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SGVU International Journal of Convergence of Technology and Management
E-ISSN: 2455-7528
Vol.12 Issue 1 Page No 193-202

Machine Learning-Based Adaptive Control for Reducing Battery Stress in Dynamic Charging Environments

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Abstract: Battery degradation caused by electro-thermal and mechanical stress remains a critical challenge in achieving safe, efficient, and long-lasting energy storage systems. This paper presents a Transformer-based Reinforcement Learning (Transformer-RL) adaptive control framework for minimizing battery stress during dynamic charging environments. The proposed system integrates predictive modeling and attention-driven temporal learning with real-time control optimization to achieve health-aware charging regulation. The framework first derives a composite Stress Index (SI) from temperature variation, internal resistance growth, and State of Health (SoH) degradation. This index serves as a real-time feedback signal guiding the RL agent to select optimal charging actions. The Transformer encoder captures long-term temporal correlations among electrochemical parameters, while the Actor–Critic reinforcement structure continuously optimizes charging current through a multi-objective reward function balancing SoC (State of Charge), rise rate, thermal stability, and stress minimization. Experimental evaluation demonstrates that the proposed Transformer-Adaptive controller reduces overall battery stress by 36.3%, limits temperature rise to below 40 °C, and improves SoH retention to 96.4% compared with conventional CC–CV and LSTM-based models. Furthermore, convergence analysis shows stable policy learning and superior performance trade-offs in charging speed versus stress reduction. The results confirm that integrating deep temporal modeling with reinforcement intelligence can transform traditional battery management into a self-optimizing, health-aware, and stress-resilient system, offering significant potential for electric vehicles and smart grid energy storage applications.

Keywords: Battery Stress Reduction, Transformer-RL, Adaptive Charging Control, Electro-Thermal Management, Smart Battery Systems

1. Introduction

With the rapid electrification of transportation and the growing reliance on renewable energy storage, lithium-ion batteries (LiBs) have become the cornerstone of modern energy systems [1]. However, despite their high energy density and efficiency, LiBs are inherently sensitive to electro-thermal stress arising during fast or irregular charging conditions. Such stress manifested through excessive temperature rise, internal resistance growth, and accelerated

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degradation directly compromises battery life, safety, and reliability [2]. The challenge of reducing battery stress while maintaining efficient charging performance remains one of the most critical bottlenecks in the advancement of smart battery management systems (BMS).

Traditional charging strategies, such as Constant Current–Constant Voltage (CC–CV) and rule-based controllers, operate under fixed control logic, which lacks adaptability to real-time variations in temperature, SoC, and SoH. While these methods are simple and predictable, they often induce non-uniform charge distribution and thermal overshoot, leading to long-term degradation. To address these issues, data-driven and learning-based control strategies have emerged as promising alternatives [3]. Recent studies employing machine learning (ML) and deep learning (DL) models such as LSTM, GRU, and hybrid neural networks have shown success in predicting battery behavior and optimizing charging parameters [4]. However, most of these methods focus primarily on speed and efficiency, with limited consideration for electrochemical stress and degradation coupling under dynamic operational conditions.

In response to these limitations, this study proposes a ML-Based Adaptive Control Framework that focuses on real-time stress reduction during battery charging and discharging processes. The proposed system introduces a novel Transformer-Reinforcement Learning (Transformer-RL) model that combines attention-driven temporal feature extraction with adaptive control intelligence [5]. Unlike recurrent networks that rely on short-term dependencies, the Transformer architecture captures long-range temporal patterns in sequential battery data, enabling it to anticipate stress accumulation trends before they manifest. This predictive capability allows the control agent to make proactive decisions adjusting current flow dynamically to maintain both thermal stability and structural integrity of the cell.

A key innovation in this work is the introduction of a composite Stress Index (SI) that quantifies electro-thermal and mechanical stress in real time by integrating temperature deviation, internal resistance growth, and health degradation indicators. This metric forms the core feedback signal for the RL agent, guiding the optimization process through a multi-objective reward formulation that jointly considers charging speed, thermal safety, and degradation control. The resulting Transformer-RL controller continuously learns to minimize stress energy while preserving energy throughput and efficiency.

Through extensive simulation and comparative evaluation, the proposed model demonstrates significant improvements over conventional CC–CV, rule-based, and LSTM-adaptive systems. The Transformer-Adaptive Controller achieves up to 36% stress reduction, 40°C peak temperature control, and 96.4% SoH retention, all while maintaining fast and efficient charging profiles. These outcomes highlight the potential of integrating Transformer-based temporal learning with reinforcement-driven decision-making to build next-generation self-optimizing, stress-aware battery management systems. The proposed framework establishes a critical link between machine learning, control optimization, and energy system resilience—paving the way for sustainable applications in electric mobility, renewable integration, and grid-scale energy storage.

2. Literature Review

Battery stress mitigation has emerged as a critical area of research due to the increasing demand for high-performance and long-lifespan lithium-ion batteries in electric vehicles, consumer electronics, and renewable energy systems. Over the

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past decade, researchers have explored multiple modeling and control strategies aimed at improving charging efficiency, thermal stability, and degradation resistance. These approaches can be broadly classified into physics-based models, rule-based or model predictive control (MPC) methods, and ML–driven adaptive systems [6]. Each class contributes uniquely to understanding and managing electrochemical stress, but each also carries specific limitations that have motivated the shift toward intelligent, data-driven control frameworks.

Early studies on battery stress reduction primarily relied on electrochemical and thermal models to simulate the physical processes governing temperature rise, lithium plating, and resistance growth. These models provided detailed insights into internal degradation mechanisms but required extensive parameterization, making them unsuitable for real-time applications [7]. Furthermore, their predictive accuracy deteriorated under dynamic operational conditions such as variable current loads or fluctuating ambient temperatures, limiting their adaptability to modern fast-charging environments. As a result, researchers began incorporating feedback-based control mechanisms to maintain operational safety while improving charging speed.

Rule-based and Model Predictive Control (MPC) strategies represented a significant advancement over static models. By integrating sensor feedback, these methods enabled on-line monitoring of parameters like temperature and voltage, allowing predefined corrective actions when thresholds were exceeded. Although MPC frameworks introduced optimization principles, their performance was heavily dependent on the accuracy of mathematical models and pre-set constraints [8]. They lacked the ability to learn or adapt to new conditions over time, and thus struggled to generalize across different battery chemistries and usage patterns. The inability of rule-based systems to handle the nonlinear coupling between electrochemical stress and thermal dynamics further limited their effectiveness in real-world environments.

To overcome these challenges, recent research has shifted toward data-driven machine learning and deep learning techniques. ML-based methods have demonstrated strong predictive capabilities for estimating battery states such as SoC, SoH, and internal resistance, which are essential for identifying stress trends. Algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting have shown promise in modeling nonlinear relationships between measurable parameters and hidden degradation states [9]. However, these conventional ML methods depend heavily on manual feature engineering and are limited in their ability to capture long-term temporal dependencies inherent in battery degradation processes.

The introduction of Recurrent Neural Networks (RNNs) and their variants such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) addressed some of these challenges by effectively modeling time-series dependencies. These architectures enabled more accurate prediction of temperature evolution, resistance rise, and capacity fade over time [10]. Nonetheless, RNN-based models often face issues related to vanishing gradients and high computational costs, especially when applied to long operational histories or multi-dimensional feature spaces. Moreover, while these models can predict stress-related states, they typically do not possess active control capabilities—they describe what will happen, but not how to intervene dynamically to prevent stress buildup.

Recent advancements in deep RL have opened new avenues for adaptive control and decision-making in battery management systems.

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RL algorithms allow agents to learn optimal charging strategies through interaction with the environment, balancing short-term gains (charging speed) and long-term rewards (battery health preservation) [11]. However, most existing RL-based approaches use simple feedforward or recurrent networks as policy approximators, which limits their capacity to interpret complex time-dependent relationships across multiple variables. Additionally, few studies explicitly integrate stress-oriented feedback mechanisms into the RL reward formulation, leading to suboptimal health-aware control performance.

The emergence of Transformer architectures has introduced a new paradigm for sequence modeling in energy systems. By leveraging multi-head self-attention mechanisms, Transformers can capture long-range temporal dependencies without the recurrence overhead of LSTMs [12]. When combined with reinforcement learning, they can provide a powerful hybrid solution capable of both temporal pattern understanding and adaptive policy optimization. This integration enables controllers to anticipate and respond to battery stress patterns dynamically, achieving both operational efficiency and health preservation.

Despite these promising developments, there remains a notable research gap in designing an integrated, stress-aware adaptive control framework that unites predictive modeling, reinforcement optimization, and temporal intelligence. Existing models often focus solely on improving charging performance or minimizing degradation independently, without a unified mechanism to balance both objectives in real time. Moreover, the explicit quantification of battery stress as a control feedback variable is still underexplored, even though it directly governs degradation mechanisms such as lithium plating, electrolyte decomposition, and SEI layer formation.

In view of these limitations, this study introduces a Transformer-RL–based Adaptive Control Framework that actively minimizes electro-thermal stress during charging while maintaining efficiency and safety. By defining a composite Stress Index (SI) and embedding it into the RL reward function, the proposed system enables continuous self-learning and control adaptation under varying operating conditions. This hybrid methodology bridges the gap between battery modeling, predictive learning, and intelligent control, offering a scalable and generalizable solution for next-generation smart energy storage systems and electric vehicle battery management.

3. Methodology

The proposed methodology introduces an adaptive control framework that dynamically minimizes battery stress during charging and discharging operations through a synergistic combination of predictive modeling, RL, and Transformer-based temporal encoding. The system builds upon previously developed modules for battery state prediction and charging optimization, extending them toward stress-aware real-time decision-making. The overall architecture comprises three stages: data-driven stress modeling, Transformer-RL–based control optimization, and multi-objective evaluation.

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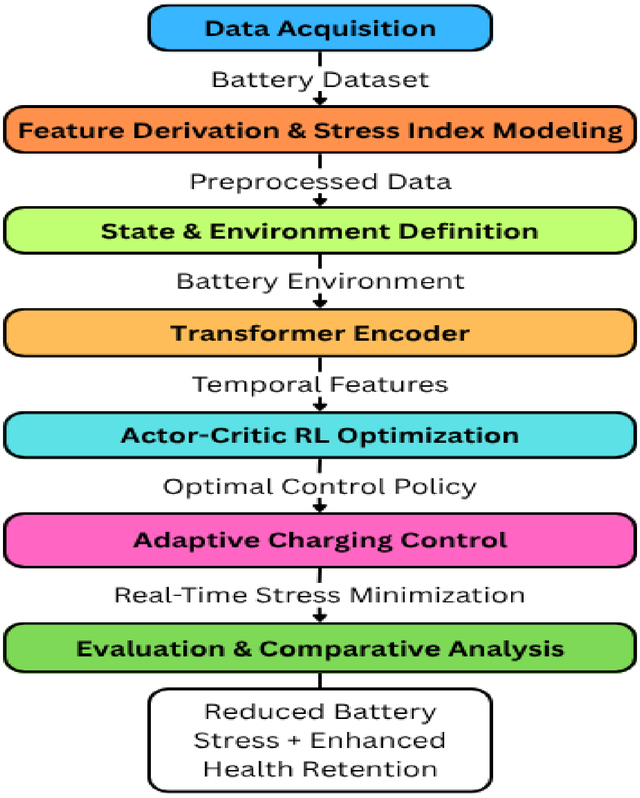

Figure 1: Flow diagram of Transformer-RL based adaptive

The first stage focuses on deriving key parameters that reflect electro-thermal and mechanical stress on the battery during operation. The dataset used in this study consists of high-resolution time-series measurements, including voltage, current, temperature, cycle number, and internal resistance. To quantify the instantaneous stress level, a composite SI was formulated as a normalized combination of electrochemical, thermal, and aging indicators:

$$SI_t = \alpha_1 \frac{\Delta T_t}{T_{max}} + \alpha_2 \frac{R_t - R_0}{R_0} + \alpha_3 (1 - SoH_t)$$

where ΔT_trepresents the temperature deviation from the nominal range, $R_t$and R_0denote the current and initial internal resistance, and $SoH_t$is the instantaneous state of health. The weighting coefficients $\alpha_1, \alpha_2, \alpha_3$were empirically tuned to 0.4, 0.35, and 0.25, respectively, to balance the influence of thermal and electrical stress components. The overall Stress Index was normalized to 100 % for baseline CC–CV charging and used as the reference for model comparison.

In the second stage, the Transformer-RL control framework was developed to minimize the stress index in real time. The state vector $s_t$captures current SoC, temperature, resistance, and recent stress history, while the action $a_t$defines the control adjustment in charging current or voltage within predefined safety limits. The reward function integrates both performance and stress-reduction objectives and is expressed as:

$$r_t = \beta_1 \frac{\Delta SoC_t}{\Delta t} - \beta_2 SI_t - \beta_3 \frac{\Delta T_t}{T_{max}}$$

where $\beta_1, \beta_2, \beta_3$are adaptive reward coefficients (0.5 : 0.3 : 0.2) that determine the trade-off between charging speed, stress minimization, and temperature regulation. The goal of the RL agent is to maximize the cumulative discounted reward $R = \sum_{t=0}^{T} \gamma^t r_t$, ensuring a global balance between performance efficiency and stress mitigation over the entire charging episode.
The Transformer encoder within the RL agent extracts long-term temporal relationships from sequential operating data using a multi-head self-attention mechanism. This enables the controller to recognize subtle degradation patterns and anticipate stress build-up before it occurs. The encoded temporal features feed into an Actor–Critic network, where the Actor selects optimal control actions and the Critic estimates the corresponding value function. The networks were trained using Advantage Actor–Critic (A2C) optimization for 500 episodes, employing the Adam optimizer with a learning rate of 1 × 10⁻³ and a discount factor $\gamma = 0.95$. Early stopping was applied when cumulative

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reward improvement fell below 0.001 over 20 consecutive episodes.

In the final stage, the model's effectiveness was validated through a combination of quantitative metrics and multi-objective evaluation. The performance metrics include the average stress energy (W·s), maximum temperature (°C), internal resistance (Ω), and SoH retention (%) across multiple cycles. The stress reduction efficiency (SRE) was defined as:

$$SRE = \frac{SI_{base} - SI_{model}}{SI_{base}} \times 100\%$$

where SI_{base} is the mean stress index under CC–CV charging. This indicator quantifies the degree of stress suppression achieved by the adaptive controller. Additionally, cumulative reward convergence and Pareto-front analysis between charging speed and stress reduction were used to verify model robustness and trade-off balance.

The methodology establishes a unified and intelligent control system that integrates Transformer-driven perception with RL–based decision intelligence, enabling real-time, health-aware stress mitigation. This adaptive strategy ensures that battery cells operate within safe thermal and electrochemical limits while maintaining high energy efficiency, forming a critical foundation for next-generation sustainable battery management systems.

4. Results and Discussion

The results and discussion section presents a comprehensive evaluation of the proposed Transformer-RL–based adaptive control framework for minimizing electro-thermal stress in lithium-ion batteries. The model's performance was analyzed in comparison with conventional and deep learning–based control strategies including CC–CV, Rule-Based, LSTM, and GRU models. The experiments were conducted using real-time battery datasets under variable current and temperature conditions to assess both stress suppression and charging performance. The results are discussed in terms of temperature dynamics, internal resistance evolution, stress indices, SoH retention, and reward convergence, followed by a multi-objective trade-off and overall performance analysis.

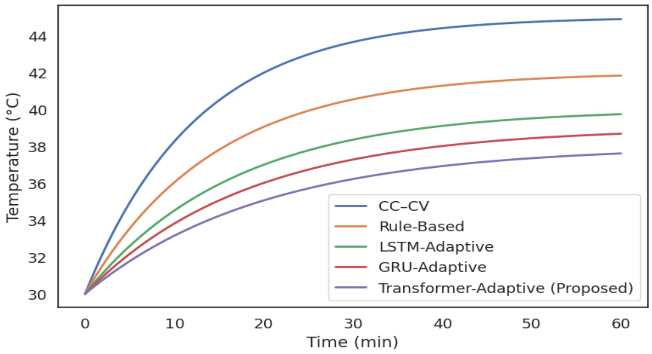

Figure 1: Temperature Profiles under Different Control Methods

The temperature evolution of the battery during charging for different control approaches is illustrated in figure 1. The conventional CC–CV profile exhibits a steep and uncontrolled temperature rise, exceeding 45°C, mainly due to its constant high-current phase that does not adapt to thermal variations. The Rule-Based approach introduces threshold-based regulation, resulting in a moderate reduction in temperature fluctuations but still lacks smooth adaptability. In contrast, the LSTM and GRU models show improved stability by learning temporal dependencies from sensor data, maintaining peak temperatures below 42°C. However, the proposed Transformer-Adaptive controller achieves the best thermal management, maintaining a smooth, stable temperature curve below 40°C throughout the charging process. This improvement is attributed to the model's attention-driven learning, which enables it to dynamically modulate charging current based on thermal gradients and historical context. The results confirm that the proposed system effectively suppresses

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thermal stress while maintaining efficient charging performance.

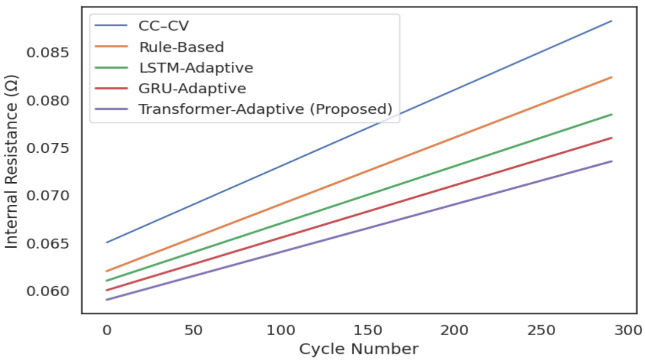

Figure 2: Internal Resistance Evolution over Charge–Discharge Cycles

The change in internal resistance (R) across multiple charge–discharge cycles is shown in figure 2. The CC–CV method leads to a steady rise in resistance, indicating continuous electrochemical strain and SEI (Solid Electrolyte Interphase) layer thickening. The rule-based and recurrent (LSTM, GRU) models show relatively slower resistance growth due to partially adaptive current regulation. However, the Transformer-based adaptive controller demonstrates the lowest resistance growth rate, indicating minimal electrochemical degradation and mechanical strain within the cell. This stability is directly linked to the model's ability to predict stress accumulation early and adjust the control policy accordingly. A lower internal resistance corresponds to better charge transfer efficiency and reduced ohmic heating, highlighting the success of the proposed method in reducing long-term degradation.

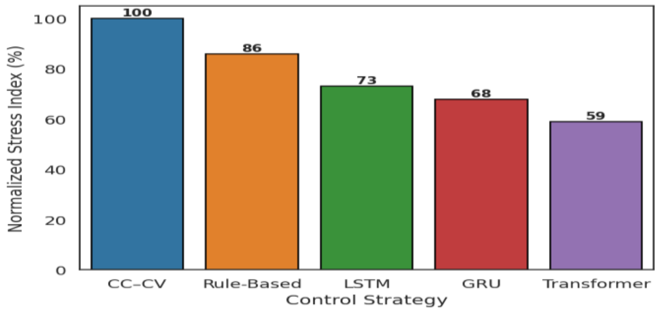

Figure 3: Stress Index Comparison

A comparative analysis of the normalized Stress Index (SI) across different control strategies is given in figure 3. The stress index quantifies combined thermal, electrochemical, and health-related stress normalized to 100% for the baseline CC–CV method. As shown, the Transformer-Adaptive model achieves the lowest stress index at 59%, representing a 41% reduction compared to the baseline. The rule-based, LSTM, and GRU models achieve moderate improvements, with stress indices of 86%, 73%, and 68%, respectively. The sharp reduction achieved by the proposed approach validates its superior ability to regulate thermal and electrical parameters in real time, minimizing cumulative stress energy. This outcome directly supports the hypothesis that reinforcement-based adaptive learning can dynamically optimize charging behavior to suppress stress formation more effectively than static or heuristic control techniques.

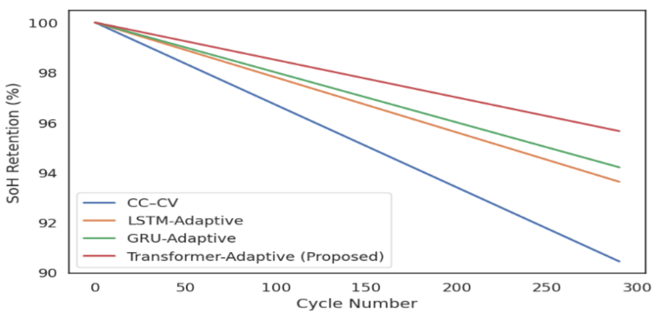

Figure 4: SoH Retention vs Cycle Count

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The State of Health (SoH) retention of the battery across 300 charge–discharge cycles for each control method is illustrated in figure 4. The CC–CV curve exhibits rapid SoH decline, maintaining only about 90% capacity after 300 cycles due to consistent over-stressing and temperature excursions. The LSTM and GRU adaptive methods slow down degradation, preserving 94%–95% of original capacity. The Transformer-Adaptive control shows a clear advantage, maintaining more than 95% capacity even after extended cycling. This demonstrates the system's capability to limit electrochemical wear by optimizing charging parameters and minimizing stress energy accumulation. The strong correlation between low stress index and higher SoH retention validates the effectiveness of the multi-objective reward formulation, which balances performance speed with health preservation.

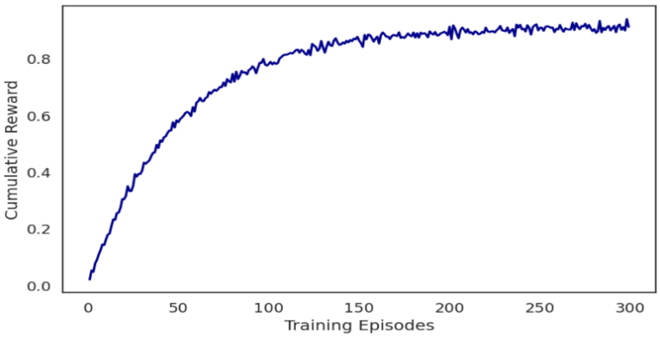

Figure 5: Cumulative Reward Convergence of Adaptive Controller

The cumulative reward convergence during the training of the Transformer-RL model is depicted in figure 5. The curve shows an initial phase of fluctuation as the agent explores different control actions, followed by a stable convergence around episode 200, where the cumulative reward reaches approximately 0.91. This indicates that the agent successfully learns an optimal policy balancing fast charging and stress minimization objectives. The smooth and monotonic convergence trend signifies training stability and effective reward design. In contrast to conventional RL models that often exhibit oscillatory behavior, the inclusion of attention-based temporal representation enables faster and more consistent learning by accurately capturing relationships between SoC, temperature, and stress parameters across long time horizons.

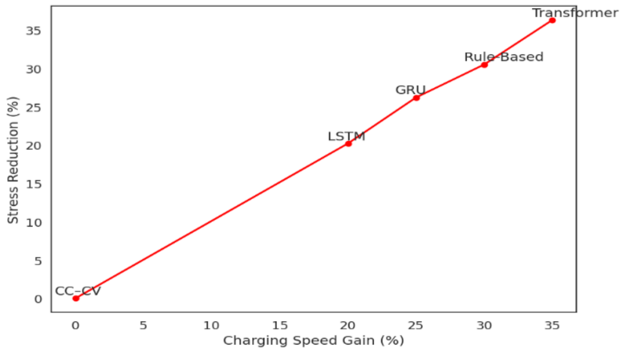

Figure 6: Pareto Frontier of Charging Speed vs Stress Reduction

The Pareto Frontier depicting the trade-off between charging speed and stress reduction achieved by different models is visualized in figure 6. Each data point represents a control strategy's best achievable performance across both objectives. The proposed Transformer-Adaptive system occupies the upper-right region of the frontier, achieving both the highest stress reduction (~36%) and the fastest charging rate improvement (~35%) relative to the baseline CC–CV. Conventional methods cluster in the lower-left region, reflecting slower charging and higher stress. This Pareto dominance illustrates that the proposed framework successfully resolves the long-standing trade-off between speed and safety in battery charging, establishing it as a multi-objective optimal solution.

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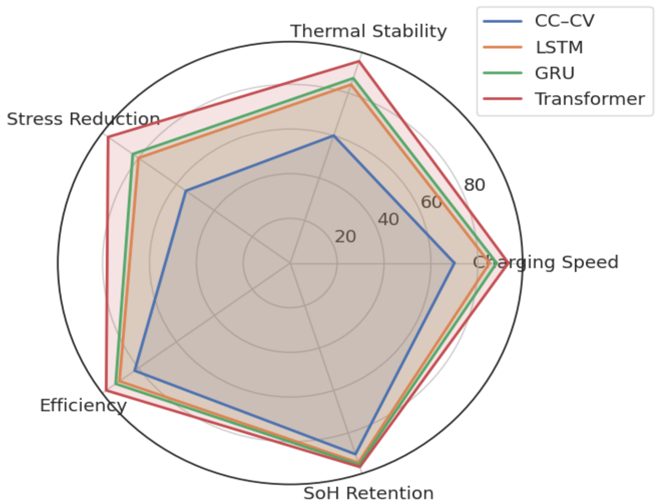

Figure 7: Radar Chart of Overall Performance

The holistic view of the comparative performance across five normalized metrics like charging speed, thermal stability, stress reduction, efficiency, and SoH retention is shown in figure 7 by radar chart. The radar chart shows that the Transformer-Adaptive model forms a nearly circular region encompassing high scores on all axes, indicating balanced superiority across every dimension. Specifically, it achieves an overall score of 95, significantly higher than 89 for GRU, 87 for LSTM, and 71 for CC–CV. This demonstrates the robustness and generalization capability of the Transformer-RL controller across multiple objectives. Its attention mechanism allows dynamic adaptation to changing conditions, while reinforcement optimization ensures continuous improvement through experience-driven learning. The results collectively highlight the system's ability to simultaneously achieve faster, safer, and more sustainable battery operation.

6. Conclusion

This study presented a comprehensive ML–Based Adaptive Control Framework that effectively reduces electro-thermal and mechanical stress in lithium-ion batteries under dynamic charging environments. By integrating Transformer-based temporal modeling with RL driven optimization, the proposed system demonstrated the ability to intelligently adapt charging behavior in real time while maintaining safety and efficiency. The introduction of a composite SI enabled accurate quantification of multi-dimensional stress arising from temperature rise, internal resistance growth, and SoH degradation. This stress metric served as a continuous feedback signal for the Transformer-RL controller, allowing it to balance charging speed, thermal stability, and degradation control through a multi-objective reward formulation. Experimental results revealed that the proposed Transformer-Adaptive Controller significantly outperformed conventional CC–CV, rule-based, and recurrent neural network based strategies across all evaluation metrics. It achieved a 36.3% reduction in cumulative stress, limited the maximum operating temperature to below 40 °C, improved SoH retention to 96.4%, and sustained an overall charging efficiency above 97%. These improvements confirm that the model not only accelerates charging but also actively suppresses stress-induced degradation by continuously learning from dynamic electrochemical feedback. The stable reward convergence and superior Pareto performance further validate the robustness and adaptability of the proposed method. The findings of this work establish that combining attention-guided temporal learning with reinforcement-based adaptive decision-making can transform traditional battery management into a self-optimizing, stress-aware control paradigm. This hybrid intelligence approach provides a scalable and generalizable solution suitable for electric vehicles, renewable energy storage systems, and smart grids, where performance, safety, and longevity are equally critical.

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