**ENGR7019 Engineering Dissertation Project Proposal**

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AI-Driven Physics Based Battery Model Parameterisation with PSO-LM

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# Background

The advanced battery technology market is growing at a significant rate and producing new ground-breaking cell chemistries. However, the technology which monitors the functional safety and performance of the battery pack in automotive and motorsport applications is still primitive and does not unlock the full potential of the new batteries coming to market.

This component is called a Battery Management System (BMS), which makes approximations for the State Of Charge (SOC) and measures other electrical conditions to decide whether the battery pack is damaged or is exceeding performance limits.

The foremost issue is not primarily a hardware-based problem, the key issue is how the battery is modelled in the BMS and the systematic approach of how the battery pack is being parameterised. Most BMS’s use Equivalent Circuit Models (ECM’s) to project SOC and functional safety breaches, but ECM’s use simulated electrical components to map the behaviour of cell. This level of modelling does not consider the physical and chemical interactions happening inside the cell, which misses the true response characteristics of the cell and takes significant testing time to obtain.

The modelling approaches this paper analyses and will look to build upon, uses physical and chemical based interactions to better measure cell performance. However, this does come at a cost of high computational effort to analyse the complex interactions, so the dependency on data-driven Artificial Intelligence (AI) is critical.

This form of research is completely new field, so any step which requires less computational effort or time to get high fitting data is highly advantageous to the industry.

# Literature review

The following literature review will pivot of three key concepts which help to conceptualise the paper.

## ECM compared to P2D

An ECM as explained in the background uses Resistor and Capacitor (RC) networks to determine the electrical behaviour, this is done by lumping RC’s together and corresponding RC values to obtain the Open Circuit Voltage (OCV) and SOC performance for a given cell’s chemistry. In R. Zhang et al [1] work it captures and discusses a few different lumped RC models of increasing order, pictured in Figure 1.

Diagram, schematic

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Figure : The commonly used battery electrical equivalent circuit model [1]

The overriding consensus from R. Zhang et al work, the key limitation using this approach is the time required to obtain the data to accurately depict the chemical behaviour, as the level of fitting to physical data is critical. Likewise, Y. Zheng et al [2] agrees by looking that Electrochemical model based approaches out performs ECM in the SOC estimation. However, Y. Zheng et al does helpfully show that level of complexity is higher, which will make it less advantageous for lower fidelity online based solvers (Figure 2).

Diagram

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Figure : Estimation error and computational complexity for the commonly studied SOC estimation methods [2]

The Pseudo Two-Dimensional (P2D) model is one type of electrochemical model, which M. S. Trimboli et al [3] covers in more depth. The fundamental of this model is that the porous material on both electrodes, is simplified to be a perfect circle in the 2D domain (Figure 3), the model then has multiple systems of partial differential equations to govern the behaviours such as the concentration gradients at temperature to the mechanics of how electrons flow through the separator.

Chart

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Figure : P2D Porous-Electrode model [3]

The systems of equations drive upwards of 26 different parameters, which are all defined in A. M. Bizeray et al’s work [4].This is incredibly advantageous as it gives much more control to idealise the behaviour of the cell in comparison to ECM models RC values.

This can be seen more prominently when looking at the how the models are deployed onto a simulated BMS. Again from M. S. Trimboli’s work from the University of Colorado [5] shows by deploying Model Predictive Control (MPC) measures to both PBM and ECM models that the performance benefit for PBM is significant (Figure 4).

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Figure : ECM against a PBM from MPC analysis [5]

Figure 4 shows ECM over projecting discharge performance, which will cause faster degradation for individual cells and ECM under projects the true performance in charging. However, this approach of MPC on PBM is not that deployable to hardware BMS’s as computational time is significant, which L. Zhang et al [6] states in their conclusion for ECM models against PBM, that the computational time for a PBM is upwards of 9600 seconds versus a negligible amount of time for ECM models.

In conclusion, the author has shown the fundamentals and concepts of an ECM and P2D model, and the overall positives and negatives of deploying the models. The author is looking to build on how PBM are implemented but wants to emphasize the goal of the paper comes from further optimisations of the 26 parameters for PBM, as the next section (2.2) will show the challenges of measuring and validating these such parameters.

## Sensitivity Analysis

The importance of understanding how the 26 different parameters of a PBM perform is critical. This is done by performing a sensitivity analysis, which use sweeps of changing values for a single parameter One-At-a-Time (OAT) and measures the how the output changes from a fixed position. The 26 parameters are grouped into 4 sub categories in W. Li et al’s [7] paper:

* Geometric parameters – 11 parameters
* Transport parameters – 9 parameters
* Kinetic parameters – 3 parameters
* Concentration parameters – 3 parameters

These parameters have applied boundary conditions which then are OAT calculated, the larger majority of papers have chosen to present how terminal voltage is affected, such as Figure 5. Terminal voltage is primarily chosen as this is much easier to validate to real world data sets, however W. Li et al’s paper [7] does show how alternative outputs can be effected.

Chart, bar chart

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Figure : Ranking of the normalized parameter sensitivity for terminal voltage under real-world driving cycles [7]

The highly sensitivity parameters are capacity related parameters which belong primarily in the Geometric and Transport subgroups. However, the challenge becomes being able to obtain the relevant data accurately and physically for the parameters.

As shown in Figure 6, it shows a few of the methods required to obtain the parameters values for a given cell chemistry.

Diagram

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Figure : Schematic of experiment-based parameter identification [8]

These methods require disassembly of the cell and expensive testing equipment to obtain individual and targeted values for the PBM, which even with just a single measured data point it does not depict the full model.

In conclusion, the author has shown the purpose of sensitivity analysis, outlined what is objectified in the analysis and some of the challenges of obtaining the data. In the next section (2.3) will shows the data-driven approach to populating the parameters.

## AI Based Optimisations

Therefore, the need for data driven optimisations is critical, to look to group parameter sets and validate the model. W. Li et al’s further work [8] shows this in Figure 7.

Timeline

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Figure : Schematic of the multi-objective multi-step data-driven identification process [8]

By integrating machine learning techniques in a multi-stage process does enable to populate close fitting values for a respective chemistry. The primary strategy W. Li et al’s work deploys is the Cuckoo Search Algorithm (CSA) which was developed by Yang et al [9]. The CSA is generational based algorithm which iteratively finds the optimal solution by replacing the worst solution in each new generation, the user defines maximum number of iterations to avoid a never-ending loop.

The performance of the Multi-Level CSA in a PBM is best captured in Figure 8, which shows the error distribution against measured data under a 2C discharge, has a better fit for the data driven approach against the experiment approach which used physically determined parameters for a PBM.

Chart, histogram

Description automatically generated

Figure : Error distributions of the invasive experimental and data-driven parameter

identification results under 2C discharge [8]

However, W. Li et al’s recognised that “A major step would be analysing the sensitivity of the thermal and physical parameters to voltage and temperature measurement” [8] and that other AI based approaches may be more efficient.

In conclusion, the author has shown one of the current approaches to populating the 26 different parameters with data-driven techniques and the level of effectiveness to the strategy against experimental datasets. In the final section (2.3.1), the author will look at another alternative AI approach and state why the strategy is at the focus of the paper.

### PSO-LM Optimisation

The final aspect of the literature review is looking at the Particle Swarm Optimization Levenberg-Marquardt (PSO-LM) model for batteries, proposed by W.-J. Shen et al [10]. The PSO-LM is hybrid model which combines the PSO method - a generative model to determine the global minimum for an objective function, matched to the LM - a nonlinear regression method to help identify optimal solutions for multiple global minimums. This approach is best visualised in Figure 9.

Diagram

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Figure : Block diagram of PSO-LM based identification approach [10]

However, this approach has only being deployed on an empirical battery model rather PBM but presented some promising results, with a good level of fitting for a 3C discharge (Figure 10).

Chart, histogram

Description automatically generated

Figure : Comparison between experimental and predicted charge voltage curves at charge rates of

1C, 2C, and 3C for PSO-LM method [10]

Therefore, there is space for development of a P2D with a PSO-LM method. Which is verified by M. Andersson et al. [11] work on analysing the methodology of different AI approaches for PBM “This approach has to our knowledge not been explored for the DFN or SPM parameters” [11].

In conclusion, the author has described the fundamental mechanics of the PSO-LM and outlined the opportunity of developing this approach into a PBM.

# Aim and SMART objectives

The main aim of the study is to see what physical based parameters can be optimised to predict cell behaviour via a PSO-LM method. Following are the SMART objectives:

1. Identify the primary use cases and limitations for ECM and P2D modelling.
2. Review the different sensitivity analysis parameters objectified in previous research.
3. Access different open-source battery modelling programmes and discuss the limitations and ease of use of each package.
4. Review the different AI and statistical based approaches for physical based modelling, to decide what solver would be suitable for the authors level of proficiency
5. Determine which physical based parameters should be parameterised to obtain motorsport focused performance or automotive focused performance.
6. Perform AI based modelling to understand the correlation and validate the physical cell’s measurements to simulated behaviours.

# Project methodology

The overall project methodology is presented in Figure 1, where it highlights where the objectives overlap with the project in different colours. Boxes with a light-yellow shade indicate literature review tasks, light blue is accessing software tools and light red is the modelling phase.

Diagram, schematic

Description automatically generated

Figure : Overall Project Methodology

## Objective 1

Primarily this objective will be a literature review for ECM and P2D models, how they can be deployed on BMS’s, and comparing the performance advantages of P2D model with the disadvantages of hardware integration.

In addition, this section intends to look at what cell’s performance characteristics are desired for both motorsport and automotive applications, in which the research into cell tab plating, concentration of electrolyte and electrode material will be discussed

## Objective 2

This objective will again be a literature oriented, where multiple different sensitivity analysis’s will be reviewed and compared. In the expectation, that other variables to measure sensitivity can be understood and replicated for Objective 5 to give what variables should be optimised for a motorsport or automotive application.

## Objective 3

This objective will both be literature oriented and software focused, where the author will access European databases, open-source packages such as PyBAMM and report the benefits and withdrawals of operating in the software package/database. This will help inform the author what physical based packages will be carried over to the entire model development.

## Objective 4

This objective will be literature based, where different previous research for AI and statistical based models for P2D optimisations will be analysed. In the expectation, that this identifies what gaps there are in the field of AI based P2D models and how the project could capitalize on methods such as PSO-LM.

## Objective 5

This objective is software based, where the initial groundwork for the model begins. As the author will experiment in replicating previous sensitivity analysis for conditions such as cell temperature change effect to terminal voltage. With the expectation, that it will be integrated into a software platform that can handle the demands of an AI solver.

## Objective 6

The last objective is software driven, where the model is in its development and validation phase. This will use the work from Objective 5 and combine it to the backend code for the AI based optimisation tool, furthermore this will utilise real life data generated from a full life characterisation of a LG M50 cell to help develop the model and train the AI to yield closer fitting simulations for cell behaviour. At this stage, if the model is unsuccessful the author can formatively review the short comings of the model and approach.

## Alternatives and limitations for objectives

In Table 1 it shows the assessment of how well the author has thought about the objectives, the limitations of each objective to the overriding project and how the objective could be altered to mitigate the limitation.

Table 1: Alternatives and limitations of project objectives

|  |  |  |  |
| --- | --- | --- | --- |
| **Objective** | **Summary** | **Limitations** | **Alternative/Focus** |
| 1 | Literature review of ECM against P2D modelling | Ensuring that the focus is on the model, rather than the application | Keep the application for the background of the paper and focus on the pure modelling methods in the literature review |
| 2 | Literature review of different sensitivity analysis | Ensuring that there are enough unique differences in other authors sensitivity analysis | If there not enough unique differences, focus on mentioning that as an opportunity for the study |
| 3 | Software tool analysis of physical based battery | There is a huge amount of battery models in varying complex and application | Focus on models which are purely P2D and packages which the author feels comfortable with using and applying in the literature review |
| 4 | Literature review of AI and statistical modelling approaches | The field for the research is new, so there may not be many resources | Start focusing on what main methods which have been deployed to P2D, then find methods which have yet been deployed |
| 5 | Decision of focus of application of model | It is very late into the project to be deciding the target industry for the model, which could put pressure on the author | In any case, opt for the automotive approach as drawing a closer relationship to terminal voltage is more beneficial for validation activities and industrial application |
| 6 | Development and validation of AI based physical battery model | The objective may be too ambitious to jump straight from model development to validation | Possibly split the task in to two objectives, one focusing on purely development of the model and the other is the validation of the data |

# Activities and plan pathway

In Table 2 it shows the critical activities related to the authors objectives, the activities dependencies and projected finish times for each activity

Table : Activity and objective pathway summary

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Main Task** | **Child Task** | **Main Dependency** | **Purpose & Activity type** | **Projected Finish** |
| Objective 1 | - | - | Open the initial scope of the project, literature review | 16/02 |
| Objective 2 | - | Objective 1 | Look at key data set (Chen2020), literature review | 07/03 |
| Objective 2 | Sensitivity Analysis | Objective 2 | Look at different sensitivity analysis, literature review | 18/02 |
| Objective 3 | - | Objective 2 + Child Task | Access open-source tools, using software | 02/05 |
| Objective 4 | - | Objective 2 | Look at different AI and statistical methods, literature review | 13/04 |
| Objective 4 | Research PSO-LM model | Objective 2 | Look at PSO-LM AI model, literature review | 04/04 |
| Objective 5 | - | Objective 3 + Objective 4 | Decision of AI modelling focus, review | 17/05 |
| Objective 5 | Motorsport focused model | Objective 5 | Decision of modelling focus application, review | 12/05 |
| Objective 5 | Automotive focused model | Objective 5 | Decision of modelling focus application, review | 12/05 |
| Objective 6 | - | Objective 5 + Child Task | Model development & Validation, software | 15/07 |
| Final report | - | Objective 6 | Combine all objectives outputs, writing report | 21/09 |

## Gantt Chart

Chart, histogram

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Figure : Gantt Chart of Objectives and final report

# Resources

This project is in collaboration with HVES, which will be using a complete data set of the LG M50 Cell, to help develop and train the AI physical based model.

The project intends on using the following software packages and tools:

* PyBaMM – Python package for battery
* Chen2020 dataset from PyBaMM for provisional sensitivity analysis
* Julia – ultra fast solver for machine learning methods
* GitHub – open access repository for code and documentation

# 

# Project risks

Table 3: Risk analysis of tasks

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Task at Risk** | | **Resource at Risk** | **Objective(s) at Risk** | **Description** | **Consequence** | **Magnitude (/5)** | **Control** | **Likelihood (/5)** | **Contingency** | **Risk Factor**  **(M x L, /25)** |
| R1 | Unable to get to grips with AI based software | Model | 6 | The software package does not have enough learning material to understand how to use it | Unable to develop a cohesive AI based Model | 5 | Select packages which are very familiar to the Author | 3 | If unable to produce an AI focused model, make it is a purely statistical based model. | 15 |
| R2 | Code gets corrupted, overwritten or lost | Model | 3,5,6 | The backend code for the overall model gets corrupted, overwritten or lost | An incomplete model | 4 | Use a repository like GitHub to store code and commit versions of code | 1 | Back up the repository on separate hard drive | 4 |
| R3 | The model does not perform closely to previous literature | Model | 6 | The model does not provide a good fit to the physical testing data | A model which is not conceived as successful | 4 | Make every attempt to make the best model the author can produce in the timeframe for the thesis | 3 | If unsuccessful, make a formative review on how the approaches taken are flawed as that will definitely inform industry on the suitable models to deploy | 12 |
| R4 | Unable to decide between a motorsport or automotive focused optimisation | Literature and model | 1,5 | The literature is too vast to determine how the P2D should be targeted to optimise motorsport performance or automotive functional safety | The model may have too much scope and does not fit data well enough | 2 | Develop the two perceptions in tandem, but understand when the scope has exceeded plausibility | 3 | If in doubt, use an automotive focused approach. As there is much more work in automotive focused models, therefore grounds the topic more firmly | 6 |
| R5 | Unable to get sufficient computational power | Model | 6 | The model takes far too long to run on personal PC | The validation phase may exceed the timeline | 3 | Ensure code is computationally efficient to MISRA C | 1 | Rent cloud computing space and run API’s | 3 |

## Risk Matrix

Visualised in Table 4 is the complete risk matrix with risks identifided from Table 3.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 5 |  |  |  |  |  |
| 4 |  |  |  |  |  |
| 3 | R5 | R4 |  | R3 | R1 |
| 2 |  |  |  |  |  |
| 1 |  |  |  | R2 |  |
| /5 | 1 | 2 | 3 | 4 | 5 |

Table 4: Risk Matrix

**Magnitude**

**Likelihood**

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