

A Linear Parameter Varying Combined with Divide-and-Conquer Approach to Thermal System Modeling of Battery Modules

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ABSTRACT

A linear parameter varying (LPV) reduced order model (ROM) is used to approximate the volume-averaged temperature of battery cells in one of the modules of the battery pack with varying mass flow rate of cooling fluid using uniform heat source as inputs. The ROM runs orders of magnitude faster than the original CFD model. To reduce the time it takes to generate training data, used in building LPV ROM, a divide-and-conquer approach is introduced. This is done by dividing the battery module into a series of mid-cell and end-cell units. A mid-cell unit is composed of a cooling channel sandwiched in between two half-cells. A half-cell has half as much heat capacity as a full-cell. An end-cell unit is composed of a cooling channel sandwiched in between full-cell and a half-cell. A mass flow rate distribution look-up-table is generated from a set of steady-state simulations obtained by running the full CFD model at different inlet manifold mass flow rate samples. This look-up-table is used to build a series of mid-cell and end-cell LPV ROMs that are used to approximate the thermal behavior of the battery module. The use of divide-and conquer system modeling combined with the LPV ROM will provide a good approximation to the thermal behavior of the battery module while significantly reducing the time required to generate the training data.

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INTRODUCTION

The full CFD modeling of battery module can be very expensive especially as the size of the mesh becomes larger. One way to remedy this is to divide the battery into smaller repeating units, create reduced order model (ROM) for each unit and then place the corresponding ROMs in cascade appropriately to build a system model for the battery module using divide-and-conquer. In this approach, the electrochemical behavior of the battery cell is captured using an electrical circuit model (ECM) [8].

It is assumed that the thermal conductivity and diffusivity are constant. For the cell temperature ranges that we are considering here, the impact of the variation of these properties with temperature on the accuracy of our results can be safely assumed to be insignificant.

Furthermore, if we could calculate or measure the temperature-dependent terms and include them as temperature-dependent functional terms with the heat source then we can use the same ROM and by having the heat tightly coupled with temperature include the effect of the aforementioned temperature-dependent terms in the system model. That is done during the consumption of ROM. Therefore, we start initially with a temperature-independent heat source and calculate temperature using the ROM. At the next time

step, we first calculate the heat using the temperature-dependent function constructed from measurement, e.g., a look-up-table then use the ROM again to calculate temperature and we continue.

As an example, the approach in approximating the temperature-dependent terms is considered by the use of an ECM to represent the battery's electro-chemical behavior. The (nonlinear) resistors and capacitors used in the ECM are functions of both state-of-charge (SOC) and temperature and can be extracted using standard measurement data such as High Performance pulse Characterization (HPPC) data. As a result, the ECM generated heat source itself is a function of temperature. There are methods to extract the resistors and capacitors as a function of SOC and temperature directly from measurements [8].

On the other hand, the thermal behavior of the battery module is then captured by the divide-and-conquer approach to system modeling. The battery cells are excited with a constant uniform heat source in the battery cell to yield thermal step-response. With this information the battery cell is fully characterized thermally for a given cooling flow rate. This is based on the concepts of Linear-Time Invariant (LTI) systems. We extract State-Space (SS) representation for the impulse response of the LTI system obtained from the thermal responses used as training data [9].

The ECM model provides the lumped capacitance electrical model for the Li-ion battery cell considered here. It is there to provide the (uniform) heat generation in battery cells due to both electrochemical and resistive heating that takes place when in use.

The combination of ECM and thermal ROM system model will create an electro-thermal model that can be used in any multi-physics simulation environment such as ANSYS Simplorer. In this work, we will demonstrate how this can be done using a twenty-cell battery module with a varying air flow rate cooling channels as an example.

The system model proposed in this work can handle different driving conditions all the way from soaking case to any other driving condition.

The paper is organized as follows. In [section II](#), we will discuss our approach in more detail while using the twenty-cell module as test case. In [section III](#), we compare the simulation results between directly creating a thermal ROM for the twenty-cell module versus using the concept of divide-and-conquer system modeling. We conclude in [section IV](#) with future extensions of the work.

II. LINEAR PARAMETER VARYING COMBINED WITH DIVIDE-AND-CONQUER

In many applications that involve the use of computationally intensive finite-element and volume modeling with large mesh size as well as control mechanism such as a Battery Thermal Management System (BTMS), it is not practical to use CFD with control closed loop system. So, instead ROM can be used to approximate the input-output behavior of the plant to be identified. As a result, using ROM allows a more practical system model with closed loop control. The ROM referred to in this work searches for a model that is able to approximate the input-output behavior of a physical system or plant.

There are two types of ROM used in practice. One that directly uses the known discretized state matrices of the physics to be solved performs reduction based on well-known projection-based methods [1], [7] and is referred to as direct method. The projection-based methods, project the large state matrix to a reduced version such that the input-output behavior is preserved. As a result, a smaller number of equations are solved and significant simulation speed-ups can be achieved without much loss in accuracy with respect to input-output behavior of the original system. While the reduced states do not have any physical meaning any more, the inverse of the same projection matrix can be used to return to the same original high-dimensional space and access the true states if needed.

The other type of ROM treats the underlying physics as an unknown system model, persistently excites the system and generates a set of training data that will later be used for system identification. This method is referred to as black-box. The reduced states of the black-box ROM do not have any physical meaning. In this work, we adopt black-box ROM method. Therefore, in applications where only the input-output behavior of the system is of interest the black-box method is adequate.

In addition, the concepts of system theory is adopted in this work where the plant to be identified for a later design of closed loop control is treated as an unknown system. Similarly, the thermal behavior of the battery module with air-cooling and varying flow rate is treated as an unknown system. To do system identification, using Fluent, we generate a set of step responses at different fixed MFR samples spanning the full dynamic range of operation that will later be used as training data to build the ROM.

Next, in order to motivate the choice of black-box ROM used to model the thermal behavior of the battery module considered in this study, we will start by discussing the physics and from there demonstrate how LPV ROM can be chosen as a good candidate to model the input-output behavior of the underlying physics.

The underlying physics involved in this cooling scenario can be described by heat convection-diffusion equations shown below:

$$\frac{\partial T(x, t)}{\partial t} = a \frac{\partial^2 T(x, t)}{\partial x^2} - v \frac{\partial T(x, t)}{\partial x} + \frac{q(x, t)}{c\rho} \quad (1)$$

where $a = \frac{\lambda}{c\rho}$ is the diffusion coefficient (m^2/s), $T(x, t)$ is the temperature field (K) as a function space, x (m) and time, t (s), c is the specific heat ($J/Kg - K$), ρ is the mass density (Kg/m^3), λ is thermal conductivity ($W/(m. K)$), ϵ is the porosity, v is the velocity of flow (m/s) and $q(x, t)$ is the heat source term (W).

Assuming the source term is uniform and using a discretization method such as finite element and control volume, the discretized Partial Differential Equation (PDE) in (1), with appropriate Boundary Conditions (BC) can be transformed into an equivalent Differential Algebraic Equation (DAE) and as a result converted into an equivalent Ordinary Differential Equation (ODE), with appropriate initial conditions, that finally will look like:

$$\dot{X}(t) = A(v)X(t) + Bu(t) \quad (2)$$

where $X(t)$ are the states and in this case the temperature field at different spatial locations and $u(t)$ is the uniform heat source [2], [16].

Assuming that the flow variation dynamics in (2) is known we could treat it either yet as another input or alternatively as a scheduling parameter [4], [5], [6]. The following shows the state-space (SS) Linear Parameter Varying (LPV) model used in this work to approximate the physics shown in (2):

$$\begin{aligned} \dot{\tilde{X}}(t) &= \tilde{A}(\dot{m})\tilde{X}(t) + \tilde{B}(\dot{m})\tilde{u}(t) \\ \tilde{T}(t) &= \tilde{C}(\dot{m})\tilde{X}(t) + \tilde{D}(\dot{m})\tilde{u}(t) \end{aligned} \quad (3)$$

where $\dot{m}$, the mass flow rate (MFR), is treated as the scheduling parameter in the SS-LPV model and $[\tilde{A}(\dot{m}), \tilde{B}(\dot{m}), \tilde{C}(\dot{m}), \tilde{D}(\dot{m})]$ are the state-space matrices, shown as a function of scheduling parameter $\dot{m}$, to be identified, $\tilde{u}(t)$ is the uniform heat source and $\tilde{T}(t)$ is the temperature at a particular location of the volume.

averaged temperature of the battery cell. Also, the uniformity assumption of the heat source is only meant across the space and not time. The heat source can vary arbitrarily as a function of time.

It is important to note that, in general, the states $\hat{X}(t)$ have no physical meaning and no relationship to the true states $X(t)$. This is the case since this work is based on black box SS-LPV identification.

There are two general methods considered in the literature for LPV identification [4], [5], [6], [13], [14], [15]. One that fixes the scheduling parameters at different operating conditions and as a result reduces the identification problem to many LTI cases and then by creating an interpolation function between the LTIs at different scheduling parameter samples the LPV model is constructed. This is known as local LPV identification method.

The second method for LPV identification, known as global LPV, performs a more direct identification of the state-space model as a function of scheduling parameters by using global training data obtained from the original dynamical system while using appropriate choices for the scheduling parameters and persistent excitations [15]. In this work, we adopt local LPV identification method.

The local LPV identification method, though simpler compared to global LPV, is not able to capture the dynamic variation of the scheduling parameter such as its rate of change or past variations. However, if the true dynamical system to be modeled has a weak dependence on the dynamic change of the scheduling parameter, such as its rate of change or its past values, then the local LPV method proves to be very useful and provides good approximation to the behavior of the true Linear Time-Varying (LTV) system shown in (2) [15].

There are many local LPV identification methods [4], [5], [6] and [14] that have been proposed. In each study, it is noted that in order to obtain a robust LPV representation, one need to make sure the states from the identified LTI at different MFR samples are consistent. One interpretation of state consistency is to make sure the states from the individual state-space models share the same basis function representation. One approach that enables the state consistency of the identified LTI at different MFR samples is to perform inner balancing of each state-space model before construction of interpolation function. That means perform balance transformation of the LTI state-space models [10] before the construction of LPV interpolation function [14].

The following algorithm summarizes the local LPV algorithm adopted in this work which is primarily based on the work described in [14]:

1. Generate a linear continuous-time state-space model of a fixed order for each scheduling parameter sample where local LTIs with real poles are preferable
 - a. LTI identification is done using frequency-domain rational fitting [3], [11]-[12] using the thermal step responses as training data

2. Find inner balance realization of each identified LTI model using suitable numerical algorithm such as the one described in [13]
3. Detect and (automatically) correct for any sign change observed in the balanced transformations
4. Create interpolation function of the state-space matrices from local LTI models, made possible by the properties of balanced realizations, to build the parameter dependent SS-LPV model.

Next, we will build a local SS-LPV model for a two-cell battery unit extracted from the original twenty-cell battery module shown in Figure 1.

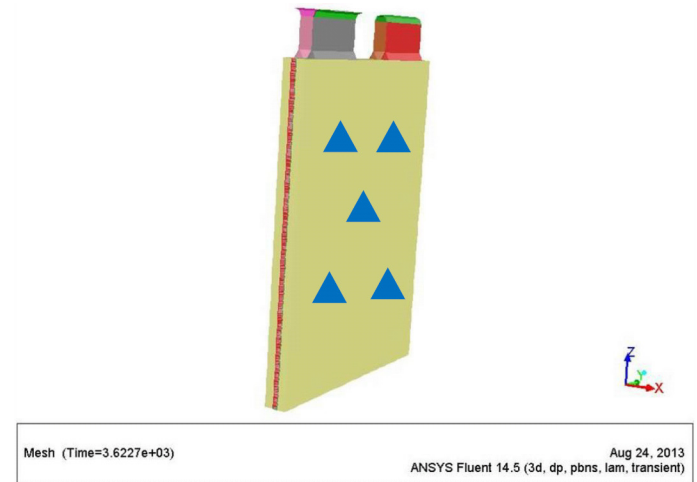


Figure 1. Air-cooled two-cell unit.

Figure 2 shows mass flow rate profile used as scheduling parameter choice and for simplicity we used a constant uniform heat source even though any other heat source profile can be used.

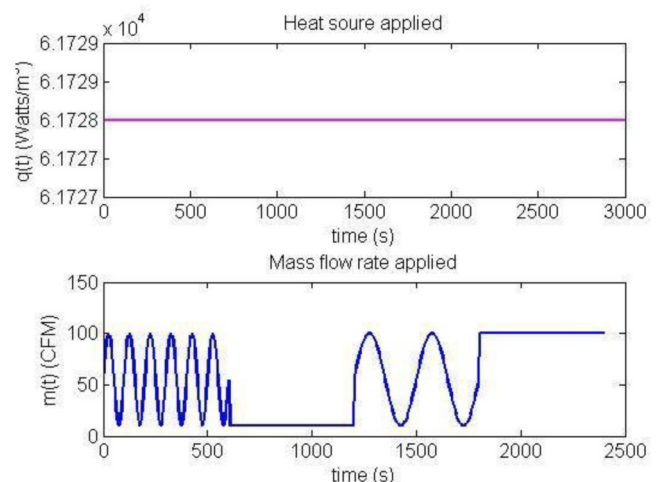


Figure 2. The constant uniform heat source and the mass flow rate profile.

The following describes the LPV construction for the two-cell unit example

1. Consider a mid-cell unit model, i.e., refer to Figure 1 which is made of two battery cells, two tabs on each cell and an interconnect connecting the 2 tabs