Design Optimization Methodologies Applied to Battery Thermal Management Systems: A Review

Authors: Takiah Ebbs-Picken[a,1], Carlos M. Da Silva[a], and Cristina H. Amon[a]

[a] Department of Mechanical and Industrial Engineering, ATOMS Laboratory, University of Toronto, 5 King's College Road, Toronto, ON M5S 3G8, Canada

Highlights

- Illustrations of the most common battery thermal management system (BTMS) configurations.
- Comprehensive review of design optimization methodologies applied to BTMSs.
- Classification of BTMS studies based on the applied design optimization methodology.
- Challenges and opportunities in BTMS design optimization.

Abstract

Heat generation during lithium-ion battery charge and discharge requires the implementation of battery thermal management systems (BTMSs) for enhanced battery performance, safety, and lifetime. Numerous design optimization methodologies have been recently implemented to improve BTMS cooling and heating performance, energy usage, efficiency, and mass. This paper provides a comprehensive and exhaustive review of BTMS studies that apply design optimization methodologies, categorizing them into surrogate-model-based, multi-objective, multidisciplinary, single objective, and design of experiments methodologies. This review paper also summarizes and discusses critical knowledge gaps, current trends, and opportunities in BTMS design optimization. Most of the literature applies multi-objective optimization methodologies with genetic algorithms, optimizing the design of structural BTMS components to minimize maximum battery temperature and spatial temperature gradients. This review paper also identifies opportunities for future applications of BTMS design optimization methodologies, including opportunities for performance improvements of hybrid BTMSs, battery lifetime, electric vehicle range, and heating strategies for battery pre-conditioning.

Keywords

Battery thermal management; design optimization; electric vehicles; lithium-ion battery; batteries

[1] Corresponding author, e-mail: takiah.ebbspicken@mail.utoronto.ca

Contents

Nomenclature

T_σ temperature standard deviation

$T_{\textbf{avg}}$ average temperature

$T_{\textbf{max}}$ maximum temperature

$\Delta T_{\textbf{max}}$ maximum cell temperature difference

Δp pressure loss

v_σ airflow velocity standard deviation

ABC artificial bee colony

ANN artificial neural network

BC boundary condition

BPNN back-propagation neural network

BTMS battery thermal management system

CCD central composite design

CFD computational fluid dynamics

COSMOS concurrent surrogate model selection

CS cuckoo search

DOE design of experiments

EG expanded graphite

EV electric vehicle

Fc coefficient of friction

FEA finite element analysis

FGRA fuzzy grey relational analysis

GA genetic algorithm

HDMR high dimensional model representation

ICE internal combustion engine

LHS latin hypercube sampling

LIB lithium-ion battery

LINMAP linear programming technique for multidimensional analysis of preference

MCDM multiple criteria decision making

MCS Monte Carlo simulation

MDF multidisciplinary feasible

MDO multidisciplinary design optimization

MOGA multi-objective genetic algorithm

MOO multi-objective optimization

MOPSO multi-objective particle swarm optimization

MRDO-UPM multidisciplinary robust design optimization under parameter and metamodeling uncertainties

MRS minimum response surface

MUNLM multidimensional unconstrained non-linear minimization

NSGA-II non-dominated sorting genetic algorithm II

NSGA-III non-dominated sorting genetic algorithm III

Nu Nusselt Number

PCM phase-change material

Pr Prandtl number

PSO particle swarm optimization

RBF radial basis function

Re Reynolds number

RSA response surface approximation

RSM response surface modeling

SA simulated annealing

SMDO surrogate-model-based design optimization

SOC state of charge

SOO single objective optimization

SPEA-II strength Pareto evolutionary algorithm II

SQL sequential linear programming

SQP sequential quadratic programming

SVM support vector machine

SVR support vector regression

TOPSIS technique for order of preference by similarity

TSEMO Thompson sampling efficient multi-objective optimization

TSSR tunicate swarm search and rescue

1 Introduction

Increasing climate change concerns have accelerated the need for sustainable alternatives to traditional internal combustion engine (ICE) vehicles to mitigate the associated generation of greenhouse gases and carbon emissions. Electric vehicles (EVs) are becoming increasingly popular, offering an environmentally cleaner, lower-carbon, and more sustainable alternative to ICE vehicles [1]. The past decade has seen significant developments in EVs, with the number of EVs on the road increasing exponentially from 17,000 in 2010 to over 15 million in 2021 [2]. Electric vehicles rely on batteries to provide the required energy for vehicle operation through chemical reactions, without the need for fossil fuels if the electricity to power EVs comes from renewable energy sources. Batteries store energy electrochemically, converting chemical energy to electrical energy while discharging, and electrical energy to chemical energy while charging. Batteries are reliable energy storage devices with a wide range of power and capacity capabilities realized by combining battery cells through parallel or series electrical connections, making them suitable for a wide range of applications.

Lithium-ion battery (LIB) technologies have advanced significantly in recent years, making them the primary choice for powering EVs due to their high energy and power densities [3]. Compared to other rechargeable battery types [4], LIBs' longer cycle life and lighter weight make them favorable for EVs and many other applications. During EV operation, LIBs undergo many charge-discharge cycles, during which heat is generated due to internal chemical reactions and Joule heating effects associated with the battery's inner resistance [5]. The continued operation of LIBs at internal temperatures outside of 20-40 °C, or at non-uniform temperatures, has detrimental effects on the battery performance, safety, and lifetime [6]. The optimal operating temperature range for LIBs has not been concretely established, with varying ranges reported in the literature: 25-40 °C [7], 20-40 °C [8], and 15-35 °C [9–11]. Regardless, battery degradation accelerates at temperatures outside these ranges. Also, high temperatures can lead to a phenomenon known as thermal runaway, which can result in the catastrophic failure of the system by fire or explosion [12]. This highlights the key role of battery thermal management systems (BTMSs), which are tasked with keeping battery temperature within an optimal range, while also ensuring temperature uniformity across battery packs, ensuring the mitigation of thermal runaway [13, 14].

Existing BTMSs can be classified based on their heat transfer medium as air, liquid, phase-change material (PCM), and heat-pipe cooling systems. The inherent strengths of the different BTMS types lead to trade-offs between their effectiveness, cost, mass, and power usage. Therefore, different BTMS types are better suited for certain applications. However, system improvements are always desirable to optimize cost, mass, and energy usage regardless of the specific application and BTMS type. Further, with ever-increasing battery energy density and fast charging-discharging requirements, it is expected that LIBs will face even more severe heating problems and require more effective cooling [15, 16]. To address these cooling needs and desired BTMS improvements, researchers have increased the use of design optimization methodologies. In recent years, the strong interest in optimizing these systems has led to numerous BTMS design optimization studies, motivating the need to comprehensively review and categorize the available literature.

This literature review covers recent studies on BTMS design optimization and classifies these studies based on the applied optimization methodology, instead of the BTMS type or system component being optimized as in past review papers [17, 18]. This review includes only studies that formally use design optimization methodologies to obtain an optimal design; it does not cover studies using single-parameter or sensitivity analyses to find a better but not necessarily optimal design. This review is exhaustive, including the most relevant BTMS design optimization studies found in the recent literature to the best of our knowledge. Most importantly, this review covers all BTMS types, whereas previous reviews focused on specific types such as air-cooling [17]. It is relevant to note that air-cooling systems have become less popular in EV applications due to their increased battery cooling and heating requirements. This highlights the need for thoroughly reviewing BTMS system types that are more relevant for current and future EV developments. In addition, BTMS design optimization methodologies have evolved rapidly since the publication of past reviews in this area [17,18], enabling this review paper to include more recent advancements, which are also classified more intuitively to better understand the trade-offs between the different optimization methodologies. Having focused on the design optimization methodologies, how they have been implemented, and to which systems they have been applied, this review allows readers to better identify which methodologies are most suitable for their requirements.

The structure of this review is as follows. Section 1.1 defines a typical optimization problem and presents the optimization methodologies into which the surveyed BTMS design optimization studies were classified. Section 1.2 includes illustrations and descriptions of the most relevant BTMS types. Sections 2-6 provide brief descriptions of each optimization methodology and a thorough review of the pertinent BTMS optimization studies. A comprehensive analysis of the design optimization methodologies is included in Section 7, which compares the methodologies' advantages, disadvantages, and scope of application. Finally, Section 8 summarizes the state of the art of design optimization methodologies applied to BTMSs and highlights critical knowledge gaps, challenges, and opportunities in this area. The supplementary materials attached to this literature review include a section titled "*Literature Summaries by Optimization Methodology*," which consists of tables summarizing the studies applying each design optimization methodology. These tables allow for a quick overview of the existing literature and include information on the system structure, battery module details, heat generation modeling, cooling medium, analysis method, optimization objectives, optimization design variables, surrogate modeling methods, optimization methods, and numerical pre- and post-optimization results. Similarly, the supplementary section titled "*Literature Summaries by Battery Thermal Management System Type*" consists of a second set of tables summarizing the same optimization studies; however, classifying the studies by the BTMS type.

1.1 Design Optimization

The area of design optimization covers many methodologies and frameworks that address different problem requirements and formulations. Optimizing the design of a system means finding a design that is as good as possible in a defined sense, i.e., a design that minimizes or maximizes some quantity given appropriate constraints. The mathematical formulation of a general optimization problem is shown in Equation 1.

$$\begin{aligned} \text{minimize} \quad & f(\mathbf{x}) \\ \text{with respect to} \quad & \mathbf{x} \\ \text{subject to} \quad & h_i(\mathbf{x}) = 0; \quad i = 1 \text{ to } p \\ & g_j(\mathbf{x}) \leq 0; \quad j = 1 \text{ to } m \end{aligned} \tag{1}$$

where $f(\mathbf{x})$ is the objective function, $\mathbf{x}$ is the vector of design variables, $h_i(\mathbf{x})$ are the p equality constraints, and $g_j(\mathbf{x})$ are the m inequality constraints. The objective and constraint functions may take the form of analytical equations; however, it is also common to use computational fluid dynamics (CFD) or physical experiments to compute objectives where there are no closed-form equations. The specific objective and constraint function forms may prevent the application of certain optimization methodologies and should be carefully considered.

Optimization methodologies search through combinations of design variables within the domain defined by the equality and inequality constraints. While it is theoretically possible to evaluate the objective function through a full search of all possible design variable combinations, in most cases, it would be extremely time-consuming and computationally expensive. Thus, efficient methodologies for searching the design domain are desired. These methodologies are referred to as optimization algorithms. A typical optimization algorithm is iterative, during which the objectives and constraints are computed at each design point. The optimization algorithm uses the objective values and other values (i.e., previous objective values, gradient values, or constraint values) to dictate the direction and magnitude to change the design variables. After each iteration, new objective and constraint values are computed, and the process continues until the optimal design is achieved. Figure 1 shows a generalized process flow for the implementation of a design optimization methodology applied to BTMSs. Note, the process shown in Figure 1 is generalized and applicable to the majority of design optimization implementations; however, there may be exceptions with additional or fewer steps.

This literature review classifies BTMS design optimization studies into five categories based on the applied optimization methodology. These categories, addressed in Sections 2-6, are surrogate-model-based design optimization (SMDO), multi-objective optimization (MOO), multidisciplinary design optimization (MDO), single objective optimization (SOO), and design of experiments (DOE). If MOO or MDO methodologies are combined with a surrogate model, these studies are classified either as MOO or MDO, not as SMDO. The SOO section covers BTMS design optimization studies that do not use coupled analysis, multiple objectives, or surrogate models. The DOE methodology may not fit strictly the definition of an optimization methodology; however, it still determines an optimal design from a set of parameters while considering parameter interactions. Therefore, this review includes DOE studies because DOE is a step further than a single-parameter or sensitivity analysis in terms of determining optimal designs. Sections 2-6 present a tailored process flow diagram for each design optimization methodology, adjusted from that of Figure 1. For simplicity, the brief descriptions of the general design optimization steps included in Figure 1 have been omitted in subsequent process flow diagrams if these steps remain similar for the corresponding methodology.

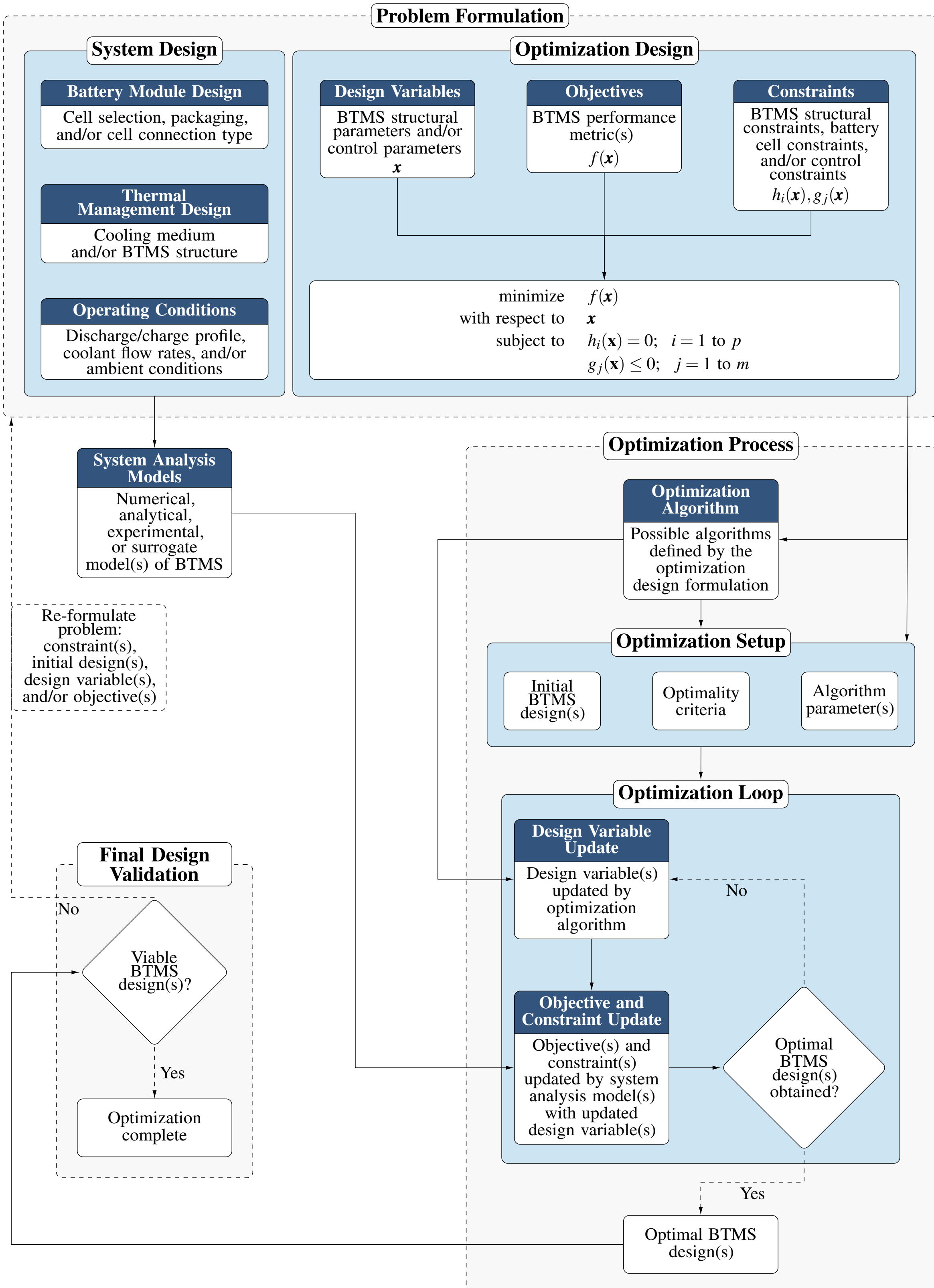

Figure 1: Generalized design optimization methodology process applied to battery thermal management systems.

1.2 Battery Thermal Management Systems

Battery thermal management systems must be able to perform the following functions: cooling to remove heat from the battery, heating to increase battery temperature in cold climates, thermal insulation to prevent sudden temperature changes, and ventilation to exhaust gases from the battery [6]. It is also required for BTMSs to be compact, lightweight, low cost, reliable, easy to maintain, easy to integrate, and have low parasitic power use. Battery thermal management systems can be classified based on their cooling medium as air, liquid, PCM, and heat-pipe systems. Recently, novel BTMSs have been developed combining these technologies into systems termed hybrid BTMSs [19].

Air-cooled BTMSs use airflow to cool the cells within the battery pack and can be further classified as passive or active systems based on how the air is supplied. Passive air-cooled BTMSs rely on natural convection and might require channeling the airflow from outside the EV to inside the battery pack [17]. Active air-cooled BTMSs rely on forced convection and require an airflow device for active control [20]. Most of the air-cooled BTMS design optimization studies surveyed in this review paper implemented active BTMSs. Figure 2 shows generic illustrations of common air-cooled BTMS inlet and outlet configurations, and Figure 3 illustrates various plenum types near the inlet and outlet of these air-cooled BTMSs.

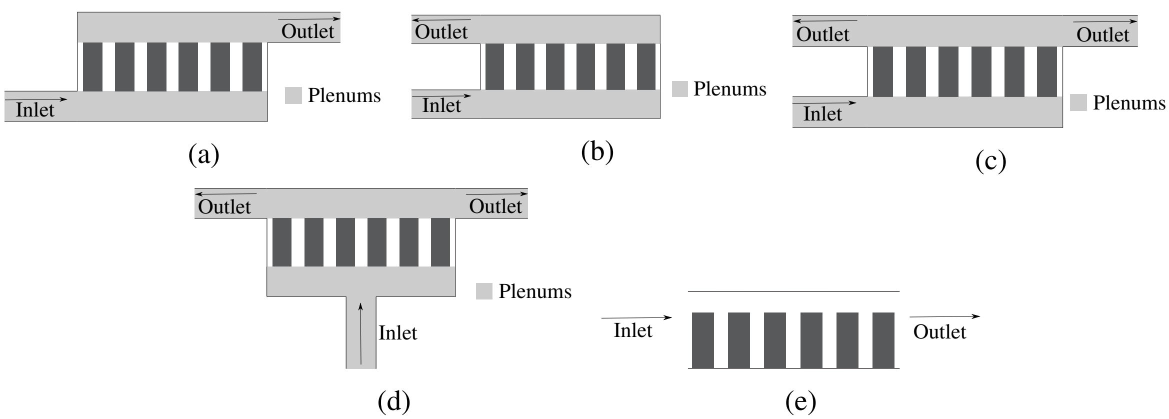

Figure 2: Air-cooled BTMS configurations: (a) Z-type [21], (b) U-type [22], (c) J-type [23], (d) T-type [24], and (e) symmetric flow configurations [25]. The light gray highlights the plenums, while the dark gray rectangles represent arbitrary battery cell arrays. Refer to the references provided in this caption for illustrative examples of each configuration.

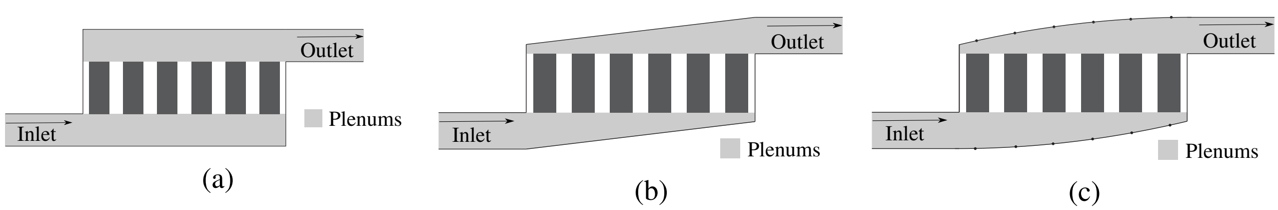

Figure 3: Air-cooled BTMS inlet and outlet plenum geometries, illustrated here for a Z-type flow configuration: (a) linear [21], (b) angled linear [26], and (c) curved plenums [27]. These plenum geometries are possible for any flow configuration shown in Figures 2(a)-(d). The light gray highlights the plenums, while the dark gray rectangles represent arbitrary battery cell arrays. Refer to the references provided in this caption for illustrative examples of each inlet and outlet plenum geometries.

Liquid-cooled BTMSs can be further classified as direct and indirect systems. Direct liquid-cooled

BTMSs use a dielectric fluid in direct contact with the battery cells and are less common in EV applications [28]. Instead, indirect liquid-cooled BTMSs are deemed safer and more widely used in EV batteries; they typically rely on bottom/top or inter-cell metal cold plates with internal channels to contain a coolant in indirect contact with the battery cells [29]. In indirect liquid-cooled BTMSs, the heat from the battery is transferred to the coolant through the metal fabrication, and the coolant then transfers the heat away from the battery pack through a recirculating coolant circuit that exchanges heat with another medium. Figure 4 shows various generic configurations typical of indirect liquid-cooled BTMSs with cold plates, and Figure 5 illustrates various channels geometries commonly used within these cold plates.

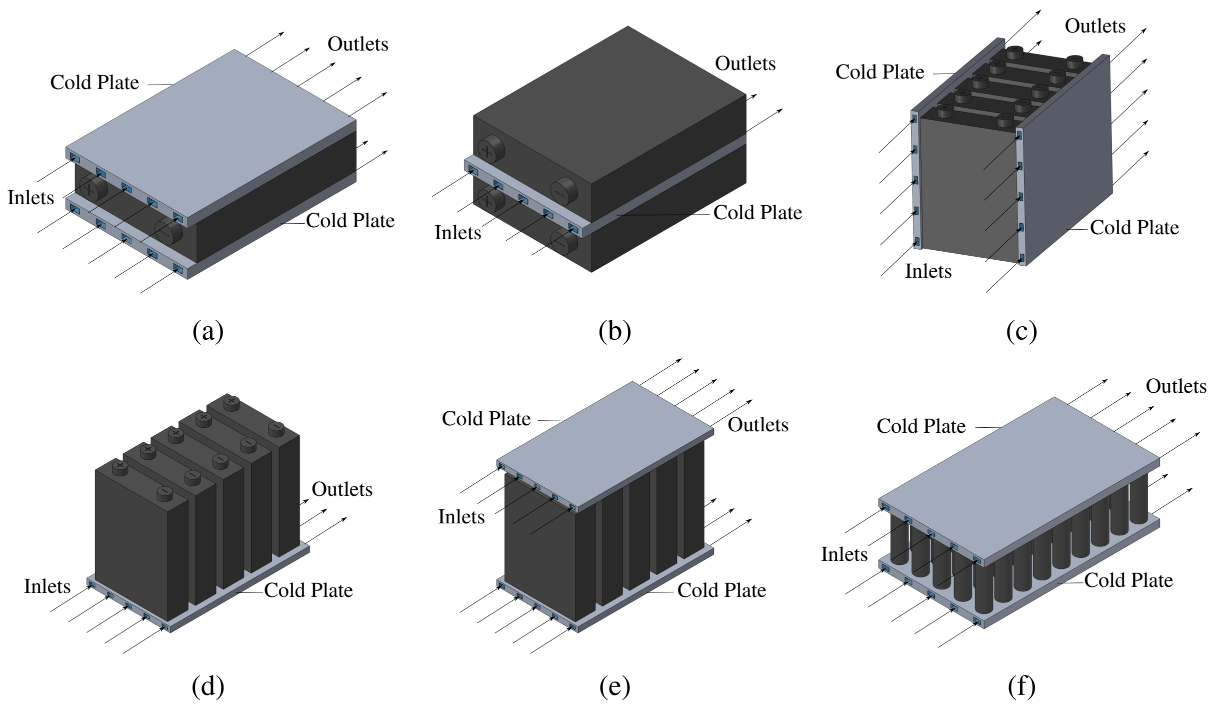

Figure 4: Indirect liquid-cooled BTMSs with cold plate configurations, shown here for cold plates with a parallel internal channel geometry with one inlet and one outlet per channel: (a) battery cells sandwiched by inter-cell cold plates (common for prismatic and pouch cells) [30], (b) inter-cell cold plates sandwiched by battery cells (common for prismatic and pouch cells) [31], (c) side cold plates (common for prismatic and pouch cells) [32], (d) bottom cold plates (common for prismatic, pouch, and cylindrical cells) [16], and bottom-top cold plates (common for prismatic, pouch, and cylindrical cells) shown here for an arbitrary array of (e) prismatic cells [33] and (f) cylindrical cells [15]. The cold plates are shown in light gray and the batteries are shown in dark gray. Refer to the references provided in this caption for illustrative examples of each configuration.

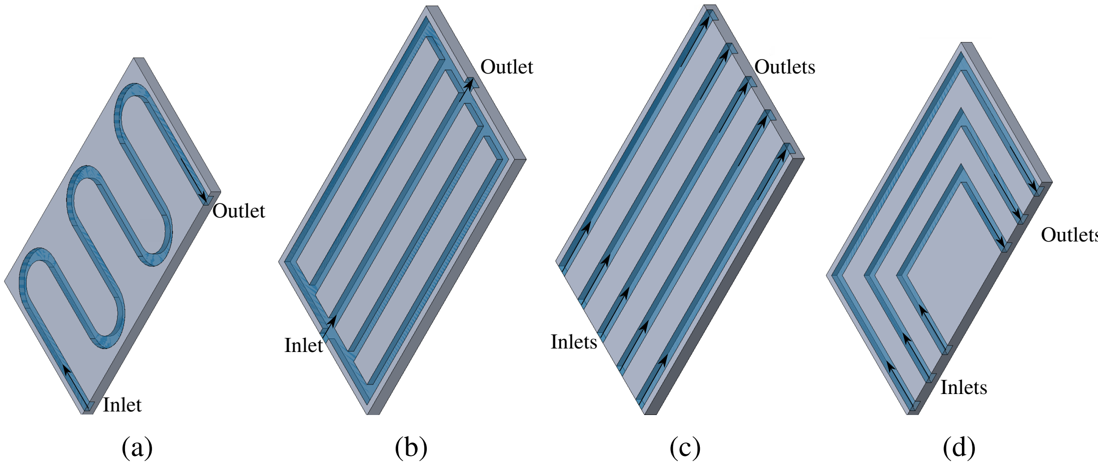

Figure 5: Cross-sectional views of cold plates illustrating typical internal channel geometries: (a) serpentine channel (inlet and outlet may be on the same or opposite sides) [34], (b) parallel channel with one inlet and one outlet per cold plate [35], (c) parallel channel with one inlet and one outlet per channel [30], and (d) three-channel U-shaped channel [36]. The light gray shows the cold plate material, while the blue areas show the channels. Refer to the references provided in this caption for illustrative examples of each configuration.

Phase-change material BTMSs leverage the ability of the PCM to absorb or release large amounts of latent heat during the phase change from one state to another at a constant temperature [37]. Phase-change material BTMSs are passive cooling systems that are often part of hybrid cooling arrangements that combine PCM-cooled with liquid-cooled or air-cooled BTMSs to remove the heat accumulated in the PCM. Another BTMS types involving a phase change heat transfer process are heat-pipe BTMSs. These systems generally consist of metallic pipe-shaped devices that encapsulate a working fluid that undergoes phase transitions through evaporator, adiabatic, and condenser sections. In the evaporator section, which is in contact with the battery cell to be cooled, the working fluid evaporates by absorbing heat. This fluid then moves to the condenser section through the adiabatic section by means of a pressure gradient. The working fluid finally condenses through external heat exchange and returns to the evaporator section [3].

Hybrid BTMSs attempt to combine favorable aspects from basic BTMSs in order to achieve higher performance. A review of hybrid BTMS was completed by Zhao *et al.* [19], reviewing a number of hybrid systems with different combinations of basic BTMS types. Common hybrid systems combine heat-pipes with air or liquid-cooling [38], PCM with air or liquid-cooling [39], or heat-pipes and PCM with air or liquid-cooling [40]. Typically hybrid BTMSs involve the combination of active and passive sub-systems. While hybrid BTMSs offer increased performance, they may not be necessary depending on the battery system's requirements. The complexity of hybrid cooling arrangements and their relatively recent development has presented the opportunity for further improvements of these BTMSs through the application of design optimization methodologies. Figure 6 illustrates possible configurations of hybrid BTMSs with PCMs, heat-pipes, and liquid-cooling. Compared to air and liquid-cooling BTMSs there is a wider range of configurations with many studies implementing unique variations or combinations of the configurations presented in Figure 6.

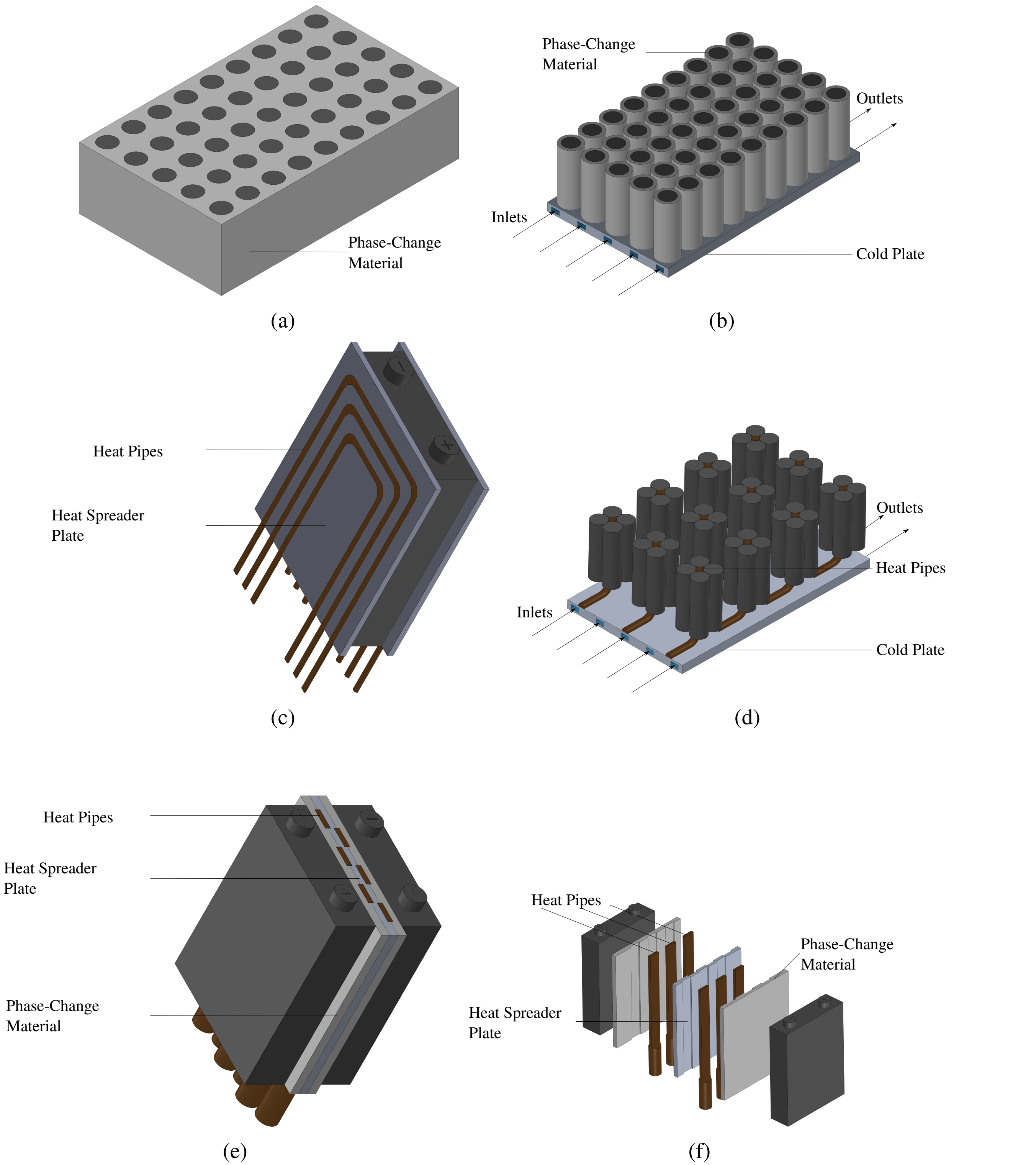

Figure 6: Hybrid BTMS configurations: (a) PCM system with embedded cells [41], (b) PCM cell casing and parallel channel bottom cold plate hybrid system [42], (c) heat-pipe embedded in heat spreading plate system [43], (d) heat-pipe surrounded and parallel channel bottom cold plate hybrid system [44], and (e) heat-pipe, PCM, and heat spreader plate sandwiched by battery cell system with (f) an exploded view [45]. Refer to the references provided in this caption for illustrative examples of each configuration.

Figures 2-6 illustrate typical battery cell arrays with different BTMS configurations that are key to understanding the terminology used throughout this manuscript. These figures are not exhaustive, but cover the majority of BTMS structures reviewed in this paper. References are provided for each sub-figure in Figures 2-6 for illustrative examples of these configurations in the literature. For clarity, we refer to these generic configurations when describing the BTMS type from each design optimization study addressed throughout this manuscript.

2 Surrogate-Model-Based Design Optimization

Surrogate-model-based design optimization (SMDO) is another term for approximation-based or meta-model-based design optimization. Instead of using computationally expensive analyses such as CFD or completing physical experiments, approximations for these analyses are created in the form of analytical models or computational networks such as artificial neural networks (ANNs). These models are often called surrogate models and the process of creating the models is referred to as surrogate modeling. Using a surrogate model can greatly reduce the computational time for the analyses and thus for the entire BTMS design optimization process. The general process for SMDO methodologies is included in Figure 7. For the sake of completeness, we have included surrogate supported MOO as an optimization process in Figure 7; however, MOO studies are discussed in Section 3.

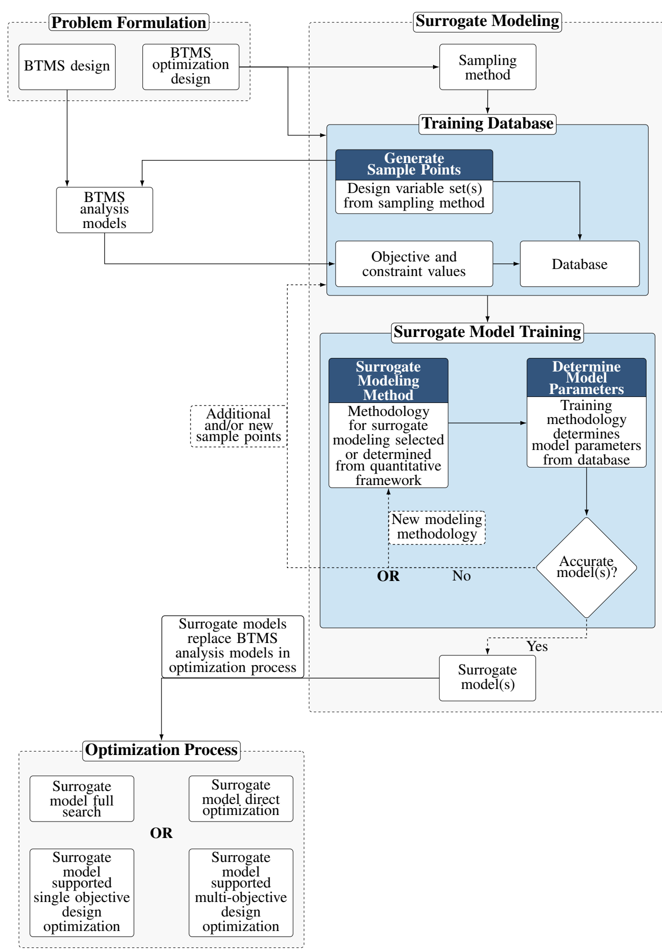

Figure 7: Generalized process of the surrogate-model-based design optimization methodology.

The general process of surrogate modeling begins with the creation of design variable sets using a sampling method. These sample points ideally offer coverage of the entire design domain. Numerical simulations or experiments are completed using the design variable sets generated by the sampling method to determine the corresponding objective and constraint values. A database or training data set is created containing the design variable sets and corresponding objective and constraint values. A surrogate modeling technique is then used with the database to develop the required models, typically separate models for each objective and constraint defining the optimization problem. The models are evaluated by comparing their output results to simulation or experimental results, and their accuracies are determined. If the accuracies of the models are too low, different sample points or a different surrogate modeling technique can be implemented, and the process is repeated until the desired accuracy is achieved. The surrogate models then replace the computationally expensive analysis wherever required in the optimization process. It is important to note that there may not be a strong enough relationship between the design variables and objectives or constraints for surrogate modeling methods to capture, making it impossible to apply SMDO methodologies in some cases.

Each surrogate modeling method presents slightly different representations and assumptions for the underlying function used to capture the relationship being modeled. Possible surrogate modeling methods range from simple linear regression to full ANNs, with some methods able to capture highly non-linear relationships. The large variety of available surrogate modeling methods makes it difficult to select which method would be best suited for a specific application. To address this challenge, quantitative frameworks such as K-fold cross-validation selection or concurrent surrogate model selection (COSMOS) have been developed. These frameworks systematically compare different surrogate modeling methods and select the method which develops the model with the highest accuracy. This section contains only literature that uses SMDO and SOO methodologies and does not address other MOO or MDO methodologies. The following subsections summarize different methods of using surrogate models in optimization processes. A summary of the literature reviewed in this section is included in Table 1 of the "*Literature Summaries by Optimization Methodology*" supplementary materials document.

2.1 Surrogate Model Full Search

Performing optimization by evaluating all possible combinations of BTMS design variables and completing a full search would typically not be possible using CFD analysis due to its high computational cost. However, surrogate models are generally computationally cheap models, allowing the objective to be evaluated for all possible design variable combinations in relatively little time. This methodology has been termed here a surrogate model full search. For applications of a surrogate model full search methodology, the design space must not be too large, and an appropriate discretization of the design space must be selected.

Battery thermal management systems have been optimized using ANN surrogate models to obtain an optimal design with a full search. Shi *et al.* [46] used this methodology to determine the optimal design of a U-type air-cooling BTMS with additional airflow outlets. Objectives of maximum temperature ($T_{\max}$) and maximum cell temperature difference ($\Delta T_{\max}$) were evaluated using an experimentally validated CFD model. A database of objective values for different design points considering the number, position, and area of additional outlets was created to train the ANN. The ANN was then used to evaluate all possible design points to obtain the optimal solution, which was able to reduce $\Delta T_{\max}$ significantly, with a slight reduction of $T_{\max}$. Similarly, Qian *et al.* [47] used Bayesian neural networks to fully search a design space; however, they considered the battery spacing of a symmetric air-cooling BTMS. Optimal battery spacing between each row and column of cells was obtained such that both objectives of $T_{\max}$ and $\Delta T_{\max}$ were reduced. Instead of using neural networks, Ye, Rubel, and Li [48] used Kriging surrogate models. In [48], the full search was able to obtain the optimal parameters for the channel widths of the liquid-cooling parallel channel bottom-top cold plate system to minimize $T_{\max}$ and pressure loss (Δp). A third surrogate modeling methodology was implemented by Sun and Dixon [49], who used response surface approximation (RSA) models developed using optimal latin hypercube sampling (LHS). These models were trained using results from an experimentally validated CFD model and a full search minimized $T_{\max}$, $\Delta T_{\max}$, and Δp for a Z-type air-cooling system compared to both baseline U-type and Z-type systems.

2.2 Surrogate Model Direct Optimization

Surrogate models may take the form of analytical equations, and if the order of these equations is not high, in some cases, they can be analyzed directly using derivative methods. This can lead to an optimal design. An important consideration for this methodology is that the surrogate model functions must be smooth with limited noise, or else derivative methods may not be feasible.

The following three studies directly optimized response surface modeling (RSM) surrogate models for varying BTMSs. Ling *et al.* [41] optimized an embedded cell PCM-expanded graphite (EG) BTMS with an unspecified active cooling method. The objectives were to minimize mass and volume for three cooling arrangements: side cooling, bottom-top cooling, and bottom-top cooling with a low mass fraction PCM. The battery spacing, PCM density, and PCM EG mass fraction were considered as design variables, while the PCM melting fraction after a charge/discharge cycle, $T_{\max}$, and $\Delta T_{\max}$ were appropriately constrained. An experimentally validated CFD model was implemented to calculate the objectives based on the central composite design (CCD) sampling method. The second-order polynomial RSM models of the objectives were then directly analyzed by considering points where the derivatives were zero, thus determining the optimal design parameters. The configuration with bottom-top cooling and a low mass fraction PCM was able to reduce the mass and volume by the greatest amount; however, it required a more intense active cooling method compared to other configurations. Similarly, Dong *et al.* [50] optimized the channel geometry of a liquid-cooling cold plate BTMS with a combined parallel and serpentine channel configuration with the inter-cell cold plates sandwiched by soft pack battery cells. The optimal channel geometry reduced the objectives of $T_{\max}$, $\Delta T_{\max}$, and Δp. Finally, Zhu *et al.* [15] obtained optimal geometric parameters of a liquid-cooling bottom cold plate BTMS with parallel channels and an added heat spreader plate. The direct analysis of RSM models was able to obtain an optimal design that showed reductions in $\Delta T_{\max}$ and Δp, at the cost of an increase in the $T_{\max}$.

2.3 Surrogate Model Supported Optimization

The most popular SMDO methodology is the replacement of CFD analyses with surrogate models for the computation of objective and constraint functions. The surrogate model acts as the objective and constraint functions, and another optimization methodology is implemented to obtain the optimal design. Here, we present surrogate model supported SOO. For surrogate model supported MOO, see Section 3.

Many BTMS optimization studies in the literature have used single objective genetic algorithms (GAs) supported by various surrogate models. Genetic algorithms are heuristic methods based on Darwin's survival-of-the-fittest theory in which superior organisms are more likely to pass on their genetic traits to future generations [51]. In applying this theory to design optimization problems, genetic traits are values of the design variables, while organisms are sets of design variables which make up a specific design. A set of organisms is termed a population. Superior organisms are determined by the objective value associated with their specific design variable values. Superior organisms have a higher chance of passing on their traits to future design iterations during the optimization process. During the GA, a population of organisms goes through iterations, during which organisms mate to create offspring who inherit traits from each parent organism. The offspring are added to the population, while the lower-performing organisms are removed from the population. As the GA iterates, the organisms move toward the optimal design. Heuristic algorithms find near-optimal solutions to problems more quickly than traditional methods; however, they sacrifice exact optimality for this increased speed.

Lin *et al.* [42] minimized $T_{\max}$ of a PCM cell casing and symmetric air-cooling hybrid BTMS using a single objective GA supported by back-propagation neural network (BPNN) surrogate models. Using the GA, optimal parameters for PCM thickness, battery spacing, battery discharge rate, inlet air velocity, and inlet air temperature were obtained, reducing $T_{\max}$. Xia *et al.* [52] also implemented a GA; however, supported by RSM surrogate models instead of BPNN for the optimization of a symmetric air-cooling system. The system analyses implemented an experimentally validated multiphysics model, which coupled an electrochemical-thermal model, a capacity fade model, and a fluid dynamics model. Reliability models, including a stochastic capacity degradation model, a system reliability model, and a universal generating function, were used in addition to the multiphysics model for the analyses of the system. An optimal battery layout and redundancy scheme were selected such that the number of charge-discharge cycles was maximized for a given system reliability. Li *et al.* [53] used a third surrogate modeling methodology, radial basis function (RBF) models, to support the optimization of a hybrid heat-pipe surrounded, embedded cell PCM, and symmetric air-cooling system. The optimization considered the fin spacing on the heat-pipe condenser section in three directions as the design variables in two separate processes. First, the structural parameters were optimized to minimize temperature standard deviation (T_σ), while constraining $T_{\max}$ and $\Delta T_{\max}$. The second optimization process minimized the inlet velocity while constraining the temperature objectives at varying heat generation rates and ambient temperatures.

Instead of selecting a single surrogate modeling method, Liu and Zhang [54] used a K-fold cross-validation framework to select the best of 62 potential models. This ensures the most accurate surrogate models are implemented for the specific problem, improving the overall SMDO accuracy compared to when only a single surrogate modeling method is considered. In [54], Maximum temperature was minimized for three types of air-cooling BTMSs: J-type, U-type and Z-type air-cooling systems. The channel sizes for the J-, U-, and Z-type BTMSs were considered as the design variables, while the manifold sizes were considered in a second optimization process for the J-type system. A Kriging surrogate model was developed for the heat generation of the LIB pouch cells using experimental data. All three BTMSs were able to decrease the temperature rise and T_σ at the cost of an increase in Δp. The optimized U-type BTMS had lower $T_{\max}$ but a higher Δp, while the J-type BTMS had advantages in $T_{\max}$ and Δp; however, it required more space than the other two configurations. The J-type manifold sizes were then optimized using the same methodology and showed further improvements in $T_{\max}$.

Instead of using GAs, Afzal *et al.* [55] used a different heuristic methodology - the particle swarm optimization (PSO) algorithm. Particle swarm optimization algorithms attempt to find optimal solutions by searching the design domain through methods similar to how swarms of organisms, for example, bees or ants, interact with each other when finding areas of interest [56]. Members of the swarm are specific designs, made up of sets of design variable values, whereas the swarm is a set of designs. Each member knows its respective location as well as the location of the current optimal member of the swarm in the design domain. During the iterative optimization process, the position of each member is updated, taking into account the position of the most optimal member and the most optimal position that the current member has had throughout the process. As a PSO algorithm iterates, the swarm moves towards the optimal design. Afzal *et al.* [55] used RSM surrogate models to support a PSO algorithm for a symmetric flow BTMS with varying coolants, including gases, oils, thermal oils, nanofluids, and liquid metals. The coolant Reynolds number (Re), conductivity ratio between the coolant and battery, battery heat generation rate, and the coolant Prandtl number (Pr) were considered as the design variables to result in an improved $\Delta T_{\max}$. This study considers a similar system to a second study completed by Afzal *et al.* [57] discussed in Section 3.6 and Section 5.5 using different optimization methodologies and design variables.

The final BTMS optimization study reviewed in this section used non-heuristic iterative methods instead of heuristic GA or PSO algorithms. Park *et al.* [58] applied sequential linear programming (SQL) and sequential quadratic programming (SQP) algorithms that are used for constrained linear and non-linear optimization problems, supported by RSM surrogate models. A loop heat pipe with external air-cooling BTMS for aircraft LIBs was optimized to minimize the weight of the system considering the heat load and system geometric parameters as the design variables. The BTMS was modeled using an energy balance equation thermohydraulic approximation model, vapour groove temperature model, and thin liquid film model for the wick heat transfer analysis. The system was optimized for three cases with constrained $T_{\max}$: fixed heat load, varying heat load, and under uncertainty considerations. Monte Carlo simulation were implemented for the reliability-based method in the uncertainty consideration case. The optimization process was completed sequentially for each case by first optimizing the thermo-hydraulic model, then the porous wick, and finally the groove section. The optimization methodology was able to obtain a design that reduced the mass of the system in all three cases.

2.4 Adaptive Surrogate Model Optimization

Adaptive surrogate model optimization involves the development of surrogate models by adding sample points until the desired accuracy is achieved. The additional sample points are typically added during the optimization process, and the surrogate modeling is no longer separated from the optimization process - instead, they occur concurrently. This allows the surrogate models to be tuned adaptively, giving the desired accuracy without oversampling and thus saving time by reducing unrequired computations. Adaptive surrogate-model-based optimization differs from other SMDO methods that develop the surrogate models with a fixed set of sample points prior to optimization. An adaptive methodology was developed by Xu, Liu, and Zhang [59] during which the adaptive sampling was informed by the optimization method. This allowed the surrogate models to become more accurate in the region of the optimal solution. Their methodology was based on the complex method, where sample points were used to establish the surrogate model while also forming complex shapes to guide the optimization search. The methodology began with initial samples from LHS for the development of Kriging surrogate models. The complex method was then used to determine which additional sample points to add based on the model accuracy and optimization process. This allowed the sampling and optimization processes to be completed concurrently, improving the accuracy of the surrogate model and obtaining the optimal solution at the same time. The new methodology was then applied to optimize a U-type air-cooling BTMS, based on the system from Li *et al.* [60] further discussed in Section 3.1. Objectives of $\Delta T_{\max}$, T_σ, and system volume were minimized by obtaining optimal parameters for cell spacing, inlet and outlet manifold heights, and inlet velocity.

Instead of adding sample points concurrently during the optimization process, Xu *et al.* [61] completed sequential optimization processes with an adaptive ensemble of surrogate models. Sample points were added based on the accuracy of the predicted optimal solution at the end of each optimization. This methodology may be less computationally efficient than the concurrent optimization and model development methodology of Xu, Liu, and Zhang [59]. However, this methodology finds the most optimal solution even as the objective space changes with increased model accuracy, something not guaranteed with concurrent methodologies. The algorithm used LHS to generate initial sample points and then compared RBF and Kriging models to construct an ensemble of surrogate models. The optimization was then completed using a PSO algorithm, and the CFD model was used to compute the objective at the optimal point and compare the two values. If the result from the ensemble of surrogate models was not accurate enough compared to the CFD results, additional sample points were incorporated using the minimum response surface (MRS) method and the algorithm began again. This allowed an optimal design that reduced $\Delta T_{\max}$ to be obtained with optimal parameters of cooling plate thickness, wall thickness, and inlet coolant temperature and velocity. Xu *et al.* [62] then developed another novel adaptive SMDO framework. In this methodology, the adaptive surrogate models were not developed concurrently, instead were completed prior to optimization. A GA was implemented to determine the optimal additional sample points using the distance density to quantify the sparsity of the sample points, and the local complexity to quantify the changing complexity of response values near new sample points. Both methodologies by Xu *et al.* were applied to a liquid-cooling cold plate BTMS that wrapped around cylindrical cells to minimize $\Delta T_{\max}$. Both considered the channel thickness, coolant velocity, and coolant temperature as design variables. A similar BTMS was studied by Li *et al.* [63] and Su *et al.* [64], further discussed in Section 3.1.

In a similar methodology to Xu *et al.* [61] where multiple optimization processes were conducted sequentially, Liu *et al.* [23] used a multi-step SMDO methodology. Liu *et al.* added samples strictly in the region of the optimal result instead of anywhere in the design space like Xu *et al.* [61]. Further, Liu *et al.* [23] used the concurrent surrogate model selection framework to select the model type, kernel function type, and values of parameters for the surrogate models. During the SMDO process, the optimal results were used to perform sequential sampling and updating of the surrogate models, and the updated models were then used for subsequent optimization processes. This allowed the surrogate models to become adaptively more accurate in the region of the optimal design similar to the methodology by Xu, Liu, and Zhang [59]. In applying this methodology, optimal values for the inter-cell spacing, inlet manifold size, outlet sizes, and inlet mass flow rate were obtained such that both objectives of T_σ and Δp were improved for a J-type air-cooling BTMS.

2.5 Summary of Surrogate-Model-Based Design Optimization Methodologies

Full search methods are simple and allow optimization to be completed without introducing a dedicated optimization process. However, full search methods still cannot be applied to complicated BTMSs considering many design variables, limiting their applicability. Direct optimization methods are computationally efficient and use established optimization processes, but the surrogate models representing the objectives and constraints must be low order, differentiable, and have smooth derivatives. This prevents applications when the relationship between design variables and objectives or constraints is higher order or noisy. Supported optimization methods are quite effective when BTMS analysis models are too computationally expensive for direct use in optimization processes. Even when the computational expense is similar for developing the surrogate models and directly using the BTMS analysis models in an optimization process, surrogate-supported optimization provides advantages. Fast iteration of the optimization process is possible with surrogate models, allowing for more effective tuning of the optimization parameters and investigation of different BTMS performance objectives. Before training the surrogate models it is difficult to predict the relationship between design variables and objectives or constraints. In some cases this relationship may not be strong enough to develop surrogate models, resulting in wasted resources generating the training database. Further, the required size of the database is generally unknown before training, often leading to oversampling. This results in wasted resources compared to direct optimization where only the required system analysis is completed. Adaptive surrogate modeling methods address this issue and allow for higher accuracy of the predicted optimal design performance. However, adaptively developed surrogate models may not be effectively used for modified optimization processes as they may lack accuracy in areas of the design space away from the optimal result.

3 Multi-Objective Optimization

In the process of designing BTMSs, it is often the case that the design variables need to be optimized based on more than a single objective. Multi-objective optimization (MOO) is the process of optimizing these multiple objectives simultaneously [65]. In order to truly classify as a MOO problem, the objectives need to be conflicting, else there exists a single optimal solution, and the objectives could be optimized sequentially with SOO methods. By modifying the general optimization formulation from Equation 1, a MOO problem can be defined as shown in Equation 2.

$$\begin{aligned} \text{minimize} \quad & \mathbf{F}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})) \\ \text{with respect to} \quad & \mathbf{x} \\ \text{subject to} \quad & h_i(\mathbf{x}) = 0; \;\; i = 1 \text{ to } p \\ & g_j(\mathbf{x}) \leq 0; \;\; j = 1 \text{ to } m \end{aligned} \tag{2}$$

The difference in Equation 2 compared to Equation 1 is that there are now k objective functions. Solving a MOO problem results in a set of solutions, which have been termed the Pareto optimal set or the Pareto Front. A solution is Pareto optimal if there exists no other feasible solution which would decrease some objective without causing a simultaneous increase in at least one other objective [66].

The general process flow for the implementation of a MOO methodology is shown in Figure 8. The main differences in the MOO methodology process compared to the general design optimization process are based on the Pareto principle. First, the optimality criteria for the optimization loop are based on the Pareto principle. Further, for many MOO methodologies, there will be multiple designs being evaluated during each iteration of the optimization loop instead of a single design. Finally, as there exists not a single solution, this leaves the selection of the final design up to the system designer based on objective preferences. Quantitative frameworks have been developed to aid in the final design selection such as the technique for order of preference by similarity (TOPSIS), multiple criteria decision making (MCDM), or linear programming technique for multidimensional analysis of preference (LINMAP). These frameworks rank the possible solutions based on some weighted and normalized combination of objective values. The remainder of this section will review BTMSs optimized using MOO methodologies, with each subsection presenting a sub-category of MOO methodologies. A summary of the literature reviewed in this section is included in Table 2 of the "*Literature Summaries by Optimization Methodology*" supplementary materials document.

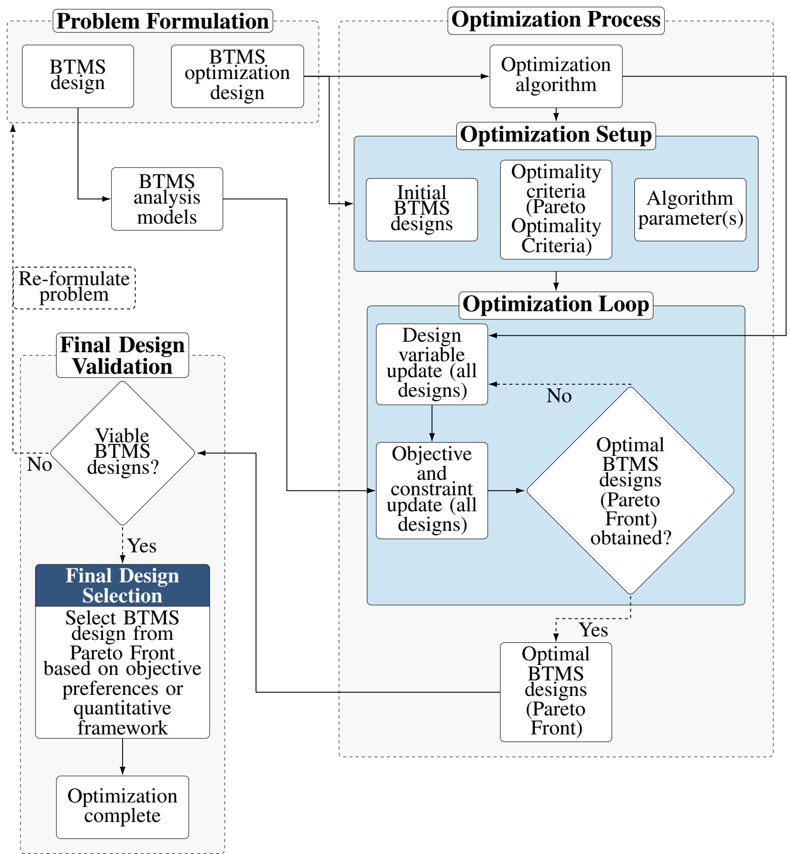

Figure 8: Generalized process of the multi-objective optimization methodology.

3.1 Genetic Algorithms

The most popular MOO methodologies applied to BTMSs were GAs, specifically the multi-objective genetic algorithm (MOGA) and the non-dominated sorting genetic algorithm II (NSGA-II). Single objective GAs were introduced in Section 2.1. When GAs are applied to MOO problems these methods must implement strategies for ranking solutions to determine which designs are more likely to pass on design variables to future iterations based on the Pareto Front principle. Further, multi-objective GAs produce a set of solutions instead of a single solution. The GA population moves towards the Pareto Front during the optimization process, with the population making up a section of the Pareto Front at the conclusion of the optimization process. This section has been separated into three subsections based on applications of the MOGA and NSGAs, as well as a section containing BTMS studies that used methods of combining objectives in order to apply single objective GAs.

3.1.1 Multi-Objective Genetic Algorithms

The general methodology applied in BTMS studies that used MOGAs supported by surrogate models followed a similar process to the surrogate model-supported optimization methodologies presented in Section 2.3. Here, optimization was completed for multiple objectives instead of a single objective. First, system analysis models are developed, where the majority of studies in this section used CFD models. Sample point sets of design variables are created using a sampling method and objective, and constraint values are computed at these sample points using the system analysis models. The database of sample design points and corresponding objective and constraint values are used to develop surrogate models, one for each objective and constraint defining the MOO problem. Finally, the surrogate models are implemented in the MOGA to compute the objective and constraint values as needed. The studies that are discussed next specifically used Kriging surrogate modeling methods.

Cheng *et al.* [67] and Li *et al.* [68] both applied this optimization methodology to air-cooling BTMSs with added herringbone fin plates distributed axially on cylindrical cells. Cheng *et al.* [67] minimized the average temperature (T_{avg}), T_σ, and Δp considering the longitudinal and transverse pitch of the battery cells, fin height and thickness, and inlet air velocity as design variables. The optimization procedure was able to locate designs from the Pareto Front, and a solution was selected that reduced all three objectives simultaneously. Li *et al.* [68] considered the battery spacing, inlet airflow velocity, and fin and sleeve geometry parameters as the design variables to minimize T_{max} and ΔT_{max}. Contrary to Cheng *et al.* [67], Li *et al.* [68] completed the optimization with and without a constraint on the cost of the system. They demonstrated that the cost constraint limited the cooling performance compared to the design achieved without the constraint.

Li *et al.* [60] first used this optimization methodology for a U-type air-cooling BTMS to minimize T_σ, ΔT_{max}, and system volume. A similar BTMS was studied by Xu, Liu, and Zhang [59] as discussed in Section 2.4. Considering the cell spacing and inlet mass flow rate as design variables, the Pareto optimal design with the lowest volume was selected as the final design, while T_{max} and T_{avg} were also reduced. Li *et al.* [35] then used the same methodology, applying it to a parallel channel liquid-cooling cold plate sandwiched by battery cells. The same objectives were minimized, in this case considering the channel geometry and inlet coolant mass flow rate as the design variables. However, different objective preferences were used to select the final design: the design with the lowest ΔT_{max} was selected for the cold plate, which also reduced T_σ, ΔT_{max}, and Δp at the cost of an increase in system volume.

Many other studies used MOGAs supported by surrogate models to optimize a range of systems, using various surrogate modeling methods. Wang *et al.* [34] and Mao *et al.* [69] used Kriging models similar to the BTMS optimization studies described above for liquid-cooling serpentine channel cold plates and microchannels, respectively. Li *et al.* [70] and Liu *et al.* [71] used fitting functions for unique channel cold plates, while Wang *et al.* [72] implemented genetic programming models for a Z-type air-cooling BTMS. Li *et al.* [70] and Liu *et al.* [71] and Wang *et al.* [72] all implemented frameworks for final design selection. Liao *et al.* [73] optimized a U-type air-cooling system and used RSM surrogate models. Karthik *et al.* [74] also used RSM; however, for a 3 U-shaped channel cold plate. Finally, Ma, Chen, and Gong [75] implemented BPNN models for a U-type air-cooling BTMS. Additional details of these studies can be found in Table 2 of the "*Literature Summaries by Optimization Methodology*" supplementary materials document.

In cases where analytical system analysis models were used, surrogate models were not required to support the MOGA. The nature of analytical models negates the need to reduce the computational cost of evaluating the objectives associated with CFD models. Hamut, Dincer, and Naterer [76] optimized an in-vehicle liquid-cooling BTMS to maximize the exergy efficiency and minimize the total cost rate and environmental impact. Exergy, exergoeconomic, and exergoenvironmental analytical models were used to evaluate the objectives. The authors considered design variables of condenser and evaporator saturation temperature, magnitude of superheating in the evaporator, magnitude of subcooling in the condenser, evaporator air mass flow rate, and compressor efficiency. A MOGA was able to find Pareto Front solutions and the LINMAP method was used to select an optimal design. The final design was able to maintain a similar exergy efficiency, while improving the environmental impact at the requirement of a higher total cost rate. Also using exergy analysis, Javani *et al.* [77] similarly optimized an in-vehicle refrigeration cycle BTMS where the shell and tube heat exchanger was filled with PCM. The objectives were to maximize the exergy efficiency and minimize the total cost rate without environmental considerations using exergy and cost analytical models. The MOGA used design variables corresponding to compressor speed and ratio, evaporator and condenser saturation temperatures, superheating and sub-cooling temperatures, evaporator and condenser air mass flow rates, and cooling capacity. As in Hamut, Dincer, and Naterer [76], the LINMAP method was used to select an optimal solution from the obtained Pareto Front results.

3.1.2 Non-Dominated Sorting Genetic Algorithms

Many BTMSs were optimized using another specific GA, the NSGA-II. The NSGA-II follows a typical GA process but uses modified mating and survival selection methods during the iterative optimization procedure. Non-dominated sorting refers to the method determining how solutions or designs are ranked and sorted during each iteration of the algorithm. The NSGA-II offers reduced computational complexity, elitism approach, and has eliminated the need for a sharing parameter compared to the first iteration of the NSGA [78]. These studies used various surrogate models during their optimization processes, again developed using databases generated from CFD model evaluations.

Using a three-layer feed-forward ANN surrogate model to support a NSGA-II, Fan, Wang, and Fu [79] optimized a double-layered dendritic channel bottom cold plate liquid-cooling BTMS. The objectives were to minimize T_{max}, T_σ, and Δp, considering the channel geometric parameters as the design variables. Latin hypercube sampling and RBF models were used to create the three-layer feed-forward ANN surrogate model. The optimal design selected from the Pareto Front solutions was able to reduce all objectives as compared to a serpentine channel cold plate. Compared to a parallel channel cold plate, T_σ and T_{max} were reduced at the cost of an increase in Δp. Garg *et al.* [80] used similar surrogate models to minimize the ΔT_{max}, T_σ, and system volume of a U-type air-cooling BTMS. The same BTMS was considered by Li *et al.* [60] as discussed in Section 3.1 and by Xu, Liu, and Zhang [59] as discussed in Section 2.4. The NSGA-II used simplex and grid search methods, and obtained an optimal design for the cell spacing, inlet height, and outlet height, that improved all three objectives.

Li *et al.* [63] optimized a U-shape cooling plate BTMS that wrapped around cylindrical cells to minimize T_σ, ΔT_{max}, and Δp. A similar BTMS was studied by Xu *et al.* [61,62] as discussed in Section 2.4. The design variables were the plate thickness, plate wall thickness, inlet coolant temperature, and inlet coolant velocity. Gaussian process surrogate models were developed using a database generated from LHS. The surrogate models and NSGA-II were able to identify a Pareto optimal solution which reduced T_σ and Δp, at the cost of a slight increase in ΔT_{max}. Su *et al.* [64] conducted a similar study with the same design variables, BTMS details, CFD model, and sampling techniques. The differences were in the objectives; this study aimed to minimize T_σ, Δp, and the temperature rise instead of ΔT_{max}. Further, this study used a genetic programming surrogate model instead of a Gaussian process surrogate model. The genetic programming surrogate model and NSGA-II were able to identify 4 Pareto optimal solutions. Of these solutions, a single design was selected that slightly reduced T_σ and temperature rise, while greatly reducing Δp.

Many other studies used similar methodologies including Chen *et al.* [36] and Cui *et al.* [81] who used support vector machine (SVM) surrogate models with the NSGA-II for a three U-shaped channel cold plate and symmetric air-cooling system, respectively. Deng *et al.* [82], Qian [83], Chen *et al.* [33], and Chen *et al.* [84] optimized four different systems using RSA surrogate models developed using

LHS with the NSGA-II: Qian [83] considered a double-layered cold plate similar to Fan, Wang, and Fu [79], while Chen *et al.* [33] studied a bottom-top parallel channel cold plate system. Deng *et al.* [82] optimized a Z-type air-cooling system while Chen *et al.* [84] considered a symmetric air-cooling system. Of particular note, Chen *et al.* [33] optimized for heating performance, while the majority of other works have focused on cooling performance. Similarly, Bao *et al.* [85] and Dong *et al.* [86] used Kriging surrogate models for U-type air-cooling and helix microchannel liquid-cooling BTMSs. Jin, Youn, and Kim [87] optimized a U-type air-cooling BTMS with polynomial regression surrogate models and the NSGA-II. Finally, Xu *et al.* [31] used Gaussian process regression models with the NSGA-II for a parallel channel cold plate sandwiched by battery cells. Xu *et al.* [31] implemented a digital twin CFD model indicating that the CFD model was coupled to a physical system. The digital twin system analysis methodology has seen limited applications in the literature. Further details of these studies can be found in Table 2 of the "*Literature Summaries by Optimization Methodology*" supplementary materials document.

3.1.3 Genetic Algorithms with Combined Objectives

Some BTMS optimization studies implemented single objective GAs for MOO problems by using *a priori* objective weighting. *A priori* objective weighting involves the combination of multiple objective functions into a single objective function using some weighting and normalization schemes before applying the optimization algorithm. This methodology can reduce a multi-objective problem to a single-objective problem, and by varying the weighting scheme, it is possible to obtain different Pareto Front solutions.

This methodology was used by Zhao *et al.* [88] to optimize a liquid-cooling cold plate with non-uniform pin-fins, configured with battery cells sandwiched by inter-cell cold plates. A multi-island GA was implemented to minimize $T_{\max}$, T_{σ}, mass, and power consumption, while considering the variable pin-fin diameters as the design variables. Elliptical basis function ANN surrogate models, varying *a priori* objective weightings, and the multi-island GA were able to determine Pareto Front solutions. An optimal solution was selected that decreased all objectives as compared to a traditional parallel channel cold plate. Instead of ANN models Deng *et al.* [89] applied this methodology using RSA models to optimize a liquid-cooling double-layer bifurcating channel cold plate BTMS configured with inter-cell cold plates sandwiched by battery cells. This BTMS was first discussed in Section 3.1.2 [82]. While the same system as the other study by Deng *et al.* [82] was considered, this study minimized $T_{\max}$, T_{σ}, and Δp as opposed to the coefficient of friction (Fc) and the heat transfer coefficient. The design variables in this study were reduced to the channel thickness, width ratio, and length ratios in the x and y axes. Finally, instead of considering battery heat generation as uniform steady heat sources, it was modeled using a steady uniform heat flux on the surface of the batteries. The optimization process was completed using 36 different objective weighting schemes, determining a set of Pareto Front solutions.

3.2 Particle Swarm Optimization

The PSO algorithm was another popular heuristic optimization methodology applied to BTMSs, previously introduced in Section 2.1. Similar to the differences between multi and single objective GAs, the main differences for the PSO include a different ranking mechanism of the designs taking into account the Pareto principle and outputting multiple designs instead of a single design. Three systems were optimized using the multi-objective particle swarm optimization (MOPSO) algorithm in two studies without surrogate models. Severino *et al.* [90] conducted two optimization procedures with the focus being on the implementation of the MOPSO algorithm. The first implementation was for the optimization of six cell positions in a symmetric air-cooling BTMS to minimize $T_{\max}$, power consumption, and area. The second implementation was the optimization of cell and inlet positions for a T-type air-cooling BTMS, here to minimize $T_{\max}$ and $\Delta T_{\max}$. A much larger battery module with 234 pouch cells was considered. The MOPSO was able to find Pareto Front solutions for both implementations. Similarly, Li *et al.* [91] used a MOPSO without surrogate models to minimize $\Delta T_{\max}$, T_{σ}, and system area of a cell embedded PCM BTMS. The MOPSO used a fitness function based on trial and improvement with $\Delta T_{\max}$ prioritized and Pareto Front solutions were obtained for the cell spacing parameters.

Two other implementations of the MOPSO algorithm used adaptive Kriging-assisted high dimensional model representation (HDMR) surrogate models. The adaptive Kriging-assisted HDMR surrogate models were constructed using similar methods to those discussed in Section 2.4. Zhang *et al.* [45] optimized a hybrid heat-pipe, PCM, and heat spreader plate sandwiched by battery cell BTMS to minimize $T_{\max}$ and $\Delta T_{\max}$. The design variables were the geometric parameters of the BTMS including the thermal conductivity of the PCM, thickness of the PCM layer, heat-pipe length, and velocity of inlet liquid coolant. An optimal design was selected which reduced $T_{\max}$ at the cost of an increase in $\Delta T_{\max}$. Huang *et al.* [92] used the same methodology to minimize the same objectives for a symmetric air-cooling system where each cell had a PCM encasement containing embedded heat fins. The inlet length, battery spacing, and composite PCM layer thickness around each cell were considered as the design variables. The MOPSO and adaptive Kriging-assisted HDMR surrogate models were able to determine Pareto Front solutions, and fuzzy set theory was used to select the final design, improving both $T_{\max}$ and $\Delta T_{\max}$.

3.2.1 Particle Swarm Optimization with Combined Objectives

Wang *et al.* [93] implemented a single objective PSO methodology by using *a priori* weighting to reduce the multiple objectives to a single objective. This methodology was similar to that used by Zhao *et al.* [88] and Deng *et al.* [89] with GAs discussed in Section 3.1.3. Considering fan power and $T_{\max}$, a single objective PSO algorithm was used to optimize a symmetric air-cooling BTMS. The transverse and longitudinal spacing between cells and the inlet airflow velocity were considered as the design variables. A BPNN surrogate model supported the PSO algorithm to determine an optimal design reducing the fan power while maintaining approximately the same $T_{\max}$.

3.3 Other Heuristics

There exist many heuristic MOO algorithms which are not as popular BTMS design optimization as the previously discussed GAs or PSO algorithms. Similarly to GAs and PSO algorithms, these methods typically take inspiration from physical or biological phenomena. Garg *et al.* [94] used the Thompson sampling efficient multi-objective optimization (TSEMO) algorithm supported by Kriging models to minimize T_{avg}, T_{σ}, and Δp. A parallel channel cold plate liquid-cooling BTMS where every two battery cells were sandwiched by inter-cell cold plates was considered for optimization. Optimal parameters for the channel geometry and inlet coolant properties were obtained that improved all objectives. Yun *et al.* [95] also used a surrogate-model-supported methodology but with the simulated annealing (SA) algorithm and support vector regression (SVR) surrogate models. A U-type air-cooling system was optimized to minimize $\Delta T_{\max}$, T_{σ}, and volume. The optimal design implemented values for inter-cell and cell-to-enclosure spacing able to improve all objectives.

Using the desirability function optimization approach supported by backward regression and RSM surrogate models, Kalkan, Celen, and Bakirci [96] optimized a serpentine channel cold plate with added oblique channels to minimize $T_{\max}$, $\Delta T_{\max}$, and Δp. An experimentally validated CFD model integrated a semi-empirical electrochemical model for battery heat generation. Response surface modeling surrogate models were generated, from which backward regression models were used to obtain objective functions. A composite desirability function was then developed, combining the individual objective functions into a single dimensionless function. Optimal values of the design variables were then obtained by minimizing the desirability function. The final design found optimal values for the channel width, distance between channel branches, channel depth, number of cross-over channel branches, and the flow rate that improved all three objectives.

Without surrogate model support, Murashko, Pyrhonen, and Laurila [43] used a Nelder-Mead multidimensional unconstrained non-linear minimization (MUNLM) algorithm with *a priori* weighting to optimize a BTMS with heat-pipes embedded in heat spreading plates. The number, diameter and position of the heat-pipe(s) were considered as the design variables to minimize $T_{\max}$, T_{σ}, and heat-pipe diameter. A CFD model was used to directly compute the objective values during the optimization. The MUNLM algorithm was able to obtain a design which reduced the objectives and recommended the use of one or two heat pipes.

3.4 Non-Heuristics

Heuristic algorithms are the most popular MOO methodologies for optimizing BTMSs. To the best of our knowledge, a single BTMS optimization study in the recent literature used a non-heuristic algorithm. Kelly, Rugh, and Pesaran [97] implemented a sequential unconstrained minimization algorithm to optimize a passive air-cooling system using design for Six Sigma Processes. Forward stepwise regression surrogate models were developed using the Box-Behnken Matrix sampling method. The design loop assumed that the design variables of cell gap, fan flow rate, and internal electric resistance of cells had normal distributions with given mean and standard deviation values. The surrogate models were implemented to obtain outputs of mean and standard deviation values of $T_{\max}$, $\Delta T_{\max}$, and Δp. The optimization then maximized the minimum value of the three-sigma quality levels using a sequential unconstrained minimization technique with the initial design specified using the D-optimal sampling method.

3.5 Direct Optimization

Much like the direct methodology described in Section 2.2, in some cases, it is possible to directly determine optimal designs from the objective functions. The difference for the study in this section is that the analysis models were used directly, while the studies in Section 2.2 used surrogate models. Leng *et al.* [98] optimized a hybrid cell surrounded heat-pipe, embedded PCM-EG, and air-cooling BTMS. Lumped heat-pipe and 2D resistance-capacity PCM coupled models were used for the system analyses, which were validated in the authors' previous works [99]. An iterative procedure was used to determine the value of the heat transfer coefficient required to limit the battery surface temperature below 323 K. The trade-off values of PCM thickness and fan power making up the Pareto Front were determined directly from the system models. The system was optimized both as a fully passive system with only natural convection and as an active-passive system introducing forced air convection cooling. It was concluded that the hybrid system introduced significant energy-saving potential to BTMSs.

3.6 Multi-Objective Optimization Algorithm Comparisons

Some works have been reported in the BTMS literature comparing the effectiveness of different MOO methodologies for applications to BTMSs. Typically, it is difficult to compare the effectiveness of optimization methodologies across BTMS studies as there is no single baseline system and varying system parameters make it difficult to compare absolute performance measures. The studies here compared multiple optimization methodologies on the same BTMS, allowing for direct comparisons between the optimal results.

Wang *et al.* [30] compared the non-dominated sorting genetic algorithm III (NSGA-III) to the NSGA-II for the optimization of a novel battery module system with cells sandwiched by liquid-cooling cold plates and negative Poisson's ratio radiators. The NSGA-III uses a reference point-based algorithm following the NSGA-II framework, prioritizing non-dominated solutions which are close to a set of specified reference points during the solution ranking [100]. The study attempted to maximize the volumetric energy density, crashworthiness, and heat dissipation. An experimentally validated side pole impact finite element analysis (FEA) model and CFD model were used to develop RBF three-layer feed-forward neural network surrogate models. The optimal structural parameters of the negative Poisson's ratio tubular structure were obtained, which improved all objectives of: maximum acceleration, specific energy absorption, $T_{\max}$, and the maximum intrusion displacement. It was further concluded that the NSGA-III more efficiently found the optimal solutions than the NSGA-II. Also considering variations of NSGAs, Chen *et al.* [101] compared the NSGA-III differential evolution (NSGA-III_DE) algorithm, to the NSGA-II and standard NSGA-III. This study was similar to the one conducted by Chen *et al.* [102], further discussed in Section 5.5, and considered the same Z-type air-cooling BTMS. The design variables included the width of battery unit, inlet airflow velocity, plate angle, and width of the convergence and divergence plenums. The NSGA-III_DE was determined to produce superior results based on the hyper-volume criteria, which is a measure of the volume of the design domain that is weakly dominated by the resulting Pareto Front. The optimal design selected from the Pareto Front was able to reduce the power consumption, $T_{\max}$, and $\Delta T_{\max}$.

Two systems compared GAs and PSO algorithms for optimization: Afzal and Ramis [103] optimized a U-type air-cooling BTMS to maximize the average Nusselt Number (Nu), while minimizing the Fc and $T_{\max}$. The objectives were evaluated using a two-dimensional CFD model, considering the battery heat generation term, coolant Re, conduction-convection parameter, aspect ratio, and cell spacing as design variables. Fuzzy logic was implemented to normalize the multiple objective functions and combine them into a single objective function. It was found that the GA resulted in a more optimal result; however, the PSO methodology gave a more diverse section of the Pareto Front. Using BPNN supporting surrogate models, Yang *et al.* [104] compared two different GAs, the strength Pareto evolutionary algorithm II (SPEA-II) and NSGA-III with the MOPSO for the optimization of a Kririgami based stretchable LIB with a PCM BTMS. Electrochemical and CFD coupled models were used to compute values of $T_{\max}$ and $\Delta T_{\max}$ objectives. The SPEA-II algorithm produced solutions that dominated solutions from the other methods. The final design for the PCM geometry and properties was selected based on the lowest $\Delta T_{\max}$ and showed reductions in both objectives compared to the system without PCM.

Comparing other heuristic methods, Afzal *et al.* [57] considered the cuckoo search (CS) and artificial bee colony (ABC) algorithms for the optimization of a symmetric flow arrangement BTMS with various coolants. This study considered the same BTMS and design variables as the previous study by Afzal *et al.* [55] discussed in Section 2.3 but used different optimization methods. A CFD model directly computed the objectives during the optimization process. The ABC algorithm produced better results for the MOO and found a better Pareto Front compared to the CS algorithm. Both algorithms considered the battery heat generation rate, conductivity ratio, coolant Re, spacing between the batteries, and coolant Pr as the design variables. It was concluded that nanofluids and thermal oils were the best coolants based on the optimized Pr. Afzal *et al.* examined both MOO and SOO methodologies in this study; however, the portion of the study examining SOO is discussed in Section 5.

In two studies, Wan [105, 106] compared five different heuristic methods. First, Wan [105] used an adaptive elephant herding optimization algorithm to determine the cell spacing of a symmetric air-cooling BTMS to minimize $T_{\max}$ and $\Delta T_{\max}$. A CFD model directly evaluated the objectives during the optimization process. Wan [106] then optimized the same system using a tunicate swarm search and rescue (TSSR) algorithm. The objectives and design variables were similar; however, in this study, the cells were modeled as unsteady instead of steady heat sources. Further, instead of considering the cell spacing in three groups, the spacing between each column and row was considered. The results from the TSSR algorithm for battery spacing optimization were compared to results from previous studies which used the enhanced elephant herding optimization algorithm [105]. Further comparisons were made to other heuristic algorithms including the tunicate swarm, search and rescue, and gray wolf algorithms. It was concluded that the TSSR algorithm was the most efficient for this problem.

3.7 Summary of Multi-Objective Optimization Methodologies

Comparing the literature on MOO methodologies applied to BTMSs is difficult as the optimization processes are similar but applied to different BTMS types. Unless the methodologies are implemented on the same BTMS, as discussed in Section 3.6, it is challenging to elucidate which methodology will be best for a certain BTMS type and problem formulation. Regardless, based on direct methodology comparison studies, GAs obtained more optimal results for BTMSs than PSOs methodologies in all cases. For all MOO methodologies, it was observed that most studies that had CFD BTMS analysis models implemented surrogate models, while the BTMSs using analytical models did not. This indicates that BTMS CFD models are typically too expensive for direct use in MOO methodologies. Heuristic methodologies provide efficient optimization methods when non-heuristic or direct methodologies may not be feasible but at the cost of exact optimality. Typical BTMS design requires the consideration of multiple objectives, as described in Section 1.2. Hence, MOO is an important tool in effectively improving BTMS designs, as demonstrated by the prevalence of this methodology in the BTMS literature.

4 Multidisciplinary Design Optimization

The area of multidisciplinary design optimization (MDO) includes design optimization methods that deal with multiple interacting disciplines [107]. Taking the interaction and interdependence of disciplines into account gives a more accurate representation of the system, and thus its performance [108]. The most general form of a MDO problem, referred to as the all-at-once formulation, is defined by Equation 3. The all-at-once formulation creates independent copies of the design variables that are required for each discipline analysis and ensures by the end of the optimization that they are equal by enforcing consistency constraints. Different MDO problem formulations, and subsequently how the problem is approached and solved, refer to different MDO architectures [108].

$$\begin{aligned} \text{minimize} \quad & f_0(\mathbf{x},\mathbf{y}) + \sum_{i=1}^{N} f_i(x_0, x_i, y_i) & \\ \text{with respect to} \quad & \mathbf{x}, \hat{\mathbf{y}}, \mathbf{y}, \bar{\mathbf{y}} & \\ \text{subject to} \quad & c_0(\mathbf{x},\mathbf{y}) \geq 0 & \\ & c_i(x_0, x_i, y_i) \geq 0; & i = 1 \text{ to } N \\ & c_i^c = \hat{y}_i - y_i = 0; & i = 1 \text{ to } N \\ & R_i(x_0, x_i, \hat{y}_{j\neq i}, \bar{y}_i, y_i) = 0; & i = 1 \text{ to } N \end{aligned} \tag{3}$$

In Equation 3, f_0 is the discipline shared objectives, with i discipline specific objectives f_i. The design variables are $\mathbf{x}$ with $\mathbf{x}_0$ discipline shared design variables and $\mathbf{x}_i$ discipline specific design variables. The discipline coupling variables are $\mathbf{y}$ with $\hat{\mathbf{y}}$ independent copied coupling variables and $\bar{\mathbf{y}}$ individual discipline state variables. The shared constraints are c_0 with c_i discipline-dependent constraints and c_i^c consistency constraints for the copied coupled variables. Finally, R_i is the discipline-specific governing equation in residual form. The all-at-once formulation contains all coupling variables, coupling variable copies, state variables, consistency constraints, and governing equation residuals.

Multidisciplinary design optimization provides methods of formulating design optimization problems that involve design variables or objectives that are interconnected between the disciplinary system analyses of the design. Hence, MDO results in the reformulation of a design optimization problem allowing SMDO, MOO, or SOO methodologies to be implemented with the new reformulated problem having taken into account the interacting disciplines and system analyses. The general process flow for the implementation of a MDO methodology is shown in Figure 9, describing how MDO is integrated into BTMS design optimization methodologies.

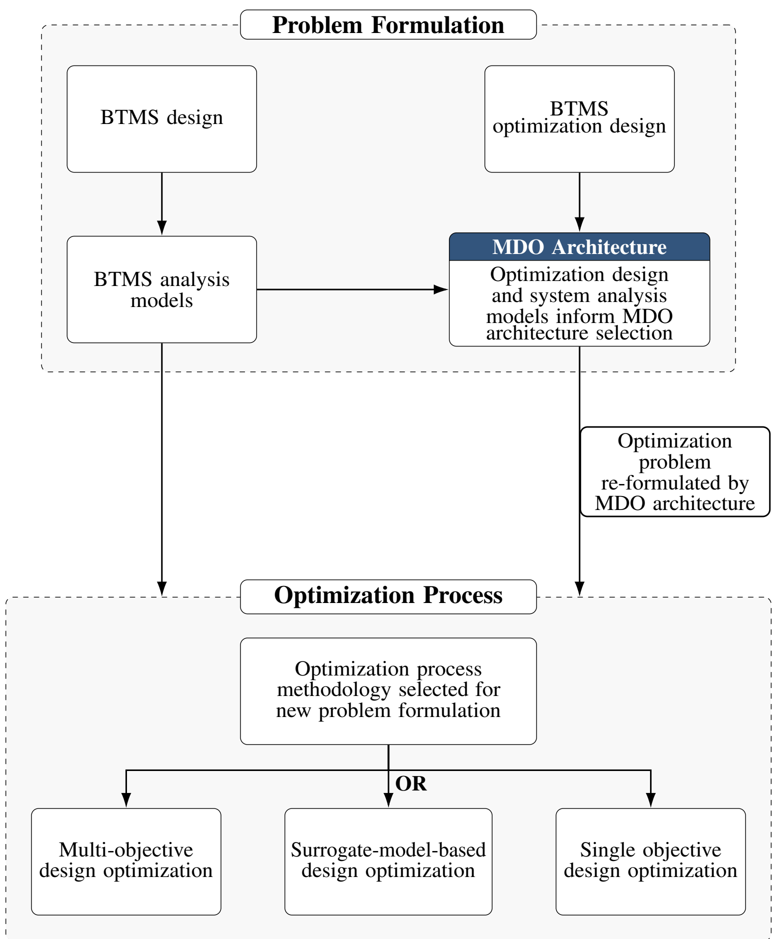

Figure 9: Generalized process of the multidisciplinary design optimization methodology.

The remainder of this section discusses studies of MDO methodologies applied to BTMSs. A summary of the literature reviewed in this section is included in Table 3 of the "*Literature Summaries by*

Optimization Methodology" supplementary materials document.

4.1 Multidisciplinary Feasible Architecture

A common MDO architecture is the multidisciplinary feasible (MDF) architecture. By eliminating the discipline specific governing equation constraints $R_i(x_0, x_i, \hat{y}_{j\neq i}, \bar{y}_i, y_i) = 0$ and consistency constraints c_i^c from Equation 3, the MDF architecture is obtained [109]. This means that the coupling variables are now implicit functions of themselves and the design variables. This reformulation allows the MDO problem to be as small as possible without dividing the problem into multiple smaller sub-problems.

Using the MDF architecture, Wang *et al.* [110] completed the MDO of an air-cooling U-type BTMS. The MDO minimized ΔT_{max}, power consumption, and system volume, while maximizing battery lifetime by considering the cell spacing, the heat flux from the battery cell, and the inlet mass flow rate. The sub-disciplines were broken into thermodynamics, fluid dynamics, structure, and battery lifetime each with its own model and coupling variables. A CFD model was used to generate a database using Sobol sequence sampling and the COSMOS framework determined the most accurate surrogate models. Separate surrogate models were selected for the thermodynamics sub-discipline analysis to compute ΔT_{max} and T_{max}, and for the fluid dynamics sub-discipline analysis to compute Δp. The surrogate models were then used with *a priori* weighting of the objectives to obtain a single objective function. The resultant optimal design showed improvements in battery lifetime, temperature uniformity, and volume at the cost of an increased Δp.

4.2 Novel Architectures

Multidisciplinary design optimization architectures are constantly being developed to improve optimization results and efficiency, combining novel optimization methods. For example, after completing the study using an MDF architecture [110], Wang *et al.* [111] developed a variable fidelity MDO architecture and applied it to a similar air-cooling U-type BTMS. This study considered the same sub-disciplines and objectives as in the previous study with the same design variables but with the addition of the inlet and outlet manifold sizes. Two separate sets of surrogate models were developed with varying fidelity, again using the COSMOS framework. The MDO process began with the lowest fidelity surrogate model. Then, after a number of iterations, the MDO process switched to the tuned surrogate model, and finally, to the high fidelity CFD model once the solution was close to optimal. As in the previous study, the multiple objectives were weighted *a priori* to obtain a single objective for the optimization process. The optimization was completed using the adaptive model switching-based approach and achieved superior results to the Co-Kriging-based approach. It was concluded that by using adaptive model switching the number of iterations during the MDO process was greatly reduced. The optimal design significantly improved the lifetime of the batteries by lowering ΔT_{max} and volume, similar to the previous study.

In another novel architecture, instead of considering varying fidelity models, a neural network filter was introduced by Li *et al.* [112], who developed a multidisciplinary robust design optimization under parameter and metamodeling uncertainties (MRDO-UPM) methodology. It was then applied to minimize ΔT_{max} of a liquid-cooling serpentine channel BTMS with inter-cell cold plates sandwiched by battery cells. The MRDO-UPM methodology used a collaboration model with a RBF three-layer forward neural network to filter feasible samples before the multidisciplinary analysis was completed to reduce computation time. The filtered samples were used to construct Gaussian process surrogate models for the objectives, constraints, and multidisciplinary coupled functions. Monte Carlo simulations were then adopted to quantify the impact of parameter and surrogate model uncertainties. The proposed methodology produced a design with better robustness compared to traditional MRDO methodologies.

4.3 Summary of Multidisciplinary Design Optimization Methodologies

Multidisciplinary design optimization methodologies allow BTMS optimization problems to be reformulated such that the interdependence of design variables and objectives between multidisciplinary BTMS analysis models can be taken into account. These methodologies are complex, with limited application to BTMSs found in the literature. Further, while the design of BTMSs involves conjugate heat transfer, the objectives and design variables typically are not interconnected such that MDO methodologies are required. Most of the studies in this section included battery lifetime as objectives, hence requiring the MDO formulation due to the interdependence of the design variables in the battery lifetime and conjugate heat transfer models. The novel architectures presented in Section 4.2 used MDO methodologies to implement novel SMDO methods, improving the optimization processes.

5 Single Objective Optimization

Some optimization processes of BTMSs do not require multiple objectives, implement a surrogate model, or perform coupled, multidisciplinary analyses. Studies applying SOO are optimized based on a single parameter with a single analysis. The SOO methodology process, very similar to that of the general process presented in Section 1.1, is shown in Figure 10. A summary of the literature reviewed in this section is included in Table 4 of the "*Literature Summaries by Optimization Methodology*" supplementary materials document.

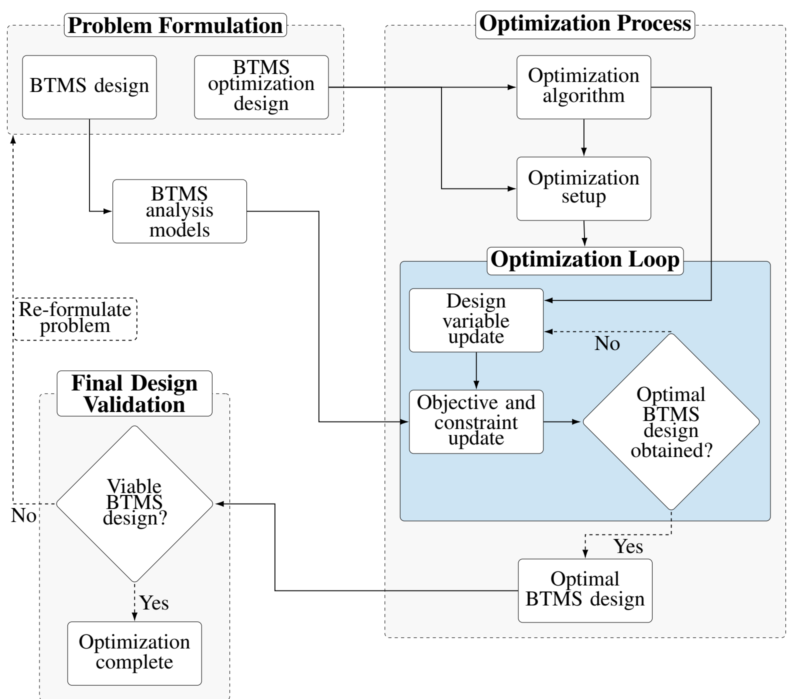

Figure 10: Generalized process of the single objective optimization methodology.

5.1 Newton Algorithm

The Newton algorithm is an iterative methodology for finding the roots of a differentiable function. When applied to the derivative of a function, the Newton algorithm can determine critical points of the function such as minima or maxima. Using a nested loop methodology combined with the Newton algorithm, Chen *et al.* [26] first optimized a Z-type air-cooling BTMS. This study aimed to minimize the airflow velocity standard deviation (v_σ) in the BTMS channels by considering the widths of the inlet divergence and outlet convergence plenums. The study introduced a network flow model for calculating the airflow velocity in the BTMS channels. The system was optimized separately considering a fixed inlet flow rate and a fixed fan power consumption. The results showed a substantial decrease in $\Delta T_{\max}$ for both optimization cases. Chen *et al.* [113] then conducted a similar study, now optimizing a U-type air-cooling BTMS instead of a Z-type system. The same objectives, design variables, and battery pack were used in the same optimization procedure. The results showed that the optimized U-type BTMS was able to significantly reduce the $\Delta T_{\max}$, and the power consumption. The optimized U-type BTMS showed a superior cooling performance to the optimized Z-type BTMS from the previous study.

5.2 Numeration Method

Chen *et al.* implemented a numeration methodology for the optimization of the cell spacing in three Z-type air-cooling systems [21,114,115]. The numeration methodology involves iteratively adjusting the design variables based on knowledge of objective sensitivity to these design variables. For example, with cell spacing, it was determined that increasing the spacing around a cell decreases this cell's maximum temperature. As a result, the numeration process increases the spacing around the cell with maximum temperature, while decreasing the spacing around the cell with the lowest temperature in each iteration until $T_{\max}$ or $\Delta T_{\max}$ are optimized.

The first study [114] used a network resistance flow model coupled with a heat transfer model to minimize $T_{\max}$. The second study [115] experimentally validated the flow model and added a correction factor to make it more accurate and used it to minimize the v_σ in the channels. Both studies considered 24 prismatic LIBs; however, the first study [114] considered steady heat generation for the optimization process, while the second study [115] considered unsteady heat generation. Better BTMS cooling improvements were obtained in the second study [115]. This was accredited to the use of a more realistic unsteady battery heat generation model, implementing the improved network flow model, and considering different optimization objectives, minimizing v_σ versus $T_{\max}$. Chen *et al* [21] optimized the Z-type system again with the same design variables and methods but used a CFD model instead of the simplified flow network model. Further, the objective was to minimize $\Delta T_{\max}$ as opposed to $T_{\max}$ or v_σ. The results indicated that the optimization using the CFD model was able to obtain better results for $\Delta T_{\max}$ compared to the previous studies.

Re-examining the plenums of a Z-type air-cooling BTMS, Chen *et al.* [27] considered curved as opposed to linear geometry with the same numeration based optimization methodology. A CFD model was used to evaluate the performance metrics of $T_{\max}$, $\Delta T_{\max}$, and Δp. The network resistance flow model was used during the optimization process to compute the velocity distribution in the channels. The objective was again to minimize v_σ; however, the design variables were the heights of the control points forming the curved plenum shapes. The optimized curved plenums were able to further reduce $\Delta T_{\max}$ compared to the optimized linear plenums without an increase in Δp.

Finally, instead of considering a specific flow configuration, Chen *et al.* [116] used the numeration optimization methodology to optimize the inlet and outlet position of an air-cooling BTMS. First, a series of inlet and outlet configurations were tested using a CFD model. It was found that a symmetric BTMS where the inlet and outlet were located in the middle of the plenums had the best performance in terms of limiting $T_{\max}$ and $\Delta T_{\max}$. The inlet and outlet positions were then optimized, and the final design showed an improvement in $T_{\max}$ and $\Delta T_{\max}$ with limited change in the power consumption compared to a standard Z-type air-cooling BTMS. Compared to the symmetric BTMS found in the first part of the paper, the optimized design showed a similar $T_{\max}$; however, $\Delta T_{\max}$ and the power consumption were further improved.

5.3 Direct Optimization

Depending on the models used to compute objective values, it may be possible to directly optimize the objective function. This methodology is similar to that described in Section 2.2, without the need for the development of a surrogate model, as well as in Section 3.5. Chen *et al.* [117] examined the direct optimization of Z-type, U-type and I-type air-cooling BTMSs. The I-type BTMS was similar to the optimal system found in the first part of their study investigating inlet and outlet positions of air-cooling BTMSs [116]. An inverse flow resistance network model was developed and solved directly to obtain the optimal flow distribution in the channels and corresponding battery cell spacing. A 2D CFD model was used to calculate the temperatures of the system. The optimal designs from the inverse flow resistance network model as well as the CFD results were experimentally validated. The optimized U-type system was found to have the best performance, while all three BTMSs showed improvements in $T_{\max}$ and $\Delta T_{\max}$ with limited change in power consumption.

Directly optimizing a field synergy equation, Hou *et al.* [118] obtained the optimal parameters of a Z-type air-cooling system. Two optimization processes were completed; the first considered cell spacing with linear plenums, while the second considered curved inlet plenum control point heights. An experimentally validated CFD model was used to evaluate the performance metrics of $T_{\max}$, $\Delta T_{\max}$, and Δp considering unsteady uniform heat generation. The synergy equation was solved to obtain the optimal flow distribution, and a network resistance flow model then determined the required structural parameters of the system to obtain this distribution. A better performance increase for $\Delta T_{\max}$ was observed with the plenum angle optimization at the cost of a higher Δp compared to the cell spacing optimization.

5.4 Sequential Quadratic Programming

As previously mentioned, SQP is a popular iterative methodology used for constrained non-linear optimization problems. Jarrett and Kim [119, 120] used a SQP methodology to optimize serpentine channel cold plate channel positions and widths with various boundary conditions (BCs). Jarrett and Kim [119] first optimized the channel geometry of the serpentine channel cold plate for a constant heat flux BC. A CFD model was developed to evaluate the optimization objectives of T_{avg}, T_σ, and Δp. No specific battery heat generation was specified; instead, uniform heat fluxes on the top and bottom surfaces of the cold plate were used as the BCs. The optimization was conducted for each objective separately, and it was shown that there was no optimal design that satisfied all objectives simultaneously. Regardless, the optimal design for each scenario was able to substantially reduce the objective value as compared to the initial design. The second study by Jarrett and Kim [120] extended the results to varying BCs considering the same analysis and optimization methods, objectives, and design variables. In the second study, four different heat flux gradients, three varying magnitude uniform fluxes, as well as three different inlet flow rates for a uniform heat flux were considered. In total, nine different BCs were studied, with each objective being optimized separately for each BC, resulting in 27 optimal systems. This study confirmed, as in the previous study, that no single optimal design satisfied all objectives and extended this conclusion for the additional BCs considered here. Further, it was shown that the T_σ optimized designs were very sensitive to the BCs - an optimal design for one BC would perform poorly for another. It was concluded that the appropriate BC should be used when optimizing for T_σ and if the exact BC is not known to use a uniform heat flux. For T_{avg} it was less important to use the correct BC, and the BCs investigated did not influence Δp.

5.5 Heuristic Methods

Many BTMSs have been optimized using SOO heuristic methodologies such as the GA, PSO, CS, and ABC methods. Many of these heuristic methods have variations for MOO problems, previously described in Section 3. Three systems were optimized using GAs: Mousavi *et al.* [121], Afzal [22], and Lyu *et al.* [122]. All three studies optimized various configurations of air-cooling systems with a range of battery types and analysis methods. Mousavi *et al.* [121] considered cylindrical LIBs with constant surface temperatures in a convective heat transfer analytical model to maximize the number of heat transfer units. The airflow cooling pipe diameter and inlet velocity were considered as the design variables, and an optimal arrangement was obtained with a GA. Instead of a symmetric flow arrangement, Lyu *et al.* [122] sequentially optimized the plenum angles of a Z-type air-cooling system followed by the cell spacing of the prismatic cells. An experimentally validated electro-thermal model was combined with a network flow resistance model to minimize the v_σ in both optimization processes. The plenum angles were optimized using a full-search methodology, evaluating all possible combinations of plenum angles defined by the constraints. The battery spacing was then optimized using a GA, and the final design was able to reduce both T_{max} and ΔT_{max}.

Afzal [22] optimized the steady uniform battery heat generation term, coolant Re, conduction-convection parameter, aspect ratio, and cell spacing of an air-cooling U-type BTMS. Three separate optimization processes were carried out with single objectives of maximizing the average Nu, minimizing the Fc, and minimizing T_{max}. This study was similar to a study previously completed by Afzal and Ramis [103] discussed in Section 3.6, and considered the same BTMS, CFD model, design variables, objectives, and optimization algorithms. This study considered the objectives individually, whereas the previous study completed a MOO process. Both studies used single objective GAs as the MOO process used fuzzy logic to combine the objectives. The previous study also considered a single objective PSO algorithm in addition to the single objective GA.

In a similar study to that by Chen *et al.* [101], discussed in Section 3.6, Chen *et al.* [102] considering the same Z-type air-cooling BTMS and system analysis models. This work implemented a stud-GA, introducing a new methodology for how the design variables are shared to subsequent iterations of the algorithm compared to traditional GAs. The best performing, or stud, solution is selected to share its design variables with subsequent designs instead of a stochastically selected solution. This study minimized the system volume while imposing constraints on T_{max} and ΔT_{max} instead of considering these as objectives. The optimization process was completed considering the convergence plenum angle and width, and the divergence plenum angle as the design variables. In comparison to the study by Chen *et al.* [101], this work did not include the width of the battery unit and inlet airflow velocity as design variables. The optimal design was able to reduce the volume while maintaining T_{max} and ΔT_{max} at acceptable values.

A PSO algorithm, instead of a GA, was implemented by Xie *et al.* [123] to optimize the cell spacing of a Z-type air-cooling BTMS to minimize ΔT_{max}. An experimentally validated analytical electro-thermal model was used for the analysis. In contrast to a majority of the literature reviewed, the battery heat generation model considered the interactions of state of charge (SOC), current, heat generation, and temperature. An inertia factor and the spatial neighborhood method were used with the PSO algorithm to improve the optimization efficiency and speed. The optimal design reduced the objective of ΔT_{max}, while also reducing T_{max} and the difference in branch current between parallel cell connections, improving the battery life.

Two other heuristic algorithms, the CS algorithm and the ABC algorithm were compared by Afzal *et al.* [57] to separately maximize the average Nu and minimize the Fc. Note that this study also compared these algorithms for MOO of the same system, discussed in Section 3.6, using the same design variables and system analysis models. The results indicated that for SOO the CS algorithm found more optimal solutions, however at the cost of less optimal secondary parameters. This is contrary to the MOO process for which the ABC algorithm found more optimal solutions. Similarly to the MOO results, the SOO concluded that nanofluids and thermal oils were the best coolants.

5.6 Summary of Single Objective Optimization Methodologies

The application of SOO is typically for simpler BTMSs, with well-behaved objective and constraint functions compared to the other methodologies. This allowed the application of more non-heuristic methodologies to BTMSs. The Newton algorithm is an efficient non-heuristic SOO methodology; however, generally, it does not allow the optimization problem to be formulated with constraints, making it difficult to apply to BTMSs where temperature or spatial constraints are commonly required. The numeration method is also efficient but requires specific knowledge of the objective function. The SQP methodology is well established and can solve non-linear optimization problems with constraints and does not require specific knowledge about the objective function. This makes it applicable to a wider range of BTMS optimization formulations than the Newton algorithm or numeration method. Heurstic methods, as with SMDO and MOO methodologies, were popular SOO methodologies that can solve problems where other methodologies fail.

6 Design of Experiments Optimization

Design of experiments (DOE) presents a methodology for evaluating an experiment or problem involving many design variables referred to as factors, with each factor having several possible values, referred to as levels. Evaluating all possible combinations of factor levels and performing a full search would be impractical in many cases. Design of experiments provides a methodology for evaluating the design without testing all possible combinations; instead, a subset of designs that offers full coverage of the design domain is determined. The subset of designs is evaluated according to the objectives and the optimal design from the subset is obtained. While DOE generally does not obtain globally optimal solutions, it does give locally optimal results based on the factors and levels specified and thus has been included in this review.

Different DOE methods have been referred to as sampling methods previously in this review when developing a database for surrogate modeling. Sampling and DOE refer to the same set of methodologies with the terminology changing based on the intended application: these methodologies are referred to as sampling methods if used for surrogate modeling, or DOE methods if used to directly obtain an optimal design. Design of experiments methodologies are applicable where the system analysis models are too expensive for direct use in the optimization algorithms, but where the relationship between the design variables and constraints cannot be represented by surrogate models. The general process flow for the implementation of DOE methodology is shown in Figure 11. Note this process is quite different than that presented for a general optimization process in Section 1.1. Instead, it is more representative of the sampling portion of the SMDO methodology process, presented in Section 2. Here, a direct evaluation of the generated database is used to determine the optimal designs instead of training a surrogate model and completing another optimization process.

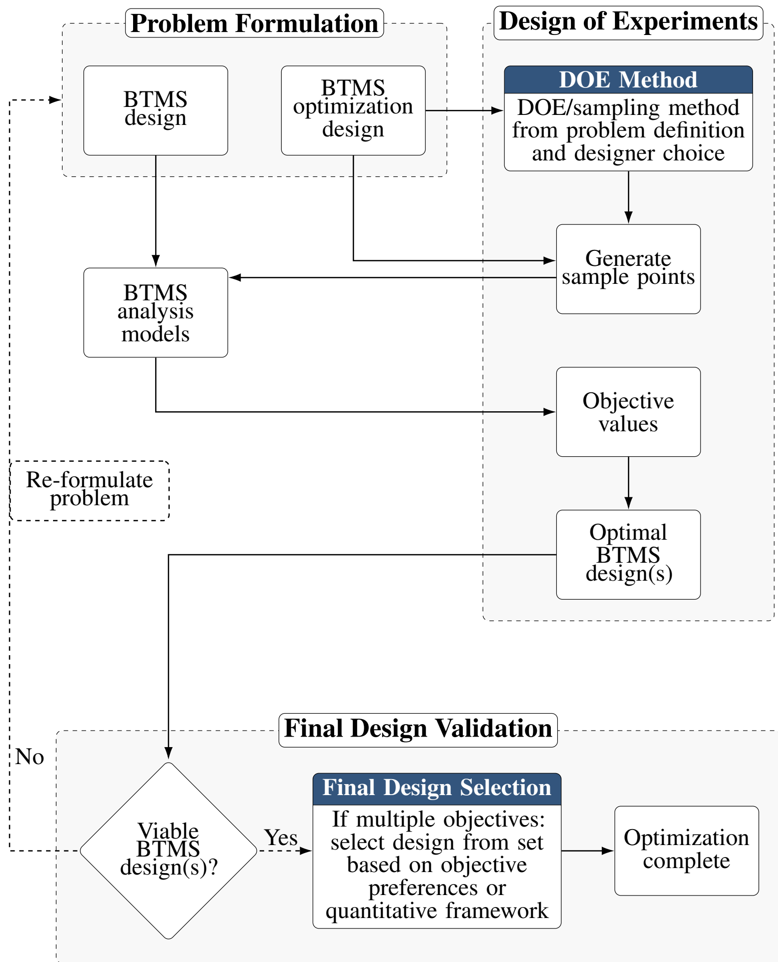

Figure 11: Generalized process of the design of experiments methodology.

All reviewed BTMS studies in this section used CFD models to evaluate the objectives. A summary of the literature reviewed in this section is included in Table 5 of the "*Literature Summaries by Optimization Methodology*" supplementary materials document.

6.1 Orthogonal Design

Orthogonal design is a specific DOE methodology that aims to extract an orthogonal array, where each row of the array represents a combination of factors to be evaluated. The array represents a subset of combinations, much smaller than the total number of combinations. Each column in the array represents a factor, and the columns of the array are orthogonal to each other. Once the array has been constructed it contains design points uniformly scattered over the design domain. The combinations in the array are all evaluated, and the best-performing combination based on pre-defined evaluation criteria is selected as the optimal design. Orthogonal design processes are described using a specific notation; for example, L8 (2^7) indicates a process which uses eight model evaluations to investigate a system with seven factors (design variables) each having two levels (values).

A number of studies were conducted using orthogonal design for air-cooling BTMSs with slightly different objectives, design variables, and battery pack parameters. Xie *et al.* [124] and Zhang *et al.* [24] both examined the inlet and outlet structures of air-cooling BTMSs but for U-type and T-type configurations, respectively. Xie *et al.* obtained a design that improved cooling performance in terms of $T_{\max}$ and $\Delta T_{\max}$ using an L8 (2^7) orthogonal design. Zhang *et al.* also obtained similar results but with an L25 (5^6) orthogonal design. Liu *et al.* [125] used an L16 (4^5) orthogonal design to optimize the design of a symmetric air-cooling BTMS with reciprocating airflow. The orthogonal design was able to obtain values of the inlet airflow velocity and temperature, and airflow reciprocation period that improved the objective values of $T_{\max}$ and $\Delta T_{\max}$. Feng and Hu [126] optimized an air-cooling system with the addition of a finned heat exchanger to minimize the temperature rise using an L9 (3^4) orthogonal design. An optimal design for the inlet airflow velocity, fin thickness and the number of fins was determined.

Similarly, a number of studies used orthogonal design to optimize liquid-cooling cold plate designs: Pan *et al.* [32] used an L16 (4^5) orthogonal design to obtain optimal parameters for the side cold plate geometry and coolant mass flow rate of a parallel channel liquid-cooling system. Experimentally validated uniform heat generation was used in the CFD model, which was able to compute the objectives of $T_{\max}$ and $\Delta T_{\max}$. The optimal design was obtained, and range analysis was completed for the design variables. Wang *et al.* [127] used an L16 (4^5) orthogonal design to obtain the optimal combination of bottom cold plate width, mini-channel interval, and inlet mass flow rate for a mini-channel cold plate BTMS. Experimentally obtained data for the heat generation during a 2C discharge was implemented in the CFD model for $T_{\max}$ and $\Delta T_{\max}$ computations.

Wang *et al.* [128], E *et al.* [129], Wang *et al.* [16], and Shang *et al.* [130] also all used orthogonal design to study cold plate channel geometry, inlet flow velocity and temperature, and cold plate arrangements. Battery pack specifications and the exact geometry of the plates varied between studies; however, the general procedures were similar. All studies were able to obtain more optimal designs through the implementation of the orthogonal design. Additional details of these studies can be found in Table 5 of the "*Optimization Methodology Literature Summaries*" supplementary materials document.

Xu *et al.* [131] and Wang *et al.* [132], and Guo and Li [133] studied variations of traditional cold plate channel geometries using L16 orthogonal design and range analysis. Xu *et al.* used L16 (4^4) orthogonal design to optimize the geometry of added channel splitters in a parallel channel bottom cold plate. Wang *et al.* used L16 (4^3) orthogonal design to optimize the geometry of bionic spider-web channels in a cold plate. Instead, Guo and Li used L16 (4^5) orthogonal design to optimize the channel geometry and inlet mass flow rate of a parallel-spiral serpentine channel cold plate with added aluminum plates. Xu *et al.* looked to minimize the $\Delta T_{\max}$, Wang *et al.* looked to minimize $T_{\max}$, $\Delta T_{\max}$, and Δp, while Guo and Li minimize $T_{\max}$, $\Delta T_{\max}$, and power consumption. Guo and Li also used variance analysis in addition to the range analysis to determine the effects of the design variables on the objectives.

Two studies used L16 (4^5) orthogonal design for hybrid BTMSs. Wang *et al.* [134] optimized a hybrid cell sandwiched heat-pipe and liquid-cooling system to minimize $T_{\max}$ and $\Delta T_{\max}$. Optimal parameters for the battery spacing, conduction element thickness and height, and the circumference angle between cells and conduction elements were obtained. Bai *et al.* [135] optimized a hybrid liquid-cooling parallel channel cold plate system with a phase change slurry as the coolant. The phase change slurry consisted of a micro-encapsulated PCM in a carrier fluid. An experimentally validated heat generation model was used in the CFD model to compute $T_{\max}$, $\Delta T_{\max}$, and Δp values.

Fuzzy grey relational analysis (FGRA) has been used to evaluate orthogonal design results for final design selection. Much like MOO problems, if there are multiple objectives, then there may not exist a single solution, and FGRA presents a quantitative method of selecting a final design. E *et al.* [136] conducted an L9 (3^4) orthogonal design for a varying configuration air-cooling system. Using FGRA and the orthogonal design results, a final design was selected for the inlet and outlet configuration parameters improving T_{avg}, ΔT_{max}, and the heat conduction coefficient. Similarly, using FGRA, He *et al.* [44] studied a heat-pipe and parallel channel bottom cold plate liquid-cooling hybrid system. The conduction plate height, thickness, and covering angles between the batteries, heat pipes and conduction plate were considered as the design variables. An L16 (4^4) orthogonal design was completed to minimize T_{max} and ΔT_{max}.

Instead of completing a single orthogonal design process, Li *et al.* [137] completed 3 sequential L27 (13^3) orthogonal designs to optimize an air-cooling system. During optimization, the number, sizes, and positions of inlets and outlets were considered as the design variables, in addition to the cell, module and pack spacing. For the sequential orthogonal designs, the most critical parameters for performance were selected and further investigated in the subsequent orthogonal design processes. Similarly, Xie *et al.* [138] used *a priori* weighting with an iteration algorithm and L27 (13^3) orthogonal design to optimize a serpentine channel side cold plate liquid-cooling system. Two separate optimization procedures were completed considering the channel geometry parameters and plate thickness as the design variables. The first was to minimize T_{max}, and the second was to minimize T_{max} and mass simultaneously. An optimal design was obtained, and a range analysis was completed for the design variables.

6.2 Latin Hypercube Sampling

Latin hypercube sampling is another specific DOE methodology, which is also a popular sampling technique used when training surrogate models as observed in the SMDO and MOO applications discussed in Sections 2 and 3. Latin hypercube sampling can generate a near-random sample of design variables with an even distribution over the design domain and can be used independently to perform a DOE optimization process. Using LHS, Bulut *et al.* [139] optimized a serpentine channel side cold plate liquid-cooling system. An experimentally validated unsteady uniform heat generation model was used in a CFD model to compute the objective values of T_{max}, Δp, and the convective heat transfer coefficient. Grey relational analysis was used to select the optimal design, determining the width and height of the serpentine channel as well as the mass flow rate of the coolant.

6.3 Summary of Design of Experiments Optimization Methodologies

All reviewed BTMS studies that implemented DOE methodologies used CFD BTMS analysis models, where the computational cost of these models limited their direct use in optimization processes. While SMDO produce more optimal results, if a relationship between the BTMS design variables and objectives or constraints is difficult to model, this means only DOE methodologies can be implemented. The CCD method was used for BTMS optimization considering a varying number of design variables and design variable values. Considering more design variables and design variable values gives a more thorough investigation of the BTMS design space but requires more computational resources. Compared to the sampling methods for SMDO methodologies where LHS was most popular, CCD was the dominant DOE method. Design of experiments allows locally optimal BTMS designs to be obtained when other design optimization methodologies are not possible.

7 Comparing Design Optimization Methodologies

The five design optimization methodologies discussed in this review - surrogate-model-based design optimization (SMDO), multi-objective optimization (MOO), multidisciplinary design optimization (MDO), single objective optimization (SOO), and design of experiments (DOE) - provide methods for solving unique battery thermal management system (BTMS) design problems. This section summarizes the general scope of application and the advantages and disadvantages of each methodology. Here, we also include general guidelines for selecting an appropriate methodology based on the problem formulation. These guidelines are formed based on the optimization of BTMSs; however, they are also generally applicable across other applications.

Designers of BTMSs choose a design optimization methodology mainly based on how they formulate the problem. The overall methodology selection is mainly a consequence of problem formulation details, including the design variables, objectives, and BTMS analysis models. Once the problem has been formulated, and the system analysis models have been developed, the resultant methodology can be determined. If the selected BTMS design variables are interdependent between the system analysis models, typically the case when considering battery lifetime and BTMS cooling performance, a MDO methodology is recommended. High-cost system analysis models will generally limit their direct use in optimization processes, instead requiring SMDO methodologies. However, even if the system analysis is expensive, it may not be possible to use a SMDO methodology in all cases. A strong relationship between the design variables and objectives or constraints is required for surrogate models to be developed. In these scenarios where the cost of the system analysis models hinders their direct use in optimization processes, and there are no strong relationships between the design variables and objectives or constraints, DOE methodologies may be required. Subsequently, the number of objectives will determine whether to use a MOO or SOO methodology.

For the purposes of classifying the literature in this review, in Section 2, we included only SMDO studies that did not implement other MDO or MOO methodologies. Similarly, in Section 3, we did not include studies that implemented MDO methodologies, only MOO methodologies. This allowed studies to be classified into single sections even if they implemented multiple methodologies. The process of determining the required design optimization methodology for a specific BTMS is summarized in Figure 12, which shows the generalized methodology selection process where multiple methodologies may be implemented.

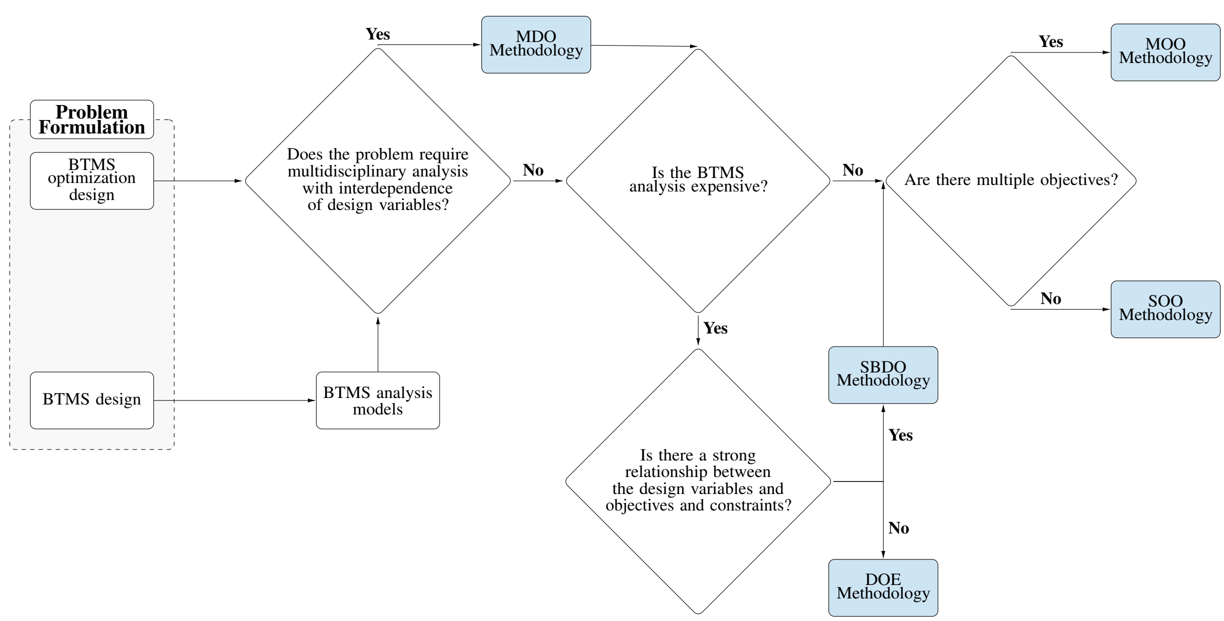

Figure 12: Generalized decision flow diagram for the selection of battery thermal management system design optimization methodologies.

The methodologies studied here have inherent advantages and disadvantages that need to be considered when formulating the BTMS design optimization problem. Here, we discuss general advantages and disadvantages; however, in practice, there may be exceptions based on specific BTMS design problems. First, implementing a MDO methodology can give more accurate results for coupled interdisciplinary problems but may introduce additional constraints, objectives, and design variables, increasing the size and complexity of the optimization problem.

When used appropriately, SMDO methodologies will reduce the cost of a BTMS optimization process. However, the surrogate model will not be a perfect representation of the BTMS analysis models, slightly changing the resultant optimal designs. When developing a SMDO methodology, the cost of obtaining the training database needs to be considered in addition to the cost of the optimization process. After this consideration, a pure MOO or SOO methodology may be more efficient. Another important consideration is that before implementing the surrogate model training process, it is difficult to know whether there will be strong enough relationships between the BTMS design variables and objectives or constraints. This could result in wasted resources or the unintended use of a DOE methodology. However, after obtaining the training database it is possible to iterate with the design optimization formulation, allowing for a more thorough investigation of the BTMS design. Once the surrogate models are obtained, it is also possible to quickly tune the optimization parameters as the majority of expense in the SMDO methodology is associated with the database generation. A DOE methodology may be necessary in cases where SMDO is not possible; it presents a computationally efficient method of determining locally optimal designs. However, DOE methodologies do not obtain globally optimal designs and where possible SMDO methodologies will produce better designs.

Implementing a MOO methodology results in BTMS designs with trade-offs between the objectives, presenting all of the possible optimal designs. However, compared with SOO, the MOO methodology is more expensive, and if the BTMS designer already has preferences for the objectives, it may not be necessary. While SOO is typically less expensive than MOO, in many real BTMS design scenarios, it is not possible to reduce the problem to a single objective, making it difficult to apply SOO methodologies in practice.

The advantages and disadvantages of the five design optimization methodologies implemented for BTMSs are summarized in Table 1, showing the impact that each methodology has on five areas of importance: Cost, Implementation, Ease of Iteration, Accuracy, Optimality, and Practical Application. Cost refers to the expense of the overall optimization methodologies, including computational or time expenses. Implementation indicates how easily a methodology is applied to a problem. Ease of Iteration refers to how quickly the problem can be iterated upon with different optimization parameters, design variables, objectives, or constraints. Accuracy indicates whether the methodology improves or reduces the accuracy of the predicted results. Optimality refers to whether the methodology obtains globally optimal results true to the system analysis models. Finally, Practical Application indicates the applicability of methodologies to real-world systems.

Table 1: Summary of battery thermal management system design optimization methodology advantages and disadvantages: (×) indicates negative impact, (-) indicates neutral impact, and (✓) indicates positive impact.

Methodology	Cost	Simplicity	Ease of Iteration	Accuracy	Optimality	Practical Application	Comments
Surrogate-model-based design optimization (SMDO)	✓	×	✓	×	×	✓	• Allows for fast iteration • May reduce accuracy and not produce globally optimal BTMS design
Multi-objective optimization (MOO)	×	×	-	-	-	✓	• Allows for multiple objectives, giving more holistic analysis of the BTMS • Increased computational cost to obtain set of optimal BTMS designs
Multidisciplinary design optimization (MDO)	×	×	-	✓	✓	✓	• Higher accuracy for optimal results when BTMS analysis, design variables, and objectives are interconnected • Increased computational cost and complexity
Single objective optimization (SOO)	-	✓	-	-	-	×	• Computationally cheap and simple process • Limited applicability for real BTMS design
Design of experiments (DOE)	✓	✓	✓	-	×	×	• Computationally cheap, simple process, and applicable when SMDO not possible • Obtains only locally optimal BTMS designs, SMDO will improve results when possible

8 Challenges and Opportunities

This literature review discussed recent design optimization studies applied to battery thermal management systems (BTMSs), categorizing them into surrogate-model-based design optimization (SMDO), multi-objective optimization (MOO), multidisciplinary design optimization (MDO), single objective optimization (SOO), and design of experiments (DOE) optimization methodologies. Most of these studies were completed over the last five years, highlighting the relatively recent and growing interest in applying design optimization methodologies to enhance BTMS design. By categorizing these studies according to the applied optimization methodology, it was possible to compare the advantages, limitations, and gaps of available design optimization methodologies and their suitability for different BTMS types. It also allowed the identification of common optimization objectives and design variables.

Most design optimization studies have focused on minimizing maximum battery temperature, spatial temperature difference, standard deviation of airflow velocities, pressure loss, or volume. Limited studies have focused on minimizing thermal resistance, surface friction coefficient, and state of charge

(SOC) difference between cells, or maximizing heat transfer coefficient, Nusselt number, battery lifetime, and exergy. Also, most studies used geometric parameters as design variables, including cooling channels or inlet/outlet geometry and position, coolant flow rate and/or temperature, and battery spacing. Multi-objective optimization methodologies were the most widely applied, while MDO saw limited applications. For MOO, genetic algorithms (GAs) were the most common methodologies, specifically the non-dominated sorting genetic algorithm II (NSGA-II) and multi-objective genetic algorithm (MOGA), while multi-objective particle swarm optimization (MOPSO) algorithms were also widely applied. Most design optimization studies used steady state, uniform heat generation or constant heat flux boundary conditions to model battery heat generation. Few studies employed transient, non-uniform models, while a single study [54] implemented a surrogate model based on experimental results to determine the heat generation rate.

The reviewed design optimization studies were applied to BTMSs considering a wide range of operating conditions (e.g., battery charge/discharge and heat generation rates) and battery models, sizes, capacities, and voltages. These variations, along with varying BTMS sizes and ambient conditions, made it difficult to directly compare different BTMSs and design optimization methodologies. Further, all optimized BTMSs were compared to different baseline systems, making it also difficult to analyze the effectiveness of the optimization methodologies. This highlights the need to establish standards, baseline systems, or metrics to evaluate BTMSs more effectively and to identify higher-performing BTMSs and optimization methodologies. In the absence of BTMS standards or comparison metrics, a performance evaluation of common BTMSs with standardized battery properties, sizes, and ambient conditions would provide a valuable benchmark and baseline with which to compare future systems.

Benchmarking BTMS design optimization methodologies requires further research. We have completed a qualitative comparison of the design optimization methodologies in Section 7; however, the literature lacks a more comprehensive quantitative analysis. The effectiveness, efficiency, and quality of results obtained from different optimization methodologies applied to BTMSs have not been systematically addressed. The area of BTMS design would benefit from benchmark studies comparing the performance of different types of design optimization methodologies applied to the same BTMS, to provide heuristics for optimization methodology selection.

The influence of different battery heat generation models on BTMS design optimization outcomes has not been investigated. Only one study suggested that more accurate battery heat generation models could improve optimization results [115]; however, this has not been further investigated. Understanding how model fidelity impacts the quality of optimal results would allow for a better selection of models and optimization methodologies based on design needs and available computational resources. For instance, adopting higher fidelity models accounting for intra- and inter-cell non-uniform heat generation rates across battery packs will result in optimal BTMS designs enabling more uniform battery temperatures and ultimately enhancing battery lifetime. However, further research is needed to better understand the trade-off between model fidelity and computation cost, as well as the scalability of the multiscale optimization problem from battery cell to module to pack.

Very few studies applied optimization objectives directly considering the influence of BTMS design on battery lifetime or electric vehicle (EV) range. Most studies considered these objectives indirectly, for example, minimizing coolant pressure drop across the system, thereby reducing BTMS power consumption and thus extending EV range. Directly optimizing for either of these objectives could lead to performant BTMS designs, incorporating more effectively the effect that cooling performance has on these metrics. The challenge with using either battery lifetime or EV range as optimization objectives lies in the need for additional, often computationally expensive models to compute these values.

Battery pre-heating is another aspect of BTMS design that has not been extensively investigated. Minimizing battery warm-up time during cold start conditions is an essential BTMS function in cold climates that is rarely addressed in design optimization studies. By improving BTMS heating functions, batteries could perform at optimal conditions for longer times, thus increasing EV range and limiting battery degradation while also allowing for faster charging. Further, none of the optimization studies considered heating and cooling performance simultaneously. Designing BTMSs for optimal heating and cooling simultaneously could identify conflicts between both objectives. Additionally, solutions could be determined that satisfy both requirements or at least highlight the possible design trade-offs.

More recent optimization studies have been applied to hybrid BTMSs incorporating different aspects from liquid, air, phase-change material (PCM), and heat-pipe cooling methods. Hybrid BTMSs offer advantages by combining favorable aspects from various cooling methods. For example, combining PCM and indirect liquid-cooling methods offers increased safety through a reduced risk of battery thermal runaway and improves temperature uniformity. Indirect liquid cooling prevents heat accumulation in the PCM at high charge-discharge rates and during long operating times. Design optimization of hybrid BTMSs is a relatively new area of ongoing research, with many opportunities for developing and optimizing novel BTMSs or further optimizing existing systems. Developments in hybrid BTMSs could further enhance the cooling performance and safety of battery systems.

This review demonstrates the capabilities of design optimization methodologies in advancing BTMS performance, while also highlighting areas of future research that could lead to further performance improvements.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC).

References

[1] Troy R. Hawkins, Ola Moa Gausen, and Anders Hammer Strømman. Environmental impacts of hybrid and electric vehicles—a review. *The International Journal of Life Cycle Assessment*, 17(8):997–1014, 2012. doi:10.1007/s11367-012-0440-9.

[2] IEA. Global EV Outlook 2022. Technical Report, International Energy Agency, Paris, France, 2022. https://www.iea.org/reports/global-ev-outlook-2022, Accessed May 2022.

[3] Jaewan Kim, Jinwoo Oh, and Hoseong Lee. Review on Battery Thermal Management System for Electric Vehicles. *Applied Thermal Engineering*, 149:192–212, 2018. doi:10.1016/j.applthermaleng.2018.12.020.

[4] Rajath Kantharaj and Amy M. Marconnet. Heat generation and thermal transport in lithium-ion batteries: A scale-bridging perspective. *Nanoscale and Microscale Thermophysical Engineering*, 23(2):1–29, 2019. doi:10.1080/15567265.2019.1572679.

[5] Daniela Galatro, Carlos Da Silva, David A. Romero, Olivier Trescases, and Cristina H. Amon. Challenges in data-based degradation models for lithium-ion batteries. *International Journal of Energy Research*, 44(5):3954–3975, 2020. doi:10.1002/er.5196.

[6] Daniela Galatro, Maan Al-Zareer, Carlos Da Silva, David A Romero, and Cristina H Amon. Thermal behavior of lithium-ion batteries: Aging, heat generation, thermal management and failure. *Frontiers in Heat and Mass Transfer*, 14, 2020. doi:10.5098/hmt.14.17.

[7] Ahmad A. Pesaran. Battery thermal models for hybrid vehicle simulations. *Journal of Power Sources*, 110(2):377–382, 2002. doi:10.1016/s0378-7753(02)00200-8.

[8] Z.Y. Jiang, H.B. Li, Z.G. Qu, and J.F. Zhang. Recent progress in lithium-ion battery thermal management for a wide range of temperature and abuse conditions. *International Journal of Hydrogen Energy*, 47(15):9428–9459, 2022. doi:10.1016/j.ijhydene.2022.01.008.

[9] Amrit Kumar Thakur, Rajendran Prabakaran, M.R. Elkadeem, Swellam W. Sharshir, Müslüm Arıcı, Cheng Wang, Wensheng Zhao, Jang-Yeon Hwang, and R. Saidur. A state of art review and future viewpoint on advance cooling techniques for lithium–ion battery system of electric vehicles. *Journal of Energy Storage*, 32:101771, 2020. doi:10.1016/j.est.2020.101771.

[10] J. P. Rugh, A. Pesaran, and K. Smith. Electric vehicle battery thermal issues and thermal management techniques (presentation). 7 2013. URL: https://www.osti.gov/biblio/1089051.

[11] A. Pesaran, S. Santhanagopalan, and G. H. Kim. Addressing the impact of temperature extremes on large format li-ion batteries for vehicle applications (presentation). 5 2013. URL: https://www.osti.gov/biblio/1082548.

[12] Qingsong Wang, Ping Ping, Xuejuan Zhao, Guanquan Chu, Jinhua Sun, and Chunhua Chen. Thermal runaway caused fire and explosion of lithium ion battery. *Journal of Power Sources*, 208:210–224, 2012. doi:https://doi.org/10.1016/j.jpowsour.2012.02.038.

[13] Kuijie Li, Huaibin Wang, Chengshan Xu, Weixiong Wu, Weifeng Zhang, Junxian Hou, Xinyu Rui, Ya Chen, Liyun Fan, Xuning Feng, and Minggao Ouyang. Multi-objective optimization of side plates in a large format battery module to mitigate thermal runaway propagation. *International Journal of Heat and Mass Transfer*, 186:122395, 2022. doi:10.1016/j.ijheatmasstransfer.2021.122395.

[14] Wencan Zhang, Liansheng Huang, Zhongbo Zhang, Xingyao Li, Ruixin Ma, Yimao Ren, and Weixiong Wu. Non-uniform phase change material strategy for directional mitigation of battery thermal runaway propagation. *Renewable Energy*, 200:1338–1351, 2022. doi:10.1016/j.renene.2022.10.070.

[15] Zehua Zhu, Xiaoyu Wu, Hengyun Zhang, Yun Guo, and Guoping Wu. Multi-objective optimization of a liquid cooled battery module with collaborative heat dissipation in both axial and radial directions. *International Journal of Heat and Mass Transfer*, 155:119701, 2020. doi:10.1016/j.ijheatmasstransfer.2020.119701.

[16] Jianguo Wang, Shuai Lu, Yingzhou Wang, Chenyu Li, and Kairang Wang. Effect analysis on thermal behavior enhancement of lithium–ion battery pack with different cooling structures. *Journal of Energy Storage*, 32:101800, 2020. doi:10.1016/j.est.2020.101800.

[17] A.A. Hakeem Akinlabi and Davut Solyali. Configuration, design, and optimization of air-cooled battery thermal management system for electric vehicles: A review. *Renewable and Sustainable Energy Reviews*, 125:109815, 2020. doi:10.1016/j.rser.2020.109815.

[18] H. Fayaz, Asif Afzal, A. D. Mohammed Samee, Manzoore Elahi M. Soudagar, Naveed Akram, M. A. Mujtaba, R. D. Jilte, Md. Tariqul Islam, Ümit Ağbulut, and C. Ahamed Saleel. Optimization of thermal and structural design in lithium-ion batteries to obtain energy efficient battery thermal management system (btms): A critical review. *Archives of Computational Methods in Engineering*, page 1–66, 2021. doi:10.1007/s11831-021-09571-0.

[19] Chunyu Zhao, Beile Zhang, Yuanming Zheng, Shunyuan Huang, Tongtong Yan, and Xiufang Liu. Hybrid battery thermal management system in electrical vehicles: A review. *Energies*, 13(23):6257, 2020. doi:10.3390/en13236257.

[20] Peng Qin, Jinhua Sun, Xulai Yang, and Qingsong Wang. Battery thermal management system based on the forced-air convection: A review. *eTransportation*, 7:100097, 2020. doi:10.1016/j.etran.2020.100097.

[21] Kai Chen, Yiming Chen, Zeyu Li, Fang Yuan, and Shuangfeng Wang. Design of the cell spacings of battery pack in parallel air-cooled battery thermal management system. *International Journal of Heat and Mass Transfer*, 127:393–401, 2018. doi:10.1016/j.ijheatmasstransfer.2018.06.131.

[22] Asif Afzal. Optimization of thermal management in modern electric vehicle battery cells employing genetic algorithm. *Journal of Heat Transfer*, 143(11), 2021. doi:10.1115/1.4052197.

[23] Yuanzhi Liu, Payam Ghassemi, Souma Chowdhury, and Jie Zhang. Surrogate based multi-objective optimization of j-type battery thermal management system. *Volume 2B: 44th Design Automation Conference*, pages V02BT03A034–V02BT03A034, 2018. doi:10.1115/detc2018-85620.

[24] Furen Zhang, Mengfei Yi, Pengwei Wang, and Chongwei Liu. Optimization design for improving thermal performance of t-type air-cooled lithium-ion battery pack. *Journal of Energy Storage*, 44:103464, 2021. doi:10.1016/j.est.2021.103464.

[25] Brian Dandurand, Paolo Guarneri, Georges Fadel, and Margaret M. Wiecek. Equitable multi-objective optimization applied to the design of a hybrid electric vehicle battery. *Journal of Mechanical Design*, 135(4):041004, 2013. doi:10.1115/1.4023553.

[26] Kai Chen, Shuangfeng Wang, Mengxuan Song, and Lin Chen. Structure optimization of parallel air-cooled battery thermal management system. *International Journal of Heat and Mass Transfer*, 111:943–952, 2017. doi:10.1016/j.ijheatmasstransfer.2017.04.026.

[27] Kai Chen, Junsheng Hou, Xiaoling Wu, Yiming Chen, Mengxuan Song, and Shuangfeng Wang. Design of flow pattern in air-cooled battery thermal management system. *International Journal of Energy Research*, 45(6):9541–9554, 2021. doi:10.1002/er.6480.

[28] Dafen Chen, Jiuchun Jiang, Gi-Heon Kim, Chuanbo Yang, and Ahmad Pesaran. Comparison of different cooling methods for lithium ion battery cells. *Applied Thermal Engineering*, 94:846–854, 2016. doi:10.1016/j.applthermaleng.2015.10.015.

[29] Weixiong Wu, Shuangfeng Wang, Wei Wu, Kai Chen, Sihui Hong, and Yongxin Lai. A critical review of battery thermal performance and liquid based battery thermal management. *Energy Conversion and Management*, 182:262–281, 2019. doi:10.1016/j.enconman.2018.12.051.

[30] Weiwei Wang, Shijuan Dai, Wanzhong Zhao, Chunyan Wang, and Tao Ma. Design optimization of a novel negative poisson's ratio non-module battery pack system considering crashworthiness and heat dissipation. *Composite Structures*, 275:114458, 2021. doi:10.1016/j.compstruct.2021.114458.

[31] Ziming Xu, Jun Xu, Zhechen Guo, Haitao Wang, Zheng Sun, and Xuesong Mei. Design and optimization of a novel microchannel battery thermal management system based on digital twin. *Energies*, 15(4):1421, 2022. doi:10.3390/en15041421.

[32] Chaofeng Pan, Qiming Tang, Zhigang He, Limei Wang, and Long Chen. Structure optimization of battery module with a parallel multi-channel liquid cooling plate based on orthogonal test. *Journal of Electrochemical Energy Conversion and Storage*, 17(2):1–16, 2019. doi:10.1115/1.4045197.

[33] Siqi Chen, Guangxu Zhang, Changjun Wu, Wensheng Huang, Chengshan Xu, Changyong Jin, Yu Wu, Zhao Jiang, Haifeng Dai, Xuning Feng, Xuezhe Wei, and Minggao Ouyang. Multi-objective optimization design for a double-direction liquid heating system-based cell-to-chassis battery module. *International Journal of Heat and Mass Transfer*, 183:122184, 2022. doi:10.1016/j.ijheatmasstransfer.2021.122184.

[34] Ningbo Wang, Congbo Li, Wei Li, Xingzheng Chen, Yongsheng Li, and Dongfeng Qi. Heat dissipation optimization for a serpentine liquid cooling battery thermal management system: An application of surrogate assisted approach. *Journal of Energy Storage*, 40:102771, 2021. doi:10.1016/j.est.2021.102771.

[35] Wei Li, Xiongbin Peng, Mi Xiao, Akhil Garg, and Liang Gao. Multi-objective design optimization for mini-channel cooling battery thermal management system in an electric vehicle. *International Journal of Energy Research*, 43(8):3668–3680, 2019. doi:10.1002/er.4518.

[36] Siqi Chen, Xiongbin Peng, Nengsheng Bao, and Akhil Garg. A comprehensive analysis and optimization process for an integrated liquid cooling plate for a prismatic lithium-ion battery module. *Applied Thermal Engineering*, 156:324–339, 2019. doi:10.1016/j.applthermaleng.2019.04.089.

[37] Maoyong Zhi, Rong Fan, Xiong Yang, Lingling Zheng, Shan Yue, Quanyi Liu, and Yuanhua He. Recent research progress on phase change materials for thermal management of lithium-ion batteries. *Journal of Energy Storage*, 45:103694, 2022. doi:10.1016/j.est.2021.103694.

[38] Ruixin Ma, Yimao Ren, Zhe Wu, Shiwei Xie, Kai Chen, and Weixiong Wu. Optimization of an air-cooled battery module with novel cooling channels based on silica cooling plates. *Applied Thermal Engineering*, 213:118650, 2022. doi:10.1016/j.applthermaleng.2022.118650.

[39] Weixiong Wu, Xiaoqing Yang, Guoqing Zhang, Xiufang Ke, Ziyuan Wang, Wenfu Situ, Xinxi Li, and Jiangyun Zhang. An experimental study of thermal management system using copper mesh-enhanced composite phase change materials for power battery pack. *Energy*, 113:909–916, 2016. doi:10.1016/j.energy.2016.07.119.

[40] Weixiong Wu, Xiaoqing Yang, Guoqing Zhang, Kai Chen, and Shuangfeng Wang. Experimental investigation on the thermal performance of heat pipe-assisted phase change material based battery thermal management system. *Energy Conversion and Management*, 138:486–492, 2017. doi:10.1016/j.enconman.2017.02.022.

[41] Ziye Ling, Jiahao Cao, Wenbo Zhang, Zhengguo Zhang, Xiaoming Fang, and Xuenong Gao. Compact liquid cooling strategy with phase change materials for li-ion batteries optimized using response surface methodology. *Applied Energy*, 228:777–788, 2018. doi:10.1016/j.apenergy.2018.06.143.

[42] Xiangwei Lin, Xuelai Zhang, Lu Liu, and Mai Yang. Optimization investigation on air phase change material based battery thermal management system. *Energy Technology*, 9(7):2100060, 2021. doi:10.1002/ente.202100060.

[43] Kirill Murashko, Juha Pyrhönen, and Lasse Laurila. Optimization of the passive thermal control system of a lithium-ion battery with heat pipes embedded in an aluminum plate. *2013*

15th European Conference on Power Electronics and Applications (EPE), page 1–10, 2013. doi:10.1109/epe.2013.6631856.

[44] Linfeng He, Xianwen Tang, Qiliang Luo, Yuepeng Liao, Xiangyi Luo, Jinlong Liu, Li Ma, Daowei Dong, Yunhua Gan, and Yong Li. Structure optimization of a heat pipe-cooling battery thermal management system based on fuzzy grey relational analysis. *International Journal of Heat and Mass Transfer*, 182:121924, 2022. doi:10.1016/j.ijheatmasstransfer.2021.121924.

[45] Wencan Zhang, Zhicheng Liang, Weixiong Wu, Guozhi Ling, and Ruixin Ma. Design and optimization of a hybrid battery thermal management system for electric vehicle based on surrogate model. *International Journal of Heat and Mass Transfer*, 174:121318, 2021. doi:10.1016/j.ijheatmasstransfer.2021.121318.

[46] Yu Shi, Shakeel Ahmad, Huaqiang Liu, Kwun Ting Lau, and Jiyun Zhao. Optimization of air-cooling technology for lifepo4 battery pack based on deep learning. *Journal of Power Sources*, 497:229894, 2021. doi:10.1016/j.jpowsour.2021.229894.

[47] Xiao Qian, Dongji Xuan, Xiaobo Zhao, and Zhuangfei Shi. Heat dissipation optimization of lithium-ion battery pack based on neural networks. *Applied Thermal Engineering*, 162:114289, 2019. doi:10.1016/j.applthermaleng.2019.114289.

[48] Ben Ye, Md Rashedul Haque Rubel, and Hongjun Li. Design and optimization of cooling plate for battery module of an electric vehicle. *Applied Sciences*, 9(4):754, 2019. doi:10.3390/app9040754.

[49] Hongguang Sun and Regan Dixon. Development of cooling strategy for an air cooled lithium-ion battery pack. *Journal of Power Sources*, 272:404–414, 2014. doi:10.1016/j.jpowsour.2014.08.107.

[50] Fei Dong, Ziyang Cheng, Decai Song, and Jie Ni. Investigation and optimization on cooling performance of serial-parallel mini-channel structure for liquid-cooled soft pack batteries. *Numerical Heat Transfer, Part A: Applications*, 80(7):368–387, 2021. doi:10.1080/10407782.2021.1947110.

[51] John H. Holland. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence*. MIT Press, Cambridge, MA, USA, 1992.

[52] Quan Xia, Zili Wang, Yi Ren, Dezhen Yang, Bo Sun, Qiang Feng, and Cheng Qian. Performance reliability analysis and optimization of lithium-ion battery packs based on multiphysics simulation and response surface methodology. *Journal of Power Sources*, 490:229567, 2021. doi:10.1016/j.jpowsour.2021.229567.

[53] Jinhao Li, Fei Lei, Wenhao Zhu, Zhifeng Qiu, and Hailong Wu. Large-scale zone-based approach to global modeling and optimization for a novel thermal management system of module-free lithium-ion battery. *Structural and Multidisciplinary Optimization*, 64(6):3621–3636, 2021. doi:10.1007/s00158-021-03042-7.

[54] Yuanzhi Liu and Jie Zhang. Design a j-type air-based battery thermal management system through surrogate-based optimization. *Applied Energy*, 252:113426, 2019. doi:10.1016/j.apenergy.2019.113426.

[55] Asif Afzal, Imran Mokashi, Sher Afghan Khan, Nur Azam Abdullah, and Muhammad Hanafi Bin Azami. Optimization and analysis of maximum temperature in a battery pack affected by low to high prandtl number coolants using response surface methodology and particle swarm optimization algorithm. *Numerical Heat Transfer, Part A: Applications*, 79(5):1–30, 2020. doi:10.1080/10407782.2020.1845560.

[56] J. Kennedy and R. Eberhart. Particle swarm optimization. In *Proceedings of ICNN'95 - International Conference on Neural Networks*, volume 4, pages 1942–1948 vol.4, 1995. doi:10.1109/ICNN.1995.488968.

[57] Asif Afzal, A.D. Mohammed Samee, R.D. Jilte, Md. Tariqul Islam, A. Muthu Manokar, and Kaladgi Abdul Razak. Battery thermal management: An optimization study of parallelized conjugate numerical analysis using cuckoo search and artificial bee colony algorithm. *International Journal of Heat and Mass Transfer*, 166:120798, 2021. doi:10.1016/j.ijheatmasstransfer.2020.120798.

[58] YongJin Park, Sangook Jun, Sanghun Kim, and Dong-Ho Lee. Design optimization of a loop heat pipe to cool a lithium ion battery onboard a military aircraft. *Journal of Mechanical Science and Technology*, 24(2):609–618, 2010. doi:10.1007/s12206-009-1214-6.

[59] Huanwei Xu, Liangwen Liu, and Miao Zhang. Adaptive surrogate model-based optimization framework applied to battery pack design. *Materials & Design*, 195:108938, 2020. doi:10.1016/j.matdes.2020.108938.

[60] Wei Li, Mi Xiao, Xiongbin Peng, Akhil Garg, and Liang Gao. A surrogate thermal modeling and parametric optimization of battery pack with air cooling for evs. *Applied Thermal Engineering*, 147:90–100, 2018. doi:10.1016/j.applthermaleng.2018.10.060.

[61] Huanwei Xu, Xin Zhang, Ge Xiang, and Hao Li. Optimization of liquid cooling and heat dissipation system of lithium-ion battery packs of automobile. *Case Studies in Thermal Engineering*, 26:101012, 2021. doi:10.1016/j.csite.2021.101012.

[62] Huanwei Xu, Hao Li, Ge Xiang, and Xin Zhang. An improved adaptive surrogate model and application in thermal management system design. *Materials & Design*, 208:109883, 2021. doi:10.1016/j.matdes.2021.109883.

[63] Wei Li, Akhil Garg, Mi Xiao, and Liang Gao. Optimization for liquid cooling cylindrical battery thermal management system based on gaussian process model. *Journal of Thermal Science and Engineering Applications*, 13(2), 2020. doi:10.1115/1.4047526.

[64] Shaosen Su, Wei Li, Yongsheng Li, Akhil Garg, Liang Gao, and Quan Zhou. Multi-objective design optimization of battery thermal management system for electric vehicles. *Applied Thermal Engineering*, 196:117235, 2021. doi:10.1016/j.applthermaleng.2021.117235.

[65] R.T. Marler and J.S. Arora. Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization*, 26(6):369–395, 2004. doi:10.1007/s00158-003-0368-6.

[66] Vilfredo Pareto. *Cours D'Economie Politique*, volume I and II. F. Rouge, Laussane, 1896.

[67] Liu Cheng, Akhil Garg, A.K. Jishnu, and Liang Gao. Surrogate based multi-objective design optimization of lithium-ion battery air-cooled system in electric vehicles. *Journal of Energy Storage*, 31:101645, 2020. doi:10.1016/j.est.2020.101645.

[68] Congbo Li, Yongsheng Li, Liang Gao, Akhil Garg, and Wei Li. Surrogate model-based heat dissipation optimization of air-cooling battery packs involving herringbone fins. *International Journal of Energy Research*, 45(6):8508–8523, 2021. doi:10.1002/er.6387.

[69] Zhaoyong Mao, Yuebang Pi, Bo Li, Chengyi Lu, and Wenlong Tian. Parametric optimization for liquid cooling microchannels of auv's battery thermal management system. *Journal of Thermal Analysis and Calorimetry*, page 1–15, 2022. doi:10.1007/s10973-022-11241-7.

[70] Qing Li, Hang-bo Shi, Gongnan Xie, Zhongliang Xie, and Huan-ling Liu. Parametric study and optimization on novel fork-type mini-channel network cooling plates for a li-ion battery module under high discharge current rates. *International Journal of Energy Research*, 45(12):17784–17804, 2021. doi:10.1002/er.6933.

[71] Huan-ling Liu, Hang-bo Shi, Han Shen, and Gongnan Xie. The performance management of a li-ion battery by using tree-like mini-channel heat sinks: Experimental and numerical optimization. *Energy*, 189:116150, 2019. doi:10.1016/j.energy.2019.116150.

[72] Ningbo Wang, Congbo Li, Wei Li, Mingli Huang, and Dongfeng Qi. Effect analysis on performance enhancement of a novel air cooling battery thermal management system with spoilers. *Applied Thermal Engineering*, 192:116932, 2021. doi:10.1016/j.applthermaleng.2021.116932.

[73] Xiangping Liao, Chong Ma, Xiongbin Peng, Akhil Garg, and Nengsheng Bao. Temperature distribution optimization of an air-cooling lithium-ion battery pack in electric vehicles based on the response surface method. *Journal of Electrochemical Energy Conversion and Storage*, 16(4), 2019. doi:10.1115/1.4042922.

[74] Aswin Karthik, Pankaj Kalita, Akhil Garg, Liang Gao, Siqi Chen, and Xiongbin Peng. A novel moga approach for power saving strategy and optimization of maximum temperature and maximum pressure for liquid cooling type battery thermal management system. *International Journal of Green Energy*, 18(1):1–10, 2020. doi:10.1080/15435075.2020.1831507.

[75] Jun Ma, Qiaoxin Chen, and Zaiyan Gong. Algorithmic and simulated based structural optimization of air-cooling heat dissipation structure for ev battery pack. *IOP Conference Series: Materials Science and Engineering*, 782(3):032080, 2020. doi:10.1088/1757-899x/782/3/032080.

[76] H.S. Hamut, I. Dincer, and G.F. Naterer. Analysis and optimization of hybrid electric vehicle thermal management systems. *Journal of Power Sources*, 247:643–654, 2014. doi:10.1016/j.jpowsour.2013.08.131.

[77] N. Javani, I. Dincer, G.F. Naterer, and B.S. Yilbas. Exergy analysis and optimization of a thermal management system with phase change material for hybrid electric vehicles. *Applied Thermal Engineering*, 64(1–2):471–482, 2014. doi:10.1016/j.applthermaleng.2013.11.053.

[78] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE Transactions on Evolutionary Computation*, 6(2):182, 2002. doi:10.1109/4235.996017.

[79] Yiwei Fan, Zhaohui Wang, and Ting Fu. Multi-objective optimization design of lithium-ion battery liquid cooling plate with double-layered dendritic channels. *Applied Thermal Engineering*, 199:117541, 2021. doi:10.1016/j.applthermaleng.2021.117541.

[80] Akhil Garg, Chaitanya Ruhatiya, Xujian Cui, Xiongbin Peng, Yogesh Bhalerao, and Liang Gao. A novel approach for enhancing thermal performance of battery modules based on finite element modelling and predictive modelling mechanism. *Journal of Electrochemical Energy Conversion and Storage*, 17(2):1–23, 2019. doi:10.1115/1.4045194.

[81] Xujian Cui, Siqi Chen, Mi Xiao, and Wei Li. A computational fluid dynamics coupled multi-objective optimization framework for thermal system design for li-ion batteries with metal separators. *Journal of Electrochemical Energy Conversion and Storage*, 18(3), 2021. doi:10.1115/1.4050509.

[82] Tao Deng, Yan Ran, Yanli Yin, and Ping Liu. Multi-objective optimization design of thermal management system for lithium-ion battery pack based on non-dominated sorting genetic algorithm ii. *Applied Thermal Engineering*, 164:114394, 2020. doi:10.1016/j.applthermaleng.2019.114394.

[83] Liqin Qian. A thermal-structure coupled optimization study of lithium-ion battery modules with mist cooling. *International Journal of Energy Research*, 44(15):12295–12311, 2020. doi:10.1002/er.5220.

[84] Siqi Chen, Xuezhe Wei, Akhil Garg, and Liang Gao. A comprehensive flowrate optimization design for a novel air–liquid cooling coupled battery thermal management system. *Journal of Electrochemical Energy Conversion and Storage*, 18(2), 2020. doi:10.1115/1.4048538.

[85] Nengsheng Bao, Li Wei, Chong Ma, Yuchen Fan, and Tuyan Li. Multi-objective optimization of structural parameters of air-cooled system for lithium battery pack based on surrogate model. *Journal of Electrochemical Energy Conversion and Storage*, 18(4), 2021. doi:10.1115/1.4051098.

[86] Fei Dong, Ziyang Cheng, Jianwei Zhu, Decai Song, and Jie Ni. Investigation and optimization on cooling performance of a novel double helix structure for cylindrical lithium-ion batteries. *Applied Thermal Engineering*, 189:116758, 2021. doi:10.1016/j.applthermaleng.2021.116758.

[87] Sungwook Jin, Min-Sik Youn, and Youn-Jea Kim. Optimization of air-cooling system for a lithium-ion battery pack. *E3S Web of Conferences*, 321:02018, 2021. doi:10.1051/e3sconf/202132102018.

[88] Rongchao Zhao, Dayang Wen, Zhaodan Lai, Weihua Li, Ming Ye, Weilin Zhuge, and Yangjun Zhang. Performance analysis and optimization of a novel cooling plate with non-uniform pin-fins for lithium battery thermal management. *Applied Thermal Engineering*, 194:117022, 2021. doi:10.1016/j.applthermaleng.2021.117022.

[89] Tao Deng, Yan Ran, Yanli Yin, Xing Chen, and Ping Liu. Multi-objective optimization design of double-layered reverting cooling plate for lithium-ion batteries. *International Journal of Heat and Mass Transfer*, 143:118580, 2019. doi:10.1016/j.ijheatmasstransfer.2019.118580.

[90] Bernardo Severino, Felipe Gana, Rodrigo Palma-Behnke, Pablo A. Estévez, Williams R. Calderón-Muñoz, Marcos E. Orchard, Jorge Reyes, and Marcelo Cortés. Multi-objective optimal design of lithium-ion battery packs based on evolutionary algorithms. *Journal of Power Sources*, 267:288–299, 2014. doi:10.1016/j.jpowsour.2014.05.088.

[91] Adriel Chi Tak Li, Wei Li, Christina M. M. Chin, Akhil Garg, and Liang Gao. Multidisciplinary optimal design of prismatic lithium-ion battery with an improved thermal management system for electric vehicles. *Energy Storage*, 3(2), 2021. doi:10.1002/est2.217.

[92] Hongfei Huang, Hu Wang, Jinqing Gu, and Yunqiang Wu. High-dimensional model representation-based global sensitivity analysis and the design of a novel thermal management system for lithium-ion batteries. *Energy Conversion and Management*, 190:54–72, 2019. doi:10.1016/j.enconman.2019.04.013.

[93] Yusong Wang, Bin Liu, Peng Han, Changsheng Hao, Shaohua Li, Zhanping You, and Meiqi Wang. Optimization of an air-based thermal management system for lithium-ion battery packs. *Journal of Energy Storage*, 44:103314, 2021. doi:10.1016/j.est.2021.103314.

[94] A Garg, Cheng Liu, A K Jishnu, Liang Gao, My Loan Le Phung, and Van Man Tran. A thompson sampling efficient multi-objective optimization algorithm (tsemo) for lithium-ion battery liquid-cooled thermal management system: Study of hydrodynamic, thermodynamic, and structural performance. *Journal of Electrochemical Energy Conversion and Storage*, 18(2), 2020. doi:10.1115/1.4048537.

[95] Liu Yun, Sivasriprasanna Maddila, Liang Gao, Xiongbin Peng, Xiaodong Niu, Akhil Garg, and Christina May May Chin. An integrated framework for minimization of inter lithium-ion cell temperature differences and the total volume of the cell of battery pack for electric vehicles. *Energy Storage*, 1(2):e41, 2019. doi:10.1002/est2.41.

[96] Orhan Kalkan, Ali Celen, and Kadir Bakirci. Multi-objective optimization of a mini channeled cold plate for using thermal management of a li-ion battery. *Energy*, 251:123949, 2022. doi:10.1016/j.energy.2022.123949.

[97] Ken Kelly, John Rugh, and Ahmad Pesaran. Improving battery thermal management using design for six sigma process, 2003.

[98] Ziyu Leng, Yanping Yuan, Xiaoling Cao, Wei Zhong, and Chao Zeng. Heat pipe/phase change material coupled thermal management in li-ion battery packs: Optimization and energy-saving assessment. *Applied Thermal Engineering*, 208:118211, 2022. doi:10.1016/j.applthermaleng.2022.118211.

[99] Ziyu Leng, Yanping Yuan, Xiaoling Cao, Chao Zeng, Wei Zhong, and Bo Gao. Heat pipe/phase change material thermal management of li-ion power battery packs: A numerical study on coupled heat transfer performance. *Energy*, 240:122754, 2022. URL: https://www.sciencedirect.com/science/article/pii/S0360544221030036, doi:https://doi.org/10.1016/j.energy.2021.122754.

[100] Kalyanmoy Deb and Himanshu Jain. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: Solving problems with box constraints. *IEEE Transactions on Evolutionary Computation*, 18(4):577–601, 2014. doi:10.1109/tevc.2013.2281535.

[101] Jiahui Chen, Xiaobo Zhao, Biao Wang, Chenghao Zhang, and Dongji Xuan. Multiobjective optimization of air-cooled battery thermal management system based on heat dissipation model. *Ionics*, 27(3):1307–1322, 2021. doi:10.1007/s11581-020-03853-6.

[102] Jiahui Chen, Dongji Xuan, Biao Wang, and Rui Jiang. Structure optimization of battery thermal management systems using sensitivity analysis and stud genetic algorithms. *Applied Sciences*, 11(16):7440, 2021. doi:10.3390/app11167440.

[103] Asif Afzal and M.K. Ramis. Multi-objective optimization of thermal performance in battery system using genetic and particle swarm algorithm combined with fuzzy logics. *Journal of Energy Storage*, 32:101815, 2020. doi:10.1016/j.est.2020.101815.

[104] Mengzhu Yang, Hu Wang, Wenquan Shuai, and Xinjian Deng. Thermal optimization of a kirigami-patterned wearable lithium-ion battery based on a novel design of composite phase change material. *Applied Thermal Engineering*, 161:114141, 2019. doi:10.1016/j.applthermaleng.2019.114141.

[105] Chaoyi Wan. Battery space optimization to limit heat transfer in a lithium-ion battery using adaptive elephant herding optimization. *Ionics*, 26(10):4993–5009, 2020. doi:10.1007/s11581-020-03636-z.

[106] Chaoyi Wan. Tssr algorithm based battery space optimization on thermal management system. *International Journal of Green Energy*, 18(12):1–16, 2021. doi:10.1080/15435075.2021.1897827.

[107] Parviz Mohammad Zadeh and Mohadeseh Alsadat Sadat Shirazi. Metaheuristic Applications in Structures and Infrastructures. *Part One: Structural Design*, pages 103–127, 2013. doi:10.1016/b978-0-12-398364-0.00005-x.

[108] Joaquim R. R. A. Martins and Andrew B. Lambe. Multidisciplinary Design Optimization: A Survey of Architectures. *AIAA Journal*, 51(9):2049–2075, 2013. doi:10.2514/1.j051895.

[109] Evin J. Cramer, J. E. Dennis, Jr., Paul D. Frank, Robert Michael Lewis, and Gregory R. Shubin. Problem formulation for multidisciplinary optimization. *SIAM Journal on Optimization*, 4(4):754–776, 1994. doi:10.1137/0804044.

[110] Xiaobang Wang, Mao Li, Yuanzhi Liu, Wei Sun, Xueguan Song, and Jie Zhang. Surrogate based multidisciplinary design optimization of lithium-ion battery thermal management system in electric vehicles. *Structural and Multidisciplinary Optimization*, 56(6):1555–1570, 2017. doi:10.1007/s00158-017-1733-1.

[111] Xiaobang Wang, Yuanzhi Liu, Wei Sun, Xueguan Song, and Jie Zhang. Multidisciplinary and multifidelity design optimization of electric vehicle battery thermal management system. *Journal of Mechanical Design*, 140(9):094501, 2018. doi:10.1115/1.4040484.

[112] Wei Li, Liang Gao, Akhil Garg, and Mi Xiao. Multidisciplinary robust design optimization considering parameter and metamodeling uncertainties. *Engineering with Computers*, page 1–18, 2020. doi:10.1007/s00366-020-01046-3.

[113] Kai Chen, Mengxuan Song, Wei Wei, and Shuangfeng Wang. Structure optimization of parallel air-cooled battery thermal management system with u-type flow for cooling efficiency improvement. *Energy*, 145:603–613, 2018. doi:10.1016/j.energy.2017.12.110.

[114] Kai Chen, Shuangfeng Wang, Mengxuan Song, and Lin Chen. Configuration optimization of battery pack in parallel air-cooled battery thermal management system using an optimization strategy. *Applied Thermal Engineering*, 123:177–186, 2017. doi:10.1016/j.applthermaleng.2017.05.060.

[115] Kai Chen, Mengxuan Song, Wei Wei, and Shuangfeng Wang. Design of the structure of battery pack in parallel air-cooled battery thermal management system for cooling efficiency improvement. *International Journal of Heat and Mass Transfer*, 132:309–321, 2019. doi:10.1016/j.ijheatmasstransfer.2018.12.024.

[116] Kai Chen, Weixiong Wu, Fang Yuan, Lin Chen, and Shuangfeng Wang. Cooling efficiency improvement of air-cooled battery thermal management system through designing the flow pattern. *Energy*, 167:781–790, 2019. doi:10.1016/j.energy.2018.11.011.

[117] Kai Chen, Dan Zhou, Xiaoling Wu, Jiajun Zhang, and Mengxuan Song. A novel optimization method based on inverse calculation model for efficient design of battery thermal management system. *Energy Conversion and Management*, 255:115290, 2022. doi:10.1016/j.enconman.2022.115290.

[118] Junsheng Hou, Xiaoling Wu, Kai Chen, and Yuan Dong. A direct optimization strategy based on field synergy equation for efficient design of battery thermal management system. *International Journal of Heat and Mass Transfer*, page 122304, 2021. doi:10.1016/j.ijheatmasstransfer.2021.122304.

[119] Anthony Jarrett and Il Yong Kim. Design optimization of electric vehicle battery cooling plates for thermal performance. *Journal of Power Sources*, 196(23):10359–10368, 2011. doi:10.1016/j.jpowsour.2011.06.090.

[120] Anthony Jarrett and Il Yong Kim. Influence of operating conditions on the optimum design of electric vehicle battery cooling plates. *Journal of Power Sources*, 245:644–655, 2014. doi:10.1016/j.jpowsour.2013.06.114.

[121] Mohsen Mousavi, Shaikh Hoque, Shahryar Rahnamayan, Ibrahim Dincer, and Greg F Naterer. Optimal design of an air-cooling system for a li-ion battery pack in electric vehicles with a genetic algorithm. *2011 IEEE Congress of Evolutionary Computation (CEC)*, 1:1848–1855, 2011. doi:10.1109/cec.2011.5949840.

[122] Chao Lyu, Yankong Song, Lixin Wang, Yaming Ge, Rui Xiong, and Tian Lan. A new structure optimization method for forced air-cooling system based on the simplified multi-physics model. *Applied Thermal Engineering*, 198:117455, 2021. doi:10.1016/j.applthermaleng.2021.117455.

[123] Yi Xie, Bo Li, Xiaosong Hu, Xianke Lin, Yangjun Zhang, and Jintao Zheng. Improving the air-cooling performance for battery packs via electrothermal modeling and particle swarm optimization. *IEEE Transactions on Transportation Electrification*, 7(3):1285–1302, 2021. doi:10.1109/tte.2020.3046735.

[124] Jinhong Xie, Zijing Ge, Mengyan Zang, and Shuangfeng Wang. Structural optimization of lithium-ion battery pack with forced air cooling system. *Applied Thermal Engineering*, 126:583–593, 2017. doi:10.1016/j.applthermaleng.2017.07.143.

[125] Yan-ping Liu, Chen-zhi Ouyang, Qing-bai Jiang, and Bo Liang. Design and parametric optimization of thermal management of lithium-ion battery module with reciprocating airflow. *Journal of Central South University*, 22(10):3970–3976, 2015. doi:10.1007/s11771-015-2941-8.

[126] Xueli Feng and Jie Hu. Analysis and optimization control of finned heat dissipation performance for automobile power lithium battery pack. *Thermal Science*, 24(00):132–132, 2020. doi:10.2298/tsci191223132f.

[127] Jianguo Wang, Shuai Lu, Yingzhou Wang, Yulong Ni, and Shude Zhang. Novel investigation strategy for mini-channel liquid-cooled battery thermal management system. *International Journal of Energy Research*, 44(3):1971–1985, 2020. doi:10.1002/er.5049.

[128] Ye Wang, Guoqing Zhang, and Xiaoqing Yang. Optimization of liquid cooling technology for cylindrical power battery module. *Applied Thermal Engineering*, 162:114200, 2019. doi:10.1016/j.applthermaleng.2019.114200.

[129] Jiaqiang E, Dandan Han, An Qiu, Hao Zhu, Yuanwang Deng, Jingwei Chen, Xiaohuan Zhao, Wei Zuo, Hongcai Wang, Jianmei Chen, and et al. Orthogonal experimental design of liquid-cooling structure on the cooling effect of a liquid-cooled battery thermal management system. *Applied Thermal Engineering*, 132:508–520, 2018. doi:10.1016/j.applthermaleng.2017.12.115.

[130] Zhuangzhuang Shang, Hongzhong Qi, Xintian Liu, Chenzhi Ouyang, and Yansong Wang. Structural optimization of lithium-ion battery for improving thermal performance based on a liquid cooling system. *International Journal of Heat and Mass Transfer*, 130:33–41, 2019.

doi:10.1016/j.ijheatmasstransfer.2018.10.074.

[131] Xiaoming Xu, Guangyao Tong, and Renzheng Li. Numerical study and optimizing on cold plate splitter for lithium battery thermal management system. *Applied Thermal Engineering*, 167:114787, 2020. doi:10.1016/j.applthermaleng.2019.114787.

[132] Jianfeng Wang, Xiaodong Liu, Fen Liu, Yiqun Liu, Fuqiang Wang, and Na Yang. Numerical optimization of the cooling effect of the bionic spider-web channel cold plate on a pouch lithium-ion battery. *Case Studies in Thermal Engineering*, 26:101124, 2021. doi:10.1016/j.csite.2021.101124.

[133] Rong Guo and Lu Li. Heat dissipation analysis and optimization of lithium-ion batteries with a novel parallel-spiral serpentine channel liquid cooling plate. *International Journal of Heat and Mass Transfer*, 189:122706, 2022. doi:10.1016/j.ijheatmasstransfer.2022.122706.

[134] Jianqin Wang, Yunhua Gan, Jialin Liang, Meixian Tan, and Yong Li. Sensitivity analysis of factors influencing a heat pipe-based thermal management system for a battery module with cylindrical cells. *Applied Thermal Engineering*, 151:475–485, 2019. doi:10.1016/j.applthermaleng.2019.02.036.

[135] Fanfei Bai, Mingbiao Chen, Wenji Song, Qinghua Yu, Yongliang Li, Ziping Feng, and Yulong Ding. Investigation of thermal management for lithium-ion pouch battery module based on phase change slurry and mini channel cooling plate. *Energy*, 167:561–574, 2019. doi:10.1016/j.energy.2018.10.137.

[136] Jiaqiang E, Yan Zeng, Yu Jin, Bin Zhang, Zhonghua Huang, Kexiang Wei, Jingwei Chen, Hao Zhu, and Yuanwang Deng. Heat dissipation investigation of the power lithium-ion battery module based on orthogonal experiment design and fuzzy grey relation analysis. *Energy*, 211:118596, 2020. doi:10.1016/j.energy.2020.118596.

[137] Hong Li, Yilun Xu, Yong Yang, and Chenlong Si. Simulation and optimization of fev limit discharge's heat dissipation based on orthogonal experiments. *Materials*, 13(23):5563, 2020. doi:10.3390/ma13235563.

[138] Jinhong Xie, Mengyan Zang, Shuangfeng Wang, and Zijing Ge. Optimization investigation on the liquid cooling heat dissipation structure for the lithium-ion battery package in electric vehicles. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 231(13):1735–1750, 2016. doi:10.1177/0954407016685457.

[139] Emre Bulut, Emre İsa Albak, Gökhan Sevilgen, and Ferruh Öztürk. A new approach for battery thermal management system design based on grey relational analysis and latin hypercube sampling. *Case Studies in Thermal Engineering*, 28:101452, 2021. doi:10.1016/j.csite.2021.101452.