Journal of Power Sources 267 (2014) 288–299

Contents lists available at ScienceDirect

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

Multi-objective optimal design of lithium-ion battery packs based on evolutionary algorithms

Bernardo Severino [d], Felipe Gana [d], Rodrigo Palma-Behnke [b, d, *], Pablo A. Estévez [b, d], Williams R. Calderón-Muñoz [a], Marcos E. Orchard [b], Jorge Reyes [d], Marcelo Cortés [c, d]

[a] Department of Mechanical Engineering, Universidad de Chile, Beauchef 850, Santiago, Chile
[b] Department of Electrical Engineering, Universidad de Chile, Av. Tupper 2007, Santiago, Chile
[c] Department of Electrical Engineering, Universidad de Antofagasta, Av. Angamos 601, Antofagasta, Chile
[d] Energy Center, Universidad de Chile, Av. Tupper 2007, Santiago, Chile

HIGHLIGHTS

- An optimization methodology for the battery thermal management design is proposed.
- The methodology is based on multi-objective PSO and multi-physics simulations.
- A theoretical case shows the trade-off between temperature operation and area.
- A real battery pack based on pouch cells for a solar car was designed.
- A novel battery packaging design framework is able to find better solutions.

ARTICLE INFO

Article history:
Received 17 October 2013
Received in revised form
13 May 2014
Accepted 17 May 2014
Available online 28 May 2014

Keywords:
Lithium-battery energy storage systems
Battery thermal management system
Battery cell arrangement
Optimal design
Multiphysics simulation
Multi-objective particle swarm optimization

ABSTRACT

Lithium-battery energy storage systems (LiBESS) are increasingly being used on electric mobility and stationary applications. Despite its increasing use and improvements of the technology there are still challenges associated with cost reduction, increasing lifetime and capacity, and higher safety. A correct battery thermal management system (BTMS) design is critical to achieve these goals. In this paper, a general framework for obtaining optimal BTMS designs is proposed. Due to the trade-off between the BTMS's design goals and the complex modeling of thermal response inside the battery pack, this paper proposes to solve this problem using a novel Multi-Objective Particle Swarm Optimization (MOPSO) approach. A theoretical case of a module with 6 cells and a real case of a pack used in a Solar Race Car are presented. The results show the capabilities of the proposal methodology, in which improved designs for battery packs are obtained.

1. Introduction

Lithium-ion cells have become one of the most used technologies for energy storage in electric mobility applications, due to its specific energy, energy density, and specific power [1,2]. They are also considered an alternative for stationary storage systems in power systems becoming the key to a high penetration of distributed renewable energy and second-timescale grid power services [3].

Despite the increasing use of LiBESS, there are still challenges to overcome in order to achieve a competitive technology that allows the full development of the aforementioned applications. Among these challenges are [1]: reducing costs, increasing life and capacity, and improving safety. To achieve these objectives not only better cells are needed, but also a better integration of them must be done, where the thermal operation is a critical issue [4,5]. Hence, a good LiBESS design must consider that each cell of the battery pack should operate at temperatures between 25 °C and mm, and the temperature difference between them should be less than 5 °C. This is in order to achieve a good balance between performance and lifetime [6]. To prevent a significant capacity fade and thermal runaway the temperature must be under 60 °C and 80 °C respectively [7]. Additionally, both energy and power of the Li-ion

* Corresponding author. Department of Electrical Engineering, Universidad de Antofagasta, Av. Angamos 601, Antofagasta, Chile. Tel.: +56 2 2978 4201.
E-mail address: rodpalma@cec.uchile.cl (R. Palma-Behnke).

http://dx.doi.org/10.1016/j.jpowsour.2014.05.088
0378-7753/

batteries are substantially reduced if the temperature falls below −10 °C [8].

A good design of the battery thermal management system (BTMS) should take into account these thermal operational constraints. The design of the BTMS includes the size of the cooling system together with the arrangement of the cells in the delimited space. In general [9], the BTMS should satisfy the following requirements: (i) Optimum operating temperature range for every cell and battery module, rejecting heat in hot climates/adding heat in cold climates; (ii) Small temperature variations within a cell and module; (iii) Small temperature variations among modules; (iv) Compact and lightweight, easily packaged, reliable, low-cost and easy for service; (v) Provision for ventilation if the battery generates potentially hazardous gases. Clearly, some of these goals are competing and it is difficult to express all of them in a single mathematical expression. In addition, some goals could become more relevant depending on the specific application [1] and/or more difficult to achieve depending on the electrothermal cell characteristics and the local application environment. Then, a multi-objective analysis is proposed to solve this design problem.

There have been several studies on the design of the BTMS for lithium-ion batteries. In literature two basic approaches can be identified: explicit optimization schemes and simulation based approaches. On the first approach, in Ref. [10] an optimum cooling plate for an electric vehicle pack obtained using average temperature of the cells, temperature uniformity and coolant pressure drop as objective functions. In Ref. [11], different alternatives for thermal management of a battery pack are evaluated using six sigma process optimization, with maximum temperature, pressure drop and temperature difference between cells as objectives. In Ref. [12], the parameters of an air cooling system for a Li-ion battery pack for an electric vehicle are optimized using a genetic algorithm.

On the second approach, [13] develops a numerical heat generation simulation model for a battery pack with cylindrical cells in order to compare the performance between an air and liquid cooling system, considering the BTMS power consumption as a critical objective. In Ref. [14], the design of an air cooling battery system is investigated and modeled, in order to satisfy required thermal specifications. In Ref. [15] a simulation model is developed in order to analyze the effect of thermal management and different ambient conditions on battery life. [16] performs three dimensional analyses of an air-cooled battery using Computational Fluid Dynamics (CFD). With the simulations, the best configurations for the pack are obtained. It is interesting to note how tailored numerical simulation models compete with the integration of Computer-Aided Engineering (CAE) as part of a simulation cycle.

The literature survey shows that despite using an optimization or a simulation approach, the general problem of designing a BTMS is necessarily divided into many pieces or sub-problems [17]. Recent efforts in the area of integrated design platforms are reported in Refs. [18,19]. Due to the huge variety of applications and the increasingly large lithium-ion cells market, the battery pack developers have focused in giving an ad-hoc solution for a specific problem [18]. In the process, a significant amount of R&D is pursued in order to achieve good results. However, the solutions are not very flexible, making it difficult addressing new requirements for new applications.

Consequently, there is a need for the development of a computational tool to improve the battery pack design process, including the designing of thermal management system. The main objective is to achieve a high degree of automation of the process and to ensure optimal design solutions. This can result in an improvement of the design periods, a reduction in the design costs, and the calculation of new/better design solutions, which are the main motivation for our research work.

The paper is organized in six sections. Section 2 shows the general framework where the proposed optimization methodology is embedded. Section 3 describes in detail the multi-objective optimization approach using an evolutionary algorithm and a CAE software as a simulation tool. In Section 4 a theoretical example is solved in order to illustrate the trade-off between space, temperature, and BTMS power consumption. Section 5 shows a real case of study with a comprehensive analysis of the results. Finally, Section 6 presents the conclusions and final remarks.

2. Proposed BTMS design framework

Although the scope of this paper is concentrated in the optimization approach for BTMS design, in this section we shortly describe the general framework under which our study is placed.

The proposed computational framework receives the application requirements as inputs: technical constraints, electrical use patterns, and environmental conditions, as shown in Fig. 1. The LiBESS design framework is composed of the following four steps:

- The first step consists of selecting the cell from a database and deciding the number of them to be used in the battery pack. Here, the goal is to minimize the present value of costs that depends on the investment cost, the number of times that the battery pack is replaced and the remaining cost.
- In the second step, both a cooling system type and a cell arrangement pattern are selected from a library of pre-defined alternatives. Hence, a multi-objective problem is defined; i.e., optimization goals, variables, constraints, and parameters.
- In the third step, the multi-objective problem is solved using evolutionary algorithms (EAs). The goal is to obtain the Pareto front of the design variables defined in the previous step. Here, the application requirements are considered in detail in order to achieve the design goals of the BTMS.
- Finally, in step four, a long-term evaluation of the battery pack is done considering results of the previous steps and a more detailed model of both the State of Charge (SoC) and the State of Health (SoH).

In this paper, we focus on the third step of the proposed framework. A multi-objective particle swarm (MOPSO) [20] algorithm is developed in Matlab® and is set in order to solve the optimal design of the battery thermal management system. COMSOL Multiphysics® is a multi-physics simulator used to simulate and evaluate the thermal response of each cell into the battery pack. An interface in Matlab is developed to connect the data generated from the simulation and the optimization modules. The scope of this study does not include a systematic experimental evaluation of the simulation software.

3. LiBESS optimization methodology

In light of the evident trade-off between the design goals of BTMS and the complex modeling of thermal response inside a battery pack, the optimal design problem is solved using a novel Multi-Objective Evolutionary Algorithm (MOEA) approach.

A general MO problem is defined as the minimization of the objective vector $\vec{F}(x) = [f_1(x), \ldots, f_k(x)]^T$ subject to a n-dimensional decision variable vector $\vec{x} = [x_1, \ldots, x_n]^T$, that is in the universe Ω that contains all possible $\vec{x}$ that can be used to satisfy an evaluation of $\vec{F}(x)$. In addition there are inequality and equality constraints, $g_i(x) \le 0$, $i = \{1,\ldots,m\}$, and $h_j(x) = 0$, $j = \{1,\ldots,p\}$, respectively [21].

The use of EAs to solve MO problems has been motivated mainly because of the population-based nature of EAs which allows obtaining multiple elements of the Pareto optimal set in a single

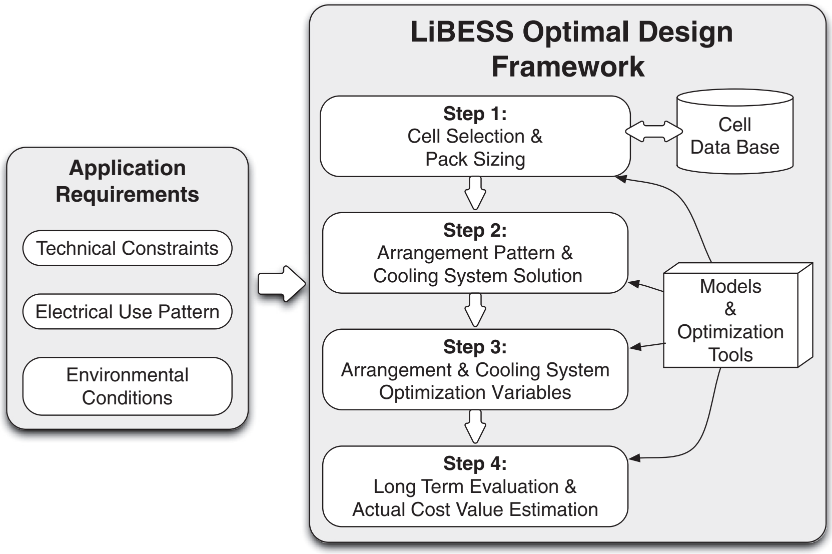

Fig. 1. General proposed framework for battery pack design.

run. Additionally, MOEA works well in complex multi-objective problems that have large search spaces, uncertainty, noise, and disjoint Pareto curves [21].

In this approach both the way in which the population evolves into a new one and a model to evaluate the objective functions are developed. Evaluation and the evolution steps are described below.

3.1. Battery pack model description

Battery pack modeling consists in defining the rules, border conditions, constraints of the thermal simulation and the characteristics of cells, and elements that interact with the cells in the simulation. In this study, cylindrical and pouch cells are used.

Each cell in a simulation is considered as an independent heat source, in which the value of the generated heat is obtained by the Joule effect shown in Eq. (1)

$$\dot{q}_{\text{source}} = R_{\text{cell}} \cdot I^2 \tag{1}$$

where I is a constant discharge current and R_{cell} is a constant internal resistance, for every cell.

At the beginning of the simulation, every cell starts at the same initial temperature T_0. The cooling of the cells is done with the flow of a fluid through the battery pack. The fluid enters from n_{inlet} sections and exits at n_{outlet} sections. Boundary conditions of pressure or volumetric flow must be imposed in the inlet and outlet sections to force the flow of cooling fluid. In addition, others boundary conditions, grouped in $\vec{\theta}_{\text{in}}$, must be set in the inlet sections as temperature, pressure, and density. The walls of the battery pack except for air cooling inlets or outlets are adiabatic frontiers, to emulate an extreme scenario in which there is not heat transfer between interior and exterior of the battery pack through walls. The temperature of the cell is calculated as the average of the temperature in the entire cell. A minimum separation is set between walls and cells, to avoid direct contact between them. There is also a minimum distance between cells avoiding contact between them.

Two-dimensional simulations in space are carried out in COMSOL Multiphysics to find the steady-state solution. COMSOL is a widely used multiphysics simulation software, hence, it has been assumed that the model gives a good approximation of the reality. A fully validation of the simulation software in the proposed context is considered for future work.

Two-dimensional simulations allow faster computational evaluations with a lot of accuracy because there is symmetry in the z-axis.The result of the simulation is obtained only when the entire simulation domain is not time-dependent, this means that the change of the dependent variables between time iterations is less than a small value. The governing equations for the heat transfer processes and fluid dynamics [22] are described in the following subsections.

3.1.1. Heat transfer model

The heat transfer mechanisms that govern the heating and cooling processes in a battery pack are conduction in solids and convection between surfaces and cooling fluids. The governing equations are:

$$\dot{q}_{\text{conduction}} = -k\nabla T, \tag{2}$$

$$\dot{q}_{\text{convection}} = h(T_s - T_\infty), \tag{3}$$

where $\dot{q}$ is the heat flux, k is the thermal conductivity media, T is the local temperature, h is the convective coefficient, T_s is the surface temperature, and T_∞ is the temperature of the cooling fluid.

3.1.2. Fluid dynamics model

The cooling fluid interacts with cells and modules. The Navier–Stokes equations are used to represent the behavior of a Newtonian fluid. In order to solve the system the non-linear differential Eq. (4) of continuity, Eq. (5) of momentum, and Eq. (6) of energy are used, as follows:

$$\frac{\partial(\rho\vec{V})}{\partial t} + \nabla\cdot(\rho\vec{V}) = 0, \tag{4}$$

$$\frac{\partial(\rho\vec{V})}{\partial t} + \nabla\cdot(\rho V\vec{V}) = -\nabla p + \nabla\cdot(\mu\nabla\vec{V}) + S_{\text{m}}, \tag{5}$$

$$\frac{\partial\rho i}{\partial t} + \nabla\cdot(\rho i\vec{V}) = -p\nabla\cdot\vec{V} + \nabla\cdot(k\nabla T) + \Phi + S_{\text{i}}, \tag{6}$$

where $\vec{V} = u\hat{i} + v\hat{j} + w\hat{k}$ is the velocity vector, ρ is the fluid density, p is the pressure, μ is the dynamic viscosity, S_m are the source of momentum, i is the internal fluid energy, k is the heat conductivity, T is the temperature, S_i is the internal energy source, and Φ is the dissipation. Additionally, the following equations for an ideal compressible gas are used;

$$p = \rho RT, \tag{7}$$

$$i = C_v T, \tag{8}$$

where R is the universal constant of an ideal gas, C_v is the heat capacity at constant volume.

The Navier–Stokes formulation does not describe the turbulent nature of the fluid, hence it is necessary to include a turbulence modeling. In this case, COMSOL is set to use the k–ε model [23], due its simplicity and effectiveness.

Heat transfer processes and fluid flow can be described through dimensionless relationships of the fluids, like the Reynolds number (Re_L), Prandtl number (Pr), and Nusselt number (Nu_L), as follows:

$$Re_L = \frac{VL}{\nu}, \tag{9}$$

$$Pr = \frac{C_p \mu}{k_f}, \tag{10}$$

$$Nu_L = \frac{hL}{k_f}, \tag{11}$$

where V is the characteristic velocity of the fluid, L is the characteristic length, ν is the kinematic viscosity of the fluid, k_f is the thermal conductivity of the fluid, and C_p is the specific heat capacity.

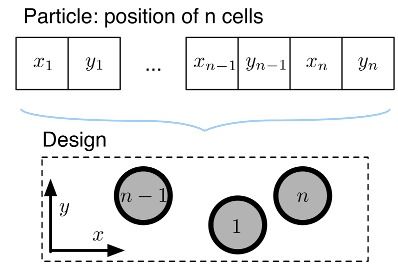

Fig. 2. Variables in a particle for a given BTMS design.

3.2. Multi-objective algorithm description

An implementation of MOPSO (Multi-Objective Particle Swarm Optimization) programmed in Matlab was used following the main structure proposed in Ref. [20]. The implementation of this algorithm incorporates communication with COMSOL, software that is used to evaluate the objective function through simulation.

In the following description the word "dominated" is used to name a solution that has at least one worst objective value than other individual in the population. Therefore, Non-dominated solutions belong to the Pareto front. Additionally, the word "particle" is used to name the n-dimensional decision variable vector $\vec{x} = [x_1, \ldots, x_n]^T$, which represents a set of variables that define the design of a battery pack. An example of a particle is shown in Fig. 2, where $\vec{x}$ is the (x,y) position of each cell in the battery.

Fig. 3 shows the steps of the MOPSO implementation communicated with COMSOL. These are described below.

Once the type of cell, cooling system, and the number of cells in the pack are chosen, the optimization of the design can start. First, the population and the velocity for each particle are initialized. This means that each particle is set in random positions. The velocity for each particle variables is set to zero in every direction. Then, the connection between Matlab and COMSOL is made through a server-slave mechanism; a connection between both softwares is

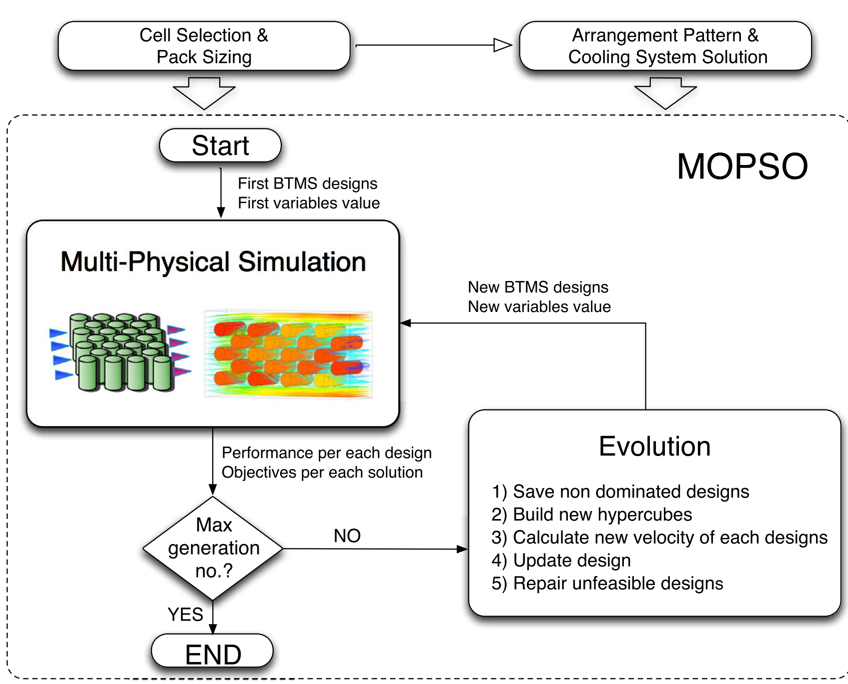

Fig. 3. MOPSO algorithm for battery pack design optimization.

Table 1
Specifications of cylindrical lithium-ion cell (IMR-18650E manufactured by MOLICEL®).

Dimension	
Diameter (mm)	18
Height (mm)	65
Thermal properties	
Density (kg m^{-3})	2100
Thermal conductivity (W m^{-1} K^{-1})	0.66
Specific heat capacity (J kg^{-1} K^{-1})	900
Electronic properties	
Nominal voltage (V)	3.2
Nominal capacity @1C at 20 °C (Ah)	1.4
Internal resistance (mΩ)	32
Maximum continuous current (A)	20

Table 2
Design parameters of a battery module.

General	
Battery cell	IMR-18650E
Electrical configuration	6s1p
BTMS properties	
Inlet volumetric air flow (m^3 s^{-1})	0.1
Inlet air temperature (°C)	25
Packing constraints specifications	
Maximum length (mm)	120
Maximum width (mm)	60
Gap between cell to wall (mm)	15
Min. gap between two cells (mm)	0.1

established. The simulation problem description and the resulting simulation results are shared through this link. With the connection established, simulation for each design in the multiphysics simulator (in this case, COMSOL) can be performed. The simulation is done to evaluate a design and to obtain the values of the objective functions. A simulation cycle is done for each particle in the population. Once finished, COMSOL extracts the values of the objective functions and send them to Matlab. If the maximum number of generations is reached, the optimization is over and the Pareto front with optimum designs is obtained.

If the maximum number of generations is not reached, then the evolution continues. In the evolution, first MOPSO saves the non-dominated solutions into a repository. MOPSO counts with a database outside the population, named repository, where the best solutions found so far are stored. The repository has a maximum size n_{rep} in order to save computation. The repository works in the following way. In the first iteration, all the non-dominated solutions are saved in the repository. In the following iterations, the non-dominated solutions that were found within that iteration are mixed with the ones that were already in the repository. Then, the solutions that are dominated by one or more solutions in the repository are eliminated in order to keep a Pareto set inside the repository. Next, MOPSO builds new hypercubes, which are used to determine those solutions in the repository that are going to be considered as leaders to guide the particle to best positions in the solution space. Each hypercube is generated by dividing the solution space in equal parts. To find the leaders, the solutions in the repository are separated into these hypercubes. If a hypercube is too populated, then their elements will have less probability to be picked up as leaders in the optimization. With the hypercubes defined, MOPSO is able to calculate the new velocity for each particle. The velocity is calculated as:

$$\text{vel}_{t+1}^{i} = \gamma \cdot \text{vel}_{t}^{i} + \alpha \cdot \left(M_t^i - P_t^i\right) + \beta \cdot \left(L_t^i - P_t^i\right). \tag{12}$$

The Eq. (12) combines the sum of three terms: the velocity at the current iteration vel_t^i, the difference between the best position ever from the particle M_t^i and its current position P_t^i, the difference between a random leader particle taken from the repository L_t^i and the current position of the particle. Each of the last two terms are multiplied by α and β respectively, which corresponds to random variables between 0 and 1. While the first term, the old velocity, is multiplied by the inertia weight γ that usually takes a value of 0.4. Finally, the velocity is added to the current position of the particle, determining the future value of the position. Then the cycle starts again. If the new design were unfeasible, for example because the positions of the cells are overlapped, then it repaired before going into the multiphysics simulation in COMSOL.

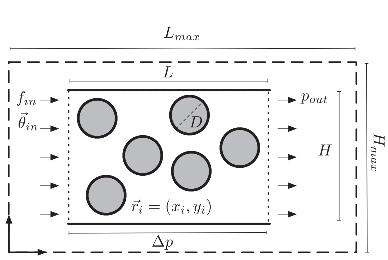

Fig. 4. Geometric configuration and parameters of a six cell battery pack module.

4. Case study 1: random arrangement of six cells

4.1. Problem description

A first theoretical case was developed in order to verify the optimization methodology and to find the trade-off between the following BTMS's design goals: maximum cell temperature $T_{\max}$, power cooling thermal system consumption P_{BTMS}, and used area A. The worst cell to cell difference of temperature $\Delta T_{\max}$ was not considered because it has a linear relation with $T_{\max}$ in this setting.

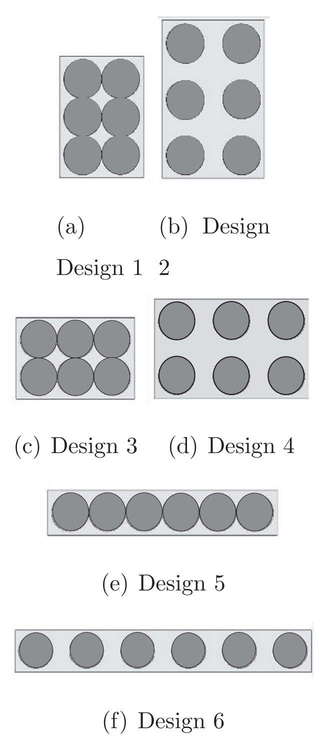

Fig. 5. Conventional designs.

Table 3
Characteristics of 6 conventional designs.

Design	#r	#c	k	P_{BTMS}	Area	T_{max}	ΔT_{max}
1	3	2	0.1	3.68	1.0	70.2	36.8
2	3	2	27	0.87	1.61	30.9	7.1
3	2	3	0.1	3.84	1.0	51.6	20.6
4	2	3	27	1.95	1.61	30.1	6.6
5	1	6	0.1	4.08	1.07	58.3	29.2
6	1	6	27	4.08	1.49	57.9	29.5

The example consists of a battery module with six cylindrical cells located in a confined space. The characteristics of the cells are shown in Table 1. The pack has a fixed air volumetric flow boundary condition at the inlet section, f_{in}, and a fixed relative pressure boundary condition, $p_{out} = 0$, at the air outlet section as shown in Fig. 4. The dotted lines in Fig. 4 represent the maximum area available, the arrows at bottom left corner represent the origin of the coordinate system, the horizontal arrows represent the air flow at the inlet (left) and outlet (right), and the circles represent the cylindrical cells in 2D. The particularity of this case is that the cells can be located in random positions, allowing finding new arrangement patterns under defined conditions of cooling and constrained space. This multi-objective problem is mathematically formulated as

$$\min_{\{\vec{r_i}=(x_i,y_i)\}} \begin{bmatrix} T_{max} = \max(T_i) \\ P_{BTMS} = \Delta p \cdot f_{in} \\ A = L \cdot H \end{bmatrix}, \tag{13}$$

where $\vec{r_i}$ is the position vector of the center of each cells $i = \{1,\ldots,6\}$ in a two-dimensional space, T_i is the average temperature of each cell, and Δp is the pressure drop between the air outlet and inlet. The area of the battery module in Eq. (13) is calculated by

$$L = \max(x_i) - \min(x_i) + D + 2\alpha, \tag{14}$$

$$H = \max(y_i) - \min(y_i) + D + 2\alpha, \tag{15}$$

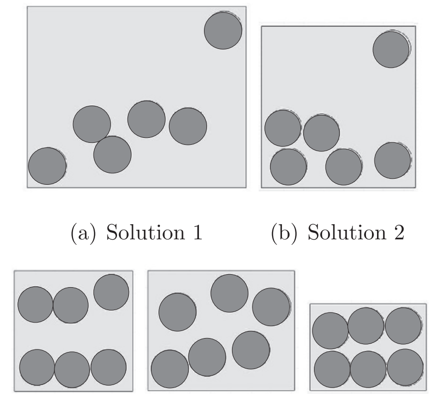

Fig. 7. Selected solutions from the Pareto front.

where L is the length, H is the width, D is the diameter of the cell, and α is the gap between the most external cell and the wall.

Each battery module design is defined by a random position of cells, hence overlapping between them could happen in the simulation. In order to avoid this the following constraint is included

$$\left\| \vec{r_i} - \vec{r_j} \right\| \geq D + \varepsilon \quad \forall i,j; \quad i \neq j, \tag{16}$$

where ε is the minimal permitted gap between two cells. Additionally, the constraints related to the limited space are included and calculated as

$$\alpha + \frac{D}{2} \leq x_i \leq L_{max} - \alpha - \frac{D}{2} \quad \forall i, \tag{17}$$

$$\alpha + \frac{D}{2} \leq y_i \leq H_{max} - \alpha - \frac{D}{2} \quad \forall i, \tag{18}$$

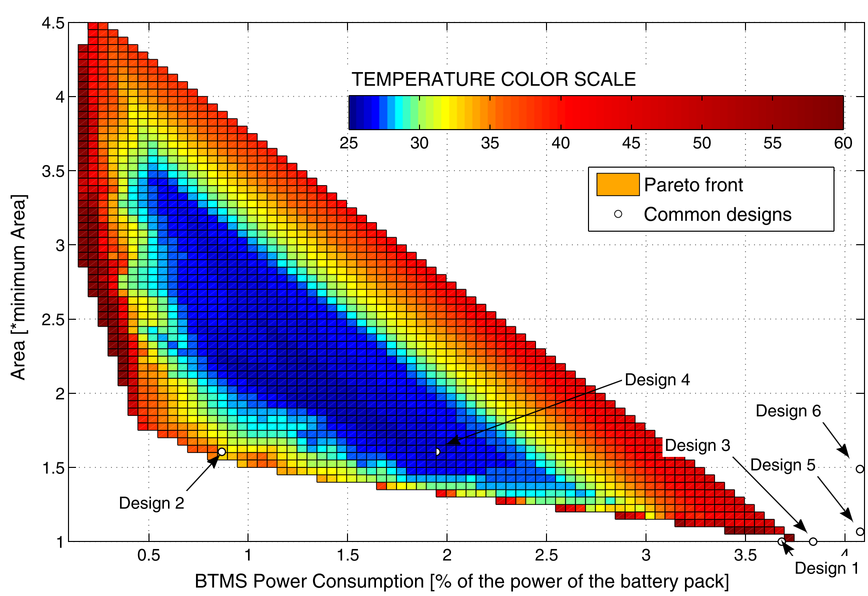

Fig. 6. Pareto surface obtained after 100 generations of MOPSO. The color scale denote the maximum temperature. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Multi-objective and cell to cell difference temperature evaluation of optimal cell arrangement designs in the Pareto front.

Solution	P_{BTMS}	Area	T_{max}	ΔT_{max}
1	0.16	4.31	42.5	11.5
2	0.2	2.69	110.8	80.6
3	0.7	1.68	33.3	9.0
4	1.38	1.85	25.6	1.6
5	3.01	1.15	31.9	7.3

where L_{max} and H_{max} are the maximum length and width of the pack, respectively (see Fig. 4).

The design parameters of the battery pack plus the parameters of the BTMS and the packaging constraints, are summarized in Table 2. The air volumetric flow was set in order to get a high cell temperature response, nearby 50 °C, at the minimum area design which will be described in the next section. The idea is to show the potential improvements when a multi-objective approach is used starting from a minimum area design approach. The battery module was simulated considering the hardest thermal continuous operating condition; i.e., at maximum continuous cell current.

4.2. Conventional designs

With the aim of being able to compare the designs obtained by the optimization methodology, 6 additional designs were developed using conventional engineering design criteria based on symmetry and intuitive thermal flux behavior (see Fig. 5). These designs are intended to be an external reference to our MOPSO algorithm, and are not used as part of the initial particle population. Furthermore, these designs are inspired on common design patterns, as putting all cells in rows and columns. A comparison with the Pareto front obtained by MOPSO can be performed, checking if the evolutionary results can outperform these common designs. Consequently, a first assessment about the quality of the LiBESS design can be obtained. Table 3 shows the characteristics of the six conventional designs, where #*r* is the number of rows, #*c* is the number of columns, and *k* is the separation between cells in (mm).

Also, Table 3 shows the value of the objective functions for each design. Here and from now on, the BTMS power consumption is shown as a percentage of the maximum power of the battery module, and the area is shown as an increment of the minimum physical area (designs 1 and 3). Also the maximum temperature and the temperature difference between the best and worst cell is shown.

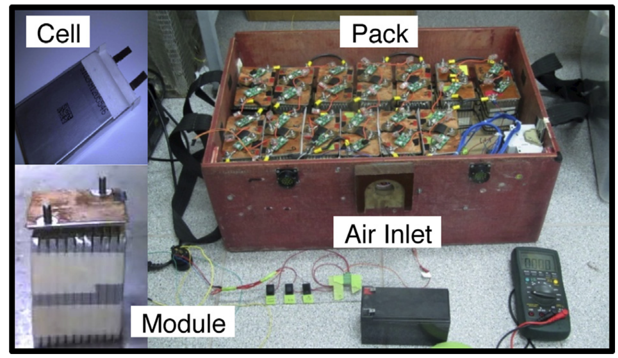

Fig. 9. Battery pack of the EOLIAN III solar race car.

4.3. Results using MOPSO

The Pareto front was obtained using 100 generations of the MOPSO algorithm. In each iteration, a population of 200 articles was evaluated by using COMSOL. The total simulation time was 4 days using a 3.2 GHz Processor with 4 GB of RAM. The average time spent for each particle simulation was 15 s. The final Pareto front contained 200 designs reaching the maximum size of the repository n_{rep}.

Fig. 6 shows the Pareto surface with the trade-offs between the 3 objectives: BTMS power consumption (*x*-axis), area (*y*-axes), and maximum temperature (color). It can be seen that at very low BTMS power consumption the solutions reach high temperatures, over 60 °C. A similar behavior, but at a lower magnitude, occurs at high BTMS power consumption and small area. Note that an unfeasible zone exists at a minimum area and BTMS power. This happens when the cells are very close, the friction increases and consequently the pressure drop also increases. In Fig. 6, the conventional designs are also shown. Only three conventional solutions are in

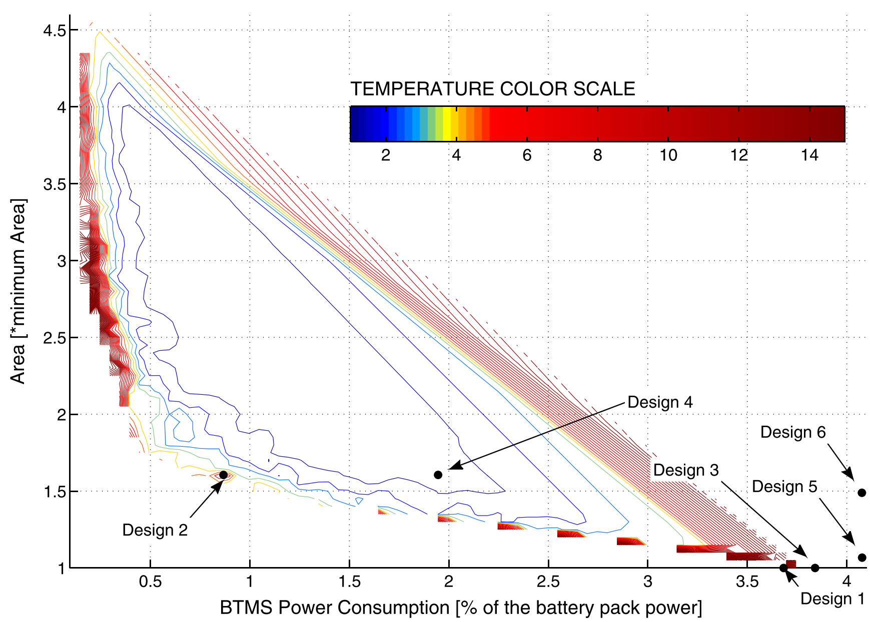

Fig. 8. Maximum cell to cell difference temperature obtained for each individual in the Pareto surface, and the 6 conventional designs.

Table 5
Specifications of pouch Li-ion polymer cell (SPB636395 manufactured by SAEHAN®).

Dimension	
Thickness (mm)	6.3
Width (mm)	63
Height (mm)	95
Thermal properties	
Density (kg m^{-3})	2100
Thermal conductivity (W m^{-1} K^{-1})	0.66
Specific heat capacity (J kg^{-1} K^{-1})	900
Electronic properties	
Nominal voltage (V)	3.7
Nominal capacity @0.2C at 20 °C (Ah)	4.5
Internal resistance (mΩ)	15
Maximum continuous current (A)	60

the final Pareto front (designs 1, 2, and 3). Moreover, two of them (designs 1 and 3) have the minimum area and would be eventually found by the MOPSO algorithm if overlapping between cells were less frequent. The results show that the multi-objective evolutionary approach allows obtaining a deeper understanding of the problem because more information and solutions are available for a battery module design.

Fig. 7 shows five selected solutions from the Pareto front and Table 4 shows the value of the objective functions for each solution. Each solution was chosen from a different region of the Pareto surface. Solution 3 has two rows of cells separated by a large gap, and the horizontal distance between them is short. This configuration allows cells to be well cooled by the air flow that goes through the channel from left to right while using low BTMS power consumption. The cells in solution 4 are arranged in diagonal orientation. In this configuration the air cooling reaches more cell surface in every cell, improving the heat transfer mechanism between cells and air. This permits a very low temperature and cell to cell temperature difference with a small increment of BTMS power consumption compared with the previous design. Solution 5 shows the smallest area found by the MOPSO algorithm close to the area of design 1 in Table 3 that is the minimum area feasible for this problem. Solutions 1 and 2 show how the algorithm is also able to explore bigger areas and lower BTMS power consumption.

Fig. 8 shows the maximum cell to cell temperature difference on each configuration in the Pareto front plus the 6 conventional designs. As mentioned before, the behavior of this parameter is very similar to the maximum temperature. This happens, on the one hand, because a small space and a small number of cells are used in this problem. Thus, the distance between the inlet and the first cell to the left is short and therefore, this cell is well cooled. On the other hand, usually the more obstructed cells on the right side of the module are the ones that have the higher temperatures, and then the largest cell to cell difference is between one of these hot cells and one of the well cooled cells next to the inlet.

Table 6
Variable boundaries.

Variable	Lower boundary (mm)	Upper boundary (mm)
d_1	40	120
d_2	1	10
d_3	1	160
d_4	1	20
d_5	1	20

Table 7
Design parameters for the EOLIAN III battery module.

General	
Battery cell	SPB636395
Electrical configuration	13s9p
BTMS properties	
Inlet pressure air flow (*pa*)	0.003
Inlet air temperature (°C)	25
Outlet pressure air flow (Pa)	0.003

Table 8
Parameter values of the best solution found by MOPSO for the EOLIAN III battery pack.

Variable	Value (mm)
d_1	50.3
d_2	2.6
d_3	47.8
d_4	11.06
d_5	12

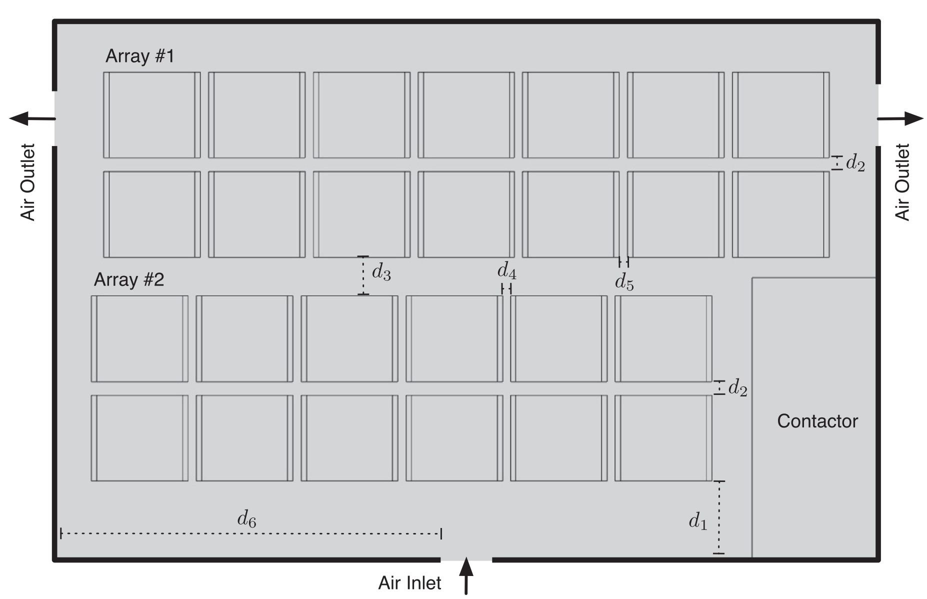

Fig. 10. 2D geometric design parameters of the EOLIAN III battery pack.

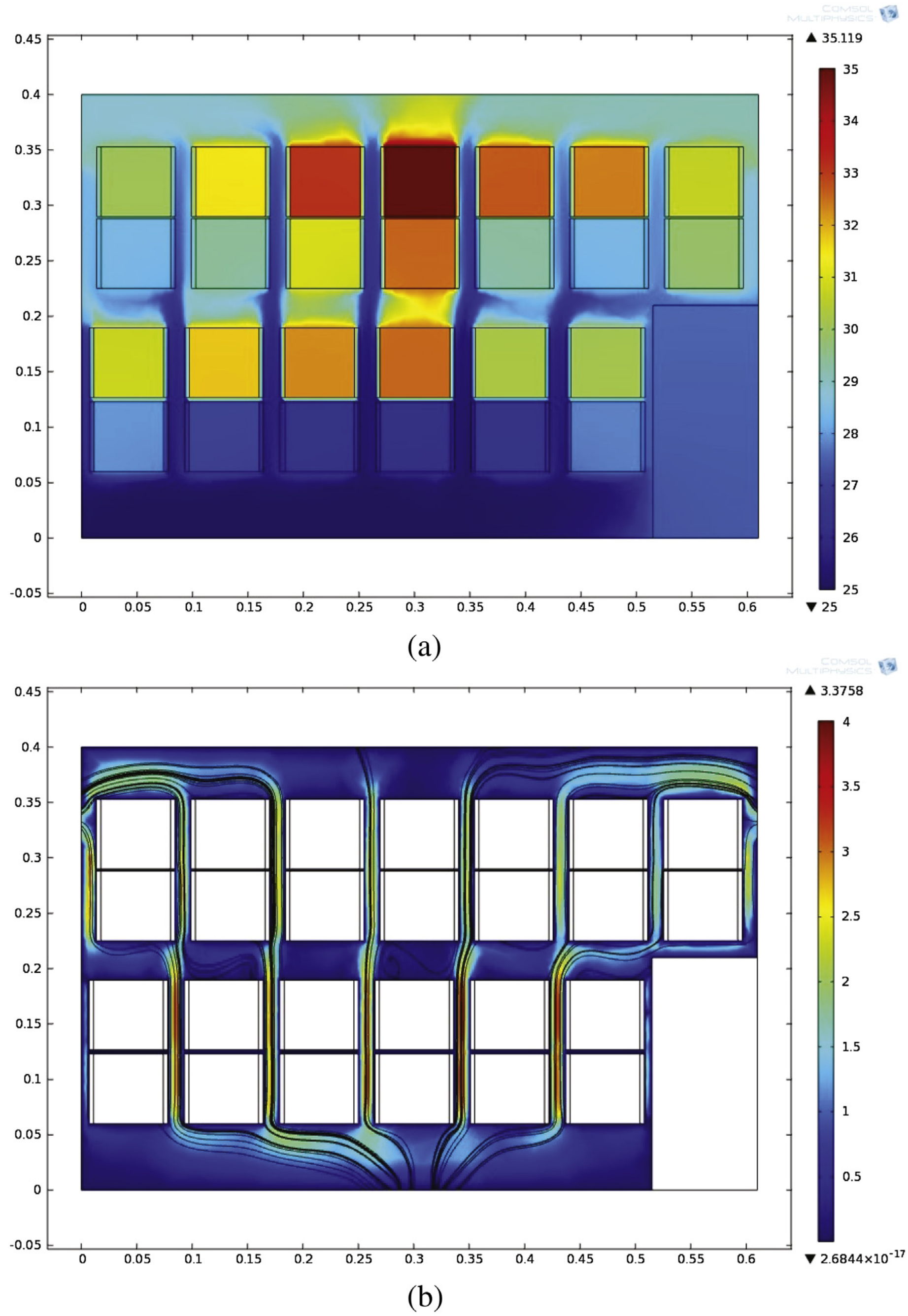

Fig. 11. Thermal behavior of the best battery pack design for the EOLIAN case, a) surface temperature (°C), and b) surface velocity magnitude (m s^{-1}).

5. Case study 2: EOLIAN III battery pack design

5.1. Problem description

Using the proposed design application methodology, the battery pack of the Solar Race Car EOLIAN III[1] was designed and built as shown in Fig. 9. The battery pack consists of 26 modules in series connected each one having 9 pouch Li-ion polymer cells connected in parallel. Table 5 shows the main parameters of the cell used. Due to the extreme environment conditions of the *Desafío Solar Atacama 2012*[2] race in Chile, the objective of this example is to arrange the modules into the pack in order to achieve low maximum module temperature $T_{\max}$ and low module to module maximum temperature difference $\Delta T_{\max}$.

Fig. 10 shows the 2D geometric considerations of the EOLIAN III battery pack. As can be seen, the modules are located in two arrays spaced in d_3 (mm) where every module has two rows of modules spaced in d_2 (mm). The array #1 has 7 columns all spaced by d_5

[1] http://www.facebook.com/eolian.uchile.5.

[2] http://www.carrerasolar.com/.

(mm). The array #2 has 6 columns spaced by d_4 (mm). The space between the bottom wall and the array #2 is d_1 (mm). The pack is cooled using a passive air system which consists of one air inlet at constant pressure p_{inlet} located at the bottom and two air outlets at constant pressure p_{outlet} on each side (upper left and right). The diameter of the inlet and outlets is 4 (cm). The size of the battery pack is 61 × 40 (cm). Finally, there is a contactor in the right-down corner that can not be moved, adding a forced degree of asymmetry to the problem.

The multi-objective problem is formulated as:

$$\min_{\{d_k\}_{k=\{1,\dots,5\}}} \begin{bmatrix} T_{\max} = \max(T_i) \\ \Delta T_{\max} = \max(T_i) - \max(T_i) \end{bmatrix}, \tag{19}$$

where d_k is the k-th spacing variable and T_i is the average temperature of the i-th module. Fixed boundaries for each variable are considered as follows:

$$d_{k\max} \le d_k \le d_{k\min} \quad \forall k = \{1, \dots, 5\}. \tag{20}$$

Table 6 shows the limits chosen which define the universe Ω of feasible solutions.

For the simulation, each module is considered as a unique body without spacing between cells. At both sides of each module two acrylic plates are fixed in order to ensure a good structural resistance. The model developed in COMSOL includes the material and thermal properties of the acrylic plates. The electrical operating condition was set at maximum current,

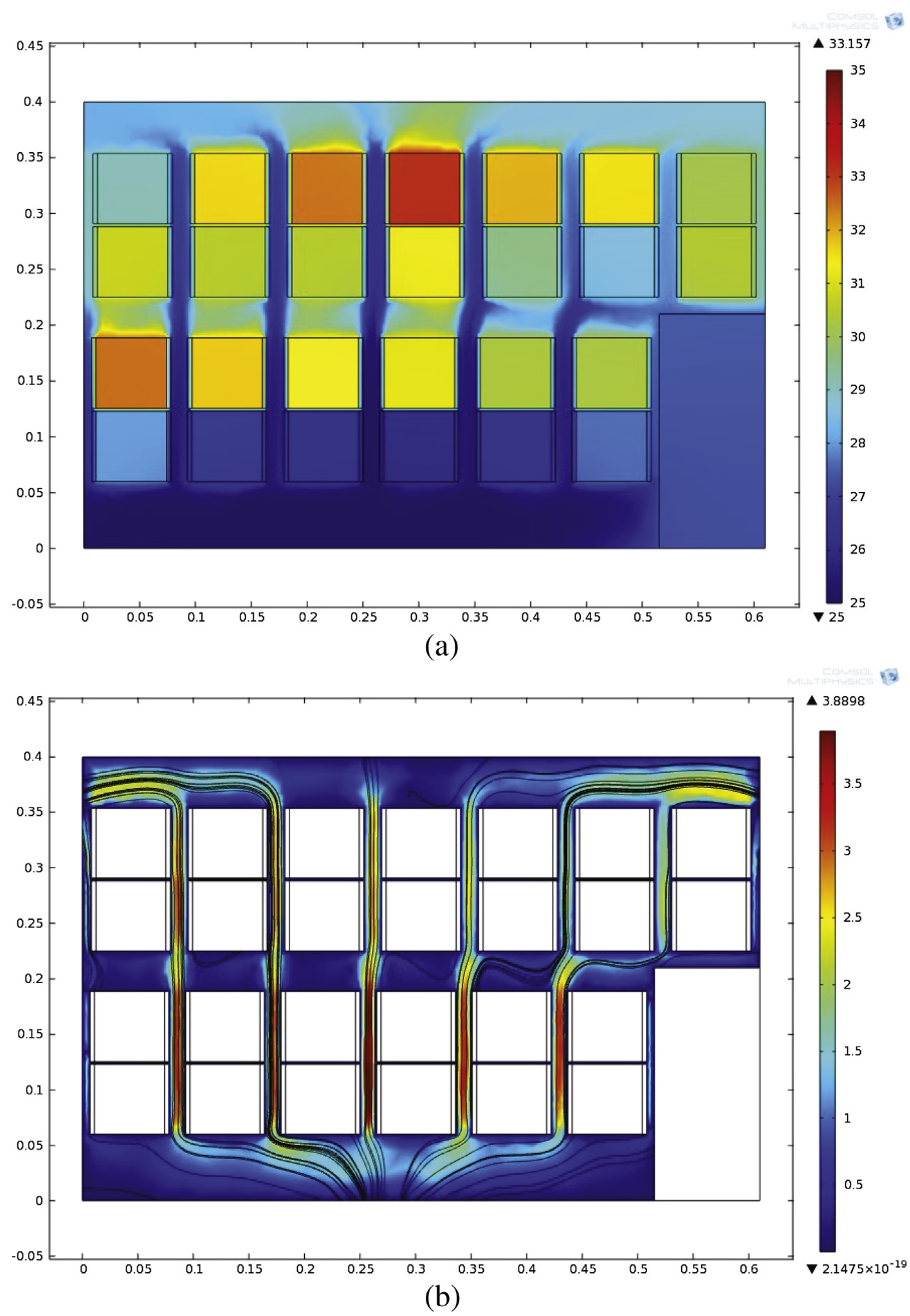

Fig. 12. Enhanced battery pack design with additional air inlet position optimization, a) surface temperature (°C), and b) surface velocity magnitude (m s^{-1}).

which corresponds to 6 Watts of heat generation for each module (Table 7).

5.2. Results

After 50 generations of MOPSO based on 100 particle evaluations per generation, and with a computational effort of 75 h, a feasible solution set was found. From the analysis of the resulting Pareto front, a convergency to a best solution shown in Table 8, is observed.

In this solution the worst cooling module reached 34.3 °C and the module to module maximum temperature difference was 8.36 °C. Compared with other battery pack solutions the results are remarkable since the battery uses only a passive air refrigeration system. Fig. 11 shows the temperature distribution behavior of the battery pack. Fig. 11(a) shows that the battery modules nearby the air inlet have the lowest temperature, and the module located in column 4 and row 1 of the array #1 shows the highest temperature. This can be explained by the air flow streamlines, which could be observed in Fig. 11(b). Air flow streamlines depend strongly on the positions of the modules.

During the *Desafío Solar Atacama* race the temperature behavior of the battery pack was observed for several operating conditions. The temperature fluctuation was within a band of 20 °C and 35 °C and the maximum temperature difference between modules was 3 °C which is coherent with the simulation results.

5.3. Enhanced BTMS

From the previous results and considering the asymmetry of the battery pack as a consequence of the contactor position, a theoretical design exercise is proposed in this section. The air inlet position d_6 is added as a new design/optimization variable for LiBESS (see Fig. 10). The new multi-objective problem only differs from the previous one by this new variable. The range limits for this new variable are 1 and 474 (mm).

Adding d_6, the MOPSO algorithm was re-run and found a new Pareto curve after 76 h. However, the solutions are very similar to each other differing only in few millimeters. The principal difference between this new design and the previous one is that variable d_1 changes from 50 to 60 (mm) and the air inlet position d_6 changes from 285 to 250 (mm).

This new design achieves a better temperature distribution than the previous design, as can be seen by comparing Fig. 11(a) and Fig. 12(a). The maximum module temperature decreases 2 °C and the maximum temperature difference reaches only 6 °C instead of 8.36 °C. Fig. 12 shows that the temperature of each module keeps the same spatial distribution but with lower values. Specifically, it can be seen that this new design allows decreasing the temperature of all modules. This is explained by the more symmetrical location of the air inlet, which allows a more homogeneous air distribution. In this way, the air can flow at higher velocities through the channels defined by the module separations.

6. Conclusion

In this paper, an optimization methodology for optimal battery pack design is proposed. Due to the complexity of battery pack modeling and the conflicting BTMS's goals, a Multi-Objective Evolutionary Algorithm was developed in order to obtain a wider range of potential solutions (Pareto front). The methodology was used in two very different problems showing its flexibility and capability to find an optimal design.

This study shows that by combining computational intelligence techniques with a multi-physics simulation tool, better solutions can be achieved for the design problem than the ones obtained using only a simulation based approach.

In the first case of study, designs were found over a very large search space in spite of difficulties such as overlapping between cells. The methodology was able to find 200 designs in the Pareto front, which are better than conventional designs. Some of these random generated designs seem to be constructible, and then useful for battery module design. This case of study also illustrates the trade-off between conflicting objectives: area, temperature, and BTMS power consumption.

In the second case of study, a battery pack for a real vehicle application was designed by using MOPSO. In this case, the optimization was able to obtain an optimal solution given the original design conditions, and also an enhanced solution by changing the position of the air inlet.

The results obtained by combining optimization with evolutionary algorithms and multi-physic simulations are promising. In both studies, significant improvements for the designs were obtained, which shows the capabilities of the methodology for finding better and constructible solutions for battery design problems.

The simulations performed in this work were based on the widely used COMSOL software. Future work will include the experimental validation of this model in the context of battery packaging. Also, new models could be developed to improve the performance of the proposed methodology.

Acknowledgments

This work could not be done to its fullest without the support of Centro de Innovación del Litio (CIL), CORFO Chile (11IDL1-10466 and 12IDL2-16296 projects), and CONICYT/FONDAP/15110019.

References

[1] A. Thielmann, A. Sauer, R. Isenmann, M. Wietschel, P. Pltz, Product roadmap lithium-ion batteries 2030, Technical Report, Fraunhofer Institute for Systems and Innovation Research ISI, 2012.
[2] M. Broussely, in: Electric and Hybrid Vehicles, Elsevier, Amsterdam, 2010, pp. 305–345.
[3] J. Leadbetter, L.G. Swan, J. Power Sources 216 (2012) 376–386.
[4] A.A. Pesaran, G.-H. Kim, M. Keyser, in: EVS-24 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium, 2009.
[5] T.M. Bandhauer, S. Garimella, T.F. Fuller, J. Electrochem. Soc. 158 (2011) R1–R25.
[6] A.A. Pesaran, J. Power Sources 110 (2002) 377–382.
[7] J. Vetter, P. Novk, M. Wagner, C. Veit, K.-C. Mller, J. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, A. Hammouche, J. Power Sources 147 (2005) 269–281.
[8] S. Zhang, K. Xu, T. Jow, J. Power Sources 115 (2003) 137–140.
[9] Z. Rao, S. Wang, Renew. Sustain. Energy Rev. 15 (2011) 4554–4571.
[10] A. Jarrett, Multi-Objective Design Optimization of Electric Vehicle Battery Cooling Plates Considering Thermal and Pressure Objective Functions, Ph.D. thesis, Queen's University, Kingston, Ontario, Canada, 2011.
[11] A. Vlahinos, K. Kelly, J. Rugh, A. Pesaran, Improving Battery Thermal Management Using Improving Battery Thermal Management Using Design for Six Sigma Process, 20th Electric Vehicle Symposium, 2003.
[12] M. Mousavi, S. Hoque, S. Rahnamayan, I. Dincer, G. Naterer, in: 2011 IEEE Congress on Evolutionary Computation (CEC), pp. 1848–1855.
[13] S. Park, D. Jung, J. Power Sources 227 (2013) 191–198.
[14] H. Park, J. Power Sources 239 (2013) 30–36.
[15] T. Yuksel, J. Michalek, Development of a Simulation Model to Analyze the Effect of Thermal Management on Battery Life, SAE 2012 World Congress & Exhibition, 2012.
[16] L. Fan, J. Khodadadi, A. Pesaran, J. Power Sources 238 (2013) 301–312.
[17] V. Ramadesigan, P.W.C. Northrop, S. De, S. Santhanagopalan, R.D. Braatz, V.R. Subramanian, J. Electrochem. Soc. 159 (2012) R31–R45.
[18] A.A. Pesaran, G.-H. Kim, K. Smith, 25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition, Shenzhen, China.
[19] S. Nallabolu, L. Kostetzer, E. Rudnyi, Simulation of Hybrid Vehicle Powertrain with an Advanced Battery Model, 2011.

[20] C.A. Coello Coello, M. Lechuga, in: Proceedings of the 2002 Congress on Evolutionary Computation, CEC'02 vol. 02, 2002, pp. 1051–1056.
[21] C.C. Coello, G. Lamont, D. van Veldhuizen, Evolutionary Algorithms for Solving Multi-objective Problems, Genetic and Evolutionary Computation, second ed., Springer, Berlin, Heidelberg, 2007.
[22] F.P. Incropera, D.P. DeWitt, Fundamentals of Heat and Mass Transfer, fifth ed., John Wiley & Sons, 2002.
[23] T.J. Chung, Computational Fluid Dynamics, first ed., Cambridge University Press, 2002.