

IMPROVING THE PERFORMANCE OF BATTERY THERMAL MANAGEMENT SYSTEM IN HARSH ENVIRONMENTAL CONDITIONS

BY

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Dedication

I have dedicated this work to my loving family, whose unwavering support and encouragement have been my guiding light throughout this journey. To my parents, whose sacrifices and belief in my abilities have shaped me into the person I am today, I owe everything. To my wife, for her constant encouragement and understanding, and her patience, love, and understanding during the long hours of study and research. And for my son, the driving power I gain my motivation and strength. This achievement is as much theirs as it is mine. Thank you for believing in me.

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LIST OF NOMENCLATURES

Ampere Hour	Ah	Longitudinal Direction	S_L
Capacitance	Q	Longitudinal Pitch	P_L
Capacity	C	Maximum Temperature	T_{max}
Charge	c	Maximum Velocity	V_{max}
Confinement Ratio	ψ	Maximum Voltage	V_o
Converging Angle	β	Milliampere Hour	mA _h
Coulombic Efficiency	CE	Minimum Temperature	T_{min}
Current	I	Nusselt Number	Nu
Density	ρ	Power Consumption	P
Diagonal Pitch	P_D	Prandtl number	Pr
Diameter	D	Pressure Drop	ΔP
Discharge	d	Resistance	R
Dissipation of Specific Dissipation Rate	Yk	Reynolds Number	Re
Dissipation of Turbulence Kinetic Energy	$Y\omega$	Specific Dissipation Rate	ω
Dynamic Viscosity	μ	State of Charge	SoC
Effective Diffusivity of Specific Dissipation Rate	Γ_k	State of Health	SoH
Effective Diffusivity of Turbulence Kinetic Energy	Γ_ω	Temperature	T
Friction Factor	f	Temperature Difference	ΔT
Generation of The Specific Dissipation Rate	G_ω	Thermal Conductivity	k
Generation of Turbulence Kinetic Energy	G_k	Time	t
Heat Capacity	cp	Transverse Direction	S_T
Heat Generation	q	Transverse Pitch	P_T
	q''	Turbulence Kinetic Energy	k
Heat Transfer Flux	pin	Velocity	V
Inlet Pressure	R_i	Voltage	V
Internal Resistance	v	Voltage after time (t)	V_i
Kinematic Viscosity	ΔT_{lm}	Volume Flow Rate	Q
Log-Mean Temperature Difference			

LIST OF ABBREVIATIONS

Ampere-Hour Integration	AHI
Battery Thermal Management system	BTMS
Carbon Dioxide	CO ₂
Carbon Monoxide	CO
Carbon-Coated Si Nanoparticles	SiCNPs
Computational Fluid Dynamics	CFD
Constant Current	CC
Constant Voltage	CV
Differential Voltage Analysis	DVA
Disorder Rock Salt	DRX
Electric Vehicles	EVs
Ethylene	C ₂ H ₄
Extended Kalman Filter	EKF
Gated Recurrent Unit	GRU
Gaussian Process Regression	GPR
Gel Polymer Electrolytes	GPEs
Greenhouse Gases	GHG
Hybrid Battery Thermal Management system	HBTMS
Hydrogen Fluoride	HF
Hydrogen Sulfide	H ₂ S
Internal Combustion Engine	ICE
Ionic Liquid	IL
Lithium Carbonate	Li ₂ CO ₃
Lithium Fluoride	LiF
Lithium Iron Phosphate	LFP
Lithium Nickel Cobalt Aluminum Oxide	LiNiCoAlO ₂
Lithium-ion Batteries	LIBs
Machine Learning	ML
Mean Absolute Error	MAE
National Aeronautics and Space Administration	NASA
Nickel Manganese Cobalt Oxide	NMC
Open Circuit Voltage	OCV
Phase Change Material	PCM
Plug-in Hybrid Electric Vehicle	PHEV
Root Mean Square Error	RMSE
Solid - Electrolyte Interphase	SEI
State of Charge	SoC
State of Health	SoH
Transmission Electron Microscopy	TEM
X-ray Diffraction	XRD

ABSTRACT

Full Name : Ahmed Saeed Mohammed Abdulraheem Saeed

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Recently, electric vehicles have become a promising solution to replace conventional internal combustion engines, which are significant contributors to global greenhouse gas emissions. Therefore, the research and development of lithium-ion batteries have become predominant, especially in the electrical vehicles industry. Lithium-ion batteries (LIBs) have shown great potential due to their high energy density, high efficiency, low self-discharge, and long life cycle. However, LIBs are strongly affected by temperature, either that of the storage medium or that associated with the charging/discharging process. In some practical situations, the temperature of the LIBs can exceed 60 °C; hence, a battery run-away will be triggered, which will cause an explosion and failure of the system. Therefore, a battery thermal management system is necessary to improve heat dissipation in the battery pack and to ensure the safety and effective performance of the LIBs system. In this research study, a battery thermal management system will be studied by using different geometries of the battery pack with various cooling materials. Firstly, a calendar aging of Lithium-Ion batteries was conducted to investigate the effects of storing temperature and State of Charge (SoC) on the cells. These investigations were conducted within the challenging climate of Saudi Arabia over a span of two harsh summer months when outdoor temperatures soared to 50 °C. A comprehensive array of performance parameters, including self-discharge, state of health (SoH), internal resistance, and coulombic and energy efficiencies, were examined. The results highlight the paramount role of storage temperature in shaping LIB performance, with heightened significance discerned at full charge (SoC = 100%). A maximum decrement of 6% in the SoH, a 6.5% increase in internal resistance, and notable reductions in coulombic and energy efficiencies (2% and 2%, respectively) were recorded under the most challenging storage scenario—cells housed in glass-covered containers, bared to direct sunlight and charged to full capacity. Furthermore, a 2D numerical investigation was conducted to examine the influential parameters on battery thermal management systems including transversal and

longitudinal distances, channel inlet angle, confinement ratio, and the velocity of airflow which used as heat transfer medium for this study. The CFD results reveals improvement of the BTMS system on the level of the amount of heat removed and the pressure drop that can occur in the system. Moreover, a new correlations for estimating the Nusselt number and friction factor were built including all the parameters that affect the hydraulic performance of BTMS. The Nusselt number correlation was compared with the existing correlation in the heat transfer books, showing good matching between the two results. Lastly, an experimental study was carried out to investigate some of the parameters from the CFD results under high discharging rates. The channel inlet angle was taken to be 10 degrees and the confinement to be 0.5 with 30 mm for both transversal and longitudinal distances. The study was wide range of airflow rate from 0.3 – 1.5 CFM. The results show the need to regulate airflow rates to improve cooling efficiency while remaining energy efficient. Furthermore, the study provides light on the issues given by rapid discharging rates, underlining the importance of strong thermal management systems to reduce temperature rise and preserve the longevity of battery cells. Overall, from this study, the findings provide a solid platform to build air-cooled battery systems that can adapt to changing operating circumstances, which will accelerate the development of sustainable and effective thermal management solutions in the field of energy storage technologies.

ملخص الرسالة

الاسم: أحمد سعيد محمد عبد الرحيم سعيد

عنوان الرسالة: تحسين أداء نظام إدارة الحرارة الحرارية للبطارية في الظروف البيئية القاسية

التخصص: الهندسة الميكانيكية

تاريخ الدرجة العلمية: مايو 2024

في الآونة الأخيرة، أصبحت السيارات الكهربائية حلاً واعداً لاستبدال المحركات الاحتراق الداخلي التقليدية، التي تعد مساهمة كبيرة في انبعاثات غازات الاحتباس الحراري العالمية. ولذلك، أصبح بحث وتطوير بطاريات ليثيوم أيون أمراً مهماً، خاصة في صناعة السيارات الكهربائية. لقد أظهرت بطاريات ليثيوم أيون إمكانات كبيرة بفضل كثافتها العالية وكفاءتها العالية وانخفاض التفريغ الذاتي وطول دورة حياة طويل. ومع ذلك، يتأثر البطاريات الليثيوم أيون بشكل كبير بدرجة الحرارة، سواء كانت ذلك لوسيط التخزين أو تلك المرتبطة بعملية الشحن/التفريغ. في بعض الحالات العملية، يمكن أن تتجاوز درجة حرارة البطاريات الـ 60 درجة مئوية؛ مما يؤدي إلى حدوث هروب للبطارية وبالتالي انفجارها وفشل النظام. لذا، فإن نظام إدارة الحرارة الحرارية للبطارية ضروري لتحسين تبديد الحرارة في حزمة البطارية وضمان سلامة وأداء البطاريات الليثيوم أيون بشكل فعال. في هذه الدراسة البحثية، سيتم دراسة نظام إدارة الحرارة الحرارية للبطارية باستخدام هندسيات مختلفة لحزمة البطارية مع مواد تبريد متنوعة. أولاً، تم إجراء تقويم تقدم بطاريات ليثيوم أيون لتحقيق تأثير درجة حرارة التخزين وحالة الشحن (SoC) على الخلايا. تم إجراء هذه الدراسات في المناخ التحدي الصعب في المملكة العربية السعودية على مدى شهرين من الصيف القاسي حيث ارتفعت درجات الحرارة في الهواء الطلق إلى 50 درجة مئوية. تم فحص مجموعة شاملة من المعايير الأدائية، بما في ذلك التفريغ الذاتي، وحالة الصحة (SoH)، والمقاومة الداخلية، وكفاءة الكولومبية والطاقة. تسلط النتائج الضوء على الدور الهام لدرجة الحرارة التخزينية في تشكيل أداء بطاريات الليثيوم، مع تمييز أهمية متزايدة عند الشحن الكامل ($SoC = 100\%$). تم تسجيل انخفاض أقصى بنسبة 6% في SoH، وزيادة بنسبة 6.5% في المقاومة الداخلية، وانخفاضات ملحوظة في كفاءات الكولومبية والطاقة (2% و 2%)، على التوالي) في السيناريو التخزينية الأكثر تحدياً - خلايا موجودة في حاويات زجاجية مغطاة بالشمس المباشرة ومشحونة بالكامل. وعلاوة على ذلك، تم إجراء تحقيق عددي ثنائي الأبعاد لدراسة المعلمات المؤثرة على أنظمة إدارة الحرارة للبطارية بما في ذلك المسافات العرضية والطولية، وزاوية مدخل القناة، ونسبة الحجز، وسرعة تدفق الهواء الذي يستخدم كوسيط لنقل الحرارة لهذه الدراسة. تكشف نتائج التحليل الديناميكي للسوائل عن تحسن في نظام إدارة الحرارة الحرارية للبطارية على مستوى كمية الحرارة المزالة وانخفاض الضغط الذي يمكن أن يحدث في النظام. وعلاوة على ذلك، تم إنشاء علاقات جديدة لتقدير عدد نسلت وعامل الاحتكاك تضم جميع المعلمات التي تؤثر على الأداء الهيدروليكي لنظام إدارة الحرارة الحرارية للبطارية. تمت مقارنة علاقة عدد نسلت مع العلاقة الموجودة في كتب نقل الحرارة، مما أظهر تطابقاً جيداً بين النتائج الاثنين. وأخيراً، تم إجراء دراسة تجريبية للتحقيق في بعض المعلمات من نتائج تحليل السوائل تحت معدلات تفريغ عالية. تم اعتبار زاوية مدخل القناة أنها 10 درجات والحجز يجب أن يكون 0.5 مع 30 مم لكل من المسافات العرضية والطولية. تمت دراسة مجموعة واسعة من معدلات تدفق الهواء من 0.3 - 1.5 CFM. تظهر النتائج الحاجة إلى ضبط معدلات تدفق الهواء لتحسين كفاءة التبريد مع الحفاظ على كفاءة الطاقة. وعلاوة على ذلك، توفر الدراسة نظرة على المشكلات الناتجة عن معدلات التفريغ السريع، مؤكدة أهمية الأنظمة القوية لإدارة الحرارة لتقليل ارتفاع درجة

الحرارة والحفاظ على عمر خلايا البطارية. وبشكل عام، من خلال هذه الدراسة، توفر النتائج منصة قوية لبناء أنظمة بطاريات تبريد هواء يمكنها التكيف مع التغيرات في ظروف التشغيل، مما سيسرع من تطوير حلول إدارة الحرارة المستدامة والفعالة في مجال تقنيات تخزين الطاقة.

CHAPTER 1:

INTRODUCTION

The rapid growth of the population around the world is associated with an enormous increase in energy demand. The energy system worldwide encounters two critical problems, providing an appropriate reliable source of energy and decreasing greenhouse gas emissions. Currently, The majority of the world's countries rely on fossil fuels, such as oil, natural gas, and coal, as fundamental energy supplies that are depleting and the leading source of greenhouse gas emissions [1,2]. As a result, it is vital to replace fossil fuels with clean, environmentally friendly, and renewable energy resources such as wind, biomass, solar energy, hydropower, and geothermal. However, most renewable energy sources, such as solar and wind, are intermittent and variable. The availability of sunlight and wind is not constant, leading to fluctuations in energy production that can pose challenges for grid stability and reliability [3]. Therefore, to have a reliable and constant energy supply sources, energy storage systems are crucial for storing excess energy generated during peak production times and releasing it during periods of low production [4].

1.1. Energy Storage Systems:

Energy storage systems play an important part in the growth of sustainable energy landscapes by addressing the intermittent and variable nature of renewable energy sources. These systems include a wide range of technologies designed to store extra energy during periods of high output and release it when demand rises or during periods of low production. Batteries, pumped hydro storage, flywheels, and thermal storage are all common types of energy storage technologies. **Figure 1.1** shows the different types of energy storage systems and their categories. Lithium-ion batteries are widely utilized for their efficiency and versatility in a variety of applications, including electric vehicles and grid-scale storage. Pumped hydro storage uses the gravitational potential energy of water to store and discharge electricity. Flywheels store energy as rotational kinetic energy, resulting in quick response times. Thermal storage includes storing heat or cold for later use, which is useful in applications

such as solar-thermal power plants. Another approach to energy storage systems is hydrogen. Hydrogen energy storage is beginning to gain popularity as a transformational solution to energy storage, helping to construct sustainable and adaptable energy systems. This storage method includes transforming electrical energy into hydrogen via a process known as electrolysis, which splits water into hydrogen and oxygen using electricity. The produced hydrogen can be stored for later use and turned back into energy using fuel cells or other combustion methods. The growth of energy storage technology is critical for improving grid dependability, increasing renewable energy integration, and creating a more resilient and sustainable energy future.

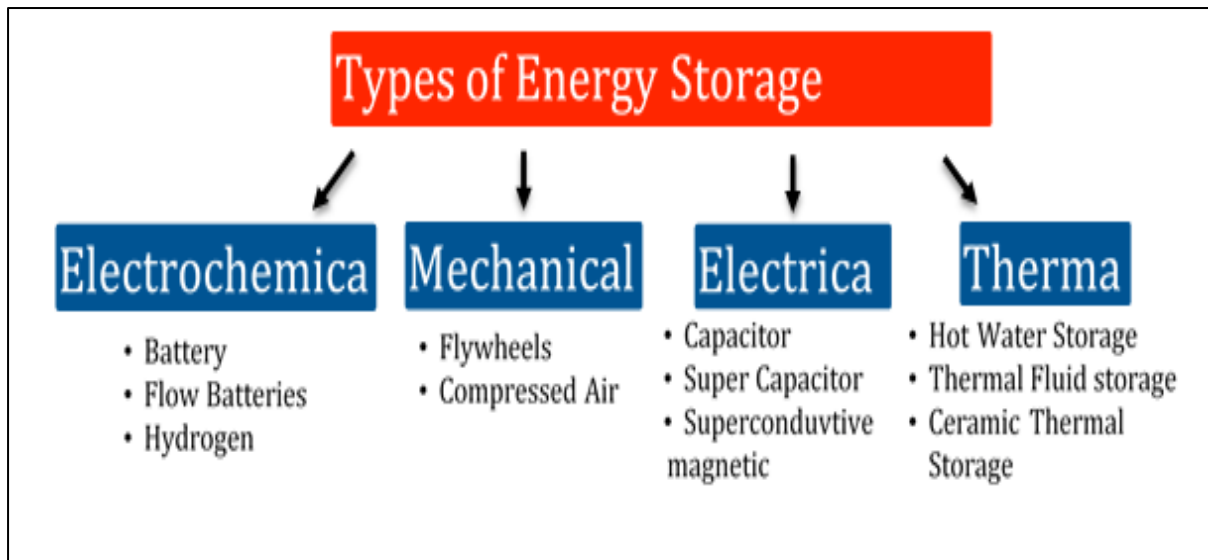


Figure 1. 1. Types of Energy Storage

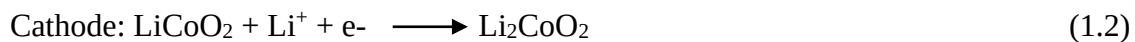
1.2. Lithium-Ion Battery Storage System:

Due to the fast emerging of electrical vehicles (EVs) as a solution to reduce the greenhouse gas emissions by the transportation sector, Lithium-ion batteries (LIBs) have become essential components of current energy storage solutions, significantly improving the efficiency and reliability of renewable energy integration. LIB is the core of electric vehicles, and the primary problem for EVs is to discover an energy storage technology that can support high mileage, fast charging, and efficient driving [5]. Due to its benefits, lithium-ion batteries are regarded as the most viable power source for EVs [6]. Furthermore, the LIB is made of environmentally acceptable components, emits no toxic gases, and is quite safe [7]. In addition, the lithium-ion battery is known for its high energy density, long cycle life, and swift charge/discharge characteristics. The reaction in a lithium-ion battery takes place during

the electrochemical operations of discharging and charging. In a lithium-ion battery, the anode and cathode materials play important roles in these processes. During the discharge process, lithium ions flow from the anode (usually graphite or other lithium-containing materials) to the cathode. During this process, lithium atoms in the anode lose electrons and become lithium ions.



Lithium ions in the electrolyte (generally a lithium salt in a solvent) pass through the separator to the cathode (which is typically formed of metal oxides such as lithium cobalt oxide, lithium manganese oxide, or lithium iron phosphate). At the cathode, lithium ions accept electrons and embed in the cathode material.



While charging, the reactions are reversed. Lithium ions return to the anode, while lithium ions in the cathode emit electrons, allowing lithium atoms to reintegrate into the anode.

Consequently, the significance of LIB arises from its capacity to address the intermittent nature of renewable energy sources like solar and wind power by storing excess energy when supply exceeds demand and releasing it when needed. This technology helps to maintain grid stability, reduces peak demand, and provides backup power during outages. Furthermore, LIB encourages the expansion of microgrids and contributes to the wider transition to greener, more sustainable energy systems. Continuous improvements in lithium-ion battery technology, together with attempts to improve recyclability and reduce environmental effects, position LIB as a key participant in the ongoing energy transition to a more robust and low-carbon future.

1.3. Heat Generation Inside Lithium-Ion Battery:

Despite of the enormous characteristics of Lithium-ion batteries, many challenges are associated with this type of energy storage. One of the critical problem is the heat generation inside the lithium-ion batteries [8]. The complicated interaction of heat generation within lithium-ion batteries is a fundamental component of their operational dynamics, influencing both performance and safety. As the battery undergoes charge and discharge cycles, internal

resistances and chemical reactions fundamentally produce heat. This heat generation, often characterized by mechanisms such as Joule heating, Solid-Electrolyte Interphase (SEI) Formation, and exothermic reactions within the electrodes, significantly impacts the performance and the safety of the battery system [9,10]. Based on Bernardi et al. [11], there are some processes affect the energy balance in the battery including the electrical power that is produced inside the battery, the reversible reaction, and entropic heating. According to Bernardi et al.'s thermal model, the simplified heat-generating model inside the battery can be indicated as follows:

$$q = I^2 R(I, SOC) - IT \frac{\partial E(SOC)}{\partial T} \quad (1.3)$$

where q is the heat generation rate, I is the charge or discharge current, R is the resistance, SOC is the state of charge of the battery, T is the battery temperature, and $IT \frac{\partial E}{\partial T}$ is the reversible electrochemical reactions heat [12].

1.4. Thermal Impact On The Performance Of Lithium-Ion Battery:

1.4.1. Lithium-Ion Battery Performance Degradation:

LIBs are subjected to degradation in the performance and the efficiency over time. There are several factors that can influence the battery's overall efficiency and capacity. The most important reason for this degradation is the cycling of the battery [13]. The repeated charging and discharging sequence causes chemical changes within the battery, leading to electrode material degradation. This can lead to a loss of active lithium ions and lower overall capacity. The next factor that affects the battery performance is the formation and continual growth of the Solid-Electrolyte Interphase (SEI) layer on the electrodes [14]. This is a natural process that occurs throughout battery use. However, an excessively thick SEI layer might obstruct ion transport, raising internal resistance and lowering performance. The other most important factor which most of the studies including this study focusing on is the high temperature. Extreme temperatures, whether caused by external environmental conditions or internal variables such as rapid charging, can speed up chemical reactions and increase deterioration. High temperature also can cause mechanical stresses during charge and discharge cycles, combined with volume changes in the electrodes, which can result in structural damage to battery materials. As a result, the electrode's integrity deteriorates with time, and performance suffers [15]. Therefore, cells at higher temperatures experience more capacity loss after each cycle compared to cells at lower temperatures [16].

1.4.2. Thermal Runaway:

Thermal runaway in lithium-ion batteries is a serious safety hazard caused by uncontrolled temperature increases, which result in a self-perpetuating loop of heat generation and temperature rise. This problem is frequently caused by internal or external forces that threaten the battery system's integrity [17]. Common causes include manufacturing flaws, mechanical damage, overcharging, and exposure to extreme temperatures. Once triggered, thermal runaway increases the release of stored energy, resulting in a rapid temperature increase, the venting of flammable electrolytes, and the potential ignition of the battery. This offers a significant safety issue, particularly in electric vehicles and portable electronics applications. Mitigation options include implementing sophisticated safety features like thermal management systems, pressure relief mechanisms, and fire-resistant materials to reduce the risk of thermal runaway and improve the overall safety profile of lithium-ion batteries. **Figure 1.2** illustrates the effect of thermal runaway on electrical vehicles. Therefore, the ongoing research is aimed at creating novel materials and engineering solutions to significantly lower the risk of thermal runaway in lithium-ion battery systems [18–21].



Figure 1. 2. Effects of thermal runaway on battery system in EVs.

1.5. Battery Thermal Management System (BTMS):

A battery thermal management system is a well-designed system for electric vehicles that is crucial in achieving performance and extending battery life under real-world driving circumstances [22]. Because temperature has a significant impact on battery performance and life, battery thermal control must be used in electric and plug-in hybrid electric vehicles

under real-world driving conditions. In recent years, automakers and their battery suppliers have placed a greater emphasis on battery heat management, particularly in terms of life cycle and warranty costs. BTMS can be built by using various methods. Hence, regardless of the method, the thermal design of each cell or module determines the basic performance of the management system. The BTMS's goal is to prevent fast battery deterioration by regulating the heat generated by its components so that it can work constantly at optimal temperatures. For effective cooling of the battery pack, the maximum temperature ($T_{\max}$) should be kept below 40 °C, and ideally, less than 35 °C, whereas the minimum temperature ($T_{\min}$) should be greater than 15°C in low-temperature conditions [23]. In addition, the battery modules and packs should maintain a temperature difference (ΔT) of less than 5 °C to ensure temperature uniformity [24]. At low temperatures, Because the electrochemical reaction cannot take place normally, both charging and discharging performance will be affected [25]. When the temperature is too low, the diffusion rate of lithium-ions in the electrolyte is significantly reduced due to an increase in electrolyte viscosity, resulting in a considerable rise in internal resistance. The quantity of lithium-ions involved in the reaction reduces, which has a direct impact on electricity storage and release, resulting in a reduction in battery capacity and power characteristics [26]. The electrolyte freezes in severe temperatures, preventing the battery from draining and the car from starting. Lithium dendrites may puncture the film during the charging of LIBs at low temperatures, resulting in an internal short circuit and endangering the safety of usage. On the other hand, at high temperatures, Lithium is chemically very reactive and easily burns. LIB packs are made up of multiple single LIBs connected in series or parallel, such that the heat created by the battery's electrochemical reaction does not overheat, resulting in combustion, explosion, or the release of poisonous gases (e.g., CO, C₂H₄, H₂S, HF) [27]. Furthermore, due to the complicated internal power circuit structure of the LIB pack [28,29], the short circuit may occur at high temperatures. High temperatures, on the other hand, have an impact on the capacity of LIBs. According to studies, LIBs lose about 70% of their capacity after 500 cycles of discharge at 55 °C [30]. This effect significantly reduces the lifetime of LIBs [31], not to mention the runaway heat that poses a serious threat to human life. All of these issues with LIBs in harsh weather due to insufficient heating or cooling will seriously impede the widespread deployment and spread of EVs. **Figure 1.3** shows the classifications of battery thermal management systems [32].

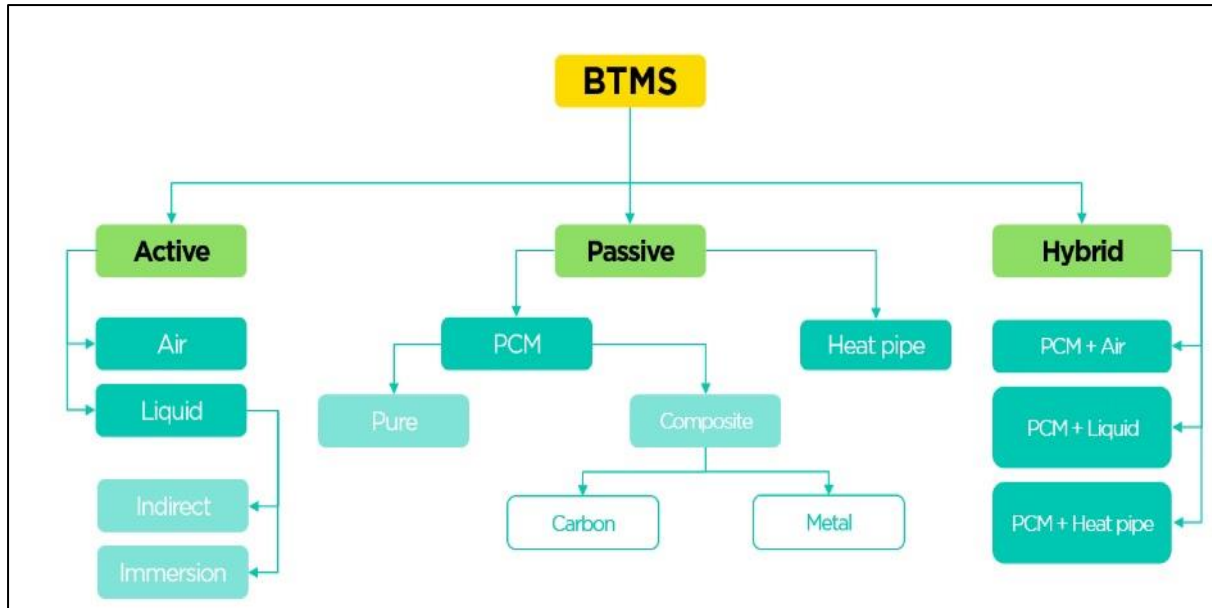


Figure 1. 3. Classification of Battery Thermal Management System (BTMS).

1.5.1. Air cooling BTMS:

Air-based cooling is one of the most extensively utilized cooling methods in our daily life, whether for household, automobile, or computer cooling [33–35]. The two primary forms of air-based BTMSs are forced and natural air flow convection. Forced air convection is performed in the BTMS by a specific energy-consuming system that drives air into the battery pack around the batteries.

In BTMS with natural airflow convection, air is supplied to the battery pack naturally via convection without the use of additional energy [36]. Forced air convection systems make up the majority of the suggested air-based BTMS because of their simple configuration, high heat transfer coefficient, ability to supply the needed cooling for the vast majority of applications, lower cost compared to alternative cooling systems, and ease of maintenance [36]. The air-based BTMSs proposed in the literature are largely for battery packs with low cooling requirements. Unlike passive systems, active systems use pre-conditioned air from an air conditioner or heater rather than air from the cabin or atmosphere. Passive systems can typically supply hundreds of watts of heating or cooling power, but active systems are limited to 1 kW. Both systems require a few components to perform cooling, such as external power, a fan, and a heater for active systems [37].

1.5.2. Liquid cooling BTMS:

Another frequent approach for cooling LIBs is liquid cooling. Because water has a higher heat transfer coefficient than air, liquid cooling is more efficient. There are two types of liquids used in heat management systems. The first is a direct-contact liquid or dielectric liquid, such as mineral oil, which may come into direct contact with the battery cells. The second type is indirect-contact liquid or conducting liquid, such as a mixture of water and ethylene glycol, which can only be contacted indirectly by the battery cells. Direct contact liquid cooling [38,39] is uncommon in vehicle battery cooling systems due to the high demands on the battery system's waterproof performance, and electrical short circuits and electrochemical reactions may occur. Many scholars have been drawn to indirect liquid cooling (such as tube cooling, cold plate cooling with mini/micro channels, jacket cooling, and so on) because of its advantages of easier implementation and higher safety. The cylindrical LIB [40] and plate LIB liquid cooling systems have been proposed and studied. The cooling device is typically designed to be compact and light [41], and new materials are employed to improve the cooling channel. For liquid cooling, preheating is also utilized. Furthermore, liquid cooling can be combined with other methods such as air cooling or heat pipes [42] to improve results. The majority of current research is on the optimization of cooling plates using simulation or experimental methods. Because of their compactness and excellent efficiency, liquid-cooled systems are commonly used in practical applications. Because of the liquid's high heat transfer coefficient and heat capacity, it is an excellent solution for electric vehicles (EVs) BTM [43]. The temperature of the battery may be maintained with 2-3 times less energy than an air cooling system. The disadvantages of liquid-cooled systems include greater weight, complexity, structure rigidity, and additional expenses. Furthermore, circulating fluid at the desired flow rate necessitates a significant increase in power, increasing the vehicle's overall energy consumption [44].

1.5.3. Phase change material (PCM) BTMS:

The PCM thermal management technology is unique in thermal management applications because it is capable of absorbing large amounts of heat via latent heat. Its melting process is kept at the phase change temperature for an extended period of time [37]. Because of its unique features, PCM-based BTM systems have garnered substantial investigation and attention in recent years. The PCM system has the potential to provide various benefits, including passive protection from high operating temperatures and life cycle extension [45]. The BTMS based on PCM can provide adequate thermal management by utilizing latent heat

throughout phase change processes such as solid gas, solid-liquid, and liquid gas. PCMs utilized in BTMS should have high latent heat, an appropriate phase transition temperature, a minimal volume change, good thermal conductivity, nontoxicity, and chemical stability [46]. Paraffin (PA) and non-PA substances like long-chain alkanes, stearic acid, and polyols are examples of organic PCMs. Inorganic PCMs are generally hydrated salts and metals. Eutectic PCMs have high latent heat and a sharp melting point due to their specific atom ratio and composition of two inorganic and organic compounds [47]. However, Eutectic combinations are uncommon in BTM because they are innovative PCM [24].

1.5.4. Heat pipe BTMS:

The thermal conductivity and phase transition of heat pipes [48] gives a novel technique for managing the temperature of an electric vehicle battery. They are BTMS with a long life cycle that requires no maintenance and is lightweight, passive, and compact [49]. Due to the phase change of the working fluid, heat is absorbed in the evaporation part and released in the condensation section in this process. Heat is transmitted between the two portions without the use of additional electricity as long as there is a temperature differential between them. Although HP has excellent thermal conductivity, it is usually combined with liquid cooling or forced air to effectively dissipate heat at the condensation section [50]. Heat pipes have been effectively placed in a range of fields due to their high thermal conductivity, including energy recovery, electron cooling, and solar heater. ΔT can be lowered via heat pipes between batteries, and the batteries can remain in an ideal working range even when operating conditions change [51]. The coolant system's large thermal capacity allows for additional cooling load reductions compared to the instantaneous cooling approach. Instead of dispersing peak heat created with high discharge rates, this system must dissipate the average heat generated. Using HPs to manage battery thermals would thus be a promising research path.

1.5.5 Hybrid BTMS:

The hybrid BTMS (HBTMS) combines passive and active approaches to improve the heat transfer process of passive systems and allow them to be actively managed. In general, PCMs are used to improve temperature uniformity, and an active system reduces the possibility of heat saturation, whereas HPs are preferred due to their high thermal conductivity, which greatly increases local heat transfer and effectively releases heat from the condensation

section [52]. Forced air can be used as an active cooling system for systems with smaller thermal loads, but liquid cooling is more efficient. HBTMSs have a number of limitations, including their size, weight, energy consumption, and complexity [53].

1.6. Performance Parameters of Lithium-Ion Battery:

Like any other equipment, system, or technology, several parameters may be used to evaluate LIB performance and define the status of the battery system defining their efficiency, reliability, and overall capability and how they react to charging/discharging loads within the system.

1. **Capacity (C):** Capacity is the total amount of electric charge that a battery can hold, measured in ampere-hours (Ah) or milliampere-hours (mAh). It determines how long a battery can deliver a certain quantity of current.
2. **Energy Density:** Energy density refers to how much energy is stored per unit volume or weight of the battery. A higher energy density enables more energy storage in a smaller and lighter package.
3. **Power Density:** Power density is the rate at which a battery can deliver energy. It is crucial for applications requiring rapid charging or high power output.
4. **Self-Discharge Rate:** The self-discharge rate is the rate at which a battery loses charge while not in use. Lower self-discharge rates result in batteries that can hold a charge for longer periods.
5. **Life Cycle:** Cycle life is the number of charge-discharge cycles that a battery can go through before losing significant capacity. Longer cycle life improves battery durability and longevity.
6. **State of Charge (SoC):** The term "state of charge" refers to a battery's present capacity as a percentage of its maximum capacity. It reveals how much charge left in the battery in comparison to a full charge.
7. **State of Health (SoH):** The State of Health (SoH) refers to a battery's overall health or state. It represents the battery's ability to supply its original capacity compared to when it was new. SoH offers information about the aging and degradation of the battery.
8. **Coulombic Efficiency:** Coulombic Efficiency is the ratio of the real charge delivered during discharge to the theoretical charge that was initially supplied during charging.

It evaluates the charge-discharge cycle's efficiency while accounting for losses incurred during electrochemical processes.

9. **Energy Efficiency:** Energy Efficiency is a measure of how well a battery turns stored energy into usable electrical energy, and vice versa. It is the ratio of the energy delivered during discharge to the energy input while charging, accounting for losses from various sources.
10. **Internal Resistance (R_i):** Internal resistance refers to the impedance to the flow of electric current within a battery. It is caused by the resistance of the battery's components and can result in energy losses, lower power output, and heating during charge and discharge operations.

1.7. Objectives Of The Study:

The main objective of this work is to enhance the efficiency of the battery thermal management system. Hence, to achieve this goal, the following objectives have been identified:

- i. Perform calendar aging of lithium-ion batteries under the Saudi Arabian summer conditions. Then, compare the performance parameters of the LIBs after the aging time.
- ii. Perform numerical modeling to optimize the performance of the BTMS under different parameters including, the transversal and longitudinal distances between batteries, wall confinement angles, and different distances between the batteries and the surrounding walls.
- iii. Experiment to validate the numerical model set in objective (ii).
- iv. Experiment to study the BTMS under parking mode using natural convection in atmospheric conditions and natural convection by immersion in a cooling dielectric fluid.

The primary goal of this work is to figure out how various variables can affect the performance of the BTMS. Furthermore, the ultimate goal of this work is to find ways to improve the system's efficiency and maintain the main performance parameters of the LIBs such as internal resistance, state of health, and capacity at the manufacturer's operating

conditions, as well as to maintain the battery's lifespan by studying the impact of these various factors on the performance of the BTMS.

1.8. Organization Of Thesis Chapters:

This thesis consists of seven chapters. Chapter 1 starts with general introduction. Chapter 2 provides a detailed literature review covering the background and most recent research related to this work. Chapter 3 outlines the first experimental work of calendar aging of LIBs and figure out the environmental impacts on LIBs in open circuit state. Chapter 4 discusses the numerical modeling of Air cooling battery management system using different configurations that can enhance the performance of the system. Chapter 5 provides a machine learning model to predict the performance of BTMS under various configuration settings. Chapter 6 discusses an experimental results of air BTMS using convergent cooling channel. Chapter 7 summaries the conclusions of this study, where recommendations for further work are also given based on this study.

CHAPTER 2:

LITERATURE REVIEW

2.1. LIB Energy Storage System:

Lithium-ion batteries (LIBs) have become an essential component of our daily lives, powering everything from smartphones to electric vehicles. The history of LIBs began in the 1970s when Stanley Whittingham proposed the concept of rechargeable lithium batteries. It wasn't until the 1980s that John B. Goodenough, Rachid Yazami, and Akira Yoshino collaborated on producing the first commercially viable LIB. This signaled the start of a transformational era in energy storage [54]. The key innovation in LIBs lies in their reversible electrochemical process during energy storage and release. The operation of LIBs depends mainly on three components, the anode, the cathode, and electrolyte. The battery's architecture typically includes a lithium-containing metal oxide cathode, a graphite anode, and an electrolyte that facilitates the movement of lithium ions between the electrodes. This design allows for more efficient cycling while also delivering a dependable and lightweight energy storage solution. Over the years, LIB research has tackled critical issues like as safety, energy density, and cycle life. Researchers worldwide have concentrated on refining electrode materials, investigating solid-state battery technologies, and optimizing production procedures.

One critical area of focus is cathode materials. While early Li-ion batteries relied heavily on cobalt oxide, ongoing research is looking into alternatives such as nickel manganese cobalt oxide (NMC) and lithium iron phosphate (LFP), with the goal of increasing energy density and reducing reliance on limited resources [55]. J. Nanda discusses the design framework for cobalt and nickel-free high-capacity lithium-ion cathodes, addressing the resource constraints and supply chain issues associated with these critical battery materials [56]. The aim is to produce cobalt-free disorder rock salt (DRX) cathodes that do not require cation ordering and may be manufactured using a variety of common metals. The study seeks to improve the high voltage redox and stability of Li-Mn-Ti-OF-based DRX compositions through synthesis and structural design. The study showed the importance of fluorine in regulating high-voltage oxygen redox and capacity retention is stressed.

L. Zhou et al. discussed $\text{Li}(\text{Ni}, \text{Co}, \text{Mn})\text{O}_2$ (NCM) cathode materials for lithium-ion batteries, specifically NCM 622 and NCM 811 compositions [57]. The study seeks to investigate the relationship between composition, structure, and battery performance to create safe batteries with increased capacity, longer cycling life, and higher energy and power densities. In charge-discharge and cycling performance evaluations, NCM 811 outperformed NCM 622 in terms of capacity and stability. In addition, X-ray diffraction and electron microscopes were used to investigate the cathodes' phase, morphology, crystal structure, and microstructure.

Anode materials have also been studied extensively, with silicon emerging as a suitable contender due to its high lithium-ion storage capacity. However, issues such as volume expansion during cycling and material deterioration demand continued research to fully realize the promise of silicon anodes [58].

D. Munaò et al. studied the preparation and characterization of Si-based nano-composite anodes for lithium-ion batteries, synthesized using Laser Assisted Chemical Vapor Pyrolysis and Electrospray Deposition techniques [59]. The silicon nanoparticles in the composite have a well-defined crystalline structure and a homogeneous, spherical-like shape, as determined by X-ray diffraction (XRD) and Transmission Electron Microscopy (TEM) research. The silicon-based electrode has a high specific capacity of around 1200 mAh g^{-1} and strong rate capability in lithium cells. Preliminary surface treatment greatly diminishes the initial irreversible potential of this class of materials. Moreover, the cycled electrodes' morphological changes are modest, and no prolonged fractures are seen, demonstrating that the layers are mechanically resistant to volume variations caused by electrochemical alloying and dealloying. Hence, The silicon-based electrode has been identified as a viable anode material for improved lithium-ion batteries.

A. Mery et al. investigated the development of a composite electrode for Li-ion batteries made up of carbon-coated Si nanoparticles (Si@C NPs) embedded in a three-dimensional graphene hydrogel (GHG) structure. The synthesis approach employs an in-situ hydrothermal process that successfully reduces graphene oxide, produces 3D graphene assemblies, and ensures homogenous distribution of Si@C NPs in the GHG matrix [60]. The study effectively developed a composite electrode for LIBs made of carbon-coated Si

nanoparticles (Si@C NPs) embedded in a three-dimensional graphene hydrogel (GHG) structure. This composite electrode demonstrated excellent specific capacity (up to 2200 mAh.g⁻¹) and good stability (200 cycles with an average C_{eff} > 99%) in electrochemical characterizations. The protective carbon layer on Si NPs played an important role in acquiring these high-performance properties. The in-situ hydrothermal technique used in the synthesis procedure allowed for uniform dispersion of Si@C NPs in the GHG matrix, enhancing sample conductivity and Li-ion transport pathways. The composite electrode outperformed electrodes created with non-C-coated Si NPs or mixed components, demonstrating the carbon shell's synergetic effects on Si NPs as well as the advantages of the one-step in-situ fabrication process.

Beyond materials, the development of improved electrolytes has been critical to improving the performance and safety of Li-ion batteries. Researchers investigate different electrolyte compositions, additives, and solid electrolytes to improve ion conductivity, reduce side reactions, and lengthen battery cycle life [61–63].

X. Gong et al. prepared gel polymer electrolytes (GPEs) using poly(acrylonitrile-polyhedral oligomeric silsesquioxane)/poly(vinylidene fluoride) (PAN-POSS/PVDF) blends as a porous membrane and ionic liquid (IL) as an absorption substance [64]. The GPEs exhibited high ionic conductivity, excellent mechanical properties, thermal stability, and fire resistance. The GPEs exhibited a high ionic conductivity of 1.91×10^{-3} S cm⁻¹ at 20 °C when the PAN-POSS content was 15 wt%. Furthermore, testing cells with Li metal anode and LiFePO₄ cathode using the GPEs showed a tolerable rate performance, indicating their potential application in lithium batteries with high safety and electrochemical performance.

Q. Zhang et al. Studied the synergetic effects of inorganic components in solid electrolyte interphase on high cycle efficiency of lithium-ion batteries [65]. The solid electrolyte interphase (SEI) in lithium-ion batteries plays a crucial role in battery performance and durability, and the inorganic components in SEI, such as lithium carbonate (Li₂CO₃) and lithium fluoride (LiF), provide mechanical and chemical protection while controlling lithium ion transport. The study showed that the contact between lithium carbonate (Li₂CO₃) and lithium fluoride (LiF) in the solid electrolyte interphase (SEI) promotes space charge accumulation along their interfaces, leading to higher ionic carrier concentration and improved lithium ion transport. This results in high current efficiency and long cycle stability.

Innovations in LIB technology range from modest improvements to revolutionary principles. Solid-state batteries, which use solid electrolytes instead of liquids, represent an era of change, providing increased energy density while also improving safety. Exponential jumps in energy storage capacity and charging speed are also on the horizon, thanks to advances in nanotechnology, AI, and innovative electrode designs. LIBs have evolved beyond their original applications, becoming a key component in solving global concerns such as climate change, renewable energy integration, and electrified transportation. As the voyage of LIBs progresses, interdisciplinary collaborations ranging from materials research to computational modeling continue to alter the direction of this critical technology, bringing in a new era of sustainable and efficient energy storage.

2.2. Battery Thermal Management System (BTMS):

The Battery Thermal Management System (BTMS) controls and dissipates the heat produced by the electrochemical reactions that take place in cells, enabling the battery to function effectively and safely. The main function of BTMS is to stop accelerated battery deterioration by controlling the heat produced by its components so that it functions constantly at the optimum temperature. The BTMS can be classified into three types: active BTMS, passive BTMS, and hybrid BTMS [66]. The active type includes forced air and liquid cooling systems, subdivided into direct and indirect cooling (immersed) [67]. The passive type includes phase change cooling materials (PCMs) and heat pipes. The hybrid type is a combination between the active BTMS and passive BTMS such as PCM with air or PCM with liquid [68].

S. Al Hallaj et al. [69] discussed a novel thermal management system for electric vehicle (EV) batteries using phase-change material (PCM). The authors proposed and investigated the use of PCM in EV battery modules to improve thermal behavior. S. Al Hallaj et al. assessed the utilization of heat generated during discharge and stored as latent heat during charge, and the transfer of a smaller part of it to the surroundings highlighting the advantage of the PCM system in EV operation under cold conditions or in space applications where the battery temperature drops significantly. The results showed that the temperature profile of the cells integrated in the module design was substantially more uniform during discharge at different rates when using the PCM thermal management

system compared to without PCM. The heat generated during discharge is stored as latent heat in the PCM and is largely utilized during charge, with a smaller part of it transferred to the surroundings. However, S. Al Hallaj et al. didn't discuss the specific EV battery module design used in the simulations, including the number and arrangement of cells, or the overall dimensions and configuration of the module. Furthermore, they didn't discuss the long-term durability or reliability of the PCM material and its impact on the overall performance and lifespan of the EV battery.

W. Weimin et al established a thermal simulation analysis model for a battery pack by combining an equivalent circuit with heat flow to assess the temperature field and guarantee thermal performance satisfies operational requirements [70]. The authors showed that the simulation method can accurately analyze the temperature field in the battery pack, which is crucial for ensuring the thermal performance meets the operational requirements.

R. Sabbah et al. [71] compared the effectiveness of passive cooling using phase change materials (PCM) with active cooling using forced air for thermal management of high-power lithium-ion battery packs. The study includes numerical simulations and experimental results for a compact Li-ion battery pack suitable for plug-in hybrid electric vehicle (PHEV) propulsion. The authors performed numerical simulations and experimental tests to evaluate the performance of the two cooling methods under different discharge rates, operating temperatures, and ambient temperatures, and to Determine the ability of the passive cooling system to meet the operating range requirements under stressful conditions (high discharge rates and high operating or ambient temperatures) without the need for additional fan power. The results of the study showed that under stressful conditions, air-cooling is not an effective thermal management system for keeping the temperature of the battery cells within the desired operating range without significant fan power. On the other hand, the passive cooling system using PCM can meet the operating range requirements under the same stressful conditions without the need for additional fan power.

Z. Ling et al. [72] investigated a hybrid thermal management system for lithium-ion batteries that combines phase change materials (PCMs) with forced-air cooling. The study highlighted the limitations of passive thermal management systems using PCMs, which

can lead to heat accumulation and system failures. The study also examined the effects of airspeed on the thermal performance of the system, with PCMs' thermo-physical properties dictating the maximum temperature rise and temperature uniformity in the battery pack. The authors found out that the studied system successfully prevented heat accumulation and maintained the maximum temperature under 50 °C in all cycles. Additionally, The study revealed that the thermo-physical properties of PCMs dictate the maximum temperature rise and temperature uniformity in the battery pack, while forced air convection plays a critical role in recovering the thermal energy storage capacity of PCMs.

I. Cornacchia et al. studied and focused on improving the cooling of the end-windings of electric motors by injecting transmission oil [73]. The researchers designed a technique that used a flat heated plate as a model to duplicate the cooling process and assess convective heat transfer. The suggested techniques enabled the evaluation of the convective coefficient within 20 times the nozzle distance. The findings revealed that convective heat transfer values of up to 7550W/m²K were obtained around the impingement point.

L. Liang et al. [74] studied the use of an inclined U-shaped flat microheat pipe array (FMHPA) for battery thermal management systems (BTMS) in electric vehicles in which the FMHPA is designed to improve efficiency and save space. The authors' objective was to assess the impact of FMHPAs on the maximum temperature and temperature difference of the battery module and the ability of FMHPAs to maintain the temperature within a suitable range during charge-discharge cycles. The inclined U-shaped flat microheat pipe array (FMHPA) has an equivalent thermal conductivity of approximately 4350 W/ m.K and serves as the core heat transfer element. L. Liang et al. showed that The presence of FMHPAs in the battery module reduces the maximum temperature by 16% and the temperature difference by 60% compared to modules without FMHPAs. The FMHPAs helped maintain the module temperature within a suitable range during the 1C charge–2C discharge cycle, even at an ambient temperature of 25 °C. Nevertheless, The experiments and comparisons are conducted under specific conditions, such as an ambient temperature of 25 °C and a 1C charge–2C discharge cycle and ignored the other affecting factors.

2.3. Calendar Aging Of LIB:

Calendar aging of lithium-ion batteries comprises all electrochemical and mechanical processes that are independent of the charging/discharging cycle. These processes are mainly affected by the storage conditions and duration. During storage, parasitic side reactions can be triggered in the electrolyte or at the electrolyte–electrode interface, leading to self-discharge and/or gradual degradation of battery components [75]. These reactions are closely related to the passage of time and external elements including temperature, voltage, and state of charge. As batteries age, irreversible side reactions can cause the creation of solid-electrolyte interface (SEI) layers, electrolyte breakdown, and structural changes in the electrodes. Temperature, a powerful predictor of battery longevity, influences the kinetics of these aging events. Higher temperatures can hasten the chemical processes responsible for capacity decline, making temperature control an important factor in minimizing calendar aging effects. Voltage, another crucial characteristic, aids in the creation of SEI layers, which function as barriers to ion movement, reducing the battery's performance over time. The state of charge in which a battery is stored has a considerable impact on calendar aging. Prolonged exposure to high or low charge levels might have negative consequences. High levels of charge encourage the growth of lithium plating on the anode, compromising the battery's safety and cycle life. In contrast, low charge states can cause the growth of metal dendrites, threatening the battery's structural integrity. Thus, calendar aging measurements are essential for many LIB applications, especially for EVs because they spend most of their lifetime in the parking mode, which resembles battery aging without cycling.

Several studies have been conducted on the calendar aging of LIB, including electric vehicle batteries [76–80]. These studies have shown that the storage temperature significantly affects the LIB storage capacity [81,82]. Furthermore, the effect of storage temperature varies according to the state of charge (SoC) [83].

Grolleau et al. investigated the effect of SoC and storage temperature on the calendar aging of a 15 Ah commercial LIB [75]. This study demonstrated that LIB cells lose more capacity (capacity fading) at higher storage temperatures. Furthermore, the initial SoC of the cells does not significantly affect the capacity loss at low temperatures (30°C) [75]. However, at high temperatures (60°C), cells with a 100% SoC exhibit higher capacity

fading than those with a 30% SoC. Thus, the SoC of the cells plays a key role in the capacity fading at high storage temperatures.

Werner et al. [84] conducted another study using an empirical aging model for graphite/NCA pouch cells. The model studied was a function of the temperature, SoC, and time under an open-circuit voltage, considering self-discharge. Different operating conditions were considered, including SoCs of 35%, 50%, 65%, 80%, and 100%, and three storage temperatures (40°C, 50°C, and 60°C). The results showed significant self-discharge at a high SoC and high temperature. The authors assumed that the dominant aging mechanism leading to degradation was the loss of cyclable lithium, which caused a shift in the electrode balance.

Store et al. studied LIB degradation at different temperatures and SoC levels at different discharge rates (4C, 2C, 1C, and 0.5C) [85]. They found that, during calendar aging, the internal resistance increased nonlinearly following a power-law function. Furthermore, with increasing storage temperature and the SoC level, the increase in the internal resistance of the tested battery cells accelerated exponentially.

Yang et al. [86] proposed an accurate model for estimating the SoC of LIBs using a new temperature-compensated model with an extended Kalman Filter (EKF). The main parameters such as open circuit voltage (OCV), capacitance, and resistance and capacitance (RC) in the estimator are temperature-dependent. Therefore, the estimator can maintain high accuracy at various temperatures. Yang reported that the accuracy of the estimation decreases when applied in a continuous high-current discharge because of the equivalent polarization resistance that decreases as the discharge current increases. Additionally, the equivalent circuit model exhibited significant uncertainty in the low SoC region.

Keil et al. [87] studied the calendar aging of lithium-ion cells by storing them in various charge levels and temperatures. Differential voltage analysis (DVA) and coulometry were used to analyze capacity fade. The study demonstrated that capacity fades in lithium-ion cells during calendar aging was mostly driven by a shift in electrode balance caused by decreased cyclable lithium inventory. Furthermore, the studies demonstrated that the capacity fade did not rise continuously with increasing SoC. Instead, two plateau regions

were detected, one with a strong capacity fade between 65 and 95 SoC and the other with a medium capacity decline between 30 and 55 SoC.

Another study by Werner et al. [84] investigated the correlation between measurements of capacity fade and impedance rise in lithium-ion batteries aged at different temperatures and states of charge. The results showed an accelerated degradation with increasing temperature, following the law of Arrhenius, and a significant impact on the storage state of charge at 100%. The degradation rate is not affected by earlier periods at different temperature levels, indicating no path dependency.

Mitigating calendar aging remains a difficult challenge that necessitates a diversified strategy. Advanced materials design, electrolyte optimization, and novel thermal management systems stand out as possible ways to increase the calendar life of LIBs. Furthermore, perfect control over charging and discharging techniques, together with clever battery management systems, can considerably reduce the effects of calendar aging.

2.4. Geometry Of BTMS:

The effectiveness of BTMS is not only limited to the type of cooling system used but certain factors can enhance the performance of the BTMS. The configuration of the system, the geometry of the system, the insulation, and the spacing between the cells have an impact on the heat dissipation of the battery pack.

Yang et al. [88] conducted an assessment of forced air-cooling on cylindrical LiFePO₄ lithium-ion battery packs focusing on the comparison between aligned and staggered cell arrangements. They analyze the effects of longitudinal and transverse spacing on cooling performance for both aligned and staggered arrays. The authors wanted to find an appropriate solution, considering design requirements such as maximum temperature rise, temperature uniformity, power requirement, and cooling index, by optimizing the combination of longitudinal interval, transverse interval, and air inlet width for the aligned arrangement. They found that The maximum temperature rise is found to be proportional to the longitudinal interval for staggered arrays, while it is inversely proportional to the aligned arrangement. Increasing the transverse interval leads to an increase in battery temperature rise

for both aligned and staggered arrangements. The authors didn't provide a detailed study of the trade-off between design criteria and how the ideal combination of longitudinal interval, transverse interval, and air intake width for the arrangement was obtained.

Chen et al. [89] have improved the efficiency of the air cooling system by changing the inlet and outlet positions in the battery pack. The results showed when the inlet and outlet regions are in the middle of plenums, the higher efficiency can be achieved. The cooling efficiency of the BTMS is significantly improved after cell spacing optimization using the developed strategy. The maximum temperature of the battery pack is reduced by about 4.0 K, and the maximum cell temperature difference is reduced by more than 69% for various inlet airflow rates.

L. Fan et al. [90] conducted three-dimensional transient thermal analyses using a commercial computational fluid dynamics code to study the module's thermal behavior under an aggressive driving profile. The main goal of the study was to Investigate the impact of gap spacing and fan flow rate on the maximum temperature rise of the battery module and determine the optimal parameters for achieving improved temperature uniformity over the module. L. Fan et al. found that Lowering the gap spacing and increasing the fan flow rate led to a decrease in the maximum temperature rise, and A uniform gap spacing of 3 mm and an airflow rate of 40.8 m³/ h were identified as the best choice for achieving improved temperature uniformity over the module. However, the study only focused on the spacing between the cells and the flow rate required ignoring the other affecting factors.

The flow and heat transport behavior around circular batteries is very analogous to that around bundles of tubes in heat exchangers or flow around fins in heat sinks. All three systems involve the transfer of heat from a high-temperature region to a lower-temperature region, aiming to maintain efficient thermal management. Additionally, they rely on convective heat transfer mechanisms, where the movement of fluid or air plays a crucial role in carrying away the heat. In both batteries and heat exchangers/heat sinks, optimization of the flow velocity, geometry, and surface area is crucial to enhance heat dissipation. Furthermore, these systems often involve considerations of pressure drop, as the fluid or air encounters resistance while passing through the channels or fins. Therefore, the similarities lie in the fundamental principles of heat transfer, convective heat transfer mechanisms, and the need to optimize design variables for efficient thermal performance.

Xie et al. [91] conducted experiments and computational fluid dynamics (CFD) simulations to analyze the influences of three factors (the air-inlet angle, the air-outlet angle, and the width of the airflow channel between battery cells) on heat dissipation. The main goal was to determine the layout of the airflow channels that provide the best cooling performance, resulting in decreased maximum temperature and temperature differences in the battery pack. The configuration of the airflow channels, according to Xie et al., has a considerable impact on the maximum temperature and temperature difference in the Lithium-ion battery pack. The optimum cooling performance was obtained with a 2.5° air-inlet angle, 2.5° air-outlet angle, and equal channel width, resulting in a 12.82% decrease in maximum temperature and a 29.72% decrease in temperature differential. The angle of the air inlet and air outlet can affect the flow of air through the channels between battery cells, influencing the distribution of heat and the overall temperature of the battery pack. However, the authors studied only one column of prismatic cells and did not explain the system's performance with multi-cell packs or cylindrical-shaped cells.

2.5. Air Cooling BTMS:

Air cooling has emerged as a potential and widely utilized BTMS technique due to its simplicity, cost-effectiveness, and environmental friendliness. Several recent studies published have looked into the optimization and performance evaluation of air cooling BTMS.

R. Mahamud et al. [92] discussed a battery thermal management system using reciprocating air flow for Li-ion cells. The authors analyzed the system numerically using a two-dimensional computational fluid dynamics (CFD) model, a lumped-capacitance thermal model for battery cells, and a flow network model. The results displayed that the reciprocating flow could reduce the cell temperature difference of the battery system by about 4 °C (72% reduction) and the maximum cell temperature by 1.5 °C compared to the uni-directional flow case.

H. Park [93] investigated the design of a cooling airflow configuration for lithium-ion batteries in hybrid electric vehicles (HEVs). The study focused on the cooling performance of a stacked multiple battery cell system in HEVs, as well as a design method for achieving the requisite cooling performance using a tapered manifold and pressure relief ventilation. The author claimed that by using a tapered manifold and pressure relief ventilation, the requisite

cooling performance can be accomplished without modifying the layout/design of the present battery system. The author only looked at one type of battery and made no mention of the usefulness of this strategy when using various cells, such as cylindrical cells, or when using a different battery arrangement.

P. Saechan et al. [94] presented an air-cooling battery thermal management system for Lithium-ion battery packs in electric vehicles (EVs) to reduce capacity fading, thermal runaway, and instability. To study the cooling performance of the pack, a transient three-dimensional heat transport model was created, which included the effects of inlet velocity, discharge rate, and cell arrangement structure on cooling performance. The results revealed that the maximum cell temperature was reduced and that the temperature distribution in the battery pack was uniform. The authors, however, only evaluated the system at low discharge rates and did not take into account the other characteristics such as cell distance and the pressure drop across the pack.

X. Zhang et al. [95] studied the optimization of air cooling BTMS with two L-type structures, L(A) and L(B), by varying the plenum angle and width, inlet position, and baffle setting. The simulation findings suggest that adjusting the plenum angle is more effective for BTMS L(A), lowering the maximum temperature by 1.79 K and decreasing the maximum temperature differential by 2.45 K. For BTMS L(B), optimizing the plenum widths is the most efficient way, lowering the maximum temperature by 1.41 K and the maximum temperature differential by 2.13 K while reducing power usage by 11.30%. The optimized systems show better cooling performance when the battery heat generation rate and air flow rate fluctuate.

G. Zhao et al. [96] proposed a unique vortex adjustment structure for air-cooling battery packs in electric vehicles that efficiently alters the aerodynamic patterns and thermodynamic properties of the battery pack, resulting in an increased heat transfer coefficient with minimum increase in energy consumption and cost. Various designs were studied and optimized, resulting in increased cooling performance at low and high airflow rates. The proposed vortex-generating design serves as a guideline for the development and optimization of high-performance air-cooling battery thermal management systems in electric vehicles.

2.6. Machine Learning & BTMS:

In recent years, the incorporation of machine learning (ML) approaches into BTMS design and optimization has emerged as a game changer. This paradigm shift derives from the awareness that, while standard CFD models are helpful, they have essential limitations in handling large datasets and reflecting the non-linear complexities found in real-world battery systems. Machine learning, with its ability to extract complicated correlations and patterns from data, is an effective addition to classical simulations.

The Gaussian Process Regression (GPR) approach is a key component of BTMS's ML applications. Unlike predictable models, GPR accepts uncertainty, making it ideal for situations with non-linear relationships and complex interactions. The combination of CFD simulations with GPR enables a synergistic approach that combines the advantages of physics-based modeling with data-driven insights. The methodology used in this type of approach entails training the ML algorithm, specifically the GPR, on large datasets derived from CFD simulations. These datasets capture a wide range of operating situations, providing a comprehensive understanding of the battery system's thermal behavior. The Exponential kernel function of GPR is particularly good at identifying subtle correlations between influential parameters and thermal performance indicators.

K. Liu et al. [97] used a machine learning-enabled calendar aging prediction model for lithium-ion batteries using Gaussian process regression (GPR) with an automatic relevance determination (ARD) kernel. The study utilizes experimental battery calendar aging data from nine storage cases for model training, validation, and comparison. The results show that the model achieves reliable prediction results for all storage cases, offering good generalization ability and accurate prediction results for calendar aging under various storage conditions.

J. Yi et al. [98] proposed a state of charge (SoC) estimation method, which is a hybrid method (HM) that combines the extended Kalman filter (EKF) and ampere-hour integration (AHI) to address issues such as overcharge, over-discharge, and mileage anxiety. Simulation results demonstrated the effectiveness of the proposed algorithm in estimating the SoC of power batteries in electric vehicles with an estimated SOC error of less than 1.6%.

S. Cui et al. [99] proposed a data-driven deep learning method that combines the Gate Recurrent Unit (GRU) and attention mechanism for accurate state of health (SoH) estimation of lithium-ion batteries. The model accuracy was assessed by using real-life datasets of batteries from NASA. The experimental results demonstrate that the proposed deep learning model has higher accuracy compared to conventional data-driven models for more effectively utilizing the energy stored in batteries and ensuring battery reliability.

C. Luo et al. [100] studied the capacity and life estimation model using automated machine learning (AutoML) of lithium-ion batteries for their large-scale commercial use in electric vehicles. The study analyzed the features of the CC and CV phases using the optimized incremental capacity (IC) curve, which shows a strong relevance between the IC curve in the CC phase, charging capacity in the CV phase, and battery lifespan. The results demonstrated that the mean absolute error (MAE) increased by 52.8% and the root mean square error (RMSE) increased by 48.3% compared to other methods using the same datasets and training method. This indicates a significant improvement in the accuracy of life prediction.

Finally, the combination of machine learning and conventional CFD simulations represents an important advancement in the field of battery thermal management systems. This innovative method provides a comprehensive, data-driven understanding of complicated thermal dynamics, opening up new possibilities in the search for high-performance, safe, and efficient energy storage systems. As sectors embrace this convergence, the path to a more sustainable and technologically sophisticated future for batteries accelerates substantially.

CHAPTER 3:

CALENDAR AGING OF LIB UNDER REALISTIC CONDITIONS*

3.1. Introduction:

The transportation sector is responsible for 23% of global greenhouse gas emissions [101]. Therefore, a transition toward emission-free transportation alternatives, including electric vehicles is inevitable. Recently, new companies, including Tesla and NIO, have been established to produce electrical vehicles, including Tesla and NIO. Additionally, conventional automotive manufacturers, such as BMW and Volkswagen, have begun producing electric vehicles (EVs) to address the environmental issues associated with greenhouse emissions. Lithium-ion batteries (LIB) have been widely used as power sources for electric vehicles owing to their high energy density, long life, and high voltage [102].

Several studies have investigated the impact of the environmental temperature on battery performance during cycling (charging/discharging). In general, LIBs can operate under cold conditions up to $-20\text{ }^{\circ}\text{C}$ and hot conditions up to $60\text{ }^{\circ}\text{C}$. However, a more restrictive operating temperature ranging from $20\text{ }^{\circ}\text{C}$ to $40\text{ }^{\circ}\text{C}$ is required to maintain the safety and performance of LIBs [103]. The temperature of LIB can exceed the aforementioned limits owing to external conditions, such as ambient temperature, and internal factors, namely, irreversible and reversible heat generation during charging and discharging. Irreversible heat generation is primarily due to Joule heating in the intrinsic internal resistance of battery components and possible parasitic reactions, whereas reversible heat generation is associated with redox reactions upon cycling [7,104–106]. This increase in temperature can lead to the degradation of capacity and an increase in internal resistance, which negatively affects the performance of LIB. This could also lead to more serious issues, such as thermal runaway and catching fire in batteries [107–109]. Therefore, electric vehicles are equipped with Battery thermal management systems (BTMSs) to mitigate the temperature increases in their LIBs.

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BTMSs are usually active air-based or liquid-based systems. While driving, most BTMSs maintain the battery temperature within an acceptable range. However, during parking, the batteries are exposed to a wider temperature range because the BTMS is inactive most of the time.

In harsh environments, such as Saudi Arabia, the outdoor temperature can reach 50 °C in summer. Additionally, the cabin temperature of a car can exceed 65°C under clear-sky conditions during the daytime [110]. Therefore, the implementation of EVs in hot countries requires the proper design of a thermal management system that can operate passively to mitigate the elevation and variation in ambient temperatures. To address the gap in understanding the impact of dynamic temperature variation on non-operating lithium-ion batteries (LIBs) and their lifespan, this study delves into investigating the effects of various realistic conditions akin to a vehicle's battery during parking. By exploring the dynamic calendar aging of commercial lithium-ion batteries (NRC18650B), this research uniquely contributes novel insights into the nuanced performance parameters affected under realistic conditions, providing a comprehensive understanding of LIB behavior in real-world scenarios. Thus, the present study aims to investigate the effect of dynamic temperature variations on the state of charge, state of health, internal resistance, and energy and coulombic efficiencies of LIBs. The process of calendar aging was conducted in Dhahran, Saudi Arabia, over a period of 60 days during the summer season, aiming to replicate the most extreme temperature conditions and thereby simulate a worst-case scenario.

3.2. Methodology:

3.2.1. Calendar Aging:

Calendar aging investigations were conducted on 27 commercial lithium-ion cells with a cylindrical shape-type NCR18650B. The cathodes of these cells were composed of lithium nickel cobalt aluminum oxide (LiNiCoAlO_2), whereas the anodes were composed of graphite. Electrochemical measurements, including constant current-constant voltage (CC-CV) cycling, were performed using a battery testing system (CT- 4008T, Neware) with eight channels and parameters of 5 V and 12 A, as shown in **Figure 3.1 (a)**. First, three CC-CV cycles were performed for each cell before calendar aging. The cells were charged with a

constant current at a charge rate of 1C (2.7 A) up to 4.2 V. Then, and the voltage was held at 4.2 V until the current reached the cutoff point (65 mA), followed by a pause for 10 min. Subsequently, a constant current was applied at a rate of 0.5C until the voltage reached 2.75 V, as recommended in several studies [87]. Similar to the charging process, the cut-off current and pause time at the end of the discharging process were 65 mA and 10 min, respectively. **Table 3.1** lists the steps for the CC-CV cycle considered in this study.

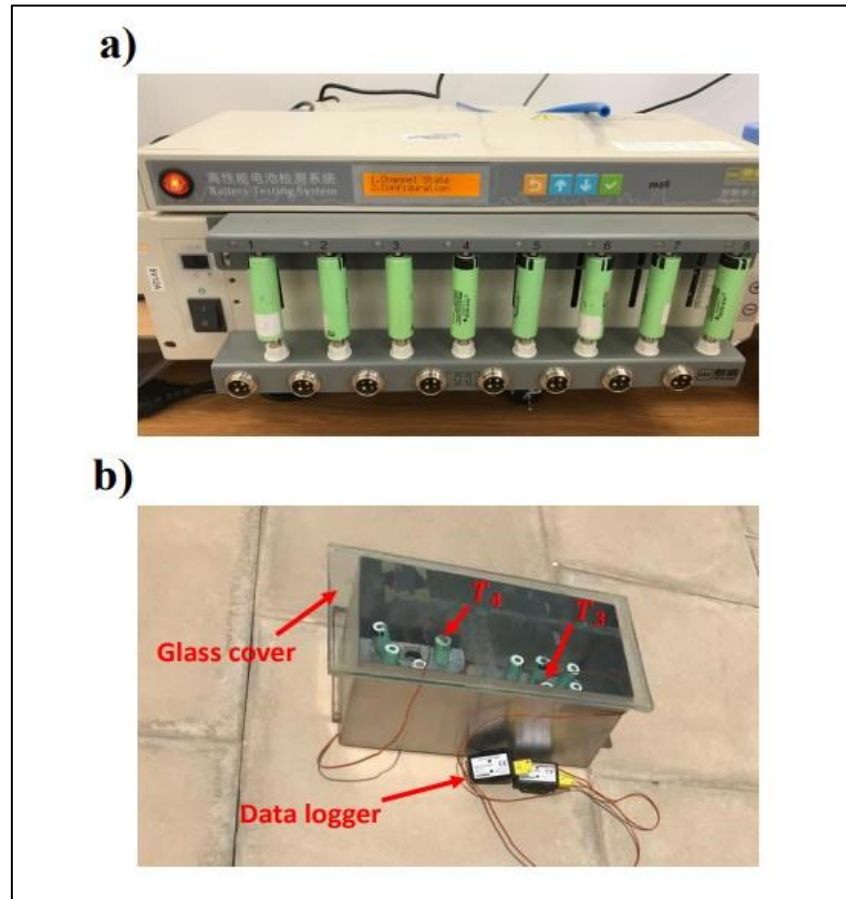


Figure 3. 1. (a) Battery testing system (CT-4008T, Neware) with 8 channels and a parameter of 5 V and 12 A. (b) 9 cells (G7, G8, and G9) placed in a glass-covered box exposed to sunlight

Table 3. 1: CC-CV cycling steps.

Step	Process
1	CC charging at 1C up to 4.2 V
2	CV charging until $I = 65 \text{ mA}$
3	Pause for 10 minutes
4	CC discharging at 0.5C up to 2.75 V

- 5 CV discharging until $I = 65 \text{ mA}$
 - 6 Pause for 10 minutes
-

Finally, after 60 days of calendar aging for each cell, another three CC-CV cycles were performed. The performance parameters of the cells were obtained from the third cycle of CC-CV cycling before and after calendar aging. The results showed that all the cells had almost the same capacity (2700 mAh) with minor differences ($\pm 50 \text{ mAh}$). **Table 3.2** summarizes the cell-test parameters.

Table 3. 2: Test parameters of the cells.

Parameter	Value	Unit
Capacity	2700	mAh
End of discharge voltage	2.75	V
End of charge voltage	4.2	V
Cutt-off Current	65	mA

Calendar aging was performed to investigate the effects of the initial SoC and storage temperature on the cell performance parameters. The cells were divided into nine groups according to their initial SoC and storage conditions. To ensure consistency of the measured data, each group consisted of three cells [75,111]. First, the cells were aged under three realistic conditions: (i) at a controlled laboratory temperature (21°C) as a baseline for comparison, (ii) in a box under outdoor atmospheric conditions but in a shaded area, and (iii) in outdoor atmospheric conditions but in an aluminum box covered with a glass plate exposed to direct sunlight. The third storage condition was selected to simulate the storage conditions of the battery packs of the electric vehicles during parking when solar radiation passes through the EV glazing and accumulates heat inside the vehicle (greenhouse effect). Therefore, this condition simulates the worst-case scenario for EV's batteries in which thermal management does not work during parking. In order to mitigate the influence of environmental factors such as humidity and wind, the cells subjected to outdoor testing, conducted under conditions closely resembling real-world scenarios, were enclosed within protective enclosures. Finally, three groups of cells with SoC of 50, 75, and 100%

were placed under each storage condition. **Table 3.3** lists the storage conditions and SoC for each cell group.

Table 3. 3: SoC and storage conditions of each group.

SoC	Storage Condition		
	Inside the Lab	Outdoor and shaded	Outdoor exposed to sunlight
50%	G1	G4	G7
75%	G2	G5	G8
100%	G3	G6	G9

After the preconditioning and initial testing mentioned above, all the cells were charged with a 1C rate to the desired SoC and stored according to the storage conditions listed in **Table 3.3**. The cells' voltage was measured periodically to check the voltage drop for each cell under the storage conditions.

3.2.2. Temperature Measurements:

Temperature was measured using four K-type thermocouples connected to four data loggers (OM-CP-TC101A, OMEGA). Data loggers can operate in harsh environmental temperatures ranging from -40°C to 80°C . Thermocouples were installed to measure the temperature at four locations: the ambient temperature outside, the temperature inside the shaded box, and the temperature inside the glass-covered box. To understand the delay in the temperature between the center of the cell and its surroundings, the fourth was inserted inside a cell similar to the cell tested above. The cells were then placed in a glass-covered box. Figure 1b shows the glass-covered box setup with the tested cells (G7, G8, and G9). It also shows the fourth thermocouple placed inside the extra cell. Data loggers were set to record the temperature at the four positions every two minutes for 60 days of aging.

3.2.3. Internal Resistance (R_i):

The internal resistance R_i of a battery is an essential parameter for evaluating irreversible and reversible capacity losses. Therefore, during the discharging process, the internal resistance (R_i) was measured at a laboratory-controlled temperature (approximately 21°C) using the voltage drop in the battery, as [75]:

$$R_i = \frac{V_1 - V_0}{I} \quad (3.1)$$

where I is the current applied during discharging (-0.5C), V_0 is the maximum voltage (i.e., 4.2 V) and V_1 is the potential drop of the current pulse after time $t = 10$ ms [112].

3.2.4. Coulombic & Energy Efficiency:

The Coulombic efficiency (CE) has been widely used to describe the performance of LIBs. The concept of Coulombic efficiency refers to the ratio of the discharge capacity C_d after full charge to the charge capacity C_c of the same cycle. The Coulombic efficiency can be calculated using the following **Equation (3.2)** [113]:

$$CE = \frac{C_d}{C_c} \quad (3.2)$$

Because the Coulombic efficiency is usually higher than 99%, the energy efficiency (EE) is also used to gain more insight into LIB performance. The EE is always less than 1 because of the decomposition of the electrolyte, battery material, storage temperature, and charge/discharge rates [114]. It is defined as the ratio of the discharged to charged energy. As LIBs do not deliver 100% of their total charging energy, these losses are converted into thermal energy losses. Energy efficiency is given by the following **Equation (3.3)** [115]:

$$EE = \frac{\int_0^{t_d} V_d I_d dt}{\int_0^{t_c} V_c I_c dt} \quad (3.3)$$

where V_d is the discharge voltage, V_c is the charge voltage, I_d is the discharge current, I_c is the charge current, t_d is the discharge time and t_c is the charging time.

3.2.5. State of Health (SoH):

The state of health of batteries refers to the loss of irreversible capacity with the aging of the cell. The state of health of a battery is a measurement that shows the extent of its deterioration and remaining capacity. This is simply the difference between the health of a battery when it is brand-new and when it is used. As batteries age, they lose their ability to store energy and deliver specific amounts of power. For safety concerns, it is essential to include the state of health as a key indicator for evaluating battery aging status. The battery should be removed from

the energy storage system and electric vehicles once the health indicator reaches a predetermined limit. The SoH can be determined using **Equation (3.4)** [116]:

$$SoH = \frac{Q_{Current}}{Q_{Fresh}} \quad (3.4)$$

where $Q_{current}$ and Q_{Fresh} are the cell capacities after and before aging, respectively.

3.3. Results & Discussion:

3.3.1. Temperature Measurements:

After 60 days under different battery storage conditions, the main performance parameters of the tested cells were compared with the initial state of the batteries. **Figure 3.2** shows the dynamic temperature variations during the storage period for the shaded outdoor box and outdoor box exposed to sunlight and covered with a glass plate. In addition, the outdoor ambient temperature was measured by placing a thermocouple in a shaded area 1.5 m above the ground. The solid lines represent the average daily temperatures, whereas the bands represent the highest and lowest daily temperatures for each condition during the aging period.

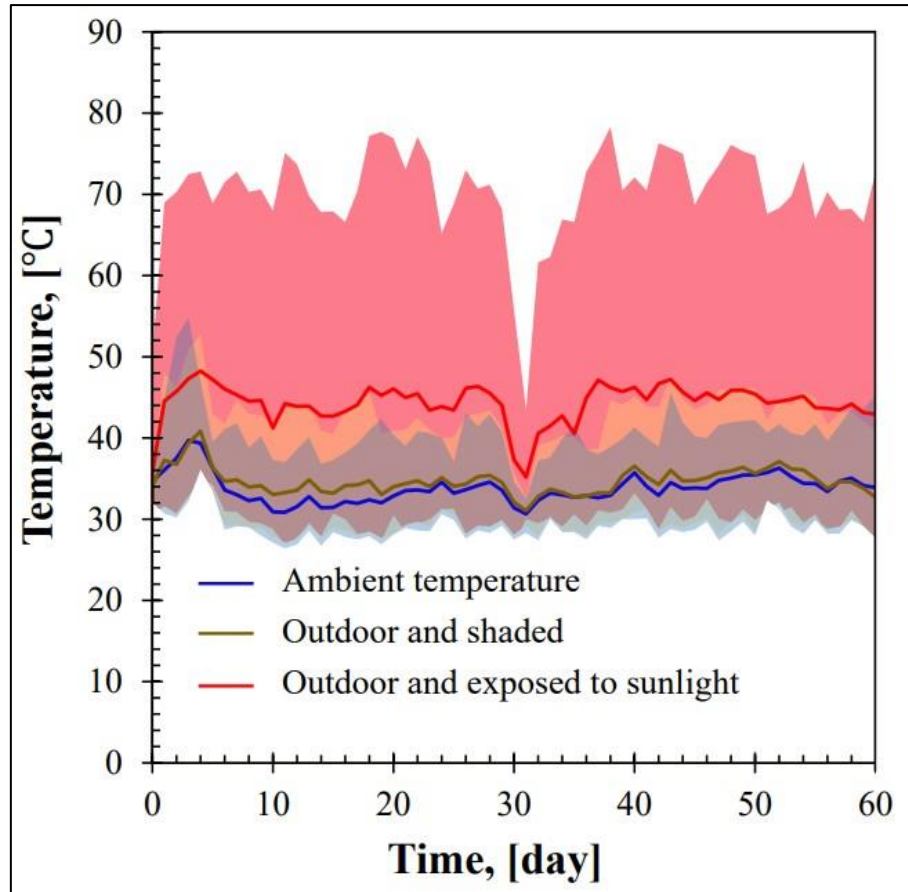


Figure 3. 2. The dynamic temperature variations during the storage period for the atmospheric temperature, inside the shaded box, and inside the box that exposed to sunlight and covered with a glass.

Figure 3.2 demonstrates that during the testing period, the measured ambient temperature increased to a maximum of 48 °C for a brief period. Furthermore, because Dhahran, Saudi Arabia, experiences high levels of solar radiation during the summer, the temperature inside the outdoor glass-covered box can reach a maximum of 80 °C. The temperature changes inside the outdoor shaded box were mostly similar to the variations in the ambient temperature. Although the ambient temperature barely reaches 50 °C, the temperature inside the glass-covered box, which mimics the worst-case scenario for an EV's cabin, can experience significant variations, that is 80 °C during the daytime and 30 °C during night. These relatively large temperature variations should be mitigated by using appropriate thermal management systems.

3.3.2. Self-discharge:

Battery self-discharge refers to the reversible reduction in the stored energy of a battery during the storage period or during the discharge process. A few factors are responsible for this energy loss, which are SoC and storage temperature conditions. **Figure 3.3** shows the potential drop during calendar aging under the three storage conditions for the initial SoCs (1) 50%, (2) 75%, and (3) 100%. The reported values are the mean values of the SoC obtained for the three cells of each group, and the error bars correspond to two standard deviations or 95% confidence intervals. Solid lines connecting the data points were plotted to guide the eyes. Cells stored under the same conditions exhibited the same behavior. First, all cells exhibited a fairly linear evaluation during the 60 days, except for the first five days. However, this initial decrease is typical for LIBs because of the internal resistance and charge characteristics of the cell.

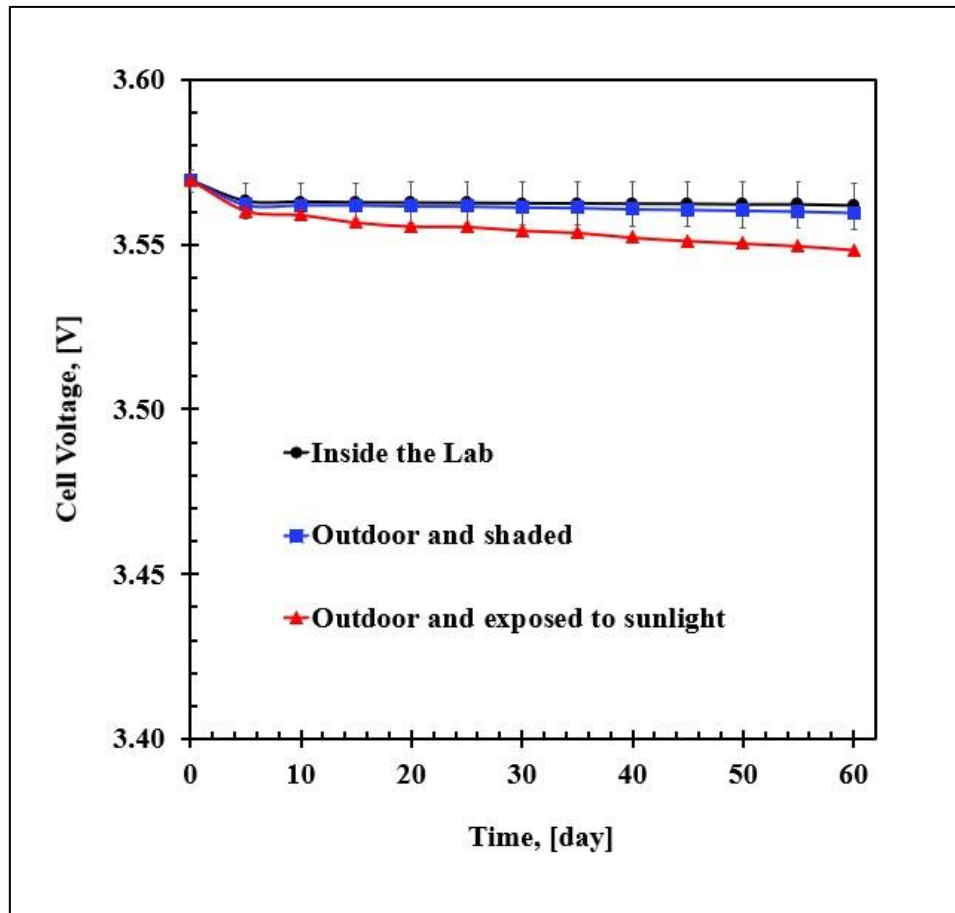


Figure 3.3. 1. The potential drop during the calendar aging under the three storage conditions for initial SoC of 50%.

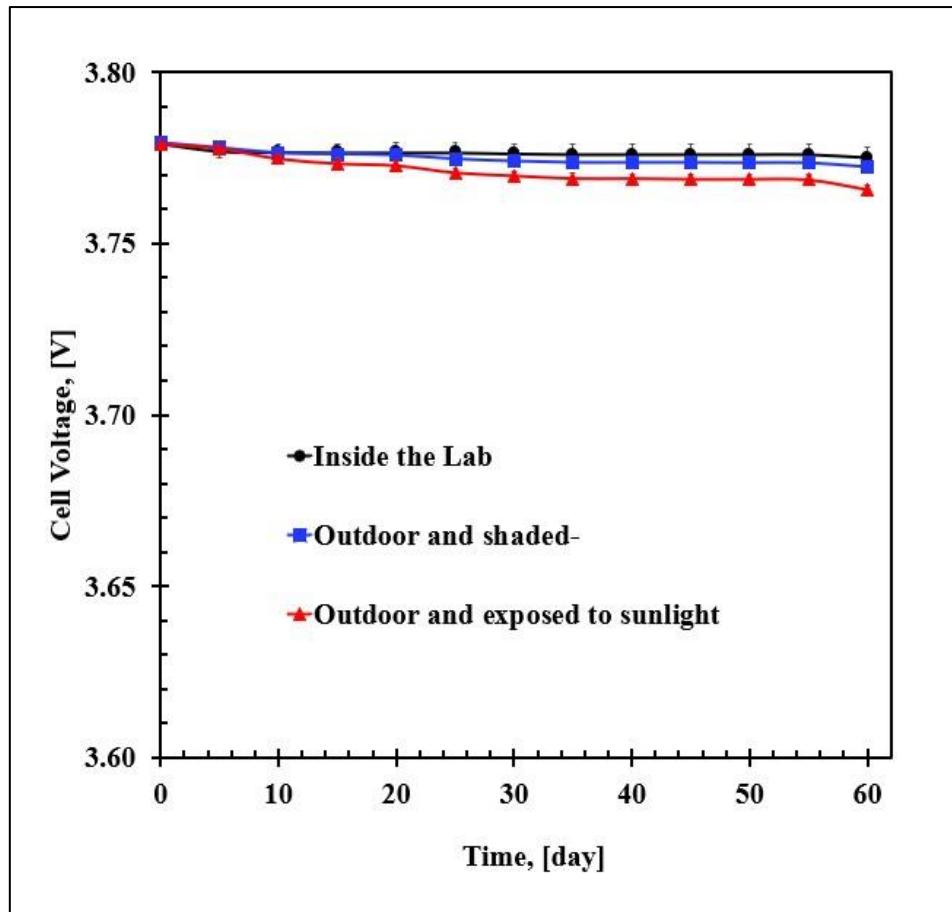


Figure 3.3. 2. The potential drop during the calendar aging under the three storage conditions for initial SoC of 75%.

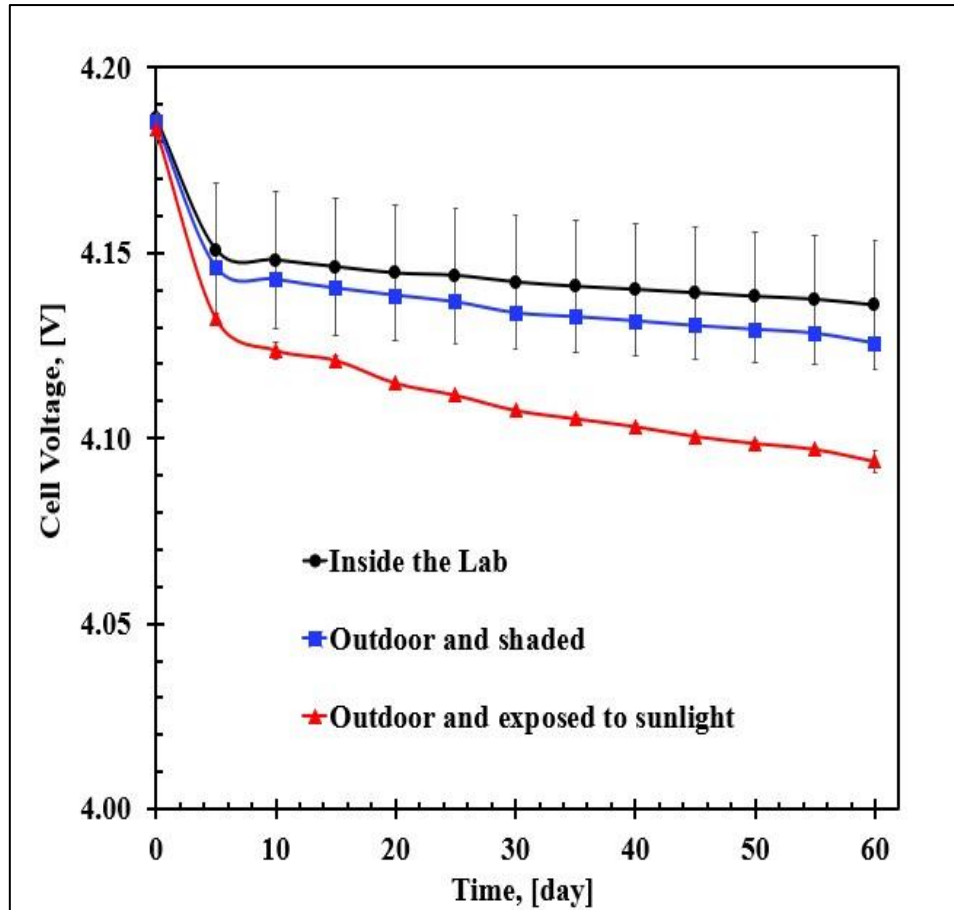


Figure 3.3. 3. The potential drop during the calendar aging under the three storage conditions for initial SoC of 100%.

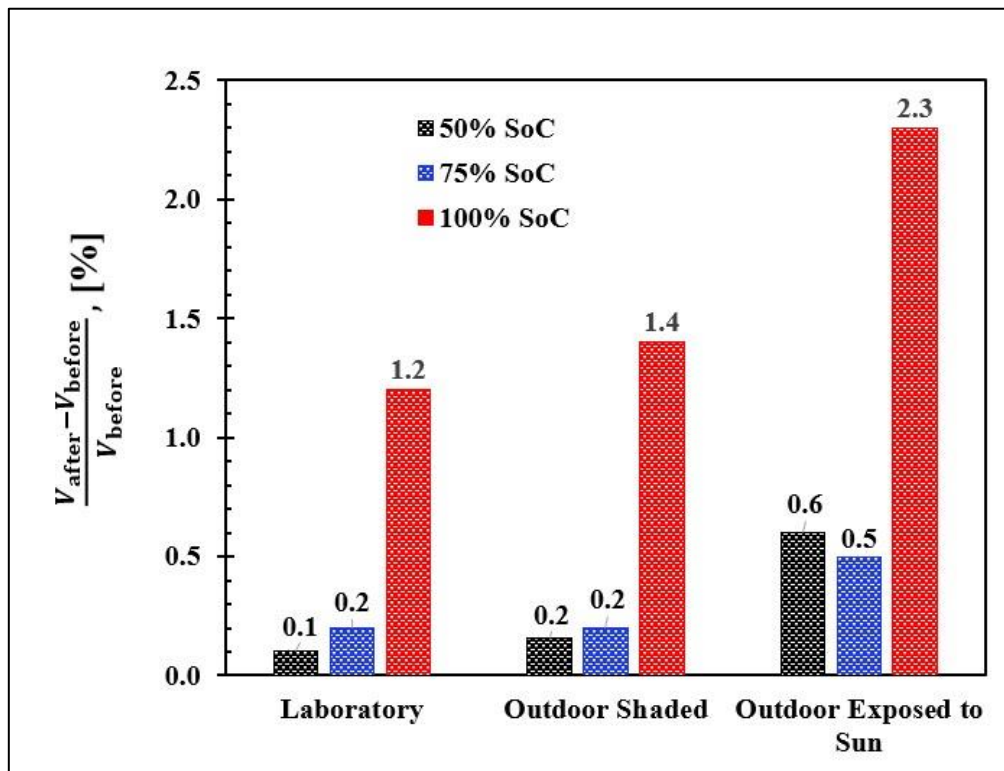


Figure 3.3. 4. Voltage drop percentage for all conditions.

Secondly, these results indicate that the storage temperature strongly influences the battery voltage capacity. Comparing the batteries at 100% SoC under the three storage conditions, it can be seen that the cells in the G9 condition showed a significant decrease in voltage capacity by almost 2.2%, whereas the other cells under shade and laboratory conditions showed approximately 1.4% and 1.2% drops, respectively. To understand the impact of the SoC on self-discharge, a comparison was conducted among the batteries in the laboratory conditions because the temperature is constant during the storage period. For SoC of 50, 75, and 100%, the voltage drops were 0.1, 0.2, and 1.2%, respectively. The same trend was observed in the outdoor and shaded groups. Evidently, the SoC has an insignificant effect on self-discharge unless the battery is fully charged (SoC = 100%). In addition, the influence of the SoC increased with increasing storage temperature. In this situation, the high temperature and charge level of the battery increase the parasitic chemical reactions inside the battery, leading to capacity loss. Finally, it can be concluded that the self-discharge becomes significant under extreme storage conditions, that is, an SoC of 100% and a temperature above 50 °C.

3.3.3. State of Health (SoH):

Figure 3.4 shows the SoH for the tested cells after 60 days of aging under different operating conditions: (i) SoC = 50%, (ii) SoC = 75%, and (iii) SoC = 100%. The results show that temperature significantly impacts the SoH of the batteries. For G9, the SoH decreased by 6% from the beginning of its life capacity.

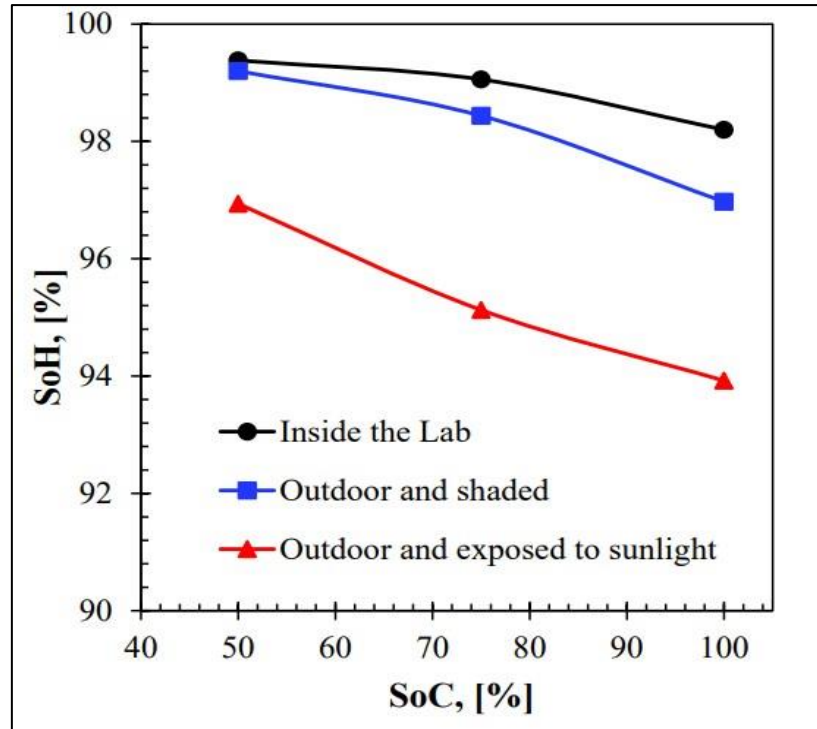


Figure 3. 4. State of health for the tested cells after 60 days of aging under different operating conditions for (i) SoC = 50%, (ii) SoC = 75%, and (iii) SoC = 100%.

The increase in the storage temperature led to an increase in the impedance of the batteries. Consequently, the lifetime of the battery is affected, which is a function of the storage temperature, SoC, and number of cycles performed by the cell. The effect of the SoC on the batteries was first investigated under laboratory storage conditions as a baseline. This indicates that the SoC has a slight impact on the SoH of the batteries tested under laboratory conditions. The variation in the SoH under this condition did not exceed 1%. Nevertheless, SoH began to decrease rapidly as the temperature increased. These two factors interact with each other, causing significant battery degradation. At higher temperatures, the solid-electrolyte interface (SEI) of the battery rapidly deteriorates, causing an increase in the electrochemical reaction in the battery. This electrochemical reaction leads to an increase in the resistance inside the cell. Hence, a more irreversible energy loss occurs [117]. Because the maximum decrease in the SoH was approximately 6%, the performance of the batteries did not show a large variation compared to the initial condition. However, it is recommended to avoid a further decrease in the SoH to prevent SEI deterioration of the cells in the long term, which could also be enhanced by fast charging/discharging [118].

3.3.4. Internal Resistance (R_i):

Figure 3.5 shows the increase in the internal resistance $(R_{i,after} - R_{i,before})/R_{i,before}$ as a function of the SoC at different storage temperatures. The internal resistance is calculated using **Equation (3.1)**. The results showed that the storage temperature of the batteries significantly influenced the internal resistance. For (G7- G9), outdoors and exposed to sunlight, the cells showed an increase in internal resistance from (4.5% to 6.5%). It can be concluded that a decrease in the SoH of the batteries is accompanied by an increase in the internal resistance of the cell.

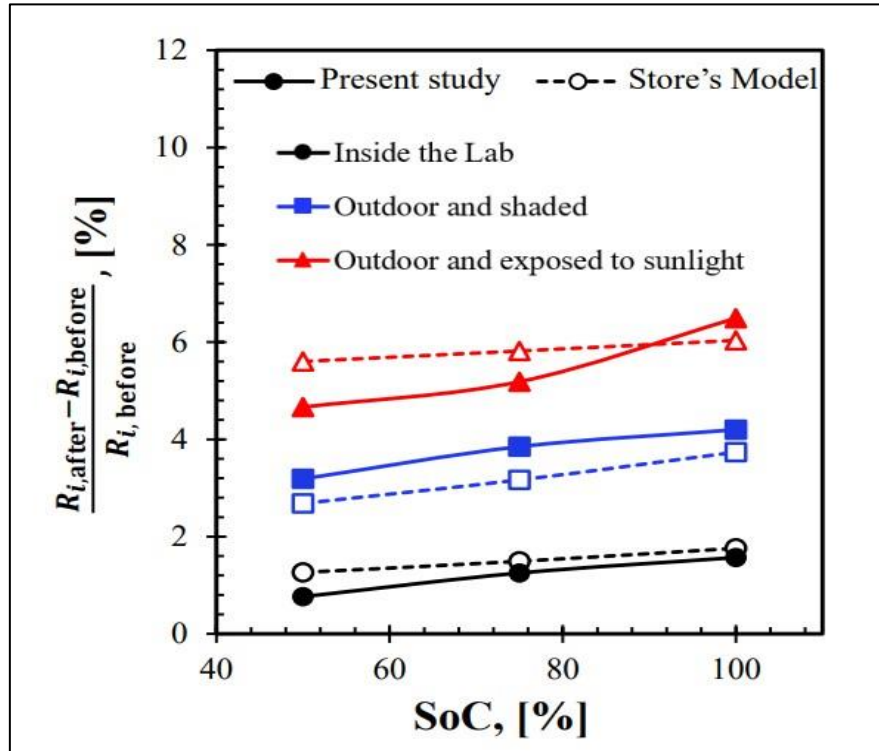


Figure 3. 5. The increase in the internal resistance $(R_{i,after} - R_{i,before})/R_{i,before}$ as a function of SoC at different storage temperatures compared with Stroe's model.

Furthermore, the increase in internal resistance can be estimated using the Stroe et al. model [85]. This empirical model correlates the increase in internal resistance with the SoC, storage temperature, and storage time as follows:

$$R_{i,increase}(t, T, SoC) = (a \times 10^{-8} \times e^{b \times T})(c \times e^{d \times SoC})(t^e) \quad (3.5)$$

where t is the storage time in months, T is the storage temperature, and SoC is the state of charge of the battery; the values of a , b , c , d and e are tabulated in **Table 3.4**.

Table 3. 4: Constants values of Equation (3.5).

Parameter	Value
a	6.9656
b	0.05022
c	2.897
d	0.006614
e	0.8

Figure 3.5 shows a comparison between the present experiment and Stroe's model. The average temperature during the storage period was used in this model. Although the model is for a constant storage temperature, it shows almost the exact behavior of the internal resistance of the cells under a dynamic storage temperature.

3.3.5. Coulombic & Energy Efficiency:

Figures 3.6 (a) shows the coulombic efficiency (CE) as a function of SoC under different storage conditions. As expected, in all the cases, the initial CE was approximately 100%. It also shows a slight decrease compared with the initial state for all SoCs and storage temperature conditions considered. **Figures 3.6 (b)** shows the changes in CE during the aging period as a function of SoC. The maximum change was approximately 2% for the storage conditions of G9 (outdoor and sunlight exposure with an initial SoC of 100%). This drop in the CE can be attributed to the degradation of battery components owing to parasitic reactions that occur at elevated temperatures [113].

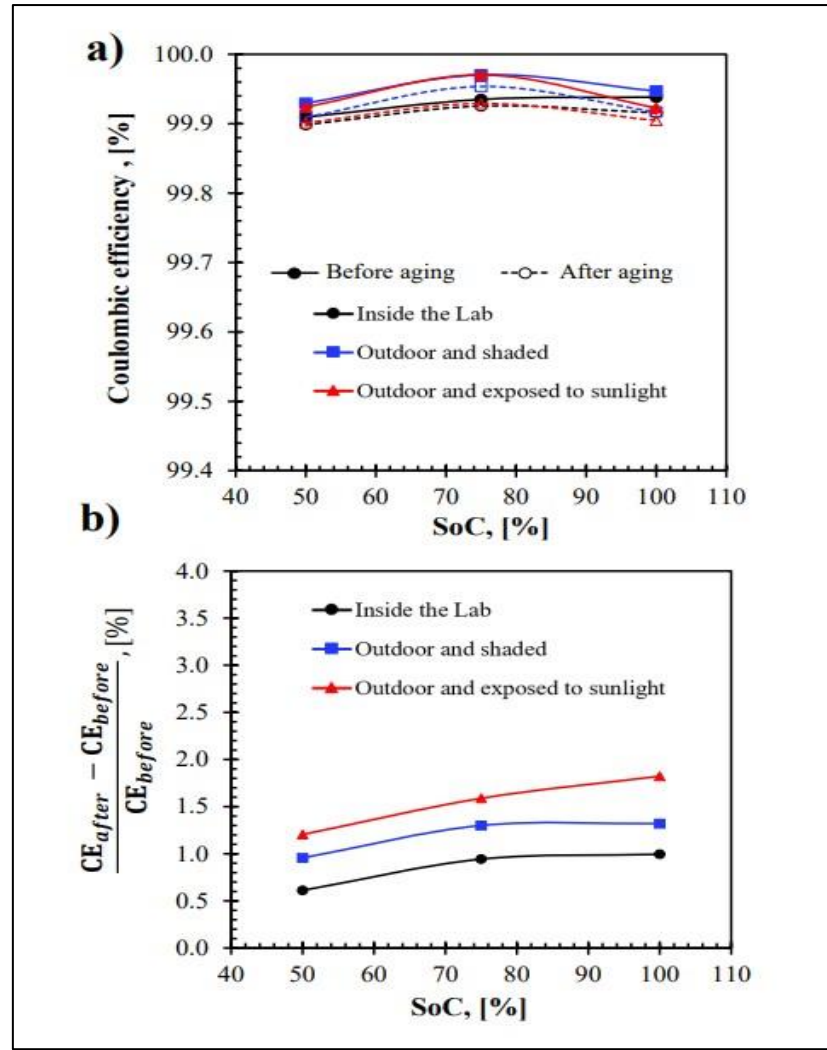


Figure 3. 6. a) Coulombic efficiency (CE) as a function of the SoC at different storage conditions. b) The change in CE over the aging period as a function of the SoC.

Figure 3.7 (a) shows the energy efficiency of the batteries at the beginning of their life and after the aging period. The greatest change occurred in G9 cells, where the difference between the initial state and the end of aging state was the highest among the other storage conditions. Although an increase in storage temperature affects the energy efficiency of LIBs, the percentage change is considerably small. Therefore, extending the aging period would help further predict the impact of the storage temperature of LIBs if the energy efficiency does not show a greater drop over a longer period. **Figure 3.7 (b)** shows the energy efficiency as a function of SoC under different storage temperature conditions. The energy efficiencies of almost all the cells tested showed the same behavior as that of the change in energy efficiency. The maximum drop in energy efficiency

was less than 2% compared with the initial test state. The maximum decrease occurred in cells stored in G9 where the maximum temperature change occurred. However, at a SoC of 50%, the storage temperature had an insignificant effect on the energy efficiency.

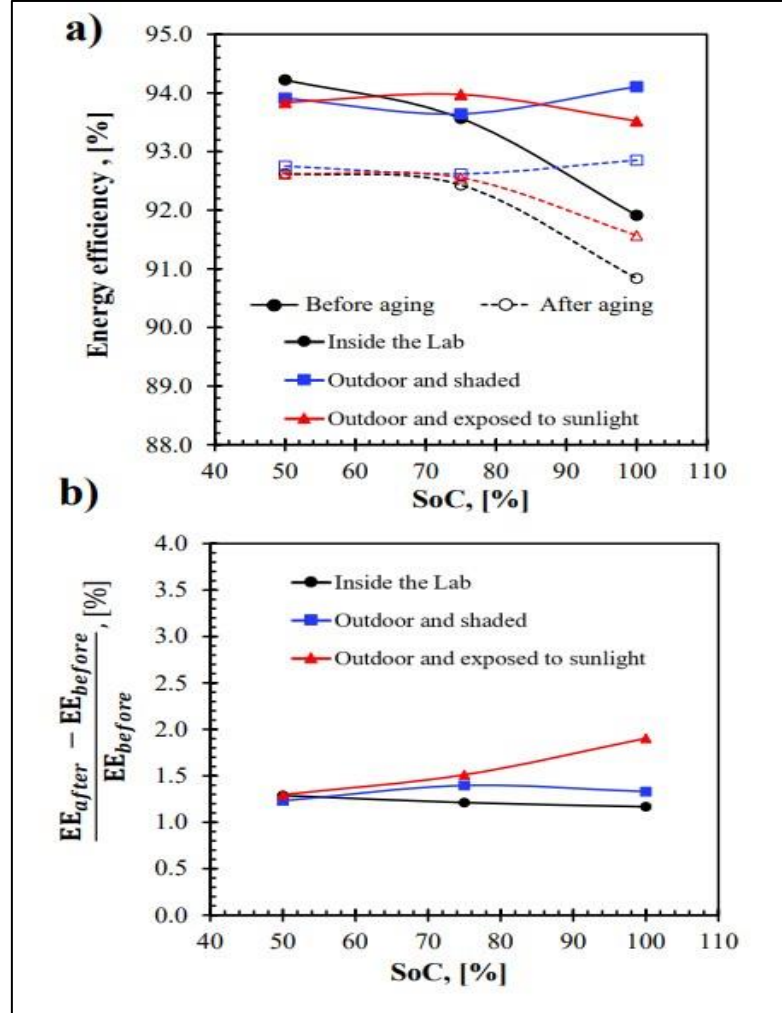


Figure 3. 7. a) Energy efficiency (EE) as a function of the SoC at different storage conditions. b) The change in EE during the aging period as a function of the SoC.

3.3.6. Heat Transfer Time Lag:

Figure 3.8 shows the three-day temperature variation at three locations: (i) the ambient temperature, (ii) inside a glass-covered box exposed to direct sunlight, and (iii) inside a battery cell placed inside the glass-covered box. It was observed that as the temperature increased inside the glass box owing to radiation, more heat was transferred to the battery core. However, the temperature inside the box increased faster than that inside the battery, particularly during the day, when the radiation reached its maximum value. In addition, there is a delay between the box

temperature and the battery core owing to the low thermal conductivity of the battery components. After the radiation peak, the box temperature started to decrease, and because of the lag in the temperature between the battery core and box, the maximum battery core temperature was always less than that of the box. It can be concluded that the temperature rise and decrease in the tested battery follow almost the same behavior as that of the box, with a delay of approximately 4 h and a lower maximum temperature. Thus, proper cooling of the cells is required to increase the heat loss from the battery, and free convection is not recommended under these circumstances. Furthermore, the cells were in an open-circuit condition; hence, the temperature of the cells could be further increased during the charging and discharging cycles, which may lead to rapid thermal runaway, and failure in the system may occur.

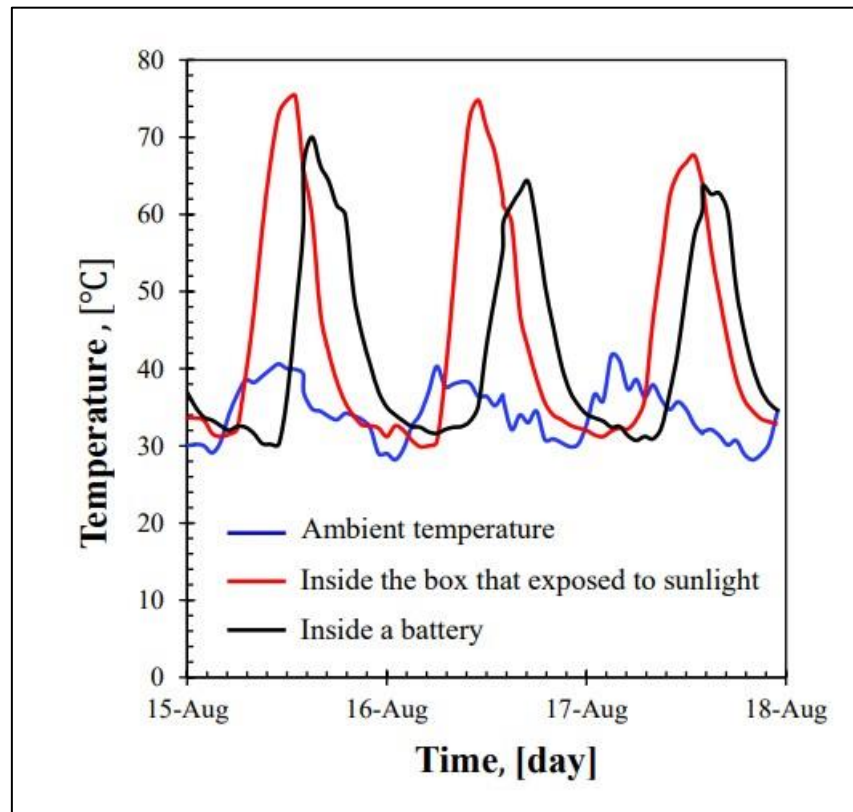


Figure 3. 8. Temperature lag between the glass box, ambient temperature and the temperature inside the battery.

3.4. Conclusion:

This study examined the effects of storage temperature and state of charge on the calendar aging of cylindrical lithium-ion cells. The 27 cells were stored under three different conditions at various SoC levels and open-circuit conditions for 60 days. The voltage capacity of the cells was monitored periodically to assess the potential degradation. The results show that the storage temperature has a significant impact on the degradation rate, with SoC having a secondary effect that increases with higher temperatures. The cells that experienced the highest capacity loss within 60 days were fully charged cells stored outdoors and exposed to sunlight, whereas the minimum capacity loss occurred at 50% SoC under laboratory conditions. The internal resistance of the cells increased significantly when stored in a glass-covered box exposed to sunlight, whereas the impact of the SoC on the internal resistance was less than 2% under the same storage conditions. An empirical model by Stroe et al. [85] was used to predict the increase in the internal resistance, which showed good agreement with the experimental measurements under static storage temperatures and minor errors under dynamic storage temperatures. Under higher storage temperature conditions, the state of health (SoH) of the cells decreased by 6% compared to the initial tested state, particularly in fully charged cells stored outdoors and exposed to sunlight. The results indicated that the increase in the internal resistance and SoH of the cells were interdependent, as both are indicators of cell component degradation.

Further research is needed to develop an effective thermal management system, which can be either passive or hybrid, to minimize the use of stored energy to run the cooling system while the battery system is in parking mode. This system should be able to prevent or delay the temperature rise by absorbing the heat accumulated within the car's cabin during the day and then releasing it during the night or using other heat rejection technology. Additionally, developing novel thermal interface materials with enhanced thermal conductivity and durability, such as advanced phase-change materials, nanocomposites, and liquid metals, can significantly improve heat dissipation within battery packs.

CHAPTER 4:

NUMERICAL INVESTIGATION OF AIR COOLING BATTERY THERMAL MANAGEMENT SYSTEM IN A CONVERGEND AND CONFINED CHANNEL

4.1. Introduction:

The increase in energy demand and supply worldwide in recent years is the main reason for the increase in greenhouse gas emissions, which causes global warming and creates many environmental issues [1,119–121]. The transportation sector has the highest reliance on fossil fuels and was responsible for 37% of CO₂ emissions in 2021 [122]. As a result, the interest in electrical vehicles (EVs) has substantial significance in reducing the GHG emissions involved within the transportation sector and are more energy efficient and environmentally friendly than conventional ICE vehicles [123–125]. The lithium-ion battery (LIB) is considered the keystone and the promising energy storage technology to increase the reliance on EVs rather than conventional vehicles. LIB has superiority over many other energy storage systems. It is characterized by its high energy density, no memory effect, long cycling life, and low self-discharge rates [126]. LIBs in a pack generate high heat during charging and discharging. The generation of heat inside the pack increases the temperature of the cells and the high operating temperature conditions lead to safety problems, thermal runaway, and electrolyte performance degradation of lithium-ion batteries [127]. Therefore, operating the battery between 20 °C and 50 °C is important to overcome the capacity fade and performance degradation [98,128]. Accordingly, for the battery to function safely and effectively, a good battery thermal management system (BTMS) is required. The Battery Thermal Management System (BTMS) controls and dissipates the heat produced by the electrochemical reactions that take place in cells, enabling the battery to function effectively and safely.

In this work, we perform a numerical study to investigate the interplay of various operating conditions to efficiently remove heat from an array of cylinders placed in a converging and confined channel. The cylinders can be a battery pack, bundle of tubes, or circular fins. In our case, we considered the battery pack as a case study to design an efficient BTMS. The heat transfer rate and pressure drop across the array of batteries are influenced by a complex interplay between several parameters. The flow and heat transport behavior around circular batteries is very analogous to that around bundles of tubes in heat exchangers or flow around

fins in heat sinks. All three systems involve the transfer of heat from a high-temperature region to a lower-temperature region, aiming to maintain high heat transfer rates while keeping the pressure drop across the pack as small as possible. Additionally, they rely on convective heat transfer mechanisms, where the movement of fluid plays a crucial role in carrying away the heat. In the case of cooling batteries, tube bundles, or fins, optimization of the flow velocity, geometry of the flow channel, and surface area is crucial to enhance heat dissipation. Furthermore, these systems often involve minimization of the pressure drop across the pack. Therefore, the similarities lie in the fundamental principles of convective heat transfer mechanisms, and the need to optimize design variables for efficient thermal performance. Studies on these convective heat transfer problems should complement each other.

Additionally, we look at the effect of transverse and longitudinal cell-to-cell distances, fluid flow rate, channel convergence angle, and channel inlet width on the performance of air-cooled BTMS. The primary objective of this study is to investigate the effectiveness of introducing a converging channel to a confined array of batteries in improving the heat removal capability. Two correlations showing the effect of the different parameters on Nusselt number, and the friction factor are presented. This work presents a useful tool for optimizing the heat transfer performance of fluid flow across an array of cylinders, especially in a confined channel.

4.2. Methodology:

4.2.1. Physical Model And Problem Definition:

In this study, a two-dimensional model of a battery pack was performed using a finite volume method. **Figure 4.1** shows the physical model of the confined battery pack inside a converging channel illustrating the important parameters. A total of 16 cells evenly distributed were placed in a staggered arrangement of 4 rows and 4 columns. The diameter of the single cell is denoted as (D). The cell-to-cell distance in the transverse direction (S_T) and in the longitudinal direction (S_L) were varied from 1.1D to 1.5D. In the second and fourth columns downstream the flow direction was shifted by half the transverse distance to form the staggered configuration. The distance between the upstream channel wall and the battery pack boundary (W) was varied between 0.5D and 2D to investigate the confinement effect on the heat removal and pressure drop. The channel has a converging shape in the direction of the flow with a

converging angle (β) that was varied between 0 to $\pi/6$. The fluid flowing across the channel was adjusted to yield a Reynolds number that was defined based on the battery diameter ($Re = VD/\nu$) that was varied between 2,500 to 55,000. The fluid selected in the simulation was air with the following properties ($\rho = 1.225 \text{ kg/m}^3$, $k = 0.0242 \text{ W/m-K}$, $c_p = 1006.43 \text{ J/kg-K}$, and $\mu = 1.7894 \times 10^{-5} \text{ Pa-s}$). The battery walls were assumed to be at a constant temperature that was selected after experimentally investigated of a single battery with a high discharging rate of 4C, see Appendix A. The difference between the battery surface temperature and the cooling fluid is taken to be 40 K.

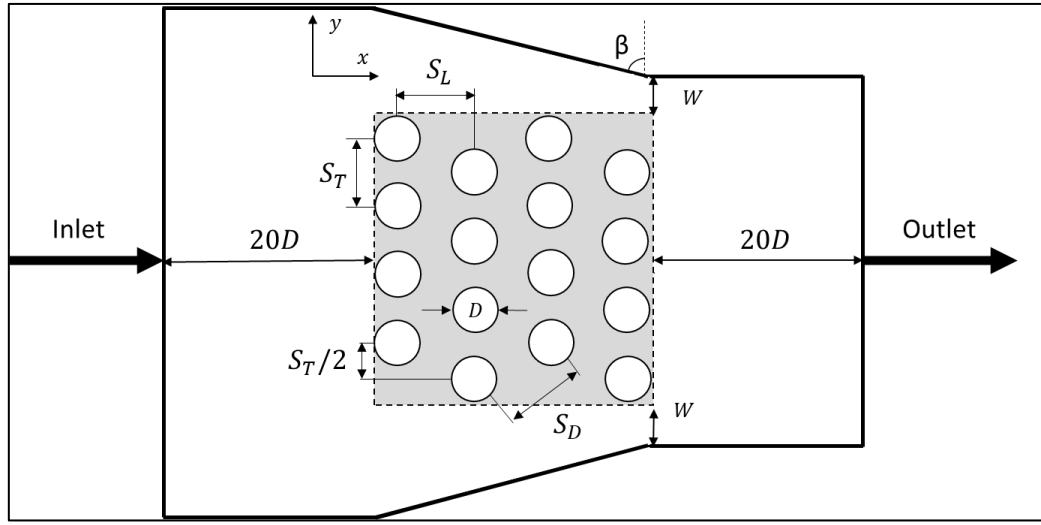


Figure 4. 1. Physical model of the simulated domain illustrating the important geometric variables.

4.2.2. Governing Equations And Boundary Conditions:

To investigate the thermal and fluid fields, a finite volume method approach is utilized to solve the governing conservation equations. Several assumptions are adopted to simplify the numerical model:

1. Thermal radiation and viscous energy dissipation are ignored.
2. The problem is assumed to be steady-state and two-dimensional.
3. Thermophysical properties are taken to be constant.
4. The battery surface is assumed to be at a constant temperature.

The governing conservation equations of mass, momentum, and energy are written respectively as [129]:

$$\nabla \cdot \vec{V} = 0 \quad (4.1)$$

$$\rho (\vec{V} \cdot \nabla) \vec{V} = -\nabla p + \mu \nabla^2 \vec{V} + \rho \vec{g} \quad (4.2)$$

$$(\vec{V} \cdot \nabla) T = \alpha \nabla^2 T \quad (4.3)$$

In addition to the above equations, the transport equations for the standard k- ω model are used to account for the turbulence effect. The transport equations of the turbulence kinetic energy (k) and the specific dissipation rate (ω) are obtained by the following **Equations** [130]:

$$\frac{\partial}{\partial t}(\rho k) + \frac{\partial}{\partial x_i}(\rho k u_i) = \frac{\partial}{\partial x_j} \left(\Gamma_k \frac{\partial k}{\partial x_j} \right) + G_k - Y_k + S_k \quad (4.4)$$

$$\frac{\partial}{\partial t}(\rho \omega) + \frac{\partial}{\partial x_i}(\rho \omega u_i) = \frac{\partial}{\partial x_j} \left(\Gamma_\omega \frac{\partial \omega}{\partial x_j} \right) + G_\omega - Y_\omega + S_\omega \quad (4.5)$$

In these equations, G_k represents the generation of turbulence kinetic energy due to mean velocity gradients. G_ω represents the generation of the specific dissipation rate, whereas Γ_k and Γ_ω represent the effective diffusivity of k and ω , respectively, and Y_k and Y_ω represent the dissipation of k and ω due to turbulence.

The fluid enters the domain in a uniform velocity profile and constant temperature conditions. The turbulence intensity was set to 5% in all simulations while the hydraulic diameter was set to be the smallest dimension within the domain, i.e. a fraction of the battery diameter. The no-slip boundary condition was set to the channel walls and battery surfaces. The only heat transfer was from the battery surfaces to the adjacent fluid enabled by a constant temperature boundary condition at the battery surfaces. Atmospheric pressure was set to the outlet backflow boundary condition.

4.2.3. Dimensional analysis:

In this section, the dimensional analysis for heat transfer and hydrodynamics is obtained using the Buckingham π -theorem to scrutinize the dependence of both heat transfer rate and pressure drop on multiple influential parameters in the context of

heat transfer and hydrodynamics of the battery pack system. This systematic approach entails a comprehensive investigation of the interplay between various dimensional quantities such as transversal distance (S_T), longitudinal distance (S_L), confinement angle (β), battery confinement (W), battery diameter (D), fluid velocity (V), temperature difference (ΔT), and all thermophysical properties. The import and dimensionless groups with their definitions are summarized in **Table 4.1**.

Table 4. 1: Summary of the most important dimensionless groups governing the problem.

Dimensionless Group	Definition	Range of study
Nusselt Number (Nu)	$q''D/k\Delta T$	—
Friction Factor (f)	$2\Delta P/\rho V_{max}^2$	—
Reynolds number (Re)	$V_{max}D/\nu$	2,500–55,000
Prandtl number (Pr)	ν/α	0.707
Transverse Pitch (P_T)	S_T/D	1.1–1.5
Longitudinal Pitch (P_L)	S_L/D	1.1–1.5
Diagonal Pitch (P_D)	S_D/D	$\sqrt{P_L^2 + 0.25 P_T^2}$
Confinement Ratio (ψ)	W/D	0.5–2

The friction factor definition was adopted from a widely used definition in the area of flow across a bundle of tubes [131]. The maximum velocity (V_{max}) is defined for a staggered arrangement as the velocity between the batteries with the following binomial **Equation**.

$$V_{max} = \begin{cases} \frac{P_T}{P_T - 1} V, & P_D \geq 0.5 (P_T + 1) \\ \frac{P_T}{2 (P_D - 1)} V, & P_D < 0.5 (P_T + 1) \end{cases} \quad (4.6)$$

The derived non-dimensional groups serve as a foundation to discern the functional dependencies and correlations between the dependent and independent variables. This will facilitate the formulation of predictive models and a comprehensive understanding of the heat transfer and flow phenomena within the system under diverse operational scenarios.

4.2.4. Comparison of 2D and 3D Simulations:

Numerical analysis using computational fluid dynamics has emerged as a valuable tool to evaluate various systems' performance and optimize their designs. By upgrading the simulation from 2D to 3D simulation, the higher accuracy and precision are achieved in the representation of the system and the physical phenomenon happening in the system. However, 3D models of sophisticated systems require huge computational resources and take a long time to obtain the results. Therefore, in this section, a comparison between 2D and 3D models of a single battery cell is carried out. The objective of this analysis is to demonstrate that both simulation approaches yield similar results, with the intention to select the 2D approach for its simplicity and computational accuracy in this study. The simulation of the two approaches has the same domain where a single cell of 20 mm diameter and for the 3D the height of the cell is 60 mm. The cell is placed in a box with dimensions of 60 mm and 100 mm long for the 2D model and the height of the box is 60 mm for the 3D model. The boundary conditions are set to maintain a constant surface temperature on the surface of the battery cell at 60 °C, and the air is used as the cooling medium with an inlet temperature of 20 °C.

Figure 2 illustrates the velocity and temperature contours for both 2D and 3D simulations (3D simulations at 3 different cross sections at (20, 30, and 40) mm of the cell height). It is observed that the velocity distribution around the battery cell is consistent between the two approaches, indicating that the flow behavior is accurately captured in the 2D simulation. Similarly, the temperature distribution on the surface of the battery cell shows negligible differences between the two approaches, confirming the validity of the 2D simulation for analyzing thermal behavior.

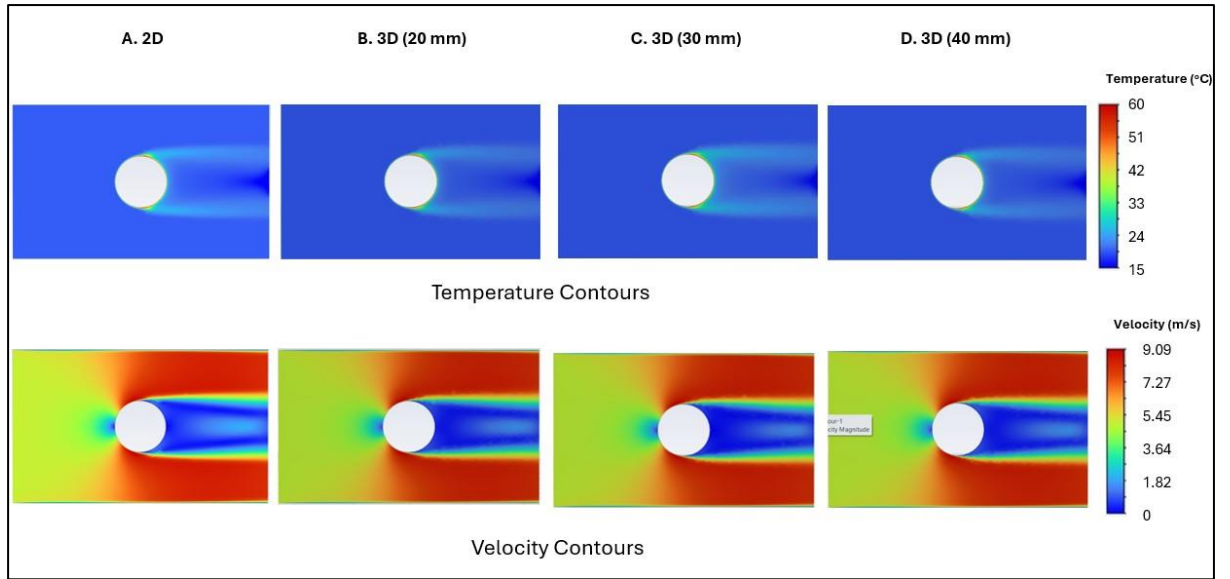


Figure 4. 2. Temperature and velocity contours under **A. 2D**, **B. 3D (20 mm)**, **C. 3D (30 mm)**, and **D. 3D (40 mm)**.

Furthermore, **Figure 3** shows the heat transfer rate [W/m] from the system for both 2D and 3D. The comparison demonstrates that the heat transfer rates are comparable between the two approaches with a maximum deviation of 5.8%, indicating that the 2D simulation accurately predicts the thermal performance of the BTMS.

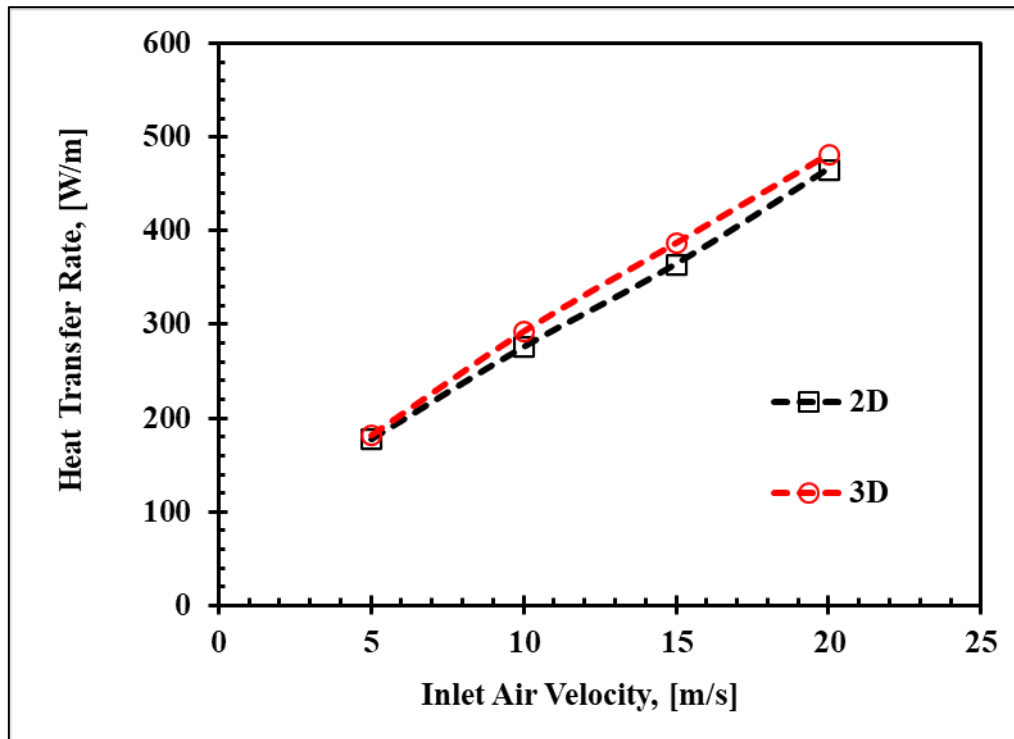


Figure 4. 3. Heat transfer rate under various velocity contours for 2D and 3D simulations.

Based on these findings and considering the computational simplicity of 2D simulations, it is concluded that the 2D approach will be utilized in our study for analyzing BTMS. This decision ensures efficient computational resource utilization without compromising the accuracy of the analysis.

4.2.5. Numerical Methodology:

The numerical analysis for this study was carried out with the ANSYS FLUENT R23.2 software, which used a 2D steady-state technique. The SST $k-\omega$ model was chosen as the turbulence model because of its ability to capture boundary layer phenomena. The wall boundary conditions for the k equation within the $k-\omega$ models are handled in the same way that enhanced wall treatments are used alongside the $k-\omega$ models. As a result, for meshes having wall functions, all boundary conditions will be consistent with the wall-function technique, whereas, for finer meshes, appropriate low-Reynolds-number boundary requirements will be applied. The fluid flow within the converged inlet channel is simulated using Navier-Stokes equations, which take into consideration the complicated interactions between the coolant and the channel walls. We use a turbulence model to account for the turbulent nature of the coolant flow, resulting in more accurate heat transfer predictions. To approximate fluid flow behavior, the numerical solver uses the finite volume method, which discretizes the governing equations. Furthermore, accurate representations of thermal boundary conditions are required for realistic simulations. Hence, convective heat transfer coefficients, thermal conductivities, and heat generation rates from battery cells were considered. This numerical methodology provides a strong basis for simulating the complicated fluid dynamics and heat transfer phenomena in the examined battery cooling system, allowing for an in-depth investigation of the thermal and flow characteristics.

4.2.6. Domain Discretization And Mesh Independent Test:

The solution domain is discretized using a quadrilateral mesh over the entire domain. **Figure 4.4** shows the details of the domain discretization illustrating the near-wall mesh refinement and mesh quality. A total of 10 layers are used near the battery and channel walls ensuring a Y^+ value of less than unity over the entire range of

calculations. A mesh sensitivity test was carried out to obtain a solution with a numerical error of less than 0.1%. The test was conducted using different mesh element sizes. **Figure 4.5** shows the result of the mesh sensitivity test for a selected case study ($S_T = 30$ mm, $S_L = 30$ mm, $V = 5$ m/s, $\psi = 0.5$, and $\beta = 0^\circ$). The results show that the temperature difference between the inlet and outlet of the cooling channel, the heat transfer rate from the battery to the flowing fluid, and the pressure drop across the battery pack are very minimal (Error < 0.1%) with almost 53,000 mesh elements. Consequently, the number of grid elements chosen from the range of calculations is sufficient to provide high-fidelity results with minimal computational cost.

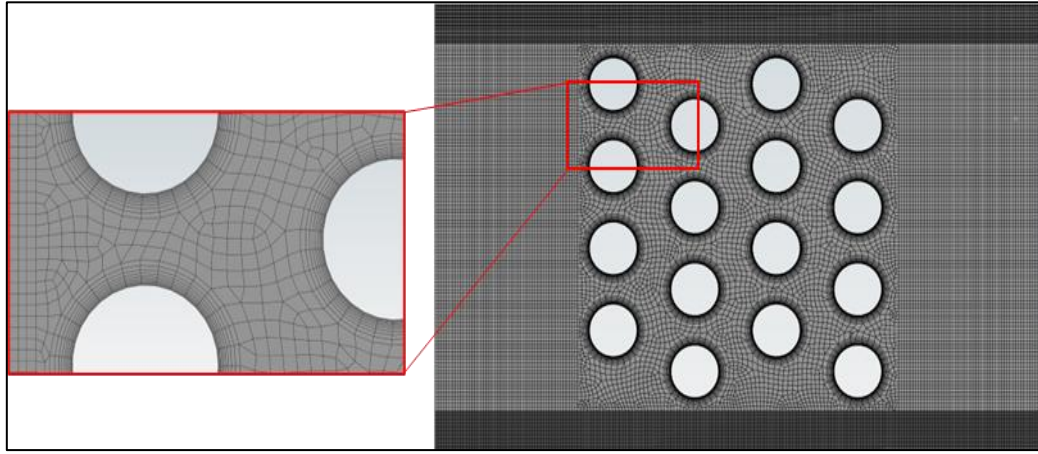


Figure 4.4. Details of the domain discretization illustrating the near-wall mesh refinement and mesh quality.

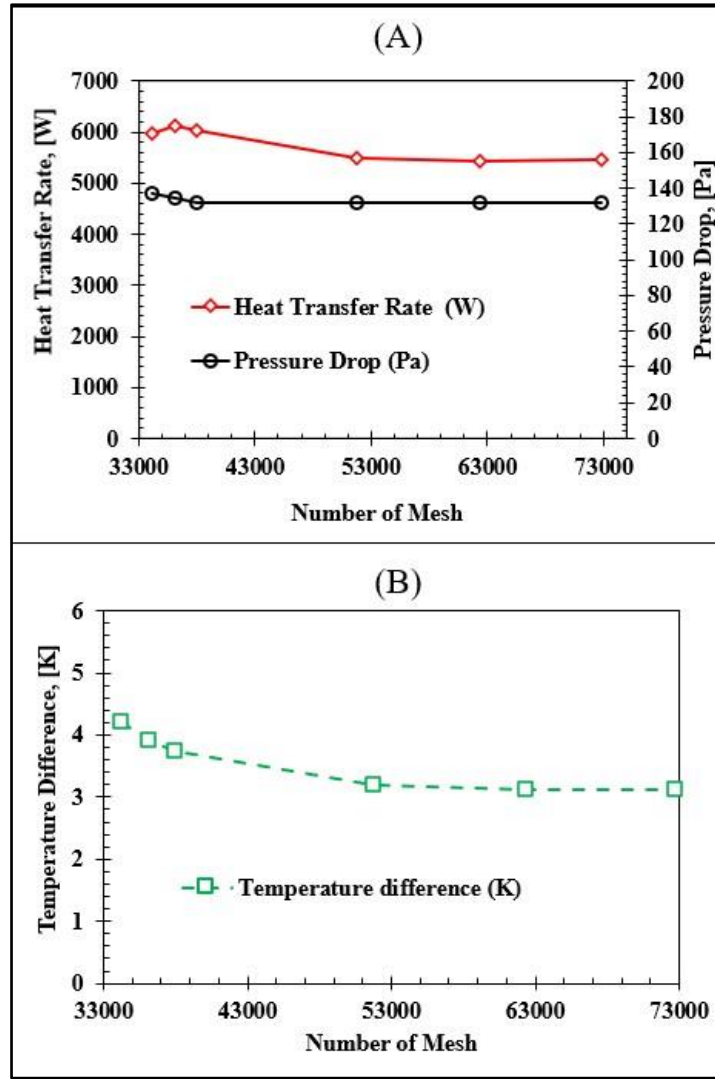


Figure 4.5. Mesh sensitivity test for a selected case of ($S_T = 30$ mm, $S_L = 30$ mm, $V = 5$ m/s, $\psi = 0.5$, and $\beta = 0^\circ$) showing A. the temperature difference between the inlet and outlet of the cooling channel, and B. the heat transfer rate from the battery to the flowing fluid and pressure drop across the battery pack.

4.2.7. Model Validation:

To validate the current model, we compare the results obtained numerically with experimental results obtained for an unconfined bundle of tubes in cross-flow conditions [132]. The empirical correlation obtained by Zukauskas was developed for unconfined channels, therefore, we modified the geometry of the domain to reflect this condition.

$$q' = N \bar{h} D \Delta T_{lm} \quad (4.7)$$

where, q' is the heat transfer rate per unit length, N is the number of cells, $\bar{h}$ is the average heat transfer coefficient, and ΔT_{lm} is the log-mean temperature difference and can be calculated by:

$$\Delta T_{lm} = \frac{(T_s - T_i) - (T_s - T_o)}{\ln \left(\frac{T_s - T_i}{T_s - T_o} \right)} \quad (4.8)$$

$$\Delta P = N_L \chi f \left(\frac{\rho V_{max}^2}{2} \right) \quad (4.9)$$

where, ΔP is the pressure drop across the system, N_L is the number of cells in the longitudinal plane, and χ and f are the correlation factor and friction factor respectively.

The confinement ratio, defined in Table 1, was chosen to be 0.5. A selected case of equal transverse and longitudinal pitches ($P_T=P_L=1.5$) was simulated. A flow of air ($Pr = 0.7$) with a varying mean velocity (2 to 40 m/s) was introduced to ensure the model fidelity at low and high Reynolds numbers. From **Figure 4.6**, it can be seen that the heat removed, and pressure of the batteries calculated by the CFD model are closer to the values obtained by empirical correlations and have roughly the same trends across the entire Reynolds number range. The highest difference between the numerical model and empirical correlation results is about 6% for heat transfer rate and about 15% for pressure drop. This shows that the current model presents a high-fidelity tool to further study the problem of battery pack in a confined and converging channel.

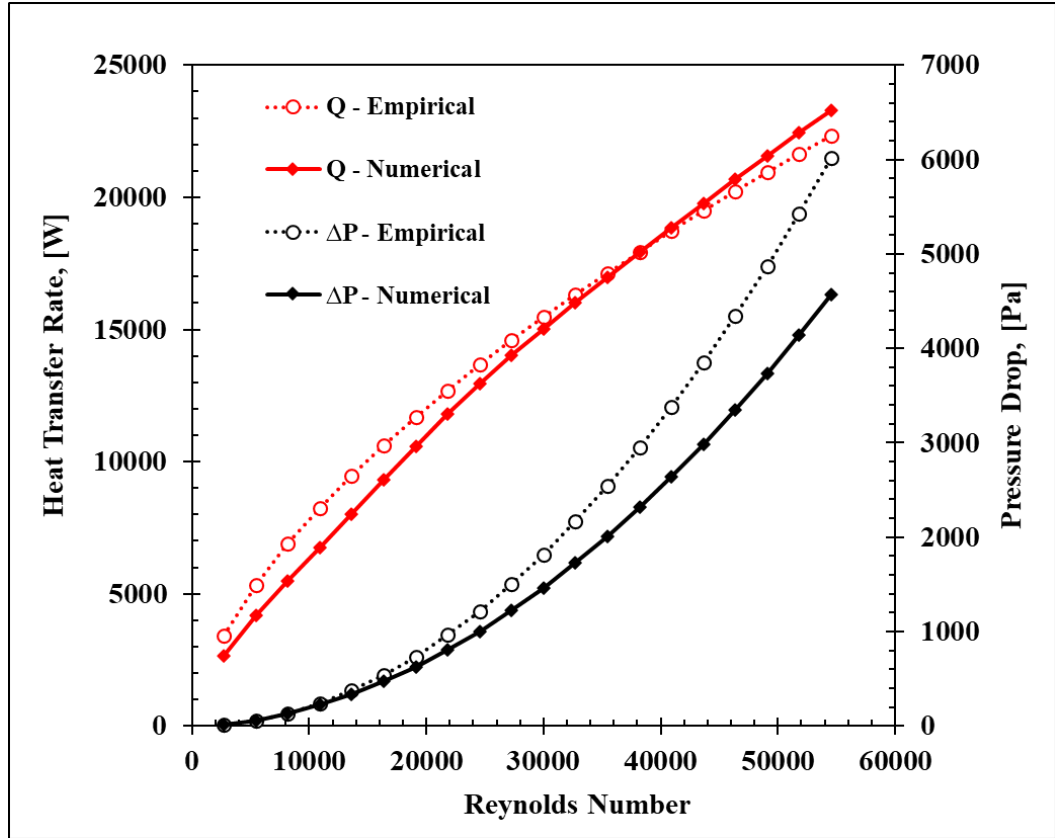


Figure 4. 6. Model validation with empirical results.

4.3. Results & Discussions:

4.3.1. Transverse And Longitudinal Distances:

Maintaining appropriate performing temperatures, preserving the longevity of battery packs, and ensuring their safety all rely on battery thermal management. The transverse (S_T) and longitudinal (S_L) distances in the thermal management system are two of the major variables affecting heat dissipation and pressure drop. The longitudinal distance denotes the distance between battery modules or packs, whereas the transverse distance refers to the space between neighboring battery cells as shown in **Figure 4.1**. Therefore, it is necessary to determine the optimum S_T and S_L for a battery system. The investigation was made by changing S_T and S_L within the range of 22 to 30 mm in both directions. The inlet airflow velocity and temperature were maintained at 5 m/s and 20 °C in all the cases. The S_T at the beginning was kept at a constant distance (22 mm) and the S_L was changing from 22 to 30 mm within 2 mm intervals. Then, the S_T changed until it became 30 mm and the same process was

repeated with S_L . Figures (16a, and 16b) show the heat transfer rate pressure drop for different S_T and S_L .

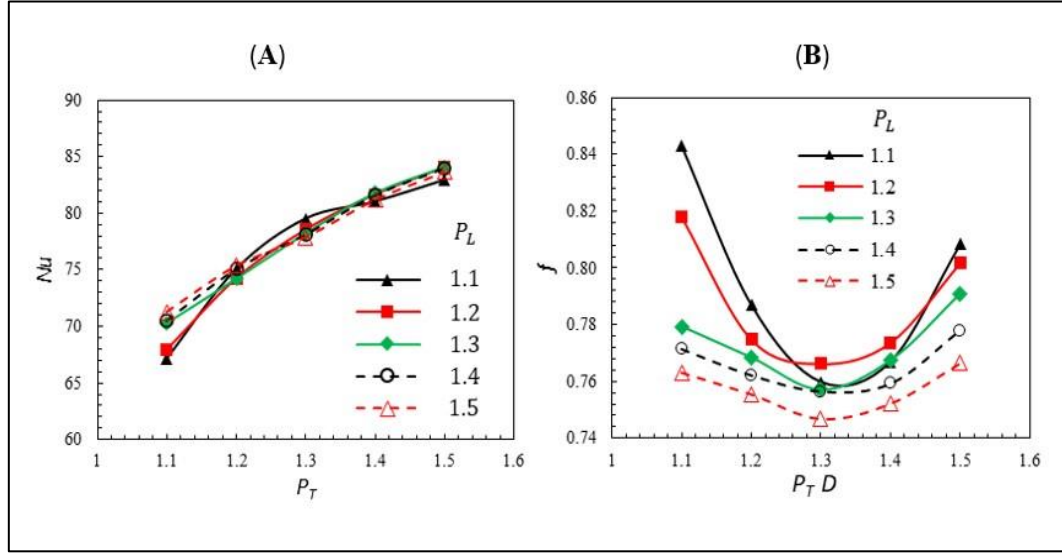


Figure 4. 7. Effect of the transversal (P_T) and longitudinal (P_L) pitches on; A. Nusselt number and B. friction factor for a selected case with $Re= 5454$, $\psi= 0.5$ and $\beta= 0$.

The results from **Figure 4.7 (A)** indicate that the transverse distance S_T between battery cells plays a significant role in heat dissipation. By increasing transverse distance, better heat transfer between cells, leading to improved thermal performance and reduced temperature gradients within the battery pack. This enhances overall efficiency and mitigates the risk of localized hotspots that can adversely affect battery performance and lifespan. However, increasing the S_T by more than 30 mm will start to reduce the amount of heat removed from the system. Likewise, the longitudinal distance S_L between the cells influences pressure drop across the thermal management system. A larger longitudinal distance allows for better airflow and reduced pressure drop, optimizing cooling efficiency. Adequate spacing between modules helps maintain uniform airflow distribution and minimizes flow restrictions, thereby enhancing the overall cooling performance. Furthermore, the results highlight the importance of considering the trade-off between heat dissipation and pressure drop. While optimizing transverse and longitudinal distances improves heat dissipation, it can also increase pressure drop across the system. Therefore, a careful balance is required to achieve optimal thermal performance and efficient cooling without compromising pressure management. However, several factors can affect S_T and S_L such as the area of the battery module and the electrical losses due to the connection

and wiring of the cells in the module. Consequently, the need for careful consideration of these distances during the design and optimization of battery packs is crucial. Depending on the particular application for LIBs cells, distances between 24 – 30 mm for S_T and S_L can strike the right balance, and battery thermal management systems can achieve optimal performance, improved safety, and prolonged battery life. **Figures 4.8 and 4.9** show the temperate and velocity contours when S_T is equal to 26 mm and S_L changes from 22-30mm, and when S_L is equal to 26 mm and S_T changes from 22-30mm.

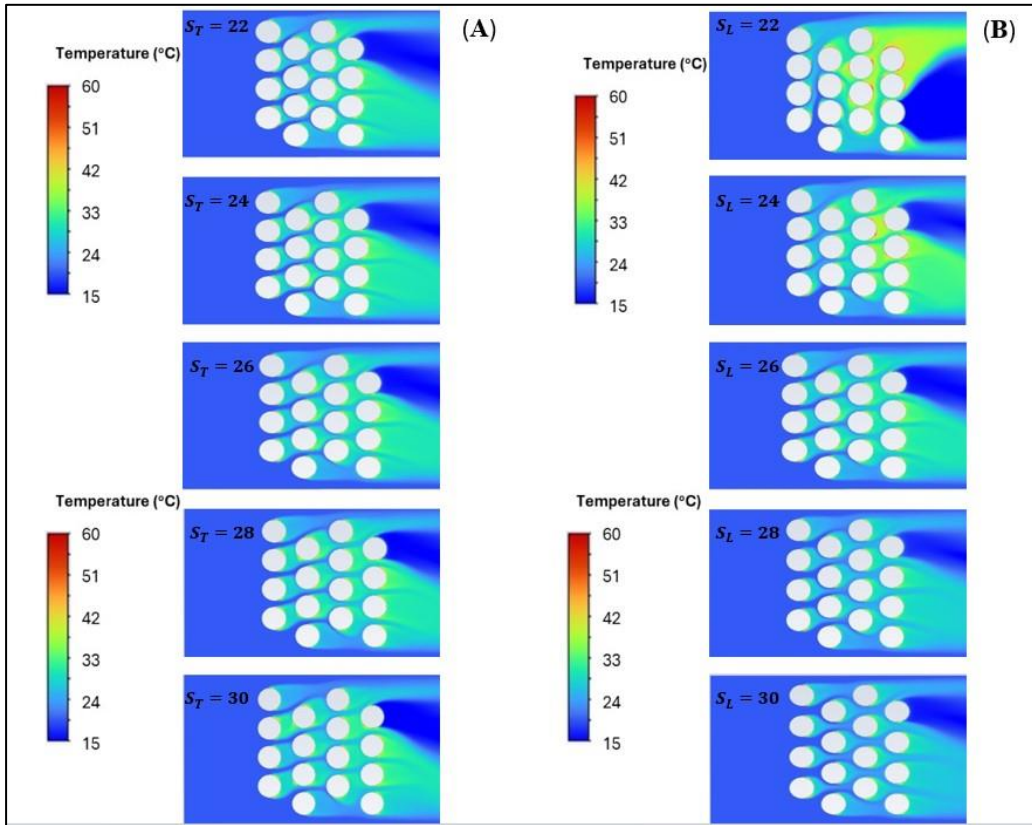


Figure 4. 8. Temperature contours at A) $S_T = 26$ mm and $S_L = (22 - 30$ mm) and B) $S_L = 26$ mm and $S_T = (22 - 30$ mm).

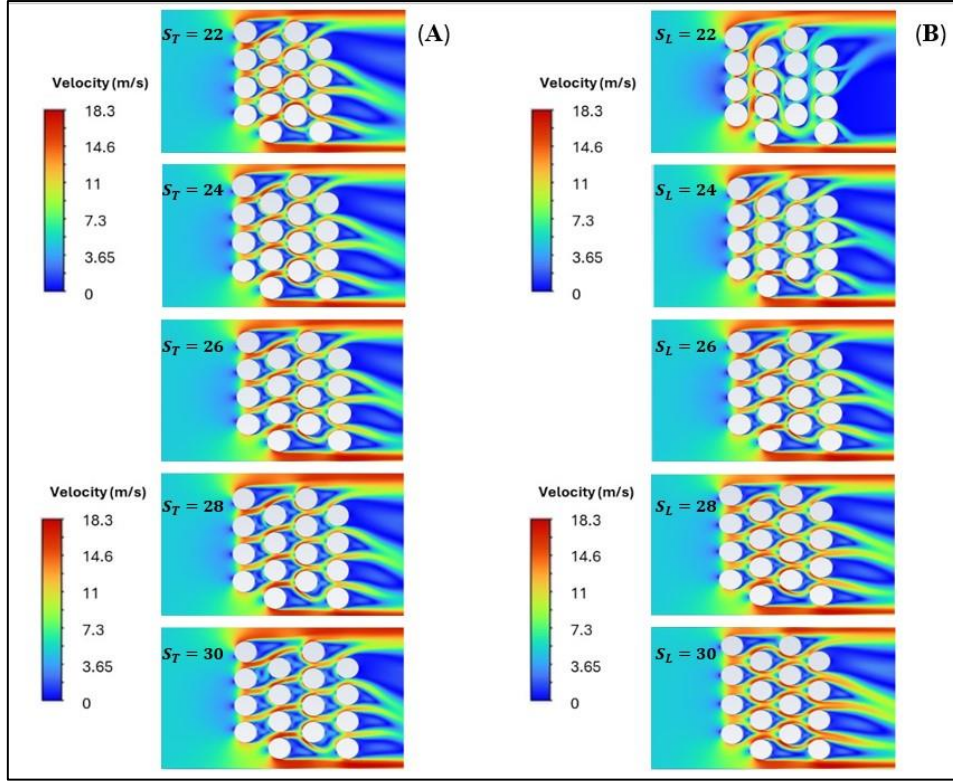


Figure 4. 9. Velocity contours at A) $S_T = 26$ mm and $S_L = (22 - 30$ mm) and B) $S_L = 26$ mm and $S_T = (22 - 30$ mm).

4.3.2. Effect of Channel Convergence Angle:

The airflow inlet channel is critical to the overall performance of battery thermal management systems (BTMS). The inlet channel's design and arrangement substantially impact the airflow distribution, heat transfer, and overall thermal performance of the battery pack. An efficient and well-designed airflow input channel guarantees uniform cooling air distribution over the battery cells, allowing for effective heat dissipation and the maintenance of ideal operating temperatures. Therefore, in this study, four-channel inlet angles (β) were studied at (0° , 5° , 10° , and 30°). The use inlet channel angle is to improve convective heat transfer by properly directing airflow, reducing temperature gradients, reducing the pressure drop in the battery module, and lowering the possibility of isolated hotspots within the battery pack. Furthermore, by creating a convergence inlet at a specific angle, part of the airflow pressure will convert into velocity based on Bernoulli's principle. Therefore, this velocity increase will lead to an increase in the turbulences and will enhance the heat transfer among the cells. The cell-to-cell distances were taken 30 mm in the longitudinal and transversal distances for simplicity. Various inlet airflow velocity was studied from 2 m/s to 40 m/s. Hence, the mass flow rate will depend on the

airflow velocity and width of the channel. **Figures 4.10 (A) and 4.10 (B)** show the temperature and velocity contours at different inlet channel airflow angles. The temperature contours of the battery thermal management system reveal significant variations with different channel inlet angles, indicating the influence of flow direction on heat dissipation. As the channel inlet angle changes, the temperature distribution within the system varies especially surrounding the back cells, indicating the influence of flow direction on heat distribution to hotter portions in specific regions. These temperature contours help identify critical areas that require targeted cooling strategies. Additionally, the velocity contours demonstrate distinct patterns, highlighting the effect of channel inlet angle on fluid flow behavior within the system, which directly impacts the efficiency of cooling. Hence, the distribution of the velocity in the system shows efficient fluid circulation contributes to enhanced heat dissipation and improved temperature regulation.

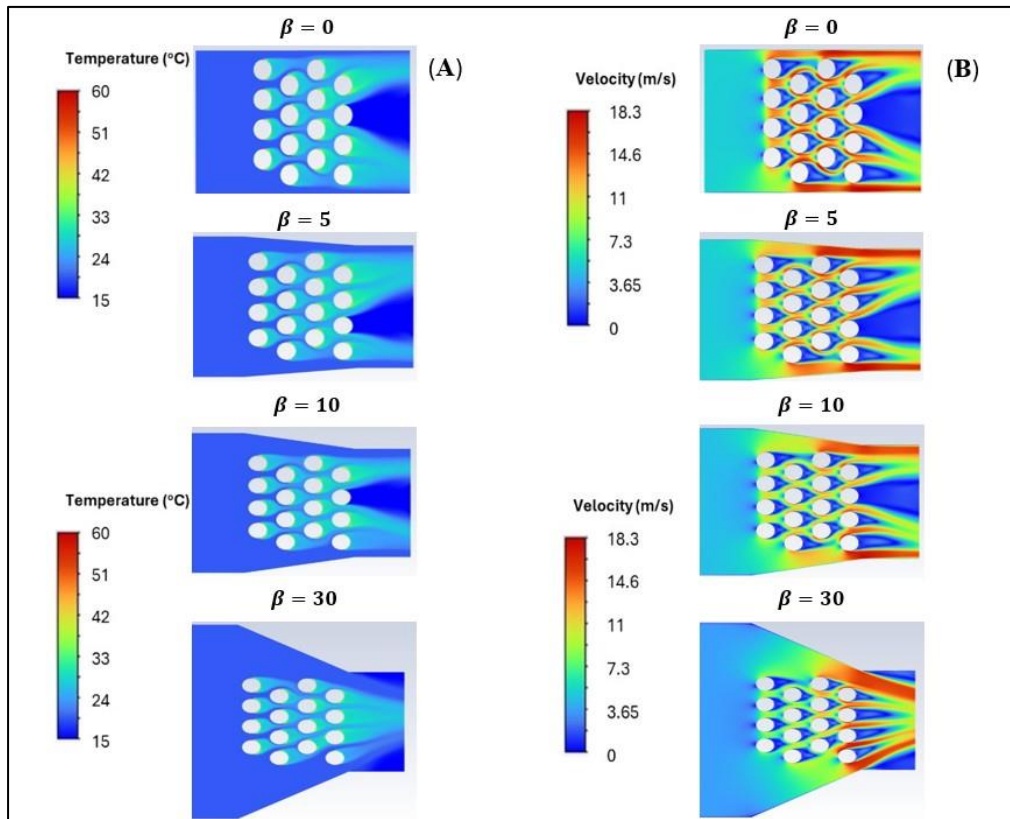


Figure 4. 10. A) Temperature contours B) Velocity contours, at $\beta = (0^\circ, 5^\circ, 10^\circ, \text{ and } 30^\circ)$ at 4 m/s airflow velocity.

Figures 4.11 (A) and 4.11 (B) show Nusselt's number and friction coefficient concerning Renold's number at each channel inlet angle. At a low convergence angle of less than 10° of the flow channel, the total heat transfer from the system is less than the system at zero degrees by almost less than 2%. By increasing the convergence

angle up to 30° , the heat transfer rate starts to improve until it reaches about 6.5% higher than the heat transfer rate at normal conditions when the battery module is at 0° . The results show that the high inlet channel angle directly influences the direction and velocity of the incoming airflow, which in turn affects the heat transfer and cooling efficiency within the battery pack causing the inlet pressure to convert into higher velocity flow leading to more turbulences and hence more heat removal from the system. However, the increase of the convergence angle at high values causes the highest pressure coefficient and hence the most friction losses among all the studied configurations. On the other hand, at a low convergence angle of less than 10° , the friction losses have improved to be about 2.5% higher than the normal configuration on average.

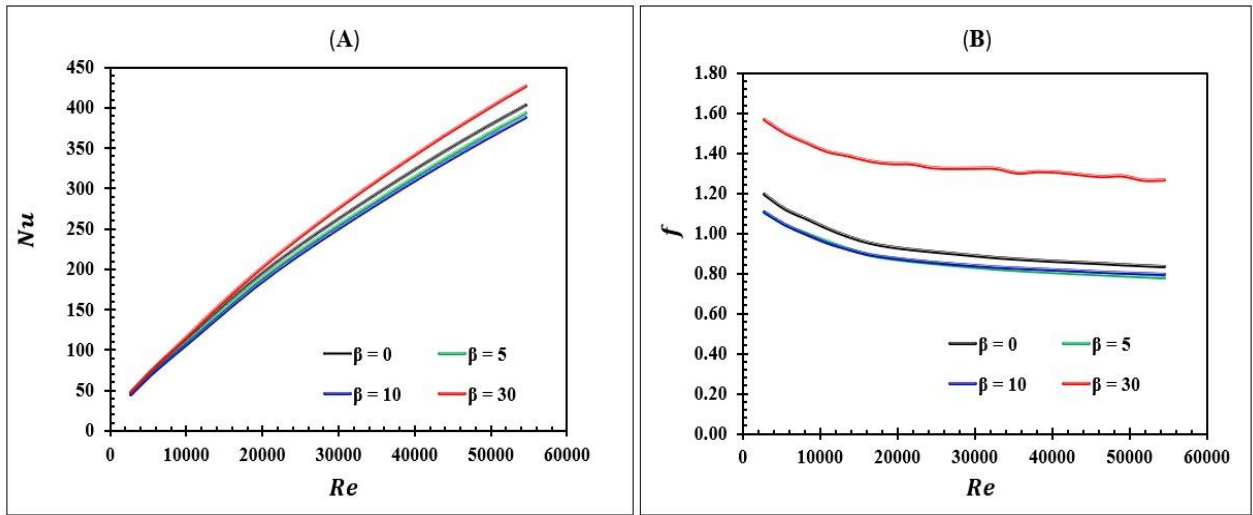


Figure 4. 11. A) Nusselt's number B) Friction coefficient at $\beta = (0^\circ, 5^\circ, 10^\circ, \text{ and } 30^\circ)$ at various airflow velocities.

Figure 4.12 shows the temperature difference between inlet airflow and exit airflow at each angle. The trends of all the studied configurations are approximately the same. They are high at low airflow velocity and then they slightly decrease. By increasing the inlet channel angle the temperature difference becomes less showing minimum temperature gradients and mitigating the risk of localized hotspots. As a result, the cooling requirements for the configurations at high convergence inlet channels do not require more cooling power to ensure efficient and uniform airflow distribution across the battery cells, promoting effective heat removal and maintaining optimal operating temperatures. As a consequence, the inlet channel angle can help prevent recirculation zones and stagnant airflow regions, facilitating the removal of heat from critical areas

of the battery pack. Proper consideration of factors such as the battery pack layout, cooling requirements, and flow dynamics is crucial in determining the optimal inlet channel angle for battery thermal management systems for various battery system applications.

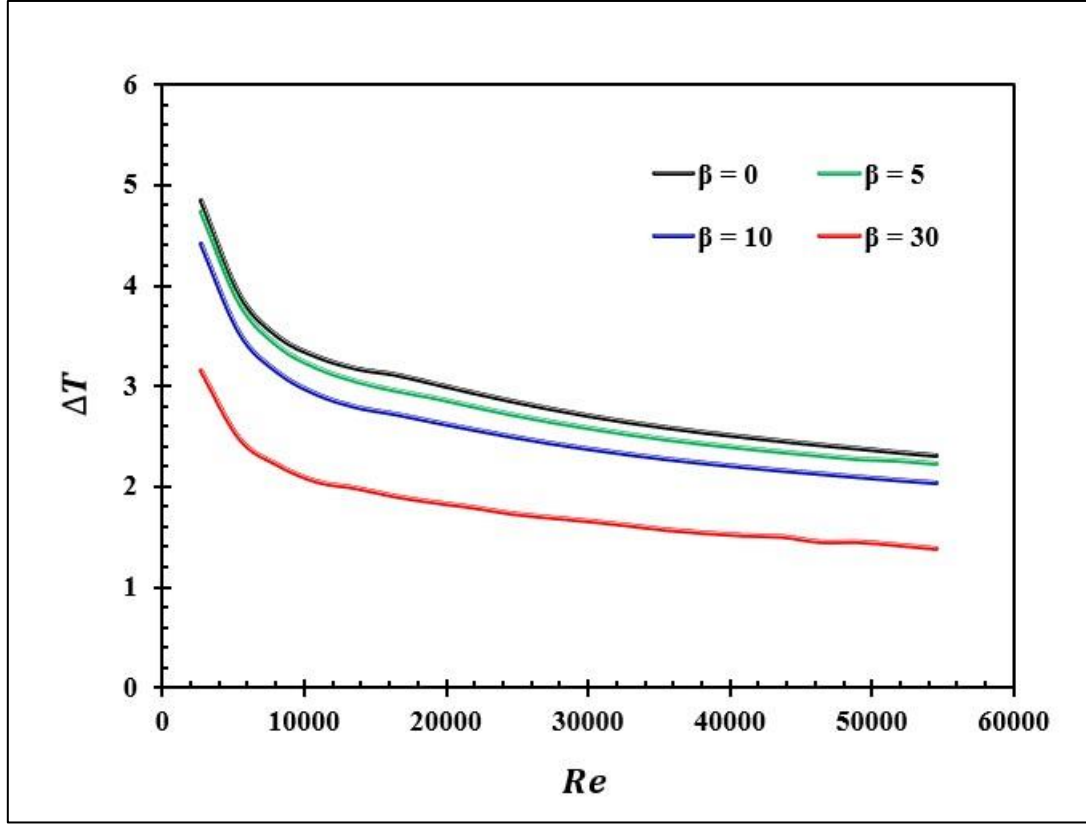


Figure 4.12. Temperature difference between inlet airflow and exit airflow at each angle.

4.3.3. Effect of Channel Confinement Ratio:

The confinement ratio (ψ) as defined above is the distance between the outer surface of the cells in the last rows and the horizontal walls of the battery pack surrounding these cells. Most of the market battery modules ignore the distance between the cells and channel walls either by direct contact or by a small distance with the wall. This may be useful in terms of the heat removal rate, but it causes high-pressure drop and high-temperature difference. Therefore, higher energy consumption in terms of pumping power and cooling power. Hence, the study investigates the effect of distance between the batteries and the channel walls based on the cell diameter. Four distances were examined when ψ is equal to 0.5D, 1D, 1.5D, and 2D, where D is the diameter of the cell. Moreover, the ψ was studied under different channel inlet angles as well. **Figures 4.13 (A) and 4.13 (B)** show the temperature and velocity contours at

inlet velocity of 6 m/s and at different ψ and $\beta = 10^\circ$. The temperature contours in all cases demonstrate almost the same temperature distribution within the system. However, the velocity contours show different patterns of flow distribution. The velocity between the cells is gradually increasing as the distance increases as a reason for the increase of the flow rate entering the system. Therefore, less pressure drop and low-temperature difference occur.

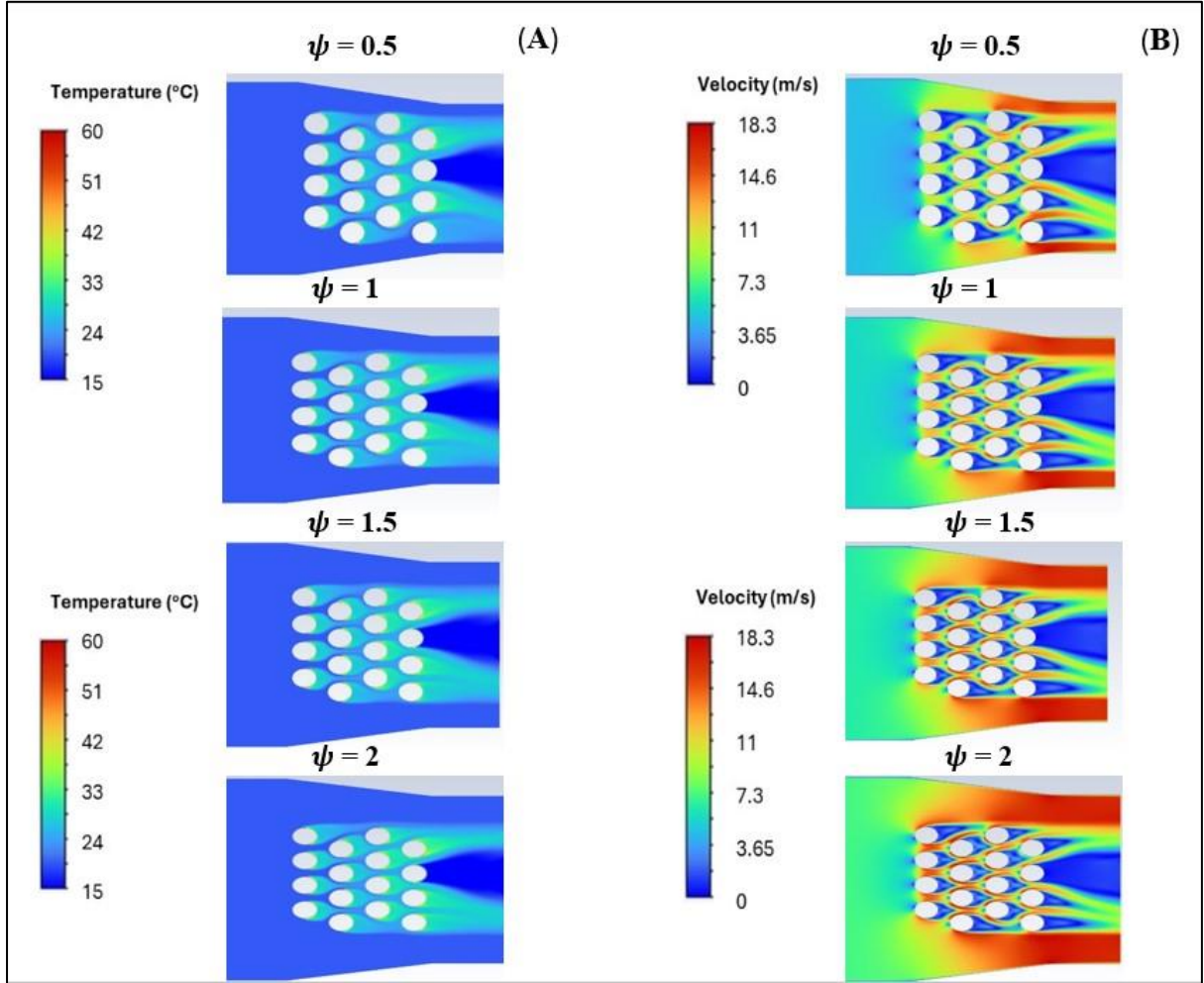


Figure 4. 13. A) Temperature contours b) Velocity contours at CR = (0.5D, 1D, 1.5D, and 2D) at V = 6 m/s.

Figures 4.14 and 4.15 show Nusselt's number and friction coefficient concerning Renold's number at each confinement ratio and channel inlet angle. In all cases, Nusselt's number and friction coefficient trends are the same. As the channel distance from the cells increases, the amount of heat transfer reduces depending on the velocity of the cooling fluid. At all examined angles and ψ , the heat removed is slightly high when CR equals 0.5D at low flow velocities. This difference starts to increase by increasing the velocity of the fluid, where at 0° , the average difference between 0.5D

and other distances is approximately 10%, 17%, and 21% when the distances are at 1D, 1.5D, and 2D respectively. However, these percentages become less when the channel inlet angle is introduced. The average differences become 8%, 13%, and 17% at 5°, and almost 5%, 10%, and 14% at 10° and 30°. On the other hand, increased CR leads to a significant improvement in friction losses. Comparing the friction coefficient at 0.5D and other distances shows that at 0°, the average differences are 32%, 50%, and 58% reduction in the friction coefficient at 1D, 1.5D, and 2D respectively. On the contrary, by increasing the channel inlet angle, the percentages are 30%, 46%, and 56% at 5° and 10, and 47%, 63%, and 73% at 30°. The results shows by start to increase the distance between the cells and channel's walls, it creates a space for the circulation of airflow for the surfaces in the last rows of the cells, and the circulation of the flow from the middle of the module to this space. Yet, as the flow velocity increases, the heat removal starts to decrease since the high portion of the flow leaves the system very fast without touching the cells. In that case, the channel convergences improve the performance a little by directing the flow to the cells. The same condition is for the pressure coefficient, which explains the improvement of the performance of the system. Consequently, a good setup for the battery management system including optimum ψ , β , and flow velocity will maintain the suitable operation of the system with high heat removal, low-pressure drop, and low energy requirement for cooling and pumping.

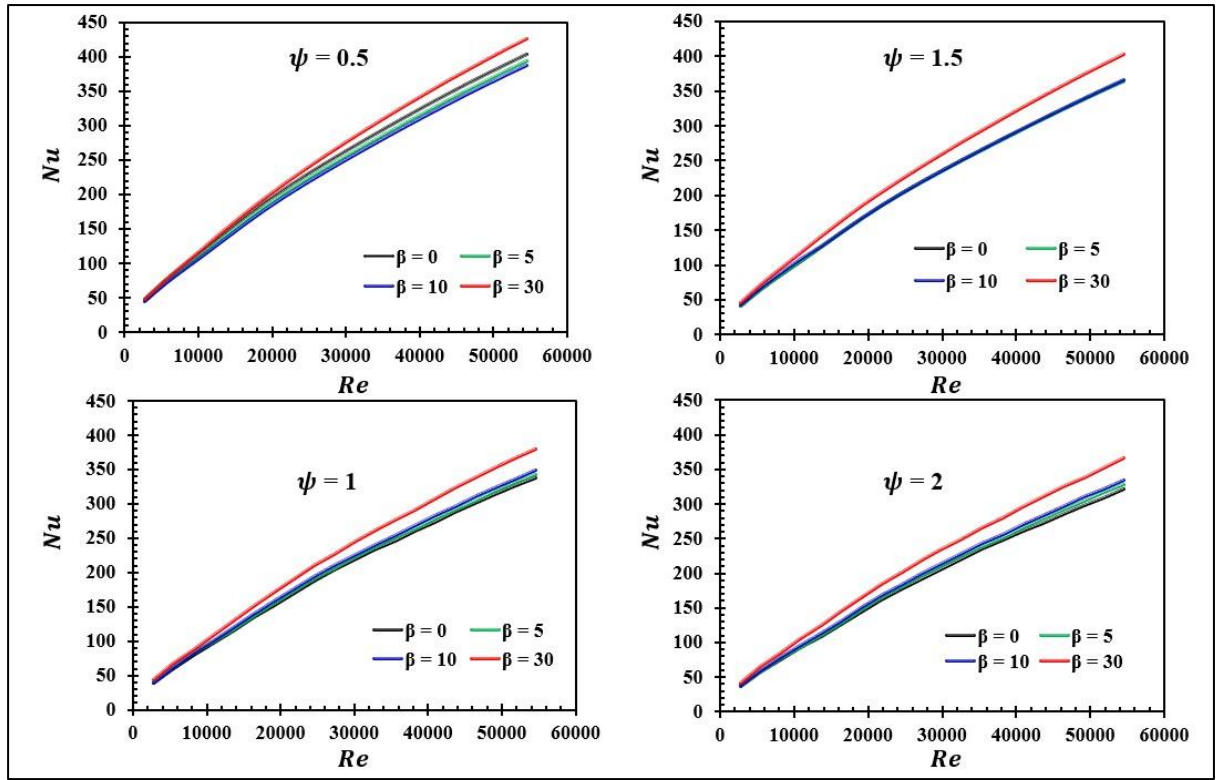


Figure 4. 14. Nusselt's number $\psi = (0.5D, 1D, 1.5D, \text{ and } 2D)$ at various airflow velocities and different channel inlet angles.

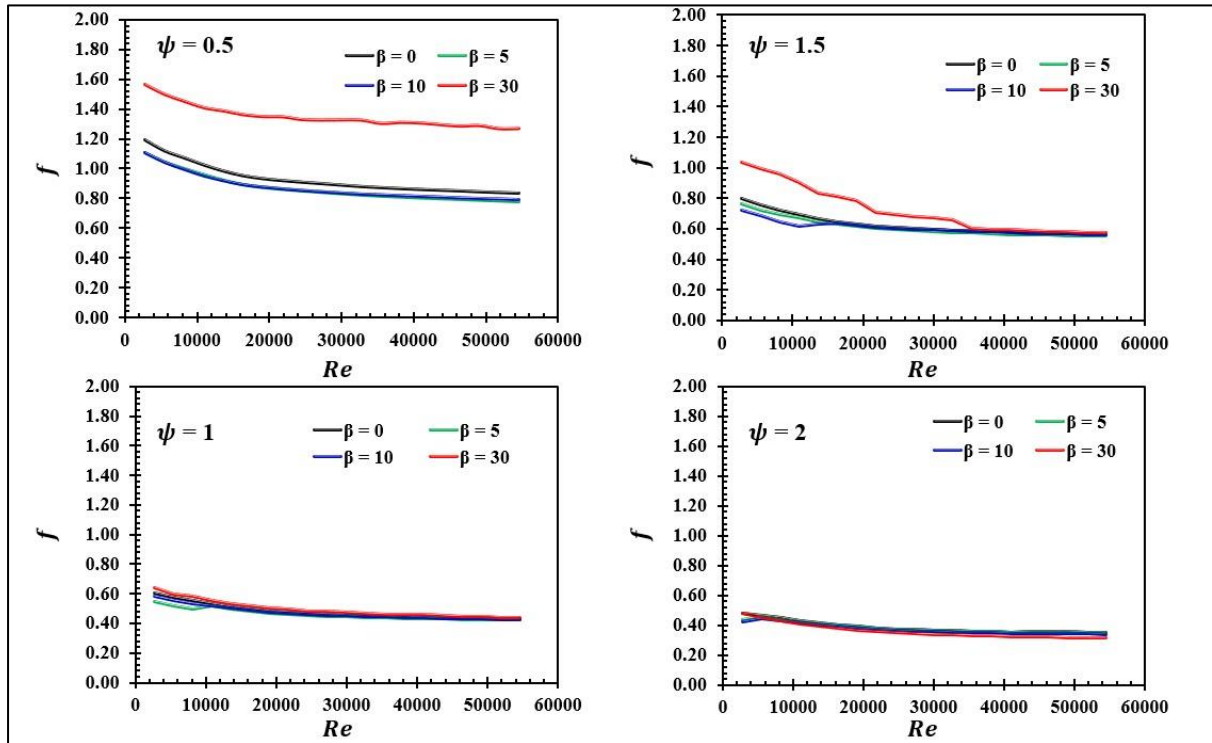


Figure 4. 15. Friction coefficient $\psi = (0.5D, 1D, 1.5D, \text{ and } 2D)$ at various airflow velocities and different channel inlet angles.

4.3.4. Proposed Correlation of Nusselt Number And Friction Factor:

The results of our investigation are presented in deriving correlations for Nusselt number and friction factor by leveraging CFD simulation results and employing machine learning methodologies. This approach involves utilizing of 4000 CFD simulations dataset encompassing a wide range of flow conditions, geometric configurations, and thermal characteristics. Through the integration of additional variables identified via these simulations, the proposed correlations aim to augment the traditional correlations found in heat and mass transfer literature. Furthermore, the utilization of machine learning techniques and the application of the regression model facilitated the analysis and identification of intricate relationships within the dataset, allowing for the establishment of more robust correlations. Therefore, the proposed correlations for Nusselt number and friction factor depend on the five parameters which are Re , $(\frac{W}{D})$, β , $(\frac{S_T}{D})$, and $(\frac{S_L}{D})$.

For Nusselt number, the proposed correlation is stated as:

$$Nu = 0.0691 Re^{0.7806} (\frac{W}{D})^{-0.1129} \beta^{0.2098} (\frac{S_T}{D})^{-0.0072} (\frac{S_L}{D})^{0.1217} \quad (4.10)$$

where, $2000 \leq Re \leq 28000$, $0^\circ \leq \beta \leq 30^\circ$, and $22 \text{ mm} \leq S_T \& S_L \leq 30 \text{ mm}$.

Figure 4.16 shows the results of the Nusselt number between the simulated results and fitted results from the correlation.

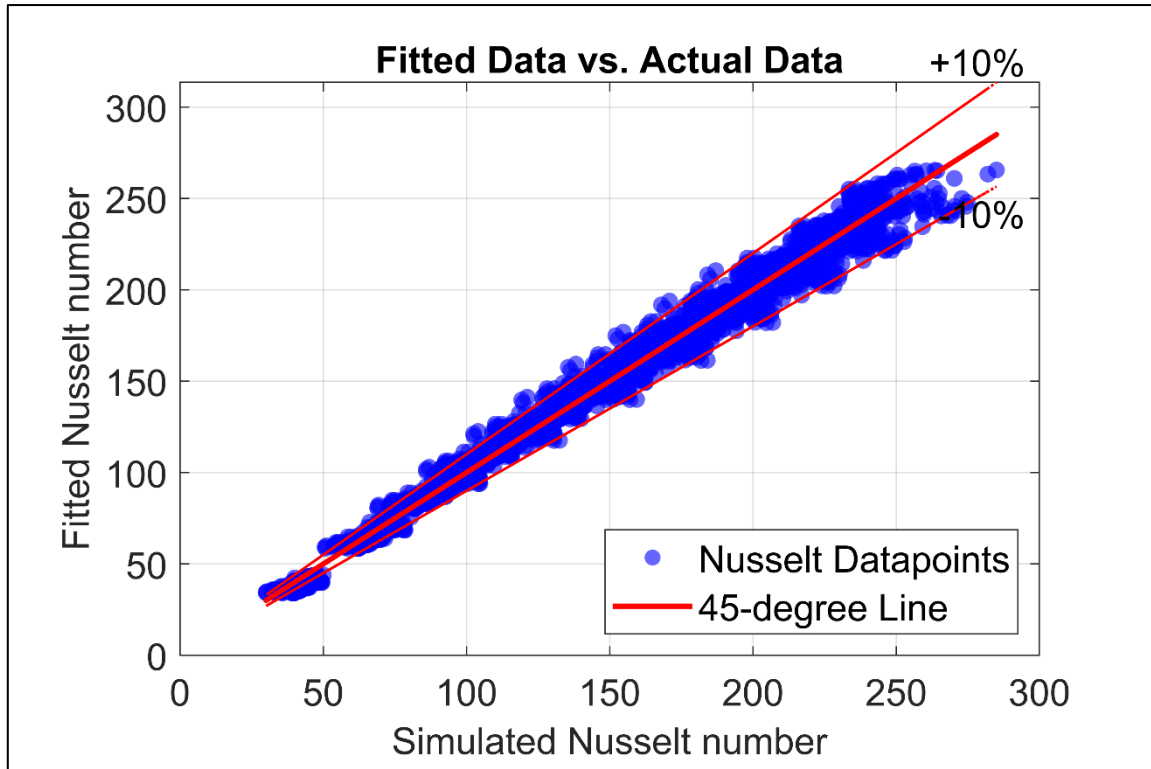


Figure 4. 16. The results of the Nusselt number between the simulated results and fitted results from the correlation.

The Figure shows good matching between the simulated results obtained by the CFD simulation and the results obtained by the proposed correlation with R^2 of 0.9885, Mean Square Error (MSE) equal to 43.047, and maximum error of 18.5% between the two results. Consequently, the correlation has good accuracy in predicting the value of Nusselt number under the stated conditions. On the other hand, the proposed correlation for friction factor is stated as:

$$f = 1.3813 Re^{-0.0777} \left(\frac{W}{D}\right)^{-0.9098} \beta^{1.3912} \left(\frac{S_T}{D}\right)^{-1.8090} \left(\frac{S_L}{D}\right)^{0.6102} \quad (4.11)$$

Where, $2000 \leq Re \leq 28000$, $0^\circ \leq \beta \leq 30^\circ$, and $22 \text{ mm} \leq S_T \& S_L \leq 30 \text{ mm}$.

Figure 4.17 illustrates the results of the friction factor obtained by both CFD simulation and fitted results from the correlation. The R^2 value achieved is 0.8685 while the MSE is 0.0225 with a maximum error of 32% between the two results. Overall, the model appears to be reasonably strong and accurate, as indicated by its R^2 value of 0.8685 and MSE of 0.0225. However, there are several instances in which the correlation results deviate significantly from the observed values by as much as 32%.

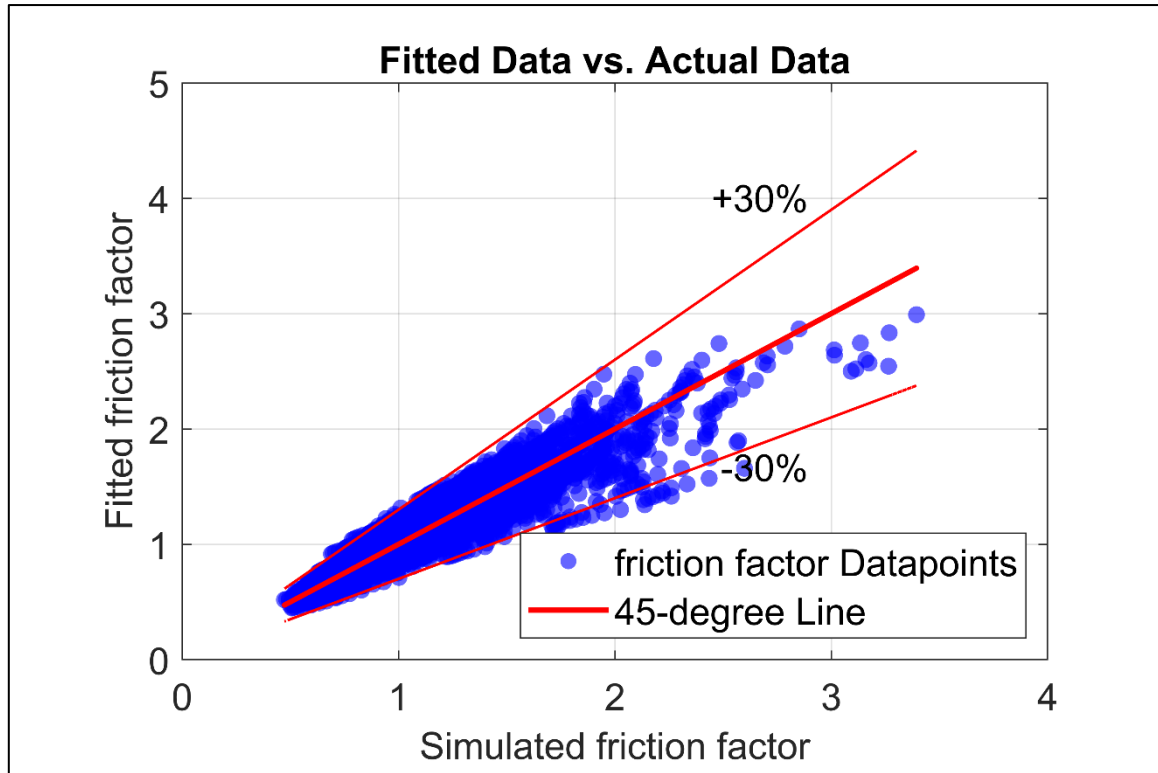


Figure 4. 17. The results of the friction factor obtained by both CFD simulation and fitted results from the correlation.

4.4. Conclusion:

In this study, A comprehensive study of the thermal and flow characteristics of an array of cylinders in a converged and confined channel, specifically designed to simulate battery cooling scenarios, has provided valuable insights into the complex interplay between fluid dynamics and heat transfer phenomena. The results shed light on how these parameters affect heat dissipation and pressure drop across the battery array. The transverse and longitudinal distances between cells are critical parameters influencing the transfer of heat and pressure drop, with an ideal range of 22-30 mm for both distances for efficient thermal performance. The study emphasizes the importance of the channel convergence angle, showing that higher angles improve heat transfer while becoming problems such as increasing friction losses. Furthermore, the impact of the channel confinement ratio on heat transfer and pressure drop is investigated. Results show that extending the distance between battery cells and channel walls improves heat removal efficiency, resulting in a smaller pressure drop and lower energy usage. The proposed correlations for the Nusselt number and friction factor, computed

from a large dataset and using machine learning approaches, show high accuracy and superior prediction capabilities when compared to traditional correlations.

In conclusion, this study provides a thorough understanding of the thermal and flow properties of battery arrays in a converging and confined channel. The findings provide useful insights for the design and optimization of BTMS, which is critical for improving the safety, efficiency, and lifetime of LIBs in a variety of applications, particularly in the quickly changing landscape of electric vehicles and sustainable energy solutions. The presented correlations provide a strong framework for estimating heat transfer and pressure loss in similar arrangements, paving the way for more efficient and environmentally friendly energy storage systems.

CHAPTER 5:

MACHINE LEARNING STUDY OF THERMAL MANAGEMENT OF A BATTERY PACK IN CONVERGED CHANNEL*

5.1. Introduction:

In the ongoing search for optimal energy storage solutions, the intersection of computational fluid dynamics (CFD) simulations and machine learning appears as a revolutionary breakthrough in the study of battery thermal management systems (BTMS). This interdisciplinary method reflects a smart synergy in which the precision of CFD models and machine learning's adaptive learning skills combine to reveal the complicated thermal dynamics that influence battery performance. As the demand for efficient and sustainable energy storage grows, understanding and controlling battery thermal behavior becomes critical, influencing safety, longevity, and overall efficiency.

CFD simulations, which are known for their outstanding accuracy in modeling fluid flow and heat transmission, provide a thorough and physics-based description of the thermal complications of a battery system. Using CFD, researchers may investigate the geographical and temporal fluctuations of temperature, fluid flow, and heat flux, providing a full understanding of the thermal problems inherent in various battery layouts. However, the sheer complexity and nonlinearity of these thermal systems necessitate creative methodologies for increased predictive capacities.

Introducing machine learning, a paradigm-shifting tool that excels at explaining complicated patterns, improving processes, and making data-driven predictions. Machine learning systems, trained on large datasets derived from CFD simulations and experimental data, can detect subtle correlations between various factors and thermal results. This collaboration enables the creation of predictive models that can optimize thermal management tactics for diverse battery configurations, paving the door for adaptive and intelligent control systems.

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In this study, a numerical model is developed to simulate an active BTMS in which a fluid flows past a staggered battery pack design. To improve advective mixing and hence heat transfer from the battery surfaces to the fluid stream, the entire battery pack is positioned in a converging channel. The transverse and longitudinal cell-to-cell lengths, fluid flow rate, channel convergence angle, and channel width all have an impact on the BTMS's performance. The overall heat transfer rate between the battery pack and the fluid flow is used to evaluate the BTMS's performance. Furthermore, the pressure drop across the battery pack is calculated to estimate the pumping power required to run the BTMS. The parameters are studied numerically over a wide range of values, which are then fed into a machine-learning algorithm. The GPR technique with a multidimensional kernel structure was employed. Consequently, this study explores the integration of machine learning (ML) techniques in BTMS design and optimization, sparking inquiries into their necessity alongside CFD-based simulations. Combining ML with CFD aims to synergize their strengths and address complexities within battery systems. While CFD simulations provide insights into fluid dynamics and heat transfer in BTMS, they demand extensive computational resources and might require a huge amount of time to simulate these cases. Conversely, ML, specifically the GPR algorithm, employed in our study, leverages large CFD-derived datasets to unravel subtle relationships between key parameters and thermal metrics. By highlighting the fusion of CFD and ML methods, our study presents a comprehensive framework beyond conventional simulations, offering deeper insights into BTMS behavior and bolstering operational efficiency and predictive accuracy in battery systems. Our current work will be an invaluable tool to further design and optimize BTMS systems.

5.2. Methodology:

5.2.1. CFD simulation:

The dataset to be fed to the machine learning algorithm was obtained by numerically solving the transport equations using a finite volume approach. **Figure 4.1** shows the two-dimensional physical model of the BTMS design with all the important geometric parameters depicted. The system consists of 16 cells divided into 4 rows and 4 columns arranged in a staggered configuration. The diameter of the single cell (D) is 20 mm which represents a typical diameter of commercially available batteries. The transversal distance (S_T) and longitudinal distance (S_L), as shown in **Figure 4.1**, were

taken to vary from 22 mm to 30 mm. The battery cells were maintained at a constant temperature of 60 °C. The cooling fluid (air in this case) used in the simulation enters the system with a velocity that ranges from 2 m/s up to 20 m/s with a temperature of 15 °C. The channel convergence angle (β) was varied from 0° to 30°. The importance of the angle is to increase the fluid flow velocity around the battery pack which will increase the turbulences in the system, and hence the heat transfer. The distance (W) in the Figure signifies the confinement of the battery pack and is defined as the distance from the last row of the cells in the module to the side walls of the channel. This distance was taken to vary from $0.5D$ to $2D$. The no-slip boundary condition was applied to the battery and channel walls. The turbulence intensity was set to 5% in all simulations while the hydraulic diameter was set to be a fraction of the cell diameter in all simulations. The different parameters being studied are summarized in **Table 5.1**.

Table 5. 1: Summary of the studied parameters and their corresponding range.

Parameter	S_T/D	S_L/D	Re	W/D	β
Value Range	1.1 – 1.5	1.1 – 1.5	2700 - 550000	0.5 - 2	0° - 30°

To model the flow and thermal performance of the BTMS, the continuity, momentum, and energy transport equations are solved in the 2D turbulent domain depicted in **Figure 4.1**. The continuity, momentum, and energy are given in Equations (9 – 13), respectively.

The numerical solution relies primarily on the quality of the mesh, especially near the solid boundary. Therefore, proper care was taken when meshing the domain near the battery and channel walls. Quadrilateral mesh was used with inflation near walls was utilized. The mesh quality was checked for each geometric variation. A mesh-independent test was performed to obtain a solution that is accurate and less computationally expensive. The test was carried out with various mesh element sizes for a representative case study. **Figure 4.3 (B)** shows the mesh-independent solution representing the temperature difference between the inlet and outlet sections of the channel. The results converge after ~53k elements in the domain with results changing by less than 0.1% for the higher number of elements.

The results from the simulation were then validated against empirical correlations used for a bundle of tubes at constant surface temperature [134]. The result of the bundle of tube convective heat transfer is analogous to the problem at hand. **Figure 4.4** illustrates the heat transfer rate from the battery pack to the fluid and pressure drop across the battery pack using the numerical model and the empirical correlations. The results show an excellent match between the two results. A maximum deviation of 6% in heat transfer rate and about 15% for pressure drop are considered acceptable.

The model developed was used to perform the simulations under different BTMS parameters as presented in **Table 5.1** (A total of 4000 simulations). To generalize the solution, we quantify the heat transfer rate from the battery pack to the working fluid by its non-dimensional form, i.e. Nusselt number, which is calculated as:

$$Nu = \frac{q'' D}{\Delta T_{lm} k} \quad (5.1)$$

Where q'' is the overall heat transfer flux, ΔT_{lm} is the log-mean temperature difference, and k is the fluid's thermal conductivity. Whereas the friction factor is calculated from the pressure drop across the batter pack as

$$f = \frac{2 \Delta P}{\rho u_{max}^2} \quad (5.2)$$

The frictional pressure drop (ΔP) across the battery pack is calculated as the total pressure drop obtained from the simulation minus the pressure drop due to the channel convergence effect, found using the Bernoulli equation. The maximum velocity (u_{max}) as:

$$V_{max} = \frac{S_T}{S_T - D} V \quad (5.3)$$

5.2.2. Machine Learning:

We utilize the Gaussian Process Regression (GPR) method as a machine learning algorithm to predict the Nusselt number and the friction factor as the output parameters. The input parameters are listed in **Table 5.1**. GPR is a non-parametric probabilistic machine learning approach based on kernel functions, which has been extensively utilized in many engineering applications as reviewed earlier. GPR leverages the concept of kernel functions, which depict the similarity between input data points, to guess the relationships between input variables and output responses. Kernel functions enable the GPR model in the context of BTMS to properly represent the complex nonlinear relationships between multiple factors, such as battery temperature, coolant flow rate, and system geometric variables. The probability distributions of GPR can be specified by **Equation 5.4** [135]:

$$f(x_i) \sim GPR(m(x_i), k(x_i, x_j)) \quad (5.4)$$

The selection of proper kernel functions is critical since it impacts the model's capability to capture various sorts of relationships, such as linear, radial basis, and periodic. Hence, the GPR models used for this study are [136]:

Squared Exponential GPR. This method represents a functional expression of a radial basis function regression model, encompassing an infinite number of basic functions. It is worth noting that the Squared Exponential GPR is essentially the same as the Exponential GPR, except for the fact that it involves squaring the Euclidean distance. The squared exponential GPR is illustrated in **Equation 5.5**.

$$k(x_i, x_j | \theta) = \sigma_f^2 \exp \left[-\frac{1}{2} \frac{(x_i - x_j)^T (x_i - x_j)}{\sigma_l^2} \right] \quad (5.5)$$

Matern 5/2 GPR. By utilizing the spectral densities of the stationary kernel and generating Fourier transforms of the RBF kernel, the Matern 5/2 kernel effectively captures the characteristics of the data. Importantly, the Matern 5/2 kernel overcomes the concentration of measure issues typically encountered in high-dimensional spaces. the Matern 5/2 GPR is evaluated using **Equation 5.6**.

$$k(x_i, x_j|\theta) = \sigma_f^2 \left(1 + \frac{\sqrt{3} r}{\sigma_l} \right) \exp \left(-\frac{\sqrt{3} r}{\sigma_l} \right) \quad (5.6)$$

Exponential GPR. This method shares similarities with the Squared Exponential GPR, with the main distinction being that it does not involve squaring the Euclidean distance. In the Exponential GPR, the inner products of basic functions are replaced with kernels that are computationally slower compared to the Squared Exponential GPR. While the Exponential GPR performs well in handling smooth functions with minimal errors, it may struggle when encountering functions with discontinuities. The exponential GPR is shown in **Equation 5.7**.

$$k(x_i, x_j|\theta) = \sigma_f^2 \exp \left(-\frac{r}{\sigma_l} \right) \quad (5.7)$$

Rational quadratic GPR. This method provides the capability to represent data that exhibits variations across multiple scales. It finds application in diverse fields such as spatial statistics, geostatistics, machine learning, image analysis, and other domains that involve multivariate statistical analysis in metric spaces. It can be calculated using the following **Equation 5.8**.

$$k(x_i, x_j|\theta) = \sigma_f^2 \left(1 + \frac{r^2}{2 \propto \sigma_l^2} \right) \quad (5.8)$$

4000 data points were collected from the CFD simulation, and using the toolbox available in MATLAB 2021, this dataset from simulation results with GPR models is trained using 80% of the data and tested using the remaining 20%. The model is evaluated using the Root-mean-square error (RSME) and R-squared (R^2) between the simulated and the predicted results.

5.3. Results & Discussions

5.3.1. CFD Results:

In this section, the data analysis and all parameters are taken from the outcomes of chapter 4. In that chapter, the key parameters assessing BTMS performance have been thoroughly studied, including transverse and longitudinal cell-to-cell lengths, channel

convergence angle, and channel confinement ratio. The findings demonstrate the importance of these factors in heat dissipation and pressure drop across the battery array. Particularly, appropriate transverse and longitudinal distances are established, highlighting the trade-off between improved heat transfer and greater pressure drop.

Furthermore, the channel convergence angle of the inlet channel is examined to determine its effect on heat transfer efficiency and friction losses. The study emphasizes the importance of taking a balanced approach to achieving optimal thermal performance. Moreover, the influence of the channel confinement ratio on heat transfer and pressure drop is investigated, indicating the significance of the distance between battery cells and channel walls in optimizing energy usage.

5.3.2. Prediction Based on GPR:

After carrying out the numerical simulations for the BTMS design, a machine learning algorithm was used to predict the Nusselt number and friction factor based on GPR. Out of the 4000 points, 80% (3200 random data points) were used as training data for the GPR model, and 20% (800 random data points) were used to test the model. The input training dataset included all influencing factors depicted in **Table 5.1**. The input-output matrix was fed into the machine-learning model for training and testing using four different kernel functions: GPR exponential, GPR Squared exponential, GPR Matern 5/2, and GPR Rational quadratic. The training and testing for both the Nusselt number and friction coefficient were conducted independently since there is no interaction between them. Thus, the predicted model will eliminate the interference of the results.

Figure 5.1 shows the training and testing results using the four different kernel functions; GPR exponential (**Figure 5.1 A**), GPR Squared exponential (**Figure 5.1 B**), GPR Matern 5/2 (**Figure 5.1 C**), and GPR Rational quadratic (**Figure 5.1 D**) for both Nusselt number (**Figure 5.1 i and ii**) and friction factor (**Figure 5.1 iii and iv**). **Figure 5.1 (i)** summarizes the training results of the Nusselt number, where the results between prediction and simulation were compared. The value of R^2 for all kernel functions was found to be very close to unity while they differ slightly in terms of RMSE. The RMSE values were 2.004, 1.644, 1.722, and 1.652 for GPR

exponential, GPR Squared exponential, GPR Matern 5/2, and GPR Rational quadratic, respectively. While the variations are not significant, the GPR Squared exponential performed better at the testing stage. **Figure 5.1 (ii)** depicts the testing results of the Nusselt number, where the results between prediction and simulation were compared. The value of R^2 for all kernel functions varied with values of 1, 0.78, 0.89, and 0.82 for GPR exponential, GPR Squared exponential, GPR Matern 5/2, and GPR Rational quadratic, respectively. The RMSE was 0.138, 6.21, 4.456, and 5.575 for GPR exponential, GPR Squared exponential, GPR Matern 5/2, and GPR Rational quadratic, respectively. GPR with the exponential kernel function outperformed the other algorithms at predicting the Nusselt number within the testing data set. The worst prediction of the testing results was associated with the squared exponential GPR algorithm.

Figure 5.1 (iii) and **Figure 5.1 (iv)** illustrate the training and testing results of the friction factor as calculated from **Equation 5.2**. The simulated and predicted values are illustrated for the different kernel functions. The RMSE values for the training data were 0.038, 0.035, 0.035, and 0.035 for GPR exponential, GPR Squared exponential, GPR Matern 5/2, and GPR Rational quadratic, respectively. All algorithms showed similar accuracy in fitting the training data set. On the other hand, when testing the 20% remaining data points great variations were observed. The lowest accuracy was obtained when using GPR with Matern 5/2 kernel function with an R^2 of 0.1 and an RSME of 0.0771. The highest accuracy was achieved using GPR with exponential kernel function achieving an R^2 of unity and an RSME of 4×10^{-5} . Consequently, based on the above training and testing results of both Nusselt number and friction factor, using GPR with the exponential kernel function outperformed the other models in predicting the performance of the BTMS within the given range of parameters.

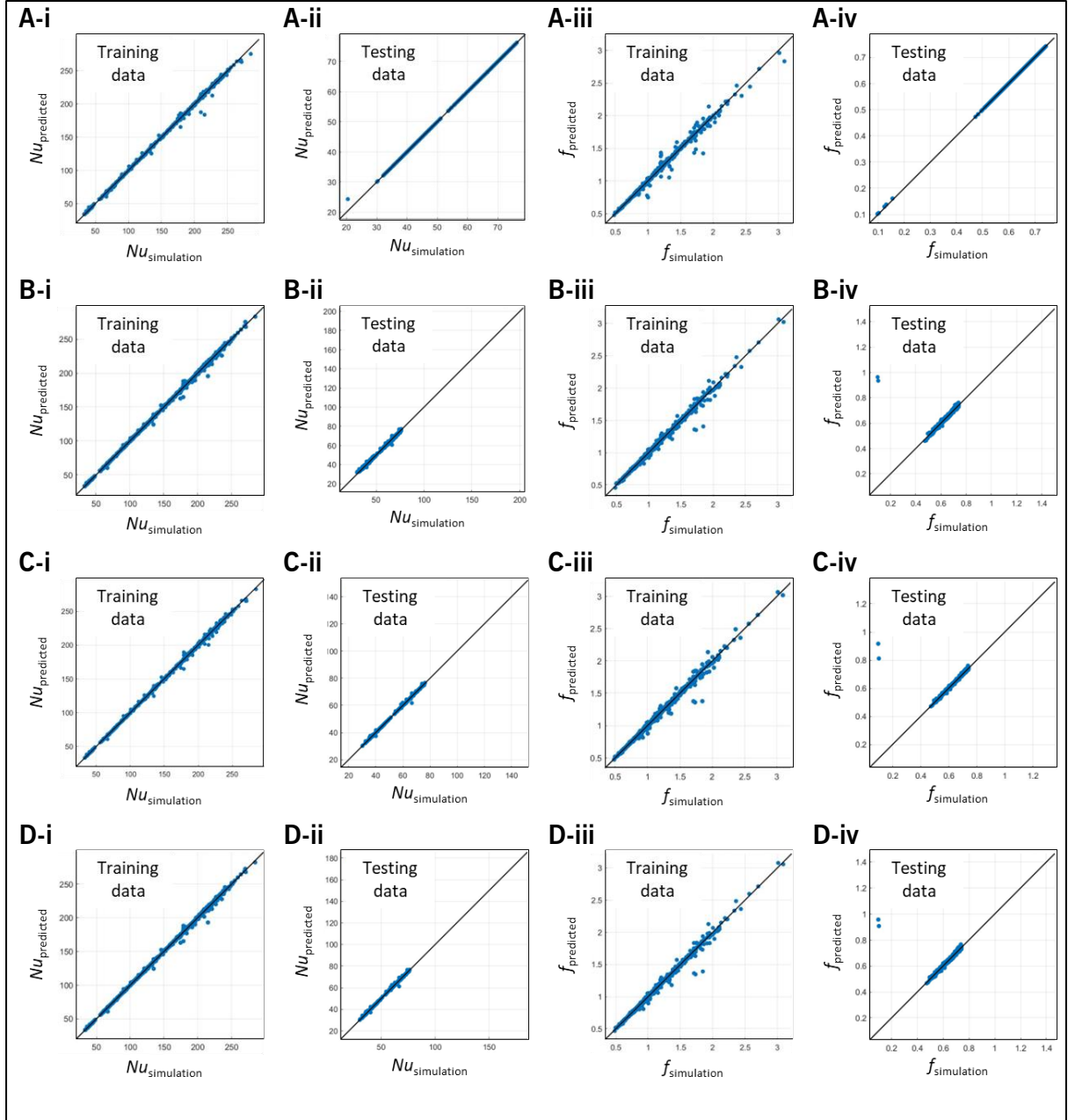


Figure 5. 1. Training and testing results of Nusselt number (i-training and ii-testing) and friction factor (iii-training and iv-testing) using GPR with four different kernel functions; A. exponential, B. squared exponential, C. Marten 5/2, and D. rational quadratic.

5.4. Conclusion:

In this study, a two-dimensional numerical model based on the Finite Volume Method was used to simulate the improved heat transfer rate associated with a confined battery pack placed in a converged channel. The model investigated the effect of different parameters namely cell-to-cell transversal and longitudinal distances, confinement ratio, channel convergence angle, and flow Reynolds number. The obtained simulation results of the

Nusselt number and friction factor across the battery pack were then fed into a machine-learning model based on Gaussian Process Regression. The model was fed a dataset of 4000 data points, from which 80% random points were used to train the model and the remaining 20% data points were used to test the model. The main concluding remarks are as follows:

- 1- Numerical results showed a complex interplay between the system parameters on both the Nusselt number and friction factor. For a selected case, the longitudinal cell-to-cell distance did not influence the Nusselt number while the friction factor was lowest with the highest longitudinal cell-to-cell distance. On the other hand, the increase of the transversal cell-to-cell distance showed a monotonic increase in Nusselt number and a nonmonotonic change of friction factor. The lowest friction factor was observed for an intermediate value of transversal cell-to-cell distance of ($S_T/D = 1.3$).
- 2- Gaussian Process Regression with four different Kernel functions were tested namely, Exponential, Squared Exponential, Matern 5/2, and Rational Quadratic. The results show that the Gaussian Process regression is a powerful tool for predicting the performance of the proposed battery thermal management design. Prediction results from the Exponential Kernel function showed the best and most accurate results in predicting the Nusselt number and friction factor with R^2 of 1 and 0.99, respectively. Furthermore, the model showed a low RMSE of 0.138 and 0.038 in predicting Nusselt number and friction factor, on the respective order.

While the result of the numerical simulations shown in this work was only for a selected case, understanding the interplay of the different parameters is a complex task. Hence, this work illustrates that machine learning algorithms could be used to have an accurate prediction tool that would be useful for researchers in the field and further optimization of the system.

CHAPTER 6:

EXPERIMENTAL INVESTIGATION OF AIR COOLING BATTERY THERMAL MANAGEMENT SYSTEM IN A CONVERGED CHANNEL

6.1. Introduction:

The persistent pursuit of sustainable energy solutions has caused an evolutionary change in the automotive and energy sectors, with electric vehicles (EVs) and renewable energy systems at the forefront of this transformative period. The energy storage infrastructure is critical to the viability and usefulness of these technologies, which mostly rely on lithium-ion batteries due to their high energy density and endurance. However, the proper functioning and preservation of these batteries rely heavily on good heat management systems. Batteries generate heat when they charge and discharge, and the accumulation of this thermal energy can have an impact on performance, safety, and overall longevity. This needs complex thermal management solutions, with air cooling emerging as a promising and widely utilized solution. The incorporation of air conditioning in battery thermal management systems can strike a delicate balance between optimal operating temperatures and energy economy. The appeal of air conditioning stems from its simplicity, cost-effectiveness, and environmental friendliness, making it an appealing choice for a wide range of applications. However, the complexities of air-cooled systems necessitate a thorough understanding of the thermal dynamics involved, which include heat dissipation, temperature uniformity, and overall system efficiency. This master's thesis takes a comprehensive look at the experimental and numerical aspects of air-cooled battery thermal management systems.

This comprehensive study represents a pioneering endeavor in the domain of Air Cooling Battery Thermal Management Systems (BTMS), forging an integrated approach between experimental assessments and numerical simulations. The primary aim is to dissect and comprehend the intricate dynamics inherent in BTMS by scrutinizing the convergence inlet channel at a 10° angle concerning various airflow patterns. Our investigation delves into the nuanced facets of heat transfer rates, temperature distribution, and pressure drop within the system. By bridging experimental insights with numerical simulations, this research offers a novel perspective on the underlying mechanisms governing airflow patterns and channel

configurations, thereby paving the way for substantial advancements in BTMS design and optimization strategies. Moreover, the study aims to bridge the gap between theoretical understanding and practical application by adopting a dual methodology: experimental studies and numerical simulations. The combination of these methodologies is expected to result in a better understanding of the complex thermal dynamics within air-cooled battery systems. Real-world data will be obtained through thorough testing, offering insights into the system's performance in a variety of scenarios. Hence, the experimental sets will be rigorously developed to simulate real-world settings, capturing the transient nature of thermal responses during charging and discharging cycles. While both the charging and discharging operations generate heat within the battery, experiments demonstrate that the rate of temperature rise during discharging cycles is significantly higher "**Appendix B**". This phenomenon results from converting stored energy into electrical energy upon discharge, which increases internal resistance and generates heat. By prioritizing discharge temperature analysis, we aim to address a fundamental part of thermal management by focusing on the most significant temperature variations in the battery system. This strategic approach enables us to focus our efforts on developing effective cooling techniques that reduce overheating hazards and improve the battery system's overall dependability and longevity.

6.2. Methodology:

6.2.1 Experimental setup:

In this study, an air-cooling battery thermal management system is designed to dissipate the heat generation inside the battery pack. **Figure 6.1** shows the schematic diagram of the experimental system. By using the numerical data obtained from Chapters 4 and 5, the experiment was done by using a converged box to simulate the typical configuration found in electric vehicles. The experiment box is made of polyethylene, and the inlet channel of this box is converged by 10° and has the following dimensions (550 mm, 185 mm, and 60 mm). The use of polyethylene for this experiment is due to its low thermal conductivity and hence can maintain the temperature of the ambient environment at a nearly constant temperature and prevent the battery pack from exchanging temperature with the surrounding environment. The battery pack was intended to provide for homogeneous heat dissipation, ensuring that individual cells experienced similar thermal conditions.

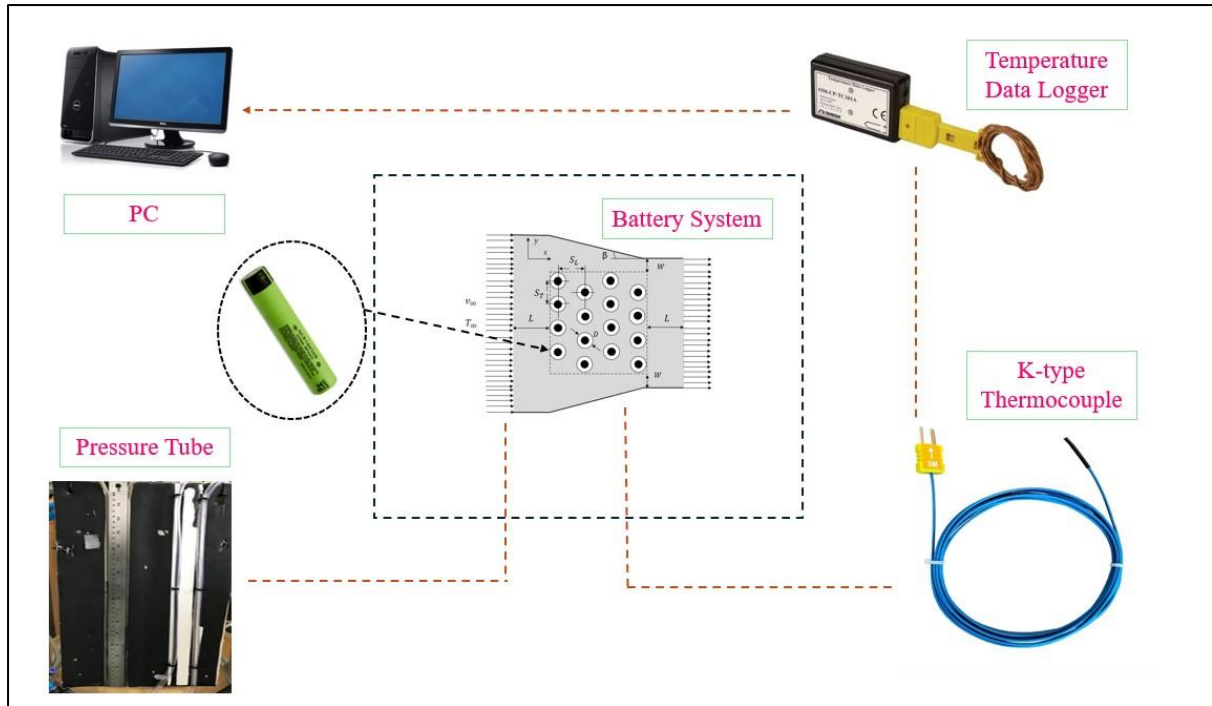


Figure 6. 1. Schematic diagram of the experiment.

The battery pack consists of 16 commercial lithium-ion cells (brand of the cell) divided into 4 rows and 4 columns with staggered distribution. The transversal (S_T) and longitudinal (S_L) distances between the cells are set to be constant in the experiment with 30 mm in both directions. These chosen distances were selected based on the numerical simulation to find the optimum distances between the batteries in which better heat transfer and pressure drop will occur. **Table 6.1** shows the technical characteristics of the lithium-ion cells (NCR18650GA) used in the experiment.

Table 6. 1: Specification of batteries.

Parameter	Value	Unit
Rated capacity	3300	mAh
Capacity (Typical)	3450	mAh
Nominal voltage	3.6	V
Charging Voltage	4.2	V
Energy density (Volumetric)	693	Wh/I
Energy density (Gravimetric)	224	Wh/kg

A distributed numbers of high-precision temperature sensors were carefully installed throughout the battery pack to detect temperature differences in important areas. Six K-type thermocouples (± 0.1 °C) are used to measure the temperatures at 6 different points. Two thermocouples are inserted in the inlet and outlet of the testing pack and the other four thermocouples are inserted into the center of each row of the pack to get the transient temperature value. Each thermocouple is attached to a data acquisition device (OM-CP-TC101A, OMEGA) and these data loggers can operate in harsh environmental temperatures ranging from -40 °C to 80 °C. as shown in **Figure 6.2**, and they are set to measure the temperature at every second of the charging or discharging rate.



Figure 6. 2. OM-CP-TC101A, OMEGA temperature data logger.

To measure the pressure difference between the inlet and the outlet, and then the friction coefficient can calculate, a barometer is used to measure the pressure difference. The barometer tubes are attached to the inlet of the experiment pack and the other tube is opened to atmospheric pressure. Water is used as a substance to read the head difference between the two tubes. **Equation 6.1** is then used to convert the pressure head in millimeters (mm) into the pressure difference in Pascale (Pa).

$$P = \rho g \Delta h \quad (6.1)$$

The cycling process of charging and discharging is done by connecting every single cell to two battery testing systems (CT-4008T, Neware) with eight channels per

testing system. **Figure 6.3** illustrates the battery testing system used for conducting this study. Lastly, the pack inlet is connected to an air compressor with a temperature of 20 °C (± 1 °C). The use of air compressors helps to control the flow rate speed and enables the experiment to go to various flow rates and velocity levels.



Figure 6. 3. CT-4008T, Neware battery testing systems.

Lastly, the required power to run the system can be calculated by using **Equation 6.2** [137]:

$$P = Q \left(p_{in} + \frac{\rho_{air} V_{in}^2}{2} \right) \quad (6.2)$$

where P is the power consumption [W], Q is the volume flow rate of air [m^3/s], p_{in} is the inlet pressure [Pa], ρ_{air} is the density of air at inlet flow temperature [kg/m^3], and V_{in} is the velocity of air [m/s].

This experimental setup aims to provide a full understanding of the thermal management system's performance under various conditions, establishing the groundwork of the numerical simulations and in-depth analysis. The combination of real-time temperature readings, configurable cooling parameters, and controlled ambient conditions creates a strong experimental platform for understanding the thermal dynamics of air-cooled battery systems.

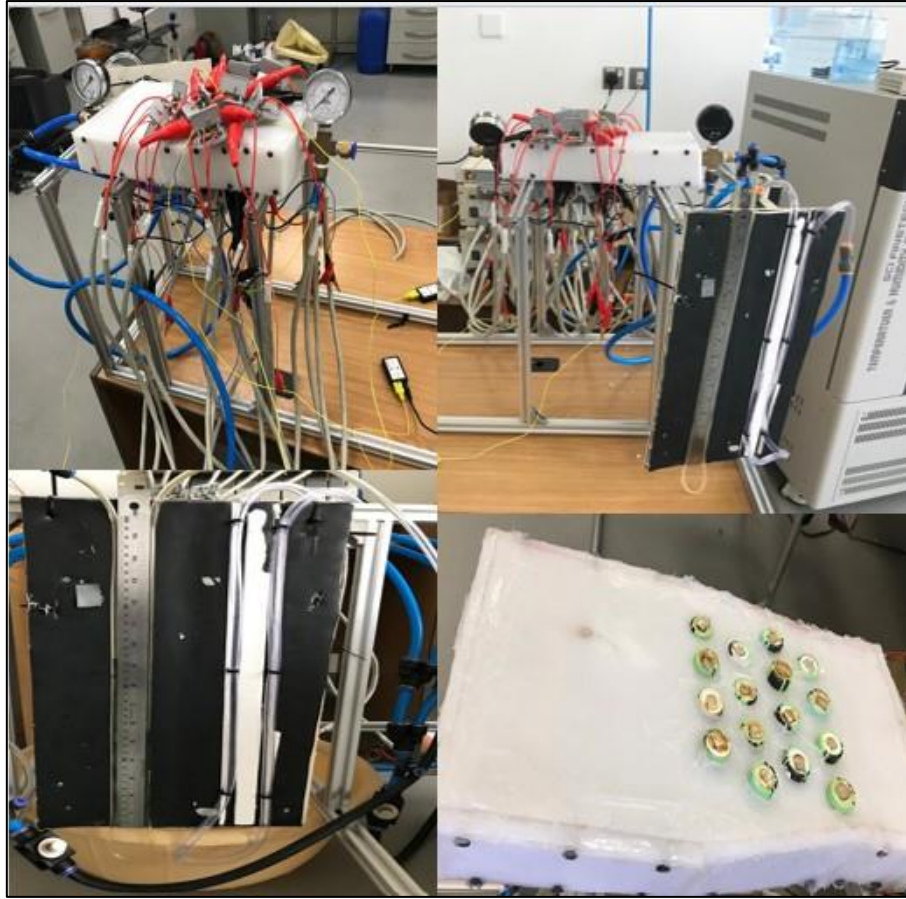


Figure 6. 4. Experimental setup.

6.2.2 Experimental procedure:

The experimental procedures used in this study seek to evaluate the thermal management system of air-cooled lithium-ion batteries completely. The method used consisted of an organized sequence of stages to simulate real-world situations and generate trustworthy data on the thermal dynamics of the battery pack. The experimental techniques replicated a variety of operational circumstances, such as standard charging and discharging cycles and rapid charging scenarios. Each experimental run was meticulously documented, including the applied current, voltage, and ambient conditions, to ensure reproducibility and permit proper analysis. First, to ensure the appropriate distribution of airflow, meshing holes of 1 mm diameter were put at 200 mm of the channel inlet to make sure the airflow was fully developed at this distance. **Figure 6.5** shows the meshing holes that were used during the experiment.

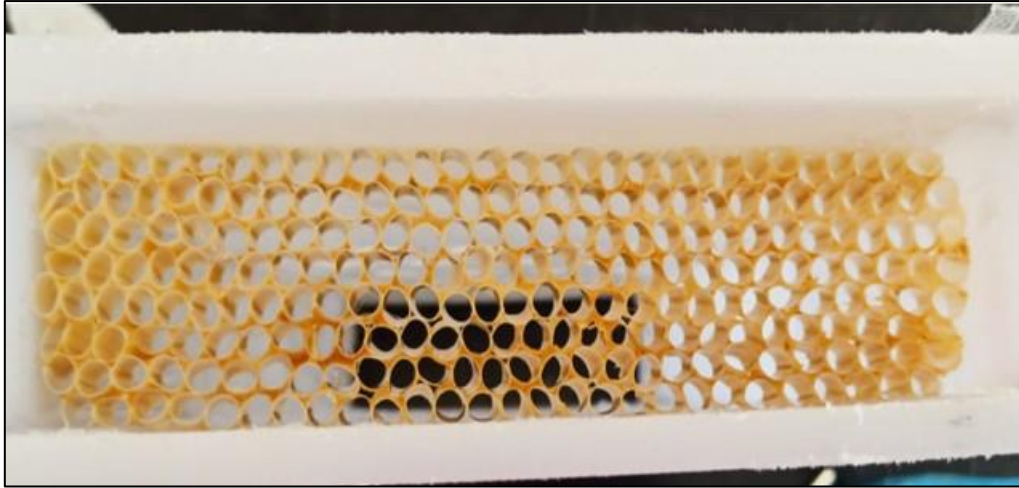


Figure 6. 5. The meshing holes that used to uniform airflow.

To begin the experiment, the charging and discharging cycles were adjusted at various rates ranging from 1C to 4C. The charging and discharging cycles were not continuous. However, after each charge or discharge, an hour interval was taken to guarantee the cells were at the reference temperature of 20 °C. Furthermore, multiple flow rates were used throughout the experiment, beginning at zero CFM (no cooling over the cells), progressing to 0.1 CFM, and finally to 1.5 CFM, with a flow rate interval of 0.2 CFM between each. The pressure drop was measured at every airflow rate whereas the temperature measurements were continuously taken over all the experiments capturing transient thermal responses during dynamic operational conditions.

These rigorously developed procedures for experiments provide a solid foundation for further research on air-cooled battery thermal management systems, to gain complete insights into the thermal dynamics of lithium-ion batteries under a variety of operating conditions. The methodical execution of these methods ensures the dependability and repeatability of the experimental results, allowing for a thorough evaluation of the thermal management system's performance.

6.2.3 Uncertainty Analysis:

The pursuit of scientific accuracy needs a detailed analysis of the uncertainties present in both the experimental and numerical components of this research. Recognizing and quantifying these uncertainties is critical for assuring the trustworthiness and validity

of the results. The uncertainty analysis considers a variety of elements, each of which contributes to the overall uncertainty elements and influences the precision and accuracy of the outcomes. First, three constant current and constant voltage (CC-CV) cycles were performed for each cell before the experiment was done. The cells were charged with a constant current at a charge rate of 1C (2.7 A) up to 4.2 V. Then, the voltage was held at 4.2 V until the current reached the cutoff point (65 mA), followed by a pause for 10 min. Subsequently, a constant current was applied at a rate of 0.5C until the voltage reached 2.75 V, as recommended in several studies [87,138]. Similar to the charging process, the cut-off current and pause time at the end of the discharging process were 65 mA and 10 min, respectively. Here, we can make sure that all the batteries used in the experiment are in the same technical condition. Moreover, the protocols used in the experiment by using battery testing systems were taken from the company manual to ensure that all steps of battery testing were correctly taken [139]. Temperature measurements were subjected to rigorous calibration processes to improve accuracy, taking into account potential sensor drift and calibration errors. Furthermore, all thermocouples and data acquisition devices used in the experiment were of the same brand to eliminate biases with (± 0.1 °C). In addition, the material of the experiment box was selected to have low thermal conductivity to ensure proper control of the environmental condition doesn't interfere with the experiment results.

The uncertainty analysis carried out in the present study acts as a critical lens through which the dependability and precision of the experimental investigations are examined. By meticulously accounting for uncertainties associated with measurement devices and experimental setups the study not only adheres to scientific rigor principles but also provides a comprehensive understanding of the potential sources of variability in the research framework. Therefore, the systematic method of uncertainty analysis strengthens the findings and gives confidence in the validity of the conclusions reached.

6.2.4 Data Analysis:

The data analysis for the experimental investigation is carried out with great attention to detail, to extract valuable insights into the battery system's thermal performance

under changing conditions. The acquired data, which includes real-time temperature profiles, airflow rates, and key parameters, is carefully studied to reveal the complex thermal dynamics within the converged channel. The temperature data profile was collected using K-type thermocouples attached to the data acquisition devices. The data was recorded in the data loggers every second during the charging and discharging cycles. Then, the statistical metrics, such as mean, maximum, and minimum temperatures during each minute, are used to identify the trends and variances in thermal behavior along the converged channel. Hence, the distribution of temperature within the battery pack and along the convergent channel is studied to determine heat dissipation patterns. Temperature variations between different channel segments where thermocouples were placed are examined to determine the efficacy of the air-cooling system. The pressure drop measured during the experiment was compared with the pressure drop obtained by numerical simulation at the same condition in which the discrepancies are carefully evaluated to refine the model and increase its prediction skills, with a cross-validation approach used to improve the results' reliability. Consequently, the key parameters of the study which include charging/discharging rates, airflow rates, temperature measurements, and pressure drop are simultaneously recorded and studied to ensure the reliability of the outcomes of the experiment. Therefore, The results of this data analysis not only contribute to a thorough understanding of the air-cooling battery thermal management system within a convergent channel but also serve as a foundation for informed recommendations to improve the system's performance. The comprehensive examination of experimental data along the converged channel improves the study's conclusions, making important contributions to the broader discussion of energy-efficient and sustainable battery temperature management.

6.3. Results & Discussions:

6.3.1 Effect of Air Flow Rate:

The study of the effect of airflow rate on the thermal management system inside the convergent channel produced interesting results, providing light on the crucial function of airflow dynamics in managing the temperature profiles of the battery system. The experiments at varying air flow rates revealed discrete thermal reactions

that serve as the foundation for understanding the system's susceptibility to various cooling conditions. As a result, this subsection presents the two most important factors for BTMS performance: pressure drop and temperature variation. **Figure 6.6** depicts the pressure drop in the system at various airflow rates. The observed pressure drop is significant since it corresponds directly with the thermal management system's efficiency. The research found that differences in airflow rates had a direct impact on the extent of pressure decrease, with higher flow rates demonstrating more resistance. This phenomenon is linked to increased convective heat transfer, which requires a particular level of pressure drop for effective cooling. The pressure drop is compared to the same configuration determined by CFD simulation. The **Figure** shows that the experimental pressure drop data are almost identical to the CFD predictions and they have approximately the same increasing trend with a maximum variation of 30% and minimum variation of 17% between the two datasets, indicating the numerical simulations' reliability and precision in capturing the complicated flow characteristics within the convergent channel. The correlation between experimental and simulated pressure drop profiles validates the numerical model's ability to simulate the complex fluid dynamics involved in air cooling.

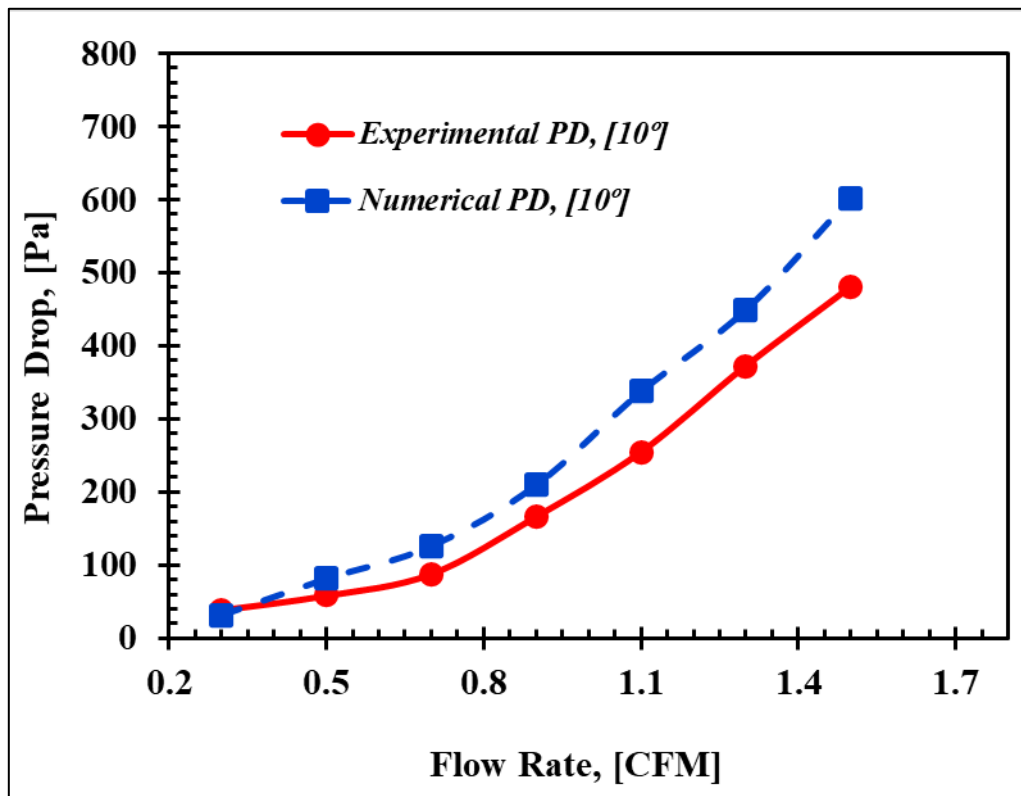


Figure 6. 6. Experimental and numerical pressure drop at 10° with various airflow rates.

Consequently, the pressure drop findings have far-reaching consequences for thermal management system optimization. Balancing the demand for increased cooling efficiency against the accompanying energy consumption becomes an important factor in system design.

Figure 6.7 shows the maximum and average heat transfer that occurred at various flow rates during battery discharging at 1C. Increasing the flow rate increases the kinetic turbulences among the batteries and hence more efficient heat transfer occurs and reduces the temperature of the battery pack. Moreover, increasing the air velocity minimizes the thermal between the battery pack and its surroundings. This reduction in thermal resistance permits faster heat transmission and lowers the highest possible temperature achieved by the battery pack during operation. Thus, it will ensure the durability of the cells and prevent any deterioration of these batteries.

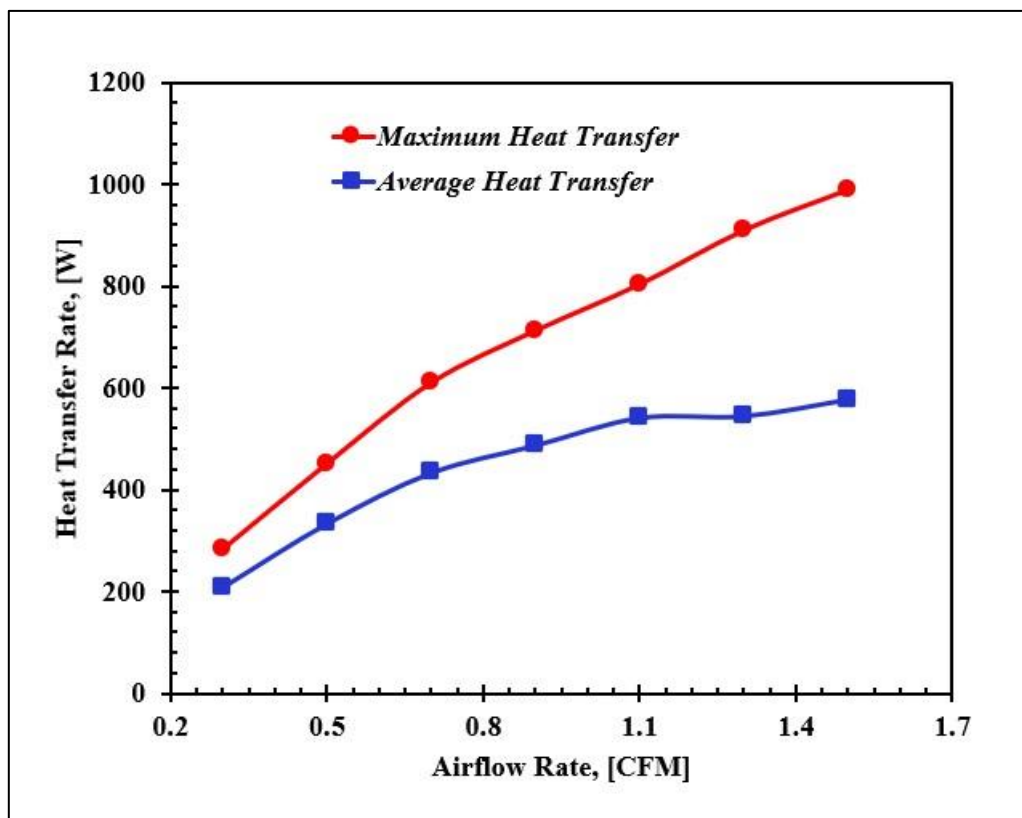


Figure 6. 7. Maximum and average heat transfer occurred at various flow rates during battery discharging at 1C.

The temperature contours provide a visual depiction of the thermal profile, indicating regions with variable temperatures along the channel's length. Warm colors indicate high temperatures, giving a clear indicator of heat concentration and dissipation

patterns. These contours provide a more complex understanding of how cooling air interacts with battery cells, assisting in the identification of possible hotspots and supporting educated temperature regulation measures. Meanwhile, the velocity contours express the changing airflow patterns within the channel. Different patterns of airflow acceleration and deceleration are visually represented, providing insight into how the cooling medium moves through the converging geometry.

After observing the overall heat transfer from the system, it is now important to investigate the temperature variations within the cells in each row of the system. **Figure 6.8** represents the temperature change in the four rows of the system at different flow rates and 1C. At zero flow rate condition, all the batteries have the same trend of temperature increase where all of them exceed the 40 °C. Here, it can be considered as the reference situation where no cooling occurs at a discharge rate of 1C. By increasing the flow rates, apparent variations present in the temperature change. The first-row temperature in all the cases remains at stable temperature conditions and does not exceed 30 °C, and at higher flow rates above 1 CFM, it is an almost straight line with 3 3-degree increase in the temperature compared to the initial state. This is because the cold air first strikes the first row without any influences from the other cells in the system. The second and the third rows are nearly close to each other with little increase in the temperature in the third row. Lastly, the highest temperature is in the last row and this is due to the increase in temperature of the cooling air and the smaller portion of the flow that comes in contact with the cells in this row as can be seen from the CFD velocity contours at **Figure 6.9**. Overall, during the 1C discharge rate, all the cells are below 40 °C which means that the battery pack is running under a suitable and stable condition without any concerns about deterioration of the system.

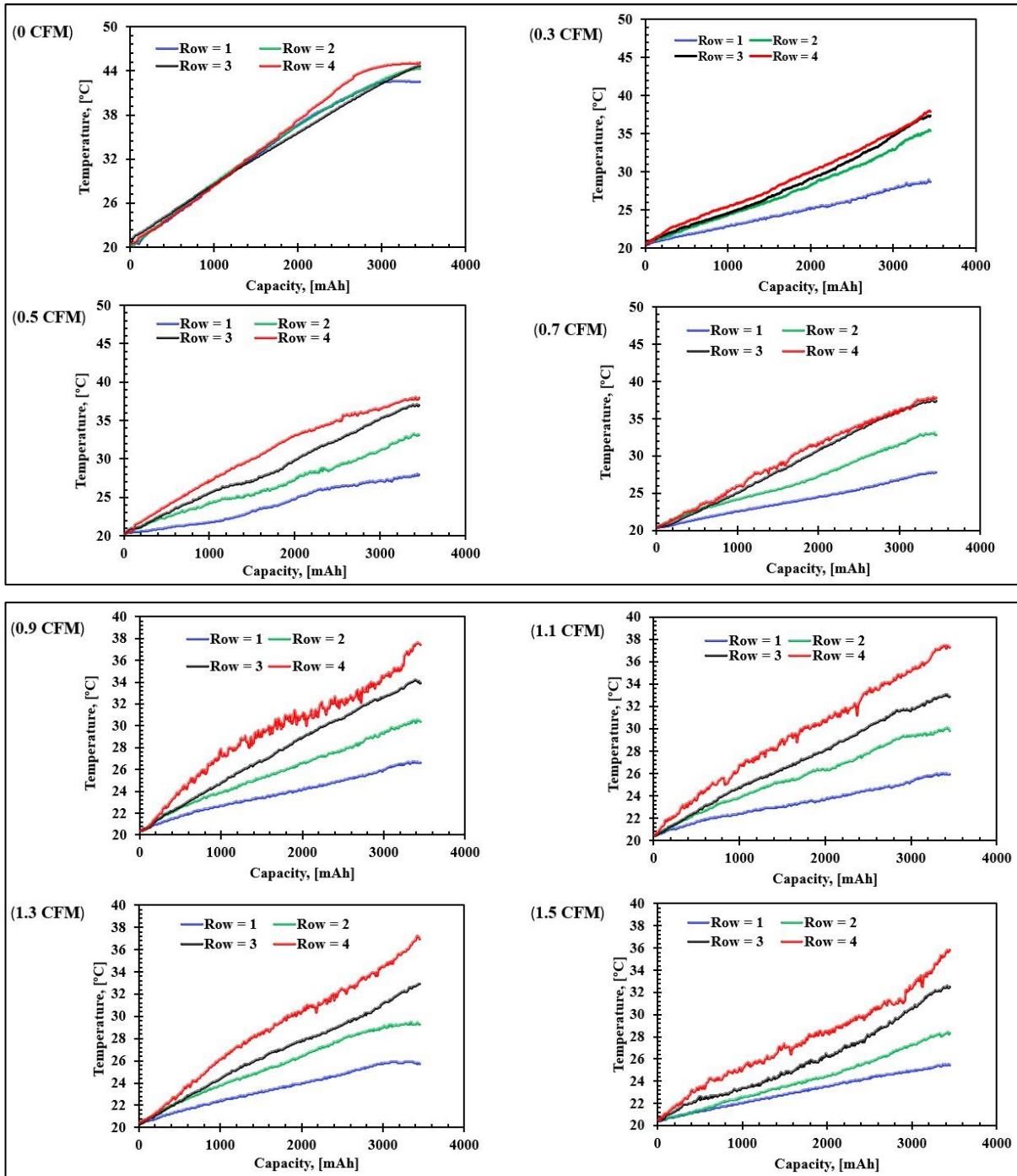


Figure 6. 8. Temperature change in the four rows of the system at different flow rates and 1C.

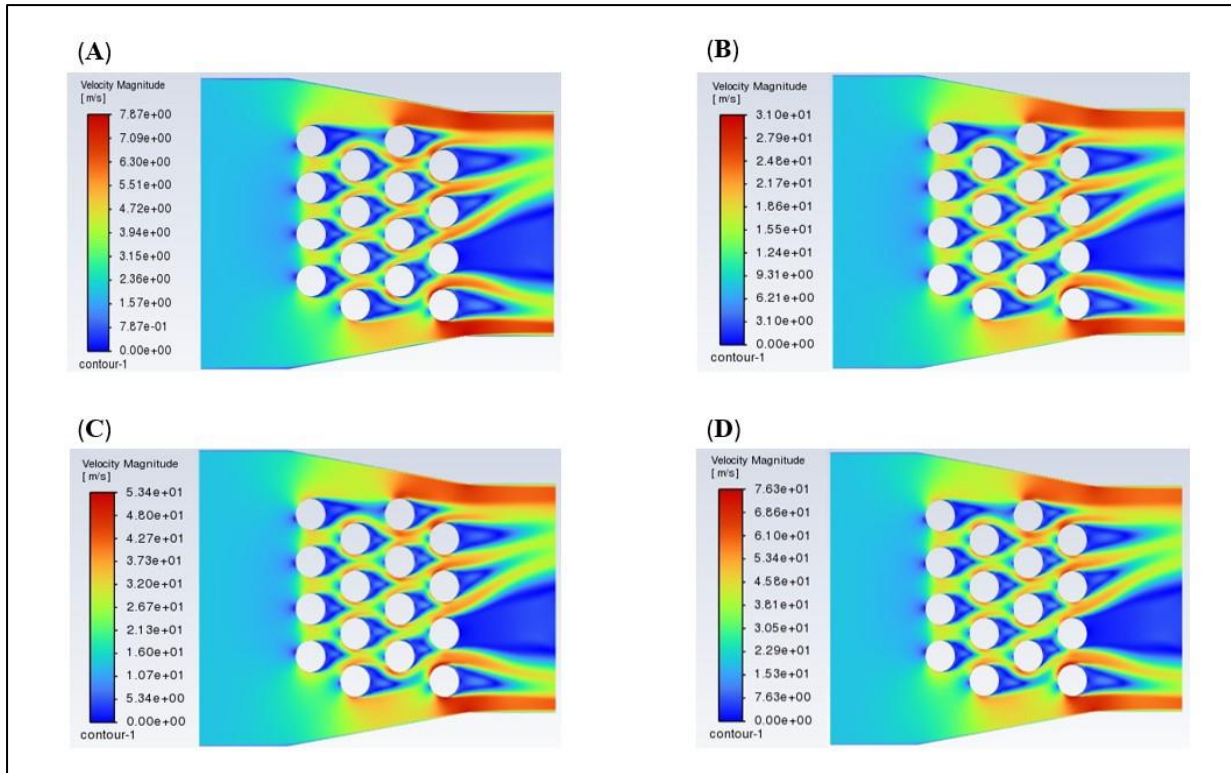


Figure 6. 9. Velocity contours using CFD simulation at 10° and A) $V= 2$ m/s, B) 8 m/s, C) 14 m/s, and D) 20 m/s.

Although this, it has been noted that increasing the flow rate from 0.3 to 1.5 CFM improves temperature uniformity, yet the difference is insignificant. As a result, the optimal flow rate must be carefully determined, as increasing the flow rate also increases power consumption, as shown in **Figure 6.10**. As the airflow rate increases from 0.3 to 1.5 CFM, power consumption increases from 0.0060 to 0.393 W.

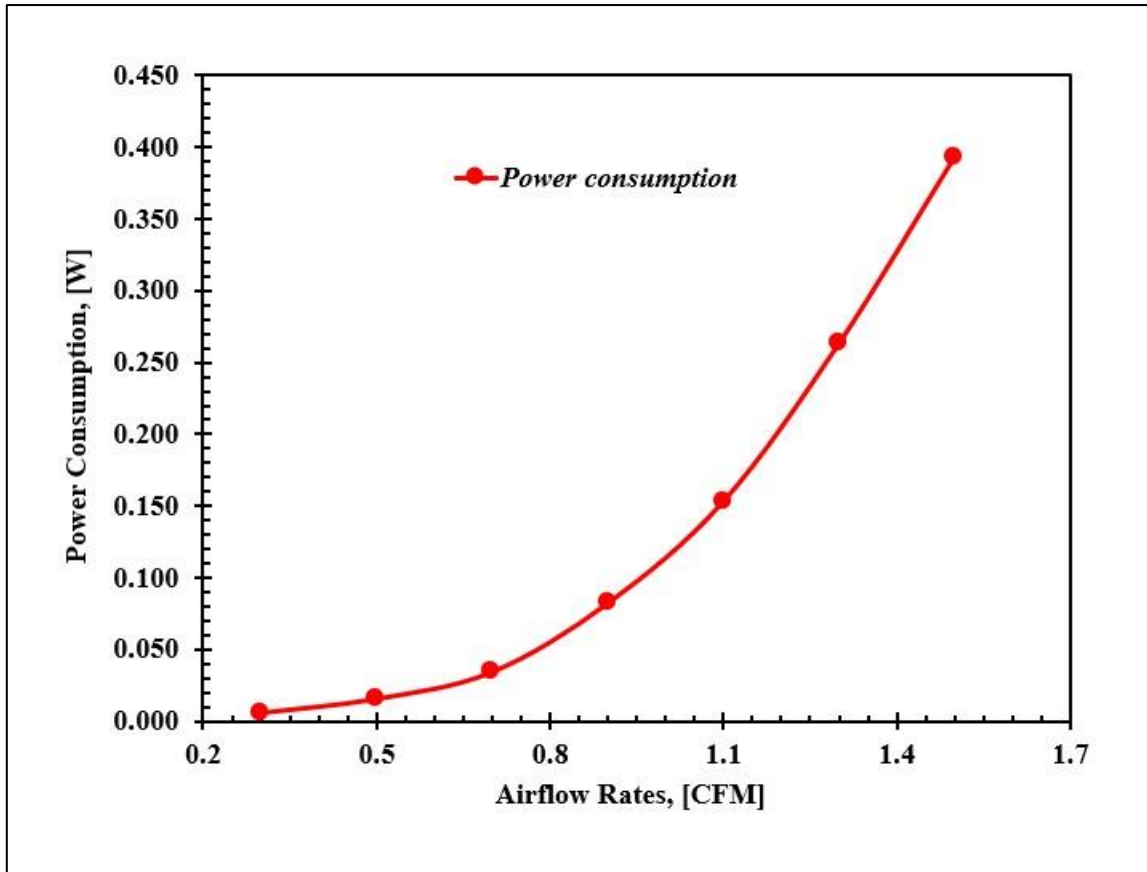


Figure 6. 10. Power consumption at various airflow rates under 1C.

6.3.2 Effect of Discharging Rate:

The influence of the discharging rate on the battery pack system is an important concern when studying the dynamic behavior and performance characteristics of energy storage systems. As the discharge rate changes, the electrochemical processes within the battery cells react subtly, affecting critical parameters such as voltage, capacity, and temperature. At higher discharge rates, the system encounters more internal resistance, which can lead to raised temperatures and a decrease in overall efficiency. This event highlights the complex interplay between electrochemical kinetics and thermal control methods, needing a thorough investigation to optimize discharge profiles for a variety of applications. As a result, studying the influence of the discharge rate provides crucial insights into the system's behavior under various operational situations, which is critical for creating resilient and adaptive battery systems capable of fulfilling the dynamic needs of the battery. **Figure 6.11** shows the effect of the discharge rate (1C – 4C) under zero airflow rate. By increasing the

discharge rates, The cells' temperatures rise as more heat is generated, and the cells' temperatures increase from 40 °C and reach about 70 °C which exceeds the safety operational limits of LIBs. Hence, the collapse of the system and the occurrence of thermal runaway in the system are inevitable in this situation. The heat generation increases with higher discharge rates due to increasing internal resistance and chemical reactions. Here, the operation of BTMS is required to reduce the heat generation in the battery pack.

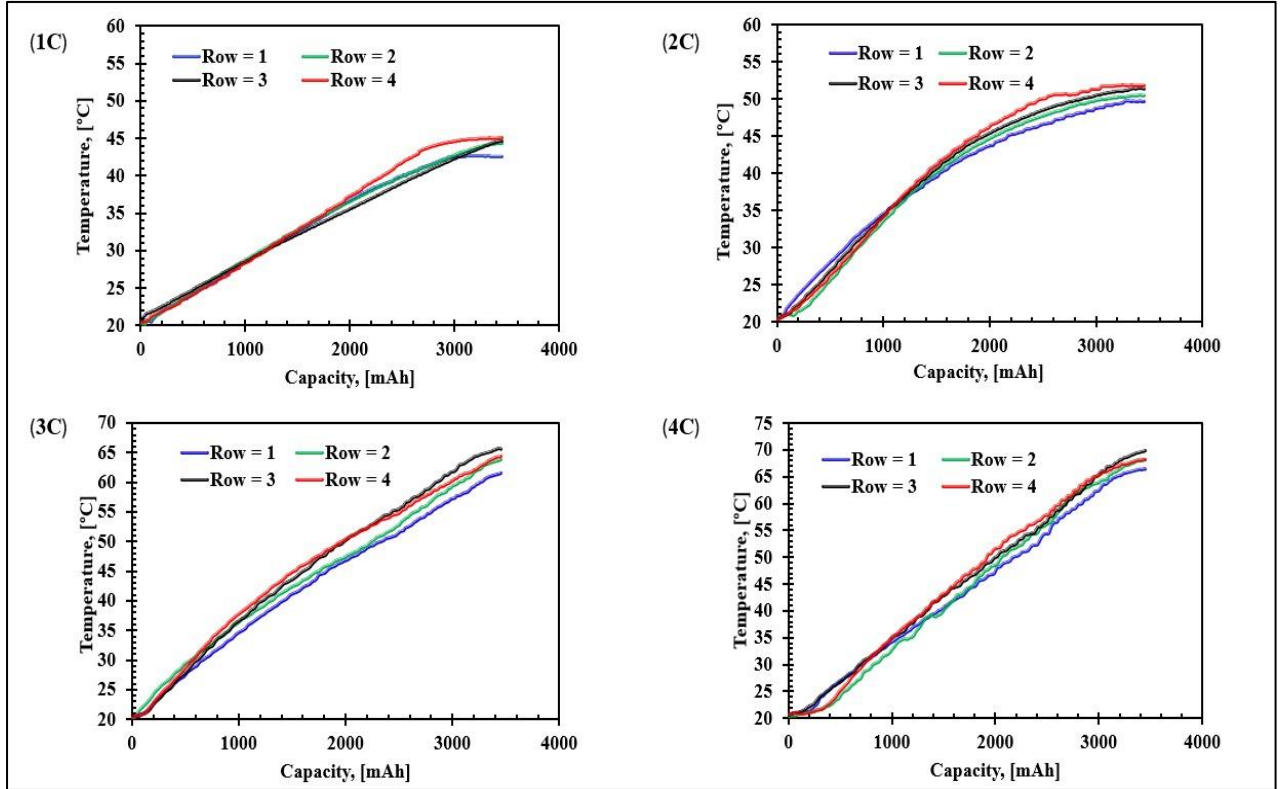


Figure 6. 11. Temperature variation of cells in the middle of the battery pack under zero flow rate and from 1C – 4C.

Figures (6.12, 6.13, and 6.14) illustrate the effects of increasing the airflow rates at high discharge rates (2C, 3C, and 4C). It is observed in all the cases, the temperatures of the first and the second rows are levelized to be within the acceptable range of operating conditions. The differences between 0.3 CFM and 1.5 CFM in the first row were about 17%, 18.1%, and 22% at (2C, 3C, and 4C) respectively. Whereas, in the second row the variation between the lowest and highest flow rates were 28.8%, 26.9%, and 30% at (2C, 3C, and 4C) respectively. Of course, by increasing the flow rate the temperature reduces more, but the variations in the first row were not the same as the second row because of the minimum increase of temperature in the first

row where the cooled airflow contacts at first with these cells and keeps them at low temperature. On the other hand, the temperatures of the third and fourth rows are approximately attached, especially at low flow rates. In almost all cases, the temperature of these cells is beyond the appropriate limits. The reason for this is due to the increase in heat generation of the battery pack, and hence the temperature of the airflow striking those cells is higher than the inlet airflow temperature. However, by increasing the flow rates above 1 CFM, more improvement of the heat generation occurs in particular within 2C. At 2C, the difference between the lowest and highest flow rates was 17% in the third row and 22.2% in the fourth row. Yet with high discharge rates, the flow rates must increase more than 1.3 CFM to reach a suitable condition for heat generation. At 3C and 4C, the differences were 16.7% and 17.8% in the third row, while in the fourth row they were 22.7% and 25.7% respectively. It is worth mentioning that the low percentage of improvement of temperature change in the third row is because the cells in this row are surrounded by warmer airflow due to the heat generation of the second and the fourth rows, but the fourth-row cells are surrounded by free space at the back of the cells allowing more convection to occur without any heat generation in among these cells. Therefore, by raising the air inlet flow rate at high discharge rates, the cooling system is more capable of handling the additional heat generation, resulting in a greater reduction in maximum temperature. Additionally, the converged inlet channel assists in directing the airflow to the cells near the boundary walls, resulting more uniform distribution of flow within the battery pack as can be shown in the CFD simulation contours in **Figure 6.9**.

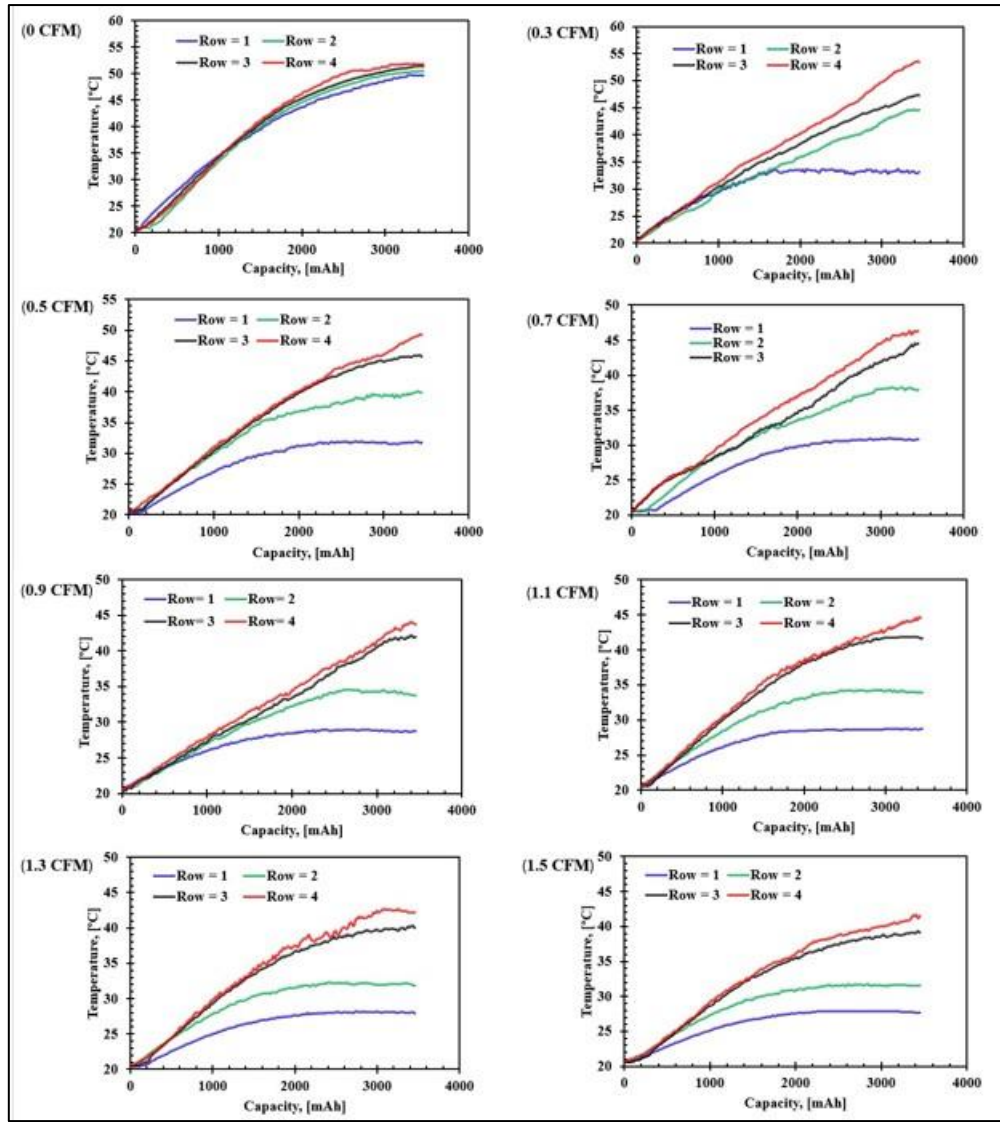


Figure 6. 12. Temperature variations at different airflow rates and under 2C.

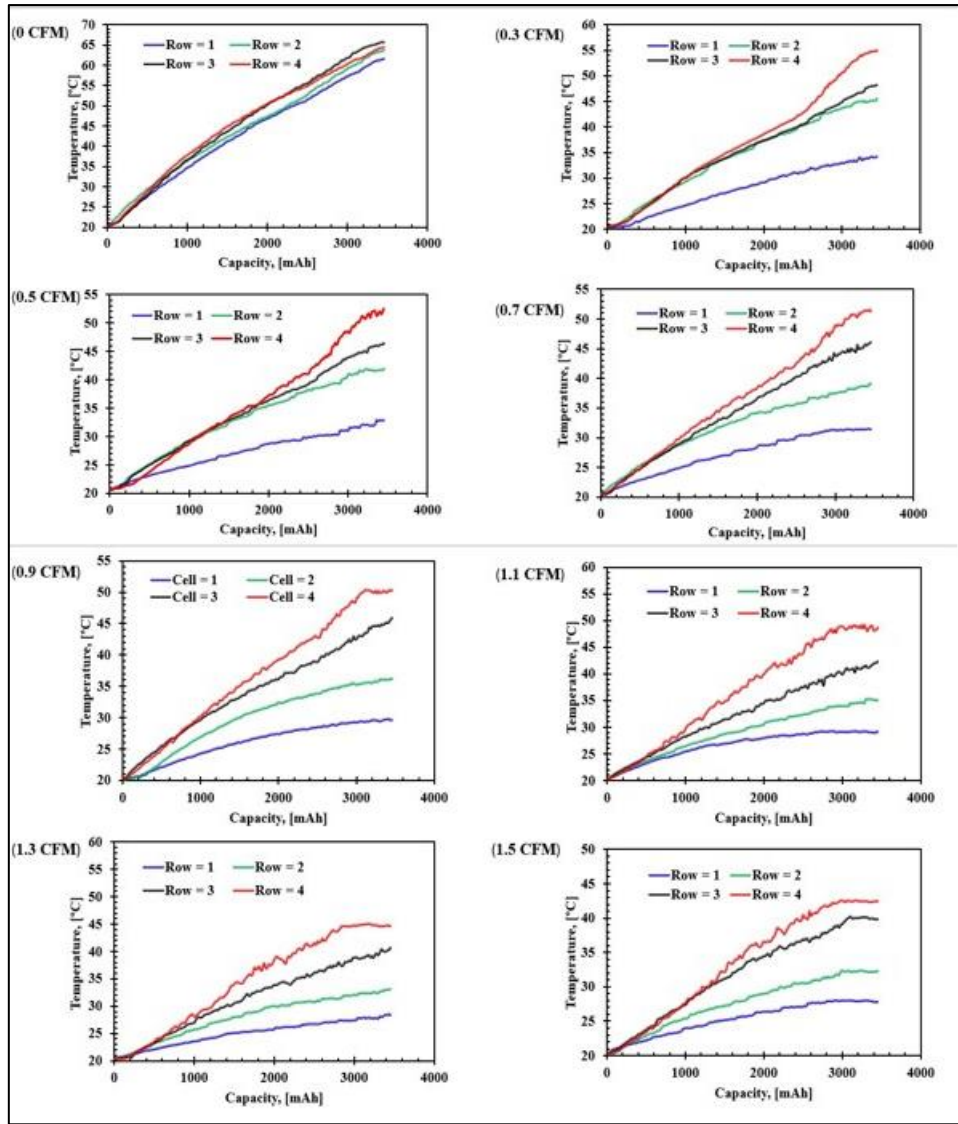


Figure 6. 13. Temperature variations at different airflow rates and under 3C.

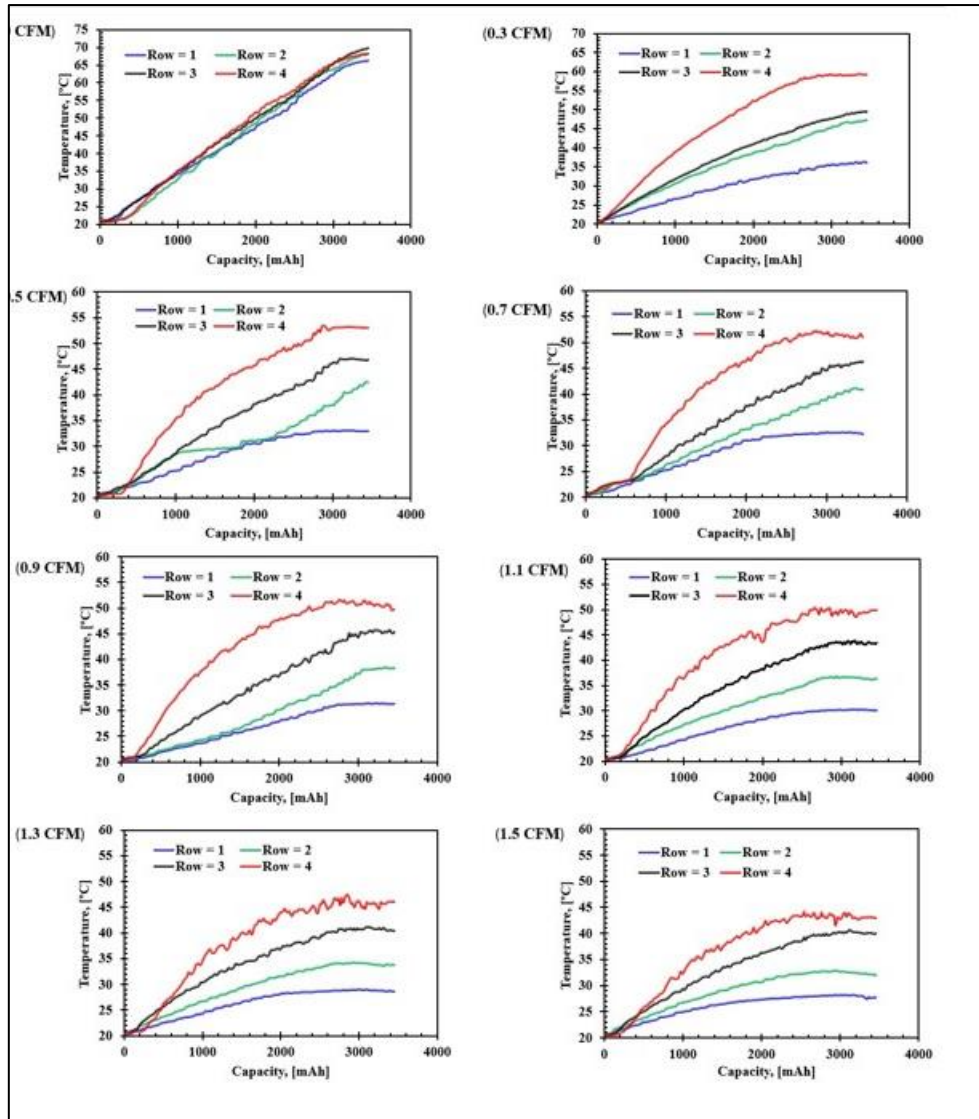


Figure 6. 14. Temperature variations at different airflow rates and under 4C.

6.4. Conclusion:

In this study, The experimental investigation of the air cooling battery thermal management system in a converged channel provided substantial insights, particularly into the implications of airflow rates and high discharging rates on system performance. The study thoroughly investigated temperature changes, heat transfer dynamics, and pressure drop, demonstrating the significant connection between airflow rates and thermal behavior. Furthermore, the effect of high discharging rates on the battery's temperature profile was thoroughly investigated. The findings highlight the need to regulate airflow rates to improve cooling efficiency while remaining energy efficient. Furthermore, the study provides light on the issues given by rapid discharging rates, underlining the importance of strong thermal management systems to reduce temperature rise and preserve the longevity of battery cells.

These findings provide a solid platform to build air-cooled battery systems that can adapt to changing operating circumstances, which will accelerate the development of sustainable and effective thermal management solutions in the field of energy storage technologies.

CHAPTER 7:

CONCLUSION AND FUTURE RECOMMENDATIONS

In this study, this work has addressed the critical challenge of enhancing the efficiency of Battery Thermal Management Systems (BTMS) in harsh environmental conditions, with a focus on Lithium-ion batteries. Through a variety of approaches encompassing calendar aging studies, computational fluid dynamics (CFD) simulations, machine learning techniques, and experimental investigations, valuable insights have been gained into optimizing BTMS performance.

Calendar aging experiments have revealed critical data on the degradation mechanisms of lithium-ion batteries over 60 days. The batteries were stored under various state of charge (SoC) and storage temperature conditions in which they were divided into nine groups. A wide range of performance metrics were investigated, including self-discharge, state of health (SoH), internal resistance, coulombic and energy efficiency. The findings emphasize the role of storage temperature in influencing LIB performance, with a greater impact observed at full charge (SoC = 100%). Under the most challenging storage scenario—cells housed in glass-covered containers, exposed to direct sunlight, and charged to full capacity—the SoH decreased by up to 6%, internal resistance increased by 6.5%, and coulombic and energy efficiencies decreased by 2% and 2%, respectively. The results highlight the significance of proper temperature control in preventing aging-related performance decline. Furthermore, this study emphasizes the importance of developing effective cooling techniques to ensure lithium-ion batteries' longevity and performance in extreme heat environments. This research focuses on the influence of calendar aging in a place with severe temperatures, expanding understanding and providing valuable insights for enhancing battery performance in similar environments.

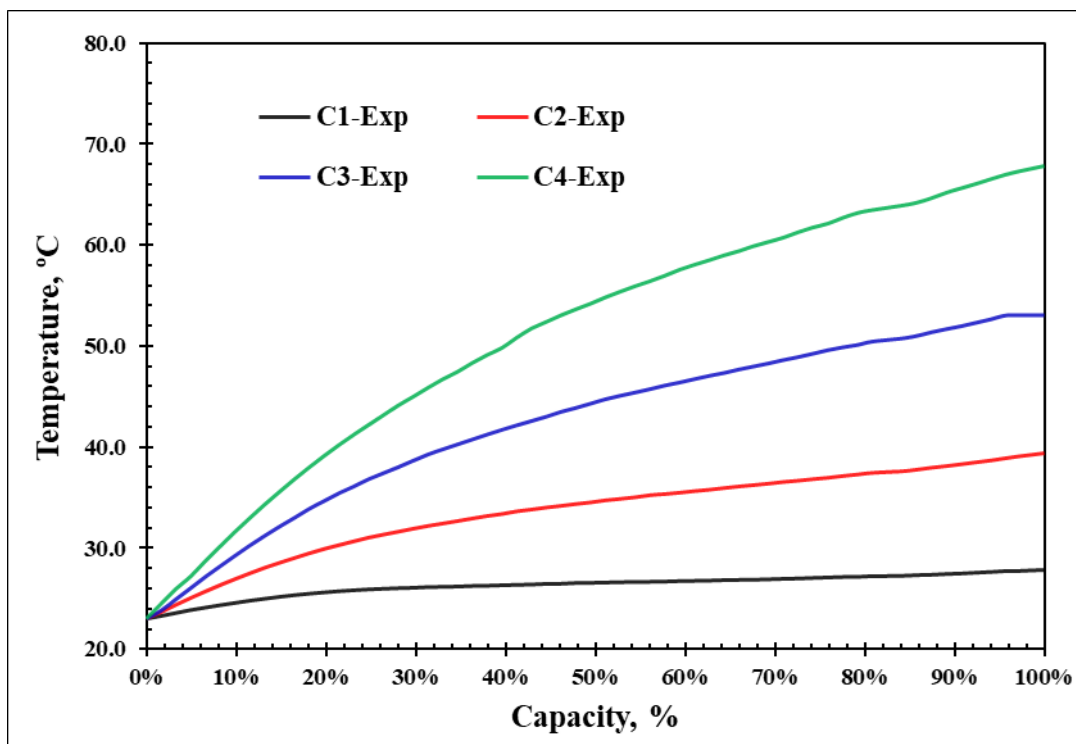
The 2D CFD simulations provided a thorough examination of air-cooling BTMS configurations, allowing for the determination of ideal design parameters to improve cooling efficiency while keeping battery temperature within safe operating limits. Different parameters were examined including the transversal and longitudinal distances, channel inlet angle, confinement ratio, and air-cooling velocity. The study reveals that increasing the transversal distance has the most impact on the amount of heat transfer and pressure drop

across the system whereas the longitudinal distance has a minor impact on the performance of the system. Moreover, the introduction of a channel inlet angle helps to improve the overall heat dissipation from the system, especially when the angle is above 10 degrees. However, with increasing the inlet angle, more friction factor results and leads to a higher pressure drop in the system. Additionally, the effect of the channel confinement ratio on heat transfer and pressure drop is investigated. The results reveal that increasing the distance between battery cells and channel walls enhances heat removal efficiency, resulting in a lower pressure drop and less energy usage. The proposed correlations for the Nusselt number and friction factor, computed from a large dataset using machine learning algorithms, outperform standard correlations in terms of accuracy and prediction capabilities.

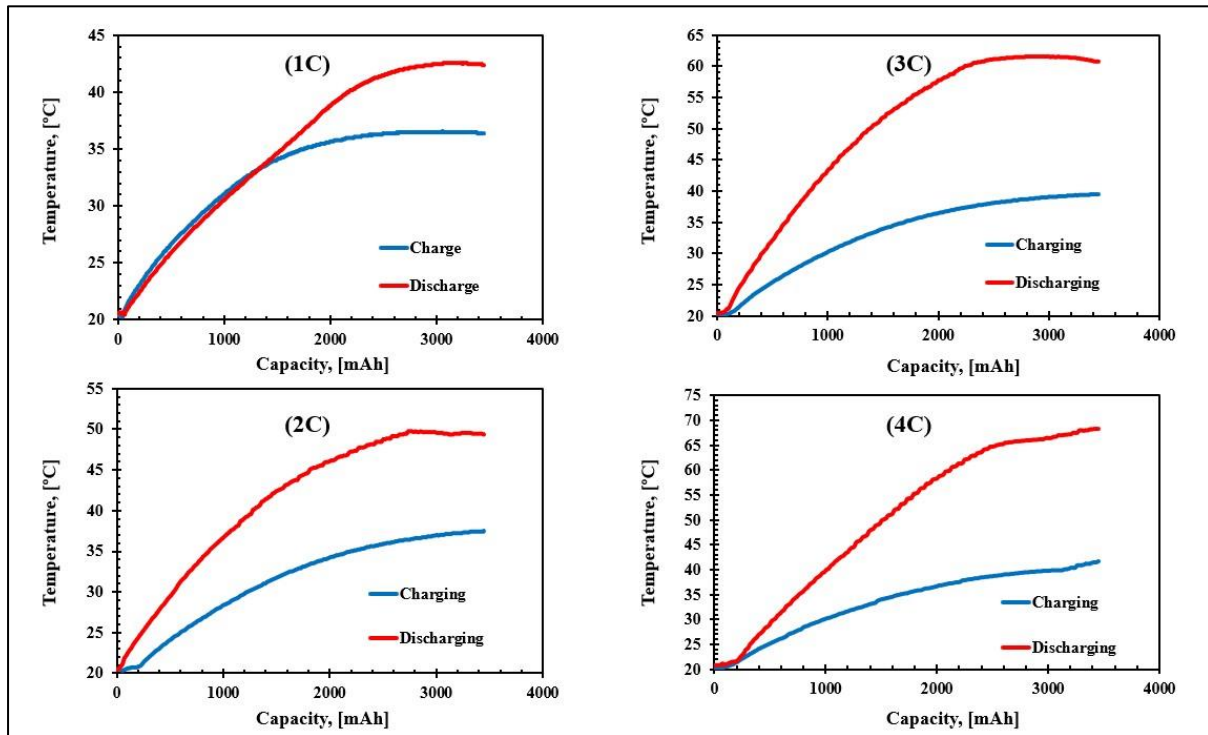
The experimental study on the effect of channel inlet angle on BTMS performance produced useful research findings, demonstrating the impact of channel geometry on cooling effectiveness and pressure drop. These findings highlight the significance of geometric considerations in BTMS design and optimization efforts. In addition, a proper airflow rate should be selected based on the amount of discharging rate from the system to achieve more heat stability of the system and reduce the amount of energy used for cooling.

In conclusion, this finding opens up various exciting possibilities for future research and advancement. To begin, the use of three-dimensional CFD models can provide a more complete understanding of airflow distribution and heat transfer inside BTMS systems, allowing for additional cooling performance optimization. Furthermore, integrating advanced control algorithms guided by machine learning models has the potential to improve BTMS's adaptive capabilities, allowing for optimal thermal management in dynamic working settings and swift response for a wide range of possibilities to ensure safe and sustainable use of battery systems. Furthermore, investigating novel cooling techniques such as phase change materials or sophisticated heat exchanger designs may provide alternate options for improving BTMS efficiency and reliability in extreme climatic circumstances. Lastly, This thesis contributes to the present efforts to advance BTMS technology for increased efficiency and reliability in difficult environmental settings, establishing the framework for future research and development efforts focused on solving the changing problems in battery thermal management.

APPENDIX A: (Maximum temperature obtained under discharging mode of a Li-Battery)



APPENDIX B: (Maximum temperature obtained under charging / discharging mode of a LIB)



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