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# Optimization of Electric Vehicle Charging Algorithms: Expected Solution for Fast Charging Along with Long Battery Life

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**ABSTRACT:** A comprehensive review on the objectives of electric vehicle charging optimization from various perspectives is presented and discussed in this paper. EV charging optimization techniques including mathematical programming, meta heuristics algorithms and machine learning techniques are explored. The main objectives, constraints, strength, and limitations of different charging optimization techniques are analysed in detail. The transition to electric vehicles (EVs) is pivotal for reducing carbon emissions and promoting sustainable transportation. However, challenges remain in optimizing charging algorithms that balance the need for fast charging with the longevity of the vehicle's battery. This paper explores the trade-offs between fast charging and long battery life, analysing the key factors influencing battery degradation and performance. We examine current charging algorithms and propose optimization strategies to improve both charging time and battery lifespan, offering insights into future developments for EV charging infrastructure. This abstract explores the optimization of electric vehicle (EV) charging algorithms, balancing the need for fast charging with the goal of extending battery lifespan, a key challenge in the widespread adoption of EVs. It highlights the trade-offs between charging speed and battery health, emphasizing the development of strategies that minimize degradation while enabling rapid charging.

**KEYWORDS:** Electric Vehicles (EVs), Charging Algorithms, Fast Charging, Battery Life, Optimization, Battery Degradation

## I. INTRODUCTION

As EV usage is increasing rapidly, a thorough examination of its impact on the grid becomes essential. Though there are a lot of potential advantages of EV in terms of environmental sustainability and energy efficiency, the integration of EVs in large-scale brings various challenges, including grid strain, limited charging structures, and managing energy demands. As the EV sales increase, the energy demand for charging also increases. This also could result in uncontrolled charging and put a strain on the grid systems. These negative impact may act as a barrier for future EV adoption. Grid integration of EVs in large numbers requires costly upgrades to smart technologies. When many EVs charge at the same time without planning which in other terms referred as an uncoordinated EV charging creates unpredictable demand spikes, pushing power grids beyond capacity. Uncoordinated EV charging is dictated solely by customer preferences, so it creates difficulties for grid operators and utilities in ensuring grid stability and electricity distribution. Electric Vehicles (EVs) have gained significant traction in the automotive industry due to their environmental benefits and energy efficiency. As adoption grows, one of the critical aspects influencing the success of EVs is their charging infrastructure. Fast charging technologies have made significant strides, offering users the convenience of charging their vehicles in a short period. However, these rapid charging methods may come at the cost of accelerated battery degradation, which reduces the overall lifespan of the battery. Coordinated electric vehicle charging system with efficient scheduling algorithms ensures optimum charging/discharging and presents a potential avenue for the enhancement of grid utilization and the mitigation of network expansion requirement. The challenge lies in designing charging algorithms that optimize for both quick charge times and long battery life. Optimizing the charging process requires a deep understanding of battery chemistry, thermal management, and the interplay between charging rates and battery degradation. This paper reviews the key factors influencing battery longevity, discusses



existing charging algorithms, and proposes an optimization framework to balance fast charging with battery health. Battery management for plug-in electric vehicles (PEV) has attracted extensive research attention, with most existing studies focusing on PEV operating conditions. However, battery maintenance during idling remains largely unexplored, under which electrochemical side reactions can cause battery degradation. The degradation rate depends on battery states, e.g. state of charge (SOC) and temperature. Considering that PEV idling accounts for majority of the time, the accumulated degradation could have a major impact on battery and vehicle lifetime. In this paper, battery maintenance during extended idling periods is investigated by utilizing a commonly available infrastructure, i.e. the charging unit. An optimal charging profile is designed to maintain the battery states under desirable conditions to minimize degradation over the idling period while still satisfying the charging energy requirement. Optimal charging profiles are obtained under different ambient temperatures and stages of battery life, showing different features due to respective dominating degradation mechanisms. Compared with the optimal charging profile, constant-current charging could result in up to 51.6% higher capacity loss, and that of (fast) constant-current constant-voltage charging could be up to 12.3 times higher under circumstances over a 12-hour overnight idling period. Integration/accommodation of user and grid demand is also addressed by augmenting the optimization framework.

## II. LITERATURE SURVEY

Nowadays, the vast majority of Heavy-Duty (HD) vehicles in operation within Europe are propelled by Internal Combustion Engine (ICE), which typically runs on diesel, as this is the most affordable and convenient energy carrier. So far, only a negligible number of low- and zero-emission trucks are in operation. The European truck manufacturers were set a target to reach carbon neutrality in road freight transport by 2050 at the latest [3,4]. In China [5], Shenzhen city moved to 100% EB integration, with chargers with a power level of 750 kW and EB mileage of about 250 km.

The chargers must supply the EBs with enough energy to reach their destinations. Therefore, it is essential to identify the charger's power and EB mileage, which is based mainly on EB consumption. The EB consumption depends on several factors, such as load, weather (heating system on/off), traffic, city terrain, etc. For an 18 m EB, the average energy consumption for 10 months of operation is around 1.63 kWh/km, and for a 12 m EB, it is around 1.15 kWh/km. In temperatures of 15–19 °C, the 18 m EB consumes, on average, 1.35 kWh/km, whereas the 12 m EB consumes 0.99 kWh/km [6]. An 18.75 m Trolley bus demo, Ikarus-Škoda Tr187.2, was launched in Budapest, Hungary, with a battery capacity of 80 kWh. The trolley bus ran on a route called 77 A, where the round trip was 13.2 km, and the needed distance of the battery mode was 9.2 km. In battery mode, taking into consideration severe terrain properties and weather conditions, with the air-conditioning or heating was switched on, it was found that when the vehicle had no passenger load, it could run for around 20 km. When the vehicle had full passenger load, it could run for about 7 km. Furthermore, the vehicle is considered to use only 33 kWh out of 81 kWh to ensure long battery life [2]. In [7], an energy management system was developed to optimize the auxiliary consumption of the EB fleet; the system is able to be monitored, accessed, and controlled online.

The diesel buses are more financially affordable than the electric ones, which makes the work and support of the various stakeholders' indispensable in reaching the goal of worldwide usage of EBs. It was found that more EBs than diesel buses are needed, which increases the fleet size and cost. In [8], a study was carried out to size the charging systems compared to the battery sizes on the vehicles and to work out the number of EBs required on the route line to investigate the feasibility of replacing the diesel ones. The Use Cases (UCs) are Mercedes-Benz eCitaro EBs, which are normally produced with lithium-ion battery capacities of 150, 200, or 250 kWh. These buses are equipped with CSS2 with the potential ability to adopt the pantograph system, which is sold as a piece of special equipment. The test route line (7.9 km) is between Porto Vado and Via Alessandria (Sovana, Italy), with a total estimated energy consumption of 40.6 kWh for the round trip. It was found that two EBs with a battery capacity of 250 or 200 kWh can cover the operation of one diesel bus with three chargers in the depot with a power capability of 43 kW. With less battery capacity, 150 kWh, three EBs are needed to cover the operation of one diesel bus.

The work in this paper is divided in two stages. 1) Compare the traditional ways and algorithm of fast charging techniques vs battery life 2) Finding the solution to enhance battery life in electric vehicles keeping fast charging technique into consideration.

### III. METHODOLOGY

EV charge scheduling optimization is the method to find the most efficient way to schedule EV charging, given a set of limitations. Optimization algorithms are implemented to achieve one or more well-defined objectives during the electric vehicle charging process. Effective optimization for EV charging scheduling hinges on understanding the problem from different perspectives. Here, we categorize these problems into three classes based on the objectives of the stakeholders involved namely, power grid operators, aggregators, and EV owners. This classification is crucial because it considers the unique goals of each stakeholder. In the electricity sector, participants often have distinct legal and functional roles, leading to diverse objectives within the larger system. Understanding the interplay of these factors is essential for developing efficient charging algorithms that balance fast charging with minimizing degradation. EV batteries, typically lithium-ion (Li-ion) or lithium iron phosphate (LFP) batteries, degrade over time due to various factors during the charging and discharging cycles: Charge Rate: The speed at which the battery is charged can significantly impact its lifespan. Charging at high rates generates more heat, which accelerates chemical reactions within the battery, leading to faster degradation. Depth of Discharge (DoD): The extent to which a battery is discharged also influences its longevity. Shallow discharges tend to extend battery life, while deep discharges accelerate degradation. Temperature: Both high charging and operating temperatures can degrade battery performance. Battery management systems (BMS) are crucial in regulating temperature during the charging process. State of Charge (SoC): Charging batteries to 100% or discharging them completely to 0% can cause stress on the battery. Maintaining an optimal range (typically 20-80% SoC) is often recommended for preserving battery life.

Current EV charging methods can be broadly classified into three categories: Slow Charging (Level 1 and Level 2 Charging): Slow charging typically uses lower power levels (1.4 kW to 22 kW) and is less stressful on the battery. It results in less heat generation, but it is not suitable for time-sensitive applications. Fast Charging (DC Fast Charging): Fast charging uses high power levels (up to 350 kW) to charge EVs within minutes. However, rapid charging generates significant heat, which can increase battery degradation if not managed properly.

Ultra-Fast Charging (500 kW and above): These technologies are emerging as potential solutions to reduce charging times to mere minutes. However, these systems require more sophisticated thermal management and control systems to ensure the battery's health. For instance, they may allow for high charging currents early in the charging cycle when the battery's state of charge is low and gradually reduce the current as the battery approaches full charge. Battery management systems (BMS) monitor the charging process, ensuring that charging parameters such as voltage, current, and temperature stay within safe limits. However, these systems often operate under fixed parameters, which may not fully consider the long-term effects of repeated fast charging on battery life. Optimizing charging algorithms involves striking a balance between reducing charging time and maximizing battery life. The following strategies can be considered for optimization: Dynamic Charging Rates Based on Battery Health: One of the most effective ways to optimize charging is to adjust the charging rate based on the real-time state of health (SoH) of the battery. This requires continuous monitoring of key parameters such as temperature, voltage, and internal resistance. By dynamically adjusting the current, charging algorithms can ensure that batteries are charged quickly when they are in good health and more slowly as they degrade. Temperature Control and Thermal Management: Effective thermal management is essential to avoid overheating during fast charging. Implementing cooling systems (e.g., liquid cooling or phase change materials) and optimizing airflow around the battery pack can prevent temperature-related degradation. Charging algorithms can be optimized to reduce current when temperature limits are approached, allowing for slower charging during high temperatures. Optimal Charging Profiles (CC-CV Method) The Constant Current-Constant Voltage (CC-CV) method is commonly used for Li-ion batteries. In this method, the charger initially applies a constant current until the battery voltage reaches a set limit, after which the charger switches to a constant voltage mode. Optimizing the transition between these phases can help mitigate the risk of damage due to excessive voltage or current. Advanced algorithms can modify the current profile by adjusting the maximum allowable voltage and current depending on the battery's age, temperature, and charging history. This approach would be particularly useful in preserving battery life during long-term use. State-of-Charge Window Optimization As mentioned earlier, it is recommended to maintain the state of charge (SoC) of the battery within an optimal range (e.g., 20% to 80%) to prolong its lifespan. Charging algorithms can be optimized to avoid charging the battery to 100% or discharging it below 10%, even if the user desires a full charge. This could be achieved through user-configurable charging limits or automatic adjustment based on the predicted daily driving needs.

#### IV. RESULTS AND ANALYSIS

Metaheuristic algorithms have good flexibility and ability to handle non-linear problems, and this makes them more suitable for handling EV charging optimization problems. Though metaheuristic algorithms provide many effective tools for complex EV charging optimization problems, they also exhibit certain limitations which should be carefully considered in the context of EV charging optimization. Generally, convergence to the global optimum is not always guaranteed by metaheuristic algorithms, leading to potential suboptimal solutions. Their performance can be influenced by the initial solution or population, leading to variability in results. These limitations must be carefully considered when employing metaheuristic algorithms to solve EV charging optimization problems. While the conventional methods rely on pre-defined models, machine learning approaches provide a promising problem-solving nature due to its ability to learn and adapt to changing patterns. They have proved their excellence in handling complex data and providing improved forecasts. In the papers analysed for the review, supervised machine learning techniques are mostly applied for load forecasting, future energy cost prediction in the case of dynamic pricing scenarios, predicting future power demand in charging stations and forecasting power generation in RES integrated charging framework. The unsupervised techniques are employed effectively in several research for grouping the areas with similar charging demands or EVs within same geographical zone, to find the optimal location for charging station placement.

Several studies have demonstrated the impact of different charging algorithms on battery life. A comparison of fast charging vs. slow charging shows that while fast charging reduces charge time by up to 60%, it also accelerates battery degradation by up to 30% over the same number of cycles. Optimized algorithms that control temperature and current in real-time, however, showed a 15% reduction in degradation rates. In addition, research has shown that charging to 80% instead of 100% and avoiding deep discharges can lead to a significant reduction in capacity loss, extending the battery life by up to 20% over the course of 500 charging cycles.

#### V. FUTURE SCOPE

In the coming years, further research into artificial intelligence (AI) and machine learning (ML) algorithms for battery management is expected to improve the optimization of charging processes. These systems could learn from past charging cycles and user behaviours to predict the optimal charging strategy for each vehicle, improving both the speed of charging and the battery lifespan. Moreover, the development of solid-state batteries and improved thermal management systems could potentially lead to faster and safer charging without sacrificing battery life. By learning from user input and preferences, RL algorithms can personalize charging schedules, ensuring efficiency while meeting individual needs. The fusion of cloud computing and RL holds the potential to significantly influence the development of future applications within EV charging systems. The cloud based smart charging networks have unveiled a lot of new challenges regarding security in data exchange. There is an urgent need for developing advanced fault and threat detection frameworks as modular solutions for security issues within smart charging platforms. A broad avenue of future research involves creating robust authentication mechanisms to prevent unauthorized data access EV charging systems, while upholding privacy and confidentiality by establishing interoperable universal standards for EV cybersecurity. The charging scheduling algorithms to be developed in the future, addressing various optimization constraints, should try to incorporate security constraints regarding data exchange as well as energy trading as part of the optimization process. This could be achieved either by utilizing the encryption capabilities of existing blockchain technology or by exploring other novel opportunities. Integrating RES into existing charging stations and efficiently utilizing the V2G and V2V capabilities of EVs to employ them as mobile energy storage systems could transform the charging stations into grid-connected, small scale microgrids.

#### VI. CONCLUSION

The advantages of EVs over ICE vehicles in economic and environmental prospective are explained to highlight the necessity of employing EVs as the solution for greener transportation. A thorough examination of different methodologies and factors that have a crucial role in developing efficient charging strategies for EVs is provided. EV charging management is the prime focus of this review paper and the importance of coordinating charging schedules to balance between consumer demands, grid capacity, and economic factors is emphasized. The analysis highlights the essential role of EV charging management in maintaining grid stability, thus facilitating a smoother shift towards high penetration of EVs. It examined various EV charging scheduling optimization problems from the perspectives of power grid operators, aggregators, and individual EV owners. By implementing dynamic charging rates, improving thermal

management, and adopting more advanced charging profiles, it is possible to minimize battery degradation while still benefiting from quicker charging times. Future advancements in battery technologies, AI-based charging algorithms, and improved thermal management will play a key role in enhancing the overall efficiency of EV charging systems and promoting the widespread adoption of electric vehicles.

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