

DATA-DRIVEN THERMAL SIGNAL MODELING FOR MATERIAL AND HEAT MANAGEMENT OPTIMIZATION IN ELECTRIC VEHICLE BATTERIES

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ABSTRACT

Thermal safety is one of the major issues affecting the battery in electric vehicles since the thermal response varies with battery chemistry as well as operating conditions. Despite the widespread use of electrochemical and thermal models, experimentally determined thermal signals are less commonly used to do a direct comparative assessment of battery behavior. This study develops a data-driven thermal signal framework to compare lithium-ion battery chemistries and state-of-charge (SOC) conditions, and to evaluate their combined influence on thermal risk. A publicly available dataset containing temperature and temperature-rate data from controlled heating tests on LFP, NCA, and NMC batteries across multiple SOC levels was analyzed. After preprocessing and outlier filtering, key thermal features were extracted, including peak temperature, maximum temperature rate, onset temperature, duration, and cumulative thermal exposure. A composite thermal risk score was then constructed using normalized thermal indicators. The results showed that LFP batteries reached the highest average peak temperature (432.17 °C) but exhibited slower thermal progression, whereas NMC batteries demonstrated the highest temperature rates (42.51 °C/min) and overall thermal risk. NCA batteries showed intermediate but more variable behavior. Thermal response varied non-linearly with SOC, with the highest peak temperature at 30% SOC and the highest temperature rates at 80-100% SOC. High-risk conditions were most evident for NMC at high SOC and NCA at intermediate SOC. These findings highlight the combined influence of chemistry and operating conditions on thermal risk.

Keywords: Electric Vehicles, Lithium-Ion Batteries, Battery Safety, Thermal Behavior, State Of Charge

1. INTRODUCTION

The transition to sustainable transport across the entire world has led to the further development of electric vehicles (EVs) because of the need to reduce the emission of greenhouse gases and dependence on fossil fuels [1]. The introduction of EVs trend will cause an enormous effect on the energy systems, infrastructure development, and electricity demand trends within several decades [2]. Despite such developments, various technological issues have remained to be addressed, particularly in terms of safety, reliability and efficiency of battery systems [3]. Li ion batteries have become the current energy storage technology of EV due to their energy density, long cycle life and positive performance characteristics [4]. However, the safe operation of lithium-ion batteries under various circumstances is a simmering topic. Thermo-safety-associated people are of extreme importance since, as a result of an adverse condition, such as overcharging, excess temperature, or internal defects, batteries can be easily subjected to thermal runaway [5]. The given phenomenon can lead to a rise in the rate of temperature increase in the short term and the appearance of hazards, which is why thermos-regulation is one of the main concerns in the work of the battery system and its design. Recent studies have also created the need to identify superior solutions to battery safety in the environment where battery systems are becoming more energy-sensitive and ubiquitous [6].

One of the most important parameters of the thermal behavior of the lithium-ion batteries is the state of charge (SOC), which highly relies on the operating conditions. Electroporation of SOC affects inner electrochemical reactions, energy supply and speed of heat production and, consequently, temperature formation during operation [7]. The larger the SOC, the larger the amount of energy that is stored in the battery, which can cause an augmentation in the severity of thermal responses in case of stress conditions. Battery control and, more specifically, SOC prediction and regulation mean everything to define the efficiency of the electric vehicle use, particularly in terms of safety and performance [8]. In addition to SOC, there are other environmental conditions like ambient temperature, which also influence battery behavior, altering their reaction kinetics, internal resistance and heat dissipation mechanisms and therefore overall performance, efficiency and safety [9]. In order to explain these thermal phenomena, a great part of the research has been conducted on the electrochemical and thermal modeling techniques. One can have a deep insight into the heat generation, heat transfer and

heat dissipation in battery systems using the techniques that enable the prediction of the temperature distribution and likely failure state [10]. However, the models are often founded on multidimensional formulations, numerous assumptions and much parameter calibration, which may also again restrict their application to practical circumstances. Meanwhile, there has been a massive effort on the creation of new and improved battery materials to improve the thermal stability, energy density, and performance in general due to the increasing demand for safer and more efficient energy storage technologies [11]. Besides, the accelerated growth in the lithium-ion battery manufacturing and implementation has heightened the issues surrounding the demand for this material, sustainability and the management of the lifecycle, thus, enhancing the significance of optimizing the material choice and operational approaches [12].

Although the battery modeling and the material development have been widely studied, there is still a gap in the systematic analysis of experimentally obtained thermal signals. The majority of investigations are based on detailed modeling methodology or single parameters, and there is a lack of direct, data-intensive analysis of the thermal performance of various chemistries and operating conditions in batteries. Specifically, battery chemistry and SOC interaction have not been fully investigated through experimental results in terms of thermal response. Thermal signals such as temperature-time profile, temperature rate-time profile are useful in giving information on thermal escalation and onset behavior, but their ability to be compared across runs is still little used. An organized, fact-based method of such signal analysis may provide useful information, but not be as limited as the intricate models employed in such analyses.

To fill this gap, the current study uses a data-based approach to modeling thermal signals using experimentally observed temperature and temperature rate profiles. The discussion will take into account three lithium-ion battery chemistries, namely LFP, NCA, and NMC, at different state-of-charge (SOC) levels. The important thermal characteristics, such as the peak temperature, rate of temperature, the beginning of behavior, and the cumulative thermal exposure, are obtained to compare thermal response in various conditions. In this context, material optimization can be seen as the comparison of battery chemistries regarding their thermal behavior, whereas heat management optimization can be viewed as determining operating conditions related to reduced thermal risk. In that regard, the paper analyzes thermal

performance at chemistries and SOC levels and compares the combined contributions between them using a data-driven thermal risk framework.

2. METHODOLOGY

2.1 Study Design and Data Source

The research design adopted to address the thermal performance of lithium-ion batteries under different operating conditions was a data-driven analytical design. The study was done in terms of experimentally obtained thermal data of controlled heating tests performed on three battery chemistries, lithium iron phosphate (LFP), nickel cobalt aluminium (NCA) and nickel manganese cobalt (NMC).

The data included time-resolved samples of temperature and temperature rate at various state-of-charge (SOC) levels and conditions [13]. Individual experimental data were thermal responses, which were independent individual experiments of a given chemistry, SOC and test configuration. The set of conditions under which the analysis was conducted was directed at the comparison of the thermal signal characteristics.

2.2 Data Preprocessing

Metadata about battery chemistry, SOC level, type of test, and replicate number was automatically and systematically deleted and assigned to each observation. The recorded variables were standardized such that the units and the format were homogeneous. The non-numeric values were coded into numbers, and observations that were repeated were removed. In both experiments, the data related to the thermal signals were chronologically ordered to preserve the time structure of the thermal signals. To increase the accuracy of the data, the filter rate of the temperature values was eliminated for the non-physical outliers. Measurements of rates that fell below a pre-specified range (-5 to 50 °C/min) were not considered during rate-based analyses. This filtering step was used to reduce the effects of measurement noise but keep significant thermal trends.

2.3 Feature Extraction

The thermal characteristics were obtained so that they can be compared systematically under various conditions. The time-series data provided important metrics that were taken in each experimental run, including peak temperature, temperature range, maximum temperature rate, mean temperature rate, duration of thermal response, time to peak temperature, and time to maximum temperature rate. The model temperature was reported as the temperature at

which the accelerated thermal behavior first appeared, which is determined by a threshold method, and the temperature at which the temperature rate was greater than 1 °C/min is considered the onset temperature. Furthermore, cumulative thermal exposure was determined by numerical integration between temperature and time curve after the time at the base temperature.

2.4 Thermal Signal Analysis

The thermal signal analysis was conducted on the experimental time-series data without the use of the predefined physical models. Temperature-time and temperature rate-time curves have been studied to describe variations in thermal evolution between battery chemistries and SOC levels. In order to compare, averaged thermal curves were computed by clustering the data at similar time intervals. This method allowed a smoothing of the thermal behavior representation without damaging the original trends of the experiments. The study was done to determine how the dynamics of thermal escalation, peak behavior and time course varied with varying operating conditions.

2.5 Statistical Analysis

The statistical processes used were descriptive as they summarized thermal characteristics among various categories. Key variables included the peak temperature, temperature rate, onset temperature, and duration, which were calculated as the means and standard deviation. Battery chemistries, state of charge (SOC), as well as combined chemistry-SOC, were compared. Such comparisons provided a systematic basis for the establishment of systematic variations in thermal behaviors in various experimental conditions.

2.6 Thermal Risk Assessment

In order to get a hybrid measure of thermal behavior, a composite thermal risk score was developed. The grading was developed based on three parameters, maximum temperature, maximum temperature rate and the onset temperature. All the parameters were put on a standard scale to be compared. Then a weighted mix was used with more weight on peak temperature and temperature rate because they are directly related to the severity of the thermal. Onset temperature was also added to explain thermal activation on an early stage. The resulting risk score was used to rank experimental conditions, as well as to identify those combinations of battery chemistry and SOC that were at high risk.

3. RESULTS

3.1 Thermal Signal Evolution Across Battery Chemistries

The changing nature of the temperature profiles over time across the chemistries in the investigated battery varied considerably (Figure 1). Lithium

iron phosphate (LFP) cells started to gain heat progressively and steadily over long periods of time, in contrast to nickel manganese cobalt (NMC) and nickel cobalt aluminium (NCA) cells that ascended in temperature at a fast rate at the intermediate stages of the tests.

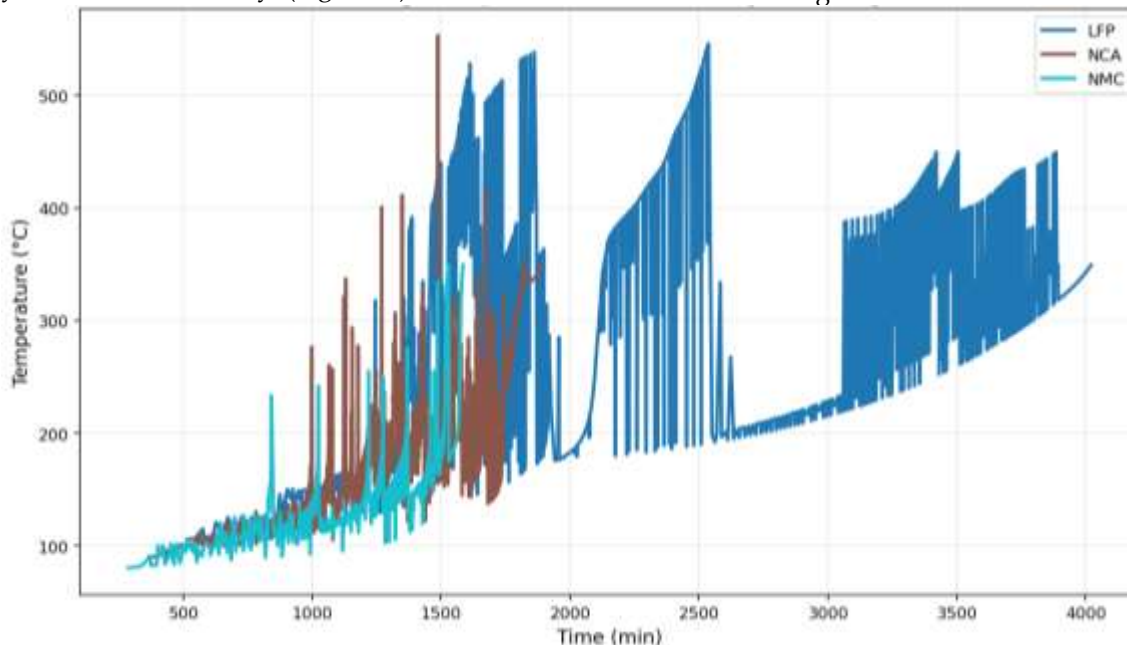


Figure 1. Temperature-Time Profiles of Lithium-Ion Battery Chemistries

This disparity can also be observed in the temperature rate-time profiles (Figure 2) in which NMC cells had pronounced peaks in temperature rate, and this implies a rapid thermal response. Conversely, the LFP systems had rather constant and lower temperature values during the majority of the thermal evolution process. NCA batteries exhibited intermediate characteristics and had observable variability in temperature rate, but less regularity than NMC.

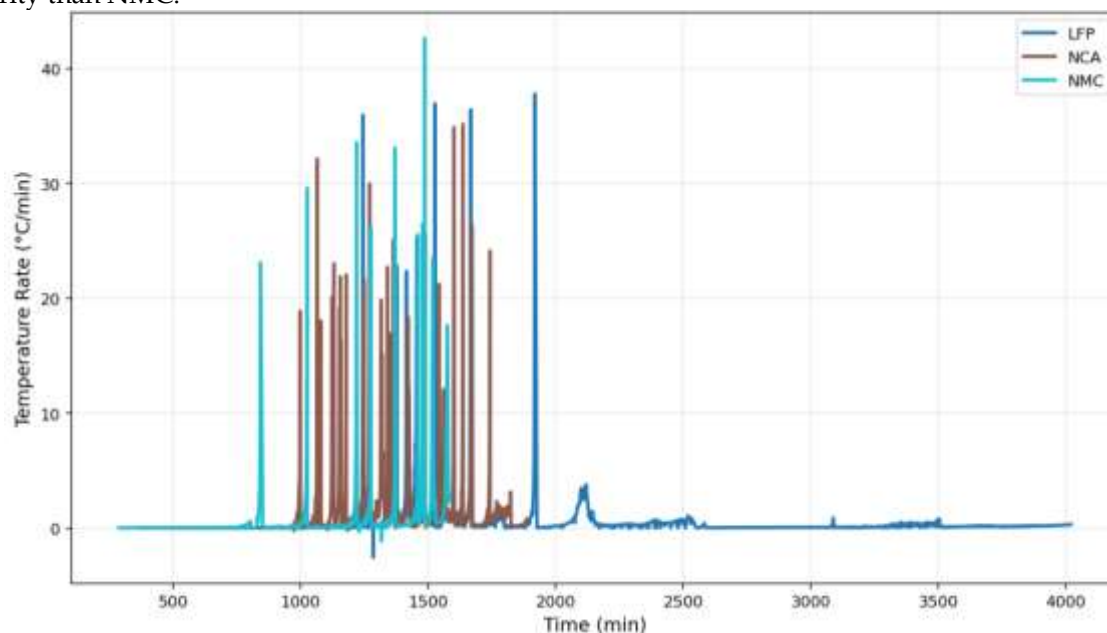


Figure 2. Temperature Rate-Time Profiles of Lithium-Ion Battery Chemistries

This suggests that LFP systems can be expected to store heat more over extended periods of time, but the NMC and NCA chemistries exhibit more rapid thermal transitions, which implies that different material systems have different heat generation behaviors.

3.2 Comparative Thermal Characteristics by Chemistry

A list of thermal properties compared quantitatively between battery chemistries is provided in Table 1. The highest average peak temperature (432.17 °C) was recorded in LFP batteries, then NCA (421.77 °C) and NMC (390.56 °C). Nonetheless, NMC had the maximum rates of average highest temperature (42.51 °C/min), which means that its thermal escalation was faster.

Table 1. Summary of thermal characteristics by battery chemistry.

Chemistry	Number of experiments	Avg. Peak Temp (°C)	SD (°C)	Avg. Max Rate (°C/min)	Avg. Onset Temp (°C)	Avg. Duration (min)
LFP	14	432.17	74.00	25.95	196.65	1640.43
NCA	31	421.77	99.59	37.09	166.91	792.05
NMC	10	390.56	58.96	42.51	167.05	891.28

NCA batteries were intermediate in nature, and the temperature rates were relatively high, and the greatest variability occurred in the peak temperature (SD = 99.59 °C). Also, both NCA (166.91 °C) and NMC (167.05 °C) had lower onset temperatures than LFP (196.65 °C), implying an earlier onset of accelerated thermal behavior in these chemistries.

3.3 Influence of State of Charge on Thermal Behavior

Figure 3 shows the effect of state of charge (SOC) on thermal behavior and Table 2 summarizes these effects quantitatively. The SOC and thermal response had a non-linear relationship. That peak average temperature was obtained at 30% SOC (472.14 °C), higher than the lower and higher SOC level values. Conversely, 0% SOC had the least thermal response using all the metrics.

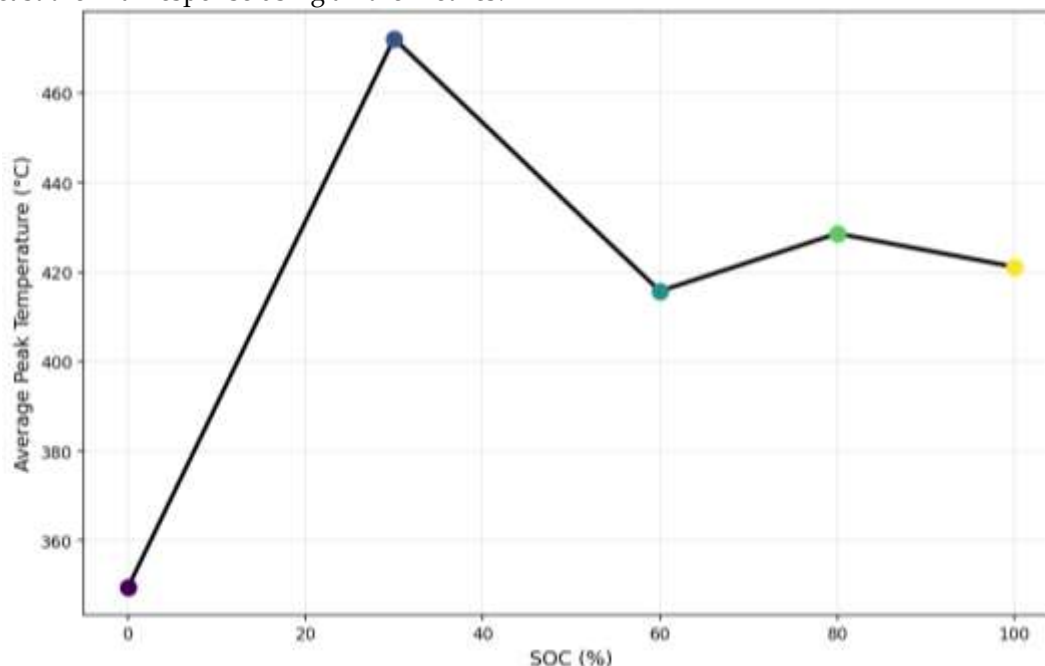


Figure 3. Variation of Average Peak Temperature with State of Charge (SOC)

Table 2. Summary of thermal characteristics across different SOC levels.

SOC (%)	Number of experiments	Avg. Peak Temp (°C)	SD (°C)	Avg. Max Rate (°C/min)	Avg. Onset Temp (°C)	Avg. Duration (min)
0	10	349.60	0.40	10.58	204.90	1290.59
30	11	472.14	84.71	36.04	181.08	1383.63
60	11	415.73	96.91	38.70	167.36	902.78
80	11	428.60	69.46	43.45	161.56	771.09
100	12	421.14	102.89	44.36	162.95	824.50

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DOI: 10.5281/zenodo.12212026644

At elevated SOC_s, the temperature rate rose tremendously, with the SOC reaching a temperature over 43 °C/min at 80% and 100%. At the same time, the onset temperature was negatively proportional to SOC, which showed that thermal acceleration was initiated at higher charge levels. These results prove that thermal behavior cannot be linear with SOC, and mid-range and high SOC conditions both play a significant role in higher thermal intensity and acceleration.

3.4 Combined Effects of Chemistry and State of Charge

The overall effect of battery chemistry and SOC is presented in Table 3 and explained also in the thermal risk heatmap (Figure 4). There were high interaction effects between battery chemistry and SOC. In the case of LFP batteries, the average maximum temperature was highest at 60% SOC (545.97 °C), which suggested that it accumulated a lot of heat under moderate charging circumstances.

Table 3. Combined analysis of chemistry and SOC on thermal characteristics.

Chemistry	SOC (%)	Avg. Peak Temp (°C)	Avg. Max Rate (°C/min)	Avg. Onset Temp (°C)	Avg. Duration (min)
LFP	0	349.34	0.33	—	3060.06
	30	449.60	6.59	195.43	2961.15
	60	545.97	12.32	207.74	1043.80
	80	456.68	43.04	193.84	692.72
	100	385.23	47.27	194.13	949.17
NCA	0	349.69	9.84	208.06	835.63
	30	498.89	46.34	172.53	717.80
	60	400.18	44.42	157.12	849.58
	80	428.53	42.12	149.73	807.82
	100	435.17	41.50	148.76	739.82
NMC	0	349.60	23.05	195.43	885.97
	30	425.73	49.31	185.23	1014.84
	60	339.93	45.06	162.84	947.94
	80	386.66	48.03	148.61	778.45
	100	450.87	47.10	143.16	829.19

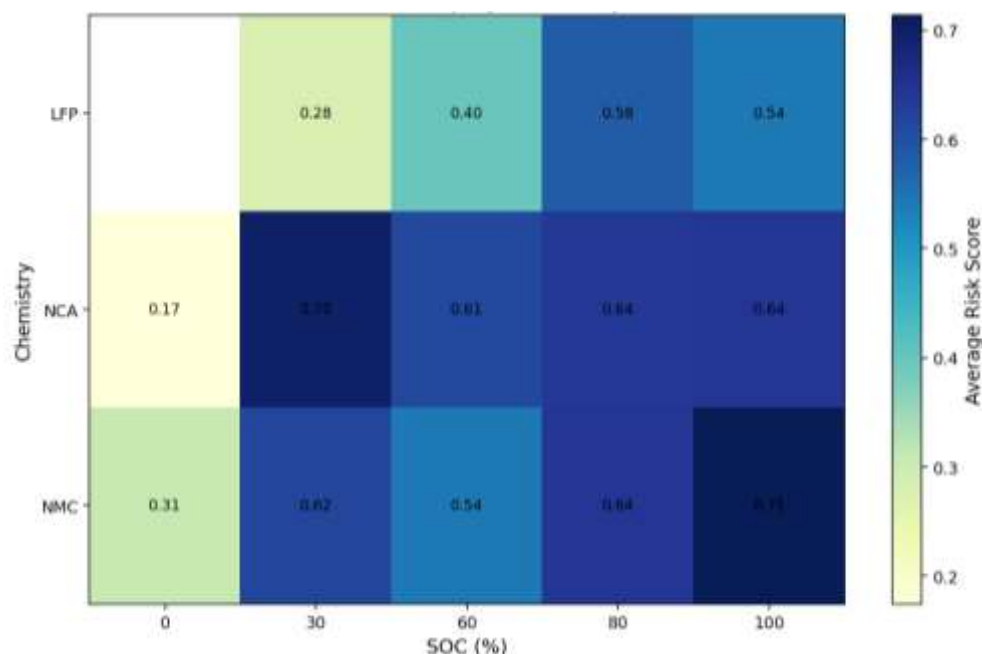


Figure 4. Thermal Risk Heatmap Showing the Combined Effects of Battery Chemistry and State of Charge

NCA batteries had higher peak temperature and temperature rates at 30% SOC (498.89 °C; 46.34 °C/min), indicating that they were more thermally unstable in intermediate SOC. Conversely, NMC batteries displayed the greatest temperature rates with high SOC rates, especially at 100% SOC (47.10 °C/min), thus showing a quick increase in temperature when fully charged in operation. At

0% SOC, every chemistry was relatively stable with low peak temperatures and sluggish or no commencement of accelerated thermal activity. These interaction-effects are further indicated through the heatmap representation that indicates the high-risk regions at both NMC and NCA at 100% SOC and 30% SOC, respectively.

3.5 Thermal Risk Assessment Across Chemistries and SOC Levels

Composite thermal risk scores are given in Figure 5. NMC batteries scored the highest on average risk, then NCA, although LFP scored the lowest on overall risk.

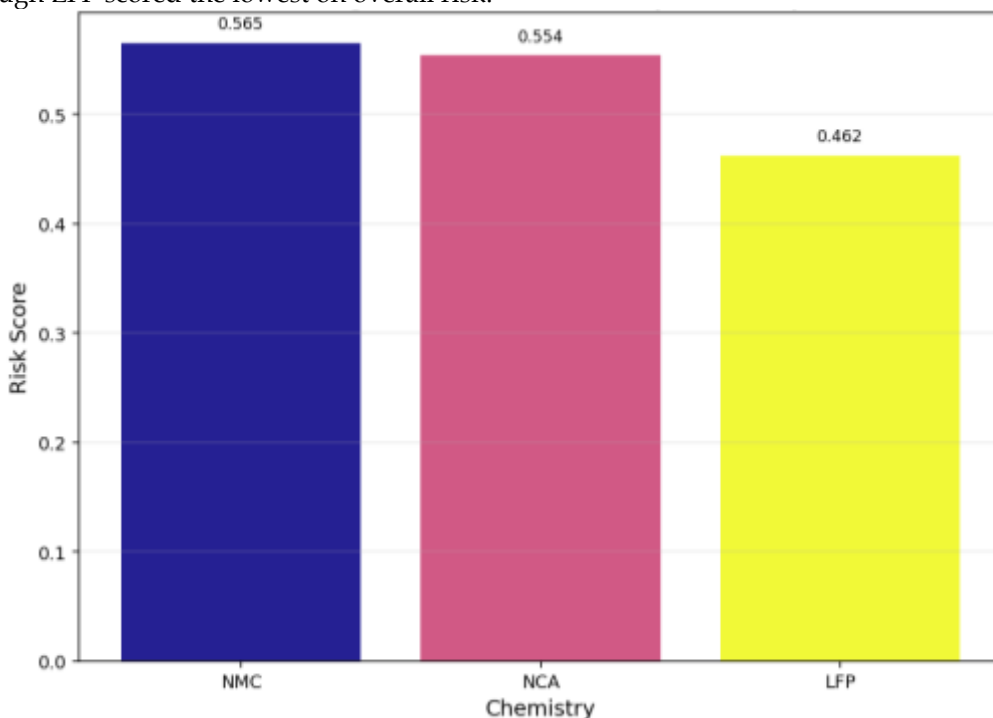


Figure 5. Comparison of Average Thermal Risk Score Across Battery Chemistries

It is this trend that is consistent with the collective observations in which NMC is typified by a high rate of temperature escalation, NCA with intermittent but higher rates of thermal response, and LFP with a sluggish but sustained thermal accumulation. At the SOC level of 0% SOC, the scores of the risk were low, and at the levels of 80% and 100%, the scores of the risk were high.

Overall, the results indicate that the thermal risk is managed when material properties and operating conditions interact, and distinctive thermal response profiles become evident depending on the various combinations of chemistry and SOC.

4. DISCUSSION

The thermal behaviour of the lithium-ion batteries is dependent on the product of the material attributes in addition to operating conditions, not

a single parameter. These results indicate that there are clearly established differences in battery chemistries, i.e. they are all different in terms of their thermal response profiles. In LFP batteries, the peak temperatures were greater, and the values of temperature-rate were relatively lower, which indicates a slow and more gradual thermal evolution. Conversely, NMC batteries had the highest temperature rates and the total risk score, which means that thermal escalation rates are high despite the comparably lower peak temperatures. NCA batteries exhibited medium behavior in a more varied fashion, which is sensitive to variation in operating conditions. The effect of the state of charge (SOC) also underlines the difficulty of the thermal response. It was found that there was no linear relationship between SOC and thermal behavior, with the least thermal activity at 0% SOC

and the same being the case with intermediate and high levels of SOC. Maximum temperature occurred at intermediate levels of SOC, but the rate increase was large at higher SOC levels. This implies that thermal risk cannot be assessed only by the content of energy, but it should also account for the rate of heat generation. The experiment of battery chemistry and SOC interaction indicated that certain combinations are correlated with increased thermal responses, which is why it is important to examine these variables jointly and not individually.

The differences in thermal behavior between battery chemistries that have been observed are in line with past literature that has pointed to the need to ensure that the thermal conditions of a battery are well characterized. Previous studies have indicated that a physics-based and data-driven method combination can be used to improve the monitoring and prediction of thermal behavior of batteries under dynamic conditions [14]. Furthermore, the more recent advances in using data-driven thermal analysis have demonstrated that experimental data are capable of capturing complex thermal patterns without necessarily depending solely on the details of the model [15]. The non-linear SOC-dependent trends that are determined in this paper are consistent with data that have shown that the thermal behavior of the battery is highly dependent on the operating conditions. Previous studies have highlighted that thermal management techniques should consider the material properties and SOC-dependent heat generation in order to reach efficient system optimization [16]. Moreover, SOC has been identified as an important variable of battery management, especially when combined with data-driven and multi-physics models to enhance precision and safety [17].

The correlation between the presence of the higher-risk condition within specific levels of SOC also agrees with other prior research related to the prediction of thermal runaway, where the variation of SOC can substantially affect early warning phenomena and mechanisms of failure propagation [18]. Along with this, one can also refer to the growing prevalence of data-driven approaches in battery system design, which represents a larger change towards experimental data being used to improve the safety and functionality of the battery system. These techniques have been addressed regarding the optimization of thermal management, wherein informative data can be used to develop a better system and run with efficiency [19]. The latter is also corroborated by multilevel data-driven battery management systems that combine

sensing, analytics, and decision-making techniques to make the systems safer and more efficient [20]. Also, current developments in artificial intelligence and predictive models indicate the possibility of better thermal failure detection and safety checks in lithium-ion battery designs [21]. In addition, the creation of digital twin models has been suggested as a potential solution to integrate experimental data with the behavior of the real-time system in order to enhance thermal control and safety [22].

The research results of this research have a practical application in material choice and thermal control in batteries of electric vehicles. Regarding the material point of view, the findings indicate that battery chemistry must be considered not only in relation to the performance indicators but also through the thermal response behavioral attributes. LFP batteries had slower thermal escalation, although with higher peak temperatures, which could be beneficial in case of a critical condition demanding more time to intervene. In comparison to NMC batteries, though, high temperature increase can be observed, which demonstrates that more responsive monitoring and control strategies should be implemented. Operationally, the non-linear effect of SOC brings about the importance of the state-dependent management that is thermodynamic in nature. High thermal responses at intermediate and high SOC phases mean that operating ranges can be carefully defined to help to limit thermal risk. These findings support the use of informative solutions so that less risky working conditions can be identified and provide more effective decision-making in the battery management system. Thermal signal analysis has been found to be helpful in providing an effective model to study the behavior of batteries based on experimentally obtained data. By this method, a comparative evaluation is possible under different conditions without the need to engage in complex modeling and this should be included in the existing monitoring and control systems.

Even though the given insights are informative, several limitations must be mentioned. Some of the factors that were not explicitly taken into account are dynamic loading, environment variability and interaction at the system level. Another limitation of the research was that the authors focused on temperature signals and did not introduce other electrochemical parameters that may also be useful when interpreting battery behavior. The thermal risk assessment model used in the given research is premised on the premise of the selected measures and weighting assumptions that can be reconsidered in the future. It can assist in

enhancing its relevance and strength, expanding the framework to other variables and testing it on actual restaurant data. The next research direction can be focused on integrating the thermal signal inspection with more sophisticated predictive algorithms to enhance safety and performance. Integration of experimental evidence with real-time tracking and adaptive modeling solutions may facilitate a more precise definition of the situations with high risks and help to sustain a better approach to thermal management in the electric vehicle batteries.

5. CONCLUSION

The thermal characteristics of lithium-ion batteries are dependent on the interaction of the battery chemistry and state of charge, and distinct variations in the heat generation and thermal exponential growth are evident. It was found that LFP batteries had larger peak temperatures but tended to have slower thermal development, and NMC batteries had faster temperature-rate responses and the greatest total thermal risk. There

was intermediate but more varied behavior in NCA batteries. The state of charge was also non-linear with high thermal responses being seen not only at high SOC but also at given intermediate SOC levels. These results indicate that the issue of thermal risk cannot be determined based on one indicator. Rather, the evolution of temperature, the rate of temperature and behavior of its onset are to be approached as a unit in order to get a more comprehensive interpretation of battery safety. Using an experimental profile of the operating system, the thermal signal analysis scheme allowed comparative analysis of chemical reactions and conditions using a data-driven thermal signal framework. The gained knowledge can be applied to the chemistry-focused tests and more thoughtful operating strategies for how to reduce thermal risk during the design of the electric vehicle's batteries. In future work, this framework would be more useful by adding live operating data and expanding its range of electrochemical variables.

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