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REVIEW

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# Electric vehicles, the future of transportation powered by machine learning: a brief review

Khadija Boudmen[1*], Asmae El ghazi[1,2,4], Zahra Eddaoudi[1], Zineb Aarab[2,3] and Moulay Driss Rahmani[1]

*Correspondence:
khadija.boudmen@um5r.ac.ma

[1] LRIT, Associated Unit to CNRST (URAC 29) Faculty of Sciences, Mohammed V-Agdal University, Rabat, Morocco
[2] GENIUS Laboratory, SUPMTI of Rabat, Rabat, Morocco
[3] SIWEB, Mohamadia School of Engineers, Mohammed V University in Rabat, Rabat, Morocco
[4] EEIS Laboratory, ENSET of Mohammedia, Hassan II, University of Casablanca, Mohammedia, Morocco

**Abstract**

Over the past decade, the world has experienced a remarkable shift in the automotive landscape, as electric vehicles (EVs) have appeared as a viable and increasingly popular alternative to the long-standing dominance of internal combustion engine (ICE) vehicles and their ability to absorb the surplus of electricity generated from renewable sources. This paper presents a detailed examination of the different categories of EVs, charging methods and explores energy generation systems tailored for EVs. As vehicle complexity and road congestion increase with the growth of EVs, the need for intelligent transport systems to improve road safety and efficiency becomes imperative. Machine learning (ML), recognized as a powerful approach for adaptive and predictive system development, has gained importance in the vehicle domain. By employing a variety of algorithms, ML effectively addresses pressing issues related to electric vehicles, including battery management, range optimization, and energy consumption. This paper conducts a brief review of ML methods, including both traditional and applied approaches, to address energy consumption issues in EVs, such as range estimation and prediction, as well as range optimization.

**Keywords:** Electric vehicles, Machine learning, Energy generation system

## Introduction

Air pollution has become a serious danger to our health, leading to both immediate and long term problems. These problems include emphysema, respiratory infections (e.g., pneumonia, bronchitis), cancer, asthma, and other chronic diseases. Increased human activities have worsened air pollution, causing a buildup of greenhouse gases (GHGs). This buildup results in unusual temperature increases. Additionally, air pollution can make existing health conditions worse and impact our overall well-being.

The transportation sector significantly contributes to worldwide GHG emissions, accounting for approximately 23% of the overall emissions (Yu et al. 2019). These emissions consist of carbon dioxide, hydrofluorocarbons (HFCs), nitrous oxide, methane, hydrochlorofluorocarbons (HCFCs), and ozone, all of which contribute to increasing concentrations of GHGs. The ICE is a major contributor to air pollution, releasing about 35% of carbon monoxide (CO), 30% of hydrocarbons (HC), and 25% of nitric oxides (NOx), as well as lead particles and particulate matter (PM2.5) directly into the atmosphere 2 as Fig. 1 shows (Macharia et al. 2023). Such a disconcerting

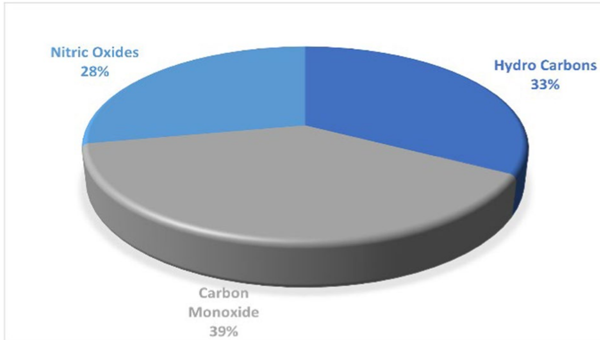


**Fig. 1** Internal combustion engine emissions

statistic led to the adoption of the 'Paris Declaration on Electromobility and Climate Change and Call to Action', a worldwide effort to combat the greenhouse effect. The declaration aims to limit the increase in global temperatures to 2 °C, a crucial milestone in mitigating the harmful impacts of climate change.

EVs have seen a rise in popularity as a greener alternative to conventional vehicles powered by gasoline in the last years. as well as being promoted as an achievable way to reduce carbon dioxide emissions ($CO_2$) in the face of ongoing global fossil fuel shortages and pollution (Xu et al. 2020; Koubaa et al. 2021). Countries worldwide have established ambitious targets to encourage the adoption of EVs or are even planning to ban the sale of petrol vehicles in the future (Chen et al. 2020). In countries where renewable energy is adopted as the primary source, the influence of electric vehicles (EVs) on the environment is more sustainable (Anwar et al. 2021; Sharif et al. 2020). EVs symbolize a remarkable stride towards fostering a sustainable and eco-friendly energy system (Vita and Koumides 2019). Renewable energy sources and electric vehicles offer the opportunity to reduce carbon emissions from power generation and transport sectors (Lazarou et al. 2018; Richardson 2013). China plans to sell 7 million EVs per year by 2025, equivalent to one-fifth of the country's total domestic demand. Norway has set a target of 100% of new car sales to be electric by 2025. The United States and the United Kingdom has promised that they will phase out petrol vehicle sales by 2040. The automotive sector aims to make EVs the largest powertrain in the automotive market by 2030 (Hertzke et al. 2018).

EVs come in multiple types such as battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs) and fuel cell electric vehicles (FCEVs). Each type has its own unique charging methods, issues and challenges. For example, BEVs require longer charging times and have a limited range, while PHEVs have a shorter electric-only range and require both electric and petrol refueling. FCEVs, on the other hand, face challenges with the availability of hydrogen infrastructure. To address these challenges, researchers and engineers have been developing various energy generation systems such as regenerative braking systems, photovoltaic cell systems and fuel cell systems as well as energy management strategies for EVs, these include rule-based and optimization-based strategies (Li et al. 2019). Machine learning (ML) techniques have also been applied to EVs, particularly in battery management, range optimization, and energy consumption prediction.

In this review article, we will present a comprehensive overview of electric vehicles and their different types, charging methods and challenges. We will also discuss the different power generation systems and energy management strategies used in EVs. In addition, we will explore the use of ML in range optimization and energy consumption prediction.

The subsequent sections of this paper are structured as follows: the employed methodology of this review is outlined in "Methodology" section. "Electric vehicles" Section provides a description of EVs types and charging methods. In "Challenges for fuel cell EVs and hybrid EVs" section, we discuss some challenges for Fuel Cell EVs and Hybrid EVs. In "Energy generation systems for EVs" section, we turn our focus to the energy generation systems that are used for EVs like photovoltaic cell systems, fuel cell systems and regenerative braking systems. We address used energy management methods for EVs in "Energy management strategies used in EVs" section, discussing rule-based strategies and optimization-based strategies. "Electric vehicles and machine learning" Section presents ML applications in EVs fields such as range optimization and energy consumption. A discussion about the most used ML algorithms in EVs optimization and management was discussed in "Discussion" section. The final part, which is "Conclusion and perspectives" section, presents our conclusion about the research as well as our perspectives on ML in the EVs field.

## Methodology

This paper will take a close look at EVs. It looks at different types of EVs, how they are charged and the challenges they face. The paper also talks about making energy systems specifically for EVs and how that affects things. It also talks about how EVs use energy.

In this paper, we look carefully at many ways of using ML. These are like tools that help computers learn and predict things. We use these tools to solve specific problems with EVs, such as managing batteries (including checking their condition, detecting problems and controlling charging) and guessing how much energy will be used for driving. The paper focuses on comparing these different tools to see which ones work best for different tasks. The review incorporates criteria for inclusion and exclusion to ensure the provision and evaluation of pertinent and current information.

The criteria for inclusion in this paper are specified as follows:

- Electric vehicles: This criterion guarantees that only articles that provide comprehensive explanations of EVs types, charging methods and challenges are included in the review.
- Energy generation systems: This criterion covers studies and articles that concentrate on the energy generation systems using in EV field.
- Energy management strategies: This criterion includes papers that explore EMSs used in HEVs, while there is still limited research on EMSs used in PEVs. However, some EMSs developed for HEVs can also be adapted for use in PEVs.
- Machine learning algorithms used in electric vehicles between 2012 and 2023: This criterion guarantees that only studies and articles discussing ML algorithms used in EVs within the last years are included in the review. This guarantees that the information presented remains current and pertinent to recent advancements in the field.

The exclusion criteria are the following:

- General papers of machine learning and old sources (below 2012): General papers on ML that don't specifically discuss its application in the EVs domain are filtered out by this criterion
- Non peer reviewed sources: A peer review is an essential phase in guaranteeing the quality of scientific research. So that, it's excluded by this criterion.
- Letters and reports: Letters and reports lacking original research or substantial additions to the domain are excluded by this criterion.
- Non-English sources: Papers that are not published in English are also excluded. This guarantees that the information presented reaches a broader audience.

## Electric vehicles

EVs have been gaining popularity in recent years due to their potential to reduce GHG emissions and dependence on fossil fuels. Unlike traditional ICE vehicles, EVs are powered by electricity held in batteries and electric motors. These vehicles have emerged as a promising solution for sustainable transportation.

EVs can be classified into different types, such as BEVs, hybrid electric vehicles (HEVs), PHEVs, and FCEVs. Each type has its own unique features, charging methods, and challenges. Understanding the distinctions between these types is crucial to grasp the diverse landscape of EVs.

### Electric vehicle types

EVs come in different types, including BEVs, which run purely on a battery with no secondary energy source and emit no emissions. BEVs typically use large battery packs to give the vehicle a satisfactory range. A typical BEV can travel between 160 and 250 km on a single charge, and some are even able to travel up to 500 km before they need to be recharged. An example of such a vehicle is the Nissan Leaf (Nissan Reveals LEAF e-Plus 2023), which runs entirely on electricity. It is currently equipped with a 62 kWh battery, which allows the user to travel up to 360 km on a single charge.

Hybrid EVs are driven by a fusion of a conventional gasoline engine and an electric motor. Contrary to PHEVs, HEVs do not have the capability to be plugged in for battery charging. Instead, the battery that powers the electric motor is charged by the gasoline engine and by the energy generated during braking. The fourth generation of the Toyota Prius hybrid had a 1.3 kWh battery. This gave it a theoretical all-electric range of 25 km (Toyota Prius PHV 2013).

PHEVs are an improved version of HEVs that can connect to the power grid for battery charging. PHEVs are powered by a traditional gasoline engine and an electric motor that is charged by an external electrical source. PHEVs can store sufficient electrical energy from the grid to substantially decrease fuel usage during typical driving situations. The Ford Escape PHEV (Ford Escape® 2024) is equipped with a 14.4 kWh battery, enabling it to travel approximately 60 km using only electric power.

Although PHEVs were developed due to the limited mileage of EVs and a low number of public charging stations, BEVs are becoming increasingly popular. This is because battery technologies are being improved to enhance their energy density. Currently, two-thirds of existing EVs are BEVs, and they have a higher priority for charging at parking lots or charging stations since they have a single energy source (Sadeghian et al. 2022). The growing popularity of BEVs underscores the need for further infrastructure development to meet the demand.

Another type of EV is the FCEV or hydrogen EV, which uses hydrogen as its fuel source. These vehicles feature an electric motor that operates on a combination of compressed hydrogen ($H_2$) and oxygen ($O_2$) from the air to generate electricity. The only by-product of this process is water. FCEVs are zero-emission vehicles, but it is important to note that most hydrogen is currently produced from natural gas, which is a fossil fuel. The Toyota Mirai FCEV (Toyota Mirai 2023) exemplifies this type of vehicle, capable of traveling 647 km without refueling. The different types of EVs discussed above are shown in Fig. 2 below.

## Charging methods

Besides autonomy, another important aspect of electric vehicles (EVs) is the charging process. For EVs to be truly successful, users need to be able to charge their vehicles quickly and easily. There are three primary charging methods: battery exchange, wireless charging, and conductive charging. Conductive charging can be further divided into pantograph charging and overnight charging as illustrated in Fig. 3.

### *Battery swap station (BSS)*

The technique known as 'Battery Exchange' involves paying a monthly rent for the battery to the proprietor of the Battery Swapping Station (BSS). The gradual charging process of the BSS helps to prolong the life of the battery (Ahmad et al. 2018). The integration of locally generated renewable energy sources (RES) such as wind and solar into the BSS system is much easier. A key advantage of this approach is that the driver can rapidly replace a discharged battery without having to leave the vehicle (Gschwendtner et al. 2021).

However, BSSs can be more expensive than refueling ICE vehicles because of the elevated monthly rental fees charged by the BSS owner. This is due to the fact that the BSS owner owns the EV batteries. BSSs also necessitate several costly batteries and a large

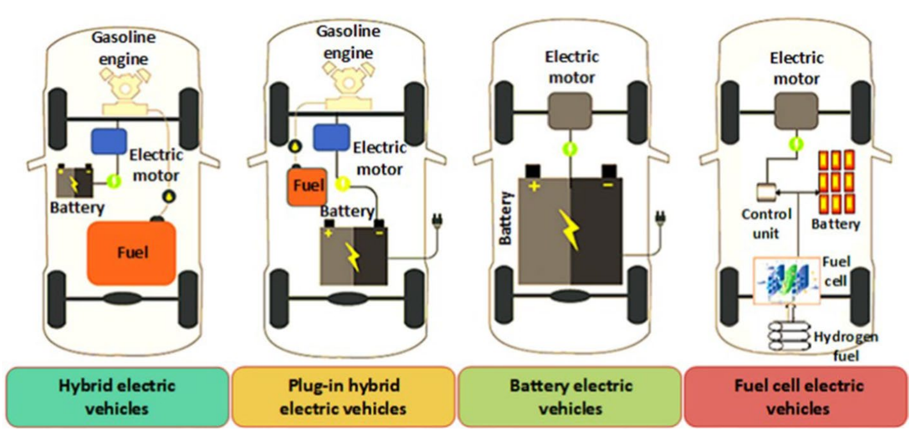


**Fig. 2** Different types of electric vehicles (Sadeghian et al. 2022)

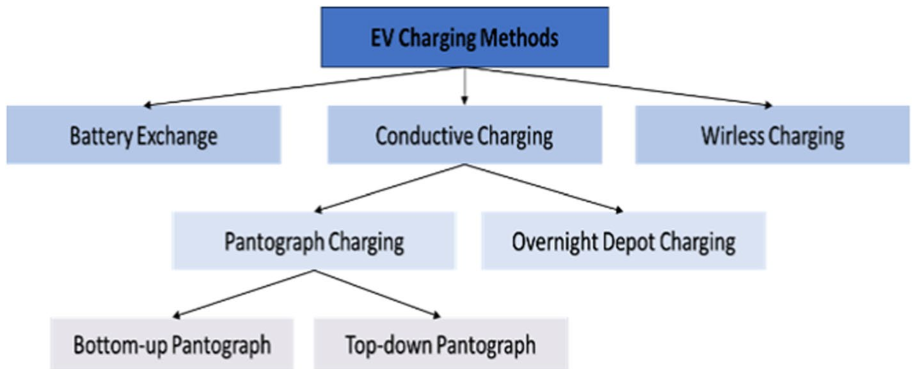


**Fig. 3** EVs charging methods

amount of space to store them, which can be expensive in high-traffic areas. In addition, a BSS may have a specific battery model, but EV batteries may have different standards (Li et al. 2018; Erdinç et al. 2017).

#### *Wireless power transfer (WPT)*

Wireless power transfer (WPT) is a technology that uses two coils to transfer energy without the need for a physical connection. WPT has attracted attention for use in electric vehicles because one coil is placed on the road surface, and another coil is positioned inside the vehicle. This technology is valued for its safety, convenience, and lack of requirement for a standard plug (though it does rely on standard coupling technology). In addition, WPT can charge a vehicle while it is moving (Sanguesa et al. 2021).

However, WPT does have some challenges. Inductive power transfer is typically inefficient, requiring an air gap of between 20 and 100 cm between the transmitter and receiver coils for optimal power transfer (Chowdhury et al. 2023). Also, eddy current losses can occur if the transmitter coil remains active. Finally, there is a risk of communication latency between the transmitter and the vehicle (Patil et al. 2017).

#### *Conductive charging (CC)*

Conductive charging (CC) necessitates an electrical link between the vehicle and charging port, providing different charging alternatives like level 1, level 2, and level 3 charging. This method boasts high charging efficiency owing to its direct connection. Public charging stations commonly utilize power charging levels 2 and 3. The initial two levels (Levels 1 and 2) exert a lesser impact on the distribution system.

CC allows for vehicle-to-grid (V2G) support, which can help to reduce grid loss, maintain voltage levels, prevent grid overloading, provide active power support, and compensate for reactive power using the battery of the vehicle (Chowdhury et al. 2023; Patil et al. 2017).

However, high-power conductive charging (level 3 charging) can have a number of negative impacts on the distribution system, including voltage deviation, reduced system reliability, and increased power losses (Dharmakeerthi et al. 2014). It can also increase peak demand and reduce transformer lifespan (Dharmakeerthi et al. 2014; Habib et al. 2018). Additionally, Level 3 charging requires a standardized connector, access to electricity from the grid, and complex infrastructure (Yang et al. 2015). V2G technology also necessitates robust communication between the grid and the vehicle, and it can reduce battery lifespan because of frequent charging and discharging (Arif et al. 2021a). Table 1 summarizes the charging methods, which include BSS, WPT, and CC stations.

For electric buses and trucks with higher battery capacity and quick charging requirements, two main charging techniques are used:

Overnight depot charging: This system can be configured for slow or rapid charging and is typically installed at the terminus of bus routes for nighttime charging. Slow charging is the is preferred as it minimally impacts the distribution grid (Arif et al. 2020, 2021b).

Pantograph charging: This is a type of opportunity charging that is used for vehicles with higher battery capacity and power requirements. Lowering the bus investment cost, pantograph charging reduces the investment in the bus battery, although it results in higher costs for the charging infrastructure (Meishner et al. 2017). Pantograph charging is further divided into two categories:

- Top-down pantograph: Referred to as an off-board top-down pantograph, this setup is mounted on the roof of the bus stop. It provides high-power direct current and has been implemented in Singapore, Germany, and the United States (Carrilero et al. 2018).
- Bottom-up pantograph: Known as an on-board bottom-up pantograph, this charging method is suitable for applications where the charging equipment is already installed in the bus (Carrilero et al. 2018).

## Challenges for fuel cell EVs and hybrid EVs

### Fuel cell EVs

Reducing manufacturing costs is essential for the commercialization of fuel cells. The US Department of Energy (DOE) aims to minimize the price of fuel cells to $40/kW by

**Table 1** Advantages and disadvantages of charging methods

| Method | References | Disadvantage | Advantage | Year |
|---|---|---|---|---|
| BSS | Arif et al. (2021a) | The monthly rent to BSS makes it more expensive than an Internal Combustion Engines (ICE) vehicle | Rapid battery replacement (fully charged) | 2021 |
| | Arif et al. (2021a) | The significant costs needed for both equipment and batterie | BSS extends battery life by charging slowly | 2021 |
| | Li et al. (2018) | Many areas needed to accommodate the batteries | Easy to integrate with the locally generated Renewable Energy Sources (RESs) | 2018 |
| CC | Habib et al. (2018) | Need a standard connector/charging level | Reduce grid losses while maintaining voltage levels | 2018 |
| | Yoldaş et al. (2017) | Electricity grid restrictions | Provide maximum efficiency | 2017 |
| | Negarestani et al. (2016) | Complex infrastructure | Provide multiple charging levels | 2016 |
| WPT | Arif et al. (2021a) | In general, power transmission is inefficient | Standard connectors not required | 2018 |
| | Patil et al. (2017) | The transmitter and EV should be able to communicate in real time | Recharge while driving | 2017 |

2025, targeting a goal of \$30/kW with the primary aim of completely replacing the traditional power system and ensuring sustained competitiveness in the long term (Borup et al. 2018, 2020). Durability and performance are the other two critical evaluation criteria for fuel cells, but reducing the load of expensive electrocatalysts to cut costs may compromise their durability and performance. Therefore, simultaneously achieving both the durability and cost targets set by the DOE is a considerable challenge. Balancing cost reduction with performance and durability remains a critical challenge in the commercialization of fuel cell technology. Fuel cells are crucial for commercial uses in transportation and stationary power generation. Introduced in 2017, Toyota's Mirai, the first commercially available FC vehicle, was priced around \$60,000 and logged over 3000 h of real-world driving. However, it failed the DOE's accelerated stress test protocol after 5000 cycles (Wang et al. 2020).

DOE aims to surpass 5000 working hours for commercial fuel cell vehicles by 2025, with the ultimate objective being 8000 h (METI Ministry of Economy, Trade and Industry 2023). Manufacturers of stationary fuel cells aspire to achieve mass production, aiming to reduce costs and enhance durability. To realize cost-effective and durable fuel cell systems, ongoing progress in manufacturing processes and materials is imperative. As evidenced by Panasonic's fifth-generation stationary fuel cell, which weighs a mere 65 kg, occupies an area of 1.7 $m^2$, and boasts a durability of 90,000 h (METI Ministry of Economy, Trade and Industry 2023; Arias 2019), advancements are already underway. Japan's hydrogen strategy aligns with ongoing enhancement, targeting an efficiency exceeding 55% by 2025 (ultimate goal: over 65%) and a durability of 130,000 h for commercial stationary fuel cells (Arias 2019). These ambitious objectives underscore the ongoing efforts to elevate the performance and reliability of fuel cell technology.

#### Hybrid EVs

HEVs emerge as a promising prospect for the future of transportation, driven by the substantial increase in crude oil prices over recent decades, prompting consumers to explore alternative energy sources (Williamson et al. 2006). In comparison to hybrid vehicles featuring ICEs, BEVs and PHEVs exhibit higher energy efficiency and nearly zero hazardous emissions. A significant body of researchers has contributed to enhancing the efficiency and performance of PHEVs, showcasing their capability to perform well within the HEV framework (Atabani et al. 2011). Existing research shows that these technologies can enable high-performance HEVs. However, the reliability and intelligent systems of HEVs still need improvement. Therefore, there are many factors that must be considered before HEVs can be fully embraced by the market, including the following challenges (Ong et al. 2012):

- Renewable energy sources for vehicle applications have low energy and power densities. Exploring advanced energy storage technologies and improving energy density are essential to overcome these limitations.
- HEVs are still expensive. Reducing manufacturing costs and increasing economies of scale are necessary to make HEVs more affordable for consumers.
- The refueling station infrastructure for HEVs needs to be expanded. Light HEVs require small storage tanks, while other HEVs may use an exchange storage tank

system. Developing a robust refueling infrastructure that supports different types of alternative fuels and storage systems is crucial for the widespread adoption of HEVs.

- Recharging plug-in BEVs is time-consuming, so rapid recharging systems need to be developed. The development of lithium-ion batteries, which are lightweight and have a short recharge time, has enabled car manufacturers to produce BEVs and hybrid vehicles. Continued advancements in battery technology and the development of fast-charging infrastructure are key to addressing the issue of lengthy recharging times and improving the convenience of plug-in BEVs.

## Energy generation systems for EVs

### Photovoltaic cell systems

Photovoltaic (PV) cells also known as solar cells, transform sunlight directly into electrical energy. They are widely used to harness renewable energy in various applications. While individual PV cells have a low power output, typically 1–2 watts, they can be connected in series and/or parallel chains to form modules or panels. These panels can then be grouped together to form PV arrays to meet greater power requirements (Kalantar and Mousavi 2010). This modular configuration allows PV systems to be scaled and customized to meet specific energy requirements. PV systems also necessitate a solar inverter to convert the direct current (DC) produced by the PV cells into alternating current (AC), along with mounting hardware, cabling, and other electrical components.

One of the main advantages of photovoltaic (PV) systems is their clean operation, emitting no pollution or greenhouse gases. They are also low-maintenance and have a long lifespan (Lo Piano and Mayumi 2017; Advantages Disadvantages of Solar Power 2023). However, high initial costs and unpredictable availability are significant drawbacks (Sukamongkol et al. 2002; Deshmukh and Deshmukh 2008). Anticipated improvements in technology and the realization of economies of scale are poised to overcome these cost barriers and enhance the reliability of PV systems in the future. PV cells can be fabricated from crystalline silicon, the prevailing material in the market, or from thin films incorporating substances like cadmium telluride (CdTe) as well as copper indium diselenide (CIS). Although crystalline silicon exhibits higher efficiency, PV cells based on thin-film technology are lighter and more cost-effective to produce (NREL 2012; Photovoltaics Report 2023).

Researchers are developing new PV technologies to improve efficiency and reduce costs. Third-generation PV cells are being developed using new materials such as solar inks, solar dyes, and conductive plastics. These advancements have the potential to make PV systems even more performant and affordable. PV systems find practical applications in various domains, including powering buildings, spacecraft, road lights, and even facilitating daytime charging for commuter vehicles (Birnie 2009). Although the direct integration of PV systems into commercial EVs remains challenging due to space constraints and limited power generation, they can still contribute to improving vehicle efficiency (10–20%) or maintaining comfortable temperatures inside the vehicle through the operation of the air conditioner (Richardson 2013).

The output current of a PV module can be presented as follows (Villalva et al. 2009; Salmi et al. 2012):

$$I = I_{PV} - I_0\left[exp\frac{q(V + R_S I)}{N_S KTa} - 1\right] - \frac{V + R_s I}{R_p} \tag{1}$$

where $I_{pv,n}$ is the current generated by the PV module at the nominal condition of solar radiation at 1000 W/m$^2$ and temperature at 25 °C. KI is the indicates the short circuit current temperature coefficient (A/°C). T and $T_n$ is the actual and nominal temperatures (K). G and $G_n$ is the actual and nominal solar radiation (W/m$^2$).

The saturation current $I_0$ depends on the temperature and described as follows:

$$I_0 = \frac{I_{sc,n} + K_I(T - T_n)}{exp\frac{q\left[V_{oc,n}+K_v(T-T_n)\right]}{aN_S KT} - 1} \tag{2}$$

where $I_{sc,n}$ is the short circuit current (A). $V_{oc,n}$ is the open circuit voltage (V) at the nominal conditions. $K_I$ is the current coefficient. $K_V$ is the voltage coefficient.

#### Regenerative braking systems

Regenerative braking systems allow vehicles to recover the kinetic energy generated during braking and store it for later use. This energy can be converted into electrical, hydraulic, or mechanical energy. Without a regenerative braking system, this kinetic energy would be wasted as heat generated by the brakes. Currently, four methods are employed for implementing regenerative braking systems: the electric M/G and batteries or SC method, hydraulic P/M and HACCs, flywheel energy storage, and spring potential energy storage (Clegg 1996; Valente and Ferreira 2008).

In terms of energy efficiency, charging and discharging ability, power density, and cost-effectiveness, each method has its own advantages and disadvantages. Of these methods, hydraulic and flywheel regenerative systems have the highest energy efficiency. Hydraulic systems also demonstrate rapid charging and discharging capabilities, enhanced power density, and a greater ability to recover maximum braking energy. However, battery-based systems are not ideal for frequent charging and discharge due to the risk of overheating, reduced lifespan, or destruction. SC regenerative systems can be expensive. Spring regenerative systems have the lowest energy efficiency (Li et al. 2019; Jiang et al. 2013; Hui et al. 2011; Zeiaee 2016). Additional research and development are required to optimize regenerative braking systems and address their limitations for widespread implementation in electric vehicles.

#### Fuel cell systems

Fuel cell (FC) systems convert chemical energy into electrical energy through chemical reactions between hydrogen (or hydrocarbons like methanol or natural gas) and oxygen from the air, aided by catalysts. The conversion process involves splitting hydrogen into protons and electrons. The electrons then flow through a circuit, producing an electric current, while the protons pass through the electrolyte. FCs are known for their quiet, reliable, and environmentally friendly operation, as well as their high efficiency (Mekhilef et al. 2012).

There are six types of FCs, classified based on their choice of fuels and electrolytes: direct methanol fuel cells (DMFCs), alkaline electrolyte fuel cells (AFCs), molten carbonate fuel cells (MCFCs), phosphoric acid fuel cells (PAFCs), solid oxide fuel cells

(SOFCs), and proton exchange membrane fuel cells (PEMFCs) (Mekhilef et al. 2012). Each type of fuel cell has its own unique characteristics, advantages, and suitability for specific applications. DMFCs, despite having high energy density, emit $CO_2$ and exhibit lower efficiency. MCFCs and SOFCs, operating at high temperatures (600–1000 °C), are typically employed in electric utilities and distributed power generation. For transportation, DMFCs, PEMFCs, AFCs, and PAFCs are common choices due to their normal or moderate operating temperatures. PEMFCs, in particular, stand out with the highest power density among FCs, offering benefits like a long lifespan, less-temperature operation, and rapid response, making them particularly appealing for transportation applications (Tie and Tan 2013; Hannan et al. 2017). Although FCs have a high initial cost, it decreases as the market expands and economies of scale improve.

PEMFCs are the most promising FC source for use in plug-in electric vehicles (PEVs), and empirical PEMFC models can be derived from the Nernst equation. Ongoing research and technological advancements are focused on improving the efficiency, durability, and cost-effectiveness of fuel cell systems for wider adoption in electric vehicles. The theoretical voltage produced by a typical fuel cell's individual cell can be expressed as (Hannan et al. 2014):

$$E_{cell} = E_0 + \frac{RT}{2F} ln \frac{P_{H_2}\sqrt{P_{O_2}}}{P_{H_2O}} \tag{3}$$

where $E_0$ is the open circuit voltage of the cell at standard pressure. R is the universal gas constant. F is the Faraday's constant. T is the absolute operating temperature. $P_{H_2}$ is the partial pressure of hydrogen inside the cell. $P_{O_2}$ is the partial pressure of oxygen inside the cell. $P_{H_2O}$ is the partial pressure of water vapor inside the cell.

However, due to factors like activation losses, internal current losses, resistive losses, and concentration losses, the actual voltage produced by a single cell is less than the ideal potential. Therefore, the output voltage of the FC stack can be described as (Hannan et al. 2014; Andrea Calvo et al. 2006):

$$V_{FC} = N\left(E_0 + \frac{RT}{2F}\ln\left(\frac{P_{H_2}\left(\frac{P_{O_2}}{P_{std}}\right)^{\frac{1}{2}}}{P_{H_2O}}\right)\right) - V_L \tag{4}$$

where N is the number of cells in the stack. $P_{std}$ is the standard pressure. $V_L$ is the voltage losses.

## Energy management strategies used in EVs

Energy management strategies (EMSs) are crucial for systems with multiple energy sources as they control power distribution within powertrains, impacting vehicle performance, efficiency, and component longevity (Sabri et al. 2016). While research on EMSs for PHEVs is limited compared to HEVs, some EMSs developed for HEVs can also be utilized in PHEVs. Therefore, this section initially introduces EMSs commonly employed in HEVs before discussing their potential adaptation for PHEVs. EMSs for HEVs are broadly classified into two main categories, as shown in Fig. 4: ruled-based strategies and optimization-based strategies.

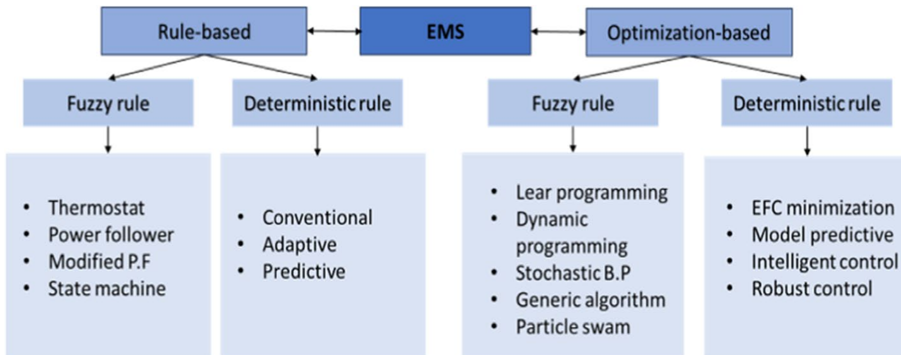


**Fig. 4** Classification of EMSs employed in HEV

### Rule-based strategies

Supervisory control of HEVs commonly employs Rule-based (RB) strategies, leveraging heuristics, expert knowledge, and mathematical models (Salmasi 2007). RB strategies can be divided into two categories: fuzzy and deterministic methods. Fuzzy RB techniques, such as traditional, adaptive, and predictive control strategies, employ fuzzy logic theory to handle approximate reasoning and are better suited for sophisticated or intricate powertrain systems. Deterministic RB approaches like state machine-based, power and modified power follower, and on/off thermostat strategies employ specific rules to assess power distribution accurately (Enang and Bannister 2017). RB strategies are immediate solutions known for their simplicity, strong reliability, and innate suitability for online applications, requiring minimal computational overhead. However, crafting RB strategies can prove time-intensive due to the challenge of establishing precise rules, frequent parameter adjustments, and calibration needed to enhance vehicle performance. Rules must be adjusted for diverse vehicle setups and evolving driving conditions. Additionally, RB strategies do not prioritize minimization or optimization, thus limiting their ability to optimize fuel economy to its fullest extent (Enang and Bannister 2017; Zhang et al. 2015).

### Optimization-based strategies

One approach to improving energy efficiency in hybrid vehicles (HVs) and EVs is the deployment of optimization-based strategies. These strategies seek to decrease fuel consumption or emissions by calculating optimum reference torques and gear ratios based on a minimizing cost function (Ramachandran and Stimming 2015). There are two main types of optimization solutions: global and real-time. Global optimization solutions aim to reduce energy losses over the whole driving cycle but can't be used in real-time energy management. These solutions are useful as control benchmarks compared to other strategies. However, real-time optimization solutions can be implemented online and involve the reduction of global optimization challenges into a sequence of local optimization challenges which excludes the need for future driving information. (Çağatay Bayindir et al. 2011).

Global optimization strategies are classified into different methods such as linear programming (LP), dynamic programming (DP), stochastic DP, genetic algorithm (GA), and particle swarm optimization (PSO) (Çağatay Bayindir et al. 2011).

On the other hand, real-time optimization strategies address global optimization issues by solving a sequence of local optimization challenges, which removes the need to obtain future driving information (Enang and Bannister 2017).

As a result, real-time optimization strategies can be employed for online applications. These strategies can be classified into several types, including model predictive control (MPC), intelligent control, robust control, decoupling control strategies (DCS), and equivalent fuel consumption (EFC) minimization, (Advantages Disadvantages of Solar Power 2023; Sukamongkol et al. 2002). Each type of optimization-based strategy has its own advantages and challenges and requires appropriate implementation and tuning to achieve optimal energy management in EVs.

## Electric vehicles and machine Learning

### Machine learning in range optimization

Range estimation (RE) is a critical step in achieving EV range optimization and is one of the key topics of research and investigation in EV technology these days. Precise RE can greatly alleviate range concerns experienced by EV drivers due to restricted driving distance It empowers EV drivers to make informed decisions about driving, parking, and charging, as well as participate more actively in vehicle-to-grid (V2G) charging. Yet, conventional RE techniques are occasionally not effective because of their failure to account for dynamically changing outside and environmental circumstances (Huang et al. 2017; Zhang et al. 2012; Pan et al. 2017).

For instance, the range predictors in Tesla's Model S predict the upcoming available range by analyzing the energy consumption from the preceding miles, without accounting for variations in driving conditions, driving habits and environmental factors (Daziano 2013). Compared to traditional RE methods, artificial intelligence (AI) has the potential to provide more precise RE by modeling the complicated relationship between RE and the factors that affect it. AI algorithms, such as ML, can reliably predict upcoming environmental and driving conditions using past and present data, resulting in a more precise range estimate.

AI algorithms have been employed for RE by explicitly leveraging environmental as well as historical driving attitude data(Sun et al. 2019; Yavasoglu et al. 2019), predicting EV battery energy and power consumption (Pan et al. 2017; Zheng et al. 2016) and recognizing driving conditions and behaviors (Pan et al. 2017; Lee and Wu 2015). Real-time historical EV discharge data is selected for applicable batteries, vehicle, and external parameters (Table 2) as well as removing missing and erroneous data for ML training. Additionally, EV historical data has the potential to be combined with historical weather data and road conditions data to incorporate external parameters, thereby enhancing the RE estimation accuracy using ML training (Sun et al. 2019; Zheng et al. 2016).

ML models are capable of learning to directly predict EV range and future EV energy or power consumption. By taking into account the evolving EV internal and external conditions in a computationally efficient manner, and without the use of complex explicit models, ML enables more accurate RE (Pan et al. 2017; Zheng et al. 2016). Parameters more influence on RE, such as battery state of charge (SOC) and external temperature, can be approximated using correlations, which reduces the complexity and training time of the ML model (Sun et al. 2019).

**Table 2** Research of ML in electric vehicle RE

| | Algorithm | Parameters | RE accuracy |
|---|---|---|---|
| Historical data | Significant parameter identification using correlation analysis and multiple linear regression (MLR) | Vehicle speed<br>Acceleration<br>Past power consumption<br>Past distance<br>Past trip run time<br>Temperature<br>Weight of loads<br>Tire pressure<br>Frontal area<br>External road elevation<br>Recent energy consumption<br>External road elevation | 1.63 km (MAE) (Nowaková and Pokorný 2020) |
| | Classification and regression tree (CART) | | 1.27 km (MAE) (Sun et al. 2019) |
| | Artificial neural networks (ANN) | | 2.2% (MSE) accuracy for a 50.4 km real-life EV trip (Rhode et al. 2020) |
| | Gradient boosting decision tree (GBDT) | | 0.82 km (MAE) (Sun et al. 2019) |
| Prediction of future energy and power consumption | Data clustering using self-organizing maps (SOM) pursued by regression tree<br>Principal component regression (PCR)<br>Multiple linear regression (MLR)<br>Support vector regression (SVR)<br>Linear regression (LR) | Battery SOC<br>SOH<br>Auxiliary load<br>Weight<br>External road type<br>Traffic<br>Temperature<br>Driving behavior<br>Voltage (min, max)<br>Current (min, max)<br>Temperature (min, max)<br>Vehicle speed (avg)<br>External temperature<br>Visibility<br>Precipitation | 0.70 km (MAE) (Yokoi et al. 2004)<br>2.07 km (MAE) (Yokoi et al. 2004)<br>1.95 km (MAE) (Yokoi et al. 2004)<br>1.95 km (MAE) (Lee and Wu 2015)<br>2.18 km (MAE) (Lee and Wu 2015) |

*MAE* mean absolute error, *MSE* mean-squared error

### Machine learning in energy consumption

To predict the remaining driving range of an EV, it is important to accurately predict its energy consumption. This prediction relies on calculating the energy required to drive the vehicle, energy lost through the drivetrain, and energy used to power auxiliary devices (Smuts et al. 2017). However, accurately estimating the range of an EV remains a challenge due to factors such as limited driving range, long charging time, high battery replacement cost, and inadequate charging infrastructure. These issues can be addressed by ameliorating battery performance and raising the number of charging stations, but both solutions are highly expensive and may not fully address drivers' concerns about the remaining driving range estimates. Therefore, adequate and precise range estimation is needed to enhance driver confidence and encourage widespread adoption of EVs. Recent studies suggest using advanced methods to accurately predict the energy consumption of EVs, resulting in increased driving range and reduced range anxiety. This promotes driver's confidence and encourages EV usage over longer distances. In recent times, ML techniques have been employed for predicting the energy consumption of EVs as summarized in Table 3.

## Discussion

Various ML algorithms are used to optimize and resolve EV's issues. According to Table 4, Multiple Linear Regression (MLR) stands out as a popular and adaptable approach for EV optimization. The importance of MLR results from its capacity to detect

**Table 3** Summary of energy consumption predicted by different ML algorithms

| Researcher | Description | ML Algorithm | Remarks | Refs. |
|---|---|---|---|---|
| Alvarez et al | Anticipate the energy consumption and driving patterns of electric vehicles using three input parameters, namely car speed, acceleration, and jerk | ANN | The dataset was only limited to 10 drivers, which may not be sufficient to represent sample characteristics | Alvarez et al. (2014) |
| Bi et al | Calculates the residual range of EVs by utilizing five internal vehicle-specific fac-tors | Neural network | The proposed model achieved good estimation accuracy, but the internal influencing factors were disregarded | Bi et al. (2018) |
| Li et al | Predict the energy consumption of electric buses in Shenzhen, China | KNN and RF models | These models are relatively traditional and less advanced than recently developed ML algorithms such as LightGBM (Ke et al. 2017) and XGBOOST (Chen and Guestrin 2016), which have shown better prediction performance in different research fields (Gu et al. 2020; Qu et al. 2019) | Li et al. (2021) |
| Abdelaty et al | Predict electric bus energy consumption | MLR<br>SVR<br>Radial basis function interpolation model (RBF)<br>Decision tree model (DT)<br>GBDT | | Abdelaty et al. (2021) |
| Chen et al | Predict electric vehicle energy consumption | XGBOOST | LightGBM outperforms XGBOOST in terms of robustness | Chen et al. (2015) |
| Wang et al | detect Transportation modes from the GPS trajectory data automatically | LightGBM | | Wang et al. (2018) |

**Table 4** ML algorithms used in EVs

| | Used ML algorithms |
|---|---|
| Range optimization | MLR<br>CART<br>ANN-based models<br>GBDT<br>PCR<br>MLR<br>SVR<br>LR |
| Energy consumption | ANN-based models<br>MLR<br>SVR<br>DT<br>XGBOOST<br>LightGBM |

correlations between various input factors and the intended result. MLR helps in the analysis of many elements impacting an electric vehicle's range, allowing for informed choices on improving driving conditions and overall performance.

In addition to MLR, neural networks (NN) have become more significant in the optimization of electric vehicles. Deep neural networks, in particular, have outstanding capacity for learning complicated patterns from input. NNs can anticipate battery performance and behavior based on many inputs when used in battery management. NNs assist optimize battery management tactics by revealing deep correlations, thereby enhancing battery life and overall efficiency.

Neural networks additionally contribute to optimizing energy consumption. By analyzing historical energy consumption data, NNs can predict and optimize energy consumption patterns in EVs. By capturing complex relationships between different factors, NNs enable accurate prediction, facilitating energy efficiency and cost reduction in EVs.

In summary, both multiple linear regression (MLR) and neural networks (NN) are essential machine learning algorithms for electric vehicle optimization. MLR's versatility allows it to identify relationships and optimize range, while NNs excel at learning complex patterns and optimizing battery management and energy consumption. By leveraging the strengths of MLR and NNs, researchers and engineers can harness the power of data-driven decision-making to improve the performance, efficiency and overall user experience of electric vehicles, contributing to the advancement and widespread adoption of electric transportation systems.

## Conclusion and perspectives

In conclusion, electric vehicles have become an increasingly popular alternative to traditional gas-powered cars. In this comprehensive review, we examined various types of EVs, charging methods, and the associated issues and challenges for some types. We also explored various energy generation systems and energy management strategies that are used to power and optimize electric vehicles. Additionally, we discussed the application of machine learning techniques in electric vehicle battery management, range optimization, and energy consumption prediction. Overall, the use of machine learning in electric vehicles has shown promising results in improving their efficiency, performance, and sustainability. However, there are still several challenges that need to be addressed, such as battery degradation, data privacy, and ethical considerations in the development and deployment of machine learning algorithms for electric vehicles. Further study and invention is needed to overcome these challenges and accelerate the adoption of EVs as a clean and sustainable transportation solution for the future. We finish by outlining our perspective on the field that requires further research and development to ensure that these ML algorithms can provide accurate and reliable results to EVs, and to make an influence on the optimization and management of EVs.

**Author contributions**

K.B. and A.E. wrote the main manuscript text and reviewed the paper, Z.E. and Z.A. prepared Figs. 1, 2, 3, 4 and Tables 1, 2, 3, 4 and reviewed the paper, M.R. reviewed and validated the manuscript.

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Not applicable.

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