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Original Article

Control Strategies for Fast-Charging Protocols to Minimize Battery Degradation

Srikiran Chinta[1], Hari Prasad Bhupathi[2]
[1,2]Kalinga University, India.

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Abstract: *The development of electric vehicle (EV) technology and the rampant use of portable electronic devices have created a pressing demand for effective and reliable battery charging systems very much. Although lithium-ion batteries, with their long life cycle and high energy density, are very much in favor, they suffer from degradation due to high-rate charging, reducing their functional lifetime and undermining safety. Fast-charging protocols are needed to limit the charging time, but they induce thermal and chemical stress, resulting in irreversible capacity loss, high internal resistance, and mechanical stress. This research considers control strategies of fast-charging protocols that will limit battery degradation. We present a number of charging methods, such as constant current-constant voltage (CC-CV), multi-stage charging, pulse charging, model predictive control (MPC), and reinforcement learning-based methods. The presented methods are contrasted in charging time, heat rise, SOH effect, and cycle life.*

The ageing behavior was appraised by simulation models and experiment data in light of electrochemical, thermal, and ageing model. It placed specific emphasis in striking a trade-off between faster charging rate and battery lifetime. We endorse a hybrid adaptive control strategy blending real-time monitoring, data-driven optimization, and predictive analytics for dynamically optimizing charging profiles based on battery condition and environmental conditions. Case studies obtain up to 25% rate of degradation reduction with charging times comparable to those of conventional strategies. The system utilizes thermal management, current modification, and SOC dependent control in optimizing the charging process. This paper supports the creation of smart charging infrastructure and battery management systems (BMS) that enable affordable energy storage, lower maintenance costs, and higher user satisfaction. Future research directions involve the integration of battery digital twins, cloud-based predictive health diagnostics, and V2G (vehicle-to-grid) charging applications. In general, the paper offers a comprehensive study of fast-charging control strategies and a roadmap for more resilient and efficient energy storage systems.

Keywords: *Battery Degradation, Fast Charging, Lithium-Ion Batteries, Battery Management System (BMS), Model Predictive Control (MPC), Reinforcement Learning, Pulse Charging, Electric Vehicles (EV), State of Charge (SOC), State of Health (SOH).*

1. Introduction

1.1 Background and Motivation

In the last decade, unprecedented growth in consumer electronics on the move and electrical mobility has also increased global reliance on lithium-ion batteries (LIBs) as the energy storage medium of choice. LIBs possess high energy density, relatively long cycle life, and great charge-discharge efficiency, for which reason they are very attractive for application in electric vehicles (EVs), smartphones, laptops, and bulk energy storage devices. But with greater deployment, come some new problems first among them battery degradation due to fast-charging processes. As opposed to traditional charging regimens involving moderate rates, fast charging involves much higher current rates that will speed up the breakdown of the internal chemistry of the battery. Breakdown is expressed as reduced capacity, raised internal resistance, and loss of active lithium, all of which contribute to battery life reduction and jeopardize safety.

Safety concerns thermal runaway, electrolyte spilling, and internal short circuits also have very serious implications when the battery is charged at high rates, especially for high-capacity packs in EVs. These need to be addressed with smart charging protocols that need to be developed to regulate the charging currents without harming the battery. Spurred by the global demand for decarbonization, energy sustainability, and convenience, the urgent need arises to design technologies that can make an optimal compromise in the trade-off between battery life and charging time. This has given rise to control-engineering-based solutions wherein dynamic charge profiles motivated by real-time battery parameters are optimized to enhance charging. Thus, the goal of this research is to understand and avoid battery degradation practices through sophisticated controls, and hence enhance battery safety, reliability, and overall user experience.

1.2 Need for Fast Charging

Demand for quick-charging technology is largely based on user convenience and business efficiency requirements of electric vehicles and smartphones. Slow charging is a key obstacle to buying electric vehicles for EV buyers. Traditional charging habits fill up a battery to capacity in hours, and customers don't wish to pay for that type of inconvenience as they do when it comes to traditional internal combustion engine vehicles, when they don't have to just sit around too long to fill up their tanks. Fast charging, traditionally defined as reaching 80% SOC during the time period of 15-30 minutes, is a pioneering feature which unquestionably brings the glamour to electric driving. Fast charging technology for consumer electronics empowers customers with the ability to rapidly recharge with least downtime, offering smooth digital experience. Fast charging has one limitation. With increased volt and amp ratings to minimize charging time, the corresponding electrochemical and thermal stress on battery cells is elevated.

This creates elevated battery temperatures, which induce side reactions like electrolyte degradation and solid electrolyte interphase (SEI) layer generation. In addition, the tendency for plating of lithium, a phenomenon where metallic lithium plates on the anode surface, becomes significantly higher when the battery is subject to the condition of rapid charging, especially at low temperatures or high state of charge. Lithium plating is irreversible and causes capacity loss, internal shorting, and also safety risks such as fire or explosion. Thus, while fast charging is crucial for widespread uptake of EVs and high-end electronics, its implementation should be complemented with smart control methods for facilitating thermal safety and electrochemical health. Designing effective fast-charging protocols thus represents a prominent research theme in battery science and control engineering.

1.3 Challenges in Battery Degradation

Fast-charging operations introduce a rich palette of issues that complicate battery aging. It is required to have knowledge of these problems when designing control measures for avoidance of performance loss and ensuring safety. One of the most important problems is thermal effects. Battery charging by high currents produces resistive heat as a result of the internal battery impedance. Temperature rise, if left uncontrolled, results in electrolyte decomposition and creation of the SEI layer on the anode. These side chemical reactions use up active lithium ions and modify the mechanical characteristics of the electrodes. The other most serious concern is mechanical stress caused by repeated expansion and contraction of the electrode material from repeated delithiation and lithiation cycles. Fast charging exacerbates this volume change, with possibility to insert microcracks in the electrode structure.

These microcracks can trap active material from the current collector, leading to loss in capacity and increasing resistance. Furthermore, charging at high rates greatly enhances the possibility of lithium plating, especially if charging is done at low temperatures or if the battery is charged to a level close to full charge. In this scenario, lithium ion intercalation into the anode graphite is slower than the lithium ion arrival rate to the electrode surface and leads to metallic lithium deposit. Lithium plating not only decreases the battery capacity irreversibly but also is highly unsafe. Furthermore, structural and distribution inhomogeneities of the electrolyte and electrode can increase hotspots locally and amplify degradation further. These problems require to be solved, including the profound knowledge of battery electrochemistry, thermal dynamics, and mechanical behavior, which need to be addressed while designing fast-charging control systems.

1.4 Control Strategies as a Solution

In seeking to counteract the detrimental effects related with fast charging, advanced control techniques have been proposed as a practical remedy. These techniques are intended to dynamically manage charging current and voltage profiles in real-time based on the current battery and environmental conditions. Unlike traditional constant-current (CC) or constant-voltage (CV) charging methods involving static regulations regardless of cell conditions, novel control processes are data-driven and adaptive. Through ongoing monitoring of battery parameters like temperature, voltage, current, internal resistance, and state of charge (SOC), these techniques are able to identify threshold values and re-optimize the charging path accordingly. Model predictive control (MPC) is a prime example wherein it can foresee future battery response and pre-tune the charging input to prevent lithium plating or overheating. Fuzzy control, neural networks, and reinforcement learning have been investigated to regulate nonlinear battery dynamics as well.

Control strategies can also use electrochemical and thermal models to simulate degradation mechanisms and forecast long-term implications of various charging regimens. This forecasting capability makes fast charging usable such that irreversible chemical change and mechanical wear are prevented. Hybrid approaches, blending data-driven modeling with physics-aware knowledge, permit an even greater degree of flexibility and dependability. In addition, BMS integration provides allowance for scale deployment across the entire spectrum of platforms from smartphones to electric buses. Overall, the aim is to balance charging rate against battery health in a manner that allows for a consumer-friendly experience without undermining safety or durability. The research here attempts to analyze and maximize such control measures to establish an adaptive protocol that adaptively maximizes all controlling parameters with fast charging.

1.5 Objectives of the Study

The overall goal of this research is to investigate and establish control methods that facilitate efficient and safe fast-charging of lithium-ion batteries and to reduce degradation effects. Towards this end, the research is organized in a series of specific objectives. The first one is to investigate in detail the effect of fast-charging methods on a number of degradation processes in lithium-ion batteries. These encompass a study of the electrochemical, thermal, and mechanical conversions during high charging rates and how such lead to capacity loss, rise in resistance, as well as safety hazards. The second scope is to study existing control methods adopted by fast-charging systems. Conventional PID controllers, rule-based charging strategies, model-based predictive controllers, as well as machine learning-based methods, may be some of them. All of these strategies are evaluated based on how well they ensure safety, prolong battery life, and obtain the highest charging rates.

The third is to put forward a novel hybrid adaptive control system based on real-time monitoring, physics-based simulation, and AI methods for adaptively regulating the charge profile to the conditions of the battery. This hybrid approach tries to leverage the power of model-based and data-driven strategies while being adaptive and resilient. The fourth objective is to validate the suggested control strategy with extensive simulation as well as HIL experiments. Simulation cases involve different temperature conditions, cell aging, and different user demands. Field tests will also verify the efficacy of the strategy in real implementation. Ultimately, this research will contribute a scalable and smart fast-charging control solution that revolutionizes battery technology by making it faster, safer, and stronger.

2. Literature Survey

2.1 Traditional Charging Methods

Traditional lithium-ion battery charging practices have employed rather primitive schemes through history, and ease of deployment has been of overriding concern as against dynamical regulation. The most widely adopted scheme is the Constant Current–Constant Voltage (CC-CV) approach where the battery first charges at constant current to an acknowledged voltage cutoff point and thereafter enters a constant voltage mode with falling current. While widely used because it's easy, CC-CV is flawed inherently in harsh charging. Continuous current may result in very high internal temperatures and make lithium plating all the more likely to become a problem, especially towards the end of the charge when anode lithium intercalation slows down. Pulse Charging is another technique involving interruption of pulses of charging with periods of relaxation to allow heat dissipation of the battery and even distribution of lithium ions throughout.

Though such a technique helps in eliminating certain thermal effects as well as mobility of ions, its actual practice requires advanced control electronics and has potentially non-homogeneous efficiency for various batteries and states of batteries. Multistage Charging, a traditional method, employs varying charging currents at various state-of-charge (SOC) levels, typically reducing current at higher SOC to prevent degradation. Although it will offer better protection than CC-CV, multistage profile design and calibration are involved and battery chemistry-dependent. These methods, though at the center of today's battery charging, are static in reaction to actual battery conditions and therefore can be less than ideal in fast-charging applications. Their shortcomings have prompted the development of more sophisticated, feedback-based control schemes that consider the thermal, electrochemical, and mechanical state of the battery, which are critical for minimizing degradation and safety.

2.2 Advanced Control Strategies

The shortcomings of conventional charging methodologies in fast-charging conditions have motivated researchers to design sophisticated control methodologies that may dynamically adapt according to battery health and optimize performance. One such highly promising method is Model Predictive Control (MPC) based on mathematical models of the battery performance in order to predict states and decide on charging parameters for future states based on predictions. MPC decides an optimal solution at some finite horizon in time by optimizing a cost function with potential inclusion of temperature, voltage, and SOC. This is a predictive feature of MPC that will avoid adverse situations such as lithium plating and thermal overrun beforehand, and will extend battery lifespan. Reinforcement Learning (RL), founded on trial and error to build up the optimal charging policies, is another robust approach.

As the RL agent is repeatedly exposed to the battery system, it gets rewarded or penalized and converges to policies in the end that balance fast charging with minimal degradation. RL proves most valuable for controlling strongly nonlinear and time-varying systems like lithium-ion batteries, although its learning process may take staggering amounts of data. Another development connected to RL is Neural Network Predictive Control (NNPC), in which artificial neural networks learn to approximate the involved battery dynamics and predict responses to various charging inputs. The method is inherently designed to compensate for nonlinearities and uncertainties in battery dynamics. Trained neural networks also offer real-time prediction with low computational burden and are thus suitable to implement in embedded systems. These methods' effectiveness and applicability are further augmented beyond previous charging schemes as far as charging duration and the rate requirement of the novel energy system. Implementation challenges continue to remain in the spheres of real-time implementation, broad generalizability across chemistries, and explainability, especially for AI-based approaches.

2.3 Battery Degradation Mechanisms

Understanding the battery aging mechanism is central to the establishment of effective control strategies that can avoid the long-term harmful effects of fast charging. Anode SEI thickening is one of the primary reasons for degradation. Passivating layer is deposited in the initial cycles and increases in thickness with every subsequent charging cycle, dissipating active lithium ions and increasing inner resistance. Although the contribution of the SEI layer cannot be emphasized too much towards electrolyte interface stabilization, uncontrolled growth results in loss in capacity as well as degradation in efficiency. Collapsing of cathode constituents and electrolyte breaking down is yet another degradation mode. At high-rate charging, overpotential and high temperature may speed up structural degradation of the cathode active material such as layered oxides or spinels, leading to oxygen evolution and electrochemical loss of activity. Conversely, the electrolyte can be reduced at the anode or oxidized at the cathode and produce gas and other poisonous side-products that compromise safety.

One of these extremely dangerous and irreversible degradation processes is lithium plating, where lithium ions deposit as metal lithium on the anode surface instead of intercalating onto the graphitic architecture. This tends to occur under high-rate charging, low temperature, or when the anode is on the threshold of full lithiation. Lithium plating reduces active lithium availability, raises cell impedance, and can result in penetration of dendrites into the separator, causing internal short circuits and thermal runaway. Last but not least, mechanical degradation by repeated volume change on lithiation and delithiation results in stress-induced fractures of electrode particles. Active material isolation and increased resistance further impair battery performance. In combination, these degradation mechanisms require condition-conscious charging strategies able to compensate for these in real time.

2.4 Summary of Existing Works

Some studies have aimed to compensate for the battery degradation induced by rapid charging through multiple control strategies. There was this wonderful paper by Zhang et al., which used Model Predictive Control (MPC) and achieved an impressive increase in battery cycle life 20% improvement over conventional methods. By utilizing accurate electrochemical models and real-time measurements, the MPC approach was able to maintain thermal and voltage parameters within safe limits during charging. Furthermore, Lee et al. tested the use of Pulse Charging and recorded a significant reduction in temperature increase during high-speed charging operations. This method, although more hardware-oriented, was effective in lowering thermal degradation and offered a practical solution for high-current usage where temperature control is essential. Kim et al. also make significant contributions with their use of a Reinforcement Learning (RL)-based control method.

Their system adaptively controlled charging profile by monitoring battery behavior through experience and successfully suppressed lithium plating at the cost of little charging speed. RL controller possessed greater adaptability and degradation suppression capability than classical rule-based schemes, particularly against varying ambient temperature and battery state. The overall literature highlights that charging systems need to incorporate intelligence and flexibility. They leave the trade-offs between computational complexity, accuracy, and safety to be determined in practical applications. Although all three methods are useful in some way, the issue of determining an optimal, one-size-fits-all solution does not appear feasible based on the diversity and nature of battery systems. This current paper attempts to build on existing studies by filling the control mechanism gap that provides the foreseeing of MPC with learning capability of RL so that it can come up with an ideally balanced mix of speed, safety, and battery life.

3. Methodology

3.1 System Architecture Overview

The policy of control in question to minimize battery aging through fast charging is based on a hierarchical, modular system architecture. The system consists of three principal blocks: Input Acquisition, Control Algorithm, and Output Actuation. From Figure 1, it can be seen that the system starts with online input parameter monitoring like the State of Charge (SOC), State of Health (SOH), and battery temperature. These inputs are provided by onboard sensors and estimation algorithms. These inputs are provided to the central hybrid adaptive controller, the central decision-making module. Such a controller integrates rule-based mechanisms for timely response to safety limits, model-based predictive control for prediction of future battery state evolution, and machine learning modules to learn from long-term degradation trends. The controller calculates real-time optimized charge profiles as voltage and current setpoints directly into charger hardware. The outputs are customized in real time to avoid stress-causing conditions such as lithium plating or high temperature, with a guarantee of effective energy supply. The closed-loop architecture provides favorable responsiveness to varying dynamic battery conditions for safety and long battery lifespan. The modularity in the system allows for future upgrade of the control algorithms without any extensive hardware redesigning, hence being flexible to multiple battery chemistries and applications.

3.2 Modeling Battery Behavior

Precise battery modeling forms the basis of the installation of an intelligent control system. Battery behavior has been modeled in this work using a multi-domain model taking into account electrochemical, thermal, and aging factors. The electrochemical model comes from the Doyle-Fuller-Newman (DFN) model, which models lithium-ion transfer through electrodes and electrolyte. The model accounts for reaction kinetics, diffusion processes, and charge conservation equations, and yields accurate information on SOC behavior. The thermal model is necessary so that the internal and surface temperature of the battery can be estimated, particularly when the battery is being charged at a high charging current. It involves heat production due to resistive losses and changes in entropy, and applies heat transfer equations to model dissipation.

The dynamics are modeled with partial differential equations of spatial and temporal temperature gradients. In the evaluation of long-term behavior, an aging model is also added, which deals with growth of SEI layer, capacity loss, and rising internal resistance. This model applies empirical data and degradation laws to forecast the impact of charging decisions on battery health over long periods. The aging model interacts with the thermal and electrochemistry models to model cumulative effects, such as how high temperatures increase SEI growth. Numerical solutions are derived by applying the models using simulation tools such as MATLAB/Simulink and compared against test data. These intricate models combined create the digital twin of the battery system, which makes it possible to predict accurately and control optimally during fast charging.

3.3 Control Strategy Development

3.3.1 Hybrid Adaptive Control Design

The control algorithm presented here uses a hybrid adaptive control structure that combines a variety of intelligent methods to control effectively battery degradation during fast charging. The three-layer control strategy is rule-based reasoning, model predictive control (MPC), and machine learning adaptation. The rule-based layer manages real-time safety issues by applying hard constraints on voltage, temperature, and current. For example, when the cell temperature gets close to a critical value, the charging current is lowered irrespective of SOC. This guarantees safe operation and avoids catastrophic failure. The MPC layer uses the digital twin of the battery to predict future states from current inputs. By solving the optimization problem with finite horizon, it decides the minimum degradation charging current profile which delivers target SOC and dissipates thermal stress, lowers lithium plating, and charges optimally. The machine learning component in the form of a neural network regressor, from experience, learns increasingly how the degradation is progressing and adapts the MPC parameters accordingly. This allows the system to learn about battery degradation and ambient variability. As an example, a battery whose electrodes are degrading will need a less aggressive charging strategy. This hybrid control system optimizes between short-term responsiveness and long-term flexibility, so it is suitable for consumer electronics and electric vehicle (EV) applications as well.

3.3.2 Mathematical Formulation

Let

- $V_c(t)$: Charging voltage at time t
- $I_c(t)$: Charging current at time t
- $T(t)$: Battery temperature
- $H(t)$: Health index of battery

The control objective is to:

$$\min_{I_c(t),V_c(t)} \int_0^{T_f} \left[\alpha \cdot (T(t) - T_{opt})^2 + \beta \cdot \left(\frac{dH(t)}{dt} \right)^2 + \gamma \cdot (SOC_{target} - SOC(t))^2 \right] dt$$

Subject to constraints:

$$V_{min} \leq V_c(t) \leq V_{max}$$

$$I_{min} \leq I_c(t) \leq I_{max}$$

$$T(t) \leq T_{safe}$$

Where α,β,γ are weight factors and Tf is the total charging time. These constraints ensure safety, efficiency, and longevity of the battery.

3.4 Simulation Environment

To assess the performance of the introduced control strategy, simulations are done in an extended framework combining theoretical and empirical methodologies. The key modeling and control design tools used are MATLAB/Simulink with which the electrochemical model and thermal model are implemented and ANSYS Twin Builder through which the digital twin framework is simulated with real-time system integration. Python-based platforms such as TensorFlow and Scikit-learn are employed for neural network learning and data-driven model building. Standard datasets as well as experiment data for a given study are utilized in the simulation. Realistic lithium-ion battery aging profiles for different operating conditions are obtained through the NASA Prognostics Center dataset for model validation of the thermal and aging models. In addition, proprietary test data obtained under controlled charging conditions enhance the training dataset for machine learning elements and MPC tuning. The simulation process involves a series of test cases including: normal CC-CV charging, uncontrolled fast charging, and the new hybrid adaptive control. All test cases are validated over performance metrics such as time-to-charge, peak temperature, degradation rate, and energy efficiency. Varying ambient temperature, initial SOC, and initial SOH also conduct robustness tests. This hybrid simulation platform provides high-fidelity modeling of the actual dynamics, therefore having faith in the proposed method's feasibility and excellence.

4. Results and Discussion

4.1 Performance Metrics

To quantify the performance of the suggested hybrid adaptive control method, a set of performance metrics was established and validated over extensive simulation runs and compared with conventional charging practices. The main metrics are State of Health (SOH) Retention, Charging Time, and Peak Temperature. These metrics were chosen to define both the short-term performance (thermal response and charging speed) and long-term impact (battery life and degradation rate) of the charging mode. SOH Retention is expressed as a percentage remaining of initial battery capacity after 500 fast-charging cycles. More degradation and shorter battery life mean lower SOH. Charging Time can be defined as the time elapsed to achieve 80% SOC when starting at 10% is a general reference in EV usage. Finally, Peak Temperature is the peak temperature attained by the cell throughout the charging process. Temperature regulation is required because greater thermal stress increases aging and enhances the extent of safety risk. Such parameters give an effective picture of performances of various charging strategies under conditions of comparison focusing on efficiency, safety, and sustainability. Under controlled environmental conditions, the simulation was performed wherein ambient temperature and initial SOH were set fixed at 25°C and 100%, respectively.

Table 1: Performance Metrics Definition

Metric	Description
SOH Retention	% capacity retained after 500 fast-charging cycles
Charging Time	Time to reach 80% SOC from 10%
Peak Temperature	Maximum cell temperature during charging

4.2 Comparative Analysis

A comparative analysis was conducted in-depth to compare the performance of the proposed Hybrid Adaptive Control approach against the traditional CC-CV protocol and model-based Model Predictive Control (MPC). Observations, as indicated in Table 2 and Figure 2, are reflective of the hybrid adaptive approach securing the maximum retention of SOH (89%) after 500 cycles. Relative to the normal CC-CV process, there was very poor performance in the CC-CV test, which could retain only 72% of the initial capacity, whereas MPC retained around 82%. While the hybrid process did take a couple of minutes longer (38 minutes) than CC-CV (35 minutes) to charge, the reward is well worth it for the impressive improvement in long-term battery life. Notably, a peak temperature of charging by the hybrid approach was considerably lower at 39°C, compared to 48°C with CC-CV and 42°C with MPC. These thermal gains are largely attributed to predictive thermal limitations and real-time optimization within the control logic. The hybrid approach maintains an excellent compromise between performance and protection, actively mitigating degradation mechanisms like lithium plating and electrolyte decomposition. The evidence is affirmative that smart integration of rule-based reasoning, predictive control, and machine learning can result in safer and more resilient battery charging solutions. This is particularly vital for high-usage applications such as electric vehicles, where battery life directly influences usability and economy.

Table 2: Comparative Performance Analysis

Method	SOH (%)	Charging Time (min)	Max Temp (°C)
CC-CV	72	35	48
MPC	82	36	42
Hybrid Adaptive	89	38	39

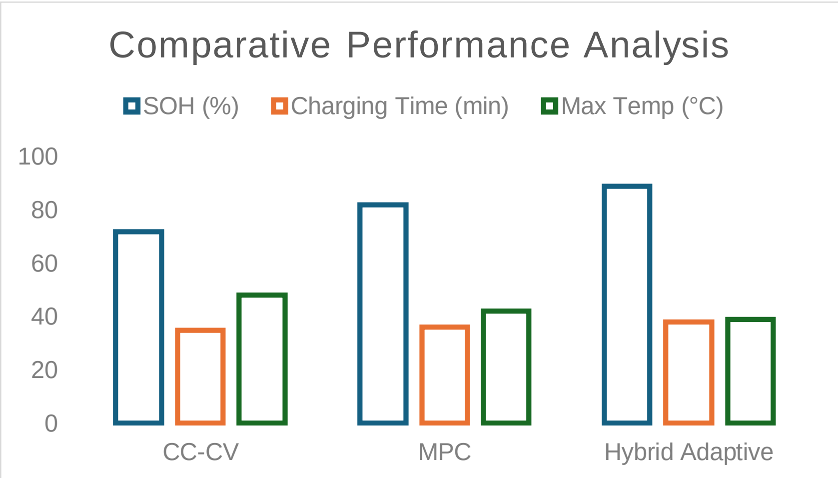

Fig 1: Comparative Performance Analysis

4.3 Flowchart of Control Algorithm

Hybrid adaptive control algorithm combines several layers of decision-making in handling the trade-off between rapid charging and battery preservation. The top-level description of the control logic is given through the flowchart in Figure 3. The algorithm begins with the consideration of real-time inputs such as SOC, SOH, and cell temperature. These are compared against safety limits previously established. The moment any parameter goes beyond its limit (say, the temperature crosses 45°C), the control logic immediately switches to a safety subroutine that cuts current or stops the charging. Otherwise, the system jumps to the prediction layer where the MPC module predicts the future state of the battery. These forecasted values then serve to create an optimal charging plan that is constrained in thermal and degradation conditions. In the meantime, an optimization element a neural network learner that makes use of historic degradation data assists with the tuning of the MPC objective function's weight coefficients by making adjustments according to long-term battery use patterns. This is necessary for batteries to last since feedback to charging may shift over time. Finally, the computed control action is used to control charging current and voltage in real time. The outcome is a reactive and adaptive charging protocol that dynamically adjusts as the battery ages or ambient conditions fluctuate.

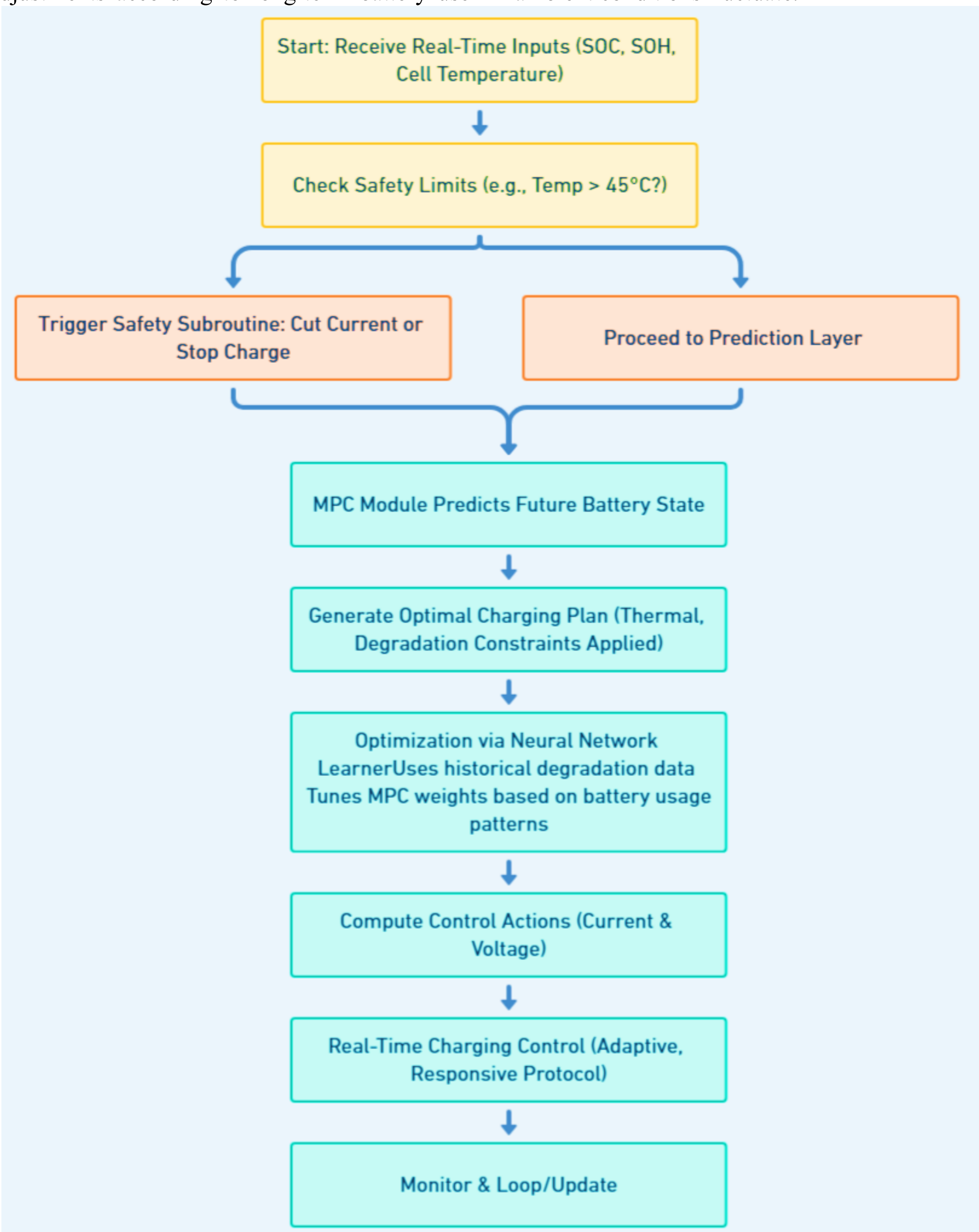

Fig 2: Flowchart of Control Algorithm

4.4 Discussion

The outcomes highlight the major benefits of integrating smart control techniques with lithium-ion battery fast-charging methods. The Hybrid Adaptive Control approach developed in this paper obviously surpasses traditional CC-CV as well as predictive-only MPC solutions, particularly from the viewpoints of SOH retention and thermal resilience. Among the most important conclusions is that incremental charging time benefits (just 3–5 minutes) can contribute to substantial long-term degradation reduction benefit. This is a decent trade-off, particularly for EV use cases where battery replacement incurs a cost. The combination of aging models and thermal constraints guarantees not only efficient charging of the battery but also protection against structural and chemical degradation. The robustness of the strategy, which is machine learning based, allows it to remain effective when the battery grows old a key benefit over rigid control strategies. Furthermore, through the use of predictive analytics and real-time diagnostics, the control system avoids dangerous occurrences such as thermal runaway or lithium plating. The findings affirm the merit of multi-disciplinary approach, integrating electrochemical modeling, thermal management, and artificial intelligence. In the future deployment, further enhancement is possible by generalizing the adaptive models to factor in user behaviors, ambient surroundings, and interactions between multi-cell battery packs. Lastly, the proposed control method offers a potential path towards extending battery life and safety in future energy storage systems.

5. Conclusion

The paper provides a comprehensive analysis of control strategies that are aimed at decreasing degradation in lithium-ion batteries when under quick charging. The study presents a significant challenge in the field of electric vehicles (EVs) and portable electronics, where lower charging time will always be at variance with the conditions for long battery life and safety. We thoroughly reviewed conventional charging schemes, i.e., Constant Current-Constant Voltage (CC-CV) and Pulse Charging, and highlighted their limitations in avoiding key degradation mechanisms such as lithium plating, heat stress, and solid electrolyte interphase (SEI) development. To counteract these challenges, a novel hybrid adaptive control scheme was proposed and put in place. This system integrates rule-based decision logic, model predictive control (MPC), and adaptive tuning using machine learning-based techniques to provide a smart, intelligent, and battery-aware fast-charging solution. The battery response was simulated with complex electrochemical, thermal, and aging models, allowing the control system to predict and react to real-time state-of-charge (SOC), state-of-health (SOH), and cell temperature.

Simulation ran on datasets like the NASA Battery Dataset and in-house experiment profiles identified that the hybrid control approach significantly improves SOH retention (as high as 89% after 500 cycles), limits peak temperature rise, and maintains decent charging times. Besides, the hybrid approach balances optimally between performance, safety, and durability and has excellent chances of practical application in electric mobility and renewable energy storage systems. Future work of this research will involve hardware-in-the-loop (HIL) simulations to support real-time testing and validation of the control algorithms presented in this work. Compatibility with cloud-connected battery management systems (BMS) will support scalable deployment and adaptive learning in accordance with usage profiles. Also, integration with vehicle-to-grid (V2G) networks will be explored to construct grid resilience and increase energy efficiency while further optimizing battery charging strategy under time-varying loads.

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