2021-01-0764 Published 06 Apr 2021

Using Virtual Product Development with Design of Experiments to Design Battery Packs for Electrified Powertrain

Ran Bao Ricardo UK Ltd.

Nikolaos Fotias and Paul McGahan Ricardo Prague s.r.o.

Citation: Bao, R., Fotias, N., and McGahan, P., "Using Virtual Product Development with Design of Experiments to Design Battery Packs for Electrified Powertrain," *SAE Int. J. Advances & Curr. Prac. in Mobility* 3(6):2893-2905, 2021, doi:10.4271/2021-01-0764.

This article was presented at the WCX World Congress Experience Digital Summit, April 13-15, 2021.

Abstract

Stringent automotive legislation is driving requirements for increasingly complex battery pack solutions. The key challenges for battery pack development drive cost and performance optimisation, growth in architecture solutions, monitoring and safety through lifetime, and faster-to-market expectations.

The battery Virtual Product Development (VPD) toolchain addresses these challenges and provides a solution to reduce the battery pack development time, cost and risk. The battery VPD toolchain is built upon scalable, validated sub-models of the battery pack that capture the interactions between the various domains; mechanical, electrical, thermal and hydraulic. The model fidelity can be selected at each stage of the design process allowing the right amount of detail, and available data, to be incorporated. The toolchain is coupled with vehicle simulation tools to rapidly assess performance of the complete electrified powertrain.

The aim of this study is to demonstrate an agile approach to battery pack concept development using VPD, enabled by Design of Experiments (DoE) and optimisation. Key battery parameters such as cell type, electrical configuration, thermal heat path design and cooling strategy are chosen as the design variables of a multi-staged DoE. The DoE test matrices of these parameters are generated and imported into the battery VPD toolchain with the vehicle simulation model to perform the energy efficiency and performance simulations.

Finally, the simulation results are analysed to create surrogate models which can be used to predict powertrain attributes and optimise the battery pack design. The ability to front-load virtual battery pack concepts with vehicle simulations allow for wholistic performance assessment, ensuring that vehicle attribute targets such as pure electric range of WLTP, acceleration and maximum speed are met and reducing concept development time by up to 50% compared to the baseline approach.

Introduction

The increasing adoption of grid connected electric vehicles (BEV and PHEV) worldwide is driving significant advances in battery technology. Indeed, such widespread electrified vehicle adoption calls for more robust system design, capable of operating efficiently in different terrains and climates. Furthermore, as automakers seek to allay end-user fears such as limited range and long charging time, there is a drive on designing for higher power levels [1]. These challenges have placed increasing demand on improved physical understanding and modelling of automotive battery packs and have brought more challenges to battery pack management and powertrain control [2, 3, 4]. The key challenges for battery pack development drive cost and performance optimisation, growth in architecture solutions, monitoring and safety through lifetime, and faster-to-market expectations.

Battery pack model is a key element in the battery pack development and can be a big potential to reduce the development cost and time when its capabilities have been fully explored. Normally, a battery pack physical model includes at least the electrical sub-model with optional thermal and/or ageing sub-models. For the battery pack electrical model, electrochemical model and Equivalent Circuit Model (ECM) are the two most common choice [5, 6, 7, 8, 9]. Battery temperature is known to have a critical influence on overall battery pack performance [10]. Therefore, it creates the need for battery thermal models to monitor the temperature. One such type of model is a 1-D lumped thermal model which can be applied to analyse single cells and battery modules [11, 12, 13, 14]. Computational Fluid Dynamics (CFD) packages are commonly used tools for studying battery cell thermal behavior and pack thermal management system analysis at later stages in a battery design process [15, 16]. Investigation of battery aging mechanisms is a hot topic in both academia and industry currently. The cause and effect of various battery ageing mechanisms is discussed in detail in [17]. Also, lots of experimental work focusing on application of EIS, Voltammetry and EPMA to investigate ageing exists in the literature [18, 19]. Although there are already lots of studies on battery modelling, most of them discuss the battery electrical, thermal and ageing modelling separately which means they cannot evaluate the synergy of different battery sub-models.

The battery Virtual Product Development (VPD) toolchain addresses these challenges and provides a solution to reduce the battery pack development time, cost and risk. The battery VPD toolchain is built upon scalable, validated sub-models of the battery pack that capture the interactions between the various domains; mechanical, electrical, thermal and hydraulic. The model fidelity can be selected at each stage of the design process allowing the right amount of detail, and available data, to be incorporated. The toolchain is coupled with vehicle simulation tools to rapidly assess performance of the complete electrified powertrain.

The aim of this study is to demonstrate an agile approach to battery pack concept development using VPD, enabled by Design of Experiments (DoE) and optimisation. Key battery parameters such as cell type, electrical configuration, thermal heat path design and cooling strategy are chosen as the design variables of a multi-staged DoE. The DoE test matrices of these parameters are generated, and imported into the battery VPD toolchain with the vehicle simulation model to perform the energy efficiency and performance simulations

The ability to front-load virtual battery pack concepts with vehicle simulations allow for wholistic performance assessment, ensuring that vehicle attribute targets such as pure electric range of WLTP, acceleration and maximum speed are met and reducing concept development time by up to 50% compared to the baseline approach.

The remainder of this work is outlined as follows. Firstly, the Battery VPD toolchain is introduced. Secondly, the toolchain is applied to an example battery concept development, including electrical configuration optimisation, packaging optimisation and design optimisation using a DoE approach. Thirdly a summary of the concept design output is presented through a combination of BoM and Heat Path Analysis. Next a vehicle level assessment is performed to estimate system level performance and lifetime. Finally, conclusions and next steps are given.

Battery Virtual Product Development (VPD) Toolchain

The well-known V-model is still commonly used for vehicle system development, which is established, tested, reliable, more rigid and less agile. Newer, innovative VPD approaches are increasingly being discussed for system development, which are agile and inspired from modern software development methodologies such as Continuous Integration/ Continuous Deployment (CI/CD) [20]. The VPD approach allows for ingest of requirements from system level and cascade back up right at either full virtual, coupled virtual physical or full physical. The VPD approach can iterate designs quickly while not blocking other system development.

The battery VPD toolchain (green part) developed by Ricardo has been integrated into the V-cycle as shown in Figure 1, and is a digital twin of real battery pack, which can be applied during the whole development processes in V-cycle. Once the battery VPD toolchain receives the system definition from the left side of the V-cycle, it can used to analyse the requirements, define the specification, implement the Virtual or Hardware-In-Loop (HIL) testing, and validate the system. Then, depend on the different testing applied, battery VPD toolchain returns the design outcome back the right side of the V-cycle. The aim of applying battery VPD is to speed-up and to realise the flexible and agile in the battery pack development.

There are a number of challenges that must be addressed at the concept feasibility stage of a battery pack development project:

1. Requirements often change at such an early stage. It is therefore crucial to be able to rapidly evaluate and compare design alternatives. This evaluation may need to be repeated multiple times and therefore having systematic tools allows for improved engineering efficiency.
2. It is important to optimize for battery pack performance (for example finding the optimal trade-off meeting as many of the requirements as closely as possible), battery solution cost (for example cell selection, cooling strategy selection, component material) and safety (it must be ensured that any concept will be robust to potential abuse).
3. It is vitally important to consider various scenarios where failures may occur and test our design against them to ensure we are designing a robust and reliable product. This is of course expensive to do physically.

The battery VPD toolchain allows for rapid concept evaluation and assessment. The toolchain is tightly coupled with our Integrated Model Based Design (IMBD) platform thus allowing us to rapidly assess not only sub-system but complete (vehicle) system requirements in simulation. This is done using a range of use cases and it is possible to consider different Battery Management System (BMS) flavours (e.g. different SoC estimation algorithms, balancing algorithms) even at this early concept stage

FIGURE 1 Ricardo Battery Virtual Product Development (VPD)

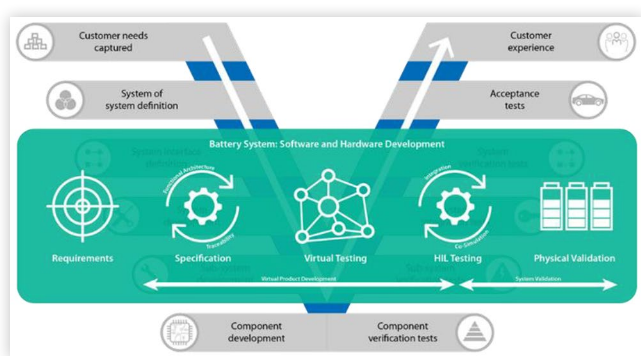


FIGURE 2 Battery Pack Concept Design Process

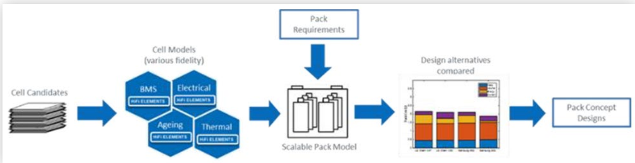
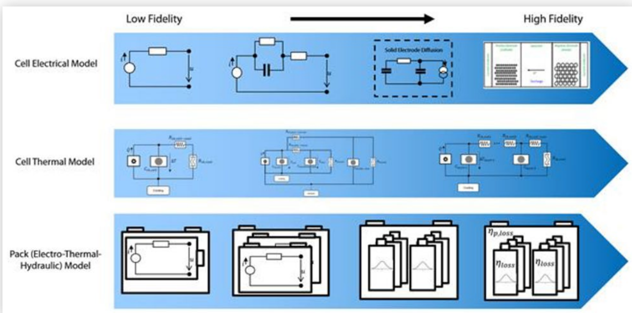


FIGURE 3 The sub-models' fidelity variants of the Battery VPD Toolchain



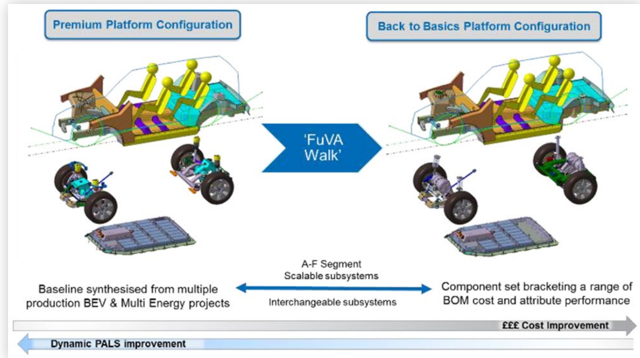
The toolchain is built upon scalable sub-models of the battery pack. These models when coupled together represent the battery digital twin. This digital twin allows us to capture the interactions that are obviously at play between the various domains (mechanical, electrical and thermal). Scalable fidelity sub-models capture interactions between mechanical, electro-chemical and thermal disciplines. Application of this approach allows to save up to 50% time and 30% cost at battery concept design stage.

At very early stages when only datasheet information is available, it still needs to be able to construct a simple yet representative model of each subcomponent in the battery pack. However as more and more data become available through e.g. testing, the modelling accuracy is reasonably expected to be able to improve. This invariably requires more complex models. Battery VPD Toolchain allow the user to select the right model fidelity at each stage of the design process, from early concept phase were simple models are used to guide initial performance expectations to later where BMS algorithms such as balancing or SoC estimation must be functionally tested and validated. The sub-models' fidelity variants of the battery VPD Toolchain is shown in Figure 3.

Future Vehicle Architecture (FuVA)

FuVA, developed by Ricardo, is a parametric multi-energy vehicle model used to develop and evaluate customer focussed design solutions at pace. Combining the FuVA approach with core capability in Systems Engineering, attribute management, design & analysis gives up to 10% Bill of Materials (BoM) material cost savings; the FuVA parametric model provides a rapid start for any new multi-energy vehicle design project. The methodology offers vehicle OEMs the benefits of:

FIGURE 4 Graphical overview of the FuVA concept



- BoM cost
- Reduced time to market
- Future proofing of new vehicle architecture

The FuVA concept is presented graphically in Figure 4

The VPD toolchain leverages the packaging envelope output of FuVA, to rapidly assess the spatial requirements and constraints of the battery pack, as presented in the following sections.

Battery Pack Concept Development Using VPD

VPD Toolchain Application

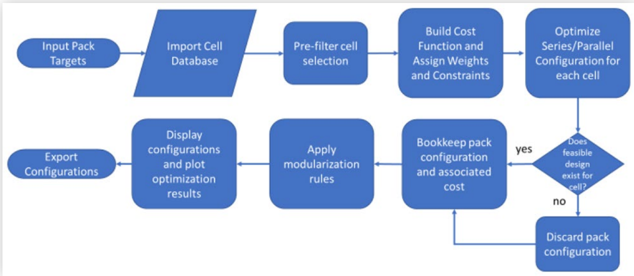
The battery VPD toolchain is comprised of a wide range of models and tools that capture the interactions between the thermal, electrical and mechanical domains. To increase the accessibility, the tools and models were incorporated in an application with a simplified Graphical User Interface (GUI). This application guides the users into following a defined workflow to rapidly assess requirements and develop battery pack concepts, from electrical pack configuration to vehicle integration.

Pack Configuration Optimisation

A systematic workflow has been developed to rapidly configure, optimise, assess and find trade-offs between battery pack electrical configurations. This is presented schematically in Figure 5.

The first steps in the workflow are importing of battery pack design requirements and connecting to a database of cell types. This comprehensive database contains information for a wide range of cells of different chemistries, form factor and capacity. It consists of both datasheet information, and where available, test data. The connection to the battery cell database is a key enabler for performing rapid pack configuration optimisation.

FIGURE 5 Pack Configuration Optimisation Workflow



The key and innovative step in this workflow is translating the battery pack concept design to an optimisation problem. The following penalty terms are considered for optimization problem construction:

- Pack Energy [kWh]

$$C_1 = \left(\frac{E_{targ} - E_{pack}}{E_{targ}}\right)^2 \tag{1}$$

- Pack Mass [kg]

$$C_2 = \frac{M_{pack}}{M_{\max}} \tag{2}$$

- Pack Volume [l]

$$C_3 = \frac{V_{pack}}{V_{\max}} \tag{3}$$

- Continuous Power [kW]

$$C_4 = \left(\frac{P_{c,targ} - P_{c,pack}}{P_{c,targ}}\right)^2 \tag{4}$$

- Peak Power [kW]

$$C_5 = \left(\frac{P_{p,targ} - P_{p,pack}}{P_{p,targ}}\right)^2 \tag{5}$$

- Pack Voltage [V]

$$C_6 = \frac{U_{pack}}{U_{\max}} \tag{6}$$

- Pack Current [A]

$$C_7 = \frac{I_{pack}}{I_{\max}} \tag{7}$$

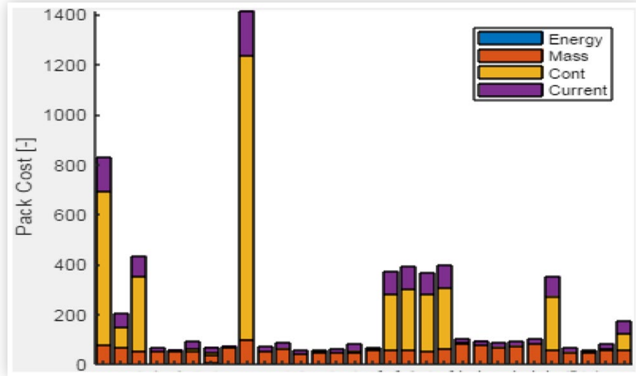
- Pack DCIR [Ω]

$$C_8 = \frac{DCIR_{pack}}{DCIR_{\max}} \tag{8}$$

- Pack Continuous Power Loss [kW]

$$C_9 = \frac{P_{c,loss}}{P_{c,targ}} \tag{9}$$

FIGURE 6 Graphical summary of pack configuration optimisation results.



- Pack Peak Power Loss [kW]

$$C_{10} = \frac{P_{p,loss}}{P_{p,targ}} \tag{10}$$

The cost function is then defined as

$$J_{pack} = \sum_{i=1}^{10} w_i C_i \tag{11}$$

For each cell that has been selected from the cell database and where w_i are the weights determined by the scaling bar in the user interface. For each of the penalty terms an upper bound (UB_i) and lower bound (LB_i) term is identified and the following optimization problem is defined to be solved, for each cell, where the decision variables are number of cells in series n_s and number of cells in parallel n_p.

$$\begin{gathered}\min_{n_s, n_p} J_{pack} \\ LB_i < C_i < UB_i\end{gathered} \tag{12}$$

The optimisation problem is solved for each cell candidate in the cell database; however, it is noted that some pre-filtering of the cell types can be applied (e.g. selecting only cylindrical cells). A comparison chart is generated that allows a rapid, unbiased comparison of design configurations in terms of the distance of a design from meeting each requirement. This comparison is presented in Figure 6, where four penalty terms have been considered.

The user can then select any number of candidate designs to take forwards and perform further design analysis.

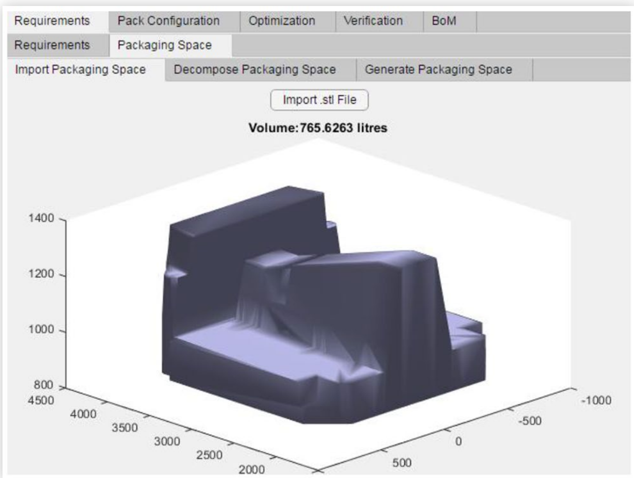
Packaging Study

The application incorporates tools that enable the user to carry out a preliminary packaging study of cells of any form factor.

The user is given the option to either import the packaging envelop in the form of a .stl file or generate an envelope from the available volume defined in the requirements and a user defined ratio between the length and the width of the packaging space. For the case study the packaging envelope of Figure 7, generated by FuVA, was imported.

To reduce the computational complexity of the packaging problem due to complex non-convex envelops, such as the one

FIGURE 7 Packaging envelop used for the packaging study



used in the case study, semi-automatic pre-processing is carried out. The application incorporates tools (Figure 8) to decompose the envelop to simpler convex components. Those simple components have their vertices and faces decimated to remove excess information, ensuring minimal loss in shape features.

Three distinct components were identified and decomposed in the imported envelop as presented in Figure 9.

The approach adopted to place the cells in the convex envelops takes advantage of the fact that commonly, the cells will have the same orientation in the battery pack. Hence, the 3-D problem can be simplified into a 2-D problem with 3-D constraints. Each of the faces of the envelop are tested and used as the plane where the first layer of cells will be placed. The configuration with the most cells packaged is then output to the user as seen in Figure 10.

Finally, it should be mentioned that provisions are taken to account for cell spacing and ancillary components, such as busbars. This is reflected in the increase of the cell dimensions by a user defined ratio.

FIGURE 8 Envelop decomposition using plane cutting

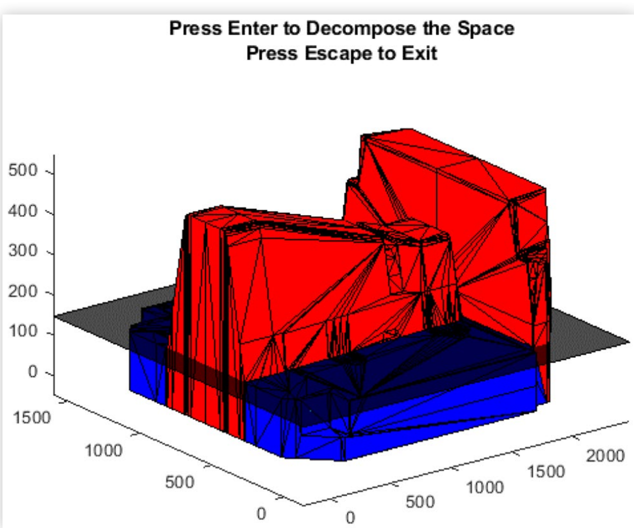


FIGURE 9 Results of the convex decomposition

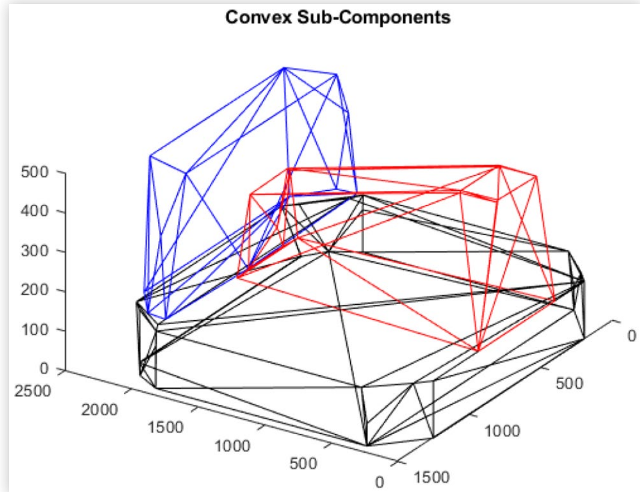
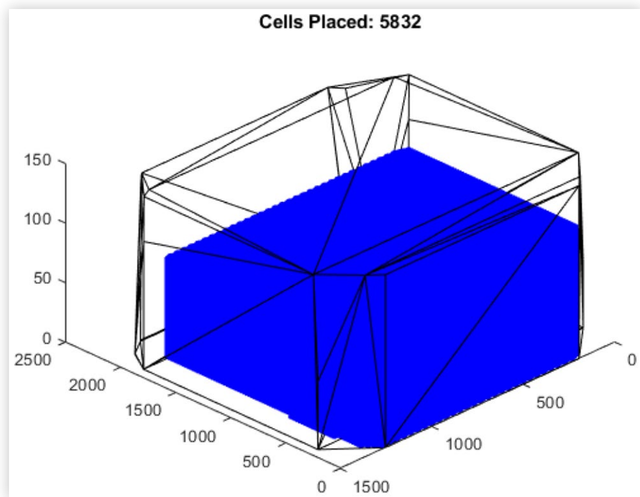


FIGURE 10 Packaged cells in the decomposed convex envelop



Parameter Optimisation Using Design of Experiments (DoE)

DoE Introduction DoE is a statistical method for modelling and optimising multi-variate systems. It was firstly introduced by Fisher in agricultural research in the 1930s [21, 22], and then adopted by the chemical and process industry in the 1950s [23]. DoE has been applied in the automotive industry since the 1980s [24, 25].

DoE is a statistical method for modelling and optimising multi-variate systems. The history of DoE development can be found in [26]. The modelling technique used in the DoE is Stochastic Process Model (SPM). A SPM is an empirical model capable of modelling multi-dimensional data; it is an interpolation-based method. Compared to the polynomial-based models of Response Surface Methodology (RSM), SPMs are better at handling highly non-linear systems, large numbers of variables, and complex interactions between input variables. The detail of SPMs can be found in Sacks et al [27].

The experiment designs used to define the test matrix are optimum space filling designs. These non-orthogonal designs are based on Latin Hypercube sampling with some enhancements to ensure adequate space filling in all dimensions.

A Ricardo developed DoE tool called the Efficient Calibration (ηCAL) Global DoE Toolkit is integrated into the Battery VPD toolchain. Therefore, in this paper, only using Battery VPD toolchain to do the battery design DoE is introduced. More information about the Efficient Calibration (ηCAL) Global DoE Toolkit can be found in [28].

Parameter Optimisation In this paper, a multi-stage DoE is used to support the battery system design. The first two stages DoE are introduced as the examples to show how the battery VPD toolchain can be applied to optimise the battery design parameters. The first stage DoE is to understand the dependence between the battery electrical configuration and cooling system design parameters. Based on the outcome of the first stage DoE, the second stage DoE is set up to investigate the electrical component and cooling system design parameter definition. These two DoE will be introduced in detailed in this section.

First Stage DoE The aim of the first DoE is to define the battery electrical configuration and cooling system size. The design variables include:

- the number of cells in series per module,
- the coolant flow rate, and
- the coolant inlet temperature.

In this DoE, the battery pack was configured to include no busbars, while the cooling strategy used was single-sided indirect cooling. The battery pack thermal and cooling model principle is shown Figure 11. By using the battery VPD toolchain, it is easy to configure the battery pack based on the requirement.

The design variables and their lower and upper bound are input to the battery VPD toolchain as shown in Figure 12. Then the DoE test matrix is created.

The design space of the first DoE is shown in Figure 13 which is a space for axes to display the design and a grid control to display the numerical values of the design. The red dots represent the main design.

The battery VPD toolchain developed a simulation management tool to execute a simulation sweep. Therefore, by using this tool, the first DoE test matrix are input for a series of simulation to get the DoE result.

The DoE result are collected to build surrogate models for the outputs relevant to the optimisation objectives. Then, these surrogate models are used to predict the response of the system at a specific test point, during the optimisation. The toolchain offers tools to evaluate the fitting of the surrogate models, by comparing the predicted value to the measured (in this case simulated) values as shown in Figure 14.

Having defined the surrogate models, multi-objective optimisation is carried out to identify the optimal values for

FIGURE 11 Battery pack thermal and cooling model principle of the first DoE

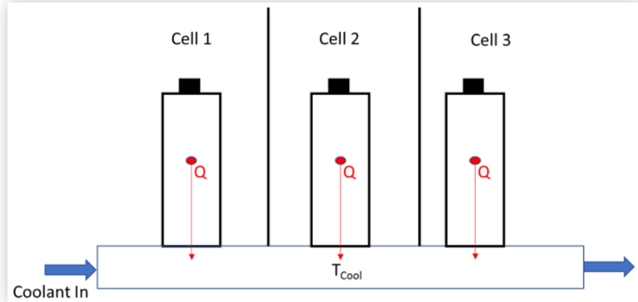


FIGURE 12 The DoE design sweep GUI in battery VPD toolchain

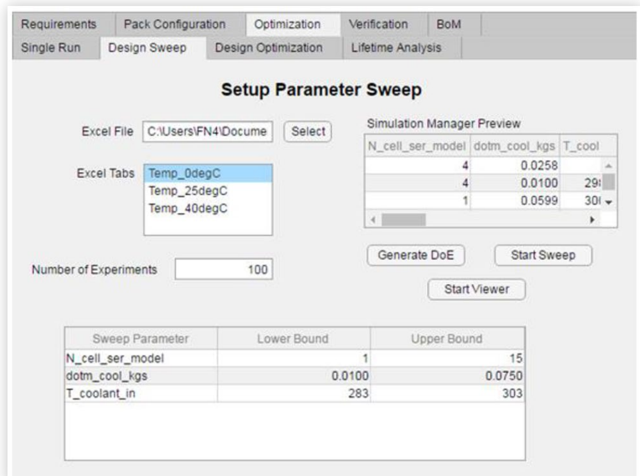


FIGURE 13 The DoE design space of the first DoE

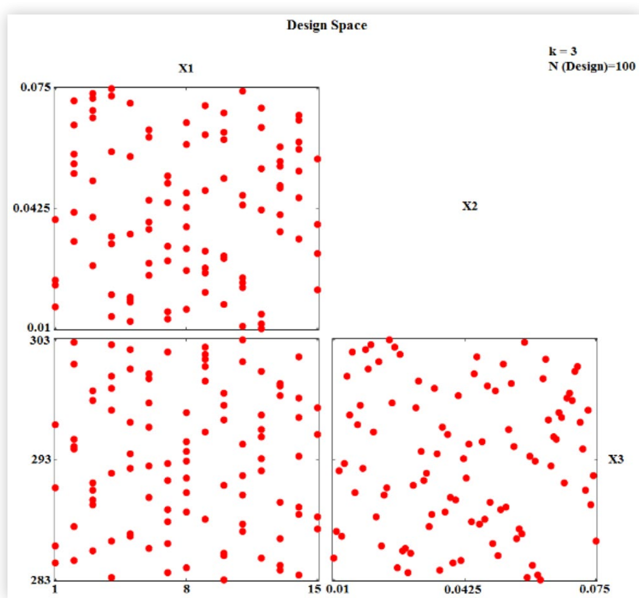
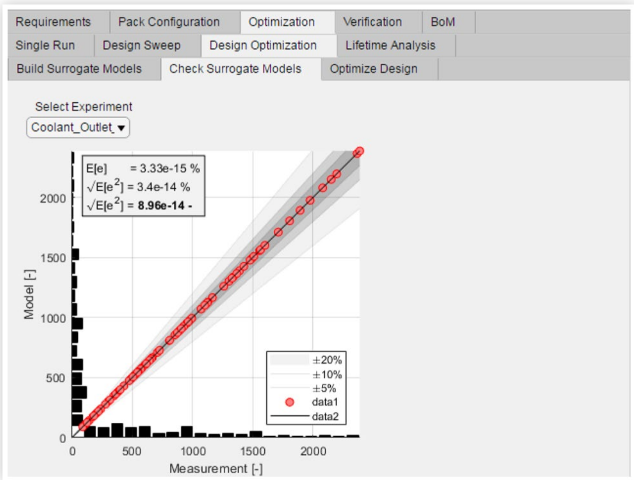


FIGURE 14 The surrogate model fitting result in battery VPD toolchain



the parameters in question, considering user defined constraints. The objectives of the first DoE are:

- Minimise the coolant flow rate; and
- Maximise the number of cells in series per module.

Some constraints are also considered, including:

- Pack voltage less than 60 V,
- Coolant temperature increase less than 3 °C,
- Coolant pressure drop less than 2.5 kPa, and
- Cell temperature less than 30 °C.

The objectives and constrains are input to the battery VPD toolchain for the optimisation as shown in Figure 15.

The resulting pareto trade-off curves (i.e. the set of points that satisfy the problem and its constraints), from the multi-dimensional optimization are presented in the Figure 16.

FIGURE 15 The optimisation set-up GUI in battery VPD toolchain

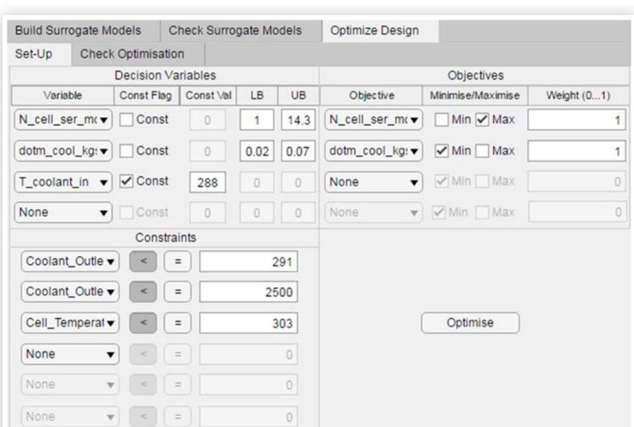
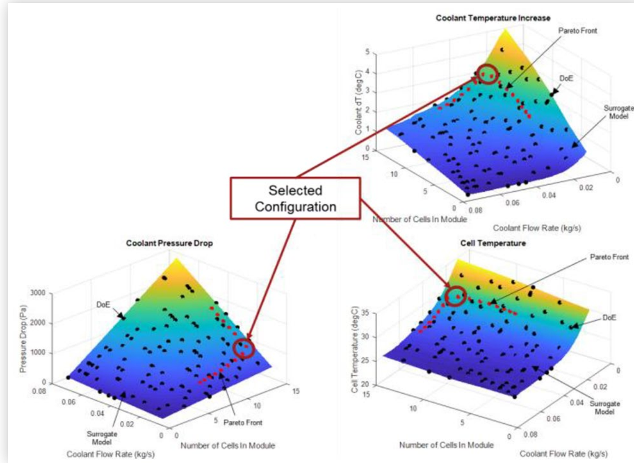


FIGURE 16 The pareto trad-offs curves of the first DoE



Based on the optimisation result, the battery electrical configuration and cooling system design parameters are chosen as below:

- Number of cells in series per module: 14
- Coolant flow: 0.0239 kg/s
- Coolant pressure drop: 835 Pa
- Coolant temperature increase: 2.92 °C
- Cell temperature: 29.33 °C

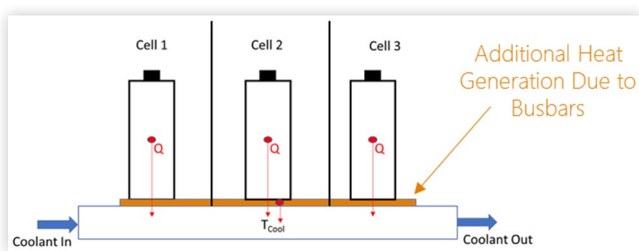
Second Stage DoE Based on the outcome of the first stage DoE, the second stage DoE is set up to investigate the electrical component (busbar) and cooling system design parameter (the coolant flow rate) definition. Therefore, the battery pack was configured to include busbars (both aluminum and copper busbars were tested), retaining single-sided indirect cooling. The model principle of the second stage DoE is shown in Figure 17. Also, because the first stage DoE had already identified the module size, the entire battery pack model was used in the second stage DoE.

The design variables for the second DoE are:

- the thickness of the busbar, and
- the coolant flow rate.

Also, the material of busbar, aluminium and cooper, were atested in the second DoE. Like the first stage DoE, the design

FIGURE 17 Battery pack thermal and cooling model principle of the second DoE



variables are input to the battery VPD toolchain to create the text matrix, and then a series of simulation is run to get the surrogate model of the second stage DoE. The objectives of the second stage DoE optimisation are:

- minimise the busbar thickness, and
- minimise the coolant flow rate.

The constraint of the optimisation is the cell temperature should be less than 30 °C.

The resulting pareto trade-off curves from the multi-dimensional optimization are presented in Figure 18 and Figure 19. And the optimal results are presented in Table 1, for both the aluminum and copper busbars.

According to those results, there is effectively no penalty on the performance when switching from copper to aluminium busbars. To support the decision of the busbar material, another set of simulations were carried out where the system was excited using a more intense duty cycle. The duty cycle selected was a 2C discharge from 95% to 10% SOC. The simulation result is shown from Figure 20 to Figure 22.

Analysing the simulation results shows that even though the selection of a copper busbar will improve the thermal behaviour of the system, the improvement is minimal. Considering the reduced cost and weight of aluminium, it was

TABLE 1 The result comparison of applying aluminium and cooper busbar

	Aluminium	Copper
Flow rate	0.48 kg/s	0.48 kg/s
Busbar Thickness	2 mm	2 mm
Cell Temperature	29.79 °C	29.71 °C

FIGURE 18 The pareto trad-off curve of applying aluminium busbar of the second DoE

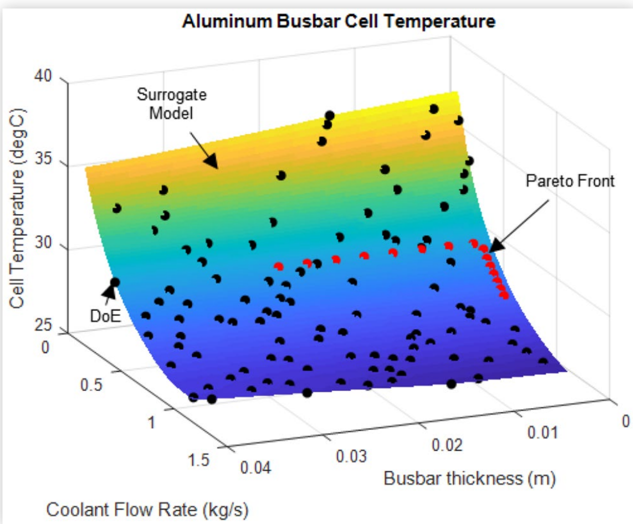


FIGURE 19 The pareto trad-off curve of applying copper busbar of the second DoE

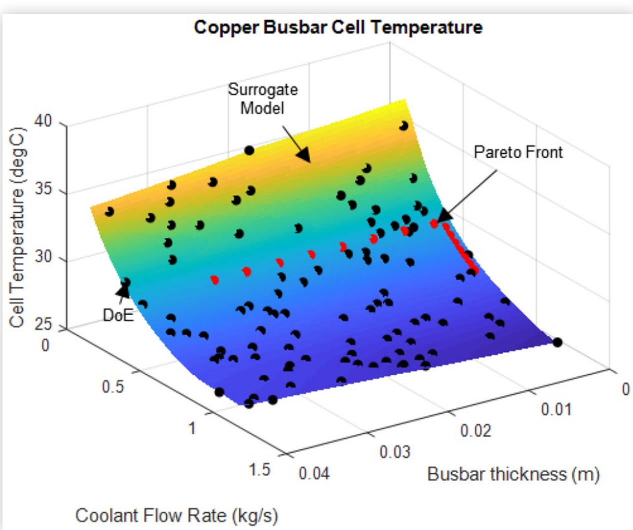


FIGURE 20 The cell temperature comparison between applying aluminium and copper busbar

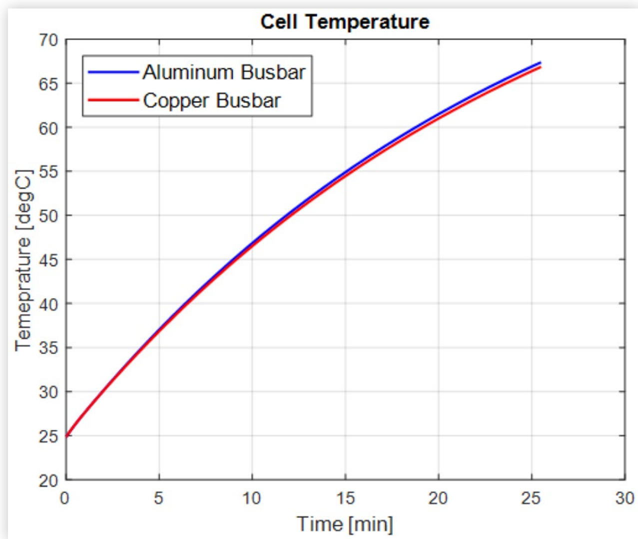


FIGURE 21 The busbar heat release comparison between applying aluminium and copper busbar

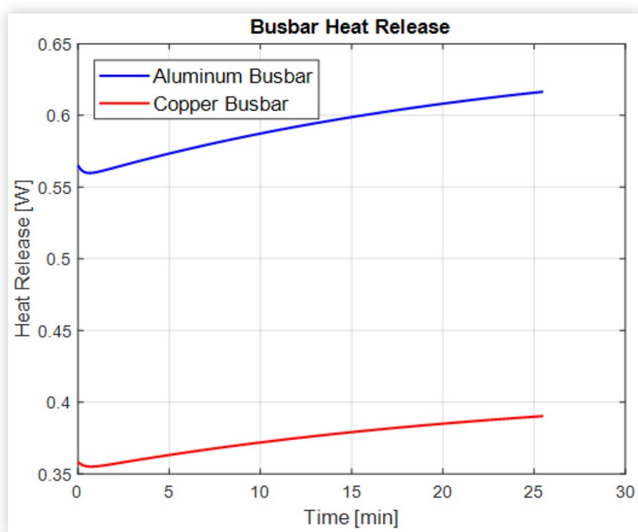
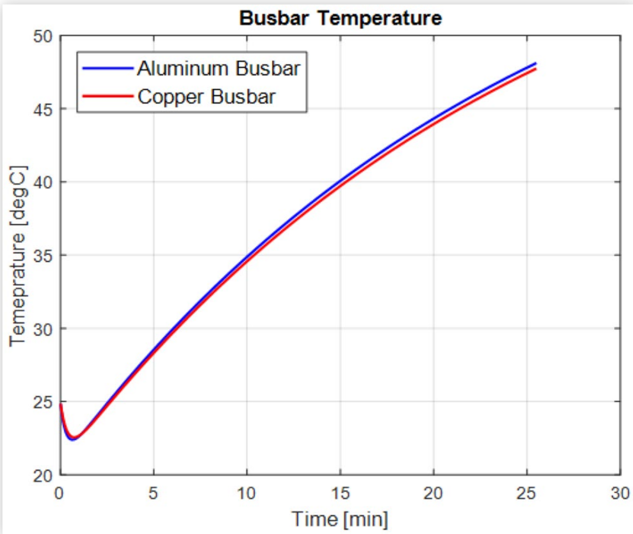


FIGURE 22 The busbar temperature comparison between applying aluminium and copper busbar



chosen as the busbar material. Therefore, the selected configuration for the second stage DoE are:

- Aluminium busbar
- Busbar thickness: 2 mm
- Coolant flow: 0.48 kg/s
- Cell temperature: 29.79 °C

Battery Concept Summary

Heat Path Analysis For definitive design of thermal systems, it is vitally important to understand the heat path from cell core (where most of the heat is generated) to coolant medium. The battery VPD toolchain provides a graphical summary of the concept heat path, for any configuration of cell (cylindrical, pouch, prismatic) and for a range of cooling solutions (forced air, liquid cold plate and immersion) as shown in Figure 23

Bill of Materials Using the application integrated in the toolchain, it is possible to generate preliminary BoM, to estimate the expected price of the battery pack (Figure 24). The generation is semi-automatic, the user is required to input the price per unit for each of the items on the list. When this activity is carried out, the table will automatically be updated, drawing information from the pack parameter file. The generated BoM can be exported to excel and used as the initial point of a more in-depth BoM.

Vehicle Front-Loading Simulation

Different simulation, such as the standalone battery pack simulation or Electric Vehicle (EV) driving cycle simulation,

FIGURE 23 Graphical representation of the battery concept heat path

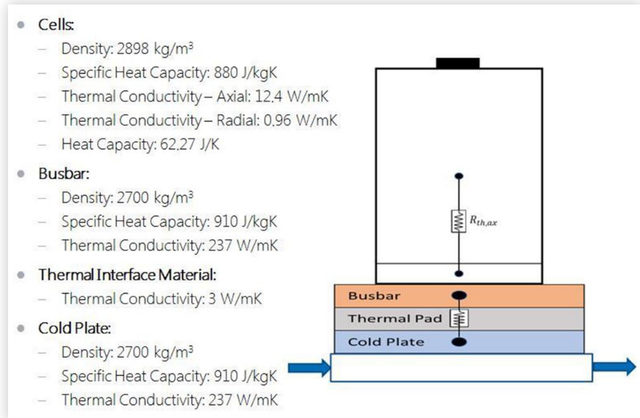
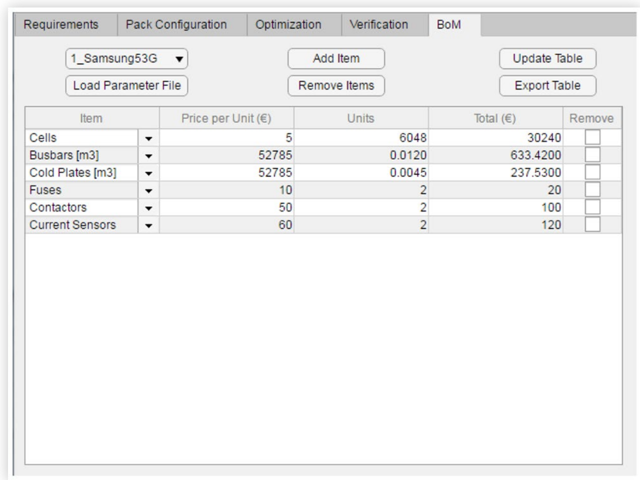


FIGURE 24 Bill of materials generation graphical user interface.

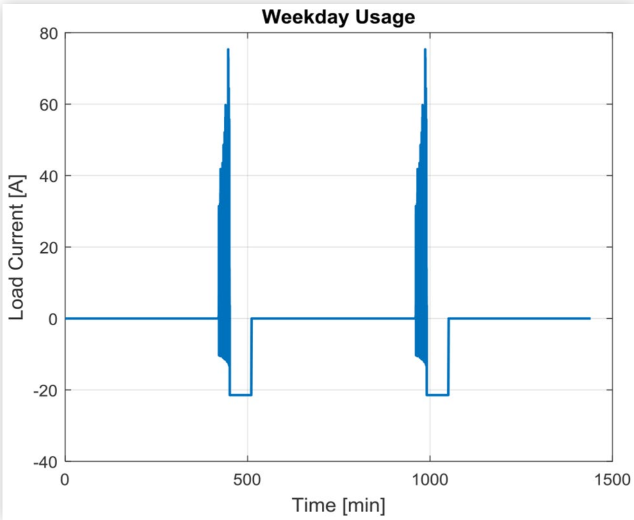


can be done with the battery VPD toolchain. Two simulation, lifetime analysis which only used the battery pack model, and vehicle co-simulation which integrated the battery pack model into an EV model, are introduces as the examples.

Lifetime Analysis To evaluate the End of Life (EoL) of the designed battery pack, lifetime analysis tools have been developed and integrated in the toolchain. The tools incorporate validated calendar and cycling ageing models. The calendar aging models estimate the increase in internal resistance and the capacity fade of the cell, under no load conditions. On the other hand, the cycling aging models estimate the same quantities, when the cell is under load.

To estimate the cell lifetime the user needs to define the usage stats. The usage stats are comprised of the predicted annual mission profile of the vehicle and the annual temperature distribution. In this case study, the mission profile was defined for each week and incorporates different drive cycles for weekdays and weekends. During the weekdays a simple drive cycle was assumed that emulates drive to and from work, with slow charging in between those drives (Figure 25). For

FIGURE 25 Weekday drive cycle



the weekends, highway drive was selected, with a period of super-fast charging and a period of slow charging (Figure 26). Finally, the temperature distribution was chosen to be Gaussian as presented in Figure 27.

Having defined the usage stats, the expected mileage of the battery pack before the end of life can be estimated. Assuming that a capacity fade of 20% marks the end of life, the battery pack designed in this case study has an expected usable life of 164 thousand km (Figure 28).

Vehicle Co-Simulation To assess the battery pack behavior achievable for a range of driving scenarios, a vehicle driving cycle simulation was done. The implementation of the battery model enables the user to integrate the battery VPD toolchain with other modeling tools such as the V-Sim library, Ignite etc. Over the past 20 years, Ricardo have developed a library of simulation models called Vehicle SIMulation (V-SIM). These models are coded in the MATLAB Simulink environment, and have been used to prepare the different models. Figure 29 shows, as an example, the V-SIM model used to simulate an EV. The model includes Drive Cycle, Controller, Gearboxes (single speed, one at each axle), E-machines (front & rear), and Vehicle. The Battery VPD toolchain was integrated into the model which inside the 'HIFI Battery Model' block. V-SIM is a forward-facing simulation code so includes a Driver model as well. In the simulation model, the vehicle input data is taken from public domain for a representative, EU vehicle - due to the limited number of EV variants on sale there is a limited range of input data

FIGURE 26 Weekend drive cycle

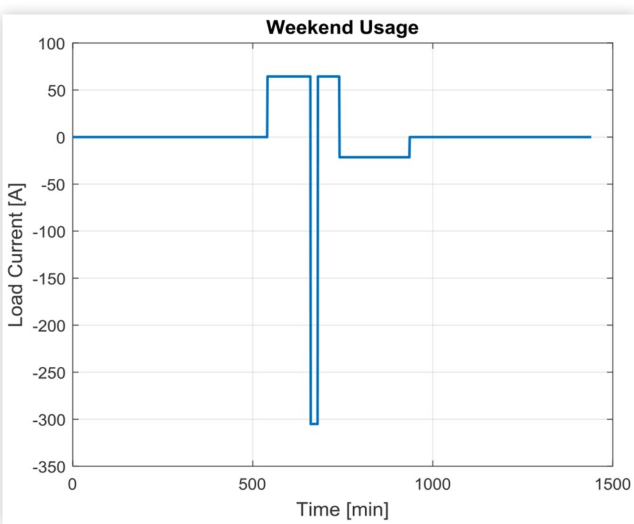


FIGURE 27 Annual Temperature Distribution

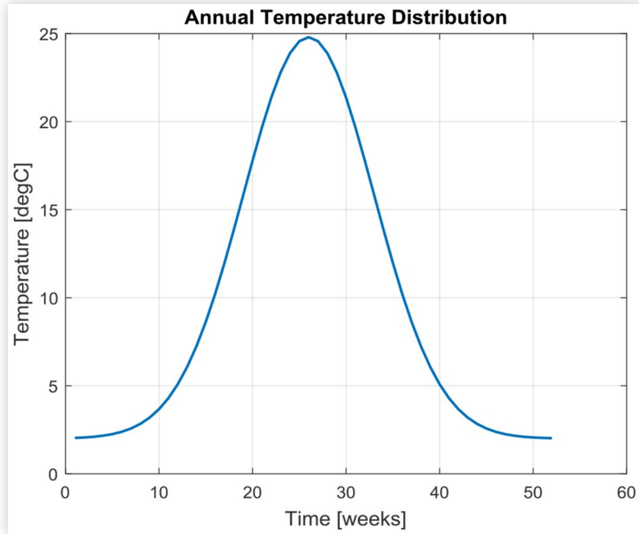


FIGURE 28 Cell capacity vs mileage in thousand km. The red line represents the EoL.

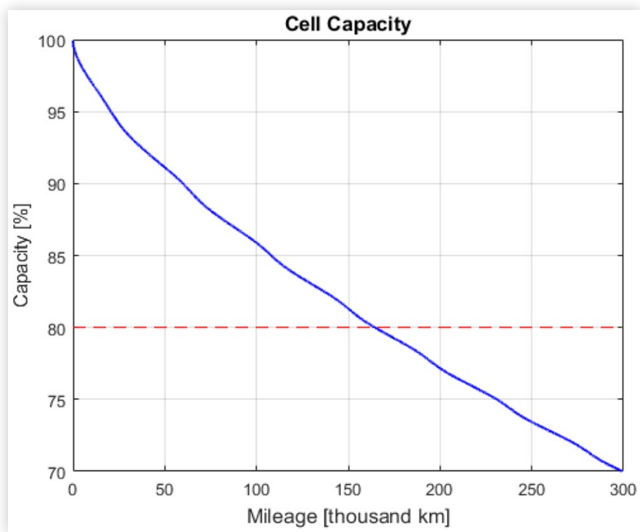


FIGURE 29 EV model built up on Ricardo V-SIM with Battery VPD toolchain

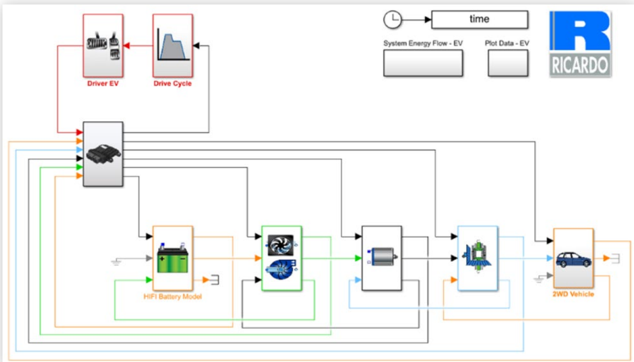


FIGURE 30 Vehicle speed of the vehicle Co-Simulation

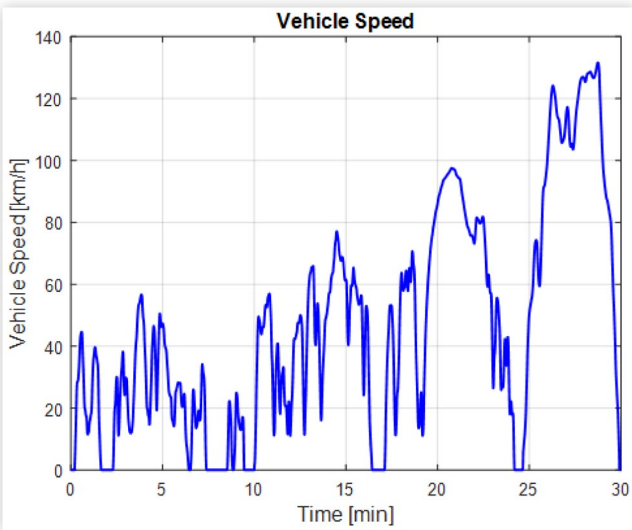


FIGURE 31 Battery pack load current of the vehicle Co-Simulation

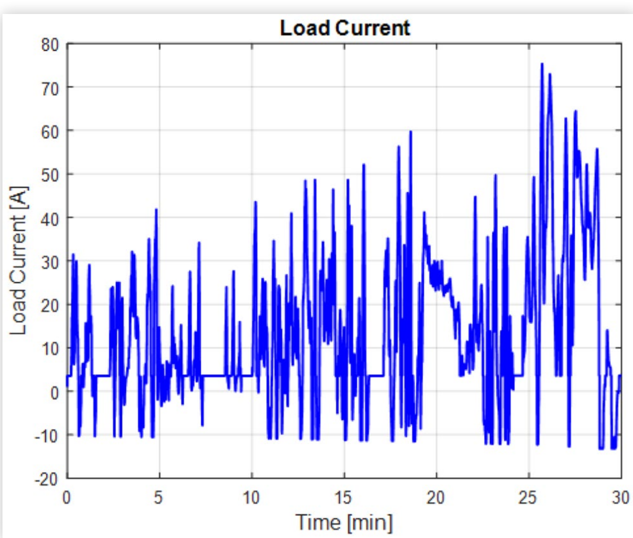


FIGURE 32 Battery pack terminal voltage of the vehicle Co-Simulation

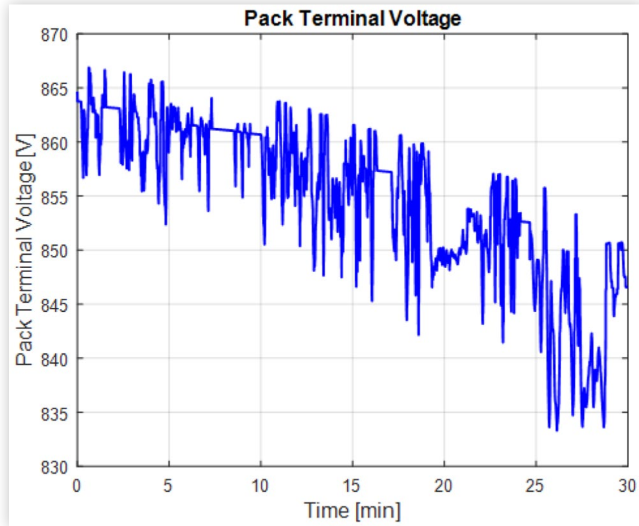
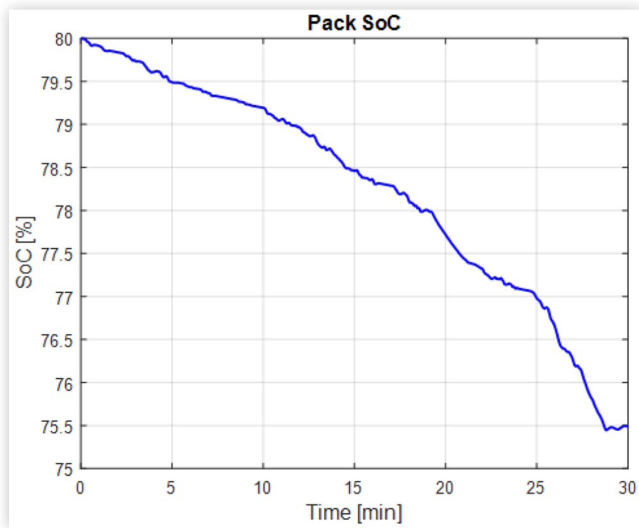


FIGURE 33 Battery pack SOC of the vehicle Co-Simulation



available. However, the exact vehicle specifications have minimal impact on the conclusions contained within this paper.

In this application, the battery pack defined previously was integrated to the EV model for a segment E vehicle, to extract the performance metrics. The driving cycle chosen was WLTC, out of a selection of driving cycles. The integration offers the possibility of assessing an extended set of metrics such as regeneration, derating etc. The simulation results are shown in the following figures. The vehicle speed is shown in Figure 30. The battery pack current, voltage, SoC and heat release are shown from Figure 31 to Figure 34, respectively. The key parameters metrics of the EV and battery pack are summarised in Table 2.

FIGURE 34 Battery pack heat release of the vehicle Co-Simulation

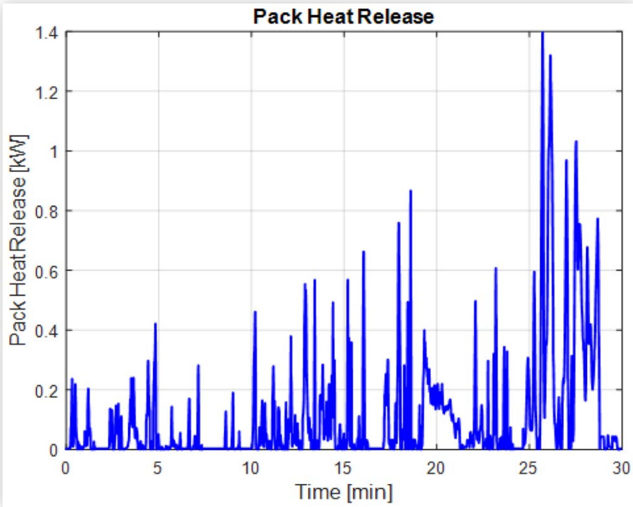


TABLE 2 Vehicle Co-Simulation performance metrics table

Metric	Value
SoC Drop per WLTC	4.5%
Vehicle Predicted WLTC Range (85% Usable SoC)	420 km
Battery Peak Discharge Power	62 kW
Battery Peak Discharge Current	74 A
Regenerative Braking Energy per WLTC	0.443 kWh

Conclusions

A battery Virtual Product Development (VPD) toolchain has been presented that enables rapid assessment of battery pack concepts with up to 50% reduction development time and can be used to address the key battery development challenges of today. The toolchain allows assessment of different battery concepts, assessment of packaging of cells into target envelopes and battery pack design optimisation using a DoE approach. The toolchain presents initial BoM and Heat Path analysis for all concepts studied. Finally, the battery pack concepts are seamlessly frontloaded with vehicle models to enable system level attribute assessment, including lifetime analysis against typical mission profiles.

A comprehensive demo case was presented that showcased the tool application to a typical battery pack concept design for a typical E segment passenger car detailing each phase of the workflow and explaining in detail the rationale behind certain decisions. Vehicle level performance metrics (including lifetime) for the proposed design were presented after front-loading of the battery concept with a vehicle model.

Future work will focus on application of the toolchain to diversified areas such as stationary, marine and aerospace battery pack developments. Further work will be carried out on feed-back of real in-service battery pack data to better inform actual product performance and provide insights into potential optimisation of future battery pack concepts.

References

1. Boulanger, A.G., Chu, A.C., . Maxx, S. and Waltz, D.L., "Vehicle Electrification: Status and Issues," *Proceedings of the IEEE* 99(6):1116-1138, 2011.
2. Cordoba-Arena, A., Onori, S., and Rizzoni, G., "A Control-Oriented Lithium-Ion Battery Pack Model for Plug-In Hybrid Electric Vehicle Cycle-Life Studies and System Design with Consideration of Health Management," *Journal of Power Sources* 279:791-808, 2015.
3. Li, J., and Mazzola, M.S., "Accurate Battery Pack Modeling for Automotive Applications," *Journal of Power Sources* 237:215-228, 2013.
4. Uddin, K., Picarelli, A., Lyness, C., Taylor, N., and Macro, J., "An Acausal Li-Ion Battery Pack Model for Automotive Applications," *Energies* 7(9):5675-5700, 2014.
5. Fan, G., Pan, K., Bartlett, A., Canova, M. and Rizzoni, G., "Electrochemical-Thermal Modeling of Li-Ion Battery Packs," in *ASME 2014 Dynamic Systems and Control Conference*, San Antonio, Texas, USA, 2014.
6. Perez, H., Shahmohammadhamedani, N., and Moura, S., "Enhanced Performance of Li-Ion Batteries via Modified Reference Governors and Electrochemical Models," *IEEE/ASME Transactions on Mechatronics* 20(4):1511-1520, 2015.
7. Guo, M., Jin, X., and White, R.E., "An Adaptive Reduced-Order-Modeling Approach for Simulating Real-Time Performances of Li-Ion Battery Systems," *Journal of The Electrochemical Society* 164(14):A3602-A3613, 2017.
8. He, H., Xiong, R., and Fan, J., "Evaluation of Lithium-Ion Battery Equivalent Circuit Models for State of Charge Estimation by an Experimental Approach," *Energies* 4(4):582-598, 2011.
9. Chen, M., and Rincon-Mora, G.A., "Accurate Electrical Battery Model Capable of Predicting Runtime and I-V Performance," *IEEE Transactions on Energy Conversion* 21(2):504-511, 2006.
10. McGahan, P., Rouaud, C., and Booker, M., "Comparison of Model Order Reduction Techniques for Real-Time Battery Thermal Modelling," SAE Technical Paper 2019-01-0503, 2019, https://doi.org/10.4271/2019-01-0503.
11. Pesaran, A.A., "Battery Thermal Models for Hybrid Vehicle Simulations," *Journal of Power Sources* 110(2):377-382, 2002.
12. Johnson, V.H., Pesaran, A.A. and Sack, T., "Temperature-Dependent Battery Models for High-Power Lithium-Ion Batteries," in *17th Annual Electric Vehicle Symposium*, Montreal, Canada, 2000.
13. Park, C., and Jaura, A.K., "Dynamic Thermal Model of Li-Ion Battery for Predictive Behavior in Hybrid and Fuel Cell Vehicles," SAE Technical Paper 2003-01-2286, 2003, https://doi.org/10.4271/2003-01-2286.
14. Nelson, P., Dees, D., Amine, K., and Henriksen, G., "Modeling Thermal Management of Lithium-Ion PNGV Batteries," *Journal of Power Sources* 110(2):349-356, 2002.
15. Sato, N., "Thermal Behavior Analysis of Lithium-Ion Batteries for Electric and Hybrid Vehicles," *Journal of Power Sources* 99(1-2):70-77, 2001.

16. Pesaran, A.A., Keyser, M. and Burch, S., "An Approach for Designing Thermal Management Systems for Electric and Hybrid Vehicle Battery Packs," in *The Fourth Vehicle Thermal Management Systems Conference and Exhibition*, London, UK, 1999.
17. Vetter, J., Novák, P., Wagner, M.R., Veit, C. et al., "Ageing Mechanisms in Lithium-Ion Batteries," *Journal of Power Sources* 147(1-2):269-281, 2005.
18. Merla, Y., Wu, B., Yufit, V., Brandon, N.P. et al., "Novel Application of Differential Thermal Voltammetry as an In-Depth State-of-Health Diagnosis Method for Lithium-Ion Batteries," *Journal of Power Sources* 307:308-319, 2016.
19. Tröltzsch, U., Kanoun, O., and Tränkler, H.-R., "Characterizing Aging Effects of Lithium Ion Batteries by Impedance Spectroscopy," *Electrochimica Acta* 51(8-9):1664-1672, 2006.
20. Zhu, D., Pritchard, E.G.D., and Silverberg, L.M., "A New System Development Framework Driven by a Model-Based Testing Approach Bridged by Information Flow," *IEEE Systems Journal* 12(3):2917-2924, Sept. 2018.
21. Fisher, R.A., *The Design of Experiments* (Edinburgh: Oliver and Boyd, 1935).
22. Yates, F., "Complex Experiments," *Supplement to Journal Royal Statistical Society* 2:181-247, 1935.
23. Box, G.E.P., and Wilson, K.B., "On the Experimental Attainment of Optimum Conditions," *Journal of the Royal Statistical Society. Series B (Methodological)* 13(1):1-45, 1951.
24. Grove, D.M., and Davis, T.P., *Engineering, Quality, and Experimental Design* (UK: Longman Scientific & Technical, 1992).
25. Taguchi, G., *System of Experimental Design: Engineering Methods to Optimize Quality and Minimize Costs*. Vol. 1 (New York: UNIPUB/Kraus International Publications, 1987).
26. Bao, R., Baxter, J., and Revereault, P., "Simulation Based Hybrid Electric Vehicle Components Sizing and Fuel Economy Prediction by Using Design of Experiments and Stochastic Process Model," SAE Technical Paper 2019-01-0357, 2019, https://doi.org/10.4271/2019-01-0357.
27. Sacks, J., Welch, W.J., Mitchell, T.J., and Wynn, H.P., "Design and Analysis of Computer Experiments," *Statist. Sci* 4(4):409-423, 1989.
28. Bao, R., Baxter, J., and Revereault, P., "Using Design of Experiments to Size and Calibrate the Powertrain of Range-Extended Electric Vehicle," SAE Technical Paper 2020-01-0849, 2020, https://doi.org/10.4271/2020-01-0849.

Contact Information

Dr Ran Bao
Senior Simulation Engineer
Ricardo UK Ltd.
Ran.Bao@ricardo.com

Nikolaos Fotias
Electronics Hardware Design Engineer
Ricardo Prague s.r.o.
Nikolaos.Fotias@ricardo.com

Paul McGahan
Technical Specialist
Ricardo Prague s.r.o.
Paul.McGahan@ricardo.com

Acknowledgments

This work has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 769935.

Definitions/Abbreviations

BEV - Battery Electric Vehicle

BMS - Battery Management System

BoM - Bill of Materials

CFD - Computational Fluid Dynamics

DoE - Design of Experiments

ECM - Equivalent Circuit Model

EIS - Electrochemical Impedance Spectroscopy

EoL - End of Life

EPMA - Electron Probe Microanalyzer

EV - Electric Vehicle

FuVA - Future Vehicle Architecture

GUI - Graphical User Interface

HIL - Hardware-In-Loop

IMBD - Integrated Model Based Design

PHEV - Plug-in Hybrid Electric Vehicle

RSM - Response Surface Methodology

SoC - State of Charge

SPM - Stochastic Process Model

V-SIM - Vehicle SIMulation

VPD - Virtual Product Development

WLTC - Worldwide harmonized Light vehicles Test Cycles

WLTP - Worldwide Harmonised Light Vehicles Test Procedure