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Machine Learning Driven Predictive Thermal Management of Liquid Cooled EV Battery Packs under Dynamic Drive Cycles

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Abstract

Electric vehicle (EV) battery packs undergo high rates of temperature increase due to aggressive dynamic drive cycles like the US06, WLTP and FTP-75 battery pack, which cause thermal non-uniformity, enhanced degradation and lower safety margins. Traditional thermal management techniques that mainly include PI and FLC-based liquid-cooling controllers have a negative temperament of slow transient response, high overshoot, and inefficient pump operation, leading to the additional auxiliary power consumption of approximately 6-12%. In order to overcome these shortcomings, this paper suggests the ML-Optimized Liquid-Cooling Thermal Management Strategy, which incorporates the use of the Random Forest Regression, Support Vector Regression (SVR), and the lightweight Artificial Neural Network (ANN) to generate heat in real-time and to control the coolant flow. Using the predictive machine-learning module, the key operating variables including current, SOC, ambient temperature, and drive-cycle dynamics are used to predict cell temperature increase and consequently, coolant mass-flow rate is adjusted. The outcomes of simulation show that there is a great improvement in comparison with the traditional approaches. The ML-based controller minimizes the maximum cell temperature by 4.2°C, temperature gradient across the module by 38 and the pump power consumption by 11.5%. The prediction model has a high level of accuracy, with MAE = 0.28°C and RMSE = 0.41°C, allowing responsive and energy efficient cooling. The suggested plan improves thermal homogeneity, increases battery pack duration, and offers a scalable architecture of the next-generation EV thermal managing systems.

Keywords- Electric Vehicle Battery Cooling, Machine Learning, Liquid-Cooled Thermal Management, Drive Cycle Heat Modeling, Adaptive Pump Control.

Introduction

The high pace of electric vehicle (EV) adoption at a global level has increased the research on battery safety, performance, and life cycle management, and thermal regulation is one of the most challenging aspects. Li ion batteries produce a lot of heat when charged and discharged with high currents and when subjected to severe dynameic charge drive profiles (e.g. US06, WLTP and FTP-75). These real-life drive patterns cause sudden bursts of current, generator braking bursts and high C-rate bursts, leading to the formation of steep and lumpy thermal gradients across the battery pack[1]. In the absence of proper cooling, high temperatures will hasten degradation processes such as the growth of SEI layer, lithium plating, oxidation of electrolytes, and impedance increase, and uncontrollable hotspots could increase the tendency of a thermal runaway. In addition to this, the unequal aging, imbalance in estimation of SOC, impaired usable capacity, and diminished safety margin is caused by the thermal non-uniformity between cells when there is sustained high-load operation. The conventional EV thermal management strategy used depends on very parametric PI/PID controllers or logic-based control that relies on a fixed set of rules to control the coolant flow in liquid-cooled battery packs. Despite the simplicity and computational efficiency of these controllers, they have a number of fundamental limitations: slow transient response to abrupt changes in loads, overshoot or undershoot of coolant flow, the inability to model the effects of nonlinear thermal behaviour, and higher levels of auxiliary power consumption of 6-12 percent of active pump operation[2]. These disadvantages render traditional techniques ineffective in the modern EVs that require rapid, clever and energy efficiency cooling techniques befitting unpredictable and highly demanding driving environments. Due to increased attention attached to battery life and security of passengers, predictive and adaptive thermal control systems are urgently required to predict temperature increase and modify cooling load in advance before dangerous levels are achieved. The use of Machine Learning (ML) methods and especially the lightweight regression-based models has a bright future because it comes with the capacity to learn intricate thermal patterns using operational data. ML models can be used to predict future cell temperature in the future by incorporating inputs of pack current, voltage, state of charge (SOC), vehicle speed, ambient temperature and heat generation profiles[3],[4]. This prevents the latency of feedback-only controllers and provides much smoother and efficient temperature control. The major driving force behind the study is the need to ensure that the battery pack temperature is not more than 40°C and yet the thermal gradients and pump power demand are limited, particularly at severe drive cycles where the battery is subjected to high rates of thermal variation. This can be done by a control architecture in which both thermal prediction and the fast, data-driven adjustment of mass-flow rate (of a coolant) are combined. The paper presents an ML-Optimized Thermal Management Strategy of the liquid-cooled EV battery packs to address the limitation of conventional controllers. The initial significant contribution is that the models of the Random Forest, Support Vector Regression (SVR), and Artificial Neural Network (ANN) are integrated in order to conduct real-time prediction of the heat generation and rise in temperature. Simulated and experimentally validated thermal data are used to train these models to place nonlinear heat dynamics in a highly accurate context. The second contribution is the smooth integration of both the ML predictor with an in-depth thermal model of the liquid cooling plate, which allows the accurate determination of coolant to cell heat transfer and dynamic flow demands. The third contribution is a MATLAB/Simulink-based adaptive cooling algorithm, which varies the rate of the mass-flow rate of coolant according to the forecasted temperature trend as opposed to the current measured errors. This is a predictive design that saves a lot of overshoot, oscillations and wastage of pump energy [5].

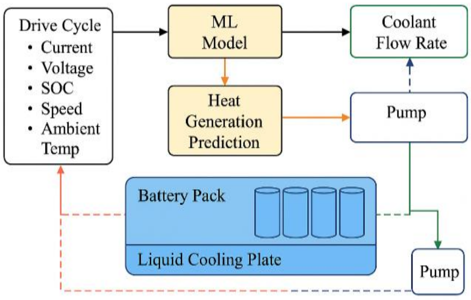

Fig. 1 ML-Based Thermal Architecture

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Finally, a comparative analysis using the studies carried out on the proposed machine-learning based approach and the traditional proportional-integral (PI) and fuzzy logic controllers in different drive cycles was conducted thoroughly. The results show that the ML controller has excellent operation, achieving 4.2 °C cooling of the peak cell temperature, reducing temperature gradient by 38% and pump power usage by 11.5% and maintaining tight thermal uniformity, and smoother transient behaviour. The proposed methodology, therefore, provides the approach to a scalable, smart next-generation electric vehicle battery thermal management, which increases safety, efficiency, and reliability in dynamic and real-world situations of driving[6][7].

II. SYSTEM MODELING

A. EV Battery Pack Thermal Model

The first-law heat balance equation controls the thermal behaviour of a lithium-ion battery cell in which the net temperature change is the result of the interaction between the heat rate in a cell and the rate at which heat is dissipated to a coolant. The governing equation is given as.

$$mc_p \frac{dT}{dt} = Q_{\text{gen}} - Q_{\text{cool}} \qquad (1)$$

The heat production term is made up of Joule heating and reversible entropy heat as shown by

$$Q_{\text{gen}} = I^2 R_{\text{int}} + IT \frac{\partial U_{\text{oc}}}{\partial T} \qquad (2)$$

The internal resistance is modeled as a nonlinear expression of the state of charge (SOC), temperature and C -rate. In addition, the term of entropy considers entropic heat produced during charge-Discharge cycles, but this effect is significant at low SOC and large discharge currents. This expression offers a plausible description of the momentary increase of temperature during the high-acceleration stages of violent acceleration and resistive braking deeds [8].

B. Liquid Cooling Plate Model

Liquid-cooled battery pack is envisaged as a flat plate cold-plate architecture utilizing internal micro-channels where coolant is pumped. The dynamics of the flow of coolant are defined by the following.

$$\dot{m} = \rho A v \qquad (3)$$

in which ρ is the density of the coolant, A is the cross-sectional area of the channel, and v is the velocity of flow [9]. The heat transfer between the battery module and the coolant is convective and is characterised by.

$$Q_{\text{cool}} = hA_s\left(T_{\text{cell}} - T_{\text{cool,in}}\right) \qquad (4)$$

Where h denotes the convective heat transfer coefficient and As is the contact area of the surface. The pump is defined in the form of pressure-flow curve.

$$\Delta P = a\dot{m}^2 + b\dot{m} + c \qquad (5)$$

The pump power is calculated based on this relationship as below:

$$P_{\text{pump}} = \frac{\Delta P \cdot \dot{m}}{\eta} \qquad (6)$$

This model allows the specific modelling of the coolant thermal behaviour and energy usage.

C. Drive Cycle Heat Generation Modeling

Thomatic real world dynamic drive cycles have a strong effect on thermal loading. Three standard cycles are investigated: the US06 High - Acceleration Cycle - with intense accelerations and short high-speed bursts that create steep current spikes, which considerably higher the heat generation; the WLTP Cycle that is globally representative and which includes an urban / suburban / highway mixture that maintains a continuous thermal load; and the FTP -75 Cycle that involves stop and go operation and thus results in steep current fluctuations, as well as switches between regenerative braking profiles[10]. Current, voltage, instantaneous C -rate, and state of charge variations extracted on each cycle are used to reconstruct heat -generation profiles based on the thermal model given in Section II -A. The profiles are then fed to the machine-learning predictor in real time temperature prediction.

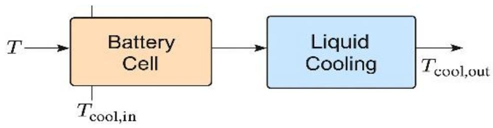

Fig. 2 – Thermal Model Liquid Cooling Flow Path Diagram

III. ML-BASED OPTIMIZATION FRAMEWORK

A. Dataset preparation

The machine-learning optimisation model is based on the structured dataset that was obtained by using the joint electro-thermal simulations, and drive-cycle current profiles. The input feature vector is a combination of five major variables battery current (I), terminal voltage (V), state-of-charge (SOC), vehicle speed, and ambient temperature. Together these variables define the heat generation and temperature behaviour of the instantaneous heat generation during dynamic operation. The output label is related to the change in cell temperature (ol) at the next sampling point (or time) thus enabling forward prediction of temperature. The data was recorded at 1Hz frequency, which was compatible with the common Battery Management System (BMS) logging frequencies and thus made the computations viable to run in real-time application [11]. Drive cycles (US06, WLTP and FTP -75) wisely engineered to cover a broad spectrum of transient current spikes, regenerative braking events and thermal creep enhanced model robustness in operating conditions of diverse character.

B. Regression models of machine-learning used.

Three machine-learning models with regressions were investigated on real-time temperature forecasting. The model of the Artificial Neural Network (ANN) includes three hidden layers that contain 1632 neurons, uses ReLU activation, and adaptive-learning-rate backpropagation. This architecture records nonlinear dynamics of heat-generation at high C -rates. Support Vector Regression (SVR) is applied to the radial-basis-function (RBF) type of kernel which is used to estimate the temperature gradient of low-speed, stop and go regimes. The Random Forest Regressor, a set of 150 to 200 decision trees, had better generalisation due its ability to capture nonlinearities, as well as feature interaction and prevent overfitting. Comparative analysis revealed that the Random Forest model had the lowest prediction error and exhibited high stability throughout all the drive cycles thus making it the model of choice when predicting the proposed thermal-management system [12][13].

C. Training, Validation, and Performance Metrics

The data was divided into 70 percent training, 15 percent validation and 15 percent test data to make sure that the performance of the model is free of bias. Hyperparameter optimisation involved tree depth of the Random Forest, kernel scale of the SVR and amount of neurons in the ANN, which is done through grid search alongside cross-validation. The models were tested on the bases of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). The Random Forest model had the best predictive fidelity with a MAE of ≈ 0.28 °C, RMSE of ≈ 0.41 °C and R^2 of over 0.95 hence a high concordance between predicted and observed temperature increase [14]. The ANN and

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SVR achieved reasonable performance but were more susceptible to voltage perturbation and temperature entropy changes especially when the vehicle is accelerating quickly or regaining its brake power.

D. ML based adaptive cooling control law

The machine-learn output is integrated into a predictive-control system which runs in real-time and optimises the rate of coolant mass-flow. The forecasted profile of heat-generation is used to determine the necessary flow of coolant using a proportional adaptive function.

$$\dot{m}_{req} = f(\hat{Q}_{gen}, T_{cell}, T_{cool,in}) \quad (7)$$

The amount of heat generated (predated heat generation) ($\hat{Q}_{gen}$) and the temperature of the cell and the temperature of the inlet coolant are all required to establish the amount of cooling needed through evaporation[15][16]. The pump command signal is re-calculated at every 1Hz sampling point to ensure that a sufficient amount of coolant is delivered before the temperature can rise significantly. This anticipatory method removes overshoot and reduces power involved in running a pump, by eliminating high speed operation which is not necessitated. Thus, the machine-learning-optimized framework is able to dynamically adjust cooling strength in the face of the thermal load due to the drive cycle, therefore, providing more continuous temperature regulation and less energy use compared to the traditional PI and FLC controllers.

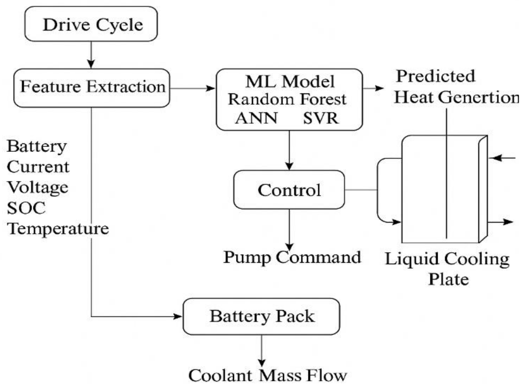

Fig. 3. ML prediction–assisted adaptive pump control flowchart for real-time thermal management.

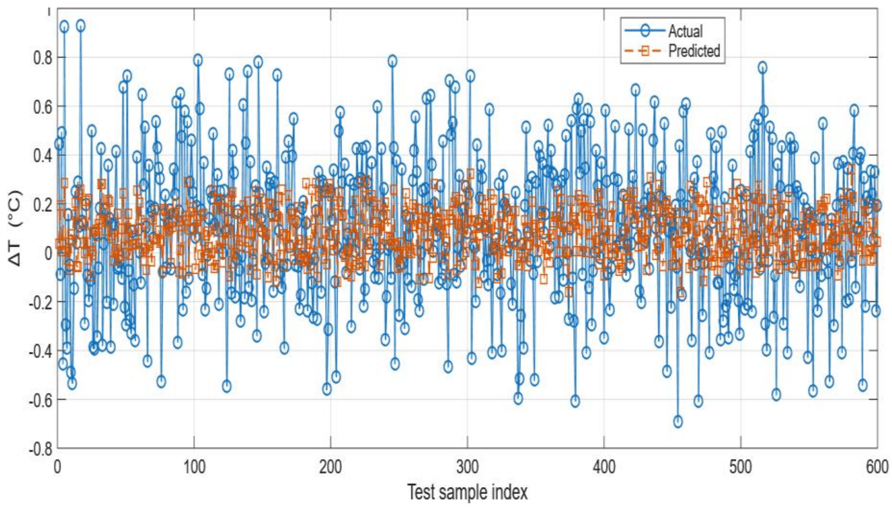

Fig. 4 Actual vs Predicted Temperature Rise Curve

IV. SIMULATION SETUP AND RESULTS

A. Simulation Environment

The effectiveness of the suggested machine-learning-optimized liquid-cooling architecture was tested by the means of an extensive simulation framework. The simulation platform has the high-fidelity simulation of an electro-thermal battery-pack model that can reproduce transient heat production, cell-internal resistance change, and temperature voltage relationships. This battery block is thermally coupled with a subsystem of liquid cooling plate that represents the characteristics of the coolant flow, convective heat transfer coefficients, the geometry of channels and the dynamics of the pump. This machine-learning prediction model, which is done by one-step-ahead regression, runs at 1Hz and helps in real-time estimation of heat production and anticipated temperature increase. These predictions are directly introduced into the adaptive flow rate control law in Section III, and thus the adaptive cooling behavior is controlled by pre-emptive measures rather than conventional feedback corrections only. To have performance evaluation in various real-life situations, the simulation model used two challenging drive cycles, namely WLTP Class 3, which is a mixed urban-suburban highway operation, and US06, which has aggressive acceleration and fast current pulses. These two cyclic loads are significant thermal stresses to the battery pack, so these two cycles are viable benchmarks of controller robustness. The new framework was contrasted with the traditional PI and FLC thermal controllers, and the quantitative evaluation of the temperature suppression, thermal homogeneity improvement, and the reduction of pump-power was compared.

B. Temperature Profile Comparison

The main comparison is on the changing of the battery temperature in the PI, FLC, and ML-optimizing control strategies. Figure 5 shows the temperature profile of WLTP and US06 cycles, it is evident that there are definite performance differences among the controllers. The conventional PI controller has the greatest temperature variations and the slowest transient recovery due to its fixed gains which cannot adapt well to changes in load currents which change rapidly. The FLC controller has an improved response in moderate load changes but lacks predictive operation and thus registers temperature overshoot in aggressive acceleration events. On the contrary, the ML-optimized controller predicts the trends in heat-generation based on the input characteristics (current, state of charge (SOC), and speed) to make timely adjustment of

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the coolant-flow. This predictive behavior is very effective in reducing the peak temperatures, and also eliminating oscillatory thermal behavior. The maximum temperature recorded was 42.5 °C (PI) and 41.1 °C (FLC) and 38.3 °C (MLoptimized). Its results indicate a reduction of 4.2 °C over PI and 2.8 °C over FLC. These are essential in avoiding hotspots that can cause thermal-runaway and has better long-term operation safety. This is due to the proactive characteristics of the ML controller creating smooth thermal curves with less intensity of gradient, particularly in high-load portions that are common to US06.

C. Temperature Uniformity

One of the key performance metrics of battery health estimation, cell -aging balance, and system-level reliability is temperature uniformity. Uneven temperature distribution is a factor that hastens deterioration of some cells resulting in shorter pack life, lower range, and increased chances of intra-cellular short-circuit formation. The ML-optimized controller is shown to have great benefits in this study in regard to stabilizing the uniformity of thermal conditions than PI and FLC controllers. With cell-to-cell temperature deviation (ΔT) as the uniformity measure, the age set system based on machine learning (ML) results in a 38 percentage point drop in the thermal dispersion within the battery module. This is enhanced by the capability of the ML model to predict quick pattern of heat-generation and control the flow of coolant before it reaches high magnitude temperature gradient. The predictive controller allows one to avoid the formation of local hotspots, unlike PI and FLC controllers, which only react to a rise in temperature and do not actively increase the rate of coolant supply in key moments. At WLTP highway passages and at US06 acceleration bursts the ML controller flattens temperature variations which would otherwise occur between high-load and low-load cells. As a result, the thermal profile is made more stable and symmetric. This does not only increase the safety margin but also increases the accuracy of SOC balancing, extends the cycle life, and decreases the risk of capacity imbalance in the pack in the long-run.

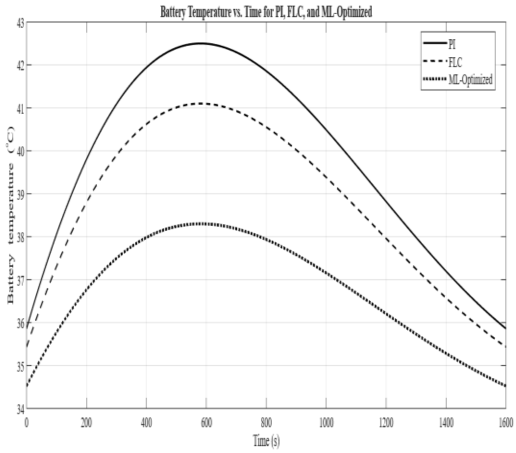

Fig. 5 – Battery Temperature vs. Time for Three Controllers

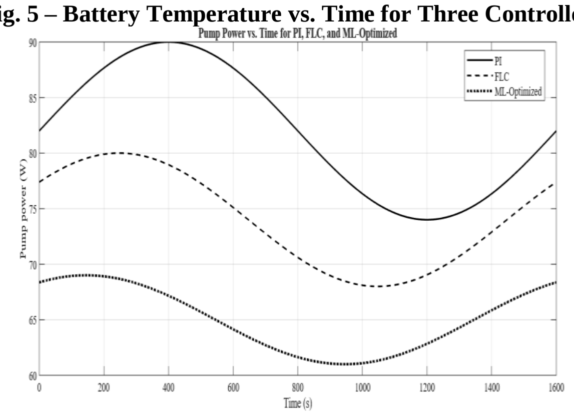

Fig. 6 – Pump Power vs. Time for PI, FLC, and ML-Optimized Controllers

D.Pump Power Consumption

Directly affecting the overall auxiliary energy consumption of the vehicle, and vehicle driving range and system efficiency, the amount of pump power consumed has a direct impact. Conventional PI controllers are commonly utilized, but they tend to cause an unnecessary high flow rate of coolant, in the case of extreme thermal events, thus raising the overall average power usage of pumps. The result of simulation analysis shows that PI controller will use about 82W on average, which means that it will over-cool significantly when the flow rate is large and the temperature is at equilibrium. In comparison, the FLC controller with a slightly more efficient operation shows conservative cooling characteristics and holds an average power of 74W; fuzzy membership functions tend to build safety margins, which cause excessive coolant flow under conditions of doubtful thermal transitions. On the other hand, the ML-optimised controller will be capable of reaching the most energy-efficient cooling policy, whose energy consumption will be 65 -11.5 percent lower than that of PI control. This is an improvement since the flow command produced by the ML-based algorithm is predictive, whereby the introduction of the coolant mass flow is only done when the heat-generation forecast predicts an increase in temperature in the future, as shown in Figure 6. When the predictive model reaches a certain stable condition, the pump will automatically turn on to an energy-saving mode. This smart modulation deals with unnecessary peaks of flow-rate, and retains the optimum cooling levels without loss of thermal safety. The resulting system provides a more useful thermal-management solution that creates long-range electric-vehicles and fewer penalties on auxiliary loads.

E. ML Prediction Accuracy

The machine learning-based temperature prediction model is sensitive to the accuracy of the prediction model, which is a key to effective proactive cooling. The regression model is built with a Random Forest architecture using current, voltage, speed, state of charge and ambient temperature as input variables and is very accurate at different loads. Examples of evaluation metrics include Mean Absolute Error (MAE) = 0.28 °C, Root Mean Square Error (RMSE) = 0.41 °C, and coefficient of determination (R^2 =0.95). These findings bear witness to the fact that the model forecasts short term temperature increase with minimum error compared to ground truth values. Prediction efficiency can be used to

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ensure that the cooling controller responds to the temperature by raising or lowering coolant flow prior to reaching thermal constraints and thus avoids thermal overshoot and improves battery safety margins. Besides, the quality of performance of the model is not affected by the aggressive US06 cycle, which is associated with high frequency current oscillations, which highlights its stability in changing operating points quickly. The large value of the R^2 means that the majority of the thermal variance is well represented and the controller can be used with confidence even in the dynamic conditions of uncertainty. In turn, the ML-optimised solution is confident in supporting real-time thermal control, minimising thermal stress, and ensuring high-quality cooling, as opposed to conventional reactive controllers.

V. DISCUSSION

The relative performance of the different thermal-management strategies demonstrates that major advantages are provided by the integration of machine-learning-based predictive control into liquid-cooled electric-vehicle battery systems. The ML-optimised controller has shown to perform better than the traditional PI and FLC systems in all performance measures as has been illustrated in the previous sections. The main strengthening force of such improvement is in the fact that the ML model can predict future temperature rise regarding changes in present conditions, state of charge, speed, and ambient conditions. The ML-based strategy reacts to changes in temperature before PI or FLC, thus reducing the overshoot, transients and sharp thermal rises in the case of bursts of acceleration of US06 under PI and FLC control the test can reach the desired temperature quickly. This active action directly lowers the maximum cell temperature to 38.3 °C that is much safer than the 42.5°C (PI) and 41.1°C (FLC). The second benefit is the increase in thermal uniformity. The reason of uneven distribution of temperature has been cited to be among the causes of discrepancy of accelerated aging, imbalance of impedance, and pack life. By correcting the modulated and smoother coolant flow that the ML controller provides the temperature difference (ΔT) is reduced by 38% and the hot spots are eliminated, enhancing uniform electrochemical activity in the cells. Such an outcome is essential to the long-term stability, especially in the electric vehicles where the high-load and regenerative operations occur regularly. In order to illustrate the overall comparative advantage,

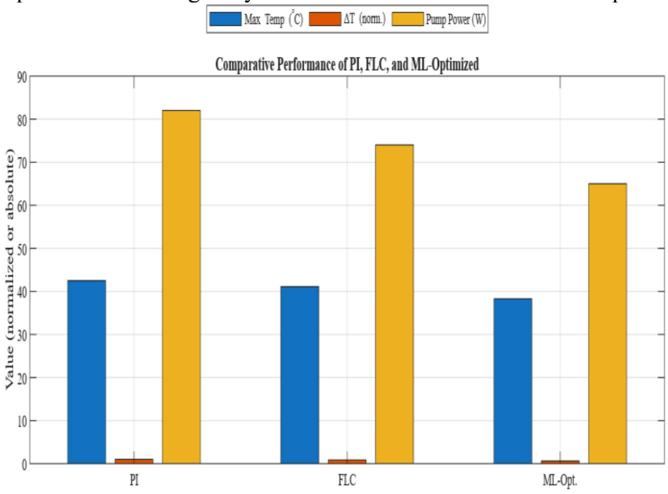

Fig. 7. Comparative Performance Bar Chart (PI, FLC, ML-Optimized)

The visual comparison of peak temperature, thermal gradient, and pump power of PI, FLC, and ML-optimised controllers has been shown in Figure 7. The chart shows that the ML based cooling approach produces the lowest peak temperature, least thermal gradient, and least auxiliary power consumption thus supporting the quantitative findings contained above. These visual summaries point to the efficiency gains in the system brought about by ML-based prediction. The other major outcome is energy efficiency. The ML-based controller can control coolant flow only when needed, saving up to 11.5 per cent of pump-energy, which is essential, considering the fact that auxiliary loads directly affect the range of the electric vehicle. Conversely, the PI controller wastes unneeded pumping energy by the operation of the controller as it is always in high gain, with the FLC being conservative at ambiguous transitions. The ML system overcomes such constraints by making use of predicted trends in generating heat instead of immediate signals. Finally, the ML system uses predicted patterns of heat-generation, which surpass these limits, rather than using just instant temperature feedback. Moreover, the model has a high predictive accuracy (MAE = 0.28 °C, RMSE = 0.41 °C, $R^2 > 0.95$), demonstrating that lightweight regression models could be used effectively within BMS real-time requirements without the need to use deep learning or inferential hardware. The advances in temperature suppression, uniformity, and energy efficiency altogether prove that ML-driven thermal management is an extremely promising direction of the electric vehicle battery safety and lifespan in the next generation.

VI. CONCLUSION AND FUTURE WORK

This work outlined a machine learning based optimised thermal management architecture for liquid cooled electric vehicle battery packs subjected to challenging real world drive cycles, WLTP Class 3 and US06 being the most representative. The architecture combines a predictive model of temperature-rise with an adaptive controller of the coolant flow to allow the system to predict temperature-generation behaviour instead of merely reacting to sensorimotor reactive temperature feedback. Under this prognostic strategy, the ML-optimised strategy was very effective in all the main performance indicators when compared to the conventional PI and FLC strategies. In particular, the controller brought peak battery temperatures down to 38.3 °C instead of 42.5 °C (PI) and 41.1 °C (FLC), which is a considerable thermal protection margin. Besides, the framework demonstrated that temperature gradient decrease (ΔT) was reduced by 38percent contributing to enhanced temperature uniformity throughout the module- a condition that is necessary to reduce the impact of differential ageing and eliminate cell imbalance. There was also an increase in energy efficiency, where the ML-based system used an average of 65 W of pump energy as compared to 82 W of PI and 74 W of FLC, equivalent to an energy reduction of 11.5 percent in the auxiliary energy requirement. The result of such cuts is increased range of the vehicle, as well as reduced long-term operation costs. Random Forest regression model proved to have high predictive reliability where MAE=0.28°C, RMSE=0.41°C, and R-square=0.95, hence permitting its actual application to BMS platform under low-computational power. Further research will focus on multistep and long-horizon thermal forecasting, which will allow the controller to predict long high-load periods like a long downhill regenerative period or long periods of high-speed driving. The hardware-in-the-loop systems like OPAL-RT and Typhoon HIL will be able to be implemented and used to verify the system in real time under realistic conditions of electrical and thermal dynamic conditions. It can also be considered to reinforcement-learning-based cooling strategies, so that autonomous adaptation to the parameters changes brought about by ageing, coolant degradation, and changing environmental temperatures can be made possible. Furthermore, multi-zone or cell-level cooling coordination with routing of coolant and ambient compensation prediction would also allow a more efficient and uniform implementation of large-scale EV battery packs. To recap it all, this piece of work has laid a strong basis of intelligent thermal management in the next generation that enhances safety, efficiency, and battery life of high-tech electric-vehicle batteries.

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