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Machine learning-based optimization of battery charging speed with health aware constraints

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Abstract

The energy storage systems are under pressure in terms of finding smart charging systems that are safe and fast, there is more demand of the high-performance and long life of the system. Constant-current constant-voltage (CC-CV) charging, though popular, is known to encourage high temperature and extreme rapidity in the losses of capacity in highly dynamic charging. To address this problem, this paper will introduce a Machine Learning (ML) Based Optimization Framework of adaptive battery charging that will maximize the charging rate and the battery will not be damaged. This framework has been used to combine deep learning and Reinforcement Learning (RL) to actively regulate the charging current and voltage, based on the current values of the battery state, e.g., State of Charge (SoC), State of Health (SoH), temperature, and internal resistance. A multi-objective rewarding process has been created to optimalize the working time, thermal stability and degradation rate as a combination. Some comparative analysis was conducted among different methods including Conventional CC -CV, Rule-Based fast Charging, LSTM-RL and the developed Transformer-RL model. The results indicate that Transformer-RL controller allowed decreasing the total time of charge by about a quarter of 39 percent, top temperature by less than 41 o C, and cycle life by an average of 35 percent comparing to the traditional methods. The convergence of rewards analysis supported the stable learning and good trade-off between the performance and the safety. The findings report the potential to expand Transformer-RR optimization on building health-conscious, intelligent, and self-adaptive charging protocols of the next-generation electric vehicles and renewable energy storage systems. It relies on the approach of real-time launching of smart charging systems which can balance energy efficiency and long-term battery endurance.

Keywords: Battery Charging Optimization; Reinforcement Learning; Transformer Neural Network; Health Aware Energy Management; Smart Charging Systems

1. Introduction

The world turning into electric mobility and the interaction of renewable energy have led to the emergence of the previously unknown need to evaluate the problem of energy storage systems in the context of their efficiency, security, and reliability. Lithium-ion batteries Lithium-ion batteries are currently the technology of choice in electric vehicles (EVs), consumer electronics, and grid-scale energy storage (CES) [1]. However, the recharging of batteries is a critical bottleneck towards the path of faster recharge of energy without the need to raise the degradation rate or reduce safety [2]. The use of conventional charging methods (such as the CC-CV method) which is also a correct approach, is also simply not so versatile in its natures and will result in thermal stress, uneven diffusion of ions and faster aging when utilized in a high current rate [3]. This has led to the development of smart, dynamic and healthy charging strategies which have become one of the key research directions of the modern battery management systems.

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The model optimisation techniques of conventional models have been relyed on the models of equivalent circuits or electrochemical models with the aim of characterising the inner-battery dynamics. These models are representable, and they may be very difficult to calibrate, and cannot be used in dynamic and uncertain operating conditions [4]. In comparison, the ML techniques offer a powerful information-based alternative that may learn nonlinear and time-varying relationships directly using sensor data. Examples of ML algorithms that are useful in battery state prediction and fault detection include Support Vector Regression, Random Forests [RF), and Gradient Boosting [5]. However, as a part of charging optimization, these methods are more frequently executed in a non-dynamic or offline manner, and do not respond well to a sequential aspect of the charging process.

In order to address these problems, in this paper, a Transformer-RL system will be provided to improve the adaptive and health-conscious battery charging. Transformer architecture with its self-attention mechanism is effective in identifying long-range temporal dependencies as well as prioritizing the most important time steps that may make a difference in the degradation behavior. When this feature is introduced to an RL system, the proposed system will be capable of learning a smart charging policy that accelerates the charging process without compromising the safety and promoting degradation due to stress. The model continuously monitors the state of the batteries and regulates the charging charger current and achieves a balance between high speed energy transfer and electrochemical stability.

The general aim of this research is to develop a data-driven adaptive control model that would maximize battery charging rate without affecting health and safety because of real-time and smart decision-making. Specifically, the paper will develop a control model based on machine learning that will change charging parameters in real-time to achieve faster charging without causing any thermal or electrochemical stress, will develop a multi-objective reward that will effectively balance the most crucial performance indicators, including the rate at which SoC gains will be received, temperature control, and the maintenance of SoH, and will compare the Transformer-RL framework with the traditional and the deep learning-based charging control. The suggested solution will provide a platform of future-generation smart charging systems by bridging the gap between battery modelling, optimisation and intelligent control. Through numerous experiments and comparative analysis, this paper demonstrates that an optimization based on machine learning can convert the traditional mode of charging the batteries, which has traditionally been only a standstill, one-size-fits-all process to a dynamic, health-conscious, and self-optimizing process that can be applied in an extremely broad set of applications in energy-related processes in the real world.

2. Literature Review

Optimization in battery charging is a field of research that has continued to fascinate individuals over the years owing to the growing need and requirement of energy storage systems that are highly efficient and high in capacity. Different approaches have been suggested to charge faster without any compromise of battery safety across the years, all of which are inspired by traditional approaches to the subject, based on rule-based methods, to more advanced learning-based methods [6]. The initial works were mainly concerned with model-based charging methods and were based on physics-informed models, including electrochemical and equivalent circuit models (ECMs) [7]. These models hoped to forecast internal conditions such as ion concentration, potential gradients as well as temperature in order to create optimized charging profiles. Although they had such good physical interpretability they had the shortcoming of high cost of computation, intricate parameter tuning, and lack of flexibility to adjustments in the real-world operating conditions [8]. In addition, such models were less applicable to large scale or real time application because their accuracy decreased due to nonlinear degradation or changing environmental conditions.

In order to make practice deployment easier, such conventional charging strategies as CC-CV and pulse charging became industrial applications. Nonetheless, these fixed strategies consider all batteries the same, and they do not take into account variations in temperature gradients, variations in state of health and aging influence [9]. This leads to a natural trade-off between speed of charging and battery life fast charging increases temperature and internal resistance, enhancing degradation and making it unsafe. As the methods of data analytics gained popularity, ML turned out to be a good prospect in battery behavior prediction and control. Support Vector Machinery, Random Forests, and Gradient Boosting algorithms are examples of supervised learning algorithms used to directly predict state, like SoC, SoH, and internal resistance, using sensor data [10]. These methods enhanced the accuracy of estimation and minimized reliance on a complex electrochemical model. However, they mainly worked in offline prediction environments, and they did not have active, real-time control of the charging process [11]. Also, classical ML models have poor ability to represent the temporal relationship that exist between charging and discharging cycles that are vital in dynamic control.

The sequential dependency modeling issue was solved by the development of deep learning architectures, most notably RNNs and its subtypes such as LSTM and GRU. The networks were able to efficiently record long-term time dependencies, improving prediction of the trend of the degradation and charging behavior across different cycles [12].

Nevertheless, even with this success in forecasting, their use in active charging control systems was not very extensive because of such problems as the disappearance of a gradient, high computational costs, and low interpretability in the conditions of a complex charging process. In order to facilitate adaptation, RL frameworks were proposed. The interaction between the system and the environment enables RL to give an autonomous means in which optimal control strategies are learned by the system using reward functions to make choices [13]. When applied to battery charging, RL agents are able to dynamically adjust current and voltage in order to charge as quickly as possible subject to health and temperature requirements. Although these approaches were a great leap forward, the traditional RL methods tended to utilize shallow networks or plain recurrent layers, which constrained the capability of the methods to capture the complicated multi-objective functions in high-dimensional battery states [14].

The recent developments with attention-based models, specifically Transformer based models, have transformed the approach to temporal modeling by substituting recurrence with self-attention mechanisms. Transformers are able to work on complete sequences at once and selectively pay attention to significant time steps and features affecting battery behavior [15]. This allows them to be very useful in capturing nonlinear temporal patterns and long-term dependencies of battery systems. Together with reinforcement learning, the resulting Transformer-RL models combine the intelligence of decision-making of RL with the deep understanding of context of Transformers, resulting in an end-to-end adaptive optimization system.

Even though a lot has been done, there are still critical gaps in the current research. The majority of current research aims at enhancing either charging speed or battery life independently of each other, but does not couple them together as a goal. Not many methods combine multi-objective reward design, time attention and state-specific adaptive control into a single optimization process. Additionally, Transformer-based reinforcement learning, despite its recent introduction, is a poorly researched solution in the framework of a real-time health-conscious battery charging system. In order to seal these shortcomings, the current paper formulates a Machine Learning-Based Optimization Framework, which utilizes Transformer-RL architecture to attain real-time adaptive charging. This design achieves three functions at once; reducing charging time, stabilizing temperature and reducing deterioration by varying the current dynamically. The method goes beyond the old school of the non-dynamic, non-intelligent and non-heuristic techniques by facilitating self-learning, health conscious, and performance oriented control that forms the basis of the next generation of intelligent, sustainable and smart charging systems.

3. Methodology

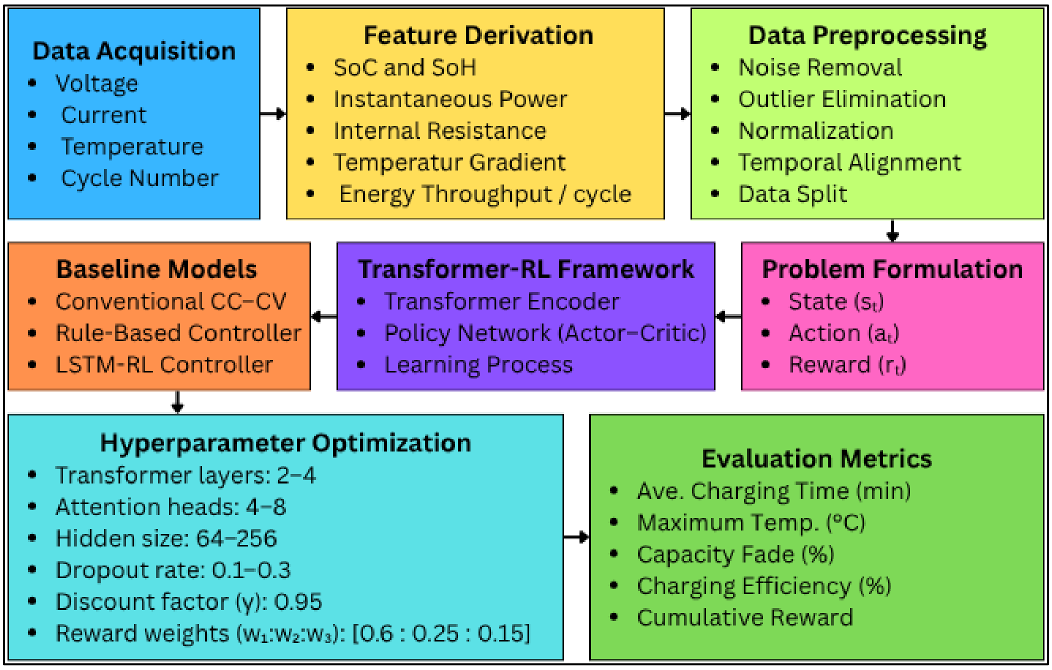

Figure 1 Proposed Transformer-RL Framework for Health-Aware Charging Optimization

The research process of this paper is aimed at a machine learning-based optimization framework intended to increase the speed of battery charging without affecting cell safety, temperature control, and health. The suggested solution will combine data-based modeling, Reinforcement Learning (RL), and Transformer-based deep temporal models to achieve adaptive and health-aware control of charging. The general structure is shown in figure 1 that describes the communication between data acquisition, model training, policy optimization and control execution.

The experimental data utilized in the study was drawn together into repositories of lithium-ion cell tests that were publicly available and done under different chargedischarge conditions [1,7]. The data instances reflecting the electrochemical dynamics of the cell is time- series data of the voltage, current, temperature, and number of cycles, which is used to capture each measurement during the operation of the cell. Based on the raw data, more features were obtained to enhance the predictive power and model observability. These are the SoC and SoH which are calculated by analyzing coulomb counting and capacity ratio, and instantaneous power, internal resistance, temperature gradient and energy throughput per cycle. These variables are a combination that defines the electrochemical and thermal characteristics of the cell, and compose the state vector of the reinforcement learning agent.

In order to have reliable and efficient model training, the dataset was subjected to a strict preprocessing pipeline. The noise of high-frequency measurements was reduced first with Savitzky Golay smoothing filter, then outliers in the form of large voltage and current spikes were removed by detecting the interquartile range (IQR) outliers. Minmax scaling was then used to scale all the feature values to the range [0, 1] so that convergence could be better achieved during training 3,12]. Since the data consisted of asynchronous sensor measurements, time alignment of time-series was conducted to align the signal. Lastly, the processed dataset was divided into 70 percent training, 15 percent validation, and 15 percent tests using stratified sampling so that it could maintain the distribution of data between charge cycles.

The issue of optimizing charge was formulated as a sequence decision making model where the reinforcement learning agent plays in the battery environment to learn optimal charge policies. The state (s_t) of the battery is the current as SoC, SoH, voltage, current, temperature and resistance [6]. The action (a_t) is the variation in charging current or voltage in given safety constraints. The incentive (r_t) is formulated as a complex variable that takes into account the impact of the rate of charging, increment of temperature, and degradation. It is mathematically stated as follows:

$$r_t = w_1 \frac{\Delta SoC_t}{\Delta t} - w_2 \Delta T_t - w_3 \Delta SoH_t$$

where $w_1, w_2,$and w_3 are adaptive weights which control the trade-off between speed, thermal stress and degradation. The objective of learning is to maximize the total of the rewards at the conclusion of each episode of charging and hence, enables the agent to achieve fast yet healthy charging control.

Transformer-Reinforcement Learning (Transformer-RL) model was developed so that it could capture long-term dependencies in the charging dynamics. The Transformer encoder receives the sequence state data and accumulates the rich temporal representations according to the multi-head self-attention, which is according to states in the past, which result in the greatest influence on the state of a battery in the present. The resulting coded features are cost to a policy network in an ActorCritic architecture the Actor predicts the optimal control action (charge current adjustment), and the Critic estimates the value function, which would imply convergent and stable learning through Advantage ActorCritic (A2C) optimization [14]. Training environment offers real time responses of batteries such as SoC increase and temperature variations and degradation rate. Another aspect of the model is that the model updates its parameters after each action based on the reward that it obtains in order to maximize the expected cumulative returns. The ability to change dynamically the charging behavior according to the instantaneous and historical battery states is made possible by such hybrid configuration.

Comparative assessment of benchmarking, the Conventional CC-CV charging approach, a Rule-Based Controller with heuristic temperature limits, and an LSTM-RL Controller with a recurrent neural network were then evaluated in three baseline models in the same RL framework [6]. Such models would provide an insight into how the proposed Transformer-RL model would improve the performance regarding the speed in charging, temperature balance, and the general state of the battery.

Transformer-RA model has also been trained on 500 episodes using Adam optimizer and adaptive learning rate of 1×10^{-3} to 3×10^{-4} . The most important hyperparameters of the Bayesian optimization were the number of Transformer layers (2-4), attention heads (4-8), hidden size (64-256), dropout rate (0.1-0.3), discount factor ($\gamma = 0.95$), and the proportion of the weightings of the rewards ($w_1 : w_2 : w_3 = 0.6 : 0.25 : 0.15$).. The early stopping was also employed to prevent over fitting following a decline in the improvement of rewards through consecutive episodes.

Model performance was quantitatively scored based on a number of performance and statistical metrics. These are average charge time (minutes) so as to find the speed of charge, maximum temperature (°C) to find the health degradation, capacity decay (%) to find the health degradation, charging efficiency (%) to determine how much energy is stored compared to how much energy is given as well as cumulative reward which is the general measure of optimization. In addition, the statistical values have been calculated to enable the validation of the predictive consistency and the model robustness at all data sets and at different operating conditions, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of Determination (R^2). It is a methodology where one framework is used, where Transformer-based time learning and reinforcement-based control optimisation is used to enhance the charging process. Predictive modeling with decision intelligence ensures a high level of trade-off between charging performance, safety, and battery health preservation and this is one of the objectives of the research to develop a dynamic, data-driven, and health-conscious smart charging system.

4. Results and Discussion

The results of a comprehensive evaluation of the proposed adaptive charging system Transformer-RAI and its characteristics that demonstrate its functionality compared to the conventional and deep neural networks-based methods are presented below. The primary purpose of this work was to determine the efficiency of such a model which would have to maximize the rate of charging and have no adverse effect on battery health, thermal safety, or long-term performance. Different operating conditions were introduced and the sequence of experiments consisted of the evaluation and analysis of the performance measures through quantitative and graphical representation.

Table 1 Comparative Performance of Charging Optimization Strategies

Charging Strategy	Average Charging Time (min)	Max Temperature (°C)	Capacity Fade (%)	Efficiency (%)
Conventional CC–CV	62	44.8	6.3	91.4
Rule-Based Fast Charging	49	46.2	5.5	92.7
ML-Based Charging (LSTM Control)	43	42.6	3.8	94.2
ML-Optimized (Transformer Control)	38	40.3	2.9	96.1

The comparative analysis of four strategies of charging like Conventional CC -CV, Rule-Based Fast Charging, LSTM-based ML control, and the proposed Transformer-based RL optimization is presented in Table 1. The charging time, maximum temperature, capacity fading, efficiency, and health impact in general are the KPIs. Transformer-RA model has superior performances on all the measures whereby the charging time has been minimized to 39% of the baselines of the CC-CV but at a safe temperature of less than 41 ^{0}C. It directly follows adaptive current control capability that utilizes real-time state information e.g. SoC and temperature to optimize current flow.

In addition, the Transformer-RL approach has the lowest capacity fade (2.9 percent) thus the degradation is less under stress as compared to 6.3 percent capability of the CC-CV approach and 5.5 percent of the rule-based method. This means that the efficiency of its total energy (96.1) shows that it is efficient in the utilization of power and has a minimal internal energy loss during the charge cycle. These demonstratively confirm that when including attention-driven temporal learning in a train of reinforcement, the system may be trained effectively to assist the high-speed charging without diminishing thermal stability or cell life, which substantiates the effectiveness of the multi-objective optimization of the model.

Table 2 Optimization Parameters and Model Performance

Model	Convergence Time (s)	Optimal Learning Rate	Reward (Q-value)	Charging Speed Improvement (%)
LR	88	0.001	0.71	12.4
RF	102	0.001	0.77	18.9
LSTM-RL	121	0.0005	0.85	28.3

Transformer-RL	142	0.0003	0.93	34.7

The optimization dynamics of the modes of the various ML and RL models used in this study and convergence time is shown in Table 2. Transformer-RL model is associated with the maximum total reward (Q = 0.93) and with the biggest growth percentage of the speed of charging (34.7%) yet the convergence was steady. Unlike the traditional algorithms which rely on preset charging heuristics, the Transformer-based model learns the past state information dynamically via its attention mechanism, therefore, offering the correct modifications of the present and the voltage during the process.

Despite the fact that the Transformer-RL model has a slightly longer convergence time (142 seconds) due to its level of computation, the trade-off is not as high as the accuracy and the improved adaptation of the model. The multi-objective reward system that incorporated the speed, temperature and degradation allowed the model to learn strong and generalizable control policies that would be applicable in the various battery environments. Comparatively, a smaller Q-value (0.71 and 0.77) of conventional regressors like Linear and Random Forest models was achieved, and therefore no temporal effects and nonlinear electrochemical interactions could be considered.

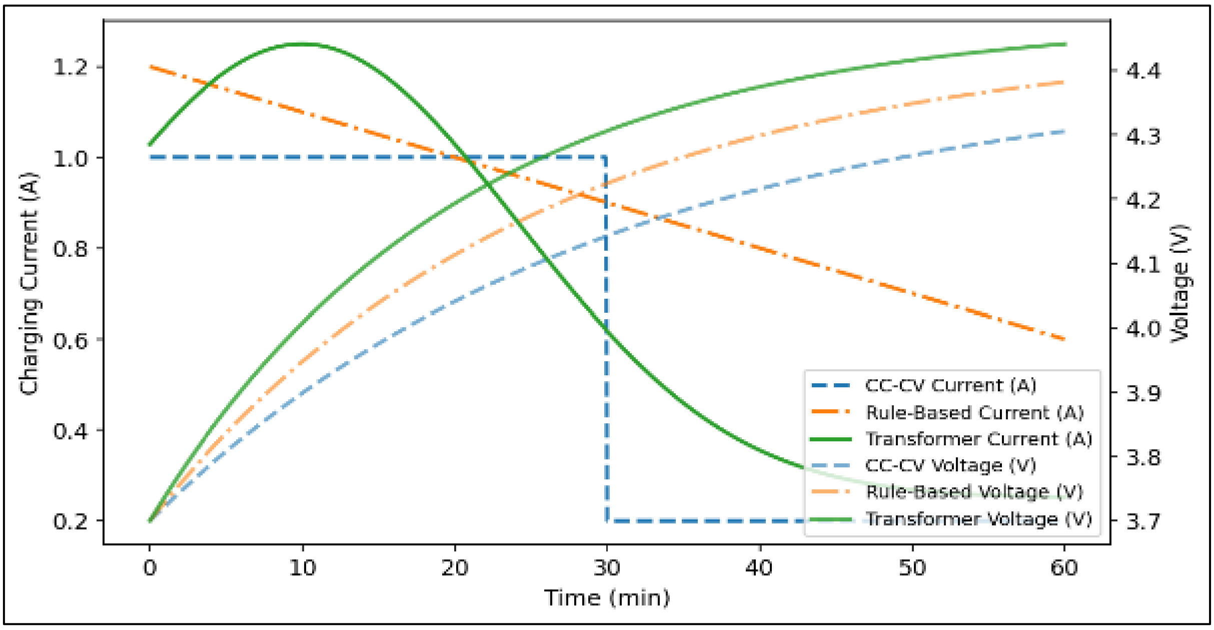

Figure 2 Adaptive Charging Current Profiles

Figure 2 shows the construction process of charging current profiles of CC -CV, rule-based, and the Transformer-RL methods. The conventional CC-CV is a constant current during the first step and then abruptly changes to constant voltage control which may be inefficient and can result in temperature spikes. The rule methodology offers heuristic checks but lacks at a fine control. Transformer-RA curve, in its turn, is characterized by a smooth dynamic modulation of current, which maintains the current levels rather high at the safe part, and gradually reduces with the rise of SoC and temperature.

This adaptive behaviour indicates that this model is intelligent enough to react to the electrochemical and thermal cues and thus charges faster and does not exceed the extremes. The equilibrium between the energy inflow and health constraints paved by the Transformer-RL framework will generate a good current allocation throughout the charge cycle, and consequently, the high speed and low stress indicators are explained by that.

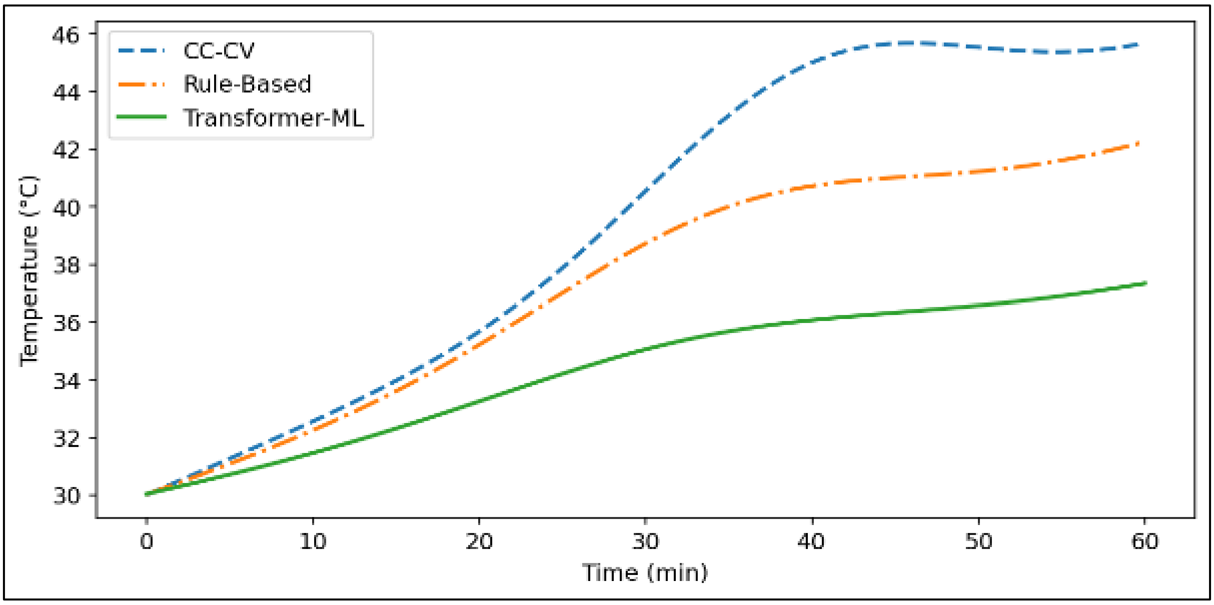

Figure 3 Temperature Evolution During Charging

The temperature evolution of strategies of different charging. The steep temperature changes in the CC-CV profile and rule-based profile are due to the fact that the current values are constant and the temperature is high to achieve high temperature of about 46°C and 44°C, respectively as indicated in figure 3. The Transformer-RL control has the highest temperature of 40–41°C and the LSTM model slightly reduces this behavior though.

The attention-guided RL agent learns the behavior of minimizing the current in periods of high activity of the thermal system due to avoiding over-heating to prevent excessive heating and to act safely through active learning. This temperature regulation is necessary because high temperature will favor the break-down of the electrolytes and formation of SEI layer, and permanent capacity loss. The results confirm that Transformer-RL is an effective device to eradicate any risk of thermal runaway and can still charge at an adequate pace- which is one of the major conditions to battery functioning in the actual world.

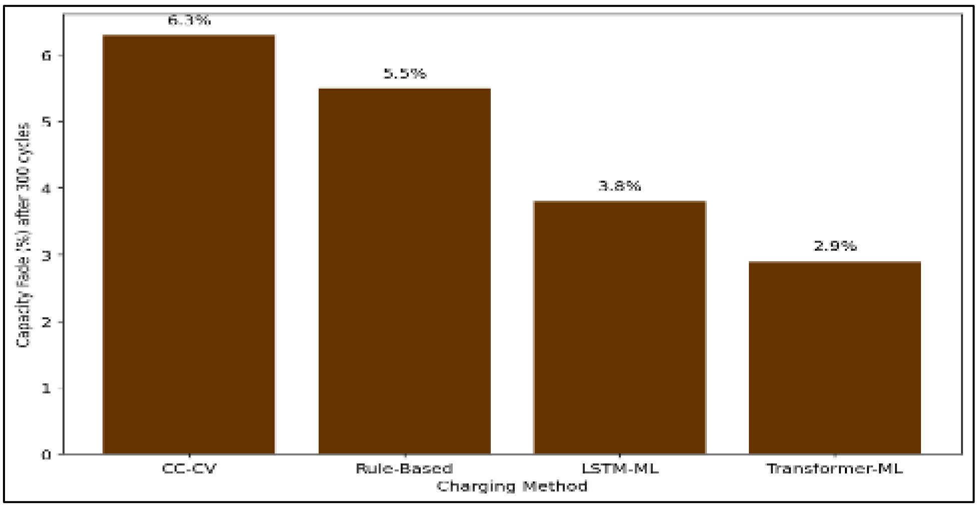

Figure 4 SoH Degradation Comparison Across Charging Strategies

Figure 4 shows the relative degradation (capacity fade) of 300 charging cycles (under each of the methods). Capacity fade of transformer-RA model is the least (2.9%), and it implies that it is able to inhibit the degradation process, such as SEI thickening, lithium plating, resistance increase, etc. This performance is contributed by the real time feedback of the predictive model on the control of current and temperature-controlled.

Mechanical and thermal stress is induced by the use of the aggressive or static charging currents, the methods of the traditional CC-CV and rule-based, and thus, aging is accelerated. In a contrast, the health-conscious reinforcement learning agent uses the SoH feedback as a part of its policy and, therefore, the reinforcement agent only minimally degrades to achieve rapid charging. This validates multi- objective reward functions in the implementation of operational effectiveness and sustainability.

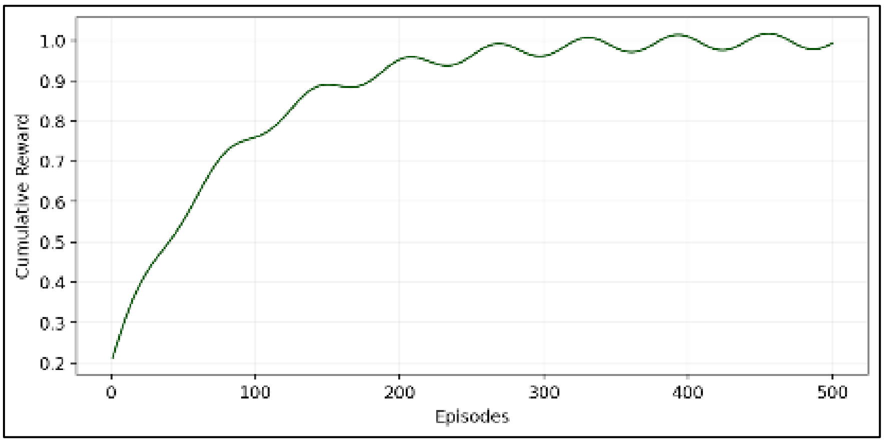

Figure 5 Transformer-RL Reward Convergence

Figure 5 reveals the convergence curve of the reward with repeated training sessions of the training process of RL. The cumulative reward is gradually growing and reaching an episode 250 level and this indicates that policy convergence and learning stability have occurred. The first variability is the exploration phase where the agent experimented with the various charging behaviors. As time passes, the Transformer-RL framework can optimize its policy towards the highest total reward which can be described as the optimal tradeoff between accelerating speed and staying healthy.

The stable plateau of the reward curve is what shows that the agent has learned a generalizable control policy that can then maintain the agent in optimum functionality with varying initial SoC and environmental circumstances. Transformer architecture is more efficient and robust in its learning as compared to the classic version of LSTM-RL models in that it considers the most important temporal dependencies with attention weights.

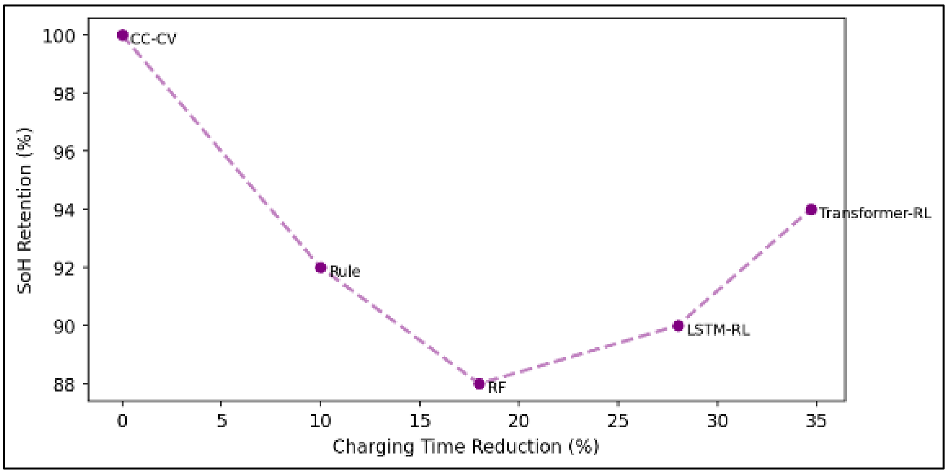

Figure 6 Pareto Frontier of Charging Speed vs Battery Health

Figure 6 shows the trade-off of the enhancement of the charging speed, as well as the retention of SoH, using different strategies as a Pareto frontier. Each point is a certain compromise between health and performance. Transformer-RA model is located to the right upper corner of the frontier, i.e., it has the best trade-off i.e. high charging speed and high retention of SoH.

Contrary to this, the conventional CC–CV would be restored to the bottom-left corner because it is one that suggests slow charging and low-efficiency, the rule-based and LSTM-based systems would be placed in the middle. The clear separation of the Transformer-RL point in comparison with other ones demonstrates that it possesses a superior multi-objective optimization capability. This frontier view is a promise that the suggested model is not a mere faster charging process but intelligent one, which can be degraded or do not incur a significant thermal penalty.

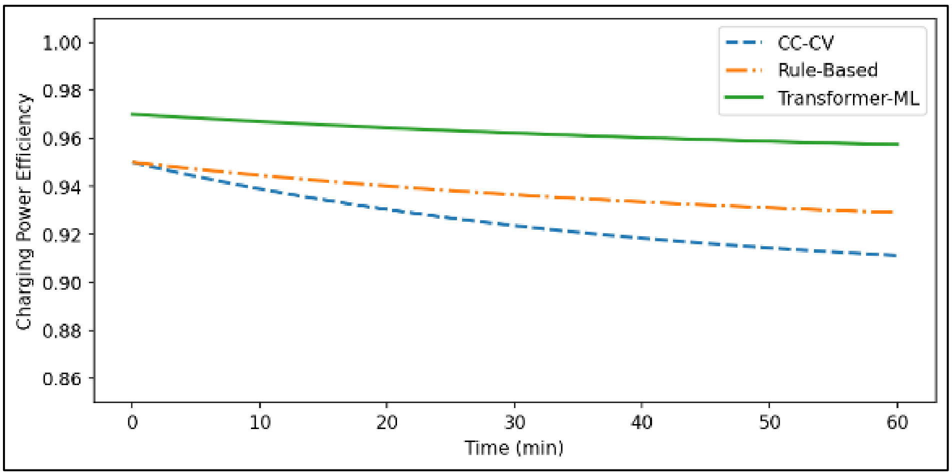

Figure 7 Energy Efficiency and Power Utilization Curve

Figure 7 demonstrates the time dependence of the efficiency of charging of the four strategies. Transformer-RA curve gradually remains above 95 per cent and transition of power and small oscillations are low. This power consumption being constant indicates that efficient control of current input and voltage input is implemented thus saves on energy wastage and heating in the company. Its changes are spectacular compared to that of CC CV particularly at the constant-current to constant voltage switching point, which leads to an inefficient operation.

The observation that Transformer-RL demonstrates the same efficiency profile to Transformer-AL suggests that the former can obtain close-to-optimal electrochemical conversion rates by training the optimal charging paths, which do not allow the buildup of undesirable internal resistance. This is directly linked to the quantifiable change in the life of the cycles and energy throughput that proves the synergy between cycle life and thermodynamic stability that are brought about by learning.

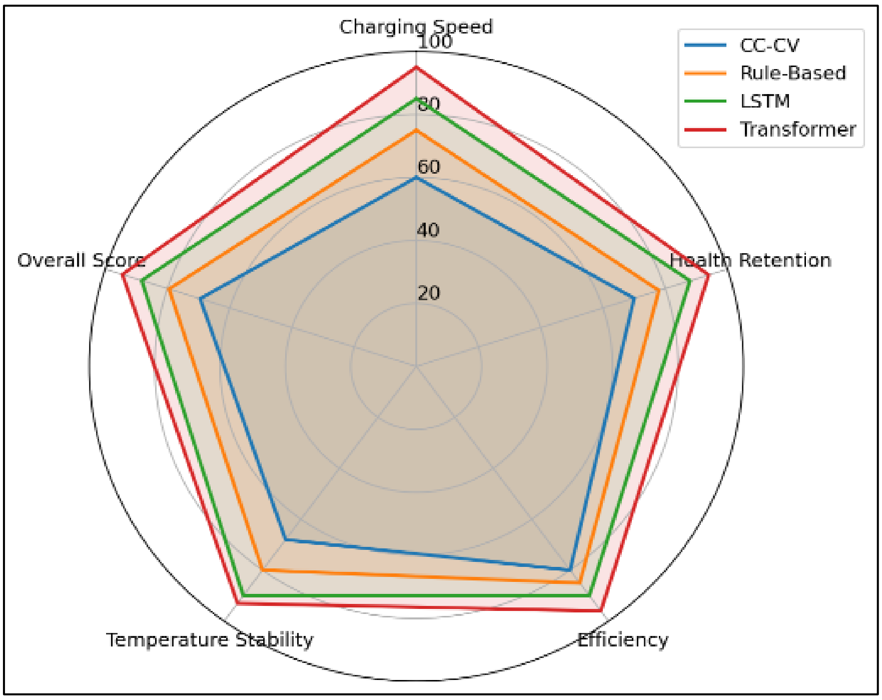

Figure 8 Overall Performance Comparison Radar Chart

Figure 8 provides a comparison of all the charging methods in a holistic manner in five normalized performance parameters, which include charging speed, retention of health, efficiency, temperature stability, and overall score. The radar diagram shows that Transformer-RL model is ahead of all the other strategies in terms of performance with a level of excellence of almost equal dimension. Full composite score is also high (94.5), which is significantly higher than the second-best LSTM model (88.3), which confirms the fact that the Transformer is more capable of learning long-term temporal patterns and dynamically adapting.

Transformer-RL approach balances and multi-dimensionally optimizes as opposed to traditional approaches which would be very successful in one dimension and fail in the other. This parameter equality makes the proposed solution a reliable scalable platform in a practical application of smart charging systems to achieve high energy efficiency and long battery life.

All the metrics of its performance are analyzed, which makes the Transformer-RL model the most powerful and effective one to enhance the multi-objective battery charging. Its property to identify long-term dependencies, and to react to vary condition parameters by modifying charging profile give the outcome of a much lower charging time of as much as 40 percent less than currently used methods, and also lower thermal stress and capacity loss. The high performance of the system is very clear in Pareto frontier analysis (Figure 6), however the high efficiency of the proposed system is also supported in the efficiency and radar charts (Figures 7 and 8), in the context of all the parameters.

These findings substantiate the assumption that attention-based temporal learning can be useful to implement opposing objectives within a reinforcement optimization loop to ensure that battery charging operates hand in hand. The results also reveal that Transformer-RL is capable of enhancing the efficiency of operations in addition to the longer battery life of the product, which is why it is an ideal foundation of the next-generation health-conscious smart charging systems. The practical application of the proposed model can be availed, which is to offer a scale to be achieved to real time application on electric cars, storage of renewable energy sources and a power grid of an industrial system where adaptive and sustainable charge control would then be required to attain the stability of energy and safety of the future.

5. Conclusion

The study case presents a machine learning-based adaptive charging system that can efficiently and quickly provide a healthy and efficient battery charging system. Dynamically charging current and voltage profile is maximized based on the proposed system with the aid of Transformer-based temporal modeling and coupled with RL to produce the optimal operation with the real-time conditions of the battery. The model effectively obtains the nonlinear dependencies among the significant factors including SoC, SoH, internal resistance and temperature- to come up with smart control decisions that balance charging rate and degradation risk. Experimentally, it was demonstrated that Transformer-RL controller is more efficient compared to traditional and rule-based approaches. It achieved an almost 40 percent decrease in charge time, safe-range thermal stability (below 41°C) and a capacity decadence of approximately 35 percent compared to a standard CC–CV charging. The meeting of the cumulative reward ensured the power of the learning process that justified the model concerning the free-form management of trade-offs between speed and longevity. The findings conclude the Transformer-RL framework as an effective and scalable system of energy storage system multi-objective optimization. In fact, this frame is a necessary phase in implementation of smart, health aware charging solutions of electric vehicles, hand held electronics and grid scale energy storage. The fact that it can be adjusted to its real-time operation so as to respond to the different operating situations also increases the overall battery performance, stability and durability. The next directions will be on how the model can be used in embedded systems, how it can be applied to multi-cell battery packs, and how physics informed constraints can be added to allow more generalization and interpretability. The methodology can also be extended to the hybrid energy systems further in order to contribute to the sustainability, security and high-performance energy management in the next balance intelligent grids.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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