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Research Article

Machine Learning Applications in Fleet Electrification: Optimizing Vehicle Maintenance and Energy Consumption

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ARTICLE INFO **ABSTRACT**

The electric vehicle (EV) market has been growing not only for passenger vehicles, where we witness high adoption of these cleaner cars, divided into Hybrid Electric Vehicles (HEVs), Plug-In Electric Vehicles (PHEVs), and Battery Electric Vehicles (BEVs), but also in buses, trucks, and vans, with an increasing conversion pressure due to regulations. In last-mile delivery, powerful optimization tools combining machine learning with operations research have become the subject of several studies, aiming to achieve efficient energy consumption in EVs by predicting drivers' behaviors or track charts. Moreover, new strategies have been developed for something known as fleet electrification, i.e., when a carrier company aiming mainly to decrease its environmental footprint combines the operation of conventional fuel-powered vehicles with electric ones; this is not a complete switchover, but an intermediate stage.

Since computational methods converged, fleet electrification attracted researchers' interest as a techno-economical optimization question related to three main research lines with a strong potential impact on environmental electricity: energy mix-related carbon emissions. The first category of services that impacted fleet electrification before the advent of machine learning was related to condition-based maintenance. As commercial gas, electricity, heating oil, and water consumption can be budgeted across a year's worth of monthly payments, fixing a price through the year could help these fleets include commercial formulations that account for released corporate emissions through approved carbon offsetting. In concrete numbers, our technical paper has two key goals: firstly, we investigate whether and to what extent the Vehicle Misuse Factor, as defined, and the initial state of relevant vehicle parts (tires, gearbox, motor, etc.) affect the electric energy consumption of EVs; secondly, we propose and solve the cost minimization model arising from this energy consumption prediction.

Keywords: Fleet Electrification, Predictive Maintenance, Energy Management, Vehicle Optimization, Machine Learning Algorithms, Battery Performance, Charging Infrastructure, Data Analytics, Route Optimization, Operational Efficiency.

1. Introduction to Fleet Electrification and Machine Learning

Many industries are beginning to look to sustainable transportation to improve company image, decrease carbon emissions associated with their operations, and decrease costs associated with fossil fuel usage. A recent trend in sustainable transportation is fleet electrification. Combining this push for electrification with a current trend of collecting big data could simplify the implementation of fleet electrification. The fleet electrification context is further combined with modern software and machine learning models. To make data analyses more applicable, the fleet electrification trend is placed in the context of its historical development. Different industries could have many relevant applications for this investigation; this research will focus on electrified busing units. Decision-making in the public transport sector is informed by data analysis of ridership and consequent route generation or adjustment. The human ability to translate complex interpretations into simple decisions can be acquired using data-driven decision-making in fleet management. How exactly can the application of data be focused on becoming an efficient aspect of day-to-day answer this broad question.

Moreover, the fleet electrification arena is complex, despite the above universal benefits of fleet electrification. Evolving battery technology and challenging central grid constraints are making fleet electrification a novel pathway for this generation.

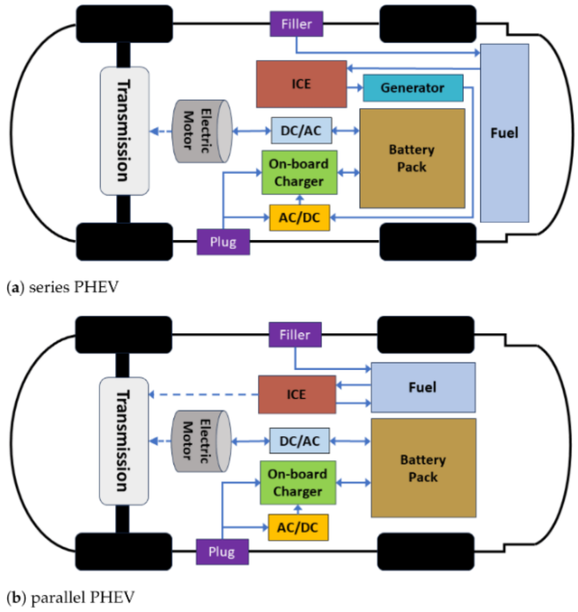

Fig 1: Optimizing Vehicle Maintenance and Energy Consumption

1.1. Overview of Fleet Electrification

The electrification of fleet vehicles is a big challenge. It is still at the beginning of the transition from full conventional to full electric energy, considering all market segments. Before plunging into the entire evolution of fleet electrification, it is essential to provide a general overview. The term 'fleet' refers to a group of vehicles, three or more, which represent an asset for a company. Light-duty vehicles are the main segment, even though some businesses have expanded to include trucks, buses, and vans in their fleets.
The reason for the transition from fuel to electricity is based on regulatory pressure toward lower emissions from greenhouse gasses. Environments are significant for vehicle emissions, especially in the context of logistics, which implies urban areas. In terms of financial aspects, investing in a fleet of electric vehicles implies a return on investment in the long term, not only cost savings obtained from decreased vehicle maintenance and energy consumption. The benefits of full electrification—the potential to achieve zero emissions and no environmental risks due to the absence of direct pollutants—outweigh the costs for now and the near future. Electrification is supported by battery technology advancements, increasing charging infrastructure availability, and forward financial models. During the transition period, the shift from internal combustion engines to plug-in hybrid technology in fleet management was beneficial. Many industries redid the comparative analysis that agreed with investing in a full electric asset. Although seemingly popular worldwide, few companies have already invested in the electrification of their fleets.

1.2. Role of Machine Learning in Fleet Management

Fleet management improves the operational efficiency of the fleet, leads to sustained growth of the business, and also reduces the amount of money spent on vehicle repair and fuel consumption. Data analytics plays a crucial role in understanding the complexities involved in vehicle operations. Machine learning comprises a set of algorithms, with their roots in pattern recognition, regression analysis, classification algorithms, and unsupervised clustering. Clustering algorithms were used to understand the type of electrical signal transmission between the source and the destination, and this information was used for the development of reinforcement learning algorithms.
Costs for big data analysis would be high, while the cost of fleet management data collected could be lower. Machine learning could be used in the following applications: (1) real-time monitoring to detect wear and tear that may raise maintenance issues between the regular checks scheduled; (2) predictive breakdowns to anticipate when a car will stop working, such as the prediction of EV battery failures; and, last but not least, (3) decision support systems to help the fleet manager in assessing, choosing, and evaluating the best strategies in terms of economic payback. All these automated approaches could help fleet managers in the systematic selection of the best fleet management. Fleet management systems have to be fed with data, and in the field of energy, this data can support operations. Renewable prediction enrichment can be approached with a hybrid approach using machine learning-trained reduced-order models.
Moreover, another important aspect of machine learning is its potential versatility in most applications. New methodologies or the ability to customize these methodologies to the variety of vehicles or machinery of a fleet will enhance the potential benefits of a good predictive maintenance system. Machine learning can provide models for different data inputs or different insights into the asset life. As a result, more information will be

gained in the asset operation. The success in the implementation of the distributed operation of vehicle fleets and their recharging is strictly dependent on precise protocols, necessary to establish the best order to reduce the plugged time and, if possible, also the recharging line length. The machine learning model can also be employed to predict the consumption-based energy needs of each vehicle's clientele. The vehicle routing with partial recharging can be used to find the minimal recharging power and line length. Some case studies prove impressive economic savings. However, some questions remain open. The first one is the data quality required to input the algorithm, which must be reliable. Then, all reactions that the algorithm is expected to provide must be analyzed in detail. Finally, one of the most challenging open questions is the transparency and interpretability of models. Satisfaction with a 50% improvement in price is a big deal for some, while for others it may seem little. A transparent approach is necessary to analyze, understand, and interpret learned models. The correlation between features can also drive innovation implementations for forecasts.Fleet management significantly enhances operational efficiency and fosters business growth while minimizing vehicle repair and fuel costs. The integration of data analytics and machine learning is pivotal in addressing the complexities of vehicle operations. Clustering algorithms aid in analyzing electrical signal transmissions, which, in turn, contribute to the development of reinforcement learning algorithms. Although the costs associated with big data analysis can be high, fleet management systems benefit from lower costs of collected data. Machine learning applications, such as real-time monitoring, predictive breakdowns, and decision support systems, empower fleet managers to optimize maintenance strategies and operational choices. The versatility of machine learning methodologies allows for customization across diverse vehicle types, enhancing predictive maintenance systems. Additionally, precise protocols for managing the distributed operation of electric vehicle fleets are crucial for minimizing charging times and energy needs. While case studies highlight substantial economic benefits, challenges remain regarding data quality, algorithm transparency, and interpretability, necessitating a thorough understanding of model performance and feature correlations to drive innovation in forecasts.

Equ 1: Gradient Descent in Linear Regression

$$Cost\ Function(MSE) = \frac{1}{n}\sum_{i=0}^{n}(y_i - y_{i\,pred})^2$$

Replace $y_{i\,pred}$ with $mx_i + c$

$$Cost\ Function(MSE) = \frac{1}{n}\sum_{i=0}^{n}(y_i - (mx_i + c))^2$$

2. Machine Learning Techniques for Vehicle Maintenance Optimization

Several approaches have been proposed in recent years to help fleet operators optimize vehicle maintenance through the use of machine learning techniques. Vehicle maintenance can be classified as corrective (unscheduled), preventive, or predictive (condition-based). Unlike preventive maintenance, predictive maintenance models do not rely on time intervals but rather use historical data to predict potential vehicle failures. Predictive models draw on data originating from vehicle components, usage intensity, road condition, vehicle type, and many other features describing component operation during the vehicle lifespan. Unlike traditional approaches using scheduled replacement intervals, predictive maintenance allows correct scheduling of interventions when needed, with the potential to reduce costs and vehicle downtime through proactive consumer vehicles. This paper discusses using machine learning frameworks, the structure of historical data, and several considered algorithms tailored to utilize the predictor features and introduce reliability constraints within a multi-objective optimization framework. The methods are tested on multiple fleet instances. Proposed artificial/multiple neural network predictors result in improved vehicle reliability and reduction of fleet energy consumption.

Machine learning algorithms such as multiple-layer perceptrons or decision trees have been utilized to optimize the maintenance of internal combustion engine-powered vehicles or vehicles with a combination of internal combustion engines and electrical components. Artificial neural networks have also been used successfully to optimize maintenance practices of electric vehicles, relying on the analysis of large amounts of aggregate data collected over many years. More specifically, the single-vehicle-wide solutions focused on the optimization of either vehicle or component maintenance through the design of data-based predictors/forecasters of relevant engine energy and wear degradation. Electrified vehicles and particularly electric vehicle users rate vehicle reliability as one of the top factors affecting their vehicle purchases. This has led to massive investment in related unsupervised and supervised machine learning techniques, aiming to overcome the challenges of data gathering and pre-processing, algorithm accuracy, and data for implemented and customer-usable outputs.

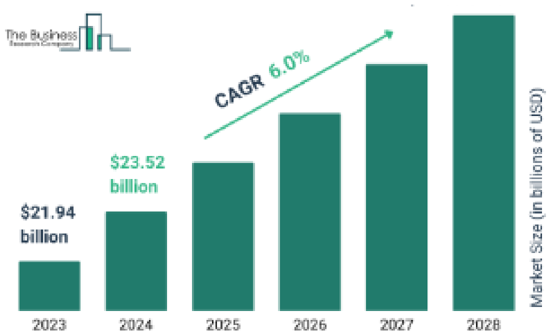

Fig : Electric Vehicle Fleet Management Market Report

2.1. Predictive Maintenance Models

Preventive maintenance is a traditional approach that uses static maintenance plans to anticipate vehicle failure. Because the parameters of vehicle operation and environmental changes are always in a dynamic state, they cannot accurately represent the current or near-future health status of vehicles. In essence, predictive maintenance technology that utilizes machine learning algorithms has attracted increasing attention in recent years to predict the remaining useful life (RUL) of vehicles. Using the key parameters and real-time telematics data collected, various machine-learning techniques have been applied for the development of predictive models.

The most cited and widely used classic modeling techniques for the RULE of vehicles include regression analysis, neural networks, and artificial intelligence-based algorithms. Although the objectives of their research are different, significant contributions to the modeling techniques used are revealed. Real-time data sources that are essential for predicting RUL with predictive maintenance models are collected from the electrified vehicles in the telematics of the fleet. The Internet of Things plays a crucial role in various application areas, including predictive maintenance models for controlling and maintaining vehicles in the fleet. Several practical case examples of predictive maintenance applications are provided. Such models, if working properly, can lead to the realization of a healthy vehicle fleet and reduce accidents caused by vehicle equipment failure. The economic advantages can be achieved by implementing the residual life of the vehicles.

2.2. Optimization of Maintenance Schedules

Machine learning techniques have been increasingly used to optimize maintenance scheduling. Several advanced algorithms have been proposed that can analyze the historical maintenance data and propose efficient future maintenance schedules. Furthermore, the algorithms can categorize maintenance operations, remove unnecessary service interruptions, and prevent swamping the maintenance workforce. Dynamic scheduling and prioritization methods have also been proposed and can provide the same benefits as optimizing the maintenance schedules.

The optimization of the maintenance schedules aims to improve fleet operability and decrease administrative and operational expenses. A practical strategy for battery electric bus fleets includes the optimization of vehicle maintenance schedules, energy consumption, and the speed profile of a bus on a set route. The application focuses on a corporate software system that predicts vehicle failures and assists service providers in managing the urban transit vehicle fleet maintenance schedule. The performance of the algorithms has been demonstrated on a real-world bus transit agency operating an automotive fleet under varying operating conditions. Operating variations result from factors such as route characteristics, climate impacts, geographic environment, and day-of-week dependent ridership rates that, during peak periods, can exceed 90,000 passenger boardings per day. To validate the study, the algorithms are tested on a fully integrated hardware-in-the-loop system consisting of the bus, the road, the battery electric, and other external systems. A user-friendly software interface is developed so that fleet managers and engineers can provide decision inputs and use the outputs to suggest improvements to the electric vehicle bus battery management.

Despite the plethora of operational improvements that can be obtained from the optimization of maintenance schedules, there are several practical challenges. The first main challenge is that it is difficult to integrate real-time operating and maintenance data for dynamic maintenance scheduling. Another challenge is how to adaptively schedule vehicle maintenance to follow the changing degradation mechanisms under different operating conditions. A fuzzy rule-based expert system has been introduced to generate the maintenance schedule. The proposed system can schedule the maintenance and replacement of vehicle components such as traction motors, batteries, and tires for every bus and vehicle. The replacement schedules for the batteries are generated based on the state of charge, age, or charge-discharge cycles.

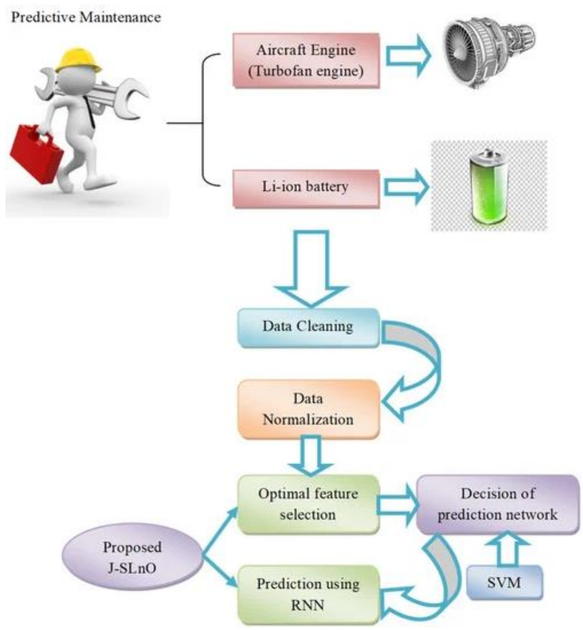

Fig 2 : Predictive maintenance planning model

3. Machine Learning for Energy Consumption Optimization

In fleet operations, machine learning can be used to optimize energy consumption strategies. Sufficient data collected from vehicle onboard sources have led to the application of machine learning techniques to develop models for energy prediction, energy usage prediction, state of health prediction, and other patterns related to energy consumption. Regression and Markov chain models are prominent for predicting energy usage due to their ability to capture patterns and trends in energy usage from collected data. A Markov chain-based model is integrated with a regression model to estimate the energy consumption value. Also, clustering is a widely used technique to profile energy consumption behavior. Clustering is used to categorize vehicles in a fleet based on their energy consumption patterns and the similarity in that consumption.

Indications of increased or decreased battery charge can also be obtained from the shifting of a vehicle's residency pattern; hence, clustering techniques can distinguish between travel and idle energy consumption. Real-time data is essential in the operation and management of electric vehicle fleets as improving the energy efficiency of the electric vehicle reduces the energy cost and plays a crucial role in the increasing interest of the private sector in electric vehicle investments. Route optimization algorithms, influenced by machine learning, profile consumption as a function of speed, time of day, and distance. The decision on the change of the operational route is triggered by new events, which include changes in traffic conditions, changes in weather conditions, time of day, etc.

An online energy prediction scheme that integrates a clustering algorithm and a regression approach has been proposed. The clustering algorithm is developed using a probabilistic discriminative prototype classifier that profiles the energy consumption patterns of electric vehicles. The regression approach is developed using Gaussian process regression to predict future vehicle energy usage for a given trip. Various successful examples have supported the effectiveness of the proposed strategy. The usage of smart meter data for inferring the impact of the weather, individuals residing, and driving behavior has been proposed, with results showing that the fuel consumption of internal combustion engine vehicles can reliably be predicted at the whole-town scale down to the level of individual streets. Real-time vehicle power modeling can improve the quality of data necessary to monitor the energy consumption of a building fleet in real-time. Developing predictive algorithms that integrate machine learning with weather, microclimate, vehicle configuration, battery capacity, and other third-party data is one of the challenges in infrastructure development.

There are several practical concerns about the direct applicability of models in the literature. There is a concern about the accuracy of commercial software. Issues arise from wrongly parameterized systems, data interpretation, and the overfitting of data. Also, little guidance is given on how to apply predictive vehicle usage to vehicle-to-grid management tools. It opens the way for predictive approaches by the already mentioned real-time vehicle modeling. Predictive approach implementation can be quite prominent in managing maintenance procedures and electric vehicle fleets. Since there is an urgent need for a practical guideline that shows how vehicle usage predictions can be implemented, model-based predictive operation of vehicle-to-grid was shown to outperform direct control, irrespective of vehicle-to-grid power level and number of participants.Machine learning is revolutionizing fleet operations by optimizing energy consumption strategies through advanced predictive models. By leveraging extensive onboard data, techniques such as regression and Markov chain models have emerged as powerful tools for forecasting energy usage and state of health in electric vehicles. The integration of clustering algorithms allows for the categorization of vehicles based on their unique energy consumption patterns, distinguishing between travel and idle states. This real-time data-driven approach enhances energy efficiency, significantly reducing costs and attracting private sector investments in electric vehicles. Furthermore, innovative online energy prediction schemes that combine probabilistic clustering with Gaussian process regression are demonstrating promising results in forecasting vehicle energy needs based on various factors, including weather conditions and driving behavior. Despite challenges such as model accuracy and data overfitting, the implementation of predictive algorithms for vehicle usage is paving the way for improved vehicle-to-grid management and optimized maintenance procedures. The need for practical guidelines in applying these predictive approaches is critical, especially as model-based strategies have shown superior performance compared to traditional direct control methods, regardless of power levels or participant numbers in vehicle-to-grid scenarios.

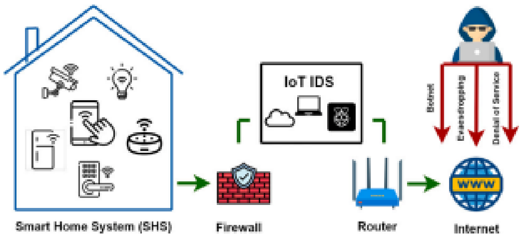

Fig 3: Energy consumption on-device machine learning models

3.1. Energy Usage Prediction Models

In the context of fleet electrification, energy usage prediction is a key enabler in defining the underlying operational strategies and objectives. The forecasted energy consumption, or electricity baselines per vehicle route, also supports optimization and control strategies. Several machine learning methodologies for energy usage predictions such as nominal value methods, time series modeling, and supervised machine learning techniques, among others, are discussed. Semi-supervised and unsupervised machine learning methods are also proposed for the prediction of electricity or gas consumption, as well as to identify inefficient driving profiles. For energy usage predictions, time series analysis is used to understand the regularities in driving patterns and, in turn, predict energy consumption.

Results show that the energy demands required by the encountered routes can be forecasted with high accuracy. This model is upgraded to handle the vehicle's maintenance tasks, showing no added benefit. Furthermore, moving from energy baselines for prediction to adaptive models using a supervised learning approach improves the accuracy of the final estimations. The prediction of the electricity baselines after the collection of years of operational data resembles the actual energy consumption, leading to a practical operating cost reduction. The inclusion of parameters such as vehicle weight, differences in load, and a dedicated fleet composition can further improve the predictive accuracy. From the collected trip data, such models yield a mean average percentage error (MAPE) ranging from 6% to 24% in electricity baselines forecast, reinforcing the case for a flexible charging management scheme. However, heterogeneous and non-homogeneous behaviors of users can lead to a higher MAPE result.

Equ 2: Cauchy's integral formula

$$
\begin{aligned}
\left|\frac{1}{2\pi i}\oint_C \frac{f(z)}{z-a}\,dz - f(a)\right| &= \left|\frac{1}{2\pi i}\oint_C \frac{f(z)-f(a)}{z-a}\,dz\right| \\
&= \left|\frac{1}{2\pi i}\int_0^{2\pi}\left(\frac{f\big(z(t)\big)-f(a)}{\varepsilon e^{it}}\cdot \varepsilon e^{it} i\right)dt\right| \\
&\leq \frac{1}{2\pi}\int_0^{2\pi}\frac{\left|f\big(z(t)\big)-f(a)\right|}{\varepsilon}\,\varepsilon\,dt \\
&\leq \max_{|z-a|=\varepsilon}|f(z)-f(a)| \xrightarrow[\varepsilon\to 0]{} 0.
\end{aligned}
$$

3.2. Route Optimization Algorithms

A range of sophisticated route optimization algorithms leverage machine learning to create superior operators in automotive fleets. These algorithms use machine learning models that learn and improve vehicle performance. The foundation of most route optimization algorithms is the ability to store and analyze traffic congestion data specific to factors like time of day, season, or occurrence of nearby events. Some advanced route optimization algorithms also consider the impact of weather on vehicle operation. These models use extensive weather forecasts that can be useful operational tools for vehicle routing services. Additionally, these models can use vehicle performance data from existing operations to simulate how a specific class of vehicles operates when impacted by external conditions, such as performing at maximum capability or with existing maintenance issues.

Many modern route optimization applications consider energy utilization, attempting to reduce total energy consumption, thus attempting to increase a service provider's profit by reducing operational expenses while ensuring maximum transportation of goods. Algorithms are designed to consider any truck type, where each truck has a weight, capacity, and fuel volume; traffic speeds decrease for heavier trucks and are greater for empty trucks based on a portfolio of regional highway data. Routing around traffic congestion on a well-planned schedule by inspecting real-time traffic data as part of a route is any routing strategy that can be added after the solution is found, where vehicle dispatch occurs at a central location. The importance of allowing for dynamic scheduling may reduce the significance of identifying routes that spend as little time en route as possible if vehicles needing maintenance will no longer avoid bridges subject to flood alerts. Often, these constructed routes outperform commercial services at both minimizing costs and maximizing customer satisfaction by avoiding traffic congestion. Real-time route optimization can save a significant portion of the service provider's operational costs compared to solutions with routes based on relatively predictable congestion patterns. Constraints with the use of such algorithms, however, are the requirement to solve NP-complete combinatorial optimization problems in a reasonable amount of time, with larger vehicle fleets being more expensive and the added difficulty of integrating the algorithms with existing fleet management systems. Increasingly, however, these algorithms will also perform real-time decisions at the discretion of users instead of only providing one high-quality solution. Future advancements in the algorithms may include integration with other learning algorithms or AI for autonomous vehicle routing decisions.

4. Case Studies and Real-world Applications

In this section, we present selected case studies of the practical applications of machine learning to fleet electrification and management. These projects offer real-world examples of the successful integration of machine learning techniques into operational technology solutions. The case studies cover a diverse set of industries, including public transportation, refuse collection, and vehicle rentals. The projects range in maturity, from exploratory pilots to multi-year industry partnerships. Across all of the projects, stakeholders successfully leveraged machine learning to reduce fuel costs, tackle route optimization, monitor vehicle energy use, and, critically, optimize the time and location for recharging activities. Lessons learned from the applications and suggested potential next steps for incorporating machine learning into industry best practices are outlined in greater detail in the following sections. In the next chapter, the exact case studies will be summarized, followed by a discussion on the relevance and implications for the deployment of machine learning.

The four case studies included are as follows: (1) Intelligent Bus Electrification, (2) Route Optimization in Refuse Collection, (3) Energy Use and Predictive Maintenance, and (4) Electric Vehicle Rentals.

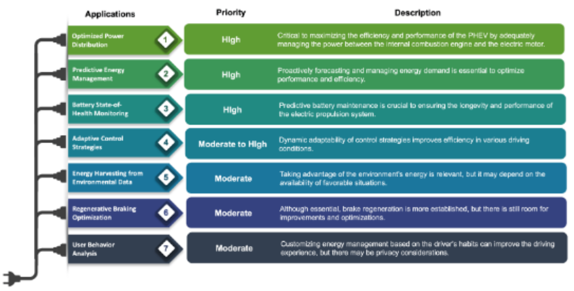

Fig 4 : ML Applications in EMS for PHEV

4.1. Fleet Electrification Projects with ML Implementation

In the past, several machine learning models and techniques have been implemented to address specific operational challenges in fleet electrification. Two recent projects that successfully implemented ML techniques together with operational insights and their impacts are presented in case 1 and case 2. The developed solutions aimed to reduce and optimize vehicle maintenance activities while minimizing the energy needed for fleet operation. Collaboration between technology providers and fleet operators is a critical component enabling the lessons learned from these practical experiences. The benefits of using data-driven methodologies were quantified based on the KPIs linked to enhanced operations, sustainability, or decreased costs. The impact was significant in both cases, and scaling was possible. During project execution, data governance, cleaning, and integration were identified as important tasks for further projects to extract high-quality datasets, maximize the use of ML algorithms, and improve performance. Case study 1: designed a propensity ML model for predicting electric vehicle failures and an advanced time-series ML model for optimizing charging plans. Improved predictive maintenance and optimized charging contribute to decreasing the ancillary energy consumption of the battery vehicle subsystems, helping the environmental mitigation of public transport services. The operational latency in the prevention of electric bus defects was validated by the buses' operational test results in a time-moving baseline in the dataset used. The charging optimization improved the recharging quality, but this was not real-time verified.Recent projects in fleet electrification have successfully leveraged machine learning (ML) techniques to tackle operational challenges, focusing on reducing maintenance activities and optimizing energy usage. In Case Study 1, a propensity ML model was developed to predict electric vehicle failures, while an advanced time-series ML model optimized charging plans. These innovations led to improved predictive maintenance and enhanced charging efficiency, significantly reducing the ancillary energy consumption of electric vehicle subsystems and supporting the environmental goals of public transport services. The effectiveness of these solutions was validated through operational test results, demonstrating a decrease in latency for preventing electric bus defects. While the charging optimization showed improved recharging quality, real-time verification remains an area for future enhancement. This collaborative effort between technology providers and fleet operators underscored the importance of data governance, cleaning, and integration in maximizing the benefits of ML algorithms for enhanced operational performance and sustainability.

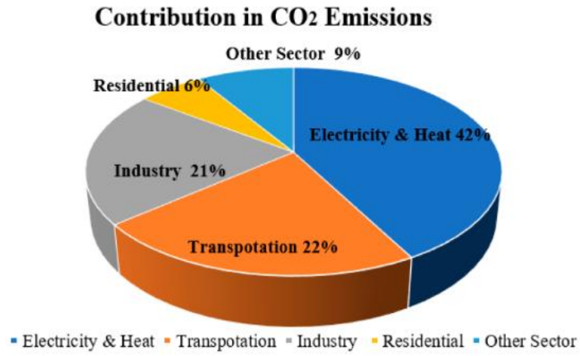

Fig : Comprehensive Review of Electric Vehicle Technology and Its Impacts

5. Challenges, Limitations, and Future Directions

Despite the potential of machine learning models, implementing them in fleet electrification could also face several challenges. The first challenge is data privacy and security. Ill-intentioned actors can access sensitive operational data when unmanned aerial vehicles collect power demand from public electric vehicle charging infrastructure. The development of highly scalable machine learning models is also lacking. Machine learning models are usually developed as generically as possible to accommodate as many types of fleet configurations. It is also difficult to generalize the machine learning models. Even minor changes in the operational environment or fleet composition can significantly affect the generalizability of developed models.

Current research and applications in machine learning generally build models based on historical data retrieved from various data collection techniques. Almost all of the research only discusses a single scenario or use case, such as emission reduction, battery life extension, load flattening, and cost and revenue allocation. Furthermore, the ethical and technical challenges need to be addressed. For instance, there is an ethical concern when tracking each behavior of a fleet owner regarding their system design use cases. Data security and privacy are also major technical challenges when modeling machine learning with large-scale and high-frequency data.

To address these challenges, researchers and practitioners should collaboratively develop few-shot learning algorithms, a unique artificial intelligence that can memorize previous knowledge with only a few examples provided. Several innovations in methodologies have advanced the applicability of machine learning in real-world operational challenges. The recent breakthroughs of jointly developing machine learning and transport systems have indirectly provided us with a broad range of interesting optimization questions in novel areas, such as machine learning, supply chain, and service systems management. The shared challenges include machine learning and time series modeling, optimization, control theory, and many others. Following this, the journal is well positioned to be common ground for machine learning experts to engage in topics relevant to the field.

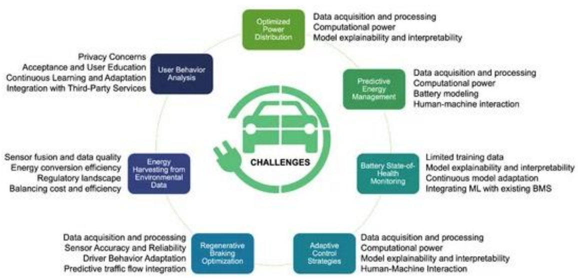

Fig 5: Challenges in ML Applications

5.1. Data Privacy and Security Concerns

Privacy and security issues related to the use of machine learning alongside colossal amounts of operational data are becoming a matter of increasing concern. The amount of operational data in the context of fleet

management is often very sensitive, and potential misuse might result in disastrous maneuvers for an organization. From that point of view, security researchers have to be vigilant not only to point out the risks but also to propose possible remedies. To assure data users that such risks are properly mitigated, a reverse engineering process can be applied directly to the collection-sharing process of collaborative projects, with a case in point those involved in the installation of predictive maintenance systems.
Several researchers discuss various methods for ensuring data integrity and privacy for any computation performed on cloud data. The privacy and security feature settings from the options in Microsoft Excel are according to the company's guidelines. Solutions including hardware implementation and secure multiparty computations come at a considerable additional cost. As data privacy and security have been of prime importance for many years in many industries, the relevant regulations and policies should be conducted and followed. The implementation of platforms for data governance that include metadata management, usage monitoring, issue identity management, and compliance qualitative testing are also proposed.
It is mentioned, thus showing the efforts undertaken to assure security and privacy. Furthermore, if IoT devices are incorporated within the asset setting, there should be AI-driven detect-control privacy to preserve data integrity and confront data intrusions. Privacy concerns are fundamental in IoT environments, and transparency contributes to trust. Transparent compliance with those regulations might be a means of fostering trust in a computation on the "digital twin on the edge." Consequently, transparent compliance with such regulations might help build confidence that no "digital twin on an edge" location will result in a "big brother" scenario, especially for the workforce. This implies that any machine learning approach could not be integrated into the field if it cannot serve these requirements. However, several challenges are to be faced, which include ethical considerations and the need to organize a concerted action to promote research and innovation by academia and industry.

5.2. Scalability and Generalizability Issues

One common critique of machine learning is scalability and generalizability. Developing a model for one fleet often requires it to be re-tailored for another. Needless to say, while electrifying vehicles behave like their traditional counterparts in some senses, they also deviate in ways that necessitate separate modeling and forecasting. Given the inherently idiosyncratic way that fleets are operated, the algorithm developed in one fleet context will diverge from another fleet's situation in a nearly countless number of ways. This adds complexity to tailoring a machine learning algorithm to suit several different fleet contexts at once. When considering fleets of different compositions and sizes, embedding an algorithm to generalize across varying fleet conditions becomes even more difficult.
Models should be tested for scalability by evaluating their performance across a large range of fleet sizes, vehicle types, and operational practices. Robust models should be able to identify the most impactful actions across a wide range of vehicle types, fleet sizes, and operations. Final remarks: It is a valid concern that by embedding human expertise into a machine learning model when it is trained in customizing the two 'ignores' used for developing the algorithm, it will not be suitable for fleets not meeting these criteria. In practice, though, this concern was rarely observed. They are usually far more damaging when fleet conditions are as multifaceted as they are in reality. To hedge these concerns throughout the validation process, continued pilot testing algorithmic recommendations across different types of vehicles and operations, using optimization results to give operators certainty. The image labeling employed a third-party assessment as a quality control metric. These studies reveal that, while some operators under some conditions may exhibit a lack of adherence, on the whole, they can be expected to follow algorithmic maintenance scheduling. While it is unknown where overwhelming adherence or overall follow-up is drawn in the case of this project study, current research shows that tweaking the model to increase generalizability would not do so in the case study.

Equ 3: Minimum Value of a Function

$$f(x) = 2(x-3)^2 - 1.5$$

$$f(x) = 2(x-3)(x-3) - 1.5$$

$$f(x) = 2(x^2 - 6x + 9) - 1.5$$

$$f(x) = 2x^2 - 12x + 18 - 1.5$$

$$f(x) = 2x^2 - 12x + 16.5$$

6. Conclusion

Fleet electrification is expected to revolutionize urban transportation systems. There is growing interest in studying the applications of machine learning methods in electric fleet management. In this review, two prominent applications of electrical fleet systems from a machine learning perspective, i.e., vehicle maintenance and energy optimization, were introduced. Current advancements and methodologies have been presented. We discovered that fleet electrification can benefit from more efficient vehicle maintenance and energy consumption management. Since maintenance and energy consumption activities are crucial for electric fleet operations, they can significantly be affected by efficient predictive methodologies. The importance of maintaining fleet operational efficiency is also reflected in improved management practices based on data-driven decision-making.

We conclude that developing machine learning methods can contribute to bridging the gap between energy management, sustainability, and technology. Future work should address some emerging issues, such as extensive quantitative studies to reveal challenging system complexities, test systems with real data other than simulation analysis for industrial experimentation, and process efficiencies in applying related machine learning methodologies. To our knowledge, there is a demand for sustainability transformation in many areas, and the automotive and transportation industries are ideal areas for undertaking such a transformation. The application of theoretical knowledge in these areas using the latest methods will create advantages for us in our future goals of transforming industries. We expect this review to brighten the future and provide guidance in these current applications. The problems encountered in the sector are opening new areas of research. We aim to see newer and more effective methodologies in the field of fleet electrification shortly.

6.1. Future Trends

The future trends in machine learning applications in the field of electric fleet electrification can witness substantial advancements in the forthcoming years. The emerging AI and deep learning-based models can significantly improve the predictive capabilities and control strategies of deployments aiming to optimize the operation of vehicle maintenance and ensure optimal energy consumption. Moreover, the timely development of 5G networks would substantially improve the data, information, and management of connected fleets. Integration of machine learning techniques with 5G and cloud technology is expected to provide efficient edge and cloud intelligence, significantly increasing the speed of data processing with reduced latencies and lower computational costs. Additionally, integration with automation and connected vehicle services for fleet management using AI techniques will result in dependable multifaceted applications. The aforementioned methods will also be a driving force for the emergence of adaptive systems that can learn from the vast amounts of data generated from diverse sources and the environment.

Nevertheless, a significant amount of research in the field of AI-based models and predictive decision-making constraints limits their applicative role in the practical domain. The speed at which technology is changing, together with the amount of data that still needs to be collected, which is extremely important, particularly in cases of data-driven electric fleet management, will create bottlenecks in integrating the transition of autonomous electric fleets and decision-making models in practical rural applications. More research is encouraged that uses machine learning-based models for electric fleet management, particularly in the aspects of increased vehicular automation that will facilitate the collection and analysis of operational vehicles' data. Also, there remains scope in the selection and application of hyperparameter tuning techniques. Random search and grid search are the traditional methods for hyperparameter optimization, while Bayesian optimization is also a promising approach. An empirical study to develop a machine learning model with enhanced performance will contribute to an improvement in the operation and planning aspects of electric vehicle fleets.

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