Life cycle assessment comparison between Internal Combustion Engines and Electric Vehicles.

of less than 59 g/km in 2030. The goal is being revised downward to align with the EU's Green Deal (Zhao et al., 2015), which seeks to achieve net-zero greenhouse gas emissions by 2050. The European Climate Law is anticipated to publish these modifications in June 2021 (Conway et al., 2021). The Affordable Fuel-Efficient Vehicles Rule mandates that tailpipe CO_2 emissions be reduced by approximately 1.5 % for model years 2021 through 2026 (U. S. D. o. Transportation, 2024). California has stricter targets; OEMs there have voluntarily committed to reducing CO_2 emissions by 3.7 % annually. According to the New European Drive Cycle (NEDC), passenger cars in China must reduce their fuel consumption by 20 % between 2021 and 2025, having an average tailpipe CO_2 of 95 g/km by that time. By 2028, China aims to reach its peak CO_2 emissions from the transportation sector and then reduce CO_2 emissions by 20 % by 2035, according to the most recent Technology Roadmap (Conway et al., 2021). By then, hybrids and battery-electric cars should account for an equal portion of the new car market.

Yuan et al. (Yuan et al., 2024). introduced a bottom-up charging demand model to estimate the electricity use and carbon emissions of best-selling battery electric vehicles (BEVs) across various climate zones in China during the 2020 s. It revealed a significant increase in operational energy demand from 601 to 3054 GWh for top-selling BEV models between 2020 and 2022, with South China accounting for more than half of this demand. These vehicles' energy and carbon intensities decreased, particularly in North China, while the overall BEV stock's energy demand rose to 12,048 GWh, with carbon emissions reaching 6.8 megatons of CO_2 in 2022. The study supports efforts to decarbonize passenger cars and advance toward a carbon-neutral future. Future emissions targets will be tightened by rules like Euro 7 in the EU and LEV IV in the United States. These regulations will emphasize additional reductions in NOx and PN limitations and include new methods highlighting the impact of cold start. Global CO_2 emissions are expected to surpass 37.0 gigatons by 2035, as reported by the International Energy Agency (IEA). Various economic sectors, including transportation, industry, construction, energy generation, heat production, and agriculture, are responsible for the production of CO_2 emissions. 41.2 % of all CO_2 emissions come from the production sector, including heat and electricity creation (Rajendran et al., 2021b).

As a major contributor to ambient/outdoor air pollution, road transportation is also accountable for 4.1 million deaths in 2016 due to heart disease, strokes, chronic lung diseases, and respiratory infections. The particulate matter consists of particles equal to 2.5 μm or smaller. The Paris Declaration on Electro-mobility and Climate Change is one of the many international policy frameworks that have emerged because of road transport on the environment and health sectors. It encourages contributions towards low-carbon economies via sustainable transport electrification to levels compatible with less than 2-degree Celsius pathway (Bonsu, 2020). Europe has also planned to electrify 80 % of its fleet of vehicles (Bonsu, 2020). Importantly, the UN Sustainable Development Goals (SDGs) heavily incorporate the worldwide shift toward low-carbon economies and clean air. With EVs essential to low-carbon economies and better air quality, the new Clean Air Strategy of the United Kingdom also aims to reduce amounts of particulate matter in vehicle emissions by 30 % by 2020 and by 46 % by 2030 (Affairs, 2019). Furthermore, the Climate Change Act 2008 of the UK was amended to achieve net zero carbon emissions by 2050 and an emission reduction of 80 %. When compared to diesel engine vehicles, smart EVs are expected to cut carbon dioxide emissions by up to 43 % (Bhatti et al., 2021). To evaluate the emissions intensity required for electric cars (EVs) to attain lifecycle greenhouse gas emissions parity with efficient petrol hybrids in the US, Singh et al. (Singh et al., 2024). created the critical emissions factors (CEFs) measure. The analysis revealed that while EVs like the Nissan Leaf and Chevy Bolt generally reduce emissions compared to hybrids like the Toyota Prius and Honda Accord, regions in the Midwest and South still require significant reductions in power grid emissions to achieve parity. The Tesla Model S, a longer-range EV, often has higher emissions than hybrids, except in the Northeast and Florida. The analysis found that increasing the capacity of renewable energy sources is less effective than retiring coal plants and imposing stronger regulations on fossil fuel producers to reduce EV emissions over the medium future.

7. Policy implications

The leading precursors provided a range of complex policy implications and shed light on the state of EV-related research today. To summarize, the first precondition was the development of the infrastructure for EV charging, which is the most researched aspect affecting EV adoption and highlights the critical role that charging stations play. Publicly available charging stations have made a substantial contribution to the improvement of the charging infrastructure globally. These stations are mainly slower chargers, and as of 2017, there were about 320,000 of them (Liu et al., 2021). Numerous recent studies have also underscored the significance of fast chargers in urban and densely populated areas (Liu et al., 2021; Alkinani et al., 2020). At present, China has the greatest number of rapid chargers that are accessible to the general public (83,395), followed by Japan (7327) and the United States (6267) (Liu et al., 2021). It undoubtedly emphasizes how important readily available fast chargers are for nations that are among the first to adopt electric cars. Measures that increase charger density must be developed to encourage the use of EVs. Apart from being available to the public, chargers used at home, at work, and in parking lots have also significantly improved the infrastructure for charging (Zhang et al., 2023b; Tete et al., 2021).

Therefore, decisions made about policies regarding installing infrastructure for charging EVs at homes, offices, and parking lots will help create an environment favorable to EVs. In addition, newer technologies like wireless and vehicle-to-grid charging have shown to be economical and capable of improving the infrastructure for charging depending on the locale (Saw et al., 2018; Burban et al., 2013). As a result, laws about wireless charging, car-to-grid capabilities, and the application of cutting-edge technology may further improve the chances of electric vehicle adoption. The next two antecedents, the purchase-based incentive schemes and the overall cost of ownership, are related to economic factors. Strong financial incentives like tax breaks and subsidies, along with the adoption of practical laws and the development of charging infrastructure, have been linked to a notable increase in the sales of EVs in several nations, including China, Norway, the Netherlands, and the United States (Liu et al., 2021). From this data, government authorities and policymakers may see that consumers are very concerned about economic problems. They should, therefore, modify their rules to guarantee that EVs are just as profitable as, if not more so than, their conventional equivalents. Based on customer preferences, Lieven (Lieven, 2015) found three unique clusters from a survey that covered 20 different nations. The first cluster focused on monetary incentives, the second on charging infrastructure, and the third on additional incentives. Our analysis of the literature expands on Lieven's (Lieven, 2015) findings and offers a perspective on adopting EVs from a worldwide standpoint.

"Range anxiety," the next antecedent of concern, is highly impacted by things like battery technology and the accessibility of charging infrastructure. This problem has severely hampered the broad acceptance of EVs. Moreover, the difficulty with range anxiety is worsened by the longer time needed for an EV to recharge. However, the implementation of rapid chargers and battery exchange programs has demonstrated the potential to mitigate the effects of prolonged charging durations on the uptake of EVs. Therefore, authorities should reduce range anxiety by implementing quick charger installation, battery swapping station construction, battery technology advancements, and other relevant measures. Even though ICEVs have higher tailpipe GHG emissions than EVs, a more thorough analysis, such as a lifecycle or well-to-wheel assessment, may show less significant benefits or drawbacks, especially in areas where a carbon-intensive energy generation mix exists. For example, in China and India, where coal is used as a major source for electricity generation, a lifecycle study may reveal even higher actual GHG emissions for EVs than for internal combustion ones (Hofmann et al., 2016). Therefore, to truly profit from the environmental advantages of EVs, nations that rely significantly on producing carbon-intensive power must prioritize decarbonizing their energy sources. On the other hand, understudied subjects, including marketing tactics, the dealership experience, and the dependability of the infrastructure for charging, provide insightful information for policymakers. For example, the dealership experience, including EV models' availability, creates an information gap and restricts prospective customers' ability to look over and test drive the cars. Furthermore, factors like sales representatives' responsiveness, dealership profit margins, and long wait times add to big problems that need to be considered when developing dealership-specific policies. Further barriers to marketing tactics include a dearth of confidence in advertising campaigns and a lack of attention to environmental and cultural factors.

To increase the adoption of EVs, our review's findings suggest that diversified marketing tactics should strongly emphasize fostering consumer trust in marketing campaigns and creating links between social marketing campaigns and cultural values (Kumar and Alok, 2020). Perceived risk was found to be negatively correlated to adopting electric vehicles by Qian and Yin (Qian and Yin, 2017). They suggested that public policies should change to encourage consumer interactions or educational programs to lessen the perceived hazards associated with sustainable technologies. The durability of the infrastructure supporting EV adoption, particularly in a natural disaster or a mass evacuation, is another issue with little consideration. Nations must develop rules for natural disasters and risk mitigation strategies related to the resilience of charging infrastructure to guarantee safe and reliable EV options during evacuation. Fig. 14 displays the risk assessment related to risk mitigation approaches that should be reflected in policies.

8. SDGs compliance

EVs are increasingly acknowledged as an essential element in the worldwide endeavor to realize the Sustainable Development Goals (SDGs) outlined by the United Nations. These SDGs represent a comprehensive framework of 17 interconnected global objectives that serve as a guiding principle for attaining a superior and more enduring future for all by 2030. EVs align with numerous objectives, providing a trajectory toward a more sustainable and ecologically sound future. Fig. 15 shows the compliance with SDGs through the adoption of EVs. Primarily, EVs substantially contribute to SDG 7, prioritizing universal access to affordable, dependable, sustainable, and contemporary energy. The switch from traditional fossil fuel-powered cars to electric vehicles (EVs) demonstrates a significant reduction in reliance on limited energy sources. This shift is necessary since the transportation sector uses much energy, much of which comes from non-renewable sources like oil. EVs are eco-friendly because they can use renewable energy sources like solar or wind power. There is another need to pay attention to the relationship between EVs and SDG 9, which is focused on building strong infrastructure, promoting equitable and sustainable industrial growth, and fostering innovation. Substantial breakthroughs such as battery upgrades, electric propulsion technologies, and charging infrastructure are necessary for the progress and widespread adoption of electric vehicles. These developments drive progress in the automotive industry and stimulate growth and job creation in emerging and developing EV-related industries. In an integrated circular economy plan that recycles and reuses EV batteries, EVs provide a more ecologically benign means of producing and consuming things. Lastly, the global transition to electric vehicles also has ramifications for other Sustainable Development Goals (SDGs), including SDG 3 (Good Health and Well-Being) by reducing health issues linked to pollution and SDG 8 (Decent Work and Economic Growth), as it creates new job opportunities in the renewable energy sector. It's crucial to realize that transitioning to electric vehicles (EVs) is not without difficulties. For example, obtaining raw materials for batteries and building sufficient infrastructure for charging them requires ethical and ecological management.

The achievement of SDG 11, which aims to promote inclusive, safe, resilient, and sustainable cities and human settlements, is also facilitated by EVs. One of the biggest problems in metropolitan areas is managing air quality. The emissions from conventional vehicles are a major source of air pollution, which harms human health. By switching to electric vehicles instead of conventional cars, cities may improve their citizens' health by increasing the air quality. Additionally, SDG 12 is supported by EVs, ensuring sustainable production and consumption patterns. Because it depends on non-renewable resources and automobile emissions have a detrimental environmental impact, the automotive industry has long been associated with unsustainable consumption. The massive adoption of EVs has also significantly impacted SDG 13, which calls for urgent action to combat climate change and its effects. The main source of greenhouse gas emissions from conventional cars powered by internal combustion engines (ICEs) is increased global warming and climate disruption. On the other hand, EVs produce far less greenhouse gas emissions, especially when they run on renewable energy. Hence, the widespread integration of EVs is a crucial component in endeavors to curtail emissions and alleviate the impacts of climate change. The

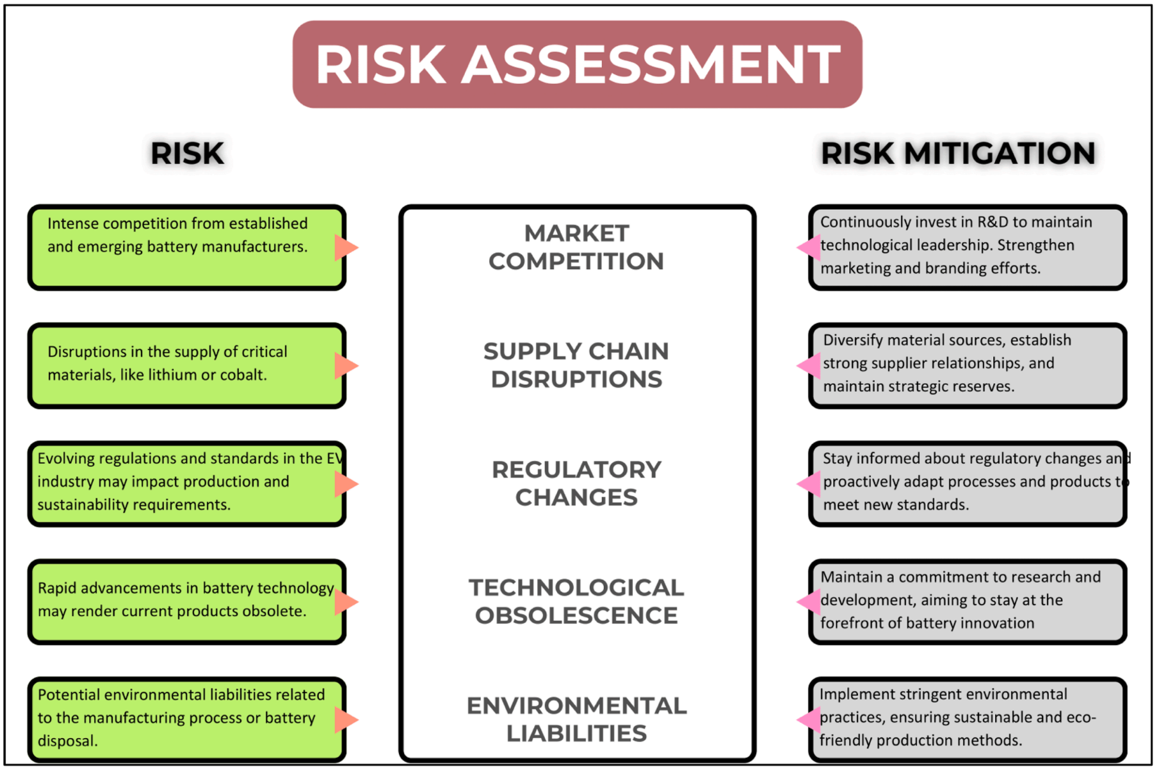

Fig. 14. Risk assessment and their mitigation linked with EVs.

Fig. 15. Adoption of EVs in compliance with SDGs.

adoption of EVs contributes to SDG 15 by reducing air pollution, thereby preserving terrestrial ecosystems and biodiversity. EVs also mitigate habitat destruction associated with traditional vehicle production and resource extraction. Through promoting sustainable land use and mitigating climate change, EV adoption indirectly supports preserving and restoring terrestrial ecosystems as outlined in SDG 14. Fig. 15 graphically displays the compliance with SDGs through promoting EV technology.

9. SWOT analysis

A SWOT analysis of EVs as future automotive options can provide insights into their strengths, weaknesses, opportunities, and threats in the automotive industry. Fig. 16 graphically demonstrates the SWOT analysis.

9.1. Strengths

The strengths of EV technology are mentioned below:

- EVs have zero tailpipe emissions; they help to cope with climate change by lowering greenhouse gas emissions and air pollution.
- EVs have lower maintenance and operating costs than conventional ICEVs due to fewer mechanical parts and cheaper electricity than gasoline.
- Electric motors are highly efficient, converting a significant portion of the energy from the grid into vehicle propulsion.
- EVs operate without noise compared to ICEVs, which may reduce noise pollution in urban areas.
- Many governments offer incentives like tax credits and subsidies to promote the adoption of EVs, making them more affordable.

9.2. Weaknesses

The weaknesses of EV technology are mentioned below:

- While the range has improved, EVs still have limited driving ranges compared to ICEVs, and charging infrastructure is not as widespread in some regions.
- The availability and convenience of charging stations vary by location, which can be a barrier to adoption, especially for those without a home charger.
- EVs possess higher initial purchase costs than similar ICEVs, although this gap is decreasing.

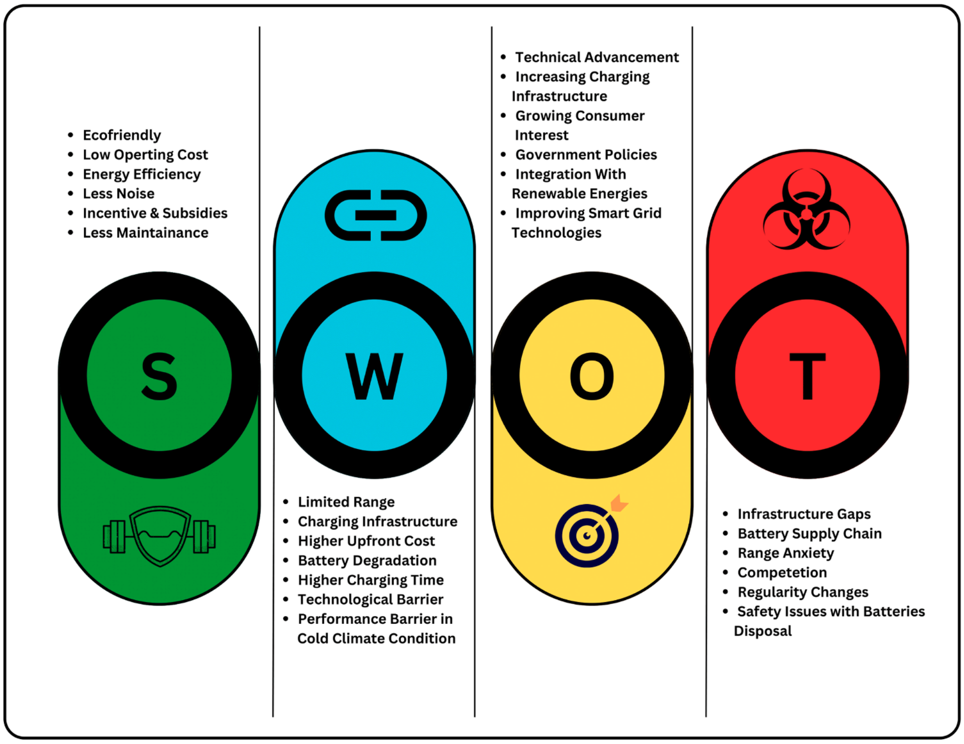

Fig. 16. SWOT analysis.

- Charging an EV takes longer time compared to filling up a gasoline tank, which can be inconvenient for long trips.
- EV batteries degrade over time, impacting range and performance, and replacing them can be costly.

9.3. Opportunities

The opportunities of EV technology are mentioned below:

- Ongoing research and development in battery technology promises longer ranges, faster charging, and improved affordability.
- Continued investments in charging networks will make EVs more accessible and convenient for consumers.
- As environmental awareness increases and EV technology advances, consumers consider EVs viable alternatives to ICEVs.
- Governments worldwide are implementing policies to promote EV adoption, such as stricter emissions regulations and financial incentives.
- EVs can be charged using renewable energy sources like wind and solar, reducing their carbon footprint further.

9.4. Threats

The threats of EV technology are mentioned below:

- The uneven development of charging infrastructure may limit the widespread adoption of EVs, particularly in rural areas.
- The supply chain for key EV components, especially lithium-ion batteries, is vulnerable to disruptions and price fluctuations.
- Concerns about running out of battery power before reaching a charging station (range anxiety) can deter some consumers from choosing EVs.
- Traditional automakers and new entrants in the EV market, increasing competition and potentially leading to market saturation.
- Shifts in government policies and regulations could impact the incentives and subsidies that make EVs attractive to consumers.

In conclusion, EVs have significant potential as the future of the automotive industry, driven by their environmental benefits, technological advancements, and government support. However, challenges related to infrastructure, cost, and consumer perceptions must be addressed to ensure their continued growth and success.

10. Technical challenges and prospective solutions

EVs represent a significant advancement in sustainable transportation, yet they face many technical challenges that must be addressed to achieve widespread adoption and optimal performance. These challenges encompass battery technology limitations, including energy density, charging times, and lifespan, as well as thermal management issues to prevent overheating. Additionally, the development of efficient and reliable charging infrastructure, along with the integration of ADAS, presents further technical hurdles. Overcoming these obstacles requires continuous innovation and collaboration across the automotive and technology sectors, ensuring that EVs can meet the demands of consumers and environmental standards. Some of the technical challenges are explained below:

- Developing an appropriate energy storage system with higher autonomy and quick charging is a critical challenge for EVs. Solid-state batteries can enhance EV autonomy by storing more energy as liquid electrolytes are replaced with solid ones. Moreover, combining IoT and machine learning technologies in EMS can optimize energy usage, resulting in effective power distribution during charging and driving. The second-life battery applications in developing effective recycling methods and stationary storage applications can also improve resource availability for new storage systems.
- The requirement for cobalt, lithium, nickel, and other rare earth metals will rise significantly due to the widespread development of EVs. It's feasible that political pressure and lobbying will have access to such materials, just as in the case of oil in the past (Dimsdale, 2019).

- The integration of renewable energy sources with the electrical grid at large is anticipated to be greatly aided by EVs (Boulakhbar et al., 2020; Colmenar-Santos et al., 2019). For example, storing energy during peak generation periods and supplying the grid with energy during peak demand. Adopting smart grid technology with real-time data monitoring for load management is important to avoid potential overload on power grids through massive EV charging. Also, renewable energy sources should be integrated to support EV charging without overloading grids. The vehicle-to-grid (V2G) mechanism needs to be implemented for load management so that users can return excess power to the grid.
- EV charging has to do with variations in voltage near nominal values. This issue may arise when excessive loading and the power system cannot meet the demand. Due to the nonlinearity of EV loads, it has been shown that EVs are largely to blame for creating voltage instability in power systems. This is particularly true when EV penetration and charging levels are high. An aggregator and a smart charging system could improve the stability and dependability of the power grid (Lebrouhi et al., 2021).
- Electrical power absorbed by charging EVs may exceed the power available in the power grid. There can be a problem for system operators when a large number of EVs are being charged at the same time (Lebrouhi et al., 2021). To avoid this, a bidirectional charging concept with a dynamic load control technique can be used to control peak loads on the power system (Ahmadi et al., 2015). It is very important to mention that the electrical power system should be able to withstand a significant level of EV penetration without being overloaded. For instance, 500,000 EVs in Ontario, Canada, and 73 % of EV penetration in the US (Lebrouhi et al., 2021).
- Different factors such as fast charging, single phase charging on AC, range of EVs and number of vehicles being charged at the same time can affect power quality and cause harmonic currents (Karmaker et al., 2019). Such uncontrolled penetration of EVs can be handled by using smart charging systems with reliable communications between charging stations and the power grid (Zahedmanesh et al., 2020).
- EVs cause most of the power grid's power losses. Choosing the best placement and capacity for charging stations, using smart metering, uniformly distributed charging and other strategies can significantly lower power supply losses (Ehsani et al., 2021).
- Transformers may overheat because of high EV grid integration. Among the techniques used to stop transformer overheating are the use of an intelligent load management technique and the use of the K-factor derating approach (Pavlićević and Mujović, 2022).
- As EVs become more connected, integrating advanced software systems while ensuring cybersecurity is a growing concern. This includes the risk of hacking and the need for regular updates and patches.
- Compared to ICEVs, the cost of EVs production, especially batteries, is still high, which drives up the price of EVs for customers. The proper disposal and recycling of EV batteries are crucial to minimizing environmental impact and cost, but current processes are expensive and inefficient.
- Regarding challenges of penetration level, the uniform deployment of EV chargers across rural and urban areas is required to avoid uneven adoption of EV facilities in urban areas. Moreover, the government should give incentives for home chargers, especially in underdeveloped areas.
- The higher initial costs linked with EVs and expensive charging infrastructure are the main hindrance to EVs market growth. The government should provide financial incentives to both manufacturers and end users. Moreover, the lithium-ion batteries of EVs should be recycled to reduce dependence on raw materials and associated costs.
- The higher initial costs linked with EVs and expensive charging infrastructure are the main hindrance to EVs market growth and price. The government should provide financial incentives to both manufacturers and end users. Moreover, the lithium-ion batteries of EVs should be recycled to reduce dependence on raw materials and associated costs. The collaboration in between government, manufacturers and energy providers should be made to develop coherent EV adoption policies. In this regard, artificial intelligence and data analytics can also predict EV demand and allocate resources effectively.
- Effective EV fleet management is important to reduce grid dependence associated with aggregated EV fleets. Cloud-based platforms should be promoted to monitor the charging/discharging of aggregated EV fleets and streamline integration between EV and grid communication.
- The user-side uncertainties can be reduced by providing flexible charging solutions (slow, fast, office, marketplaces and parks), diversified pricing models, enhanced EV range and prolonged life-cycle of EV batteries.
- The adoption of EVs should be aligned with environmental sustainability, just like EV charging networks should use renewable energies, sustainable manufacturing processes with minimal carbon footprints, recycling of lithium-ion batteries to minimize waste material disposal to the environment and educating people regarding the environmental benefits of EVs.

As previously stated, the charging of EVs must be properly scheduled with planning and an ideal management approach to prevent overloading caused by EV load and to safeguard the power grid from potential threats. It's interesting to note that, even for nations with comparable shares of the renewable energy sector, there can be differences in management strategies used to support the charging of a larger number of EVs. It depends on several types of generation renewable energy and conventional power generation systems in different countries. Coordination for the energy demand for electric vehicles might be a major issue in nations that use variable renewable energy supplies. In some areas with an inadequate power infrastructure network, more grid reinforcement and significant charging techniques are necessary.

11. Future recommendations and research directions

Despite the rapid adoption of EVs and ongoing technological advancements, several critical areas in EV technologies, such as regenerative braking systems, developing lightweight materials, driver assistance systems, battery thermal management systems, charging system architecture, digital twin technology, and tribological aspects etc., still require further research and development. Addressing these gaps is essential to fully harnessing the potential of EVs. The future of EVs is filled with exciting possibilities, driven by technological advancements, environmental concerns, and the need for sustainable transportation. Here are some future ideas and possible research directions related to EVs.

- For example, optimizing brake force distribution in regenerative braking systems requires the development of advanced algorithms to balance regenerative and friction braking for maximum energy recovery—an important area for future research. Similarly, exploring adaptable systems that adjust energy recovery based on driving conditions, such as urban, highway, or off-road scenarios, will gain significance. Additionally, research into high-efficiency motor-generators to enhance energy conversion during braking, along with the advancement of control systems utilizing machine learning and AI to predict braking events and optimize regenerative braking in real-time, will further accelerate the adoption of EV technology.
- Research into advanced materials and manufacturing techniques for EV components will play a crucial role in accelerating the widespread adoption of EVs. For instance, exploring hybrid material systems that combine metals and composites for optimal

performance, as well as developing nanostructured materials with superior mechanical, thermal, and electrical properties, are promising areas of investigation. Additionally, employing advanced manufacturing methods, such as 3D printing, to create lightweight components with complex geometries and minimal waste, along with devising cost-effective techniques for large-scale production, will further support EV technology. Future research could also focus on designing materials that provide both structural support and thermal management for battery systems, as well as investigating lightweight materials with high thermal resistance to enhance battery safety and efficiency.
- Research in driver assistance systems is critical for advancing EV technology. This includes developing advanced sensor technologies such as high-resolution LiDAR, radar, and camera systems for precise object detection and environmental mapping, as well as integrating data from multiple sensors to enhance situational awareness and decision-making. Additionally, low-power sensor systems specifically designed for EVs can help conserve battery life. Similarly, designing AI models capable of predicting driver behavior, road conditions, and potential hazards for proactive assistance, as well as enhancing AI capabilities to process data and make real-time decisions in dynamic environments, are essential. Furthermore, enhanced safety features, such as advanced algorithms for collision warning and emergency braking in complex scenarios, and systems that adapt driver assistance based on adverse weather conditions, will significantly contribute to the widespread adoption of EV technology in the future.
- Continued research and advancements in battery technology are expected to significantly increase the driving range of EVs, addressing "range anxiety" and making them more suitable for long distance travel. A key challenge for EVs is the reduced range at lower temperatures. This issue could be mitigated in the future through the development of solid-state batteries, which offer improved performance in cold weather, faster charging, and greater resilience to extreme temperatures. Additionally, enhancing thermal management systems to maintain optimal battery temperatures is crucial. Research into the integration of phase-change materials or advanced insulation techniques can assist in maintaining optimal battery temperatures and ensuring consistent performance.
- Research in charging system architecture, including ultra-fast chargers capable of high-power delivery to minimize charging times, advanced thermal management to address heat generation during rapid charging, advancements in dynamic charging systems, vehicle-to-grid (V2G) integration, AI-driven charging management, modular charging units, and distributed charging networks, can significantly enhance the efficiency and scalability of charging infrastructure, supporting the mass adoption of EVs.

Manufacturers will increasingly use recycled and sustainable materials in EV production, reducing their environmental impact. Developing efficient and environmentally friendly battery recycling methods will become crucial as EV adoption grows, ensuring the responsible disposal of old batteries. EVs of the future will be highly connected, allowing for the personalization of settings, continuous software updates, and integration with smart home and IoT devices. These future ideas demonstrate the potential for EVs to play a central role in sustainable transportation and energy systems. As technology advances and infrastructure improves, the transition to electric mobility will likely accelerate.

12. Conclusions

This review explores recent technological advancements in electric vehicles (EVs), including innovations in regenerative braking systems, EV design and aerodynamics, advanced driver-assistance systems, battery thermal management, charging system architecture, economic and market analyses, and EVs' sustainability. The following conclusions can be drawn from this review:

- Vehicle-to-grid (V2G) technology represents the future of electric vehicles, enabling a two-way power flow from the EV's battery. V2G faces challenges from various load conditions, which impact voltage levels and the efficient power distribution within the electrical network. The V2G concept aligns with the 5Ds framework, encompassing decentralization, decarbonization, digitalization, deregulation, and democratization, aiming to address the shortcomings in the contemporary power grid.
- The advancements in regenerative braking systems have significantly enhanced energy recovery and efficiency in EVs through innovative designs and control strategies such as single-pedal operation, Neural Inverse Optimal Control, and optimized switched reluctance machines. These innovations not only improve braking performance but also extend driving range and economic viability while addressing challenges like torque ripple and energy consumption. Continued research into advanced control methods and system optimization holds promise for further breakthroughs in EV regenerative braking technology.
- Solid-state batteries are a potent technology that can substitute the liquid electrolyte in conventional LIBs with a solid electrolyte. They have the potential to significantly reduce the risk of thermal runaway and overheating because they are less prone to leakage and dendrite formation. Moreover, lithium-sulfur batteries possess higher energy density than LIBs, which can lead to longer driving ranges. They are also less likely to overheat due to their inherent chemical properties. Addressing raw material access and battery recycling challenges is essential for long-term viability.
- To optimize the fundamental framework for digital twin applications in battery manufacturing, a combination of critical technologies and solutions should be considered, such as enhancing digital twin data in cloud storage systems by leveraging IoT technology, 5 G technology, internet technology and artificial intelligence.
- LCA findings highlight the significance of concentrating on greenhouse gas (GHG) emissions and resource-related risks during the battery production phase. GHG emissions can be mitigated in the short term through efficient battery material recycling and remanufacturing. In the long run, the development of eco-friendly material recovery methods and greener energy structures holds the potential to reduce GHG emissions substantially.
- The development of the electric car sector depends on cooperation between technological companies, government agencies, and manufacturers of electric vehicles. These collaborations tackle problems, including a lack of charging infrastructure and reluctance on the customers' side, while fostering innovation, sustainability, and economic growth.
- Maximizing the environmental benefits of EVs requires increasing the share of renewable energy in electricity generation, promoting energy-efficient practices, and expanding EV charging infrastructure.
- Continued research and advancements in regenerative braking systems, developing light-weight materials, driver assistance systems, battery thermal management systems, charging system architecture, the strategic use of digital twin technology and AI, along with supportive government policies, are key to securing the future success of EVs.

CRediT authorship contribution statement

Sadaf Zeeshan: Validation, Resources, Methodology; **Syed Qasim Raza Zahidi:** Investigation, Data curation; **Md Abul Kalam:** Writing – review & editing, Supervision, Project administration; **Adeel Ikram:** Writing – original draft, Writing – review & editing, Investigation, Data curation, Methodology, Formal analysis, Conceptualization; **Muhammad Ali Ijaz Malik:** Writing – original draft, Methodology, Investigation, Conceptualization, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

UTS Strategic Research Support 2024 under Md Abul Kalam.

Data Availability

Data will be made available on request.

References

F. Achermann et al., WindSeer: Real-time volumetric wind prediction over complex terrain aboard a small UAV, arXiv preprint arXiv:2401.09944, 2024.
Adnan, N., Nordin, S.M., Rahman, I., Rasli, A.M., 2017. A new era of sustainable transport: an experimental examination on forecasting adoption behavior of EVs among Malaysian consumer. Transp. Res. Part A: Policy Pract. 103, 279–295.
Adnan, N., Nordin, S.M., Amini, M.H., Langove, N., 2018. What make consumer sign up to PHEVs? Predicting Malaysian consumer behavior in adoption of PHEVs. Transp. Res. Part A: Policy Pract. 113, 259–278.
D. f E.F. a R. Affairs. Clean Air Strategy 2019. ⟨https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/770715/clean-air-strategy-2019.pdf⟩ (accessed.
Afianto, D., Han, Y., Yan, P., Yang, Y., Elbarghthi, A.F., Wen, C., 2022. Optimisation and efficiency improvement of electric vehicles using computational fluid dynamics modelling. Entropy 24 (11), 1584.
Afzal, M.Z., et al., 2023. A novel electric vehicle battery management system using an artificial neural network-based adaptive droop control theory. Int. J. Energy Res. 2023 (1), 2581729.
Agency, I.E., 2024a. Global EV Outlook 2024. ⟨https://iea.blob.core.windows.net/assets/a9e3544b-0b12-4e15-b407-65f5c8ce1b5f/GlobalEVOutlook2024⟩.
I.E. Agency. (2024b) "Global EV sales by scenario, 2020-2030." ⟨https://www.iea.org/data-and-statistics/charts/global-ev-sales-by-scenario-2020-2030⟩ (accessed.
Ahmadi, M., Mithulananthan, N., Sharma, R., 2015. Dynamic load control at a bidirectional DC fast charging station for PEVs in weak AC grids. 2015 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC). IEEE, pp. 1–5.
Ahmadi, M., Adewuyi, O.B., Danish, M.S.S., Mandal, P., Yona, A., Senjyu, T., 2021. Optimum coordination of centralized and distributed renewable power generation incorporating battery storage system into the electric distribution network. Int. J. Electr. Power Energy Syst. 125, 106458.
Ahmed, H., 2022. A comparative study on different motors used in electric vehicles. J. Indep. Stud. Res. Comput. 20 (2).
Al Badawi, A.K., Nashwan, A.J., 2024. The future of prehospital emergency care: embracing AI applications in ambulance services. Int. Emerg. Nurs. 72, 101385.
Ali, S.U., Waqar, A., Aamir, M., Qaisar, S.M., Iqbal, J., 2023. Model predictive control of consensus-based energy management system for DC microgrid. PloS One 18 (1), e0278110.
Aliasand, A.E., Josh, F., 2020. Selection of motor foran electric vehicle: a review. Mater. Today.: Proc. 24, 1804–1815.
AlKawak, O.A., Kumar, J.R.R., Daniel, S.S., Reddy, C.V.K., 2024. Hybrid method based energy management of electric vehicles using battery-super capacitor energy storage. J. Energy Storage 77, 109835.
Alkinani, M.H., Khan, W.Z., Arshad, Q., 2020. Detecting human driver inattentive and aggressive driving behavior using deep learning: recent advances, requirements and open challenges. Ieee Access 8, 105008–105030.
Almughram, O., Abdullah ben Slama, S., Zafar, B.A., 2023. A reinforcement learning approach for integrating an intelligent home energy management system with a vehicle-to-home unit. Appl. Sci. 13 (9), 5539.
Alolaiwy, M., Hawsawi, T., Zohdy, M., Kaur, A., Louis, S., 2023. Multi-objective routing optimization in electric and flying vehicles: a genetic algorithm perspective. Appl. Sci. 13 (18), 10427.
Alsharif, A., Tan, C.W., Ayop, R., Dobi, A., Lau, K.Y., 2021. A comprehensive review of energy management strategy in Vehicle-to-Grid technology integrated with renewable energy sources. Sustain. Energy Technol. Assess. 47, 101439.
An, Y., Gao, Y., Wu, N., Zhu, J., Li, H., Yang, J., 2023. Optimal scheduling of electric vehicle charging operations considering real-time traffic condition and travel distance. Expert Syst. Appl. 213, 118941.
Ancuta, A.-A., Rentea, C.-A., Iozsa, D.-M., 2024. Research on the Dynamic and Energetic Performances of an Electric SUV in Real Driving Conditions.
Antonopoulos, I., et al., 2020. Artificial intelligence and machine learning approaches to energy demand-side response: a systematic review,". Renew. Sustain. Energy Rev. 130, 109899.
Balan, G., et al., 2022. An improved deep learning-based technique for driver detection and driver assistance in electric vehicles with better performance. Int. Trans. Electr. Energy Syst. 2022, 1–16.
Baptista, P.C., Silva, C.M., Lopes, J.P., Soares, F.J., Almeida, P.R., 2013. Evaluation of the benefits of the introduction of electricity powered vehicles in an island. Energy Convers. Manag. 76, 541–553.
Barman, P., et al., 2023. "Renewable energy integration with electric vehicle technology: a review of the existing smart charging approaches. Renew. Sustain. Energy Rev. 183, 113518.
Basu, K.S.H.S., Kolake, S.M., Song, T., Sohn, D.K., Yeo, T., 2016. Coupled electrochemical thermal modelling of a novel Li-ion battery pack thermal management system. Appl. Energy 181, 1–13.
Bautista, P.B., Cárdenas, L.L., Aguiar, L.U., Igartua, M.A., 2019. A traffic-aware electric vehicle charging management system for smart cities. Veh. Commun. 20, 100188.
Behera, A., Swain, B., Sahoo, D.K., 2020. Fiber-reinforced ceramic matrix nanocomposites. Fiber-Reinforced Nanocomposites: Fundamentals and Applications. Elsevier, pp. 359–368.
Behera, S., Dev Choudhury, N.B., 2021. A systematic review of energy management system based on various adaptive controllers with optimization algorithm on a smart microgrid. Int. Trans. Electr. Energy Syst. 31 (12), e13132.
Bekel, K., Pauliuk, S., 2019. Prospective cost and environmental impact assessment of battery and fuel cell electric vehicles in Germany. Int. J. Life Cycle Assess. 24, 2220–2237.
Beşkardeş, A., Hameş, Y., Kaya, K., 2024. A comprehensive review on fuzzy logic control systems for all, hybrid, and fuel cell electric vehicles. Soft Comput. 28 (13), 8183–8221.
Bhatti, G., Mohan, H., Singh, R.R., 2021. Towards the future of smart electric vehicles: digital twin technology. Renew. Sustain. Energy Rev. 141, 110801.
Björnsson, L.-H., Karlsson, S., 2016. The potential for brake energy regeneration under Swedish conditions. Appl. Energy 168, 75–84.
Bonsu, N.O., 2020. Towards a circular and low-carbon economy: insights from the transitioning to electric vehicles and net zero economy. J. Clean. Prod. 256, 120659.
Boulakhbar, M., et al., 2020. Towards a large-scale integration of renewable energies in Morocco. J. Energy Storage 32, 101806.
Budiprasojo, A., Firmansyah, M.R., 2022. Aerodynamic analysis in the design of an electric vehicle model tobacco style M-164 with computational fluid dynamic (CFD) method. J. Rekayasa Mesin 13 (2), 435–442.
Burban, G., Ayel, V., Alexandre, A., Lagonotte, P., Bertin, Y., Romestant, C., 2013. Experimental investigation of a pulsating heat pipe for hybrid vehicle applications. Appl. Therm. Eng. 50 (1), 94–103.
Burd, J.T.J., Moore, E.A., Ezzat, H., Kirchain, R., Roth, R., 2021. Improvements in electric vehicle battery technology influence vehicle lightweighting and material substitution decisions. Appl. Energy 283, 116269.
Cai, P., Mei, X., Tai, L., Sun, Y., Liu, M., 2020. High-speed autonomous drifting with deep reinforcement learning. IEEE Robot. Autom. Lett. 5 (2), 1247–1254.
Cao, W., Bukhari, A.A.S., Aarniovuori, L., 2019. Review of electrical motor drives for electric vehicle applications. Mehran Univ. Res. J. Eng. Technol. 38 (3), 525–540.
Carlstedt, D., Asp, L.E., 2020. Performance analysis framework for structural battery composites in electric vehicles. Compos. Part B: Eng. 186, 107822.
Chandrakar, A., Ch, S.P.K., Jain, S., 2021. Kim-Sul algorithm based FOC for electronic pole changing induction motor drive in EV applications. 2021 IEEE International Power and Renewable Energy Conference (IPRECON). IEEE, pp. 1–6.
E. g f charging. (2024) EVgo for Everyone. ⟨https://www.evgo.com/⟩ (accessed.
Chen, W.W.K., Yuan, F., Chen, L., Wang, S., 2019a. Cooling efficiency improvement of air-cooled battery thermal management system through designing the flow pattern. Energy 167, 781–790.
Chen, X.P.S., Bao, N., Garg, A., 2019b. A comprehensive analysis and optimizationprocess for an integrated liquid cooling plate for a prismatic lithium-ion battery module. Appl. Therm. Eng. 156, 324–339.
Choi, W., Song, H.H., 2018. Well-to-wheel greenhouse gas emissions of battery electric vehicles in countries dependent on the import of fuels through maritime transportation: a South Korean case study. Appl. Energy 230, 135–147.
Colmenar-Santos, A., Muñoz-Gómez, A.-M., Rosales-Asensio, E., López-Rey, Á., 2019. Electric vehicle charging strategy to support renewable energy sources in Europe 2050 low-carbon scenario. Energy 183, 61–74.
Conway, G., Joshi, A., Leach, F., García, A., Senecal, P.K., 2021. A review of current and future powertrain technologies and trends in 2020. Transp. Eng. 5, 100080.
E.V. Database.(2024) Electric Vehicle Database. ⟨https://ev-database.org/car/1996/BMW-iX1-eDrive20⟩ (accessed.
Deb, N., Singh, R., Brooks, R.R., Bai, K., 2021. A review of extremely fast charging stations for electric vehicles. Energies 14 (22), 7566.
Dhara, S., Shrivastav, A.K., Sadhu, P.K., 2022. Smart grid modernization: opportunities and challenges. Electr. Grid Mod. 5.
Diaz, N.L., Luna, A.C., Vasquez, J.C., Guerrero, J.M., 2016. Centralized control architecture for coordination of distributed renewable generation and energy storage in islanded AC microgrids. IEEE Trans. Power Electron. 32 (7), 5202–5213.
Dimsdale, T., 2019. Rules of the road: the geopolitics of electric vehicles in Eurasia. E3G.
Duan, G.F.N.X., 2010. Heat transfer in phase change materials for thermal management of electric vehicle battery modules. Int. J. Heat. Mass Transf. 53, 5176–5182.
Ebadpour, M.J.M., Talla, Jakub, Hashemi-Dezaki, H., Peroutka, Z., 2023. A digital twinning approach for the internet of unmanned electric vehicles (IoUEVs) in the metaverse. Electronics 12.
Edenhofer, O., et al., 2011. IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Intergovernmental Panel on Climate change (IPCC). Cambridge University Press, Cambridge/New York.
Ehsani, M., Singh, K.V., Bansal, H.O., Mehrjardi, R.T., 2021. State of the art and trends in electric and hybrid electric vehicles. Proc. IEEE 109 (6), 967–984.

Elumalai, N., Karthik, M., Giridharan, V., Kumar, C.S., 2020. Mechanical properties of titanium carbide reinforced aluminum metal matrix composites. In: AIP Conference Proceedings, 2271. AIP Publishing.
A. Energy. (2024) Charging, Incentives and Resources. ⟨https://austinenergy.com/green-power/plug-in-austin⟩ (accessed.
Fan, Y., Bao, Y., Ling, C., Chu, Y., Tan, X., Yang, S., 2019a. Experimental study on the thermal management performance of air cooling for high energy density cylindrical lithium-ion batteries. Appl. Therm. Eng. 155, 96–109.
Fan, Y.B.Y., Ling, C., Chu, Y., Tan, X., Yang, S., 2019b. Experimental study on the thermal management performance of air cooling for high energy density cylindrical lithium-ion batteries. Appl. Therm. Eng. 155, 96–109.
Fang, B., Li, B., Li, X., Jia, Y., Xu, W., Liao, Y., 2021. Multi-objective comprehensive charging/discharging scheduling strategy for electric vehicles based on the improved particle swarm optimization algorithm. Front. Energy Res. 9, 811964.
Fantuzzi, N., Bacciocchi, M., Benedetti, D., Agnelli, J., 2021. The use of sustainable composites for the manufacturing of electric cars. Compos. Part C: Open Access 4, 100096.
Finnveden, G., et al., 2009. Recent developments in life cycle assessment. J. Environ. Manag. 91 (1), 1–21.
G. E. O. 2023. Electric car sales break new records with momentum expected to continue through 2023. ⟨https://www.iea.org/reports/global-ev-outlook-2023/executive-summary⟩ (accessed.
Ganesh, A.H., Xu, B., 2022. A review of reinforcement learning based energy management systems for electrified powertrains: progress, challenge, and potential solution. Renew. Sustain. Energy Rev. 154, 111833.
Gnanavendan, S., et al., 2024. Challenges, solutions and future trends in EV-technology: a review. IEEE Access.
González-Rivera, E., García-Triviño, P., Sarrias-Mena, R., Torreglosa, J.P., Jurado, F., Fernández-Ramírez, L.M., 2021. Model predictive control-based optimized operation of a hybrid charging station for electric vehicles. IEEE Access 9, 115766–115776.
Gutsch, M., Leker, J., 2024. Costs, carbon footprint, and environmental impacts of lithium-ion batteries–From cathode active material synthesis to cell manufacturing and recycling. Appl. Energy 353, 122132.
Hassanzadeh, M., Rahmani, Z., 2022. A predictive controller for real-time energy management of plug-in hybrid electric vehicles. Energy 249, 123663.
Hawkins, T.R., Singh, B., Majeau-Bettez, G., Strømman, A.H., 2013. Comparative environmental life cycle assessment of conventional and electric vehicles. J. Ind. Ecol. 17 (1), 53–64.
He, H., et al., 2024. Deep reinforcement learning based energy management strategies for electrified vehicles: Recent advances and perspectives. Renew. Sustain. Energy Rev. 192, 114248.
He, X., Zhan, W., Hu, Y., 2018. Consumer purchase intention of electric vehicles in China: the roles of perception and personality. J. Clean. Prod. 204, 1060–1069.
Heng Li, M.B.K., Chiu, I.-Ju, Gao, Dianzhu, Peng, Jun, Huang, Zhiwu, 2023. An intelligent digital twin model for the battery management systems of electric. Int. Journel Green. Energy.
Hernandez, M., Messagie, M., Hegazy, O., Marengo, L., Winter, O., Van Mierlo, J., 2017. Environmental impact of traction electric motors for electric vehicles applications. Int. J. Life Cycle Assess. 22, 54–65.
Hofmann, J., Guan, D., Chalvatzis, K., Huo, H., 2016. Assessment of electrical vehicles as a successful driver for reducing CO2 emissions in China. Appl. Energy 184, 995–1003.
Holmberg, K., Erdemir, A., 2019. The impact of tribology on energy use and CO2 emission globally and in combustion engine and electric cars. Tribol. Int. 135, 389–396.
Holmberg, K., Andersson, P., Erdemir, A., 2012. Global energy consumption due to friction in passenger cars. Tribol. Int. 47, 221–234.
Hong, J., et al., 2024. Multi-forword-step state of charge prediction for real-world electric vehicles battery systems using a novel LSTM-GRU hybrid neural network. eTransportation 20, 100322.
Hong, X.Z.S., Chen, K., Wang, S., 2018. Design of flow configuration for parallel aircooled battery thermal management system with secondary vent. Int. J. Heat. Mass Transf. 116, 1204–1212.
Hu, J., et al., 2024. Performance analysis of AI-based energy management in electric vehicles: a case study on classic reinforcement learning. Energy Convers. Manag. 300, 117964.
Huang, R., He, H., Zhao, X., Wang, Y., Li, M., 2022. Battery health-aware and naturalistic data-driven energy management for hybrid electric bus based on TD3 deep reinforcement learning algorithm. Appl. Energy 321, 119353.
Huo, Z.R.Y., Liu, X., Zhao, J., 2015. Investigation of power battery thermal management by using mini-channel cold plate. Energy Convers. Manag. 89, 387–395.
Hussain, A., Tso, C.Y., Chao, C.Y., 2016. Experimental investigation of a passive thermal management system for high-powered lithium ion batteries using nickel foam-paraffin composite. Energy 115, 209–218.
Hussain, C.Y.T.A., Chao, C.Y.H., 2016. Experimental investigation of a passive thermal management system for high-powered lithium ion batteries using nickel foam-paraffin composite. Energy 115, 209–218.
Ijaz Malik, M.A., et al., 2023. Response surface methodology application on lubricant oil degradation, performance, and emissions in SI engine: a novel optimization of alcoholic fuel blends, 00368504221148342 Sci. Prog. 106 (1), 00368504221148342.
Ishaque, M.R., et al., 2021. Fuzzy logic-based duty cycle controller for the energy management system of hybrid electric vehicles with hybrid energy storage system. Appl. Sci. 11 (7), 3192.
Jafari Kaleybar, H., Brenna, M., Li, H., Zaninelli, D., 2022. Fuel cell hybrid locomotive with modified fuzzy logic based energy management system. Sustainability 14 (14), 8336.
A. Jatavallabha, Tesla's Autopilot: Ethics and Tragedy, arXiv preprint arXiv:2409.17380, 2024.
Javadi, M., Baghramian, A., 2024. Electricity trading of multiple home microgrids through V2X based on game theory. Sustain. Cities Soc. 101, 105046.
Javani, I.D.N., Naterer, G.F., Yilbas, B.S., 2014a. Heat transfer and thermal management with PCMs in a Li-ion battery cell for electric vehicles. Int. J. Heat. Mass Transf. 72, 690–703.
Javani, I.D.N., Naterer, G.F., Rohrauer, G.L., 2014b. Modeling of passive thermal management for electric vehicle battery packs with PCM between cells. Appl. Therm. Eng. 73, 307–316.
Jayaram, J., Chetan, J., Nayak, B., 2024. Electric vehicle health monitoring with electric vehicle range prediction and route planning. J. Inform. Web Eng. 3 (1), 265–276.
Jelen, G., Babic, J., Podobnik, V., 2022. A multi-agent system for context-aware electric vehicle fleet routing: a step towards more sustainable urban operations. J. Clean. Prod. 374, 134047.
Jenn, A., Azevedo, I.L., Fischbeck, P., 2015. How will we fund our roads? A case of decreasing revenue from electric vehicles. Transp. Res. Part A: Policy Pract. 74, 136–147.
Jia, C., Qiao, W., Cui, J., Qu, L., 2022. Adaptive model-predictive-control-based real-time energy management of fuel cell hybrid electric vehicles. IEEE Trans. Power Electron. 38 (2), 2681–2694.
Jiaqiang, D.H.E., Qiu, A., Zhu, H., Deng, Y., Chen, J., Zhao, X., Zuo, W., Wang, H., Chen, J., Peng, Q., 2018. Orthogonal experimental design of liquid-cooling structure on the cooling effect of a liquid-cooled battery thermal management system. Appl. Therm. Eng. 132, 508–520.
Jouda, B., Al-Mahasneh, A.J., Mallouh, M.A., 2024. Deep stochastic reinforcement learning-based energy management strategy for fuel cell hybrid electric vehicles. Energy Convers. Manag. 301, 117973.
Jungmeier, G., Dunn, J., Elgowainy, A., Ehrenberger, S., Widmer, R., 2015. Estimated environmental effects of the worldwide electric vehicle fleet: a life cycle assessment in task 19 of the international energy agency (IEA) on hybrid and electric vehicles (HEV). Proc. EEVC.
Kalaivani, P., Joice, C.S., 2024. Design and modelling of a neural network-based energy management system for solar PV, fuel cell, battery and ultracapacitor-based hybrid electric vehicle. Electr. Eng. 106 (1), 689–709.
Kaluva, S.T., Pathak, A., Ongel, A., 2020. Aerodynamic drag analysis of autonomous electric vehicle platoons. Energies 13 (15), 4028.
Karaaslan, E., Noori, M., Lee, J., Wang, L., Tatari, O., Abdel-Aty, M., 2018. Modeling the effect of electric vehicle adoption on pedestrian traffic safety: An agent-based approach. Transp. Res. Part C: Emerg. Technol. 93, 198–210.
Karmaker, A.K., Roy, S., Ahmed, M.R., 2019. Analysis of the impact of electric vehicle charging station on power quality issues. 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE). IEEE, pp. 1–6.
Katuri, R., Gorantla, S., 2021. Math function-based controller combined with PI and PID applied to ultracapacitor based solar-powered electric vehicle. Afr. J. Sci., Technol., Innov. Dev. 13 (4), 509–526.
Ke, W., Zhang, S., He, X., Wu, Y., Hao, J., 2017. Well-to-wheels energy consumption and emissions of electric vehicles: Mid-term implications from real-world features and air pollution control progress. Appl. Energy 188, 367–377.
Khaleel, M., et al., 2024. Electric vehicles in China, Europe, and the United States: current trend and market comparison. Int. J. Electr. Eng. Sustain. 1–20.
Khamari, S.S., Kiran, K., Behera, R.K., Yegireddy, N.K., Sharma, R., Muduli, U.R., 2023. Optimized design and improved performance of IPM-BLDC Motor for light electric vehicles. 2023 IEEE 3rd International Conference on Sustainable Energy and Future Electric Transportation (SEFET). IEEE, pp. 1–6.
Khateeb, S.A., Selman, J.R., Al-Hallaj, S., 2004. Design and simulation of a lithium-ion battery with a phase change material thermal management system for an electric scooter. J. Power Sources 128, 292–307.
Khateeb, S.A.S.A., Farid, M., Selman, J.R., Al-Hallaj, S., 2005. Thermal management of Li-ion battery with phase change material for electric scooters experimental validation. J. Power Sources 142, 345–353.
Konijeti, M.S.N.K., Murugan Lakshmi, B., 2024. Charging control of lithium-ion battery and energy management system in electric vehicles. Energy Storage 6 (5), e667.
Kumar, R.R., Alok, K., 2020. Adoption of electric vehicle: a literature review and prospects for sustainability. J. Clean. Prod. 253, 119911.
Lan, J.X.C., Qiao, Y., Ma, Y., 2016. Thermal management for high power lithium-ion battery by minichannel aluminum tubes. Appl. Therm. Eng. 101, 284–292.
Lan, Y., Frikha, M.A., Croonen, J., Benômar, Y., El Baghdadi, M., Hegazy, O., 2022. Design optimization of a switched reluctance machine with an improved segmental rotor for electric vehicle applications. Energies 15 (16), 5772.
Lebrouhi, B., Khattari, Y., Lamrani, B., Maaroufi, M., Zeraouli, Y., Kousksou, T., 2021. Key challenges for a large-scale development of battery electric vehicles: a comprehensive review. J. Energy Storage 44, 103273.
Lee, G., Song, J., Han, J., Lim, Y., Park, S., 2023. Study on energy consumption characteristics of passenger electric vehicle according to the regenerative braking stages during real-world driving conditions. Energy 283, 128745.
Lemeski, A.T., Ebrahimi, R., Zakariazadeh, A., 2022. Optimal decentralized coordinated operation of electric vehicle aggregators enabling vehicle to grid option using distributed algorithm. J. Energy Storage 54, 105213.
Li, D.Z.X., Zhang, G., Wang, C., Lin, R., Zhong, Z., 2019b. Experimental investigation of the thermal performance of silicon cold plate for battery thermal management system. Appl. Therm. Eng. 155, 331–340.

Li, F.H.X., Zhang, G., Huang, Q., Zhou, D., 2019a. Experiment and simulation for pouch battery with silica cooling plates and copper mesh based air cooling thermal management system. Appl. Therm. Eng. 146, 866–880.
Li, J.Y.K., Chen, H., Wang, Q., 2018. Water cooling based strategy for lithium ion battery pack dynamic cycling for thermal management system. Appl. Therm. Eng. 132, 575–585.
Li, M.R. Weihan, Badedae, J., Jöst, D., Schultef, D., Sauer, D.U., 2020. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. J. Energy Storage 30. https://doi.org/10.1016/j.est.2020.101557.
Li, P., Yang, M., Tang, Y., Yu, Y., Li, M., 2021. Robust decentralized coordination of transmission and active distribution networks. IEEE Trans. Ind. Appl. 57 (3), 1987–1994.
Li, Z., Shi, Z., Gao, J., Xi, J., 2023. Research on regenerative braking control strategy for single-pedal pure electric commercial vehicles. World Electr. Veh. J. 14 (8), 229.
Lieven, T., 2015. Policy measures to promote electric mobility–a global perspective. Transp. Res. Part A: Policy Pract. 82, 78–93.
Lim, K.L., Speidel, S., Bräunl, T., 2022. A comparative study of AC and DC public electric vehicle charging station usage in Western Australia. Renew. Sustain. Energy Transit. 2, 100021.
Lin, S.X.C., Chang, G., Liu, J., 2015. Experiment and simulation of a LiFePO4 battery pack with a passive thermal management system using composite phase change material and graphite sheets. J. Power Sources 275, 742–749.
Lin, Y., et al., 2024. Progress and summary of reinforcement learning on energy management of MPS-EV. Heliyon 10 (1).
Ling, J.C.Z., Fang, X., Zhang, Z., Xu, T., Gao, X., Wang, S., 2014. Experimental and numerical investigation of the application of phase change materials in a simulative power batteries thermal management system. Appl. Energy 121, 104–113.
Liu, B., Yang, J., Zhang, X., Li, X., 2023. Development and low cost control of glass fiber reinforced thermoplastic composites-based electric vehicle tailgate. J. Mater. Eng. Perform. 1–22.
Liu, B., Wei, X., Sun, C., Wang, B., Huo, W., 2024. A controllable neural network-based method for optimal energy management of fuel cell hybrid electric vehicles. Int. J. Hydrog. Energy 55, 1371–1382.
Liu, J., Jayakumar, P., Stein, J.L., Ersal, T., 2017. Combined speed and steering control in high-speed autonomous ground vehicles for obstacle avoidance using model predictive control. IEEE Trans. Veh. Technol. 66 (10), 8746–8763.
Liu, J., Zhao, W., Xu, C., 2021. An efficient on-ramp merging strategy for connected and automated vehicles in multi-lane traffic. IEEE Trans. Intell. Transp. Syst. 23 (6), 5056–5067.
Lü, X., et al., 2022. Hybrid electric vehicles: a review of energy management strategies based on model predictive control. J. Energy Storage 56, 106112.
Ma, Z., Sun, D., 2020. Energy recovery strategy based on ideal braking force distribution for regenerative braking system of a four-wheel drive electric vehicle. IEEE Access 8, 136234–136242.
Malik, M.A.I., Usman, M., Bashir, R., Hanif, M.S., Zubair, S.W.H., 2022. Use of methanol-gasoline blend: a comparison of SI engine characteristics and lubricant oil condition. J. Chin. Inst. Eng. 45 (5), 402–412.
Malik, M.A.I., Mujtaba, M., Kalam, M., Silitonga, A.S., Ikram, A., 2023b. Recent advances in hydrogen supplementation to promote biomass fuels for reducing greenhouse gases. Int. J. Hydrog. Energy.
Malik, M.A.I., Kalam, M., Mujtaba, M., Almomani, F., 2023a. A review of recent advances in the synthesis of environmentally friendly, sustainable, and nontoxic bio-lubricants: recommendations for the future implementations. Environ. Technol. Innov., 103366
Merkle, A.S.S.L., Torben Grummel, J., Lienkamp, M., 2019. Architecture of a digital twin for enabling digital services for battery systems. IEEE Int. Conf. Ind. Cyber Phys. Syst. (ICPS) 155–160.
Millo, F., Rolando, L., Tresca, L., Pulvirenti, L., 2023. Development of a neural network-based energy management system for a plug-in hybrid electric vehicle. Transp. Eng. 11, 100156.
Min, D., Song, Z., Chen, H., Wang, T., Zhang, T., 2022. Genetic algorithm optimized neural network based fuel cell hybrid electric vehicle energy management strategy under start-stop condition. Appl. Energy 306, 118036.
Moawad, A., Kim, N., Shidore, N., Rousseau, A., 2016. Assessment of vehicle sizing, energy consumption and cost through large scale simulation of advanced vehicle technologies.
Mohammad, K.S., Jaber, A.S., 2022. Comparison of electric motors used in electric vehicle propulsion system. Indones. J. Electr. Eng. Comput. Sci. 27 (1), 11.
Mohammadian, S.K., Zhang, Y., 2015. Thermal management improvement of an air-cooled high-power lithium-ion battery by embedding metal foam. J. Power Sources 296, 305–313.
Mohammadian, Y.Z.S.K., 2015. Thermal management optimization of an aircooled Li-ion battery module using pin-fin heat sinks for hybrid electric vehicles. J. Power Sources 273, 431–439.
Mohammed, A., Saif, O., Abo-Adma, M., Fahmy, A., Elazab, R., 2024. Strategies and sustainability in fast charging station deployment for electric vehicles. Sci. Rep. 14 (1), 283.
Mohanty, A.K., et al., 2023. Sustainable composites for lightweight and flame retardant parts for electric vehicles to boost climate benefits: a perspective. Compos. Part C: Open Access 12, 100380.
Mohanty, S.B., Mohanty, S., 2024. A novel state machine-fractional order PID control strategy for energy management framework to optimize the consumption from fuel cell in DC microgrid. IEEE Access.
Najafi, A., Jasiński, M., Leonowicz, Z., 2022. A hybrid distributed framework for optimal coordination of electric vehicle aggregators problem. Energy 249, 123674.
Nasab, M.A., Al-Shibli, W.K., Zand, M., Ehsan-maleki, B., Padmanaban, S., 2024. Charging management of electric vehicles with the presence of renewable resources. Renew. Energy Focus 48, 100536.
Nguyen, D.-D., Pham, T.-T., Le, T.-T., Do, T.D., Goto, T., Yukita, K., 2023. Impact of parameter mismatch on three-phase dual-active-bridge converters. Electronics 12 (12), 2609.
Nguyen, N.-D., Yoon, C., Lee, Y.I., 2022. A standalone energy management system of battery/supercapacitor hybrid energy storage system for electric vehicles using model predictive control. IEEE Trans. Ind. Electron. 70 (5), 5104–5114.
Niri, A.J., Poelzer, G.A., Zhang, S.E., Rosenkranz, J., Pettersson, M., Ghorbani, Y., 2024. Sustainability challenges throughout the electric vehicle battery value chain. Renew. Sustain. Energy Rev. 191, 114176.
Noel, L., et al., 2019. The technical challenges to V2G. Vehicle-to-Grid: A Sociotechnical Transition Beyond Electric Mobility 65–89.
Noel, L., McCormack, R., 2014. A cost benefit analysis of a V2G-capable electric school bus compared to a traditional diesel school bus. Appl. Energy 126, 246–255.
Nouri, A., Lachheb, A., El Amraoui, L., 2024. Optimizing efficiency of Vehicle-to-Grid system with intelligent management and ANN-PSO algorithm for battery electric vehicles. Electr. Power Syst. Res. 226, 109936.
Olabi, A.G., Abbas, Q., Shinde, P.A., Abdelkareem, M.A., 2023. Rechargeable batteries: technological advancement, challenges, current and emerging applications. Energy 266, 126408.
Onat, N.C., Kucukvar, M., Tatari, O., 2015. Conventional, hybrid, plug-in hybrid or electric vehicles? State-based comparative carbon and energy footprint analysis in the United States. Appl. Energy 150, 36–49.
Pandey, D., et al., 2022. Energized composites for electric vehicles: a dual function energy-storing supercapacitor-based carbon fiber composite for the body panels. Small 18 (9), 2107053.
Pavlićević, A., Mujović, S., 2022. Impact of reactive power from public electric vehicle stations on transformer aging and active energy losses. Energies 15 (19), 7085.
Peng, X.Z.Y., Song, Y., Liu, D., 2019. A low cost flexible digital twin platform for spacecraft lithium-ion battery pack degradation assessment. IEEE Int. Instrum. Meas. Technol. Conf. 1–6.
Pereira, D.F., da Costa Lopes, F., Watanabe, E.H., 2020. Nonlinear model predictive control for the energy management of fuel cell hybrid electric vehicles in real time. IEEE Trans. Ind. Electron. 68 (4), 3213–3223.
Petrauskienė, K., Galinis, A., Kliaugaitė, D., Dvarionienė, J., 2021. Comparative environmental life cycle and cost assessment of electric, hybrid, and conventional vehicles in Lithuania. Sustainability 13 (2), 957.
Pindoriya, R., Rajpurohit, B., Kumar, R., Srivastava, K., 2018. Comparative analysis of permanent magnet motors and switched reluctance motors capabilities for electric and hybrid electric vehicles. 2018 IEEMA Engineer Infinite Conference (eTechNxT). IEEE, pp. 1–5.
Pipitone, E., Caltabellotta, S., Occhipinti, L., 2021. A life cycle environmental impact comparison between traditional, hybrid, and electric vehicles in the European context. Sustainability 13 (19), 10992.
Prajapati, P., Balamurugan, S., 2023. Leveraging GaN for DC-DC power modules for efficient EVs: a review. IEEE Access.
Punyavathi, R., Pandian, A., Singh, A.R., Bajaj, M., Tuka, M.B., Blazek, V., 2024. Sustainable power management in light electric vehicles with hybrid energy storage and machine learning control. Sci. Rep. 14 (1), 5661.
Qian, L., Yin, J., 2017. Linking Chinese cultural values and the adoption of electric vehicles: the mediating role of ethical evaluation. Transp. Res. Part D: Transp. Environ. 56, 175–188.
Qiang, X., Zhong, C., Ziqi, Z., Xueliang, H., Xiaohui, L., 2020. Route planning and charging navigation strategy for electric vehicles based on real-time traffic information and grid information. In: IOP Conference Series: Materials Science and Engineering, 752. IOP Publishing, 012011.
Qiu, D., Wang, Y., Zhang, T., Sun, M., Strbac, G., 2022. Hybrid multiagent reinforcement learning for electric vehicle resilience control towards a low-carbon transition. IEEE Trans. Ind. Inform. 18 (11), 8258–8269.
Qu, Y.S.X., Liu, D., Cui, X., Peng, Y., 2024. Lithium-ion battery performance degradation evaluation in dynamic operating conditions based on a digital twin model. Microelectron. Reliab. 220 (114).
Raj, J.A.P.S., et al., 2024. Thermal management strategies and power ratings of electric vehicle motors. Renew. Sustain. Energy Rev. 189, 113874.
Rajendran, G., Vaithilingam, C.A., Misron, N., Naidu, K., Ahmed, M.R., 2021a. Voltage oriented controller based vienna rectifier for electric vehicle charging stations. IEEE Access 9, 50798–50809.
Rajendran, G., Vaithilingam, C.A., Misron, N., Naidu, K., Ahmed, M.R., 2021b. A comprehensive review on system architecture and international standards for electric vehicle charging stations. J. Energy Storage 42, 103099.
Ramachandran, R., 2018. Recursive Estimation of Battery Pack Parameters in Electric Vehicles. IEEE Int. Conf. Comput. Intell. Comput. Res. 1–7.
Regragui, Y., Moussa, N., 2023. A real-time path planning for reducing vehicles traveling time in cooperative-intelligent transportation systems. Simul. Model. Pract. Theory 123, 102710.
Rezaei, H., Ghomsheh, M.J., Kowsary, F., Ahmadi, P., 2021. Performance assessment of a range-extended electric vehicle under real driving conditions using novel PCM-based HVAC system. Sustain. Energy Technol. Assess. 47, 101527.
Rietmann, N., Lieven, T., 2019. How policy measures succeeded to promote electric mobility–Worldwide review and outlook. J. Clean. Prod. 206, 66–75.
Rind, S.J., Ren, Y., Hu, Y., Wang, J., Jiang, L., 2017. Configurations and control of traction motors for electric vehicles: a review. Chin. J. Electr. Eng. 3 (3), 1–17.

Rudbari, A., Khosravy, M., Witkowski, O., 2024. Genetic algorithm applications to power management. Frontiers in Genetics Algorithm Theory and Applications. Springer, pp. 157–175.

Ruz-Hernandez, J.A., Djilali, L., Ruz Canul, M.A., Boukhnifer, M., Sanchez, E.N., 2022. Neural inverse optimal control of a regenerative braking system for electric vehicles. Energies 15 (23), 8975.

Saha, S., Mukherjee, K., 2023. An asynchronous exciter fed brushless wound field synchronous motor drive for electrified vehicle application. 2023 International Conference on Power, Instrumentation, Control and Computing (PICC). IEEE, pp. 1–6.

Salari, A., Zeinali, M., Marzband, M., 2024. Model-free reinforcement learning-based energy management for plug-in electric vehicles in a cooperative multi-agent home microgrid with consideration of travel behavior. Energy 288, 129725.

Saldarriaga-Zuluaga, S.D., López-Lezama, J.M., Muñoz-Galeano, N., 2021. Hybrid harmony search algorithm applied to the optimal coordination of overcurrent relays in distribution networks with distributed generation. Appl. Sci. 11 (19), 9207.

Salvatti, G.A., Carati, E.G., Cardoso, R., da Costa, J.P., Stein, C.M. d O., 2020. Electric vehicles energy management with V2G/G2V multifactor optimization of smart grids. Energies 13 (5), 1191.

Samimi, A.B.F., Azizi, M., Karimi, G., 2016. Thermal management analysis of a Li-ion battery cell using phase change material loaded with carbon fibers. Energy 96, 355–371.

Savari, G.F., et al., 2023. Assessment of charging technologies, infrastructure and charging station recommendation schemes of electric vehicles: a review. Ain Shams Eng. J. 14 (4), 101938.

Savari, G.F., Krishnasamy, V., Sathik, J., Ali, Z.M., Aleem, S.H.A., 2020. Internet of Things based real-time electric vehicle load forecasting and charging station recommendation. ISA Trans. 97, 431–447.

Saw, L.H., et al., 2018. Novel thermal management system using mist cooling for lithium-ion battery packs. Appl. Energy 223, 146–158.

Saw, Y.Y.L.H., Tay, A.A.O., Chong, W.T., Kuan, S.H., Yew, M.C., 2016. Computational fluid dynamic and thermal analysis of lithium-ion battery pack with air cooling. Appl. Energy 177, 783–792.

Schuitema, G., Anable, J., Skippon, S., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transp. Res. Part A: Policy Pract. 48, 39–49.

Sebai, M., Rejeb, L., Denden, M.A., Amor, Y., Baati, L., Said, L.B., 2022. Optimal electric vehicles route planning with traffic flow prediction and real-time traffic incidents. Int. J. Electr. Comput. Eng. Res. 2 (1), 1–12.

Senecal, P., Leach, F., 2019. Diversity in transportation: why a mix of propulsion technologies is the way forward for the future fleet. Results Eng. 4, 100060.

Sergiy Korotunov, G.T., Okhmak, V., 2020. Genetic algorithms as an optimization approach for managing electric vehicles charging in the smart grid. Natl. Univ. "Zaporizhzhia Polytech.

Shang, H., Sun, Y., Huang, D., Meng, F., 2024. Life cycle assessment of atmospheric environmental impact on the large-scale promotion of electric vehicles in China. Resour., Environ. Sustain. 15, 100148.

Shikata, T.Y.H., Arai, Kouji, Nakano, T., Hatanaka, K., Fujikawa, H., 2019. Digital twin environment to integrate vehicle simulation and physical verification. SEI Tech. Rev.

Shukla, V., Mukherjee, V., Singh, B., 2024. A hybrid optimization for coordinated control of distributed generations. Eng. Appl. Artif. Intell. 136, 109023.

Siddula, S., 2024. Optimizing electric vehicle energy consumption with fuzzy based energy management system. 2024 IEEE International Conference for Women in Innovation, Technology & Entrepreneurship (ICWITE). IEEE, pp. 631–636.

Singh, M., Yuksel, T., Michalek, J.J., Azevedo, I.M., 2024. Ensuring greenhouse gas reductions from electric vehicles compared to hybrid gasoline vehicles requires a cleaner US electricity grid. Sci. Rep. 14 (1), 1639.

Sorour, A., Fazeli, M., Monfared, M., Fahmy, A.A., Searle, J.R., Lewis, R.P., 2022. MILP optimized management of domestic PV-battery using two days-ahead forecasts. IEEE Access 10, 29357–29366.

Stennikov, V., Barakhtenko, E., Mayorov, G., Sokolov, D., Zhou, B., 2022. Coordinated management of centralized and distributed generation in an integrated energy system using a multi-agent approach. Appl. Energy 309, 118487.

Su, G.-J., 2018. Comparison of Si, SiC, and GaN based isolation converters for onboard charger applications. 2018 IEEE Energy Conversion Congress and Exposition (ECCE). IEEE, pp. 1233–1239.

Suganthi, K., Kumar, M.A., Harish, N., HariKrishnan, S., Rajesh, G., Reka, S.S., 2023. Advanced driver assistance system based on IoT V2V and V2I for vision enabled lane changing with futuristic drivability. Sensors 23 (7), 3423.

Ta, M.C., Nguyen, B.-M., Vo-Duy, T., 2022. Fuzzy logic control for motor drive performance improvement in EV applications. Intelligent Control and Smart Energy Management: Renewable Resources and Transportation. Springer, pp. 395–427.

Tagliaferri, C., et al., 2016. Life cycle assessment of future electric and hybrid vehicles: a cradle-to-grave systems engineering approach. Chem. Eng. Res. Des. 112, 298–309.

Tang, H.H., Ahmad, N.S., 2024. Fuzzy logic approach for controlling uncertain and nonlinear systems: a comprehensive review of applications and advances. Syst. Sci. Control Eng. 12 (1), 2394429.

Tang, J.L.A., Lou, L., Shan, C., Yuan, X., 2019. Optimization design and numerical study on water cooling structure for power lithium battery pack. Appl. Therm. Eng. 159.

Tao, F., et al., 2019. Digital twin-driven product design framework. Int. J. Prod. Res. 57 (12), 3935–3953.

Tete, P.R., Gupta, M.M., Joshi, S.S., 2021. Developments in battery thermal management systems for electric vehicles: a technical review. J. Energy Storage 35, 102255.

Thakur, A.K., et al., 2020. A state of art review and future viewpoint on advance cooling techniques for Lithium–ion battery system of electric vehicles. J. Energy Storage 32, 101771.

Tie, S.F., Tan, C.W., 2013. A review of energy sources and energy management system in electric vehicles. Renew. Sustain. Energy Rev. 20, 82–102.

Torkan, R., Ilinca, A., Ghorbanzadeh, M., 2022. A genetic algorithm optimization approach for smart energy management of microgrids. Renew. Energy 197, 852–863.

U. S. D. o. Transportation. (2024) National Highway Traffic Safety Administration. ⟨https://www.nhtsa.gov/report-a-safety-problem?gad=1&gclid=Cj0KCQjw9fqnBhDSARIsAHlcQYTOi4YkgtBZMdhRfR245kHMuJOlmyzOq23DJDG4HX_6Ouuu9_LHvyMaAkviEALw_wcB&gclsrc=aw.ds#index⟩ (accessed.

Usman, M., et al., 2023a. Experimental assessment of performance, emission and lube oil deterioration using gasoline and LPG for a sustainable environment. Case Stud. Therm. Eng. 49, 103300.

Usman, M., et al., 2023b. Comparative assessment of ethanol and methanol–ethanol blends with gasoline in SI engine for sustainable development. Sustainability 15 (9), 7601.

Vandana, A.G., Ketan Panigrahi, B., 2021. Multi-dimensional digital twin of energy storage system for electric vehicles: a brief review. Energy Storage 1–14.

Verma, S., Dwivedi, G., Verma, P., 2022. Life cycle assessment of electric vehicles in comparison to combustion engine vehicles: a review. Mater. Today.: Proc. 49, 217–222.

Viji, D., Dhanka, S., Binda, M., Thomas, M., 2024. Hybrid STO-IWGAN method based energy optimization in fuel cell electric vehicles. Energy Convers. Manag. 305, 118249.

Wang, C., et al., 2022b. High heat-resistant (250° C) epoxy resin composites with excellent dielectric properties. J. Appl. Polym. Sci. 139 (40), e52963.

Wang, D., Mei, L., Xiao, F., Song, C., Qi, C., Song, S., 2024a. Energy management strategy for fuel cell electric vehicles based on scalable reinforcement learning in novel environment. Int. J. Hydrog. Energy 59, 668–678.

Wang, G.Z.C., Meng, L., Li, X., 2017b. Liquid cooling based on thermal silica plate for battery thermal management system 1–12.

Wang, L., Sharkh, S., Chipperfield, A., 2018. Optimal decentralized coordination of electric vehicles and renewable generators in a distribution network using A* search. Int. J. Electr. Power Energy Syst. 98, 474–487.

Wang, X.L.Z., Zhang, G., Lv, Y., Wang, C., He, F., Yang, C., Yang, C., 2017a. Thermal management investigation for lithium-ion battery module with different phase change materials. RSC Adv. 7, 42909–42918.

Wang, Y., Biswas, A., Rodriguez, R., Keshavarz-Motamed, Z., Emadi, A., 2022a. Hybrid electric vehicle specific engines: State-of-the-art review. Energy Rep. 8, 832–851.

Wang, Y., Chen, Z., Sun, M., Sun, Q., 2024b. Enhancing active disturbance rejection design via deep reinforcement learning and its application to autonomous vehicle. Expert Syst. Appl. 239, 122433.

Wazeer, A., Das, A., Abeykoon, C., Sinha, A., Karmakar, A., 2022. Composites for electric vehicles and automotive sector: a review,". Green. Energy Intell. Transp., 100043

White, L.V., Sintov, N.D., 2017. You are what you drive: environmentalist and social innovator symbolism drives electric vehicle adoption intentions. Transp. Res. Part A: Policy Pract. 99, 94–113.

Xie, Z.G.J., Zang, M., Wang, S., 2017. Structural optimization of lithium-ion battery pack with forced air cooling system. Appl. Therm. Eng. 126, 583–593.

Xiong, S., Ji, J., Ma, X., 2020. Environmental and economic evaluation of remanufacturing lithium-ion batteries from electric vehicles. Waste Manag. 102, 579–586.

Xu, B., et al., 2020. Parametric study on reinforcement learning optimized energy management strategy for a hybrid electric vehicle. Appl. Energy 259, 114200.

Yang, D., Sarma, N.J., Hyland, M.F., Jayakrishnan, R., 2021b. Dynamic modeling and real-time management of a system of EV fast-charging stations. Transp. Res. Part C: Emerg. Technol. 128, 103186.

Yang, G., Liu, S., Ye, M., Tang, C., Fan, Y., Liu, Y., 2023. A game lane changing model considering driver's risk level in ramp merging scenario. World Electr. Veh. J. 14 (7), 172.

Yang, H., et al., 2024b. Life cycle assessment of secondary use and physical recycling of lithium-ion batteries retired from electric vehicles in China. Waste Manag. 178, 168–175.

Yang, H., Fulton, L., Kendall, A., 2024a. A Review of charging infrastructure requirements for US electric light-duty vehicles. Renew. Sustain. Energy Rev. 200, 114608.

Yang, L., Yu, B., Yang, B., Chen, H., Malima, G., Wei, Y.-M., 2021a. Life cycle environmental assessment of electric and internal combustion engine vehicles in China. J. Clean. Prod. 285, 124899.

Yang, W., Tan, Y., Yoshida, K., Takakuwa, S., 2017. Digital twin-driven simulation for a cyber-physical system in Industry 4.0. DAAAM Int. Sci. Book 201, 227–234.

Yang, X.Z.N., Li, G., Hua, D., 2015. Assessment of the forced air-cooling performance for cylindrical lithium-ion battery packs: a comparative analysis between aligned and staggered cell arrangements. Appl. Therm. Eng. 80, 55–65. https://doi.org/10.1016/j.applthermaleng.2015.01.049.

Yavasoglu, H.A., Tetik, Y.E., Ozcan, H.G., 2020. Neural network-based energy management of multi-source (battery/UC/FC) powered electric vehicle. Int. J. Energy Res. 44 (15), 12416–12429.

Yavuz, M., Kivanç, Ö.C., 2024. Optimization of a cluster-based energy management system using deep reinforcement learning without affecting prosumer comfort: V2X technologies and peer-to-peer energy trading. IEEE Access.

Yılmaz, M., Özdemir, S., 2021. Review of motors used in commercial electric vehicles. Proc. 5th Int. Mediterr. Sci. Eng. Congr. (IMSEC 2020) Antalya, Turk. 21–23.

Yuan, H., et al., 2024. Battery electric vehicle charging in China: energy demand and emissions trends in the 2020s. Appl. Energy 365, 123153.

Zahedmanesh, A., Muttaqi, K.M., Sutanto, D., 2020. Coordinated charging control of electric vehicles while improving power quality in power grids using a hierarchical decision-making approach. IEEE Trans. Veh. Technol. 69 (11), 12585–12596.

Zeng, X., Xie, C., Xu, M., Chen, Z., 2024. Optimal en-route charging station locations for electric vehicles with heterogeneous range anxiety. Transp. Res. Part C: Emerg. Technol. 158, 104459.

Zhang, S., et al., 2023b. Near-infrared persistent phosphor-mediated smart sensing light-emitting diodes for advanced driver assistance systems. Adv. Photonics Res. 2300011.

Zhang, S., Jia, R., Pan, H., Cao, Y., 2023a. A safe reinforcement learning-based charging strategy for electric vehicles in residential microgrid. Appl. Energy 348, 121490.

Zhang, Y., Wei, W., 2020. Decentralized coordination control of PV generators, storage battery, hydrogen production unit and fuel cell in islanded DC microgrid. Int. J. Hydrog. Energy 45 (15), 8243–8256.

Zhang, Y., Rysiecki, L., Gong, Y., Shi, Q., 2020. A SWOT analysis of the UK EV battery supply chain. Sustainability 12 (23), 9807.

Zhang, Y.Z.Z., Zhou, Teng, Zhang, X., Xu, Zhifeng, 2021b. Energy consumption prediction of electric vehicles based on digital twin technology. World Electr. Veh. 12.

Zhang, Z., Zou, Y., Zhou, T., Zhang, X., Xu, Z., 2021a. Energy consumption prediction of electric vehicles based on digital twin technology. World Electr. Veh. J. 12 (4), 160.

Zhang, Z., Liu, J., Bastidas, J.P., Jones, S., 2024. Charging infrastructure assessment for shared autonomous electric vehicles in 374 small and medium-sized urban areas: an agent-based simulation approach. Transp. Policy 155, 58–78.

Zhao, Y., Noori, M., Tatari, O., 2016. Vehicle to Grid regulation services of electric delivery trucks: economic and environmental benefit analysis. Appl. Energy 170, 161–175.

Zhao, Z.R.J., Li, Y., 2015. Thermal performance of mini-channel liquid cooled cylinder based battery thermal management for cylindrical lithium-ion power battery. Energy Convers. Manag. 103, 157–165.

Zhao, Z.R.J., Huo, Y., Liu, X., Li, Y., 2015. Thermal management of cylindrical power battery module for extending the life of new energy electric vehicles. Appl. Therm. Eng. 85, 33–43.

Zhou, W., Wang, L., 2019. The Energy-Efficient Dynamic Route Planning for Electric Vehicles. J. Adv. Transp. 2019 (1), 2607402.