Numerical Simulation of a Battery Thermal Management System Under Uncertainty for a Racing Electric Car

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La simulation pour la mobilité électrique, NAFEMS
November 13, 2019

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1 Industrial and Research Objectives

2 Battery Thermal Management System

3 Low-Fidelity Numerical Model

4 Numerical Simulation Under Uncertainty
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Battery Thermal Management for Electric Vehicles

E-racing Car requirements

- Several charge/discharge cycles in small time intervals
- High Power from the Electrical Engine and Fast recharging: increased heat loads on Battery Pack
Battery Thermal Management for Electric Vehicles

**Immersion Cooling System by EXOES**

- Electric Cells immersed in dielectric cooling fluid.
- Heat exchanged directly from cells to the fluid.
- Good thermal homogeneity within the Battery Pack.
Main PhD project overview (2018-2021)

- **Numerical Simulation of Battery Thermal Management Systems (BTM):**
  - High-Fidelity Model (HF): based on Computational Fluid Dynamics (CFD)
  - Low-Fidelity Model (LF): "0D Model" based on energy balance equations

- Uncertainty Quantification Methods to take into account uncertainties related to BTM Systems.

- Multi-Fidelity numerical tool: coupling LF and HF models
  - Reduce computational costs
  - Perform UQ methods including High-Fidelity simulations
Main PhD project overview (2018-2021)

- Numerical Simulation of Battery Thermal Management Systems (BTM):  
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  Reduce of computational costs  
  Perform UQ methods including High-Fidelity simulations

Today’s focus:  
Performances Analysis of the LF Model with Uncertainty Quantification methods.
1 Industrial and Research Objectives

2 Battery Thermal Management System

3 Low-Fidelity Numerical Model

4 Numerical Simulation Under Uncertainty
The Exoes Battery Thermal Management System (BTMS)

Cooling Circuit

Battery Module

Expansion Vessel
Radiator
Pump
Battery Modules

Coolant Fluid
Battery Cells
<table>
<thead>
<tr>
<th></th>
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</tr>
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<tbody>
<tr>
<td>2</td>
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The Low-Fidelity Model

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Case Study: Race

- Race duration: 20 minutes
- Maximal Power required by the electrical engine: 180 kW
- More than 70 accelerations and braking sequences.
Industrial and Research Objectives

Battery Thermal Management System

Low-Fidelity Numerical Model

Numerical Simulation Under Uncertainty

What the LF model computes

![Graphs showing battery thermal management parameters over time](image)

- **State of Charge (SOC)**: The graph shows the state of charge of the battery over time, with parameters such as ambient temperature (Tamb), mass flow rate, and other variables.
- **Temperatures (°C)**: Graphs for core temperature (Tcore) and Trad-ex, showing changes over time.
- **Pressure (kPa)**: Graph demonstrating pressure changes, also over time.

**Parameters**: Tamb=20.12, Mass Flow Rate=1.1, wfluid=312.88, ESR=0.0224, SOH=101.94

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November 13, 2019 11 / 23
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4 Numerical Simulation Under Uncertainty
Choice of **4 uncertain parameters** : lack of knowledge to set an exact value.

<table>
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<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Range</th>
<th>Unit</th>
</tr>
</thead>
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<tr>
<td>Massic Flow Rate</td>
<td>$\dot{m}$</td>
<td>$[1.08; 1.3]$</td>
<td>kg.s$^{-1}$</td>
</tr>
<tr>
<td>Heat Transfer Coefficient</td>
<td>$h_{\text{cond}}$</td>
<td>$[250; 360]$</td>
<td>W.m$^{-2}$.K$^{-1}$</td>
</tr>
<tr>
<td>Equivalent Serie Resistance</td>
<td>ESR</td>
<td>$[0.01; 0.025]$</td>
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</tr>
<tr>
<td>State Of Health</td>
<td>SOH</td>
<td>$[98; 102]$</td>
<td>%</td>
</tr>
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Take Uncertainties Into Account

Choice of **4 uncertain parameters**: lack of knowledge to set an exact value.

\[
\begin{align*}
  x_1 & : \text{Massic Flow Rate} \quad \dot{m} \quad [1.08; 1.3] \quad \text{kg.s}^{-1} \\
  x_2 & : \text{Heat Transfer Coefficient} \quad h_{\text{cond}} \quad [250; 360] \quad \text{W.m}^{-2}.\text{K}^{-1} \\
  x_3 & : \text{Equivalent Serie Resistance} \quad \text{ESR} \quad [0.01; 0.025] \quad \Omega \\
  x_4 & : \text{State Of Health} \quad \text{SOH} \quad [98; 102] \quad \% 
\end{align*}
\]

Goals of Uncertainty Propagation:

Estimate the **variability of the QOI with respect to the input parameters uncertainties**.
(Statistical moments, Quantiles, Sensitivity analysis, ...)

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STEP 1: Sampling of the 4 uncertain inputs. $N_5$ sample points following uniform distribution.

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<tr>
<th>$x_1$</th>
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STEP 2: Perform $N_S$ simulations with the Numerical Model, seen as a Black Box

**Uncertain Inputs**

$$x_i = \begin{pmatrix} \dot{m}_i \\ h_{\text{cond},i} \\ \text{ESR}_i \\ \text{SOH}_i \end{pmatrix}$$

**Black Box Model**

$$f(x_i)$$

**Quantity Of Interest**

$$Y_i = f(x_i)$$

$$i = 1, \ldots, N_S$$
STEP 3 : Compute the variability of the QOI with respect to the input uncertainties of the system
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Distribution of the QOI $\max_{t\in[0,T_{\text{FIN}}]}(T_{\text{center}}(t))$, with 115 sampled points
STEP 3 : Compute the variability of the QOI with respect to the input uncertainties of the system

Distribution of the QOI $\max_{t \in [0,T_{FIN}]} (T_{\text{center}}(t))$, with 115 sampled points

But 115 points is not enough to get accurate distribution. Monte Carlo method too expensive with computational model $f(x)$. Need to replace $f(x)$ by a fast-to-compute surrogate model.
Kriging Surrogate Model

Need to replace $f(x)$ by a fast-to-compute surrogate model

$$\hat{Y} = \hat{f}(x)$$

Kriging Based Surrogate Model

Based on Gaussian Process Regression

? Compute an estimation $\hat{Y} = \hat{f}(x)$ of the QOI, built on the 115 training samples from the numerical model $f(x)$
Distributions of the QOI

Computation of the PDF for each QOI at $T_{\text{amb}} = 15^\circ C$

estimated with surrogate model

$$\min_{t \in [0, T_{\text{FIN}}]} (\text{SOC}(t))$$

$\text{COV} = 11.99\%$

$$\min_{t \in [0, T_{\text{FIN}}]} (V(t))$$

$\text{COV} = 4.54\%$
Uncertainty Propagation

Distributions of the QOI

Computation of the PDF for each QOI at $T_{\text{amb}} = 15^\circ C$

*estimated with surrogate model*

\[
\max_{t \in [0,T_{\text{FIN}}]} (T_{\text{center}}(t)) \\
\text{COV} = 21.49\%
\]

\[
\max_{t \in [0,T_{\text{FIN}}]} (T_{\text{wf-out}}(t)) \\
\text{COV} = 20.21\%
\]
Distributions of the QOI

Computation of the PDF for each QOI at $T_{\text{amb}} = 15^\circ \text{C}$

*estimated with surrogate model*

$$\max_{t \in [0, T_{\text{FIN}}]} (\delta T(t))$$

$\text{COV} = 28.37\%$
Results for 2 different $T_{\text{exterior}}$ scenarios

Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^\circ C$ and $T_{\text{exterior}} = 15^\circ C$

$$\min_{t \in [0, T_{\text{FIN}}]} (\text{SOC}(t))$$
Results for 2 different $T_{\text{exterior}}$ scenarios

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$$\min_{t \in [0, T_{\text{FIN}}]} (V(t))$$
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$$\max_{t \in [0, T_{\text{FIN}}]} (T_{\text{center}}(t))$$
Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^\circ C$ and $T_{\text{exterior}} = 15^\circ C$
Results for 2 different $T_{\text{exterior}}$ scenarios

Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^\circ C$ and $T_{\text{exterior}} = 15^\circ C$
Goal of Sensitivity Analysis:

Show which uncertain input parameter has the most influence on the variability of our quantity of interest.

→ Gain more knowledge about the behavior of a complex model.
Sensitivity Analysis Study

Show which uncertain input parameter has the most influence on the variability of our quantity of interest.

Mathematical Framework: ANOVA Decomposition

Analysis Of Variance

Input $x = (x_1, x_2, x_3, x_4)$

Black-box numerical model $f$ seen as:

$$f(x) = f_0 + \sum_{i=1}^{4} f_i(x_i) + \sum_{i_1=1}^{4} \sum_{i_2=i_1+1}^{4} f_{i_1i_2}(x_{i_1}, x_{i_2}) + \cdots + f_{1,...,4}(x_1, ..., x_4)$$

Sobol Index for a QOI: $Y_{QOI} = f(x)$
Sensitivity Analysis Study

Show which uncertain input parameter has the most influence on the variability of our quantity of interest.

Mathematical Framework: ANOVA Decomposition

Sobol Index for a QOI: \( Y_{QOI} = f(x) \)

First Order Sobol Index for input \( x_i \):

\[
S_i = \frac{\text{Var}(\mathbb{E}[Y_{QOI}|x_i])}{\text{Var}(Y_{QOI})}
\]

\( \text{Var}(\mathbb{E}[Y_{QOI}|x_i]) \) = variance of the mean value QOI "knowing" the input \( x_i \)
\( \text{Var}(Y_{QOI}) \) = main variance of the QOI

\( S_i \) quantifies the main effect of \( x_i \) on the contribution to the variance of \( Y_{QOI} \)
First Order Sobol Indices Results

$\min_t (\text{SOC}(t))$

$\min_t (V(t))$

$\max_t (\delta T_{\text{cell}}(t))$

$\max_t (T_{\text{wf-out}}(t))$

$\max_t (T_{\text{center}}(t))$

First Order Sobol Indices for each QOI (case $T_{\text{exterior}} = 15 \, ^{\circ}\text{C}$)
What we learned from UQ Analysis

- Set up of a Low-Fidelity Model: gives an insight of the system behaviour with low computational costs

- Predicting the behaviour of the system while taking into account uncertainties on the physical input parameters

- Sensitivity Analysis gave robust estimation of the impact of some parameters on the Quantities Of Interest
  - ESR is the most determinant parameter for all QOI related to the temperature of the cells or the cooling fluid
  - SOH must not be neglected for minimal voltage of the cell
Perspectives

- From the results of Sensitivity Analysis: reduce the number of inputs, set-up simpler models
  - example: for \( \max(T_{\text{center}}(t)) \), get direct relationship between this QOI and ESR parameter

- Set up a High-Fidelity Model: based on CFD (Navier-Stokes + Energy Conservation 3D equations). Improve current simulations (influence of the geometry, find local heat spots on battery cells etc...).

- Represent the same physical case with HF model and LF model to perform multi-fidelity simulation of BTM Systems

Thank you for listening

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