



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

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

crédit : Jaguar MENA

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R. Daccord***, M. Guadagnini***



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

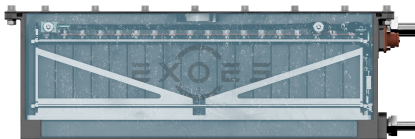
E-racing Car requirements

- 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.



Multi-Fidelity Simulation and Uncertainty Quantification

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

Multi-Fidelity Simulation and Uncertainty Quantification

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Today's focus :

Performances Analysis of the LF Model with Uncertainty Quantification methods.

1 Industrial and Research Objectives

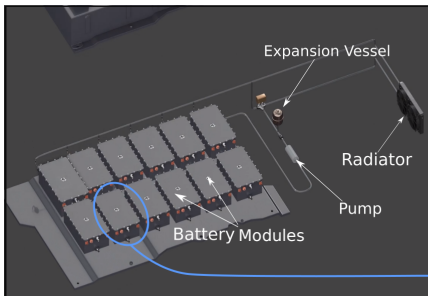
2 Battery Thermal Management System

3 Low-Fidelity Numerical Model

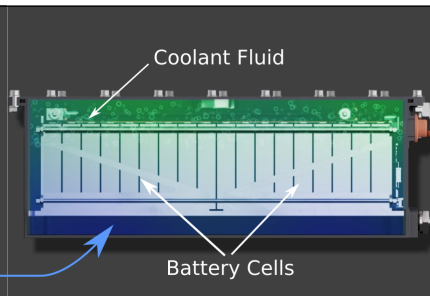
4 Numerical Simulation Under Uncertainty

The Exoes Battery Thermal Management System (BTMS)

Cooling Circuit



Battery Module



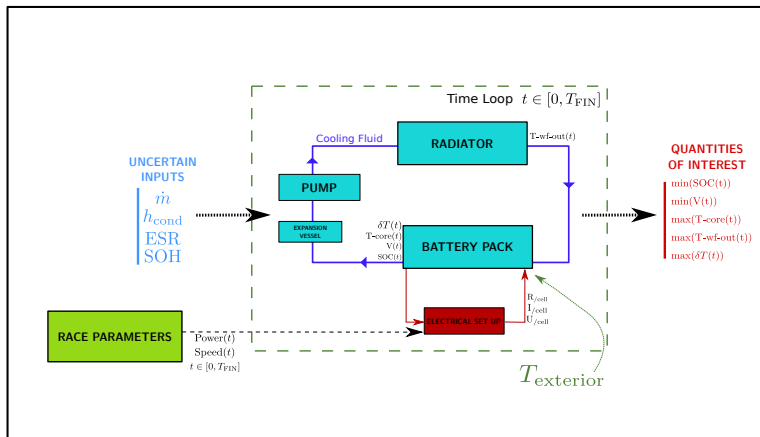
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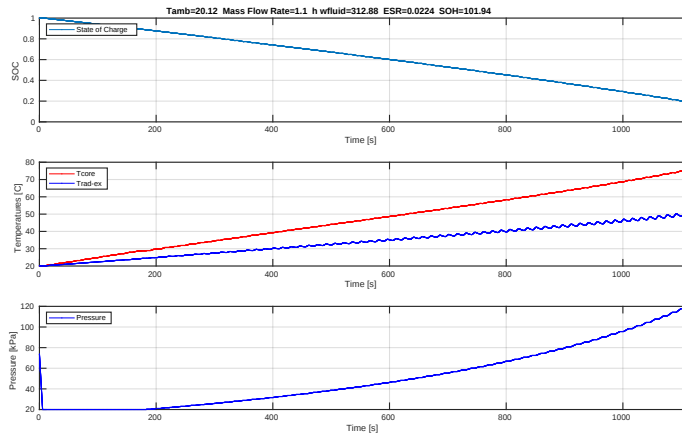
The Low-Fidelity Model



Case Study : Race

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

What the LF model computes



- 1 Industrial and Research Objectives
- 2 Battery Thermal Management System
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Take Uncertainties Into Account

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

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

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Goals of Uncertainty Propagation :

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

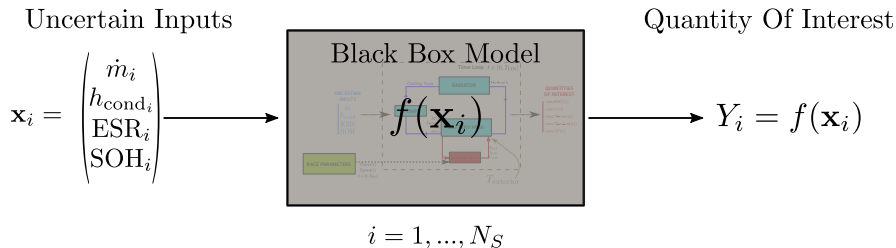
Uncertainty Characterization

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

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

Uncertainty Propagation

STEP 2 : Perform N_S simulations with the Numerical Model, seen as a Black Box



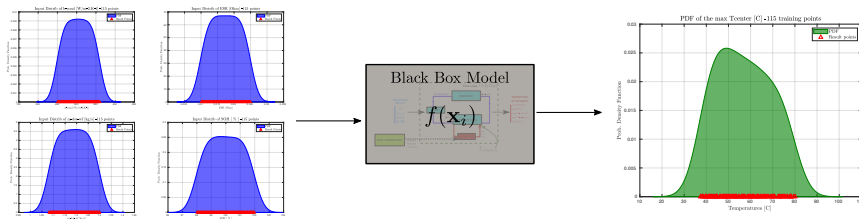
Uncertainty Propagation

STEP 3 : Compute the variability of the QOI with respect to the input uncertainties of the system

Uncertainty Propagation

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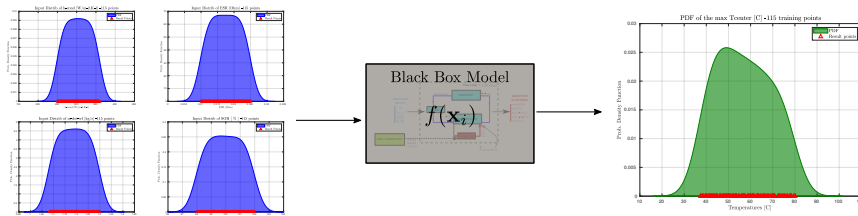
Distribution of the QOI $\max_{t \in [0, T_{FIN}]} (T_{center}(t))$, with 115 sampled points



Uncertainty Propagation

STEP 3 : Compute the variability of the QOI with respect to the input uncertainties of the system

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



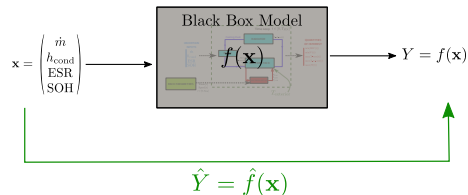
But 115 points is not enough to get accurate distribution.

Monte Carlo method too expensive with computational model $f(\mathbf{x})$.

Need to replace $f(\mathbf{x})$ by a fast-to-compute surrogate model

Kriging Surrogate Model

Need to replace $f(\mathbf{x})$ by a fast-to-compute **surrogate model**



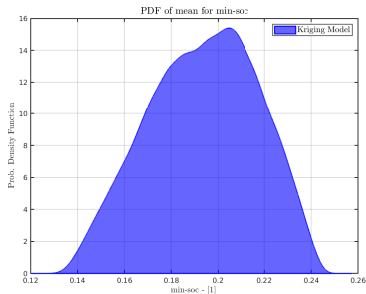
Kriging Based Surrogate Model

Based on Gaussian Process Regression

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

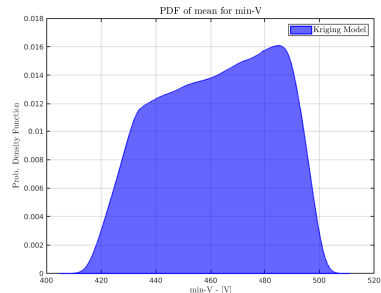
Distributions of the QOI

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



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

COV = 11.99%

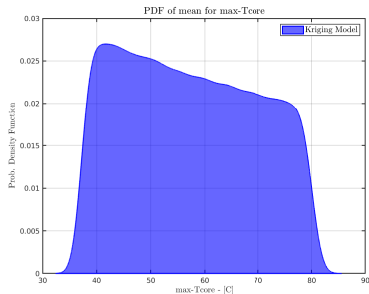


$$\min_{t \in [0, T_{\text{FIN}}]} (V(t))$$

COV = 4.54%

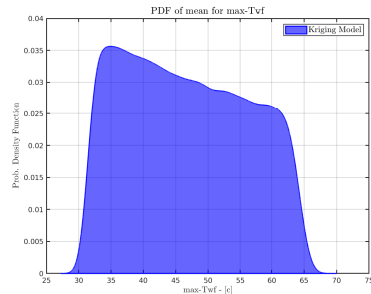
Distributions of the QOI

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



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

COV = 21.49%

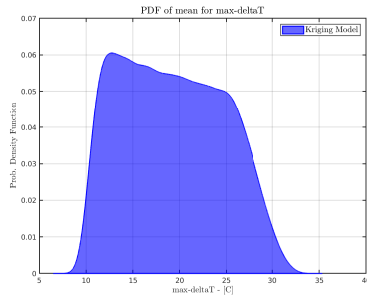


$$\max_{t \in [0, T_{\text{FIN}}]} (T_{\text{wf-out}}(t))$$

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

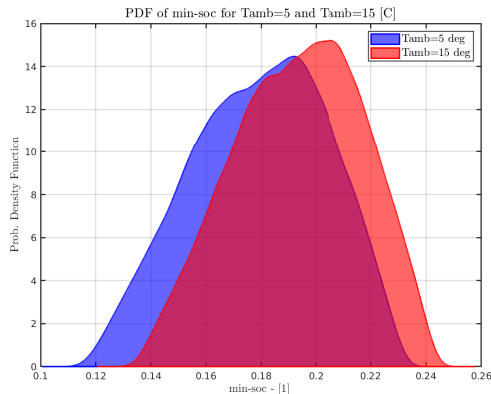


$$\max_{t \in [0, T_{\text{FIN}}]} (\delta T(t))$$

COV = 28.37%

Results for 2 different T_{exterior} scenarios

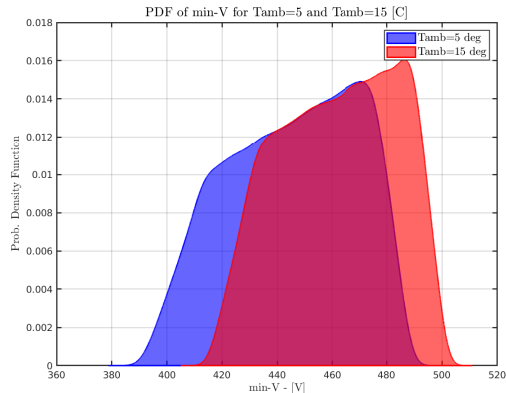
Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^{\circ}\text{C}$ and $T_{\text{exterior}} = 15^{\circ}\text{C}$



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

Results for 2 different T_{exterior} scenarios

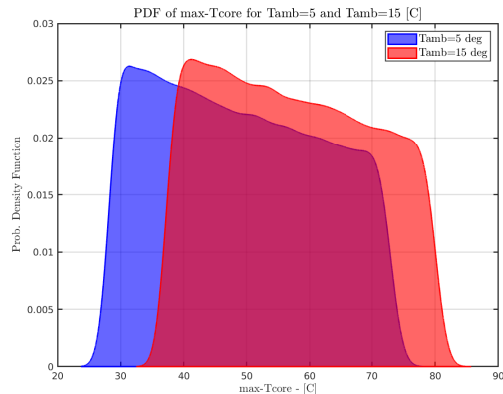
Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^{\circ}\text{C}$ and $T_{\text{exterior}} = 15^{\circ}\text{C}$



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

Results for 2 different T_{exterior} scenarios

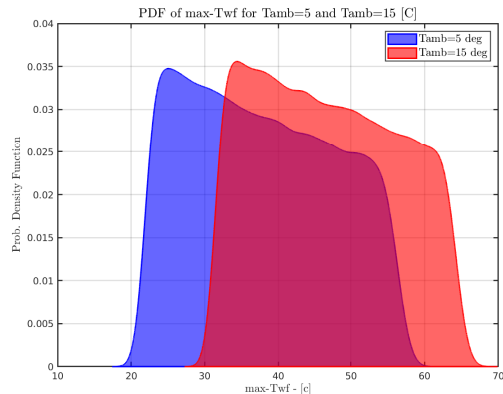
Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^{\circ}\text{C}$ and $T_{\text{exterior}} = 15^{\circ}\text{C}$



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

Results for 2 different T_{exterior} scenarios

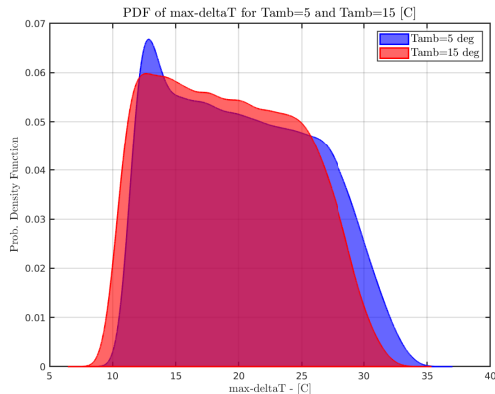
Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^{\circ}\text{C}$ and $T_{\text{exterior}} = 15^{\circ}\text{C}$



$$\max_{t \in [0, T_{\text{FIN}}]} (T_{\text{wf-out}}(t))$$

Results for 2 different T_{exterior} scenarios

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



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

Sensitivity Analysis Study

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 $\mathbf{x} = (x_1, x_2, x_3, x_4)$

Black-box numerical model f seen as :

$$f(\mathbf{x}) = \underbrace{f_0}_{\text{mean}} + \underbrace{\sum_{i=1}^4 f_i(x_i)}_{\text{first order}} + \underbrace{\sum_{i_1=1}^4 \sum_{i_2=i_1+1}^4 f_{i_1 i_2}(x_{i_1}, x_{i_2})}_{\text{second order}} + \cdots + \underbrace{f_{1,\dots,4}(x_1, \dots, x_4)}_{\text{fourth order}}$$

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

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 : $Y_{\text{QOI}} = f(\mathbf{x})$

First Order Sobol Index for input x_i :

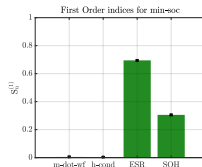
$$S_i = \frac{\text{Var}(\mathbb{E}[Y_{\text{QOI}} | x_i])}{\text{Var}(Y_{\text{QOI}})}$$

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

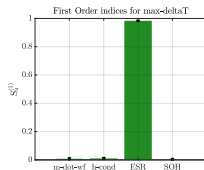
$\text{Var}(Y_{\text{QOI}})$ = main variance of the QOI

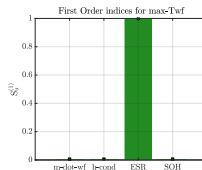
S_i quantifies the main effect of x_i on the contribution to the variance of Y_{QOI}

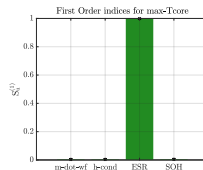
First Order Sobol Indices Results



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


$$\min_t(V(t))$$


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


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


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

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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