### Planning Report 2024

# Optimized Discharge of EV Batteries

Implementation and evaluation of MPC and PID control strategies for discharging batteries at a constant temperature

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## 1 Introduction

The rapid proliferation of Electric Vehicles (EVs) has led to a significant increase in demand for batteries. The global demand for lithium-ion (Li-ion) batteries increased by about 65% to 550 GW h between 2021 and 2022 which implies a growing increase in the interest of maximizing the potential usage of each battery [1].

First Life - During the primary service life of an EV battery, the battery is subjected to various operating conditions, charge and discharge cycles, aging, and thermal stress. These factors contribute to the degradation of a battery performance over time. As the performance decreases, the battery might not meet the requirements for usage as an EV battery and might need to be switched out.

Second Life - The concept of a second life in EV batteries stems from retiring these batteries and repurposing them in different use cases. Batteries are tested and analyzed to determine whether they are available for a different use case or if they are in their end of life cycle and are to be recycled. The batteries can be repurposed for a multitude of tasks, two examples being charging stations and residential photovoltaic energy storage systems [2].

Batteries that have degraded past their use case in a second life are completely discharged and are recycled. The capacities of the batteries are often unknown and to ensure that the temperature doesn't increase to problematic levels, the batteries are currently discharged at a relatively low rate while switching between states of constant current (CC) and constant voltage (CV) steps. Optimizing this process could save time but at the same time imply complications regarding thermal stress on the battery. By utilizing intelligent modelling of the batteries and control algorithms, this project aims to reduce the time needed for discharge by discharging the batteries at a constant temperature (CT).

# 1.1 Theory

This section is aimed towards explanation of concepts that will be used and discussed in the master's thesis. Some subjects are included for clarification purposes and are meant to clarify the specific use cases in the context of this project.

### 1.1.1 Modelling Approaches

When modelling a physical system for automatic control, the approach differs in relation to the level of understanding of the system's dynamics. The concepts that are important to know to understand this project are *white* and *black box* modelling techniques.

If the underlying mechanics of the system are well understood, it can be appropriate to utilize a *white box* model, often also referred to as *first principle modelling*. In this approach, the system dynamics are described using mathematical equations derived from physical principles. This way, a white box model can be accurate in predicting the systems response to inputs on the assumption that the equations describing the system are relevant and at an adequate level of detail.

If explicit knowledge of a system is lacking, or the dynamics are unknown, one can view the system as a *black box* which relies on data to create a model. Here, instead of relying on fundamental principles to gain understanding the system, the inputs and outputs are studied and the gathered data is combined with statistical or machine learning-techniques to infer input-output relations and predict system behaviour. Since it is possible to vary the complexity of

the model based on the data gathered, his approach is flexible in comparison to white box modelling at the expense of theoretical grounding and possibly interpretability.

Because of the complex structure of battery modules and lack of knowledge regarding placement of internal temperature sensors, heat dissipation and cooling, this project will mainly focus on utilizing black box modelling techniques. This approach is also taken with the intention of being applicable to batteries from different manufacturers and internal structure, while still aiming to provide accurate control of the temperature during a discharge cycle.

#### 1.1.2 System Identification

This section will show a brief overview of how the model is created from data, a thorough derivation of the method can be found in System Identification, Theory for the User by Lennart Ljung [3]. Assume that the output at time k, y(k), is a function of the input, u(k), multiplied with a transfer function, G(q), where q is the discrete time-shift operator. The transfer function is a function consisting of unknown constants  $\{a_i\}_{i=1}$  and  $\{b_i\}_{i=1}$  which are to be identified using gathered data multiplied with the time-shift operator as

$$G(q) = \frac{b_0 + b_1 q^{-1} + b_2 q^{-2} + \dots}{1 + a_1 q^{-1} + a_2 q^{-2} + \dots}$$
(1)

The expression for the output can be expanded and rewritten in the following manner

$$y(k) = G(q)u(k) \tag{2}$$

$$= \frac{b_0 + b_1 q^{-1} + b_2 q^{-2} + \dots}{1 + a_1 q^{-1} + a_2 q^{-2} + \dots} u(k)$$
(3)

$$\implies y(k) + a_1 y(k-1) + a_2 y(k-2) + \dots$$
 (4)

$$= b_0 u(k) + b_1 u(k-1) + \dots (5)$$

$$\implies y(k) = b_0 u(k) - a_1 y(k-1) + \dots \tag{6}$$

$$y(k) = \begin{bmatrix} y(k-1) & \dots & u(k) & \dots \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ b_0 \\ \vdots \end{bmatrix} = \phi^{\top} \theta$$
 (7)

which, for all time steps, can be rewritten as

$$\begin{bmatrix} y(k) \\ y(k-1) \\ \vdots \end{bmatrix} = \begin{bmatrix} y(k-1) & \dots & u(k) & \dots \\ y(k-2) & \dots & u(k-1) & \dots \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ b_0 \\ \vdots \end{bmatrix}$$
(8)

or equivalently as

$$Y = \Phi\theta. \tag{9}$$

This kind of model is also known as autoregression with exogenous inputs, or an ARX model. The process of determining the constant in  $\theta$  can thus be determined using least squares. To ensure that there exists a solution, the matrix  $\Phi$  needs to be full rank. This is mitigated by utilizing a pseudorandom binary sequence (PRBS).

#### 1.1.3 PRBS

To generate a control signal to analyze the system response, it is generally desired that the input signal's spectral density is flat, meaning that all frequencies are represented spectrally equivalent to white noise. PRBS produces a sequence of binary outputs which can be compared to repeated step inputs lasting for different amounts of time.

#### 1.1.4 MPC

MPC is a constrained-based control approach that considers a predefined number of time steps in the future, referred to as the horizon N, and calculates the optimal control policy based on minimizing the penalties of the future states and control actions. This is combined with constraints on the states and control signal based on predefined sets for each quantity such that the control policy doesn't violate these constraints. The optimal control policy for future time steps k = 0: N - 1 is calculated by minimizing the objective function

$$\min_{\mathbf{u}_{0:N-1}} J_N + \sum_{k=0}^{N-1} ||\mathbf{x}_k - \tilde{\mathbf{x}}||_{\mathbf{Q}_{\mathbf{x}}}^2 + ||\mathbf{u}_k - \tilde{\mathbf{u}}||_{\mathbf{Q}_{\mathbf{u}}}^2$$
(10)

where  $J_N$  denotes the terminal state cost,  $\mathbf{x}_k$  and  $\mathbf{u}_k$  the state of the system at time step k and the control signal at time step k,  $\tilde{\mathbf{x}}$  and  $\tilde{\mathbf{u}}$  the references for the state and control signal,  $\mathbf{Q}_{\mathbf{x}}$  and  $\mathbf{Q}_{\mathbf{u}}$  penalty matrices for the state and control signal, respectively.

### 1.2 Purpose

The current process of discharging batteries which are going to be recycled is intended to prioritize safety and minimize the risk of excessive degradation which may lead to thermal runaway. Since the capacities and the respective SoH is unknown, the maximum temperature deemed as safe during discharge may vary between batteries and may differ from the limit stated by the manufacturer. To achieve a safe discharge, the current process uses a relatively low discharge rate with the intent of keeping the internal temperatures in the batteries from rising to problematic levels. This method could be seen as somewhat rudimentary given that the temperatures during discharge could be higher without causing excessive damage to the batteries at the expense of causing a slow process with regard to discharge time. Furthermore the temperature measurements only act as safeguards to interrupt the discharge if the temperatures exceed their set limits.

The purpose of this work is to create a discharge cycle that utilizes the temperature measurements in a control loop such that discharge time decreases while maintaining a constant temperature as to optimize the trade-off between a fast discharge policy while maintaining a safe discharge temperature.

# 1.3 Objective

The research question which will be investigated during this thesis are

• Using system identification, investigate whether a controller utilizing proportional-integral (PI) control or Model Predictive Control (MPC) based on modelling temperature movement can decrease discharge time for battery modules compared to an industry standard discharge cycle

• Evaluate controller relevance based on discharged capacity over time, computing power and model complexity

### 1.4 Scope

To clarify the contexts of this project, this section aims to explain what the main focus points are and what areas are to be researched and which are to be disregarded or not deeply analyzed.

#### 1.4.1 Limitations

A facility which receives battery modules for discharging and transportation to recycling plants may receive batteries with different specifications and from different manufacturers. This study assumes homogeneity between battery models with no assumed specific characteristics within the batteries. As discussed in section 1.1.1, employing black box and data driven modelling may trade interpretability and model transparency for the ambition of being applicable to different battery models. The efficiency of control methods may differ based on the batteries internal structure but these effects will not be thoroughly researched in this project. The focus point of this work is on the controller, therefore there will not be a large focus regarding safeguards in accordance to safety protocol standards more than monitoring the temperature and cancelling the discharge based on if the temperature exceeds a certain limit. What the limit should be needs to be further discussed and depends on how well the controller keeps the target temperature and if the controller will tend to overshoot when discharging with a higher current in the beginning of the cycle.

#### 1.4.2 Boundaries

This project focuses on optimizing the discharge cycle of EV batteries for recycling purposes. This implies that the batteries are not meant for redistribution or further use. The intention is to work with the same battery model from the same manufacturer during the entire project but depending on the availability of different models, this may have to be subject to change or compromise. Utilizing black box modelling, the aspiration is to mitigate the effects of using different battery modules as discussed previously. The two main control algorithms that will be used are evaluated based on their effectiveness in reducing discharge time and ability to maintain a constant temperature. A possible byproduct of this project is that the control policy could be utilized also for charging EV batteries. This will not however be a focal point during the project itself but could very well be subject to further research depending on the results.

# 2 Method

This section will explain how the work is to be completed and show the intended initial process of the project.

#### 2.1 Data Collection

The necessary data will be collected using a pseudorandom binary sequence (PRBS) at different points in the discharge cycle. The data will consist of measurements on temperature and

voltage, and current as the input.

## 2.2 Data Processing

After gathering data, it is possible to utilize system identification to create models of the temperature dynamics. This will be done according to the theory in section 1.1.2. This will give a data-based model of the temperature dynamics and provide insight on how often the model needs to be revised during a discharge cycle to effectively control the system.

## 2.3 Tuning and Validation

The dynamics of the batteries change with charge level and therefore an analysis will be made to analyze how the system changes and how it affects the control performance. This is to determine how often a recalibration of the system model is necessary or if it is possible to consider the system as being time-independent. This stage also contains tuning parameters for the controllers. Specific parameters for the MPC and PID control will be produced using the previously obtained system models.

## 2.4 Testing and Evaluation

Evaluation of the control systems will be made on the Stena Recycling testing facility in Halmstad, Sweden. The success rate will be dependent on the capacity discharge rate of the batteries as compared to the currently used method of discharge. The ability to maintain constant temperature during discharge, robustness and controller assessment will also be taken into account in the evaluation.

## 3 Timetable

The initial time plan of this project is provided as a Gantt chart and can be seen in Fig. ??. This may be subject to change during the course of the project.

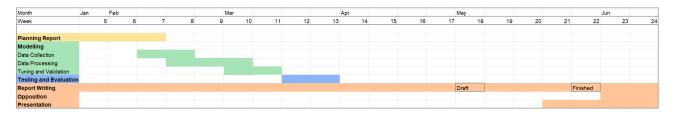


Figure 1: Time plan and work flow of the master's thesis project

# 4 Sustainability Aspects

The Directorate-General for Environment of the European Union states that by the year 2030, EVs are expected to reach a total market share of 16% [4]. In the same article, it is estimated that supporting the power grid with using second life batteries could avoid up to 1.2 kilotons of battery waste. Optimizing the cycling of these batteries is a natural step towards evolving the process of evaluating batteries for a second life or recycling.

The risk of thermal runaway poses not only a risk to the workers involved but also a negative environmental aspect. A battery module that has undergone thermal runaway may not be eligible for recycling to the same extend as a battery which hasn't. Furthermore, using control systems to adjust the discharge rate may also require a higher energy consumption when running and in the case of using a real battery as opposed to a simulation, this implies additional required energy resources as opposed to the current industry standard.

With the intent of avoiding thermal runaway during the charging cycle, the allocated time for cycling the battery is expected to lessen. By preventing thermal runaway and minimizing the degradation of the battery, the aspiration is that the environmental impact of this work is to assist the cycling will be a net positive in optimizing the process of determining the second life possibilities of the batteries.

# 5 Ethical Aspects

It is important that the people working with examining the batteries are adequately safeguarded from possible danger regarding cycling used batteries. There are already safety precautions taken to ensure that people do not get hurt and by avoiding thermal runaway, the project aspires to further decrease the risk of excessive degradation that may lead to thermal runaway.

In a potential second life of the batteries, there must also exist a safety protocol to determine that the batteries are safe to use after cycling. This is especially crucial should the batteries be used for energy storage to support the power grid or in residential areas. This project does not, however, aim to produce these safety guidelines and is therefore out of the scope of this thesis.

It is possible that necessary data from EV batteries are not publicly available if the information is considered sensitive. In this scenario, a possible mitigation strategy is to create a model for the thermal profile of the battery ourselves. This implies that there may be need for additional safeguards to ensure robustness and reliability and it may require further analysis into what precautions are necessary to provide a safe baseline for the discharge.

# References

- [1] IEA, "Global ev outlook," *IEA*, 2023. [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2023.
- [2] E. Sandberg, Second life applications for de-graded ev batteries, 2023.
- [3] L. Ljung, System Identification: Theory for the User (Prentice Hall information and system sciences series). Prentice Hall PTR, 1999, ISBN: 9780136566953. [Online]. Available: https://books.google.se/books?id=nHFoQgAACAAJ.
- [4] E. C. D. E. N. A. Service, "Renewable energy storage from second-life batteries is viable but may benefit from subsidies," *European Commission*, 2023. [Online]. Available: https://environment.ec.europa.eu/news/renewable-energy-storage-second-life-batteries-viable-may-benefit-subsidies-2023-09-13\_en.