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Sizing tool for rapid optimisation of pack configuration at early-stage automotive product development

James Taylor[1], Robert Ball[2], Andrew McGordon[1], Kotub Uddin[1], James Marco[1]
[1]*Warwick Manufacturing Group, The University of Warwick, Coventry, UK; J.E.Taylor@warwick.ac.uk; A.McGordon@warwick.ac.uk; k.uddin@warwick.ac.uk; James.Marco@warwick.ac.uk*
[2]*Tata Motors European Technical Centre, The University of Warwick, Coventry, UK; robert.ball@tatamotors.com*

Abstract

The specifications that define an automotive development project are established at an early point in the process and define the direction of such a development, and changing these decisions becomes more costly the further the project progresses. Tools to enable better consideration of choice can help prevent this. The tool presented is designed to aid with the decisions needed when embarking on the development of a vehicle that incorporates electric-vehicle technologies and the important choices made regarding the battery pack required by such a vehicle. The tool incorporates a sizing model for determining the number of cells and the configuration required to meet a specified battery requirement. The tool then uses a 1-d model to determine some of the basic thermal and power characteristics that can then be used to inform other parts of the design specification. When attached to a database containing cell information, the tool can pre-select candidate cells to meet the requirement, and rapid execution time of the tool means that it can be used to quickly compare between cell choices, at a level understandable by all stakeholders in the decision making process.

Keywords: Electric Vehicles, Hybrid Electric Vehicles, Batteries & Energy Storage, Design Tool

1 Introduction

When undertaking the development of a new automotive product, a set of initial requirements is drawn in order to meet the intended market space, covering aspects such as performance, lifespan, cost of use, cost of manufacture, price point and many other factors of its design [1]. This leads to other requirement specifications such as sizing, technologies to use and other more engineering aspects of the initial design [2].

When one of the technologies involved for consideration is electric vehicle (EV) technologies, the engineering design further evolves to include factors specific to this technology:- drive trains, power distribution systems, charging systems, electric motors and batteries [3]. Within these, the battery is at the core of the eventual performance of an EV product, governing factors such as range, dynamic performance and lifespan. The battery also represents a significant proportion of the product's value [4], and its design can inform other aspects of system design such as cooling and electronic management systems.

2 Aims and Modelling Parameters

The lithium ion battery systems currently favoured by EV systems are a rapidly growing market, with the number of providers of lithium ion cells growing at a steady rate [5]. Ideally, a battery design for an EV product would analyse and compare all the available cells to arrive at a perfectly informed choice. This would require highly detailed models and a quantity of time that makes such an approach impractical; for example, to demonstrate the performance of a battery over 10 years, 10 years of data for every cell type would need to be collected. The design of the battery is central to the overall design, and needs to be established quickly so that the rest of the design process can continue.

This tool aims to provide a means to quickly compare cells against high-level requirements, allowing an informed choice of battery and cell characteristics as soon as possible during the design process. The models used prioritise rapid approximation over precise accuracy, but enables the selection of a few 'best candidates' that meet the performance requirements, and produce details of factors that impact other areas of design; thermal output and physical dimensions. This allows other areas of design to proceed with knowledge of the battery design, carried out in parallel with the detailed finalisation of the battery design.

To achieve this, the model was designed to test cells against multiple drive cycles that simulate the power demands of an EV system matching the requirements of a design. A sizing model would determine the number and configuration of a given cell type required to meet this power demand and generate a pack specification. A thermal model is then used to determine the amount of heat generated during drive cycles against different internal cooling models, and overall heat generation and temperature rises calculated. An accuracy target of ±15% was chosen for both the cell power model and thermal generation, suitable for high-level candidate selection and scope for selecting models based on speed.

3 Sizing Tool Models

For ease of use and portability, the models were constructed using Microsoft Excel, combining spread sheets and macros to produce the desired models while keeping the execution time for models to a minimum within the constraints of the software. This means reducing the complexity of the models as far as possible while maintaining the desired accuracy level.

3.1 Pack Sizing

The pack sizing model takes several factors into consideration from the EV design specification: pack weight, pack dimensions, peak power output, nominal power output and total capacity. The number of series cells required is based on pack voltage requirements, calculated as

$$n_{series} = \frac{V_{PACK}}{V_{CELL}} \quad (1)$$

The parallel number of cells is calculated from either the total energy capacity or peak power requirements. The parallel strings determined by energy requirement are calculated by

$$n_{PARALLEL(E)} = \frac{E_{PACK}}{n_{series} \times CAP_{CELL}\,(Ah) \times V_{CELL}(V)} \quad (2)$$

or by power requirement as

$$n_{PARALLEL(P)} = \frac{P_{PACK}}{V_{CELL} - (Imax_{CELL} \times Rint_{CELL}) \times Imax_{CELL} \times n_{SERIES}} \quad (3)$$

The internal resistance of the pack is calculated using

$$Rint_{PACK} = Rint_{CELL} \times \frac{n_{SERIES}}{n_{PARALLEL}} \quad (4)$$

The maximum pack current is calculated using

$$Imax_{PACK} = \frac{\left(V_{PACK} - \sqrt{V_{PACK}^2 - 4 \times Rint_{PACK} \times P_{PACK}}\right)}{2 \times Rint_{PACK}} \quad (5)$$

The pack weight, dimensions and costs are calculated from configurable scaling factors based on the estimated proportion of the contribution to the total pack made by the cells.

3.2 Thermal Generation Model

Once the pack has been sized, a basic estimate of its heat generation can be made for use in the thermal and cooling models. The maximum pack heat generation is calculated by

$$HEAT_{PACK} = Imax_{PACK}^2 \times Rint_{PACK} \quad (6)$$

The maximum cell heat generation is equation 6 divided by the total number of cells.

The heat transmission coefficient, expressed in W/m^2, is also calculated as a guideline for the amount and type of cooling required by a pack configuration. This is calculated by

$$K = \frac{HEAT_{CELL} \times 10^6}{AREA_{COOL} \times (T_{MAXCELL} - T_{COOL})} \quad (7)$$

3.3 Cooling Model

The cooling model calculates the heat transfer between the pack and a coolant. This is achieved by constructing a 1-d thermal network between the pack and the coolant, shown as an electrical equivalent representation in figure 1.

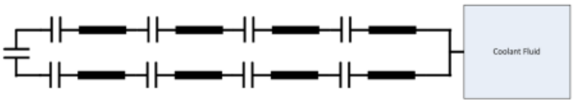


Figure 1 Thermal network used by cooling model

The cell is attached to the left hand of this model, and the coolant attached to the right of the model. The capacitances and resistances represent the heat capacity and thermal resistance of the various connecting components within the cell. The precise configuration of thermal components depends on a combination of cell format (cylindrical or pouch) and cooling method (none, tab, surface heat-transfer plate).

The parallel paths represent the thermal paths through the positive and negative tab connections. The other components represent other interface elements of the thermal path, such as cell wall, tabs, glue, coolant plate and coolant wall. The heat capacity and thermal resistances of each individual component are calculated based on dimensions and material [6, 7], and then used in the thermal network illustrated in figure 1.

Using this cooling information, the maximum amount of heat extraction is calculated. This is subtracted from the pack heat generation, and the remaining heat energy used to calculate the temperature rise of the pack based on the heat capacity of the pack.

4 Parameter Data and Assumptions

4.1 Parameterisation

To parameterise the models, a quantity of cell data is required, as well as some knowledge about predicted cooling design.

For the cells, the information required is available from detailed data sheets. As part of the Catapult project, the relevant data has been collected into a unified database which can be used to select cell data and provide a rapid means to compare candidate cells for a given set of requirements.

For the cooling model, knowledge about the dimensions and materials likely to be used as part of the cooling systems is required. This is configurable within the tool, and the current iteration of the sizing model includes systems currently under consideration by the Catapult project.

4.2 Assumptions

In constructing this model, certain assumptions have been made. Much of the parameterisation data is sourced from data sheets, and so represents an ideal mean; the accuracy considerations of the natural variations in manufacture are not explicitly considered, but can be included as part of a sensitivity analysis.

For the sizing model, no restrictions are placed on cell number or configuration, and so do not take into account the size of available module units (for instance, the available cell module requires the cells to be used in multiples of 12). Nominal resistances and voltages are used throughout, ignoring any voltage variation affects that may occur due to load, ageing or variations in state of charge.

The 1-d nature of the thermal model prevents the modelling of any thermal gradients and the all of the heat flow is through the considered heat path, ignoring the possibility of alternatives.

5 Tool usage and data presentation

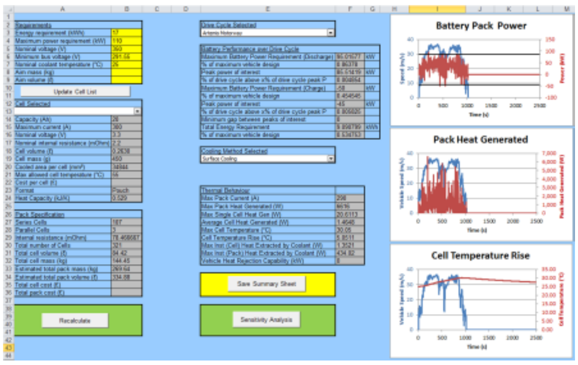


Figure 2 Full tool overview

Once the models have been configured, the tool can now provide a rapid means of comparing candidate cells. The user first enters their pack requirements in the first yellow section, followed by updating the cell list. This compares the requirements against the cell database collected by the Catapult project, collated from available datasheets from cell manufacturers, and pre-selects the 10 best candidates for consideration.

5.1 Sizing Results

Requirements	
Energy requirement (kWh)	17
Maximum power requirement (kW)	110
Nominal voltage (V)	350
Minimum bus voltage (V)	291.55
Nominal coolant temperature (°C)	25
Aim mass (kg)	
Aim volume (ℓ)	

Update Cell List

Cell Selected	
Capacity (Ah)	20
Maximum current (A)	300
Nominal voltage (V)	3.3
Nominal internal resistance (mOhm)	2.2
Cell volume (ℓ)	0.2630
Cell mass (g)	450
Cooled area per cell (mm²)	34844
Max allowed cell temperature (°C)	55
Cost per cell (£)	
Format	Pouch
Heat Capacity (kJ/K)	0.529

Pack Specification	
Series Cells	107
Parallel Cells	3
Internal resistance (mOhm)	78.466667
Total number of Cells	321
Total cell volume (ℓ)	84.42
Total cell mass (kg)	144.45
Estimated total pack mass (kg)	269.64
Estimated total pack volume (ℓ)	334.88
Total cell cost (£)	
Total pack cost (£)	

Recalculate

Figure 3 Sizing results

The user can now select a cell of interest, and the sizing model reacts dynamically to the selection of the user, updating the results immediately.

5.2 Thermal Results

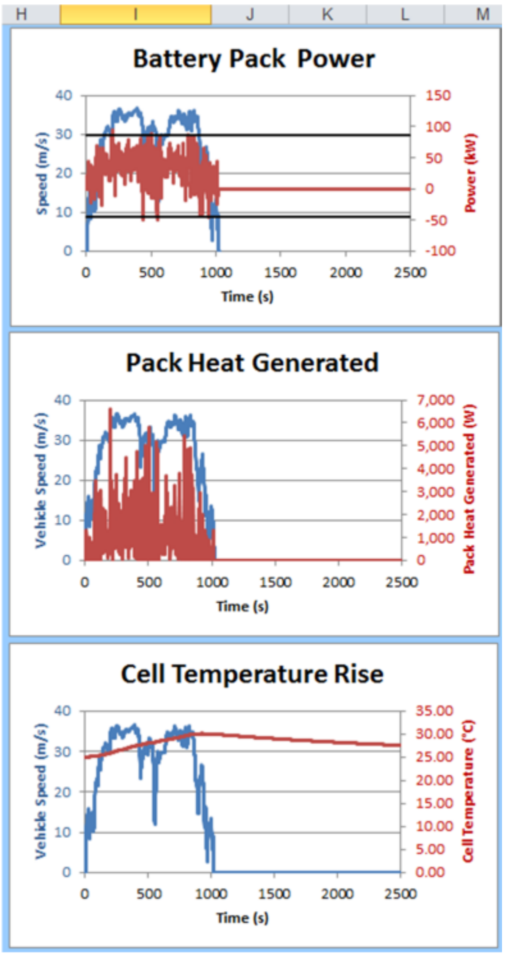
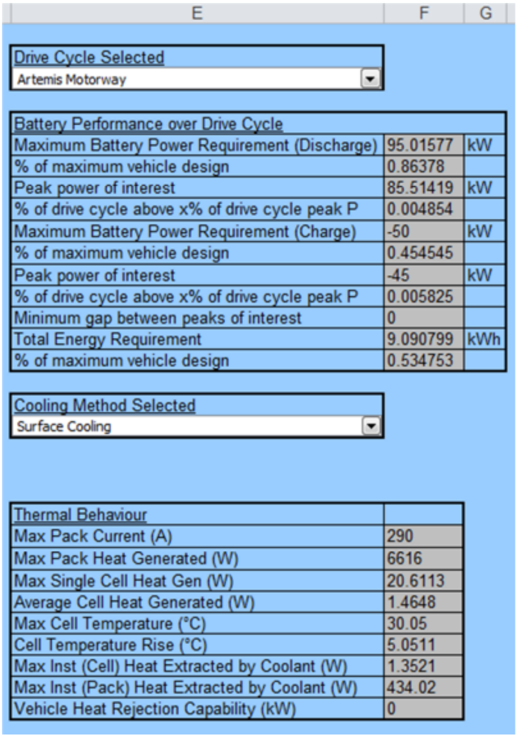


Figure 4 Thermal Results

Once a cell has been selected, the thermal performance of the cell over various drive cycles can now be considered. A number of drive cycles are included with the tool (Artemis, FTP, NEDC), although additional drive cycles can be configured into the tool, based on either a power requirement profile or a velocity profile and a simple road vehicle model (with configurable vehicle). Once a drive cycle is selected, the user can now examine the differences in thermal performance by choosing between difference cooling approaches. The execution time for the cooling models is the greatest, and computation takes a few seconds on a standard Windows computer.

5.3 Other Information



Drive Cycle Selected		
Artemis Motorway		
Battery Performance over Drive Cycle		
Maximum Battery Power Requirement (Discharge)	95.01577	kW
% of maximum vehicle design	0.86378	
Peak power of interest	85.51419	kW
% of drive cycle above x% of drive cycle peak P	0.004854	
Maximum Battery Power Requirement (Charge)	-50	kW
% of maximum vehicle design	0.454545	
Peak power of interest	-45	kW
% of drive cycle above x% of drive cycle peak P	0.005825	
Minimum gap between peaks of interest	0	
Total Energy Requirement	9.090799	kWh
% of maximum vehicle design	0.534753	
Cooling Method Selected		
Surface Cooling		
Thermal Behaviour		
Max Pack Current (A)	290	
Max Pack Heat Generated (W)	6616	
Max Single Cell Heat Gen (W)	20.6113	
Average Cell Heat Generated (W)	1.4648	
Max Cell Temperature (°C)	30.05	
Cell Temperature Rise (°C)	5.0511	
Max Inst (Cell) Heat Extracted by Coolant (W)	1.3521	
Max Inst (Pack) Heat Extracted by Coolant (W)	434.02	
Vehicle Heat Rejection Capability (kW)	0	

Figure 5 Other information

As well as thermal information, details about the electrical performance and energy requirements of a drive cycle are also included. This is useful to compare the differences in maximum levels (of, for example, power) with those seen in typical duty cycles.

5.4 Sizing Sensitivity Analysis

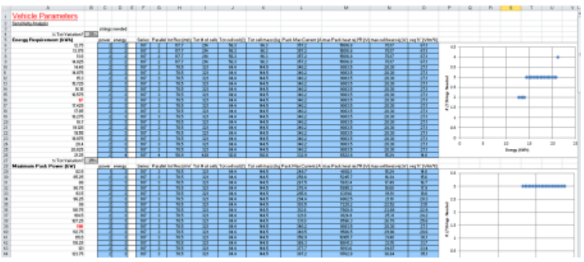


Figure 6 Sample from the sensitivity analysis

In addition to the performance results, a sensitivity analysis of the pack sizing model is included. This shows how the number of series or parallel strings of cells will alter in response to a change in requirements, allowing the user to see at a glance where possible improvements or concessions can be made. This also allows possible effects on vehicle performance to be investigated (e.g. the effect of ageing modelled by increasing the cell resistance).

6 Model Validation

In order to validate the models used by the tool, the results generated were compared to real data collected by TMETC and obtained through the Low Carbon Vehicle Technology Programme (LCVTP). This was done at cell and module level for the collective thermal and cooling models.

To analyse the performance of the model, the mean temperature error was calculated

$$Mean\ error = \sum \frac{|x_{model} - x_{measured}|}{n} \quad (8)$$

If the mean error for a cycle lay within ±15% of the measured value, the model was deemed to have performed well for the purpose of this tool.

6.1 Cell

A sample cell was instrumented with thermocouples at 5 points on its surface. This cell was then subjected to full discharge cycles at 1C, 3C, 5C and 10C, a full charge cycle at 1C and two drive cycles based on collected drive cycles from a BEV (battery electric vehicle) and HEV (hybrid electric vehicle).

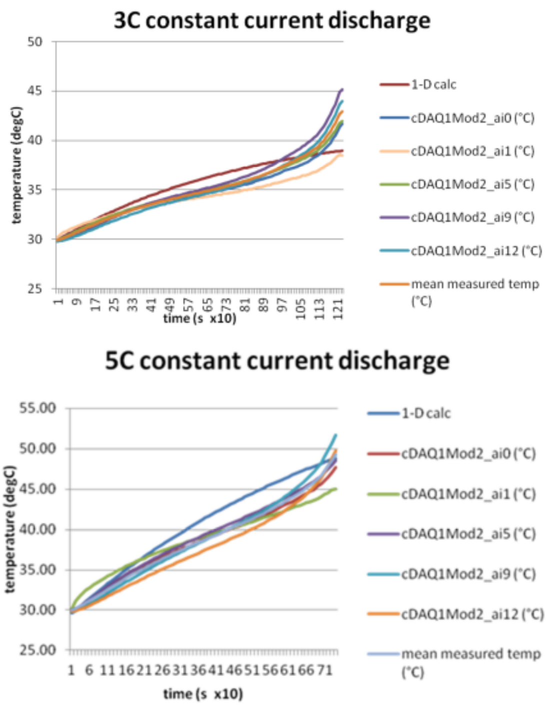


Figure 7 Temperature rise of the sample cell under discharge conditions against the 1-d thermal model

The constant performance tests, representative examples shown in figure 7, when compared to the results provided by the 1-d model used by the tool, show a mean error of 0.9°C for the 3C test, and 1.9°C for the 5C test. This represents an error <10% and well within the required accuracy for this model. There is greater variance at the extremes of state of charge; however this could be expected of the coarse model, since the internal resistance increases considerably at low state of charge.

The dynamic drive cycle tests shown in figure 8 performed similarly to the constant performance tests, with a mean error of 0.7°C for the BEV cycle and 5.6°C for the HEV cycle, and within the required 15% accuracy, with a noted over-response to high C-rate transients.

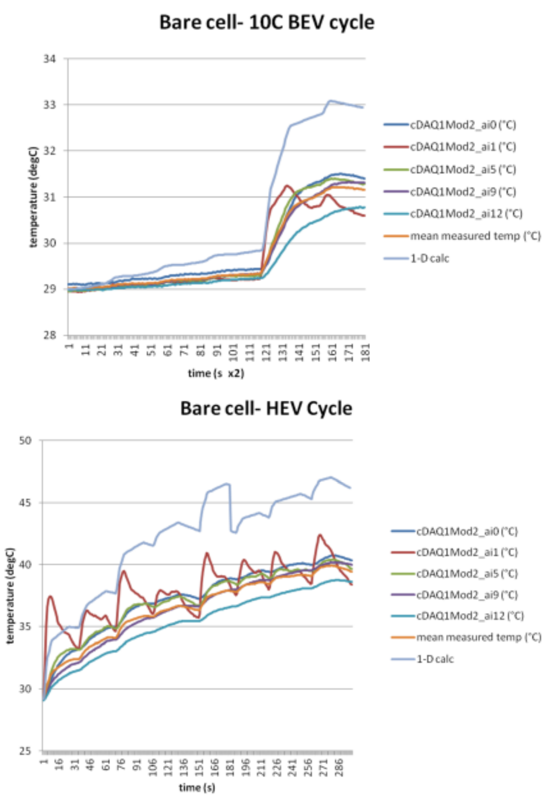


Figure 8 Temperature rise of the sample cell during BEV and HEV drive cycles against the 1-d thermal model

6.2 Module

A module was constructed using the same types of cell as used during the cell validation, and the central cell of the module was instrumented with 8 thermocouples attached to its surface at different points. The module used a surface heat transfer plate as its cooling strategy.

The module was subjected to 4 tests: discharge at 1C and 4C, and the same BEV and HEV drive cycles. Figure 9 shows how the module during the constant discharge tests. These tests matched the 1-d model with a mean error of 1.2°C for the 1C test and 4.2°C for the 4C test. This matches closely to the <10% error of the individual cell, and showed the same inaccuracy at extreme state of discharge.

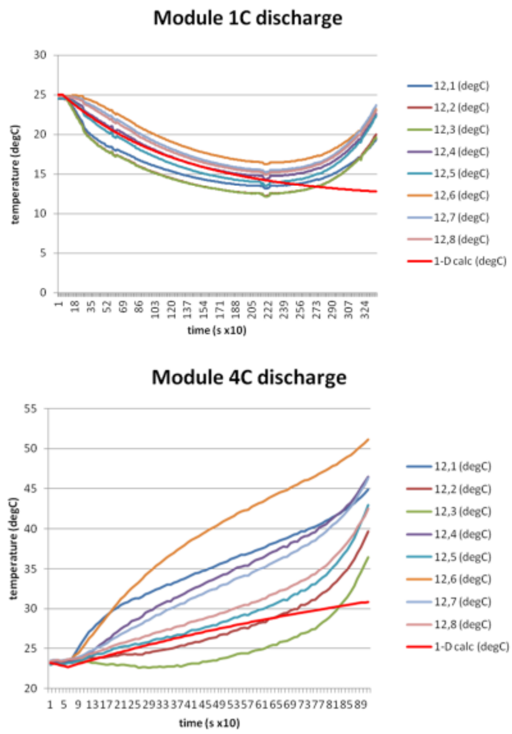


Figure 9 Temperature rise of the sample module under discharge against the 1-d thermal model

Figure 10 shows a dynamic behaviour from the model that closely matches the real module data, with mean error of 1.6°C for the BEV cycle and 0.3°C for the HEV cycle. This suggests that the model performs better when considering modules or packs exercised over a realistic state of charge range as seen in vehicles.

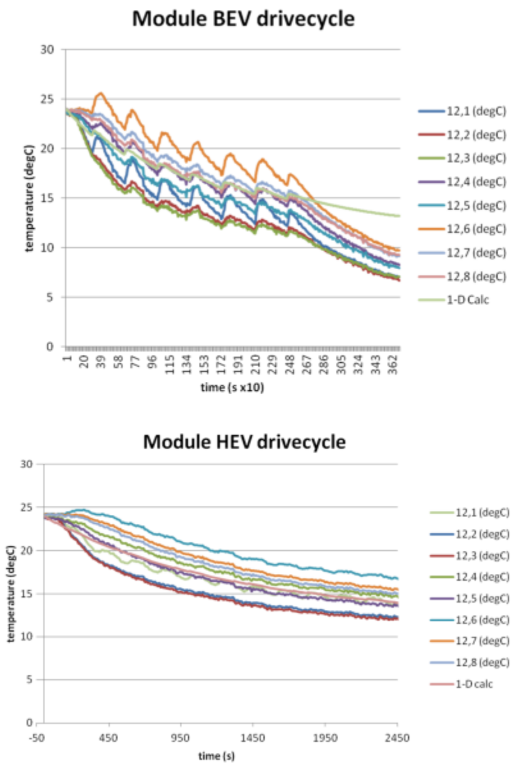


Figure 10 Temperature ruse of the sample module during drive cycles against the 1-d thermal model

7 Conclusion

In this paper, a tool has been presented that allows rapid comparison between cell choices for high-level pack design decisions. A sizing model generates a battery pack using a selected cell, and can be altered quickly to compare cell types. The 1-d model used by the tool then generates useful power and thermal data that can be used to further inform design decisions. The tool executes in a few seconds, allow consideration of many cell types within a small timeframe, and it can be automated.

The models used are fairly simple and make some broad assumptions. More complex models would improve the accuracy of the 1-d model results, but this would come at the expense of speed. The purpose of this model is to provide early-stage information to guide initial design decisions, and so more accurate models were deemed unnecessary for this stage, and should be reserved for the more detailed design work further down the development process.

Validation work carried out on the 1-d model shows that the model performs well within the 15% accuracy target under standard conditions, although extreme conditions (low/high state-of-charge, high C-rate transients) present problems to the model. This was deemed acceptable for the purposes of this tool for the same reasoning as above, and more detailed design work can be carried out to address these situations.

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Authors

Dr James Taylor has a MEng degree in Electronic Engineering and a PhD in 'Novel convolution-based processing techniques for application in chemical sensing' at the University of Warwick, UK. James joined WMG in October 2012 as part of the Catapult High-Value Manufacturing programme, and is currently a Research Fellow in the Energy Storage and Management group at WMG, working on data management approaches, data mining and statistical analysis of energy storage data.

Robert Ball is a Lead Engineer at Tata Motors European Technical Centre, where he develops HV batteries. He has worked on electric and hybrid vehicles of various types for over 20 years, in both academia and industry. Robert started as an engineering apprentice at BAE, graduated with a BSc Hons in Electronics, Computer and Systems Engineering from Loughborough University (UK) and later with an MPhil in automated testing from Lancaster University (UK).
He has worked in the automotive industry since 2002,in which time he has been involved in the design and development of a variety of HV systems, from the first KERS systems for F1 racing through to hybrid commercial vehicle powertrains.

Dr Andrew McGordon has a BSc (Honours) degree in Physics, and a PhD in 'The Current-Voltage and Noise Properties of High Temperature Superconductor SNS and Grain Boundary Junctions' at the University of Birmingham (UK).
Andrew joined WMG in May 2005 working on the Premium Automotive Research and Development Hybrid Vehicle projects and developed the hybrid powertrain simulation tool, WARPSTAR. Andrew is currently a Principal Engineer in the Energy Storage and Management group at WMG, working on energy storage and vehicle modelling, alternative range extender technologies, and real world fuel economy.

Dr Kotub Uddin holds a doctorate in Theoretical Physics. After graduating he joined the Department of Research at Jaguar Land Rover as a Senior Research Engineer working on design optimisation and control. He later transferred to the Hybrids Research team working on mathematical modelling of electrochemical systems for energy storage and automotive battery design. Kotub is currently employed as a Senior Research Fellow at The University of Warwick researching energy storage systems and applications to low carbon transport.

Dr James Marco is a Chartered Engineer and holds an Engineering Doctorate. He has worked for several years within the automotive industry on a number of different projects including those involving Ford (North America and Europe), Jaguar Cars, Land Rover and Daimler Chrysler. He is currently employed as an Associate Professor in Vehicle Electrification and Energy Storage at Warwick Manufacturing Group, University of Warwick.