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Lithium-ion battery thermal management via advance cooling parameters: State-of-the-art review on application of machine learning with exergy, economic and environmental analysis

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Abstract:	Background: Lithium-ion (Li-ion) batteries are one of the most attractive and promising energy storage systems that emerge in different industrial sectors –at the top of them electrical vehicles (EVs) and electronic devices –regarding the tight collaboration of scientific community and industry. Among crucial factors on performance of Li-ion batteries, thermal management is of great importance as it directly impacted the system from different views. Methods: In the present review, state of the art of advance cooling systems' (such as air/liquid-based cooling, PCM, refrigeration, heat pipe and thermoelectric) parameters of Li-ion batteries from different aspects are scrutinized. Exergy, economic and environmental (3E) analysis used as powerful tools to realize important parameters in battery thermal management. Furthermore, data-driven and machine learning applications in thermal regulation of Li-ion battery and their impact on putting the next steps in this context have been discussed. Significant findings: The pros and cons of each system considering aforementioned tools are realized. Particularly, it was realized that machine learning can be play a vital role in this context while other parameters with respect to 3E analysis can put several steps for better thermal management. Finally, concluding remarks and recommendations and research gaps as the future directions presented.

March 30, 2023
From: Seyed Masoud Parsa (PhD Student)

School of Civil and Environmental Engineering, University of Technology Sydney, Australia

To: respected Editor-in-Chief of the journal of *"Journal of The Taiwan Institute of Chemical Engineers",* Professor Heng-Kwong Tsao

Dear Professor

I am honored to submit the revision of our manuscript entitled "**Lithium-ion battery thermal management via advance cooling parameters: State-of-the-art review on application of machine learning with exergy, economic, environmental analysis"** to be consider for publication in the special of "Optimisation in Energy and Process Engineering" at the Journal of The Taiwan Institute of Chemical Engineers

All of the respected editor and reviewers comments are addressed point-by-point.

Thank you for your consideration

Respectfully Yours

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The review article covers a wide range of topics in the area of the advanced cooling systems of Lithium-ion battery. As per the title and the content in the manuscript, the authors are focused specifically on the machine learning approach in the analysis of the battery thermal performances. Over 104 articles are cited in the development of the review work. While the reader appreciates the efforts to bring up these all references into one pull of article, the article is still under work in progress and the following recommendations are provided for improvement:
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Dear Reviewer: It's added

- Advance cooling parameters in Li-ion battery reviewed
- Exergy, economic and environmental parameters contribution in cooling methods of Li-ion battery
- Machine learning and data-driven methods are powerful tools to realize important cooling parameters
- Recommendations, future directions and research gaps are suggested

Lithium-ion battery thermal management via advance cooling parameters: State-of-the-art review on application of machine learning with exergy, economic and environmental analysis

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Abstract

Background:

Lithium-ion (Li-ion) batteries are one of the most attractive and promising energy storage systems that emerge in different industrial sectors –at the top of them electrical vehicles (EVs) and electronic devices –regarding the tight collaboration of scientific community and industry. Among crucial factors on performance of Li-ion batteries, thermal management is of great importance as it directly impacted the system from different views.

Methods:

In the present review, state of the art of advance cooling systems' (such as air/liquid-based cooling, PCM, refrigeration, heat pipe and thermoelectric) parameters of Li-ion batteries from different aspects are scrutinized. Exergy, economic and environmental (3E) analysis used as powerful tools to realize important parameters in battery thermal management. Furthermore, data-driven and machine learning applications in thermal regulation of Li-ion battery and their impact on putting the next steps in this context have been discussed.

Significant findings:

The pros and cons of each system considering aforementioned tools are realized. Particularly, it was realized that machine learning can be play a vital role in this context while other parameters with respect to 3E analysis can put several steps for better thermal management. Finally, concluding remarks and recommendations and research gaps as the future directions presented.

Keywords: Li-ion Battery; Thermal Regulation; Artificial Neural Network (ANN); Deep Learning; Data-driven Methods; Energy Storage

Nomenclature	
AC	Alternating current
BTMS	Battery thermal management system
EV	Electrical vehicle
Exe	Exergetic

Ene	Energetic
HEV	Hybrid electrical vehicle
PCM	Phase change material
PSO	Particle Swarm Optimization
Li-ion	Lithium-ion
LIB	Lithium-ion Battery
COP	Coefficient of performance
TMS	Thermal management system
FVM	Finite volume method
P&ID	Piping and instrument diagram
SVR	Support Vector Regression

1. Introduction

Energy in any form is the one of the important parts of human being. It is among the most constant-consumed goods that consistently have emerged through history and a vital element for global development. Generally speaking, energy in whatever forms, it can be commonly categorized into two parts: primary and secondary. Primary energy forms can be defined as those that only need to be extracted or captured with/without separation, cleaning, and /or grading before the energy contained in. In general, primary energy forms converted either to heat or mechanical work. This from of energy commonly would be found in nature and it can be referred any transformation and/or conversion processes. Obviously, most of the renewable and non-renewable energy sources can put into this category. Some instance of primary energy forms are natural gas, oil, coal (in non-renewable context and wind, geothermal, tidal, solar, biomass, water (flowing-falling) for renewables. On the other side of the coin, secondary form of energy comprise all type of energy that obtain as the result of transforming primary energy form. Interestingly, the second forms of energy are the most utilized for end-users as they can be directly employed by human- also called energy carriers- and some of the prominent examples are diesel, gasoline, electricity, hydrogen, ethanol just to name a few. Moreover, by increasing the population the rate of the energy demand through the world is exponentially on the rise. According to the IEA report in the less than 50 years the rate of energy consumption on in the world becomes twice. As a result, many scenarios to provide energy (whether the primary or secondary forms) are proposed. Meanwhile, different types of batteries are one of the most attractive methods to provide energy in this context. In this regard, lithium-ion batteries over other novel energy storage systems is of great importance due to the numerous advantages over other type of battery such as high energy density, low rate of self-discharging, low maintenance, broad application thorough different purpose, environmentally benign and high number of charging cycles [1]. Applications of lithium-ion batteries were defined in broad ranges from electrical vehicles to electronic devices. Figure 1 shows some of the most commonly used and emerged applications of lithium-ion batteries.

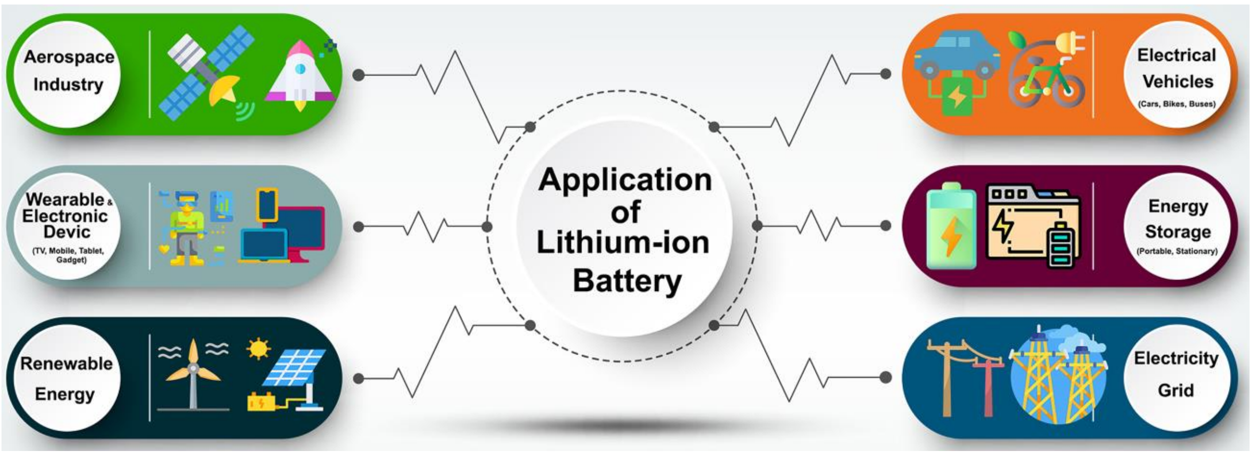

Figure 1. Different applications of lithium-ion battery through industry

Likewise any novel technology Li-ion battery also confronted with many challenges (Figure 2). In recent years among important challenges that associated in development of lithium-ion batteries, thermal management came into spotlight since it directly/indirectly would affect other parameters. Regarding the importance of battery thermal management numerous reviews from different views have been conducted in this context. A huge number of these reviews are highlighted advances and comparisons between different active/passive thermal management systems [2–7]. Moreover, other approaches such as the type of materials [8], degradation of battery [9], safety issues [10], modeling approaches [11], high performance anode and cathode electrodes[12–14], electrodes modification through thermal management improvement [15] and nanomaterials assisted in cooling of systems [16,17] were reviewed. However, the role of important thermodynamic, economic, environmental and artificial intelligent parameters in thermal management of lithium-ion batteries has been outshined. Hence, the main focus of present review is to highlight the important parameters in cooling of lithium-ion battery considering exergy, economic, environmental and machine learning application.

In the first part of manuscript various thermal management scenarios and their pros and cons are concisely discussed. In the second part, we discussed on exergy, economic and environmental analysis regarding different battery thermal management systems. Additionally, application of machine learning, data-driven and numerical methods for thermal management of Li-ion batteries examined. Finally, prospects and future works based on existing research gaps in open literature are recommended.

Figure 2. The most well-known challenges in development of lithium-ion batteries

2. Battery thermal issues

The process of providing energy via batteries is on the basis of electrochemical reactions. In essence, exothermic reactions and ohmic losses are two main factors which have contribution in generating heat in batteries. As the heat generated, series of chain reactions in cells and modules occurred. Since temperature of cells as well as modules in battery is not mutually exclusive, increasing temperature directly affect cells and modules. It means, when a cell's temperature increases it impacted the adjacent cell too which results in rising temperature through the module, hence, the heated module also transfer heat to its neighbors module. This chained-like phenomenon in cells and modules is the reason for increasing and distributing temperature in battery's packs. Increasing temperature of batteries has several side effects from different viewpoints in broad ranges from performance to reliability and beyond that, the safety. From performance viewpoint, increasing temperature negatively impacted battery's performance and diminished efficiency whilst it directly related on the reliability of using Li-ion batteries - particularly in electrical vehicles (EVs)- as the supplied-energy would not enough to drive EV in different conditions. Importantly, the vital factor that directly connected to battery's temperature is safety of passengers, since increasing temperature further than a specific threshold leading to thermally runaway in battery and it can lead to gas leaking, fire, and even explosion [18]. Generally, in Li-ion batteries there is an optimum temperature range between 15-35 °C where the battery performance is maximized in this range. Therefore, uniform temperature distribution and controlling the maximum temperature of batteries is the great matter of importance. Hence, thermal management of battery can be important from two prospects: (i) providing a uniform temperature distribution across cell-to-cell and module-to-module. (ii) preventing unusual temperature enhancement in cells and modules. In this regard, a number of methods have been proposed for battery thermal management system. Fig. 3 depicted the different cooling techniques to improve performance of batteries.

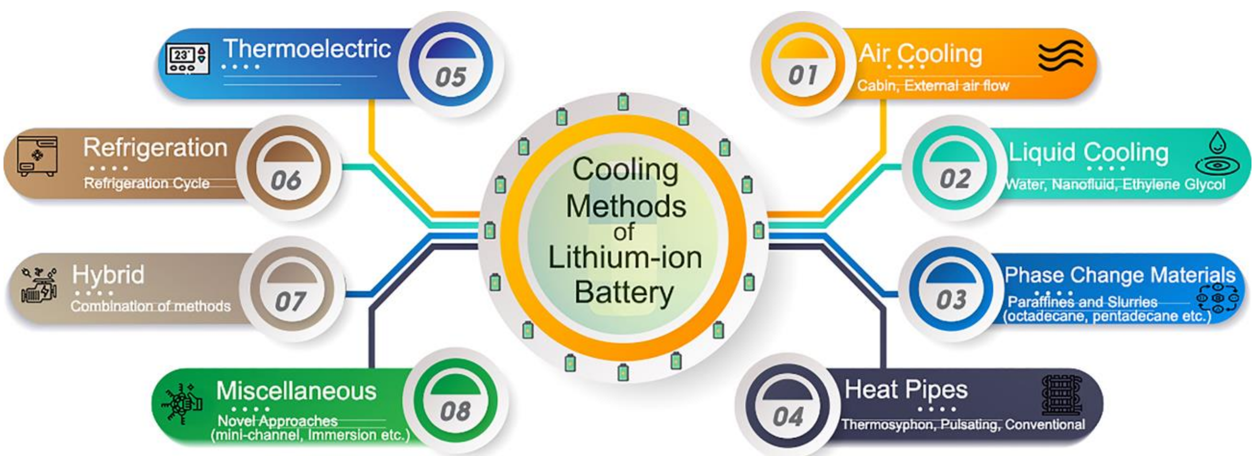

Figure 3. Various methods applied for lithium-ion battery cooling

3. Methods for cooling Li-ion battery

3.1 Air cooling

Air as the most common fluid around us has been scrutinized tremendously for Li-ion BTMS and is broadly implemented for commercial purposes. A good example is two hybrid EVs of Honda (Model "Insight") and Toyota (Model "Prius") that utilized cabin air for thermal management [19]. Typically, air-based battery cooling has been divided to passive and active mode where the passive mode defined when air (i.e., ambient air) is passing through the battery's pack without using any electrical energy (and /or pre-cooled and post-cooled air) while in active cooling, many parts such blowers, air-condition system etc. are involved and the battery pack used the pre/post air-cooled of cabin [20,21]. Among three modes of radiation, convection and evaporation heat transfer in air-based cooled systems, cooling of battery is on the basis of convective heat transfer. Interestingly, it was proved that convective heat transfer coefficient in active mode has superior performance by higher rate of heat dissipating rather than passive mode. Although active cooling shows higher performance [22], passive mode air cooling systems has several advantages such as lower cost/maintenance, simple structure, and lightweight [23]. Therefore, trade-off should be managed considering the pros and cons of each method; however, regarding the importance of thermal management system in battery lifespan and its performance, active mode primarily brought more into the spotlight from academic context to commercial application. In recent years, modifications on active mode air cooling system is predominantly focused on modifying geometry of structure, optimizing parameters and developing thermal models.

3.2 Liquid cooling

The other method for thermal management of batteries is liquid-based cooling systems which has prominent advantages such as higher temperature uniformity and compactness [24]. When liquid-based cooling system in term of heat transfer approach weigh up with air cooling, it is elucidated that the it has some advantages over air-based cooling system. Generally, the prominent advantage of liquid is that it has higher thermal conductivity rather than air-based cooling (natural and force) systems which makes it more interesting alternative compare to air. Practically, liquid-based cooling categorize as direct and indirect cooling [5]. Briefly, direct liquid-based cooling defined whereas coolants are in direct contact with battery modules and it can realize by submerging battery's modules in the cooling medium. The indirect cooling-as its name is obvious- method is realized when the cooling medium is not in direct contact with modules and there is a jacket-like (or tube) heat exchanger that modules are located and by passing cooling fluid the heated jacket/tube transfer heat to the coolant [25]. One of the important differences between direct and indirect cooling methods is that the thermal resistance during indirect cooling unavoidably increases since the heat first should pass through the heat exchanger and after that it absorbed by the cooling medium while direct cooling is more efficient from this prospect. However, the disadvantage of direct cooling is high power consumption (because in this scenario usually coolants with high viscosity such as oil utilized) whilst in the case of the indirect cooling, water (which have lower viscosity) is an appropriate as well as conventional medium. Various types of liquids (experimentally and theoretically) such as water [26], ethylene glycol-oil [27,28] and nanofluids [29–31] were suggested.

3.3 Phase change materials (PCM)

Compare to the air-based and water-based cooling, thermal management by phase change materials (PCMs) has some advantages over the above mentioned systems. Although utilizing PCMs consider as passive cooling method, it has a high potential to regulate the temperature of battery [2]. The advantage of using PCM can be mention as: (i) less components are needed compare to other cooling systems. (ii) generally, less space is required in PCM-based cooling system and the cost of installing is low. (iii) no need to electrical components such as pump and blower, thus, no power consumed. (iv) high latent heat which results in absorbing a huge amount of energy. (v) non-corrosive/toxic and good thermal stability characteristics which make it a safe and reliable medium for cooling [20]. In PCM-based system, the process of regulating temperature directly happened which means battery's cells are in direct contact with PCM. Generally, there are two types of the PCM-based cooling systems - solid-to-liquid and liquid-to-gas- for BTMS [32]. However, in a new approach, Xu et al. proposed a new method of using PCM comprising heat transfer via solid-to-solid process [33]. It should be noted that all sides of PCM are surrounded by metal absorber to dissipate the absorbed heat by PCM into the environment. It is worthy to mention that our point about PCM in this paper is referred to solid-to-liquid PCMs such as paraffin wax.

3.4 Heat pipes

Utilizing heat pipe is another innovative strategy for thermal management of batteries. Actually, heat pipes can be consider as a sub-sector PCM-based cooling systems because thermal regulation in this method is also based on evaporation and condensation process of working fluid. Heat pipes are more attractive compare to it counterparts PCM-based systems because of their excellent thermal conductivity and low thermal resistance [4]. Heat pipes consist of three important parts that are evaporation, condensation and adiabatic section [34]. Briefly, the working fluid in the beginning is located in the evaporator section and by raising the temperature fluid (heat sink), the liquid phase transform to gas [20]. Due to the internal pressure difference the gas moves to the condenser section where it release the absorbed heat (by natural or force convection using as liquid or air) to the environment and turn to the liquid phase again. Then the liquid back to the evaporator section through the adiabatic section that usually equipped by wicks. As it can be see, heat pipes are also consider as passive cooling method without any need to electricity.

3.5 Thermoelectric

The other method that recently suggested by researchers for thermal management of batteries is thermoelectric modules. Thermoelectric modules can utilize as a triple-purpose device. It can generate electricity by temperature difference in the hot and cold sides [35]. It can consider as heating device [36] as well as cooling device where it needs to dissipate the generated heat by systems (as well as surfaces) [37]. The structure of thermoelectric is based on metal (or semiconductor) legs that electrically and thermally connected each other in series and parallel respectively. In the battery thermal management systems, the main application of the thermoelectric is to diminish battery's temperature pack. It is worthy to be mentioned that increasing the temperature of hot side of thermoelectric has negative effect on the cooling performance and efficiency, therefore a number of strategy to dissipate the generate heat from the hot side such as aluminum heat sinks [38], air-cooling etc. are employed.

3.6 Refrigerator cycle

The refrigeration cycle for battery thermal management is almost like the liquid-based cooling systems but with some extra components. Same as the air-condition system of car; it uses a vapor compression cycle. The evaporator of refrigerator cycle is attached in parallel with evaporator of vehicle's air-condition and the vapor compression cycle runs both of them. Utilizing the refrigerator cycle alongside vehicle's air-condition system leads not only to reduce the vehicle weight but higher temperature of cooling with respect to improving specific energy consumption and economic benefits are also obtained [2,4]. In this type of cooling system, the liquid pumped into the evaporator where it absorbed the heat of battery and change the phase from liquid to vapor at low pressure and low temperature. Afterwards, the vapor passes through the compressor where it compressed and turns into the high-pressure high-temperature fluid and it enters to condenser section and discharge the absorbed heat into the environment and turn to liquid again. The refrigerant's liquid expanded by an expansion valve and pump to the evaporator section.

3.7 Hybrid methods

Each method for BTMS has it pros and cons and there is no "grand-master" method with only positive in which covered all aspects. Subsequently, researchers have been employed other methods to benefit all of their advantages simultaneously. Thus, different cooling strategy methods can be integrated together. It seems that air-based cooing system because of the simple structure and flexibility is one of the appropriate candidates to combine with other methods. However, it is not a law and it possible for other methods to be utilized in an integrated design. Table 1 presented the pros and cons of different cooling methods.

Table 1. A general comparison between different cooling scenarios

Cooling Type	Strong Points	Weakness Points
Air cooling (passive)	Low primary and operation cost Simple layout and easy maintenance Direct contact Lightweight	Low efficiency Low specific heat Non-uniform air flow distribution
Air cooling (active)	Simple layout and easy maintenance Direct contact Lightweight	Low efficiency Low specific heat Non-uniform air flow distribution Additional costs due to utilizing fans
Liquid Cooling (passive)	Low primary and maintenance cost Easy maintenance High efficiency Superior specific heat capacity Superior thermal conductivity	Leakage
Liquid cooling (active)	High efficiency Direct contact Superior specific heat capacity	Complex layout High cost Short lifetime Leakage
PCM cooling	Cheap method Longtime operation Uniform temperature regulation Superior latent heat High efficient	Low thermal conductivity Leakage
Heat pipe cooling	Exceptional thermal conductivity Superior efficiency	Costly Leakage Complex layout High primary and operation cost
Refrigerator cycle	High efficiency Superior low-temperature operation Adjustable temperature ranges Reliable operation	High cost Leakage Complex configuration

Thermoelectric cooling	No moving part None chemical reaction Noise free Longtime operation None GHGs emission Low to moderate maintenance cost	Low efficiency External electricity requirement

4 Exergy analysis

The most beneficial work that can be produced by any energy system (whether the renewable or non-renewable) in the pursuit of thermodynamic energy balance is exergy [39]. For evaluating the performance of energy system diverse methods of thermodynamic are adopted, among them exergy analysis is of great interest of researchers. Exergy is a powerful tool to evaluate the performance of thermal system considering the second law of thermodynamics, and the mass/energy balance [40]. Generally, exergy analysis brought the processes of systems in practical applications and comparing them to elucidate the causes/locations of thermodynamic losses more plainly in comparison of energy analysis. In this regards, exergy approach would be assisted for modifying and optimizing of designs [41]. Table 2 displayed the summary of different researches on thermal regulation of Li-ion batteries based on exergy. The results showed that the highest amount of exergy efficiency was obtained in electrical vehicle with using heat pipe, refrigerator cycle and air condition as a cooling method, which was equal to 44.2% at temperature of 35 ^{o}C. Additionally, the ambient temperature has a negative influence with exergy efficiency and positive influence with exergy destruction in the cooling system of Li-ion batteries.

Table 2. Summary of exergy-based studies on the thermal regulation of lithium-ion batteries

Ref.	Type of system	Type of study	Capacity of battery	Coolant	COP (Exe)	Exergy Efficiency	Remarks
[42]	Electrical Vehicle	Mathematical modeling	145 Ah	Air/R134a	0.32 (0.26-39)	-	Heat transfer between system-environment as well as fluid's friction with components were the major contributors in irreversibility
[43]	Hybrid EV	Mathematical modeling	NA	Octadecane	2.78-2.85	32.2-34.8%	Exergy Efficiency in the scenario of Using PCM was higher 5.04% rather than no PCM Low exergy efficiency of system components can be address by diminishing the mean temperature difference of working fluids
[44]	Electrical Vehicle	Numerical simulation	7 Ah	Heat pipe Refrigerator cycle Air condition	2.61-4.71 (T=25°C) 2.94-5.76 (T=30°C) 3.33-7.19(T=35°C)	42.1% (T=25°C) 43.17% (T=30°C) 44.2% (T=35°C)	The maximum temperature of battery remind below 40°C and the large difference between temperature at initial stage make up by compressor cooling capacity
[45]	Electrical Vehicle	Theoretical and experimental	51.2 Ah	Water	-	-	The highest performance of the system was obtained in water-cooled system was in inlet to middle-positioned.
[46]	-	Numerical	-	-	-	30-40 %	Ambient temperature has an inverse relation with exergy efficiency of EVs but it directly related to exergy destruction.
[47]	Electrical	Theoretical and	-	R134a	1.7-4 for various	26-29%	Exergy destruction has an

Ref.	Type of system	Type of study	Capacity of battery	Coolant	COP (Exe)	Exergy Efficiency	Remarks
	Vehicle	experimental		R290 R600 R600a R1234yf DME	evaporation and condensation temperatures		inverse relation with COP_{exe} By applying exergoeconomic and exergoenvironmetal optimization exergy efficiency can be improved by about 13% and 5% respectively
[48]	Hybrid Electrical Vehicle	Numerical simulation	60 Ah	Refrigerant-cooling	2.9-3.9	22-28%	Exergy efficiency can increases improved by optimizing the heat exchanger components due to their high exergy losses
[49]	Hybrid Electrical Vehicle	-	-	R134a (in refrigerator cycle) Water- glycol (in battery)	1.5- 4.5 (COP_{ene}) 0.27-0.52 (COP_{exe})	-	Increasing the evaporation temperature results in higher energetic/exergetic COPs while decreasing condensation temperature lead to diminish energetic/exergetic COPs of system
[50]	Hybrid Electrical Vehicle and Electrical Vehicle	Theoretical	-	R134a (in refrigerator cycle) Water (in battery)	2 (COP_{ene}) 0.32 (COP_{exe})	33%	-
[51]	Electrical Vehicle	Theoretical	-	R744 R152a R134a R290 R600 R600a R1234yf DME	0.25-0.31 (COP_{exe}) 2.21- 2.76 (COP_{ene})	-	Although integrating two-level transcritical CO2 lead to improvement of the system, the COP_{exe} of the proposed system still is lower in comparison with refrigerants-based cooling methods.

Ref.	Type of system	Type of study	Capacity of battery	Coolant	COP (Exe)	Exergy Efficiency	Remarks
[52]	Electrical Vehicle	Theoretical	16.1 Ah	Refrigerator cycle (R134a) PCM (octadecane and pentadecane)	2.5	16.7%	From exergetic point of view the PCM-cycle has superiority over the refrigerator cycle but the PCM-cycle required greater of amount of energy for circulating of PCM. The required power for PCM circulation depended on the number of parameters such as concentration, tube configurations and operational conditions
[53]	Electrical Vehicle	Experimental	20 Ah	-	-	-	-

Hammut et al. [42] mathematically applied the exergy analysis on thermal management system of an electrical vehicle with putting the ambient temperature as the main objective of the study to evaluate the performance of the system at high temperatures (ambient temperature between 0-60°C). The values of energetic COP, exergetic COP and sustainability index calculated by around 2, 0.32, and 1.32 whilst it varied between 1.8 - 2.4, 0.26 - 0.39 and 1.28 - 1.37 respectively. Findings elucidated that the major effect on COP_{exe} is the temperature of ambient. Fig. 4 illustrates the effect of ambient and evaporator temperatures of the system.

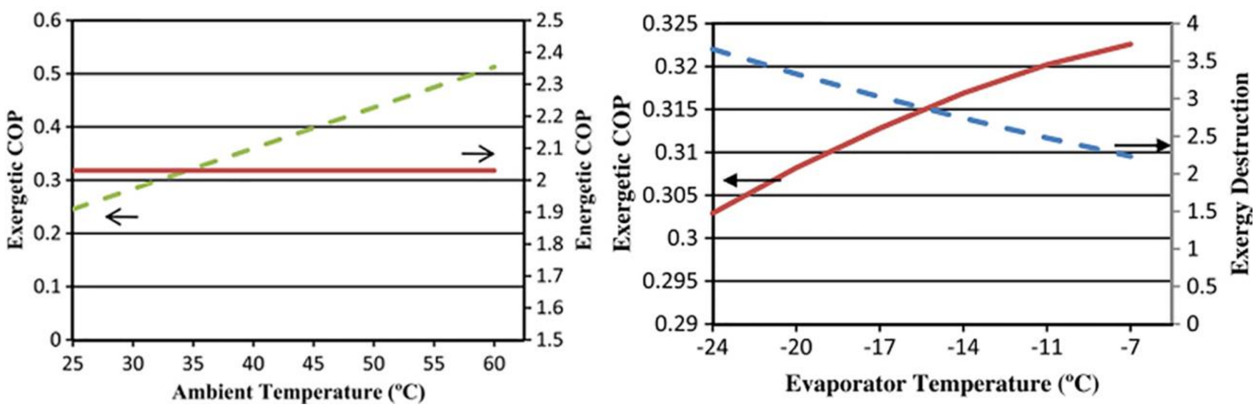

Figure 4. Effect of ambient and evaporator temperatures with exergetic COP Reprinted with permission from Ref [42]

Javani et al. [43] examined the effect of mass fraction of phase PCM on BTMS of a hybrid EV by utilizing octadecane from exergetic and energetic viewpoints by applying multi-objective optimization to maximize the exergy efficiency. The results revealed that augmenting PCM mass fraction play an important role in enhancing exergy efficiency whereas increasing 15% of PCM mass fraction leads to improvement in COP_{exe} and exergy efficiency by around 0.08 and 1.1% respectively. Yao et al. [44] suggested the use of heat pipe and refrigerator cycle in an integrated design with an AC system for cooling of Li-ion battery of EVs. The proposed cooling apparatus for cooling the battery package was set for three preset temperatures of 25, 30 and 35°C. The findings revealed that the at higher preset temperatures (i.e., 35°C) higher energy, exergy and COP improvement was obtained because of higher evaporation temperature. The average exergy efficiency of systems when the temperature increased from 25°C to 30°C and 35°C improved by around 2.63% and 5.07% while for COP it improved 16.95% and 38.41% respectively. Xu et al. [45] theoretically and experimentally examined the effect of water entering position on the cooling performance of lithium ion battery considering exergy approach. Their results based on exergy optimization for four scenarios showed that entering cooling fluid from the middle of the Li-ion battery pack not only lead to lowest exergy loss of system but lead to highest temperature uniformity in package. Ramandi et al. [46] employed exergy analysis as a tool to scrutinize the effect of PCM in different configurations comprises single-PCM shell and double-PCMs shells as the heat sink for BTMS with and without walls insulation. A numerical study by implementing finite volume method (FVM) for four scenarios showed that the double-PCMs shells (consists of cobaltous nitrate and capric acid) in terms of exergy efficiency has superiority over single-PCM shell while walls are insulated whilst the highest overall exergy efficiency exceeded 40%. Hamut [47] in a comprehensive experimental investigation and theoretical validation examined the performance of thermal management system with a refrigerator cycle with different coolant from different point of views including energetic, exergetic, environmental and economic analysis, as depicted in Fig. 5. Results elucidated that among different scenarios the Dimethylether has the highest exergy efficiency. Interestingly, due to the nature of exergy destruction of components which can be express as exogenous/endogenous and unpreventable/preventable, they declared as exogenous exergy is substantial part of the exergy destruction in components and it could be potentially diminished.

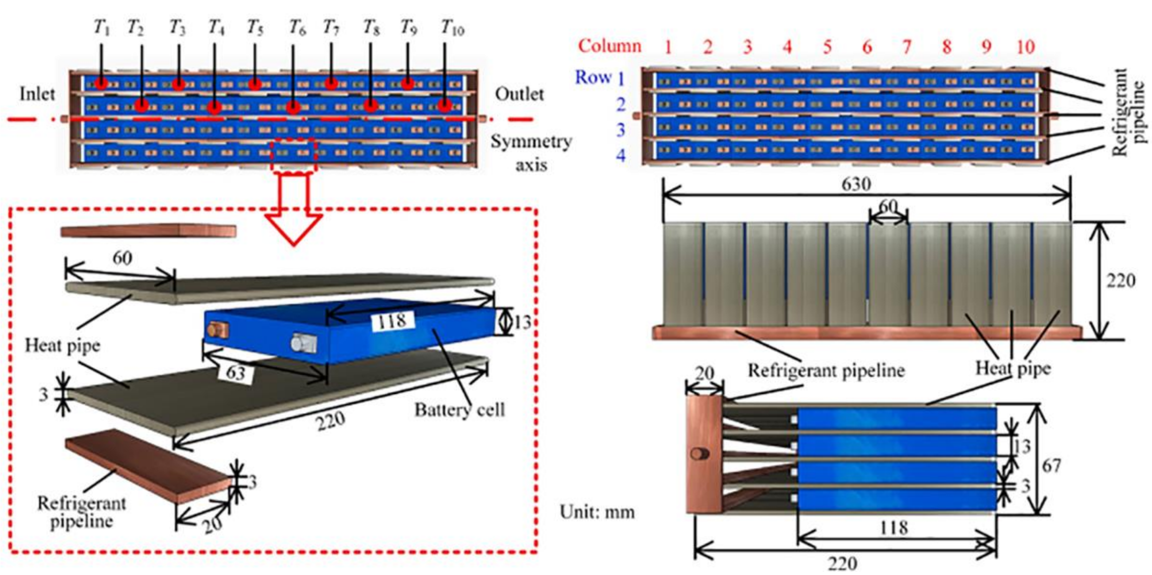

Figure 5. Module structure of lithium-ion battery with cooling Reprinted with permission from Ref [44]

As shown in Fig. 6, Shen and Gao [48] theoretically studied the dynamic interaction of a refrigerator cycle with air condition system of an electric vehicle under high temperature and high speed dynamic conditions. The simulation results for the high speed conditions and 1000 W/m^2 solar radiation falling to the cabin elucidated that augmenting the rate of discharge as well as heat generation lead to higher reduction in energetic and exergetic COPs.

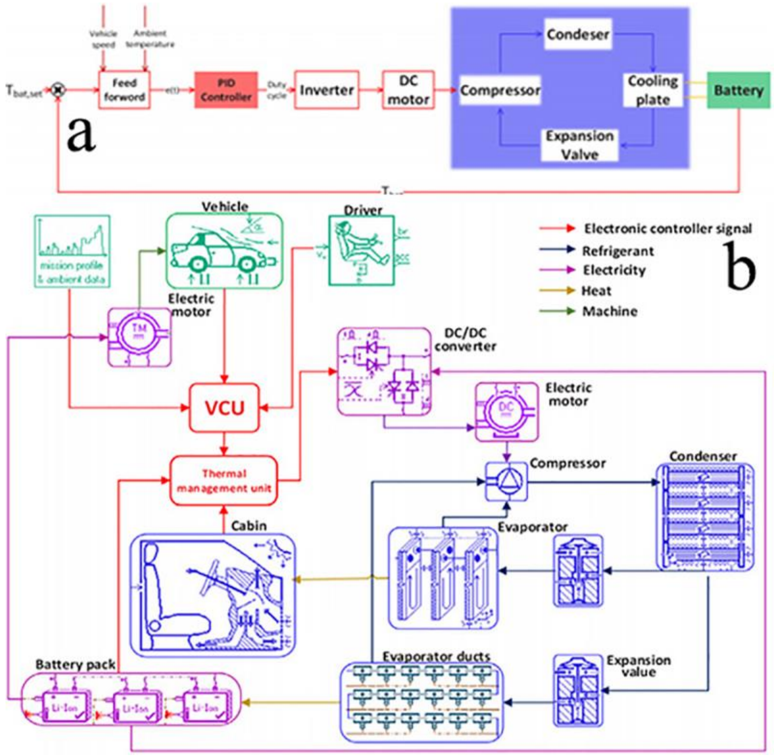

Figure 6. a) P & ID diagram b) Thermal regulator system of the electrical vehicle Reprinted with permission from Ref [48]

Hamut et al. [54] examined the effect performed a multi-objective optimization based on exergy approach. Their findings showed that exergy efficiency, cost and environmental impacts can improve by about 27%, 10% and 19% respectively at the state of non-optimized results. Fig. 7 displayed the hybrid electrical vehicle BTMS.

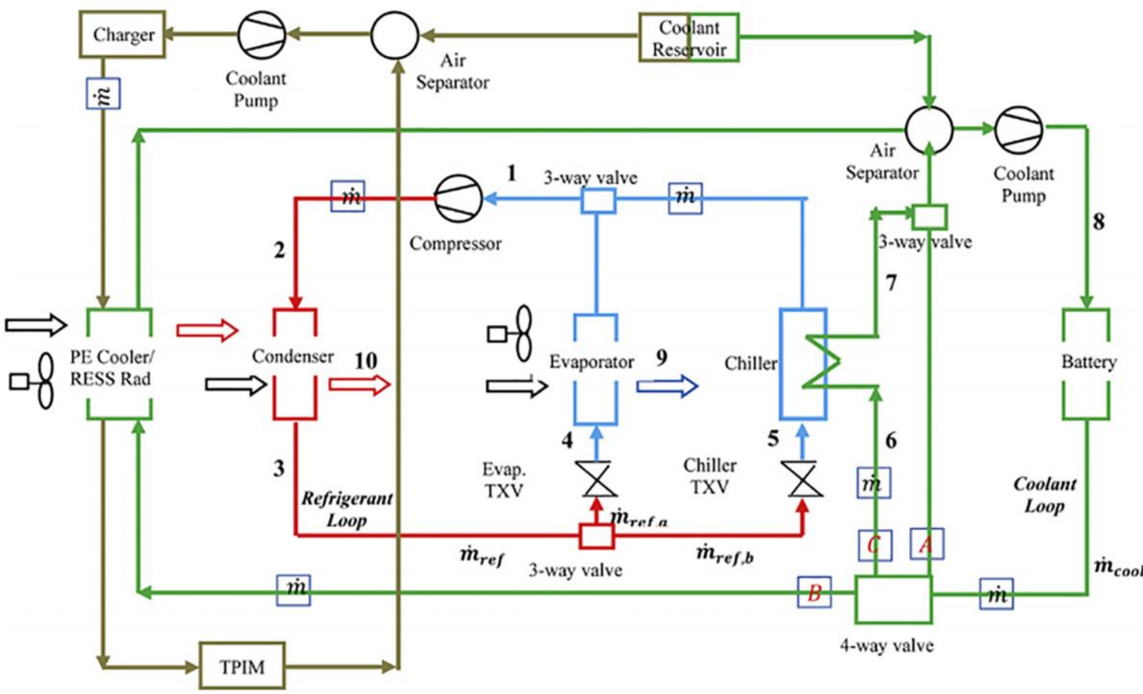

Figure 7. Illustration of a hybrid electrical vehicle thermal management system Reprinted with permission from Ref [54]

Hamut and Dincer [49] conducted a theoretical study on a refrigerator-based system of cooling system of battery for a HEV. Based on various design parameters consists of pressure drop, air mass flow rate (max 0.5 m/s), sub-cooling superheating temperature (max to 15°C), varied evaporation (0-15°C) and condensation (40-55°C) temperature, the exergetic COP increases by around 8% by applying sub-cooling and superheating in heat exchanger while pressure drop in the system due to augmenting flow rate up to 60 kPa results in reduction of exergetic COP by around 12%. Hamut et al. [50] compared three methods of passive cooling (air), active (R134a) and hybrid active (R134a+Water) cooling for Li-ion BTMS in terms of increasing and uniformity of cells temperatures as well as entropy generation. Their results showed that increasing cells temperature were 5.2°C, 4.6°C, 3.9°C while the median temperatures uniformity stands on 7.75°C, 10°C, 2.52°C and entropy generated were 0.037 W/K, 1.315 W/K, 0.012 W/K for passive, active, and hybrid active scenarios respectively, which indicated that the active hybrid methods is the most appropriate option. Acar et al. [55] investigated the use of phase change materials in three different scenarios for cooling Li-ion battery from energetic and exergetic point of views and concluded that the system that has better and uniform temperature distribution obtained higher exergy efficiency. Hamut [51] utilized multi-level vapor compression transcritical CO2-based refrigerator alongside internally heat exchanger with water-glycol coolant for Li-ion TMS. The results showed that using multi-level compression leading to 8% improvement in exergy efficiency while integrating internally heat exchanger with multi-level compression results in 22% enhancement in exergy efficiency. Moreover, among different refrigerants applied, Dimethylether has slightly (~3%) higher COP based on exergy compare to R290, R600, and R600a. Hamut et al. [56] in a comparative study utilized a number of commercial refrigerants including R134a, butane, isobutene, tetraflouropropene and Dimethylether for Li-ion cooling in EV and HEVs. Their findings revealed that using Dimethylether as refrigerant the COP_{ene} and COP_{exe} of the system improved by about 7.9% and 8.2%, however, when tetraflouropropene used in the cycle the COP_{ene} and COP_{exe} were reduced 4.9% and 4.2% compared to reference model respectively. Zhang et al. [52] compared the performance of three cooling methods of battery in EV which are direct cabin air blower, refrigerant cycle, and PCMs. The cabin air method chose for mild climatic conditions while two scenarios of R134a-based refrigerator cycle as well as octadecane and pentadecane as PCMs are selected for extreme hot and cold climate conditions respectively. Their findings illustrated that the PCM-based cycle in terms of exergy efficiency has 23% greater over the refrigerator cycle under cooling and heating modes. Fig. 8 shows the use of nano/PCM in cooling of Li-ion battery.

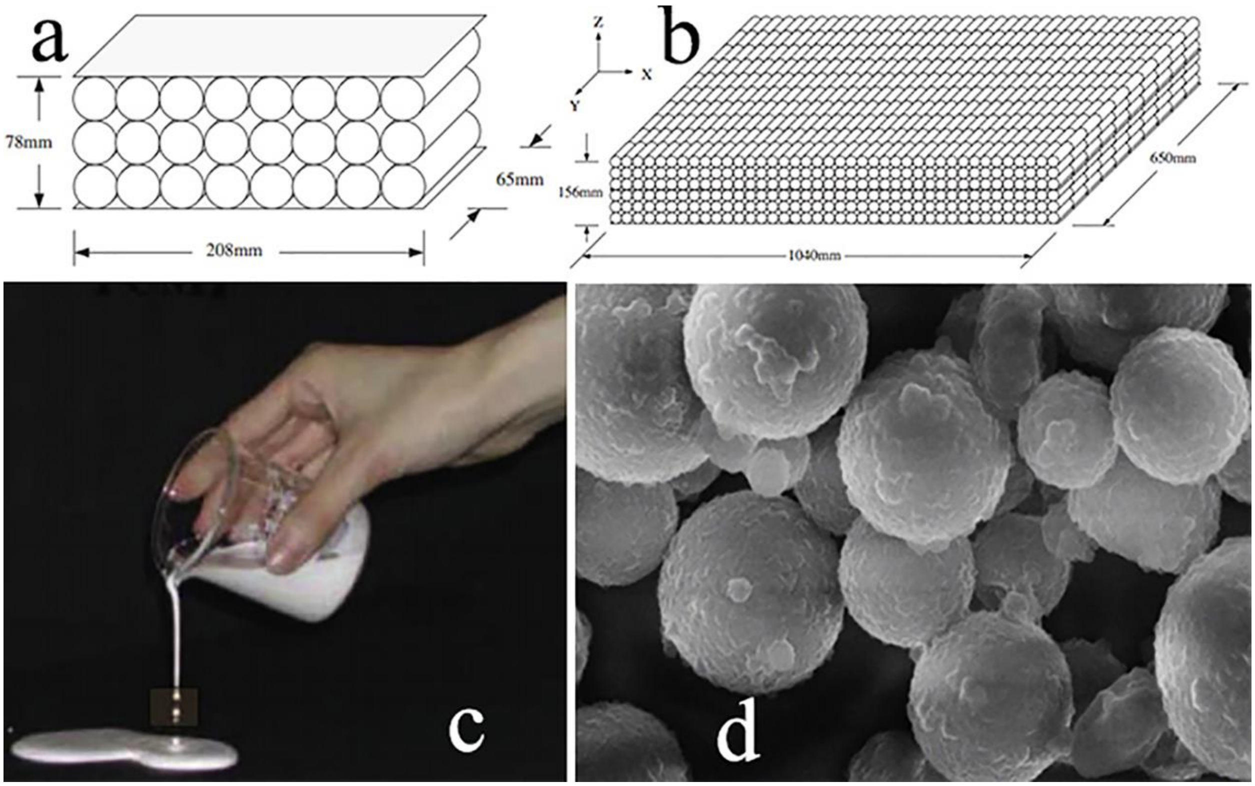

Figure 8. illustration of a) battery module, b) pack c) actual view of slurry PCM d) Fe-SEM image of Nano-PCM Reprinted with permission from Ref [52]

Malik et al. [53] used a braze plate heat exchanger made by aluminum and water as cooling fluid to evaluate the effect of different coolant temperatures (from 10°C to 40°C) and discharge rates (from 1C to 4C) on the electrical, energy and exergy efficiencies of the system and found that 30°C fluid temperature is the most optimum temperature in terms of energy and exergy efficiency. Furthermore, it was elucidate that the rate of exergy destruction augmented by increasing the rate of discharge. Similarly, Hamut et al. [57] reported system's exergy efficiency of a refrigerator-based cycle for TMS of Li-ion battery by around 24%.

5 Economic analysis

Economic analysis is the most crucial part in any project from macro to micro/nano-scales. It is vital to realize the cost assessment of systems since the proposed structure/system may have a great results from technical point of view but economically would not be feasible due to the high costs or the economic conditions for a some regions (such as poor communities in developing world). Economic analysis based on the type of system can be applied for different types of energy systems, subsequently, involving different parameters from insurance costs to salvage value, added value, sinking fund factor, etc. [58] are of great importance. Furthermore, in the context of lithium ion battery thermal management this is verily imperative as the BTMS is usually related to the economic analysis of EVs. Subsequently, from economic standpoints a part of developing EVs are related to the cost analysis of battery and cooling apparatus. It should be noted that from technical viewpoint if the temperature uniformity in the cell package maintain in a logical range as well as the increasing temperature remain in a specific rational range (the preset temperature) the lifetime of the battery would increase. Therefore, from the economic view of EVs, the cost associated with battery which is one of the main obstacles in developing EVs is also decrease. Meanwhile, evaluating the system from exergoeconomic that is the combination of exergy+economic to realize a cost-effective approach on the feasibility of the system is also of great importance. Importantly, the battery lifespan is directly related to the economic analysis because of the fact that if battery degraded more than 80% of its nominal value, it cannot be consider as competitive as normal vehicle (with internal engine) from this prospect [59]. Table 3 depicted the economic and exergoeconomic comparison of various methods on cooling of Li-ion batteries. The outcomes depicted that the by increasing the life span of battery, the cost of the system decreases. Also, the highest sensitive parameters on performance of the Li-ion are the chiller dimension and compressor speed.

Table 3. Summary of the economic-based analysis of Li-ion cooling methods

Ref.	Study type	Objectives	Concluding Remarks
[59]	Theoretical study	Formulating economic charging-cost realizing the impact of voltage cut-off, resistance, surrounding temperature on the performance of charging Developing a high-reliable economy-conscious charging regarding the speeding charge and thermal changes	The constant current has great impact on the charge of battery.
[60]	Theoretical study (Case study)	To bring the cost of into the life cycle analysis To compare different cooling methods regarding their cost-benefits To realize different cooling scenarios with respect to main contributors of costs in the context of life cycle cost	By increasing the battery lifetime by around 2 folds the cycle cost reduced 33% while decreasing the lifetime by about 50% results in 52% augmenting in lifespan costs The total life cycle cost of optimized tab-cooled decrease 40% compare to air-cooled
[61]	Theoretical study	To develop a predictive model for power generation of Li-ion battery Coupling the power model in the framework of predictive non-linear economic model based on important parameters Developing a high accurate model with considering all constrains with least errors	Implementing model predictive control on the basis of economic lead to solving complex multi-variable inputs and constraints of battery. The accuracy of model in predicting state of power in a wide range of operating conditions and dynamic loads is high enough that only less than 0.2% error was observed.
[62]	Theoretical study	The five energy storage methods (EES, SHTES, PCM, CAES, LAES) were applied as a coolant to improving the performance of the Li-ion battery.	The couple of LAES and PCM can have a high effect for cooling technique in comparison with EES, SHTES, CAES methods.
[63]	Theoretical study	Feasibility investigation Li-ion and Pb-Acid batteries for EVs and PVs based on economic analysis Comparing three Li-ion cooling systems for different applications Parameters such as the period of return investment, battery applications and operation years chose as the most important criteria for BTMS.	Type of application is an important criterion for selecting the battery on the basis of economic analysis Pb-acid is preferable for 3 and 5 years of operation but Li-ion for 10 and 15 years operation. Regardless of economic aspects, the space

Ref.	Study type	Objectives	Concluding Remarks
			need for BTMS is also an important factor
[57]		Applying exergoeconomic and cost analysis on components of refrigerator cycle for BTMS	From exergoeconomic point of view the pump and expansion valves has the least priority because of their high exergy efficiency
[64]		Realizing a cost-effectiveness approach by applying conventional and advance exergoeconomic. Splitting the investment cost to avoidable and unavoidable costs. Components efficiency and operating conditions can lead to cost optimization of BTMS system.	Trade-off should be managed between efficiency and operating conditions of components with investment cost Theoretically, on the basis of advanced exergoeconomic, up to 81% of total cost is avoidable
[65]	Theoretical study	Evaluating the performance of two enclosure shapes filled by PCM for BTMS from economic viewpoint.	The shape of enclosure is of great importance where elliptical shape enclosure from energetic and economic viewpoints is more preferable than circular
[66]	Numerical and experimental studies	The proposed model was used of the Li-ion thermal management system to optimize three various standard driving cycles with different variables including the compressor rpm, fan rpm, chiller dimension, radiator dimension, and condenser dimension.	The highest sensitive parameters on performance of the Li-ion are the chiller dimension and compressor speed.
[67]	Theoretical study	Developing a transient method for Li-ion battery temperature regulation for two active (fan) and passive (PCM) methods Examining the life cycle cost assessment when fan and PCM used as the cooling method	While the rate of cooling by active method is better than passive but battery's temperature is more uniform in passive method. Active cooling method in term of cyclic cost has superiority over passive method
[68]	Experimental study	The F2-type of the cooling fluid system using M mode shape of cooling sheet with considering the discharge rate, inlet temperature and flow rate was evaluated.	The high cooling water flow rate at various charging and discharging cycle were showed the cooling water flow rate should be no lower than 6 and 12 L/h when batteries are discharged at the rates of 1 and 2C, respectively.

Liu et al. [59] coupled the costs of electrical-loss and battery-age in design of the Li-ion battery charging in different scenarios from economical point of view by multi objective optimization using genetic algorithm. The rate of battery degradation for different cycle from 0-1200 cycles via five cases was evaluated. Their findings indicated that until the first 70 cycles the rate of battery degradation for both objectives of minimum charge-cost and minimum charge-time is similar but by increasing the number of cycles to 1200, the rate of degradation in the scenario of minimum charge-time is 9.9% (almost 0.245 Ah) lower than the case of minimum charge-cost. Lander and co-workers [60] developed a mathematical model and coupled the Li-ion cells' temperature as the function of battery lifespan for thermal management of packing by taking the life cycle cost of the system into the consideration via four important parameters which are battery, vehicle, electricity, and maintenance costs. Meanwhile, they compared four TMS methods of air-cooling, tab-cooling, surface-cooling and immersion-cooling with respect to the battery degradation and number of cycles and reported the surface, and immersion methods are best scenarios (Figure 9-a). The life cycle cost of system for immersion method showed 27% improvement (almost 0.06 $/km) than the air-cooling method while the cost of investment of immersion-cooling system is more than 2 fold compare to air-based cooling. Sensitivity analysis indicated that by doubling the lifespan, life cycle cost reduced by around 33% while reducing lifespan by around 50% lead to increasing the life cycle cost nearly 52% (Figure 9-b).

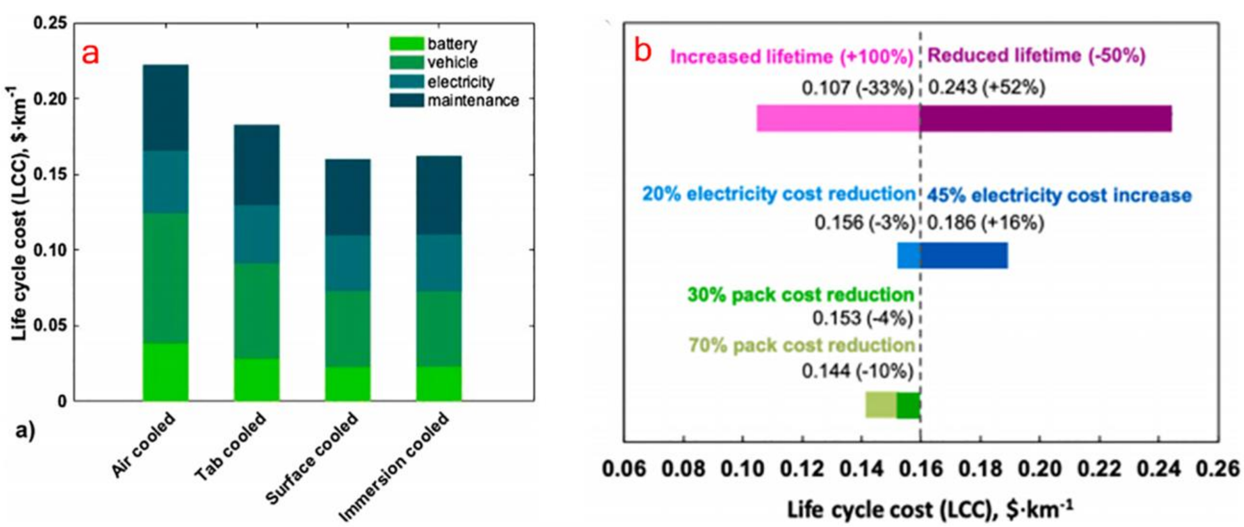

Figure 9. Life Cycle cost a) for different cooling methods b) Considering the effect of lifetime Reprinted with permission from Ref [60]

Zou et al. [61] developed an economic-based non-linear model for power generated by Li-ion battery under dynamic loads regarding parameters of charging states, cell's temperature, currents and voltage. Furthermore, they considered dynamic temperature during state of power (which usually is negligible in modeling) in non-linear economic model for high accurate model. The simulation outcomes indicated while considering temperature make the procedure complex but the temperature of battery is beyond the allowable limits (43.9°C) during charging process which showed the importance of using a proper BTMS for safety and lifetime of battery. Comodi et al. [62] performed a techno-economic analysis on using Li-ion battery alongside four technologies of chiller, PCM and air/liquid energy storage as cooling methods for different capacity of energy systems. Their findings based on different criteria of which are complexities, technology, availability, safety and sustainability elucidate that Li-ion scenario is an inappropriate option and most expensive cooling method for energy application regardless of the size of system. Importantly, this can bring one interesting note into the spotlight that the Li-ion energy storage as a standalone technology of cooling cannot be consider as previously discussed; in the capital investment cost of Li-ion battery packs, the cooling cost of the battery is a small portion of total cost (less than 7%) and the rest of costs belong to Li-ion battery. Khan et al. [63] conducted a comprehensive techno-economic comparative analysis for Li-ion battery and lead-acid battery with respect to the three cooling systems that are: air-cooling, water-cooling, and refrigerant cycle for two different applications of the EV and photovoltaic modules. The findings in different lifespans from 3 to 15 years of operation showed that in the short term scenario when the system intended to work less than 5 years on the basis of returning investment, the lead acid system is most appropriate option but for long-term applications when the system is to work up to 15 years or higher the Li-ion battery is the most appropriate option. Furthermore they concluded that the type of cooling system for Li-ion battery based on economic criteria is a depended on the application where the liquid-cooling with refrigerator is more suitable for EVs and the refrigerator cycle and air-cooling is better options for PVs. Hamut et al. [57] applied exergoeconomic analysis on the refrigerator-based cooling system for Li-ion BTMS. Their findings revealed the cost in the case that a component has a low exergoeconomic value; it is still possible for saving costs for the whole system by augmenting components efficiency even if the total cost of component escalates. Hamut et al. [64] performed conventional and advanced exergoeconomic analysis of on a refrigerator-based BTMS for a hybrid EV. The results elucidate that the compressor investment cost has the highest impact on total cost of BTMS, whilst the higher compressor efficiency leads to the higher total cost as well as higher exergoeconomic values. Subsequently, it was concluded that there is an optimum point while the compressor maintain its efficiency (that is 0.77) the cost and exergy destruction get minimize. Furthermore, the advanced exergoeconomic analysis showed that while Li-ion battery's cost play the dominant in economic, reducing the cost of evaporator and condenser (while maintain the compressor and chiller as the same) also results in cost-benefits BTMS. As shown in Fig. 10, Tian et al. [65] compared the performance of PCM-based system (in two different enclosure shapes) as the passive mode and air blower as active method for BTMS of Li-ion from thermodynamic and economic point of views for three countries of the UK, Finland and France. Economic analysis performed based on the different air blower velocities of 0.0005-0.002 m/s and different cost of electricity at each country. Their findings revealed that from economic standpoint in all countries, when the blower work at moderate speed there is not difference between power's cost but increasing blower's speed (up to maximum 0.002 m/s) augmented cost of electricity substantially for the UK rather than Finland and France due to higher rate of price. However, they have not presented an optimum speed for the blower to satisfy both criteria.

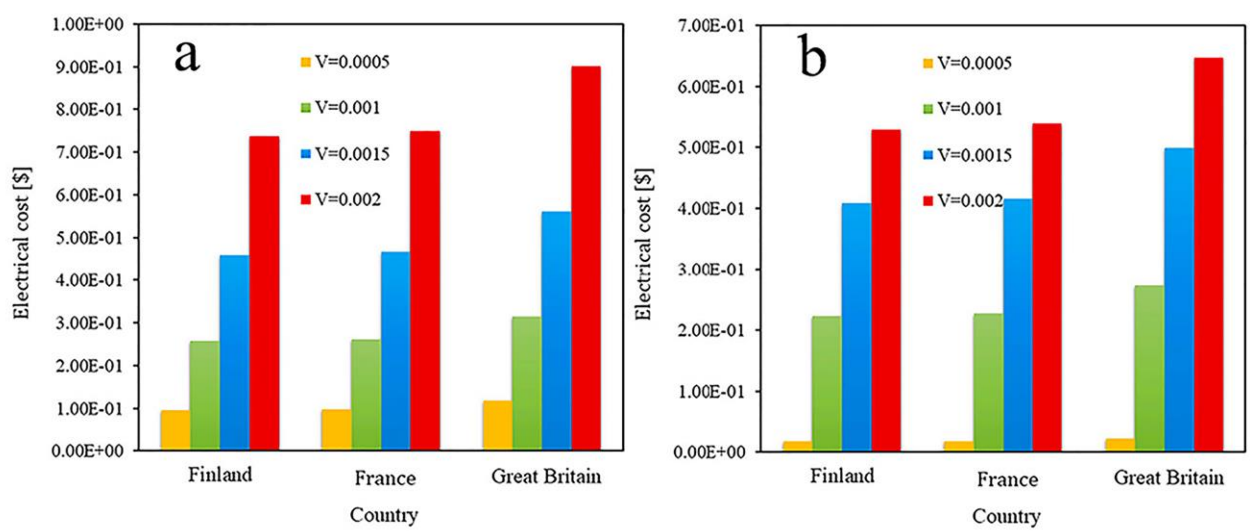

Figure 10. Electricity costs for different countries in different shapes of BTMS a) eliptical, b) circular. Reprinted with permission from Ref [65]

Asef et al. [66] developed a transient simulation and optimization on a Li-ion TMS for actual conditions with a focus on total cost ownership and concluded that chiller size and the compressor speed are sensitive parameters of cooling system from economic point of view. Chen et al. [67] performed a cost analysis on two methods of air cooling and PCM for Li-ion thermal regulation system. They proposed an economic correlation indicator which acts as a bridge between battery's cost, power consumption and battery life cycle to translate the performance of cooling methods into the cost. Their findings revealed that air-cooling system in terms of cyclic cost is much profitable than PCM-cooling because the cycle life of PCM due to its limitation is lower than air-cooling. Xu et al. [68] designed and experimented aluminum roll liquid plates in three honeycomb shapes with different heat transfer areas as the lithium-ion thermal management system, as depicted in Fig. 11. The cooling systems worked with water as coolant. The economic analysis for the system was not performed, however, the cost of plate heat exchanger examined as low as 7.8 $ which can consider as one of the lowest BTMS systems presented so far.

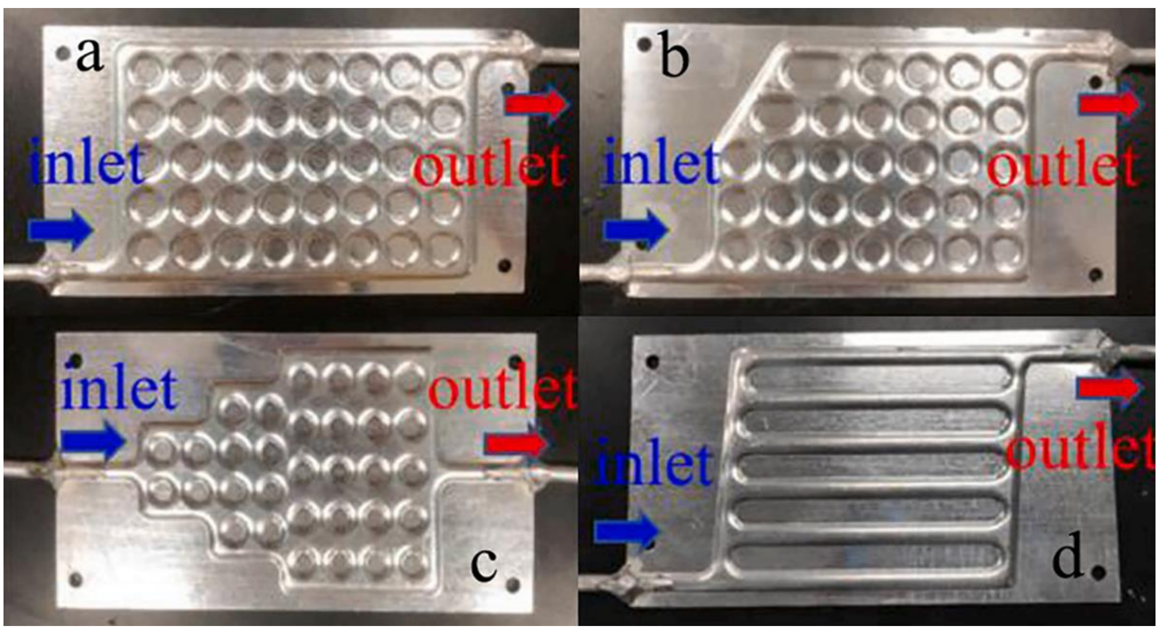

Figure 11. Roll-bond liquid cooling plate a) rectangular shape b) partial rectangular c) partial cone-rectangular d) paralell pipeline Reprinted with permission from Ref [68]

6 Environmental Analysis

Anthropogenic activities lead to heavy barriers to the environment via different routes from wastewater and contaminated biological that severely affected the aqueous environment [69–71] to greenhouse gas emission- at the forefront of them CO_2- that negatively impacted the atmosphere, leading the climate change side effects [72,73]. In this regard, realizing the environmental impacts of energy systems is the most important parameter since the multi-dimensional environmental issues turn to a global challenge. However, environmental analysis in battery thermal management systems has not been explicitly and extensively studied and the number of studies in this context is limited. It should be noted that environmental analysis of battery can be categorized in four sub-sectors which are: (i) the production stage (ii) during the use of battery (iii) after cascade utilization and (iv) battery recycling. Briefly, the battery production refers to the process of producing battery including battery materials and electricity consumption which results in the carbon emission. The cascade utilization refers to reuse retired batteries in a different scenario such as electricity supply or residential [74]. In the present study our aim is to discuss environmental impact of batteries during usage which involve the operation conditions as important parameters including the battery's pack temperature since it is critically important to realize the pros and cons of a thermal management system from environmental point of view. Hamut et al. [75] combined the environmental analysis with exergy approach and developed a model to realize the exergoenvironmental analysis on the Li-ion battery with liquid cooling. Findings revealed the highest environmental impact associated with anode and cathode of battery which used copper and gold. Seemingly, the study highlighted the environmental impact of the battery at production stage and not during the usage. Similarly, Hamut et al. conducted an environmental analysis on battery thermal management and examined that the lifetime of battery which directly related to the thermal management connected to the environmental impact where 5% improvement in battery efficiency results in 23% reduction global warming potential [56]. Importantly, Lander et al. [60] comprehensively investigated the effect of different cooling scenarios of Li-ion battery in an EV on the life cycle cost and carbon footprint for some of the European country conditions. It was realized that among four scenarios of air cooling, tab-cooling, surface cooling and immersion cooling; tab-cooling has more promising results in terms of life cycle and carbon footprint.

7 Machine Learning

Machine learning is one of the ever-fastest growing methods of artificial intelligent in the new millennium which vastly emerged from laboratory to the real world applications [76]. In essence, machine learning aim is to answer two fundamental scientific questions. (i). How can one construct computer systems spontaneously modify via experience? (ii). What are the fundamental statistical computational-information-theoretic laws that govern all learning systems, including computers, humans, and organizations? [77]. Generally, machine learning algorithms categorized to three branches of supervised, unsupervised, and reinforcement learning. Machine learning assisted across of different algorithms from nature-inspired approaches to statistical methods. In the last two decades machine learning consider as an effective tool in different disciplines and fields such as biological/medical related sciences including drug delivery [78], genetics & genomic [79], cardiovascular [80], wildlife conservations [81], cancer diagnostics [82,83], surgery [84], mental disorders [85], medical images [86] as well as in physics comprises discovering new fundamental in physics [87], high energy density physics [88], astrophysics [89], photonics and light-matter [90,91], and chemistry and material including colloidal [92], nanoparticle synthesizing [93], exploring chemical compounds [94], catalysis [95], alloys [96] solar-driven power generation [97,98], desalination and energy storage. In the context of energy storage -particularly Li-ion battery- huge attention have been devoted to assist machine learning to further develop and optimize different battery parts. Figure 12 shows some of the most important machine learning review topics in Li-ion batteries. In this regard, machine learning vastly implemented for thermal management of li-ion battery from different point of views. Table 4 illustrates the summary of machine learning technique applied on performance of Li-ion battery using different cooling methods. As can be seen, the machine learning methods have been used on various cooling methods of Li-ion battery with errors less than 10%. Therefore, this method can help to researchers to find a best cooling methods on increase performance of batteries. Moreover, the error of system with input parameters of air flow rate, air temperature, PCM thickness, spacing unit and discharge rate was lower than 2.73%.

Figure 12. Major machine learning reviews for lithium-ion batteries

Table 4. Summary of the machine learning, data-driven and numerical methods applied on thermal regulation of Li-ion batteries

Refs	Input	Output	Coolant	Charge/ Discharge rate	LIB Model	Applied Method (ML/optimization)
[99]	Thermophysical properties of Negative electrode, separator and Positive electrode	Temperature	Copper foam+ Paraffin wax	1/3 C	Newman pseudo model	convolutional neural networks
[100]	Ambient temperature Compressor speed Air flow rate of the external condenser	COP. Cooling capacity	Water+ EG with heat pump-based AC	NA	Not available	SVR + PSO
[101]	Voltage Current Temperature of Surface	Temperature	Water+ EG cooling	NA	Lumped model	RBF NN
[102]	Current Heat generated	Temperature deviation Maximum temperature Power consumption	Water+ EG cooling (50% + 50%)	0.5C, 1C, 1.5C, 2C, and 2.5	-	Regression neural network
[103]	Initial temperature Mass flow rate Heat source	Temperature Next time step	Air	Variable during operation	-	Neural network with Levenberg–Marquardt algorithm (LMA)
[104]	Coolants' velocity Coolants'	Temperatures of battery, PCM, and	Air Water	-	Fourier Model	Neural network

Refs	Input	Output	Coolant	Charge/ Discharge rate	LIB Model	Applied Method (ML/optimization)
	temperature Time Heat generation by battery	pack	PCM			
[105]	Coolant's flow rate temperature Rate and depth of discharging	Average battery temperature Maximum surface temperature	Water	1-5 C	Experimental study	Neural network
[106]	Space between channels Air flow rate	Temperature Power consumption	Air	1.5 C	A commercial battery used as reference	Neural network with PSO
[107]	Liquid rate Charging rate	Temperature	PCMs (Paraffin & RT-18)	1C, 1.5C, 2C	A commercial battery used as reference	Neural network
[108]	Discharge current, Temperature (Ambient) Inlet flow rate	Maximum temperature	Ethylene glycol as coolant and Polyethylene glycol as PCM	2C, 3C, 4C	Second order circuit mode	Neural network
[109]	Maximum temperature	Heat transfer coefficient Skin friction coefficient	Water	1/5 C	NA	Non-dominated sorting genetic algorithm II (NSGA-II) Response surface optimization
[110]	Density and concentration of PCM Position of PCM	Maximum temperature Temperature difference	Graphite with paraffin wax (GPCM)	1C, 3C, 5C	Doyle/Fuller/Newman (DFN) model	PSO, NSGA-III, SEPA-II

Refs	Input	Output	Coolant	Charge/ Discharge rate	LIB Model	Applied Method (ML/optimization)
	Height and radius of PCM					
[111]	Air flow rate Air temperature PCM thickness Spacing unit Rate of discharge	Maximum battery temperature	Air+ PCM	2-5 C	Commercial battery	Neural network + GA
[112]	Air flow rate Tube's diameter	Number of heat transfer units	Air		Commercial battery	GA
[113]		Maximum temperature Temperature difference	Air	-	Commercial battery	GA
[114]	Plate thickness Coolant flow rate Water temperature	Maximum temperature Temperature difference	Water	3C	Bernardi Model	second-generation non-dominated sorting genetic algorithm (NSGA-II)
[115]	Capacity/nominal voltage maximum discharge rate Cut-off voltages for charging The length, width and thickness of cells Fins Diameter	Maximum temperature	Water	5C	Commercial battery	Multi-island genetic algorithm (MIGA)
[116]	Size of battery Rated capacitance	Maximum temperature	Water	0.8C	3D thermal model based	GA

Refs	Input	Output	Coolant	Charge/ Discharge rate	LIB Model	Applied Method (ML/optimization)
	Rated voltage Internal resistance Convective heat transfer coefficient	Temperature difference Pressure drop			rectangular coordinate	
[117]	Angles convergence Widths convergence Air flow rate	Maximum temperature Temperature difference Power consumption	Air		Heat dissipation model	Stud Genetic
[118]	Angles convergence Widths convergence Air flow rate	Maximum temperature Temperature difference Power consumption	Air		Heat dissipation model	Stud Genetic Algorithm NSGA-III_DE
[119]	Properties of a commercial (brand Samsung) Li-ion battery	Spacing units	Air		Bernard Model	Tunicate Swarm (TS) Search & Rescue optimization algorithm (SROA) Enhanced Elephant Herding (EEH)
[120]	Thermo-physical parameters of the sleeve, water and battery Diameter Flow rate Pitch	Maximum temperature	Deionized water	5 C		NSGA-II with MCDM

Refs	Input	Output	Coolant	Charge/ Discharge rate	LIB Model	Applied Method (ML/optimization)
[121]	Pitch Number of fins Flow rate	Maximum temperature	Air		Heat dissipation model	GA

Felix et al. [99] applied convolutional neural networks in combination with a 2D finite element method to study the performance of copper-foam@paraffin passive method of cell's temperature during charge/discharge for cooling a lithium ion with six cells. To realize the accuracy of the neural network (NN) method compare to FEM, the maximum temperature rise for both methods depicted and for two scenarios the highest temperature difference was less than 0.005% and 0.015%. Further findings showed the rise of cell's temperature during discharging process is greater than charging while it was revealed that using CNN lead to high-precise prediction of temperature rather than implementing fully-FEM whilst using multi-scale approach results in high accurate prediction and strategy for coolants medium with complexity. Tang et al. [100] integrated the particle swarm optimization (PSO) method with support vector regression (SVR) to examine the cooling capacity and coefficient performance BTMS of a Li-ion battery with water+ethylene glycol coolant alongside heat pump based air conditioning system regarding three parameters of air flow rate , ambient temperature, and compressor speed. Results indicated that the COP of 2.36 under harsh condition when the ambient temperature is greater than 40 °C can be maintained. Furthermore, it was concluded that when the PSO applied to three parameter of SVR the correlation of coefficient for system's cooling capacity and COP were improved by around 2.1% and 2.8% respectively. Furthermore it was declared that the developed SVR-PSO method can make an interrelation between COP and cooling with other parameters not limited to those evaluated. Afzal et al. [122] compared a single-layer with a deep NN for predicting the average Nusselt number as the important factor in BTMS considering six inputs of velocity, type of coolant, battery dimension, thermal conductivity, cell's space and heat generation. The findings with 85% of data for training comprise used four functions of linear, Gaussian, Hyperbolic, and sigmoid based on the random errors and correlation of coefficient for all scenarios showed Gaussian outperform over other functions for both NN methods, however, it was realized that deep NN is predicted the Nusselt number better than single-layer NN. Liu et al. [101] theoretically estimated the cell's temperature of Li-ion battery and validated with laboratory experimented data. The radial basis kernel used as the activation function and extend Kalman filter utilized to increase the reliability of the model and improving accuracy. The developed model is precisely estimated the internal temperature where the maximum errors in estimated temperature is lower than 0.25°C. It was declared that the model was generalized and would use for other types of battery's temperature estimation by combined lump thermal model and neural network. Chen et al. [102] developed a neural network model based on the linear regression for thermal management of Li-ion battery during the fast charge process. The NN model was trained by 81 sets of data from laboratory experiments of eight cells that connected in series. The experimented conducted for different charging process and liquid flow for 0.5 C, 1.5 C, and 2.5 C and 36 mL/min, 72 mL/min, and 108 mL/min respectively. The optimal design by NN validated by experimental data and the results of regression for three objectives of maximum temperature, temperature deviation, and consumed power achieve high accuracy of 99.35%, 99.33%, and 98.38% respectively. Liu et al. [103] assisted the MPC strategy alongside with neural network that used LMA training algorithm to predict and develop a self-adjustable intelligent method using a fan for cooling of Li-ion battery in an EV, as depicted in Fig. 13. The findings revealed that the integration of MPC with NN results in better temperature uniformity rather than standalone NN strategy while energy consumption at optimum condition evaluated by around 14.67 kJ, leading to 15.8% improvement rather than NN method. Interestingly, they showed the advantage of MPC-NN strategy over standalone NN is that it is consider the changes in inputs and external sources where NN just consider temperature in the last step.

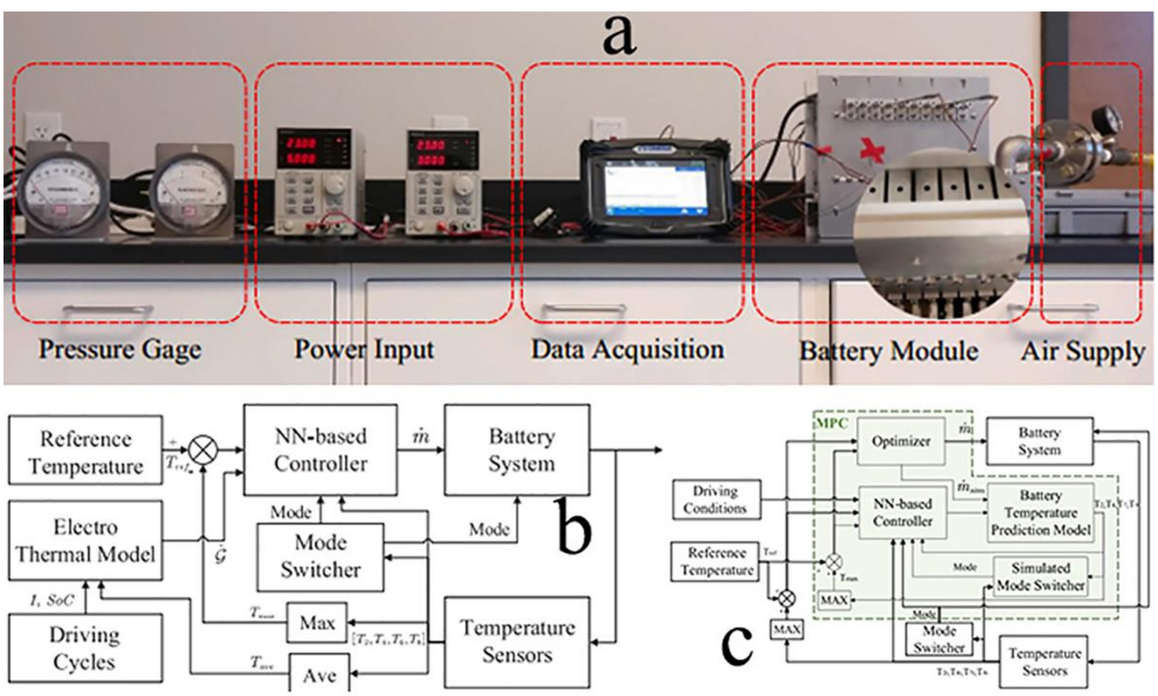

Figure 13. Experimental setup of air-based cooling of Li-ion battery b) A framework for thermal control of the J-type lithium-ion battery thermal management system c) The whole

framework of the neural network-based MPC strategy Reprinted with permission from Ref [103]

Mesgarpour et al. [104] utilized NN method and compared two methods of air and water cooling alongside PCM for battery temperature management, as shown in Fig. 14. Since the developed machine learning method was physics-informed it can predict the stability of temperature of battery's pack for a long period of time in order to give an appropriate insight between cooling methods. It was revealed that the water cooling results in greater temperature reduction compare to air cooling. Further results showed that while increasing the air velocity improve the temperature regulation, after a certain value, increasing the flow rate has not any effect on the temperature. As it mentioned before, application of nanofluids and fins in through data-driven and numerical methods has extensively brought into the spotlight by researchers. Kiani et al. [123] numerically scrutinized the effect of nanofluid at two concentrations of 1% and 2% in a PCM-based cooper foam BTMS and compared the results with conventional water cooling system in LI-ion battery. They verified the numerical results with experimental apparatus and it was revealed that higher concentration of leading the extend the PCM melting time leading the better temperature regulation, however, the pressure drop of nanofluid in the channel remains a challenge wich should be addressed. Wu and Rao [124] developed a Lattic Boltzmann model to examine the effect of copper nanofluid in concentration of 0-6% with 1% increment rate and reported higher temperature shrinks by around 6.5% for nanofluid at 6%. Similarly, Hou and Rao [125] investigated the effect of alumina nanofluid at different concentration of 1-4% in cylindrical shape BTMS and reported 7% cells' temperature reduction at 4% nanoparticle fraction. Abdullah utilized hybrid nanofluid with nano-PCM in two different circular and elliptical shapes of BTMS and developed a mathematical model based on FEM method where reported 13% higher rate of temperature reduction in circular shape compares to elliptical. Mohammadian and Zhang [126] presented a 3D transient model that utilized aluminum pin fins and foams in four scenarios where fins and foam utilized simultaneously as well as solely to examine the cooling performance of BTMS. Their findings indicated that utilizing fins and foam leading to higher battery pack temperature reduction while it maintains more temperature uniformity across cells. Ping and co-workers. [127] implemented 1D electrochemical model in 3D transient thermal model to realize the effect of fins in a PCM-based BTMS cooling system. The fins distance as an objective function optimized and it was revealed that the PCM-fins would minimize the maximum temperature by around 34%. Egab et al. [128] in a 3D thermal model evaluated the effect of using fins and dimples in an air-based cooling in different scenarios of using fins and dimples solely and simultaneously. The findings revealed that simultaneous use of dimples and fins in low Reynolds number results in higher rate of cooling the battery by around 3°C.

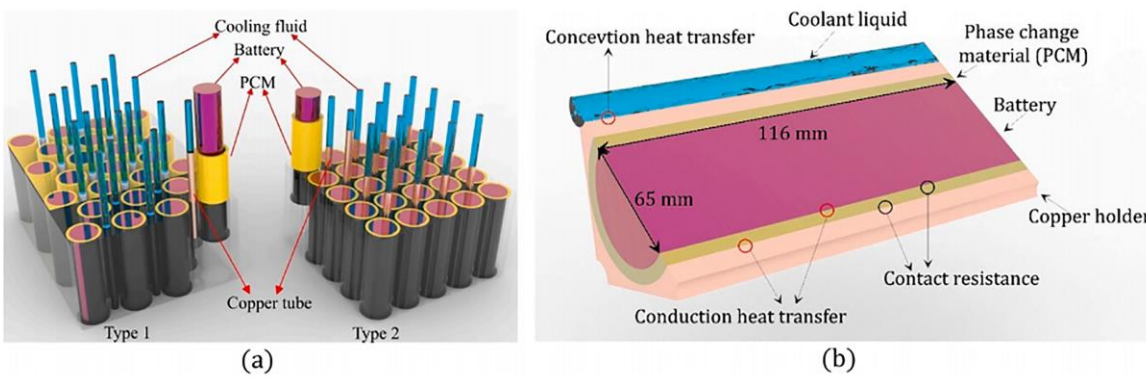

Figure 14. a) different arrangements of cells' cooling b) schematic of two considered surfaces for contact resistance Reprinted with permission from Ref [104]

Kalkan et al. [105] experimentally studied the performance of liquid-based cooling method of Li-ion battery with two different shapes of mini-channel plate and serpentine tube. Among experimental data around 70%, 15%, and 15% were used for training, validating and testing model. It was showed that develop FF-BLP-NN method lead to high accuracy in predicting and optimizing the important inputs for the temperature management of the battery's pack. Fig. 15 depicted the experimental setup of thermal management system in Li-ion battery using cooling method by mini-channel cold plate.

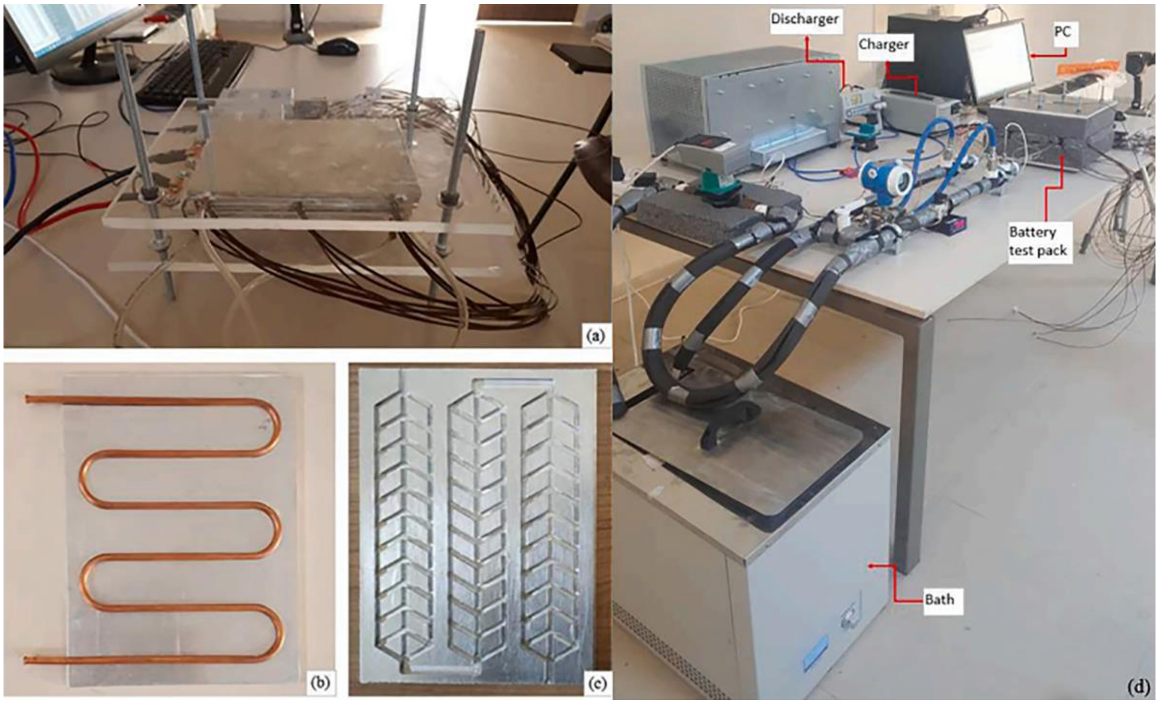

Figure 15. a) the battery and cold plates composition, half section views of b) serpentine tube cold plate c) mini channel cold plate d) overview of experimental setup Reprinted with permission from Ref [105]

Due to the high cost and uncertainties of other cooling methods in practical application, Wang et al. [106] focused on optimizing an air-cooling system (as the most used method) in Li-ion battery. A multi objective optimization based on NN and PSO developed to optimize the energy consumption of the fan while maintain constant the cost and weight of structure. The optimization results indicated that the cells space in X-axis and Y-axis should not be equal whilst the optimize spaces are examined. Talele et al. [107] evaluate two PCMs (Paraffin wax and RT-18) for cooling a Li-ion battery and compared the results with reference battery without PCM cooling. A neural network that trained by numerical raw data taken form a CFD simulation alongside with linear regression model employed to evaluate the maximum time taken for cells to reach the highest temperature. Multi-objective optimization for optimal condition of each scenario of charging was performed. The findings showed that paraffin wax has better performance than R18, because of its low melt temperature, leading battery cells cooled faster (or prevent to reach higher temperatures in lower time). As illustrated in Fig. 16, Yang et al. [108] in an experimental study used a honeycomb-shape with hexagonal/rectangular cooling plate and PCM in an integrated design for efficient cooling of lithium-ion battery. Effects of different parameters such as the shape of plate, the number of plates on the thermal management of battery are examined. It was revealed that the hexagonal shape cooling has slightly better performance in terms of maximum temperature (0.36 K) whilst between the number of plates (1, 2, 3 plates) the difference in temperature difference of module was marginal, however, using two plates recommended. A back propagation neural network was utilized for two driving pattern (in urban regions) considering the inlet flow rate to realize the battery temperature and temperature difference. Based on the 80% of trained data it was estimated that the cell's temperature and temperature difference for long-term drive are 312 K and 3.5 K respectively. Further results showed that the flow rate has highest impact on the maximum temperature while the temperature difference substantially affected by the ambient temperature and rate of discharge. Regarding the findings of machine learning in the open literature in battery thermal management systems, increasing the rate of discharge was leading to the raise of temperature. Importantly, the machine learning results and experimental data showed that temperature raise in cells during discharge time at 1C was not significant while higher fluctuation occur at higher discharge rate [110]. In this regard, many researchers utilized discharge rate higher than 2 C up to 10 C to examine the performance of the thermal management systems. It should be point out that, even though 2 C discharge rate in many studies used as the starting point, other researchers argue that temperature raise in battery pack in 2 C is not high enough and consider 3 C as the input [121]. Furthermore, for fluid-based cooling methods (i.e., air and water cooling) the results of optimization and prediction of ML methods alongside with experimental data showed that increasing the fluid flow reduces cells' temperature significantly, however, higher rate of fluid flow in the case of active method (i.e., when using fans and pumps) leading to increase the power consumption by system which could be affected the system from economic standpoint. Hence, one important thing that should be consider when implementing machine learning is to consider electrical costs in calculation to make the most efficient decision among different scenarios.

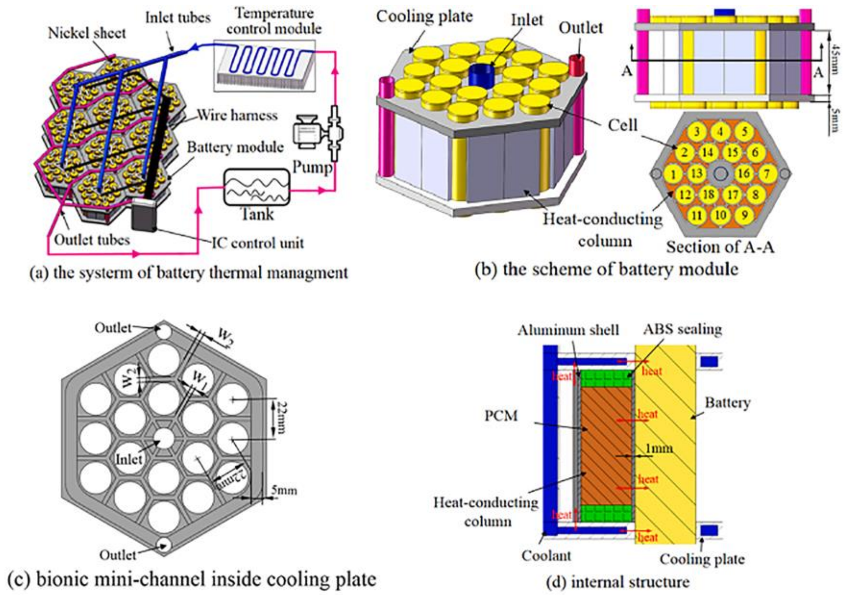

Figure 16. Detail schematic of honey-comb shape battery thermal management system Reprinted with permission from Ref [108]

Deng et al. [109] applied multi objective optimization with an experimental study to realize the effect of double layer bifurcation cooling plate for Li-ion battery thermal management system to maximize and minimize convective heat transfer and skin fraction coefficients respectively. Findings elucidated that the thickness of channel and length ration have critical impact on the cooling performance of system. Importantly, based on NSGA II and RS optimization it was revealed that the pressure drop in the proposed cooling plate is half of conventional serpentine tube. Yang et al. [110] numerically studied the cooling performance of stretchable Li-ion battery in three scenarios of without cooling and with graphite paraffin wax (GPCM) for initial and optimized conditions. The authors applied three different optimization methods of PSO, NSGA III, and SEPA-II and concluded that SEPA-II has the most promising results whilst the scenario of the GPCM in optimal design results in the best cooling performance by improving the maximum temperature and temperature difference 11.94% and 10.27% compare to case without cooling respectively. Liu & Li [129] developed a neural network-based algorithm for temperature distribution of a cylindrical lithium ion battery and based on the physical model and numerical simulation reported that the model is appropriate for real-time monitoring. Lin et al. [111] integrated NN with GA to find optimal parameters of a Li-ion battery thermal management that used by phase change materials and air as cooling. Their results showed that while the rate of discharge is constant, the air speed and air temperature are the most important parameters on the maximum temperature of battery pack. Furthermore, it was realized that thickness of PCM has the main role in maximum temperature of battery while spaces between unit cell is has the key role in cells temperature difference. Mousavi et al. [112] used genetic algorithm to find the optimum condition of the air-cooled based Li-ion battery with respect to the tube diameter and reported that increasing the tube diameter while the air flow rate remain constant at 2.55 m/s maximize the number of transfer unit. As shown in Fig. 17, Wang et al. [113] proposed to locate spoilers in spaces of air-based cooling system of a Li-ion battery to augment and improve the temperature uniformity and decrease the maximum temperature. Impact of different spoilers' parameters on the temperature of battery by applying genetic algorithm was examined. It was determined that among three shapes of straight, arc, and parabolic; the straight-shaped spoiler results in higher reduction in maximum temperature. Meanwhile, it was showed that increasing the length of spoiler directly impacted the maximum temperature but the number of spoiler is not proportional with temperature.

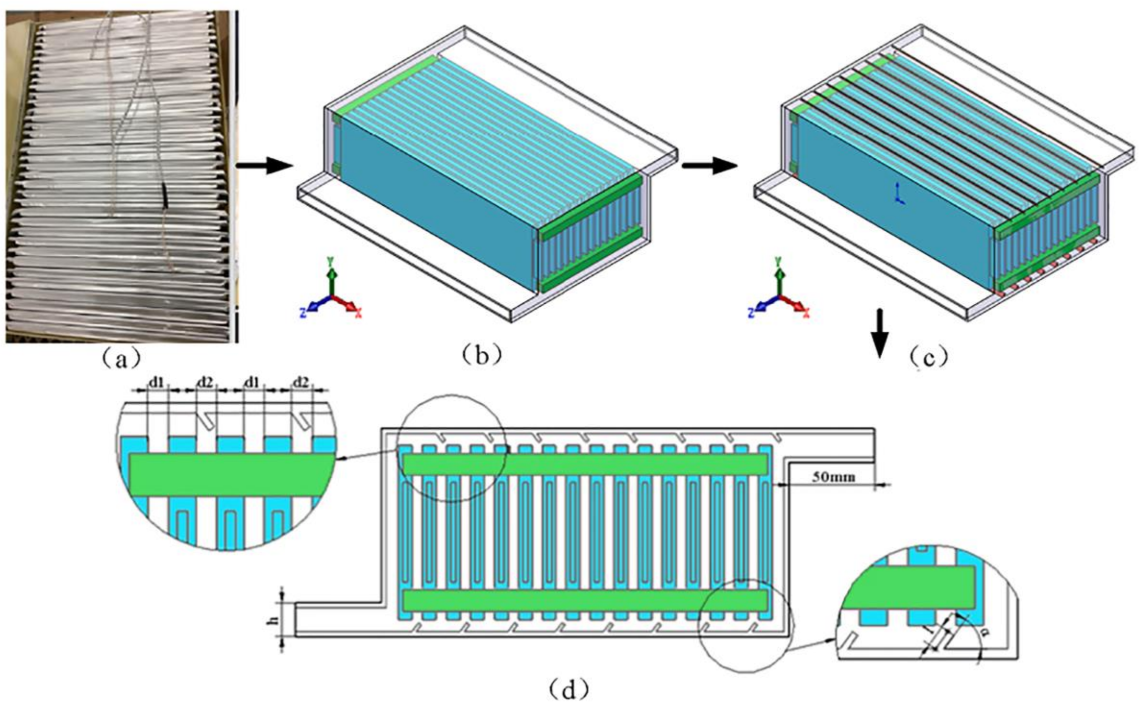

Figure 17. A 50AH battery model. (a) actual view (b) Initial view. (c) Plan 1 view. (d) Front view of plan 1. Reprinted with permission from Ref [113]

Su et al. [114] incorporated NSGA II algorithm with a surrogate Li-ion battery thermal model to optimize the maximum and uniformity of Li-ion battery temperature in a U-shape box with cooling water regarding four variables of the cooling plate's wall and bottom thickness, cooling water temperature and flow rate velocity. The findings revealed that the inlet temperature of cooling water with 59.8 % contribution in examining the maximum temperature has the crucial impact on these parameters whilst with 12.1% it has little effect on the temperature distribution battery. On the other hand, the geometry of plate and cooling water velocity has the most impact in regulating temperature distribution. Based on the NSGA II results, it was concluded that the optimum conditions can be obtained when the cooling plate is increased while the walls thickness was small and the cooling water has low temperature with high velocity. Zhao et al. [115] carried out an experimental study assisted by CFD simulation on the effect utilizing non-uniform pin-fins in the cooling channel of Li-ion battery to modify the arte of heat dissipation as well as temperature uniformity in cells. They used multi-island genetic algorithm to optimize the variables for optimal conditions. The results illustrated that under optimum conditions of pin-fins the electricity consumption, channel's weight, and standard temperature deviation would be diminish by around 29.8%, 29% and 17.4% while the highest cells temperature decreased by about 1.04°C. Wang et al. [116] realized the effect of coolant direction in three different scenarios in an aluminum channel plate for cooling Li-ion battery and realized that the when cooling water direction interchange alternately the best BTMS was obtained. Multi objective optimization based on the genetic algorithm revealed that under optimum conditions the average temperature difference of battery reduced by around 4.9% while the pressure drop in the channel due to optimizing the inlet flow rate was reduced nearly 13.2% which directly affected the consumed pumping power. Further results showed that the maximum temperature of battery modified and can reduced by around 2.79°C. Chen et al. [117] used genetic algorithm to realize crucial parameters for optimizing the maximum temperature and temperature difference as well as the battery area. Their results indicated that the convergence and divergence of plate's angle and minimal convergence width are directly related to the temperature difference while by minimizing the battery unit and minimal width divergence the maximum temperature of the pack is optimized and remained in allowable regions. Further results indicated that by optimizing the rate of air flow in the battery the pack's space reduced by around 6.24%. Chen et al. [118] used heat dissipation and flow resistance approach to model the air flow rate and a Li-ion battery heat generation respectively, and incorporated the NSGA-III Differential Evolution algorithm assisted by sensitivity analysis to find optimal condition of important parameters in thermal management system. The outcomes indicted that the utilizing large angles and minimum widths of convergence modified the important objectives in thermal management system where the temperature difference and power consumption reduced by around 60.7% and 16.7% respectively and highest temperature decrease by about 3.4°C compare to the baseline case. Wan [119] combined Tunicate Swarm and Search & Rescue (TSSR) optimization algorithms to optimize the spacing between channels of a battery in order to reduce the maximum temperature of Li-ion battery. The performance of TSSR algorithm for similar conditions to examine the optimal spacing was compared with other methods such as EEH, ANN, and NN from computational time viewpoint and it was revealed that the TSSR has lower computational time more than 55%, 110% and 170% respectively. Dong et al. [120] theoretically investigated the performance of liquid-based battery thermal management system with double-helix by consider three objects of liquid flow rate, diameter, and pitch groove to minimize the Li-ion cells' temperature. It was found that augmenting the flow rate until the certain rate of 0.0002 g/s and pitch at 60mm results in to maintain the temperature less than 40 °C. The NSGA-II with MCDM multi objective optimization was employed it was found that the optimum conditions for flow rate, diameter, and pitch grove are 0.000194 g/s 0.04 m, and 0.1 m respectively. Cheng et al. [121] examined the effect of using fins on air-cooled Li-ion battery by applying multi objective-optimization with genetic algorithm. The results revealed the using fins in the channel of battery leads to substantial reduction on the maximum temperature and standard deviation temperature by about 17.63% and 39.3% respectively. Multi objective optimization results showed that standard deviation temperature can be reduce by about 50.19% while the cooling volume enhanced nearly 74.13%. Afzal et al. [130] performed a multi objective optimization by two algorithms of cuckoo search and artificial bee colony optimization considering generated heat, conductivity, Reynolds number, spacing and Prandtl number to optimize parameters of maximum temperature, Nusselt number and coefficient friction. The outcomes revealed multiple results. Increasing heat generation has not effect significant effect on the Nusselt number and coefficient fraction while it highly affected the maximum temperature. In the same way, conductivity ratio showed on similar effect on those parameters. Importantly, spacing is the only parameters that impacted three parameters. Eventually, they compared the performance of both algorithms and it was revealed that greater convergence fitness by artificial bee colony obtained rather than cuckoo search.

8 Conclusions and future directions in field

In the present review, various active and passive cooling methods of lithium-ion battery through different approaches of exergy, economic, environmental and machine learning are discussed. Each type of passive and active cooling methods has their pros and cons. Generally, passive cooling has simple structure than active cooling. Air-based cooling system (Through the natural and/or forced convection) -whether from ambient or cabin- as one of the simplest method has been widely utilized, however, regarding the low efficiency and specific heat capacity it would not be an appropriate for under high-load conditions. Thus, an auxiliary passive cooling approach such as PCMs, fins, dimples etc. could be as an appropriate strategy to improve the performance. Moreover, PCMs as another innovative passive approach should be carefully selected based on battery conditions as the melting temperature can significantly impacted cooling of battery while viscosity of PCM when it intend to circulate through the battery and the electrical energy consumption is another parameter that would take into account. In active cooling methods, refrigerator-based systems has prominent advantage for high-load conditions, however, further improvement can be achieved through reducing compressor's exergy destruction, however, using high efficient oil in compressor also suggested as an appropriate physical modification. Moreover, for liquid-based cooling system the optimum flow rate and the entering path of fluid considering the pressure drop in channels as one of the important functions should be consider in this context. Developing novel modeling methods based on the artificial intelligent to obtain accurate results is highly desirable. Furthermore, integration of machine learning and data-driven methods would lead to more reliable results while utilizing novel deep learning approaches which outshined in this context is greatly recommended. Interestingly, it was revealed that some algorithms leading to more accurate results than other, therefore comparing the results of different algorithms for future studies is suggested. Since lifespan of the battery has substantial impact on the economic and environmental analysis, more research on life cycle assessment and carbon footprint are suggested as interesting topics for future researches. Besides all of aforementioned criteria, there are other factors that could affect the thermal management of Li-ion batteries such as driving pattern, however, in modeling and simulation researchers consider a standard driving pattern. Thus, developing novel modeling approaches for battery temperature regulation based on different driving patterns under various climatic conditions would be another step toward more practical and realistic cooling scenarios for Li-ion batteries.

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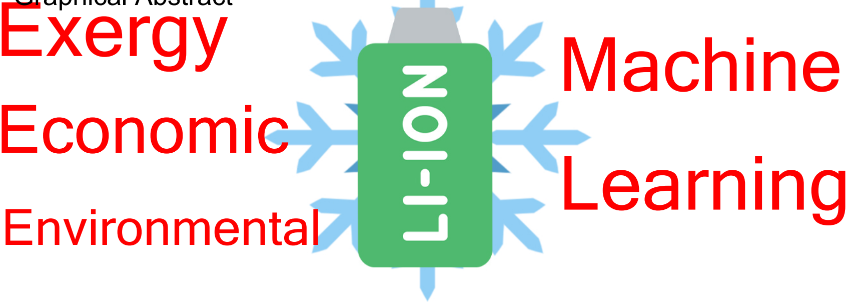
Graphical Abstract



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