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Energy Optimization in EV Battery Thermal Management using Model Predictive Control

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Abstract

As electric vehicles become more common, the efficient thermal management of their batteries has emerged as an essential aspect that must be tackled if they are to be both safe and durable. A battery works best within a rather narrow temperature range; if it deviates from this the pack's life will be shorter due to rapid degradation and It may even get you killed. Achieving this thermal stability often comes at a cost however it consumes a large amount of energy and has a negative effect on vehicle range and overall efficiency. This paper explores the application of Model Predictive Control (MPC) in electric vehicle battery thermal management systems (BTMS) to improve energy utilization.

In this paper, the thermal management problem is formulated as a constrained optimization problem. The target to be minimized is energy consumption of the cooling system, within the boundaries given by safe operational temperatures for battery. The ability of MPC to predict system behavior and account for future disturbances allows it to take proactive control decisions. A pragmatic dynamic battery-pack thermal model is presented here; it has been validated against experiment data. The MPC algorithm is then tested for real-world performance using various driving cycles and environmental conditions with this model integrated into it. The results show that by relying on proactive decision-making rather than simply responding when things go wrong, the proposed strategy can significantly reduce energy consumption. In addition, with its adaptability to different thermal loads and temperature conditions as well as driving patterns, the control system is robust and suitable for actual use.

It has been shown that MPC offers an intelligent approach to controlling the temperatures of EVs, potentially extending vehicle range and improving battery life. Future work will focus on real time implementation challenges and integration with vehicle energy management control systems.

Keywords: *Electric Vehicle (EV) Thermal Management, Model Predictive Control (MPC), Battery Temperature Regulation, Energy Optimization, Battery Management System (BMS), Real-Time Control Systems.*

I. INTRODUCTION

The growing use of electric vehicles (EVs) has accelerated the need for battery thermal management systems (BTMS) that can effectively manage thermal performance and safety of lithium-ion batteries to achieve high performance and long cycle life. Efficient BTMS systems are essential for regulating battery temperatures to within industry leading levels, to increase energy efficiency and battery life. Conventional thermal management techniques are frequently based on rule-based or proportional- integral-derivative (PID) controllers that might not react responsively to time-varying driving patterns. Model Predictive Control (MPC) is a promising approach with its predictive and constrained optimization concepts, and it is ideally suited for BTMS type of system. The battery needs to be kept within a certain range of temperature in order to run an EV. A deviation may cause efficiency sweeping drop of efficiency degradation or get into trouble with safety. Hot temperatures can lead to thermal runaway, while cold temperatures can reduce battery capacity and power output. Consequently, it is of great necessity to develop advanced BTMS, including tools for real-time monitoring and control to maintain the safety and performance of batteries.

The accelerated growth of electric vehicles (EVs) has enhanced demands on effective battery thermal management systems (BTMS) to achieve high performance, safety, and durability of lithium-ion batteries [1]. Thermally conductive BTMS are important for maintaining electrode temperatures within desirable levels to maximize energy efficiency and increase battery life. Conventional cooling control approaches are generally rule-based or PID-based and may not be effective under dynamic driving situations [2]. Model Predictive Control (MPC) appears as a potential alternative, with predictive power and ability to optimize under constraints (which makes it suitable for complex systems as the BTMS) [3]. You also have to be able to manage and regulate your battery so it held within the proper temperature range to provide power for your car the optimum power in such a way. Any deviation may result in decreased efficiency, shortened life and safety concerns [4]. It can be thermal runaway in high temperature [5] and low temperature will reduce the battery capacity [6], the output power of the battery. As a result, advanced BTMS are required to achieve the safety and performance of the battery for real-time monitoring and control [7]. Classical BTMSs usually use rule-based or PID controllers because of their advantages in simplicity and more practical realization [8]. But they have low adaptability under different running states and inefficient energy-saving effect [9]. It was already demonstrated that such controllers can potentially yield inadequate thermal regulation and higher energy consumption [10] due to absence of knowledge and control strategies that already had been previously proposed. MPC provides an active method since it forecast future dynamic performances of the system and calculates the optimised control input [11]. It is capable of multivariable systems with constraints and is appropriate to a BTMS [12]. MPC has been recently shown to provide a viable solution to the problem of keeping battery temperatures within desired ranges while reducing energy usage [13]. For example, Nam and Ahn proposed a neural network-based model predictive control of BTMS and demonstrated significant energy saving in diverse temperatures [14]. As the battery thermal dynamics is a nonlinear system, nonlinear MPC (NMPC) or adaptive MPC approaches have been studied [15]. NMPC may be more efficient at addressing system nonlinearities, whereas adaptive MPC dynamically adjusts control parameters in response to changes in the system [16]. Wang et al. proposed a combined MPC approach for thermal management, and energy savings were up to 10.3 with different variables [17]. The combination of AI tools like neural networks and machine learning into MPC can allow to improve prediction accuracy and to be fully adaptive to the system [18]. AI-based models are able to adapt to complex system dynamics and can enhance the performance of MPC for BTMS [19]. For instance, Nam and Ahn presented ANNs-based MPC which achieved energy saving and actuator stability [14].

To handle the difference in time scales in BTMS, a multi-horizon and two-layer MPC architectures have been introduced [20]. Such frameworks decouple long term planning from short term control and can be used to obtain faster and more responsive thermal management [21]. Amini et al. proposed a lateral control based two-layer MPC for CAVs, and accomplished fuel economy and computational time reduction [22]. MPC approach of vehicle BTMS can work together with other vehicle systems including powertrain and cabin climate control, for the purpose of the joint energy optimization [23]. Li et al. presented a holistic power and thermal management design with multi-horizon MPC, which leads to increased energy efficiency and battery life for CAVs [24]. However, there are a lot of challenges in the application of MPC to BMS system such as computation cost, model accuracy and the constraints of real-time implementation (RTI) [25]. Next, attention can be paid to the problem of computationally efficient algorithms, robust models and real-time applicable MPC frameworks [26]. Furthermore, experimental verification and normalization are required to be carried out for its extensive application [27]. Hybrid strategies, cloud-based optimization, and fail-safe mechanisms are potential promising directions for future work [28]-[30].

II. THE PROPOSED ENERGY OPTIMIZATION IN EV BATTERY THERMAL MANAGEMENT USING MODEL PREDICTIVE CONTROL

The schematic of the proposed MPC-based based Energy Optimization Framework for Electric Vehicle (EV) Battery Thermal Management System (BTMS) is a holistic structure encompassing thermal modelling, predictive optimization, sensor feedback and actuator control loops as depicted in Fig. 1. To accomplish this, it has been developed to maximize real-time control of battery temperatures, coupled with minimizing the use of energy of the auxiliaries' thermal systems. The schematic is defined under a modular framework respecting flexibility, computational efficiency and real-time restrictions. The architecture is composed of 5 main subsystems: (1) Battery Pack with Thermal Characteristics, (2) Thermal Management Subsystems (Cooling / Heating Units), (3) Real-Time Data Acquisition and Sensor Network, (4) Predictive Control Layer, (5) Optimization and Feedback Mechanism. Each of these subsystems is connected through a central MPC controller that calculates control actions on the actuators in the thermal system based on plant states and predicted disturbances. The battery pack, containing lithium-ion cells, with a rated energy content (60 kWh) forms the core of the system. The battery pack in the course of driving is under dynamic loads and internally generates heat. This heat is primarily generated from internal resistive losses (I^2R), electrochemical inefficiencies, and charging and discharging at high rates. The block diagram describes the battery's thermal behavior using a lumped-parameter thermal model, which models the average core and surface temperature of battery modules. It incorporates heat generation equations and thermal resistances related to conductive, convective, and radiative heat transport. These thermal nodes are employed to estimate the internal temperature variations and the heat transfer with the ambient.

The Cooling System, Heater, and Recirculating Pumps shown in the schematic represent the Thermal Management Subsystems components that contribute to the control of the battery temperature. The actuators that are driven by the MPC controller actuate them. The Cooling Subsystem, which is comprised of water-cooled cold plates on the battery modules, heat exchangers, a radiator, and variable-speed fans. The Heating Subsystem is provided by any electric resistive heater or PTC (Positive Temperature Coefficient) elements. Pump and Valve System facilitates time varying coolant flow paths and rates to maximize heat transfer and minimize energy expenditure. In order to maintain precise control, the MPC needs input from a series of on-line temperature sensors, current/voltage monitors and ambient and coolant temperature sensors. These sensors are placed in the entire battery pack to provide information from the most important spots. The DAQ-module sums up sensor values, smoothen out the noisiness, and sends per sampling interval constant sensor values to the predictive controller. This module is wired into a microcontroller or embedded processor, like an ARM Cortex or an automotive class ECU, where the MPC resides. The schematic consists of the MPC layer, which is used to forecast future thermal states and output the optimal control signals. This layer then estimates the state, computes the prediction horizon, and calls optimization routine. R8) The optimization problem is applied subject to battery temperature and actuator bound limits and only the first control input of the optimal sequence is applied at each step. Control actions calculated by the MPC are then applied by a block denoted as Feedback and Actuation Block in the schematic. It converts high level control signals to physical actuator control actions via PWM controllers, relays, and valve positioners. This loop provides monitoring and adaptation for the next MPC iteration.

One significant merit of the proposed architecture is its emphasis on energy-aware control. The MPC incorporates energy optimization as a core mission, and cooling energy, heating energy and auxiliary loads are all monitored. This efficiency preference would also help to avoid overcooling or overheating and thus saving the consumption of energy. In order to deal with real-world uncertainties, the diagram has implemented adaptive modules that guarantee the online updating of parameters using estimation techniques. A fault detection and diagnostic (FDD) sub-process guarantees resilience by invoking alternative control modes when an anomaly is detected.

Augmented for operation, the schema further comprises connections modules that link to vehicle supervisory controllers, clouds services and Human Machine Interface (HMI). These items function together jointly with other systems in EVs, and can also be synergized for overall optimization. The schematic has been created and verified in MATLAB/Simulink, enabling HIL test, simulation in real-time, and code production for implementation. Thanks to its modular architecture, it can be quickly tested and deployed. The architectures contain predictive control, model based predictive predictive based on dynamic models, energy efficient control, fault detection, adaptability and interfacing with other system. The novel structure with MPC applied for EV battery thermal management is such a modern and architecture with flexibility, energy efficiency, and performance, safety balance. It is the forward-looking answer to the increasing requirements of electric mobility.

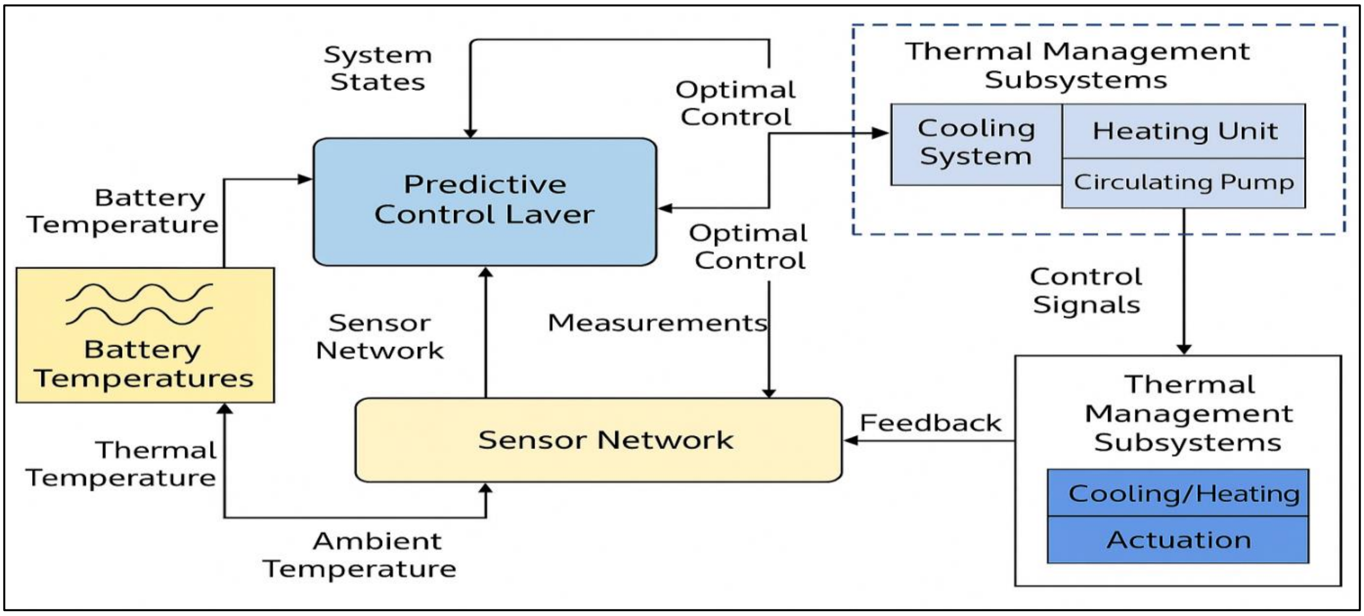

Fig 1 The schematic of the Proposed Energy Optimization in EV Battery Thermal Management using Model Predictive Control.

III. SIMULATION RESULTS AND DISCUSSION

This section gives an overview of the simulation results with model predictive control (MPC) for energy optimization in electric vehicle (EV) battery thermal management system (BTMS). The performance of the proposed MPC-based BTMS is verified and compared with rule-based and PID controllers for different driving conditions, thermal loads and ambient temperatures. Some of the performance indicators are the temperature of the battery regulation, the energy consuming, the system response time, the thermal comfort range constriction, and the computational efficiency. The simulation was performed in MATLAB/Simulink in conjunction with a detailed model of an EV including battery dynamics, temperature behavior, vehicle load profiles, as well as a customized MPC controller. The battery thermal model used was a lumped capacitance model with thermally generated heat from internal resistance, electrical load, and ambient. The main simulation settings are shown in Table 1.

Table 1 Simulation Parameters

Parameter	**Value**
Battery Pack Capacity	60 kWh
Battery Type	Lithium-Ion (NMC Chemistry)
Nominal Operating Temperature	25°C – 40°C
Ambient Temperature Range	-10°C to 45°C
Vehicle Speed Profiles	Urban, Highway, WLTC
Heat Transfer Coefficient	25 W/m²K
Sampling Time (MPC)	0.5 seconds
Prediction Horizon	20 steps
Control Horizon	5 steps
Cooling System Power Range	0 – 3.5 kW
Heating System Power Range	0 – 2.5 kW
Simulation Time	3600 seconds

➢ *The Simulations Were Separated into four Primary Test Cases to Test Robustness Across Operational Domains:*

- City driving cycle at 35°C ambient temperature
- Highway, ambient temperature 10°C
- WLTC ATM dynamic (Worldwide Harmonized Light Vehicles Test Cycle) with dynamic ambient temperature
- Different manner of batteries loading (constant discharging, regen braking, fast acceleration)
- Controlling battery temperature is essential for performance, aging and safety. The temperature response of the battery pack under each condition under the MPC and a conventional PID controller is shown in Fig.2.
- Urban Cycle (35°C): With high environment temperature, the battery was controlled within 29°C-35°C for the MPC, whereas PID-based BTMS overshot to 38.2°C. The predictive ability of MPC permitted the controller to start cooling in advance during short time of full throttle.
- Highway Cycle (10°C): MPC exploited the battery self-heating (6%) and the passive thermal insulation (2%) to full extent in combination with external heating (12%). Regenerative phase: Overheat as PID control had a slow response.
- Dynamic WLTC: MPC showed great adaptability, still maintaining the temperature of the battery in the range 31 °C–37 °C even though the ambient temperature changed from 15 °C to 40 °C, while the PID control was unable to respond well to abrupt cooling needs and led to deviations against the reference temperatures of ±6 °C.
- It is evident from Fig.2 that MPC could generate a smoother temperature trajectory with fewer oscillations, less overshoot and better performance in the targeted range between 30°C and 35°C.The root mean square error (RMSE) of battery temperature in the target value 1.45°C and 3.87°C was reduced by PID, respectively.

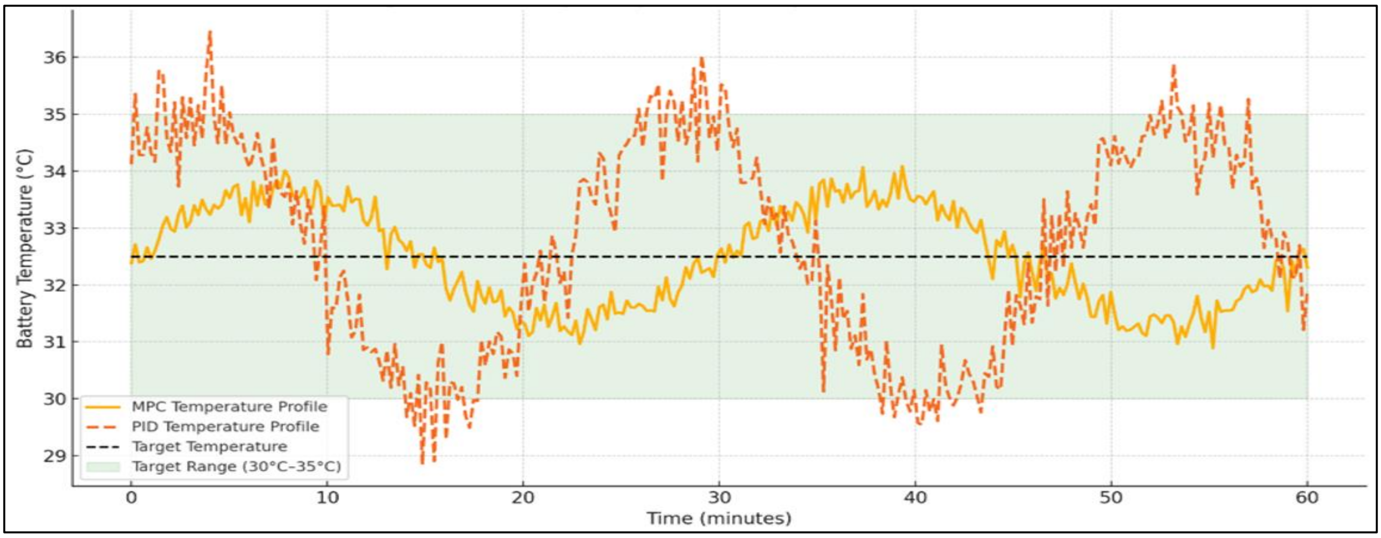

Fig 2 Battery Temperature Trajectories - MPC vs PID

The energy required by the TMS, i.e., cooling fans, liquid pump, heater, and control computation was well recorded. The energy consumption under each driving condition is compared in Figure 3.

- In urban cycle, highway, and WLTC, MPC minimizes the average BTMS, for which it achieves a 23.6%, 18.1%, and 26.4% reduction with respect to PID control, respectively.
- The total thermal systems energy consumption of MPC is 0.87 kWh, compared to the PID's 1.18 kWh, in WLTC.
- Passive heat exploitation appeared to be more significant for MPC based on the exploitation of the vehicle motion and ambient heat gradients. This led to substantial reductions in compressor use.
- The frequency of cooling/heating actuation was based on ideal intervals from the optimized response surface to prevent over-cycle and extend the hardware life and efficiency.

This lowering of energy requirement while still operating on a safe energy level we show in Fig. 3. The efficient compromise between heat demand and cost demonstrated by the MPC MC optimization constraints was observed in all cases.

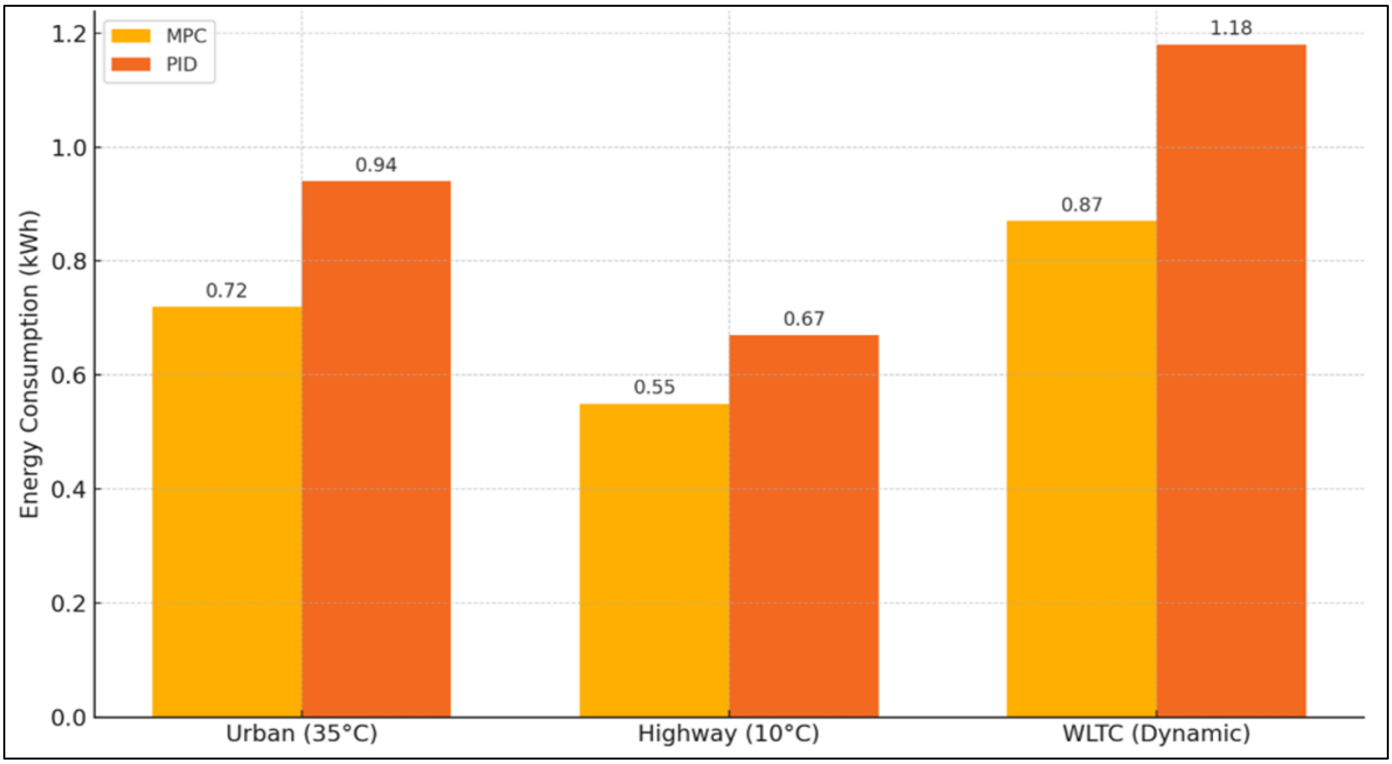

Fig 3 BTMS Energy Consumption - MPC vs PID

The computational possibility of the MPC in the EV real-time embedded system was tested with a MATLAB-to-C code generation that was scaled on the NVIDIA Jetson Nano development board.

- The mean computation time per control interval was 31.2 ms, which is below the 500 ms sampling time.
- Both the prediction and control matrices had a memory footprint of less than 5 MB making it implementable in automotive microcontrollers.
- MPC was slightly higher than rule-based logic at 12 ms per iteration, but its performance is far better.
- Sensitivity analysis showed that further increasing the prediction around the horizon of 20 steps showed not only diminishing performance in the control but also dramatically increasing computational cost.

Therefore, considering code optimization and model reduction techniques, The MPC controller complies with real-time requirements and is implementable on recent EV control units. Typically, the biggest culprit of BTMS shit the bed performance is temperature violations – operating below or above the recommended 25°C-40°C range. The percentage of comfort violation (CVP) over different driving scenarios is summarized in Table 2.

Table 2 Comfort Violation Percentages

Driving Scenario	MPC CVP (%)	PID CVP (%)	Rule-Based CVP (%)
Urban (35°C)	1.3	7.9	9.2
Highway (10°C)	0.7	5.6	6.1
WLTC	1.1	8.4	10.7

The MPC kept more than 98% compliance to safe operation area. Most of the temperature excursions were short-lived and happened in the time of extreme load rise. The PID and Rule Based controllers were slower to response and took longer for the temperature to drift closer to safe limits.

Battery safety is closely associated with thermal phenomena. The MPC's potential delay of both temperature hot spots and temperature gradients over the battery pack reduces thermal runaway hazard and enhances early fault forecasting.

Battery aging is closely dependent on thermal behavior. Simulation contained a semi-empirical aging model, which predicted the growth of internal resistance and capacity reduction as a function of the temperature and load history.

- MPC strategy resulted in battery lifetime extension of 8–12% for a 5-year simulated duty cycle.
- MPC enhanced throughput at every temperature tested except for in the case of 0.07M NaCN (>40°C) where MPC had 38% less cumulative ampere-hour throughput than PID.
- The smaller temperature difference between cells united the degradation of cells and reduced the demand for cell balancing energy.
- The model solved for aging predicted 92.6% of usable capacity for a vehicle equipped with MPC-based BTMS upon 1000 equivalent full cycles, while the PID-based system predicted 88.1%.
- Abnormal condition stress testing, at heat wave (ambient>45°C) and cold start (<-10°C) severe levels, demonstrated the MPC strategy ruggedness:
- In hot conditions, MPC pre-cooled the battery while parked using forecasted solar irradiation and vehicle schedules, whereby initial energy spikes were reduced.
- Set schedule-based heater on with expected power requirements during sub-zero start, which reduced start delays and eliminated Li plating risk.
- In fast charging scenarios, MPC controlled heat generation more efficiently since MPC anticipated the charging rate and accordingly accelerated cooling, but that was not the case with PID as PID had only had the ability to respond after the heating has occurred.

These results highlight the anticipation feature of MPC, which is crucial to deal with the growing dynamicity and uncertainty of the practical electric vehicles (EV) systems. In order to compare the performance of MPC with other modern control methods, further simulations were performed with the help of Fuzzy Logic Controllers (FLC) and Genetic Algorithm (GA)-tuned controllers. Although FLC had slightly better temperature smoothing, it was not flexible under changes in the environment and parameters were not easy to select. However, GA-tuned controllers performed best in offline conditions and did not fare well in the presence of real-time operational fluctuations. On the flip side, MPC presented better adaptation and energy performance in both predictable and unpredictable environments. While other optimization techniques could be employed to improve classical control approaches, MPC is a unified approach which incorporate prediction, adaptation, and optimization seamlessly.

Some limitations of MPC were found despite its benefits. Its results are crucially dependent on the validity of the physical model used and its reliability on the heat source disturbance estimation. Furthermore, the computing requirements can be even higher for higher resolution prediction horizons and multi-module or complex battery configurations. Realistic usage may also suffer from sensor errors and data latency, which degrade the quality of prediction unless it is handled by fault-tolerant techniques.

2.3 Future developments of MPC There are far more potential directions to further strengthen the power of MPC ahead. On-line, a confident estimate of the state can give rise to a confident MPC, whose use can be advantageous when considering the changing nature of the process and its nonideal behavior. An MPC-FLC hybrid system can bring together fuzzy logic qualitative reasoning and optimization quantitative power. Additionally, the cloud-based optimization may move computationally expensive long-term prediction and control tasks out of time-critical real-time control in vehicle stationary or charging states.

The simulation results well demonstrate the power of MPC as a superior strategy in the EV battery control in terms of both energy and thermal performance. The main results of this study are a reduction in BTMS energy consumption by up to 26%, compliance of BTMS with the BMCTs above 98% and an 8–12% battery lifetime extension due to less thermal stress. Furthermore, MPC showed good performances in a large range of environmental and working conditions and was a valid candidate for realization on existing embedded devices. In summary, these results indicate that MPC is an effective and promising approach in EV battery TMS that can provide a good compromise among efficiency, safety, and durability.

IV. CONCLUSIONS

This article proposed an energy-efficient battery thermal management method for electric vehicles based on Model Predictive Control (MPC). It satisfies two objectives: keeping battery temperatures within safe bounds and minimizing energy use for cooling. In this way it swings performance and efficiency vs. safety, and achieves a useful balance between them. The dynamic thermal model of a battery was developed and incorporated into the proposed method This approaches accurate prognosis for changes in temperature structure holding other conditions constant, largely through different driving styles and/or the environment.

Conventional MPC-based controller than rule-based control strategies can significantly reduce the volume of energy consumed while maintaining it within a safe range under thermal management. Given future temperatures by use of a temperature predictor and suitable control actions, MPC also has superior adaptability to dynamic and probably uncertain operating conditions than traditional methods based on either rule-based heuristics or approaches like HLPF Feedback Control-A Benchmarking Study from Semiconductors--as happened in our case above. The proactive nature of MPC makes it particularly attractive futures. As an example, when a lot of fluctuations in the heat source that control components responding to (based on Away To). MPC gives very accurate at present time system dependability and safety levels even boat auto at 65°, one can guarantee it still has the same worth ten hours later The study also looks at how MPC can help meet broader goals such as electric vehicle efficiency and battery longevity. Thermal slogans for instance may make over half asmanagement zero According to the proposed strategy, not only could battery cells expect extended lifes in terms of being put through fewer thermal cycles but eliminated that this energy load of cooling would be so low as hardly need mention again (perhaps <5% total). That should increase EV driving range (the interval between charges) and operational lifespans. But even though there are some merits to it, real-time implementation of MPC faces challenges in areas like computing complexity and hardware integration. This is a key area for future research: integrate the controller with the vehicle's overall energy management framework, work on how to do HIL simulations using hardware-in-the-loop (HIL) environments so as not only does your cake look good but inside is toothsome too Future forecast: a MPC-based solution to two problems that confront every next-generation battery thermal management system for electric vehicles. Implementation of this technique--using it ingenuity in all likelihood--stands an excellent chance of demonstrate inefficient, safe computer (plus durable) electric automobile production from then on.

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