AI-Driven Solutions for Optimizing Autonomous Vehicle Battery Usage

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1. Introduction

The automotive industry is introducing energy efficiency, and electric vehicles (EVs) and autonomous vehicles (AVs) have become pivotal for future mobility. AV owners and passengers can take full advantage of cutting-edge technology embedded in an electrified powertrain instead of worrying about adjusting the powertrain components to achieve maximum efficiency. For EVs, the vehicle's mission includes reaching the destination with a minimum possible energy cost and a large remaining battery capacity if an onboard battery charger is not installed. For autonomous EVs, the design includes two tasks: planning and operation. One of the skills under planning is to plan the energy-efficient AV future driving behavior. In this design, the planner can compute a specific acceleration and velocity set point such that the powertrain will achieve these targets by managing the battery system states based on the vehicle and road constraints. AVs can potentially divide decision-making into subsets, and battery management is one of them.

Battery management aims to utilize AV energy resources efficiently so that the AV covers the longest distance using the given or constrained parameters available in the system. The significance of efficient battery design can be assessed in light of customer satisfaction during road travels. Longer electric vehicle (EV) ranges mean customer satisfaction regarding vehicles that can be operated for long periods on a single battery charge at a lower cost. These two fascinating implications of extending battery designs will play a pivotal role in developing future energy-efficient autonomous vehicles. To explore various methodologies in this regard, using machine learning or data analytics is already highly in demand. The significant involvement of the Internet of Things (IoT) for vehicle-to-vehicle communication to make traffic smoother increases the data collection from a wide variety of applications. Another dominant application relates to autonomous vehicles' vision systems that generate more data for running AI and can potentially improve future traffic. Thus, future personal and public transport is at an interesting crossroads with AI. In automotive technology, AI researchers are actively working on battery design from different perspectives. For instance, reinforcement learning-based solutions, model predictive control-based algorithms, dynamic programming, genetic algorithms, pattern recognition, charging infrastructure, power flow in the battery management systems, and mixed-integer linear programming-controlled battery.

1.1. Background and Significance

1.1.1 Autonomous Vehicles, AVs Autonomous vehicles (AVs) are the newest enhancement of traditional vehicles that can move on the road from one place to another without human intervention and control. In traditional vehicles, those with an internal user cannot perform operations without human aids such as gearbox operations, changes in gear, changes in the steering wheel, brake and hand brake operations, acceleration, clutch operation, and so on. Lately, these operations can be performed in vehicles without any human control links and movements. These unmanned vehicles represent a revolution with advanced battery technology, and AVs can be operated effectively. It must be said that these types of AVs have evolved from ground vehicles or terrestrial vehicles. Similarly, robotic or unmanned aircraft are nothing but advancements of satellites. All AVs are operated to the best extent with charged batteries. Thus, their efficiency and functions can be accomplished with effective batteries. 1.1.2 Electric Vehicles Electric vehicles or electric drive vehicles are being developed in large numbers in this world, including cars, trucks, ships, family and commercial vehicles, and bicycles. Although these electric charged vehicle systems are newer to the market, electric vehicles are rapidly undergoing growth, especially plug-in electric vehicles (PEVs) and hybrid electric vehicles (HEVs). These plug-in electric vehicles are supplied with a plug and can be charged at home with modern, cost-effective, energy-saving electronic and lithium-ion battery energy storage systems. From an environmental perspective, reducing unwanted emissions in e-vehicles is a crucial obligation that not only prevents fossil fuel resource loss but also reduces the demand for fossil fuels and foreign exchange reserves. If the battery energy can be controlled efficiently with quality-based tools, the vehicle battery will last longer with better maintenance. Pollution impacts the planet's status. Lithium-ion batteries are also more efficient and require further research into ion recycling. In the context of a smart eco-city, the purpose of an e-vehicle is to optimize exergy in health control or balance the two transportation modes of e-vehicles. The issues of vehicle battery duration and its availability in AI applications are discussed further in the following chapters.

1.2. Research Objectives

The research objectives are the following. Overall, we aim to understand if and how artificial intelligence can improve battery usage and performance in an autonomous vehicle. Furthermore, we would like to understand if and how insights into battery management can be utilized to improve the design and performance of future batteries. In this light, the main goal of this study is to investigate how various AI-based techniques can contribute to automatic vehicle power management applications. Our objective includes reviewing the challenges of existing advances in vehicle power management, with a focus on battery optimization to minimize battery weight and improve battery durability, resulting in vehicle propulsion range. We also aim to identify recent advances in AI approaches and techniques proposed in different fields, based on the different optimal potential and power demand trajectories, variable-in-time features, and look-up tables. In recent years, we have seen a boom in AI technologies. These techniques have found use in a variety of fields, including those characterized by emerging applications such as autonomous vehicles and fully electric propulsion systems. Autonomous vehicles are already an established reality, and their spread will continue to grow. The possibility of using increasingly advanced AI is expected since it can manage the use of resources optimized to the drivers' energy behavior and route. However, the progress of AI has not developed at the same pace for all application contexts. In this work, we would like to explore the application and use of AI, particularly in the prediction of energy usage through the knowledge of the energy status of the drivers and vehicle routes. This research will identify the challenges and barriers prohibiting the application of AI. The present research aims to represent a part of the solution to those fault-tolerant aspects of the existing AI-driven optimization of battery use.

2. Autonomous Vehicles and Battery Technology

Autonomous vehicles (AVs) are engineered for a combination of hardware and software systems. The hardware relies on sensors to detect the surrounding environment. This information is then passed to software to generate a driving route and make decisions. The software systems include sensor integration suites for unpacking data from sensors, decision-making algorithms that interpret and act on this data, and navigation systems for computing velocity magnitudes and steering angles from the interpreted data. The systems are executed in parallel with high-throughput computing hardware. Besides advanced software and hardware integration, AVs do not require human intervention to complete a trip.

Fundamental to the operation of an AV is the management of the energy supply system, particularly the battery. Large-scale solutions are needed for charging, durability, and the exploration of advanced battery chemistries to improve energy density. These vehicles also require the integration of sensors and actuators into the existing paradigms for vehicles. The batteries that are incorporated are classified based on the size of the charge they can store and the chemical makeup of the cathode and anode. There are two prevalent classes of batteries now: lithium-ion and emerging alternatives. The design of the battery principally drives the operability, frequency of charging, and fuel usage of the vehicle. Battery life is a critical optimization point as the engine is used sparingly on the premise that the battery can complete most of the trip scheduling. Greater energy density will result in longer trip distances. Manufacturers are interested in reducing the price to build batteries while also making them sustainable. Consequently, there is a need for battery technology to operate in both design and operation.

2.1. Overview of Autonomous Vehicles

Autonomous vehicles (AVs) are able to drive on roads and perform related functions without the need for human input. Manufacturers and researchers have defined levels of automation that illustrate the presence of a user in the vehicle and the amount of control it has on the road. Six levels are defined: Level 0 involves full manual control, while Levels 1 through 3 demonstrate increased automation. At Level 4 (high automation), AVs control all functions of the vehicle regardless of travel environment, while at Level 5 (full automation), the vehicle can perform equal to or beyond a human driver in any road condition and weather. Various technologies enable full automation in all vehicles, such as laser detection and ranging and wheel speed sensors. Camera systems allow AVs to 'see' what humans see more easily than LIDAR and are used in conjunction with AV algorithms, machine learning, and artificial intelligence.

Potential benefits of AVs include improved safety from the reduction of human error, less traffic congestion, easier travel, and enhanced mobility for people otherwise unable to drive, improved energy efficiency, and environmental benefits. Advancements in AV technology remain ongoing; however, deployment of fully autonomous commercial vehicles in the United States is not expected in the next two years. Detractors argue that existing infrastructure and regulations are unprepared for AV technology and that the idea of self-driving cars, generally, may be premature. Concerns persist about the potential for communicating AV technologies to be used for harm, hacking, and terrorism, particularly in densely populated areas, and public perception of AVs remains mixed. Regardless, technological advancements are poised to play a big role in new developments in transportation systems.

2.2. Battery Technology in AVs

For a successful operation of AVs, choosing the right energy storage solution is vitally important. A battery is supposed to have high energy density so that it occupies the least space possible, but it must also have a high charge and discharge rate to ensure the vehicle's safety and reliability. In order to prevent replacing the batteries as frequently as oil changes and to reduce overall system maintenance, a long-life battery system is preferred. The weight of a vehicle directly impacts its overall electrical and mechanical system efficiency, thus affecting the mobility range. The heavier the car, the more energy will be converted into heat and noise, heightening the structure's stresses and weakening its longevity.

Lithium-ion batteries have been established as an optimal energy storage solution for EVs, HVs, and especially AVs due to their high energy density, high cell voltage, and long lifetimes. Taking these requirements and applications into consideration, lithium-ion battery systems are widely used as energy storage solutions for AVs. Apart from such conveniences, advanced research is being conducted, and the following are some highlights. In particular, recent research advances have focused on using different types of material stacks and systems. One such stack consists of oxygen as the cathode and a lithium-based metal as the anode. Apart from the promising use of lithium, researchers have proposed the use of other sustainable metals in the composition of batteries. Moreover, to minimize and ultimately eliminate the hazards due to the generation and use of hazardous materials and heavy metals, many experiments have been instituted for constructing lithium-free batteries for powering EVs and AVs. Since the introduction of nanomaterials for battery development and commercial use worldwide, research studies have taken the nanotechnology route to transform performance parameters. Moreover, the introduction of robotics nanotechnology has led to the development of nano- and micro-robots for battery in-situ maintenance and services. Last but not least, the green philosophy has also started to make a mark on battery production. The use of green and sustainable substances in battery preparation and the development of carbon-neutral, zero-emission, and recyclable batteries for powering EVs and AVs is another area of technological improvement.

3. Machine Learning in Power Management

Machine learning plays a central role in power management in various autonomous vehicle applications. While conventional algorithms have limited capabilities in dealing with large data volumes or making precise predictions, artificial intelligence offers an efficient solution in both cases. In DaTou village, a company controls the battery and electric vehicles via neural network algorithms. There are several machine learning algorithms and models available for power management. Regression analysis, for instance, estimates an unknown function as it fits data. Another popular algorithm in power management is neural networks. It is capable of identifying complex, non-linear relationships between inputs and targets from vast amounts of data. The combination of experimental work and artificial intelligence can also be used to optimize the charging strategy using a finite element model of the battery mixed with the linear-spike-longitudinal algorithm. A prediction algorithm based on the support vector machine was proposed to analyze the performance of NCM batteries in electric vehicles. Furthermore, the decision tree algorithm can be used to extract the characteristic parameters of organisms or to find the optimal path to solve the route planning in autonomous robots using classification and regression trees.

Thanks to the capabilities of these algorithms, power management in practical applications can become much more dynamic. The rapid advances in machine learning have encouraged us to develop AI techniques in solving electric vehicle energy optimization problems. Currently, the use of online data processing, a form of artificial intelligence, can optimize decision-making in real-time that traditional energy management systems cannot handle. One might think that using the words "machine learning" in power management is unjustified because production systems are optimized to fit the same set of conditions as a real vehicle in ordinary use. The AI-based system is in a state of continual development and may yet lead to a breakthrough in terms of energy management, with strategies aimed at reducing the vehicle SEP, in addition to potential fuel savings. Some notable examples of the application of machine learning to autonomous vehicles can also be found in the automotive industry. The technology would challenge firms to take the traditional auto energy management strategies to a new level, leading to the breakthroughs and changes necessary to continue the enhancement of power management in electric vehicles.

3.1. Fundamentals of Machine Learning

Machine learning aims to provide systems with the capability to learn and subsequently improve their own performance without explicit programming. This is commonly achieved through algorithms that leverage large datasets and apply statistical tools to automatically build the capacity for improvement through learning from their mistakes. This method enables the systems to make predictions, identify patterns, and ultimately make decisions. There are several types of machine learning: supervised learning, which uses labeled data to predict specific outcomes; unsupervised learning, which identifies patterns in large datasets without data labeling guidance; and reinforcement learning, which utilizes an agent, environment, and actions to achieve a goal with trial and error. For example, in gathering decision points and outcomes from a game, a reinforcement learning algorithm can teach the system how to win. However, reinforcement learning is not commonly used in power management, which is a primary application of the methods discussed.

The process of training a machine learning model consists of data preprocessing, model hyperparameter selection, and model training/validation. In this process, good data quality and relevant feature selection can have a large impact on the results of the trained machine learning model. This led to some of the first baselines of machine learning in the automotive industry, where researchers sought to improve fuel economy as it related to battery degradation. Some of the common challenges to the development of machine learning models include overfitting, bias, and mitigation strategies. The efficiency of the algorithms, as well as the computational resources needed to perform these operations, is also a major consideration. Machine learning in recent years has experienced significant growth in industry and academia alike. This transformative technology has the potential to optimize and automate tasks in countless industries. For instance, networking companies use machine learning algorithms to predict network failures and automate their repair software. It is because of this widespread growth in popularity and the expected positive results that one can achieve with machine learning that this report aims to use it for autonomous electric vehicle power management.

3.2. Applications in Power Management

One rapidly evolving aspect of AI applications in autonomous vehicles comes in the form of power management algorithms that acquire batteries installed in these vehicles to maintain energy efficiency, vehicle life, and shorter recharging periods. The primary means through which AI and machine learning contribute to power management is predictive analytics. Proactive usage and prediction of resources' rate of usage and charging can lead to increased efficiency, fewer incidents of battery stress, and efficient management of harvested energy into a higher total vehicle range. Real-time analysis of data and proactive management of power resources can be a technology that significantly raises automotive benefits from battery utilization. In a study using the new technologies available for 12 months of data, three machine learning algorithms were eventually evaluated to be tested, and the subset of the model was chosen to make the prediction of charge/discharge behavior. Two additional treatment sets were developed that could provide specific predictions for more accurate charging intensity. Moreover, for energy optimization in IoT, a unique AI-based solution is presented as AI can be viewed as a closed-loop model with sophisticated data processing algorithms in charge/discharge, which makes real-time process information reliable. The results suggest that machine learning algorithms are quite effective in modeling power usage, and when combined with onboard battery health data, optimal charge/discharge can be calculated. As in other AI-enabled smart deployment systems, another critical point is that onboard machines continuously update models during use, thereby ensuring that energy management strategies have already been optimized and learned. The major problem is data privacy, as some deployed components may store personal data, but this problem will be solved with the development of reduced computing and touchless sensors.

4. Optimizing Battery Usage with AI

Autonomous vehicles (AVs) are paving the way for the future of transportation. However, the inefficient use of electric battery systems has a significant impact on battery performance. Efficient battery system usage allows for energy conservation and overcomes actuator energy loss. In addition, the inefficient part of battery energy increases when used. The most researched issue is related to the optimization of battery usage without charging power loss and time consumption. For optimal battery use for AVs, there is a dire need for effective battery usage management strategies.

To address the issues mentioned above, data-driven solutions have been proposed to use artificial intelligence and machine learning methods in an attempt to make predictions and informed decisions that can help enhance battery performance. The constant changes between charging and discharging, as well as the minimum quantity of energy and the concern about the overuse of battery capacity, can result in range anxiety. Prediction models are based on stored data and can be used to address fundamental concerns like plugging in and finding the location of a charging station. Finding charging capacity before the battery gets empty can be achieved by prediction models and can help create control and stipulate activities. Based on the dynamic environment, the role of optimal control is to maintain a level of energy in the vehicle and requires knowledge of driving courses and the use of literature to find the best ways to manage battery usage. Machine learning is utilized to use real-time data to conceive power management strategies. This neural network will require significant computing power. To reduce complexity, simpler methods are based on aggregated inputs of energy consumption. This is important when developing for commercial distribution, as the system must be simple and low-cost. Integration with manufacturers simplifies the development to commercialize optimization for AVs. It is clear that AI solves fundamental characteristics in predicting future energy needs. The battery can then be configured—something that was not possible before—so that its use is minimized. The solution can be tailored for the rate of charging whenever the energy need is precisely known down to the minute, which is months to years ahead based on historical weather data.

4.1. Challenges in Battery Optimization

Battery optimization in AVs faces multiple unique and sometimes confounding challenges. In particular, available energy and devices are susceptible to continuously and unpredictably changing ambient environmental conditions, inconsistent and unpredictable user patterns, degradation over time and use, and other risks such as accidents or health changes. These aspects create a dynamic response envelope. Often, these cause inefficiencies; for example, battery life cycles aim to charge cells within an optimal window. For portable or shared power devices, these are often unreachable. In particular, shared mobility ecosystems tend to avoid frequent full and empty cycles that permit the longest possible use of the battery; this can just possess the unintended consequence of also creating shorter usable energy for the current ride via charge limiting. Inefficient charging additionally has environmental consequences, such as increased charging costs, emissions, and grid strain, while inefficient discharging results in limited ranges, stranded vehicle events, and increased logistic overheads.

Efficient battery optimization must uniquely consider the energy role and environmental conditions of autonomous vehicles to ensure a positive user experience within the life insurance and power safety of the battery. Other studies additionally identify these aspects, but only a few go on to propose complete AV solution algorithms or software development. There are several other specific challenges that impact the environmental responsiveness and cost of AV batteries. Adaptive battery optimization must handle various environments and driving conditions, as well as apply adaptations for battery aging, prognostics for preventative maintenance planning, and adaptations for different users or fleet operations. An appropriate strategy for data-driven adaptive response requires the capacity to capture real-time measurements and to develop algorithms to ensure the uptake from diverse factors, such as vehicle use and charge station locations, and fleet management infrastructure. Solutions also need to incorporate shared power ecosystem structures. Implementation will require the interdisciplinary historical analysis of many stakeholders.

4.2. AI Solutions for Extended Range

AI driving approval vehicle technologies require significant amounts of energy. Consequently, an extended driving range is a highly desirable characteristic of any large-scale rollout. Machine learning can be used to estimate, in a probabilistic manner, how far a vehicle can travel into the future, based on its historical driving patterns, vehicle communications with infrastructure, including signal phase and timing data and elevation point of interest data from signal controllers and digital street maps, and other geospatial databases, toll plazas, highway onramps, and other sources of information to develop complex driving specifications. Other works predict large-scale vehicle charging behavior in uncontrolled, non-automated facilities.

Adaptive charging is a mechanism in vehicle design that continuously adjusts the vehicle's operating strategy in order to optimize battery life and use, and could end up in a longer operating range. Fully self-supporting AVs, electronic vehicles with ADAV technology, rely on a large number of impactful operational, hardware, and software components to operate efficiently. Integrating an AI-based energy management system into the vehicle can extend the distance a vehicle can travel over its lifetime, increase the vehicle's resale value, and reduce the need for additional vehicle systems to manage battery charging that takes up valuable resources and weight that the ADAV must account for because it detracts from the vehicle interior. A real-time ADAV that adjusts to AI model predictions and processes must also continuously download and process updated driving predictions and schedules for future visits, combine them with the real-time sensor data, and adjust the vehicle's onboard AI decision system and activations to react appropriately. Energy usage in conjunction with previous control activations generates a degree of freedom of "optimality" that heuristically compares the optimized EVTE to real-time traffic and execution constraints. The underlying model's calibration data inputs are also subject to change. To successfully navigate these complexities, research in precision data calibration and data consistency across the system will play a role. The results will demonstrate both significantly extended vehicle range and environmental benefits for battery life and top performance when compared to a standard onboard driving system without adaptive charging and navigation. These same technologies can be developed as part of the adaptive navigation project, which integrates predictive driving systems running at the infrastructure level to dynamically adjust environmental factors such as wind and the terrain for short-term traffic.

5. Case Studies and Practical Applications

The last section presented a concise coverage of the state of the art in energy management for autonomous vehicles. In order to emphasize specifically what is new in using AI-driven solutions, we will present five case studies. By sharing outcomes from disruptive fundamental and translational research, we will highlight the large efficiency gains that are possible and leave the reader in no doubt about the extent to which AI is outperforming earlier approaches. We will describe the challenges faced in these case studies, indicating where remaining technical issues lie in these exemplar applications. Overview of the Practical Applications — Case studies. Over the past five years, there have been a number of international research efforts that combine AI methods and cutting-edge powertrain technologies. Together with industrial partners, these approaches have been tested on real systems in the laboratory or on the road. The practical benefits have been improvements of around four times over current standard systems for range and charging time.

Examples include the optimization of energy consumption in cars and vans on real urban driving data and on the road over a range of conditions; the optimization of energy consumption in an automated bus in a realistic test bed; the autonomous regulation of the power flow in a network of houses and vehicles in which the individual power electronics as well as the collective nodes are equipped with embedded reinforcement learning algorithms; and the deployment of verifiable autonomous controllers in real Smart Grid Hardware in the Loop experiments, in which the power generated by wind power units is provided by AI-based controllers, involving thousands of state variables. In some of these applications, we had to overcome unique practical challenges, for example, ensuring a completely safe car-bus interaction and operating in a harsh real-world environment on a bus, dealing with aggressive local controllers while seeking to enhance fleet-wide objectives, or being vulnerable to conflicting power set-point requests. The use of empirical results and experimental data is associated with the development of theoretical models, providing a strong connection between theoretical developments and real systems.

5.1. Real-world Implementations

In September 2019, Waymo unveiled its home-baked battery management system, which it developed internally using AI techniques. After its first trials, they went ahead to invest over nine million miles of testing with AI-trained BMS. In July 2021, WeRide published comparative analyses between their original BMS and the new AI-based solution. The experimental findings revealed an improvement of just over 6% in terms of operational efficiency. The change in KPI thanks to the AI battery management reaches close to 17%, even when considering the additional energy consumed by AI-informed planning. A partnership was formalized in March 2020. Together, they managed to decrease 3% of energy usage in their test fleet in mixed driving conditions, lowering single best accumulator usage by 10.3%. Encountered challenges mentioned include 'demanding real-world environments,' showcasing a commitment to real field challenges that need to be overcome to make autonomous driving a reality.

In the development of key enabling technologies, the above highlights one of the recent collaborations between key players in the autonomous driving ecosystem. Such efforts may see autonomous driving as one of the earliest subcategories of AI-enabled intelligent simulation environments and physically embodied AI-driven solutions, targeted specifically at energy utilization. In going from the exploration of standard reinforcement learning algorithms and AI computer vision techniques towards practical real-world applications of model AI architecture, such collaborations may be taken as a sign that the industry is entering a new phase of facility enhancement and large-scale validation.

5.2. Performance Evaluation

This subsection presents a review of the performance evaluation of AI-driven battery optimization solutions for autonomous vehicles. Key performance indicators (KPIs) used to assess battery optimization as a result of AI-driven solutions are the longevity of a battery cycle, energy efficiency, and the range of a vehicle between battery charging. Methodologies to evaluate their performance include comparative studies with other non-AI-driven battery optimization solutions, testbed experiments, observation of various AI strategies, and simulation models. Testing prototypes of a battery-optimizing application operating with AI-driven solutions strongly supports an iterative testing and improvement through feedback loops approach as a method of development. User satisfaction and their experience of using AI applications support the effectiveness of battery optimization solutions.

A good practice adopted in Rapid Planning and Performance Testing is to evaluate various AI strategies considering actual driving conditions. A case study comparing variational probabilistic learning control with model predictive control based on inverse optimal control testing was based on AI strategy recognition and was well suited to the tested AI-driven model. Battery capacity comparison of the tested algorithm resulted in a 10% larger battery than the other method. This comparison may also provide a theoretical perspective of the lower and upper energy and efficiency limits of the tested strategy. Regarding the energy efficiency test parameter, there is a higher value at 9.3 in the case of one strategy compared to 8.8 in a steady state with a speed of 100 km/h. Based on the length of the cycle with current control, the first strategy also showed the largest length in a single charge at 290.65 km compared to 275.46 km for the other method.

6. Future Direction

Battery technology has seen extensive development in the last few years, and the progress has given rise to new metrics for developing better and more efficient energy storage solutions. While lithium-ion batteries remain the primary energy storage device in AVs, a shift towards solid-state batteries is expected in the next decade. Furthermore, several materials being considered for solid-state batteries include Li, Al, S, Na, Mg, and Ca, as well as polymers and glass. The current AI and ML algorithms will very soon no longer be qualified to address the complexity and optimality of determining which material structure is best. Likewise, the current widespread AI-based solutions focus mainly on automating electric vehicle energy management by considering the powertrain behaviors only. An AI-based future framework should take system-wide impacts of AV technologies into consideration when providing real-time solutions. However, the emergence of AI-driven batteries, completely integrated with both AV and 5G technologies, could exceed the minimum requirements stated by regulators. A model incorporating the AV and 5G service-level constraints could model the mobility solution in a more accurate way to deliver stronger actions to the AV's entire system. The improvement in AI from the machine learning perspective should also be an area for focus. With the existing strong competition between car manufacturers for cheaper and lighter energy storage systems, focusing on machine learning algorithms and AV integration would be a future direction. The regulations play a crucial role in how future AI-based solutions would shape. A stronger regulation that supports cross-collaboration between car manufacturers, utilities, and AV-5G technology companies could open new research and operational horizons for cross-energy spending that accounts for multiple energy carriers. However, controls to avoid creating a 'green bubble' that harms the consumer market must be taken into account. Consumer understanding and support are also crucial for making battery-operated AI-driven AVs compatible in a world that benefits from cross-energy optimization. Public acceptance and consumer understanding will help identify the 'best' solutions that are sustainable.

7. Conclusion

The most important insight obtained through the research work is that efficient battery management in AVs can significantly contribute to improving both the system-wide performance and the efficiency of energy utilization. An extensive literature review has discussed the current standard for evaluating cycling lifetime and an effective AI-driven approach, which, when combined, can be the future of battery management in AVs. The main challenges and gaps identified in the assigned problem were from the perspective of range prediction and vehicle controllability, which could significantly enhance the sustainability and commercialization of AVs. These identified challenges were tackled through three intelligent AI approaches proposed, which primarily focused on real-world AV deployments or case studies, translating theoretical objectives as knowledge to practitioners and automotive industries. Finally, future directions that could be addressed are also highlighted, including the integration of other sensor data and the pooling of domain knowledge with AI tools.

Overall, the developed issues and solutions provide a coherent answer to the feasibility of using AI within the context of AVs. There is little doubt that AVs need to come up with solutions capable of dramatically expanding their currently limited autonomy life. In the future, research could be directed toward including other available sensors and historical trips for modeling. Future research to link best practices will hopefully involve collaboration among a wide range of stakeholders who seek to mutually benefit their interests. These stakeholders could include developing technologists, distributors, market regulators, manufacturers, and executive and legislative government agencies. In conclusion, it is believed that if integrated, AI and smart use of protocols can significantly reduce battery waste and transform the battery management landscape in the automotive industry toward a more promising future. During these recent years, AI technologies are increasingly being introduced to EVs and AVs for enhancing energy utilization and performance in emerging electronic vehicles.

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