System Simulation of a Calibration Bench for Heat Flux Sensors based on a FEM-Model optimized by means of parameter calibration

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Abstract

A coupling among measurements, finite element model simulations in ANSYS and system simulations in Matlab is shown in this paper for a calibration bench for heat flux sensors. A simulated step of its finite element model was calibrated using optiSLang with a measured temperature step. This allowed a characterization of the model by variation of the boundary conditions, the material properties and the thermal contacts between the components and gave the possibility to reduce the model that represented the bench best with the tool mor4ansys. With the reduced model a feedback control for the bench in a system simulation was designed.

Keywords: calibration bench, heat flux sensor, parameter calibration, model order reduction, system simulation

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1 Introduction

A Heat Flux Sensor (HFS) is a sensor which transduces the heat flux driven by a temperature difference between the sensor faces into an electrical signal. This operating principle is based on the Fourier's law of heat conduction Incropera und DeWitt (1996). HFS are widely used in different fields such as meteorology, agriculture, medicine and civil engineering. Before a sensor can be used, it is necessary to know the relationship between the generated electrical signal and the heat flux. It can be determined with a sensor calibration.

A calibration bench for HFS was developed at the Institute for Process Measurement and Sensor Technology of Technische Universität Ilmenau Hohmann u. a. (2014). In this, a HFS under test is positioned between two normalization blocks made of steel (fig. 1). The normalization blocks are brought to a defined temperature by means of the energy applied to their respective electrical heaters. The surface temperature of each normalization block is determined by extrapolation of three temperatures along the centerline of each block, measured by means of thermocouples (TC). The calibration bench is insulated to ensure homogeneous temperature distribution in the normalization blocks and to deaden the effects of the environment in the calibration process.

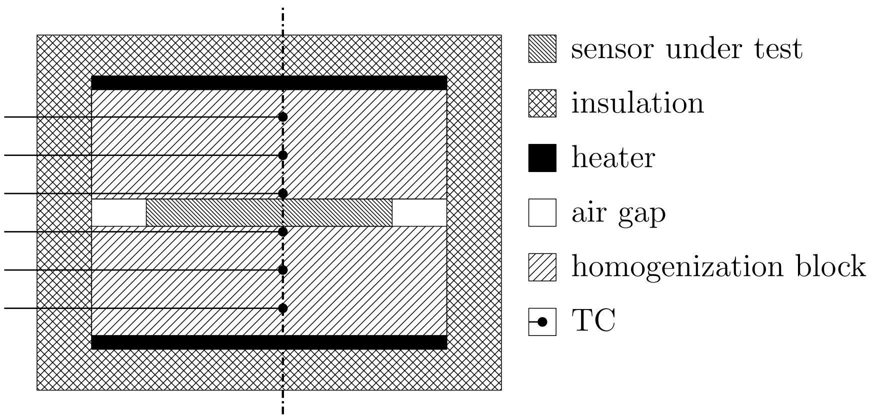

Figure 1: Design of the calibration bench

2 Workflow

For the developed calibration bench, the possibility of coupling field simulations (finite-element-simulations, FEM) and system simulations to create a feedback control for the calibration bench is evaluated. The workflow is shown in the fig. 2.

It is intended to use a model of reduce order (model order reduction, MOR) of the calibration bench for the design of the feedback control. The found controller can be implemented in the real bench in order to validate the potential of designing a feedback

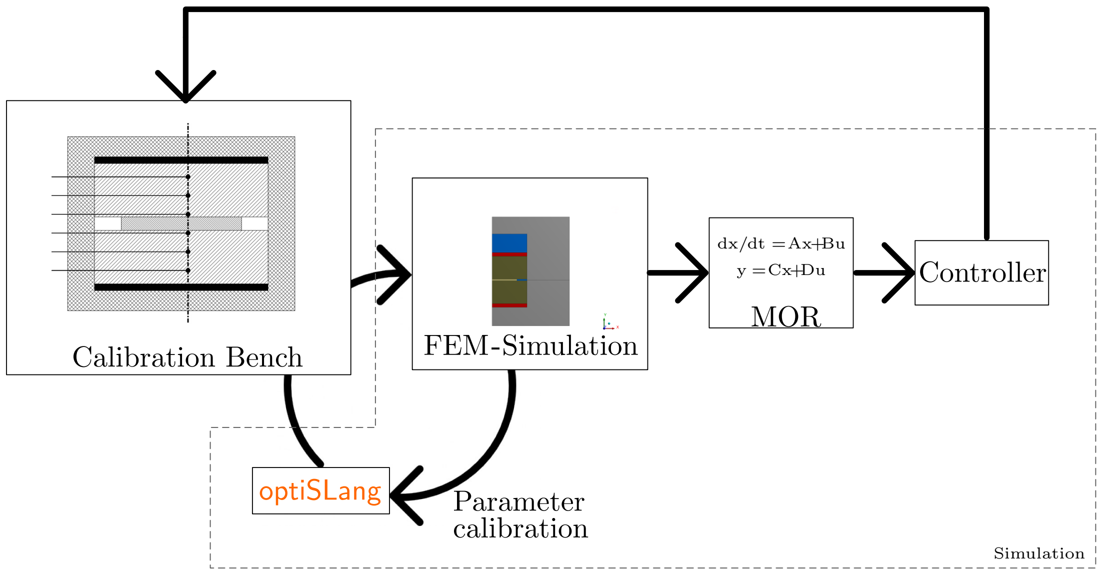

Figure 2: Simulation workflow

control for a system before its fabrication.

3 Measurement

The surface temperature at the lower normalization block was measured for a step response of a defined power input of 10 W in the lower electrical heater. The calibration bench was cooled by free convection to room temperature after the steady state has been reached (fig. 3). Thus, there are two step responses of the bench for the lower normalization block, one for the heating and one for the cooling process. In this paper the system model will be assumed as single input single output system (SISO system).

4 FEM-simulation

The cool down step of the calibration bench starting from the steady state of the heat up step was simulated (fig. 3). For this, a steady state simulation for the heating process followed by a transient simulation for the cooling process were performed. Since the cool down curve represents the system dynamics adequately, this curve was used to calibrate the system parameters. The steady state, defined by the heating process, was used to define the energy input of the system properly.

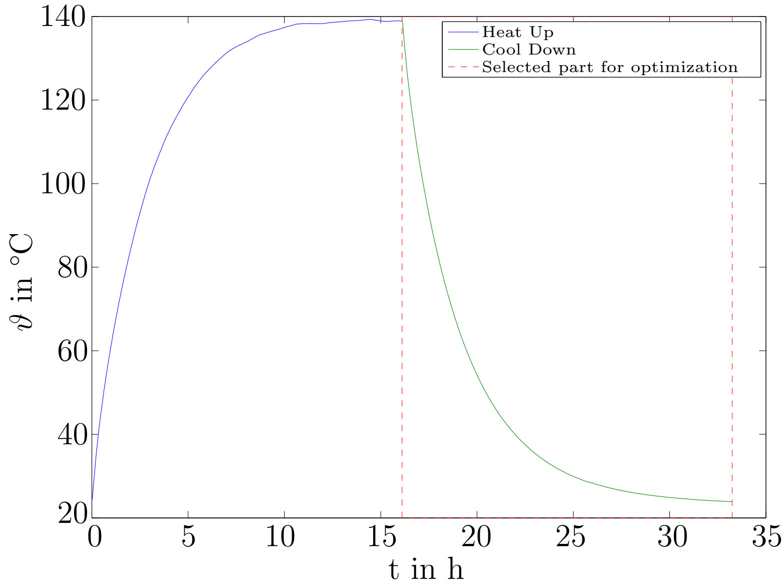

Figure 3: Measurement and its selected part for the parameter calibration

4.1 FEM-model

For the FEM-simulation, the calibration bench was modelled as 2D-Axisymmetric (fig. 4). The bench has an air filled space above the upper electrical heater, which allows the compensation of different thickness of HFS. For this and for the air gap next to the sensor under test, bodies with material properties of air were defined. This was necessary since the tool used for the model order reduction, mor4ansys, only allows to reduce linear models. Thus is not possible to include radiation as boundary condition. The model was meshed with 10500 Quad8 elements and has 32600 nodes. The mesh quality measured by the skewness is less than 0,02 for all elements. The energy input applied to the lower electrical heater was defined as heat generation and the energy outputs to the ambiance were defined with two heat transfer coefficients. Due to the location of the calibration bench on a table in the laboratory.

4.2 Parameter calibration

An well-defined FEM-model of the calibration bench is necessary to get a reduced model (MOR-model) for the design of the feedback control. Thus a parameter calibration using optiSLang was made. The FEM-model input parameters to calibrate it to the measurement by the parameter variation in optiSLang can be divided into 3 categories, as show in tab. 1. The thermal properties of air were not varied, because they are well known for different temperatures. The thermal conductivity of the insulation was varied in a large range of typical values for insulation materials, because it is not accurately known. Thermal contacts were defined between the heaters and the normalization blocks and between them and the HFS. The calculation of these contacts supposes there is an air layer of variable thickness between the elements in contact. This value should not be considered

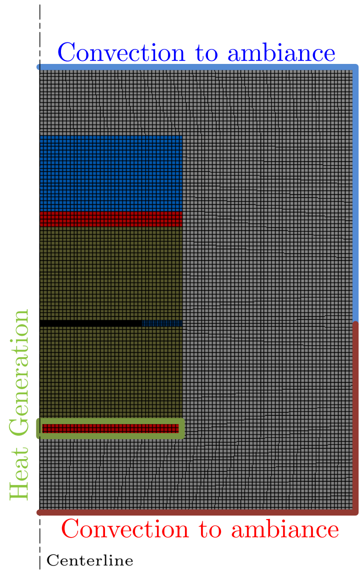

Figure 4: FEM-model with mesh and boundary conditions

as a physical distance but rather as the average thermal resistance value that opposes the heat flux from one element to another. If this value is zero, then is no opposition. The boundary conditions were varied as well. These variations covers the possible power change of the energy source and the uncertainty of heat transfer coefficients to the ambiance.

The difference of the simulated temperature curve and the measured temperature curve for the cool down process was the output parameter to perform an optimization. For the steady state simulation a temperature difference between measurement and simulation at the end of the heat up process of less than 1 °C was set as constraint.

Table 1: Parameters of the sensitivity analysis (*nb normalization block, htc heat transfer coefficient*)

Category	Input parameters	Components	Variation	CoP (MoP) in % Steady state	Transient	#
Thermal material properties	Heat capacity c in $\mathrm{J\,kg^{-1}\,K^{-1}}$ (Only transient)	Insulation	10%	-	-	1
		Normalization Blocks	10%	-	-	2
		Heaters	10%	-	-	3
		HFS	10%	-	-	4
	Thermal conductivity λ in $\mathrm{W\,m^{-1}\,K^{-1}}$	Insulation	85%	81	85	5
		Normalization Blocks	10%	-	-	6
		Heaters	10%	-	-	7
		HFS	10%	-	-	8
	Density ρ in $\mathrm{kg\,m^{-3}}$ (Only transient)	Insulation	10%	-	-	9
		Normalization Blocks	10%	-	6	10
		Heaters	10%	-	-	11
		HFS	10%	-	-	12
Thermal contacts	Separation between components in mm	Upper heater - Top NB	1×10^{-6} - 3	-	-	13
		Upper NB - HFS	1×10^{-6} - 3	-	-	14
		Lower NB - HFS	1×10^{-6} - 3	-	-	15
		Lower heater - lower NB	1×10^{-6} - 3	-	-	16
Boundary conditions	Energy input in $\mathrm{W\,m^{-3}}$	Lower heater	10%	10	7	17
	Energy output α in $\mathrm{W\,m^{-2}\,K^{-1}}$	Upper htc	3 - 10	-	-	18
		Lower htc	3 - 10	6	10	19
Total CoP (MoP)				99	88	

The most sensitive input parameters according to a sensitivity analysis, their CoP and the total CoP are shown in tab. 1 as well; both were calculated in the MoP. A total CoP of 88% for the transient and 99% for the steady state simulation, with an input parameter reduction from 19 to 4 are considered to be suitable for the model description with the MoP and for a subsequent optimization on it. Figure 5 shows the steady state and the transient simulations response surfaces of the two most sensitive input parameters in the steady state constrain and in the transient optimization output parameter respectively. A temperature difference close to 0 °C and a difference between the measured and simulated curve near to 0 are desired.

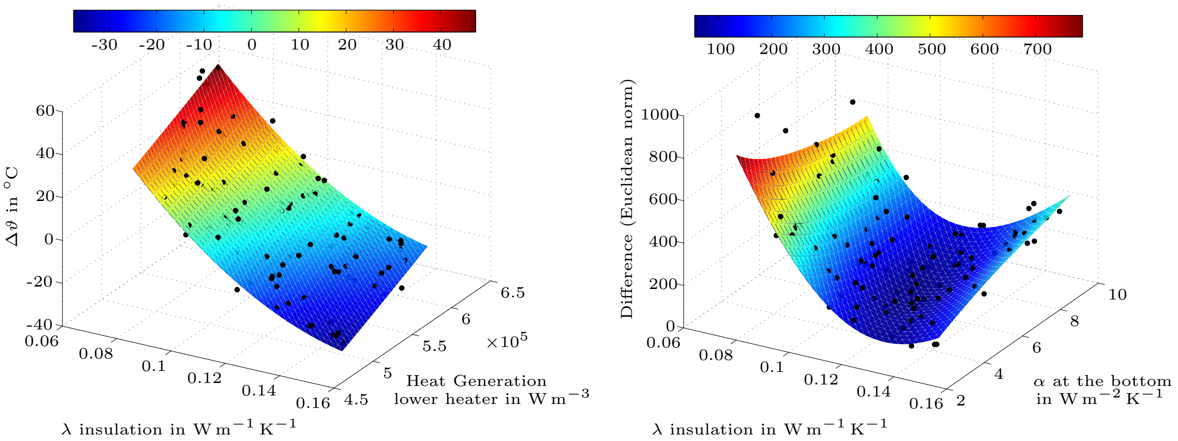

Figure 5: Response surfaces of the difference between measurement and simulation for the most sensitive input parameters (left steady state simulation, right transient simulation)

For this, a sensitivity analysis and an optimization in the MoP using a global evolutionary algorithm was carried out. The simulated curve and the measured curve were calibrated with the variation of the 4 most sensitive input parameters. Another three optimizations were performed for comparative purposes and to evaluate the model description of the MoP. Here a global evolutionary algorithm for the 4 most sensitive parameters (not in the MoP), a global evolutionary algorithm followed by an local evolutionary algorithm for the 19 input parameters and a NLPQL algorithm for the 19 input parameters were used for optimization respectively.

Figure 6 shows the measured and simulated curves for the pre-optimization (starting point) and for each of the optimizations mentioned above. The successful adjustment with the change in the parameters calculated by optiSLang with the different algorithms can be seen. Figure 7 shows the average difference to the measurement of the optimizations in the fig. 6 and the number of performed simulations to reach those values by the different methods. A suitable compromise between simulation time and accuracy of the response was obtained with the optimization in the MoP. This justifies the assumption above, that the model is well described with the total CoP's of 88% and 99% and the 4 selected input parameters after the sensitivity analysis. In addition the model description with only 4 input parameters enables a detailed study of their respective influence on the output parameter and the possibility of designing an effective feedback control only by simulation (see the dashed line fig. 2). They could be evaluated by a robustness analysis

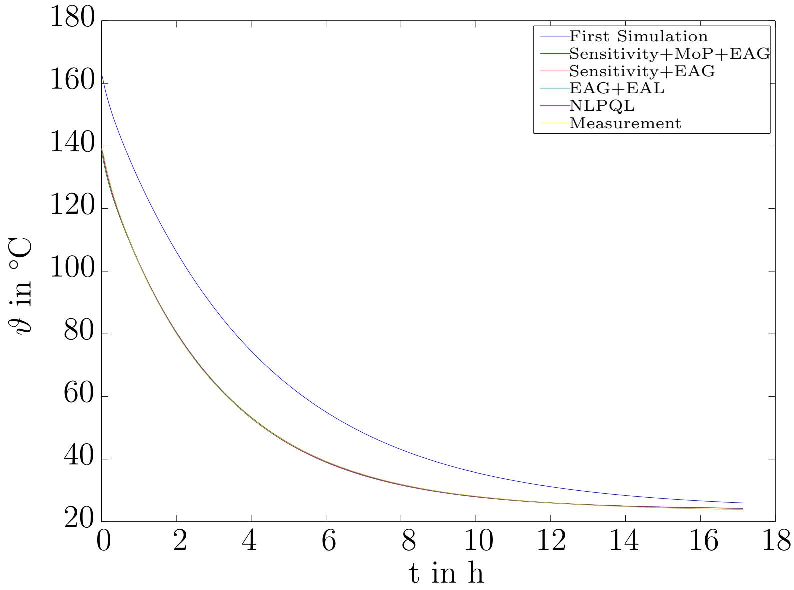

Figure 6: Measurement, first simulations and calibrated simulations by different methods

within possible ranges of availability.

4.3 MOR

The aim of the model reduction is to find a projection matrix that allows to project the state space of the FEM-model onto a state space of lower order with a minimum error Rudnyi und Korvink (2006). This happens by using Krylov subspaces. The reduced matrices in implicit form provided by the used application mor4ansys can be easily converted to their explicit form using e.g. Matlab. These matrices define the state space of lower order. This reduced state space model (MOR-model), is independent of the system inputs Gödecke u. a. (2012), which permits to simulate harmonic or transient system simulations. In many cases, the aim of simulations using MOR-models is to perform faster simulations compared to FEM-models. The goal in our case is to design a feedback control based on a MOR-model, which models the real device after calibrating it by optimization with optiSLang and afterwards to implement the feedback control on the device. As discussed in the section measurement, the MOR-model will have only one input (heat generation). Therefore the further comparisons will be only made for the heat up curve from fig. 3. Figure 8 shows the differences between the measured heat up and the FEM-model optimized in the MOP and between the former and the MOR-model. The difference between both models are shown as well. A comparison between fig. 7 for the cool down process and fig. 8 for the heat up process confirms that the calibrated FEM-model and the reduced MOR-model reflect the thermal behaviour of the calibration bench. The differences between the two process for both models are less than 5%.

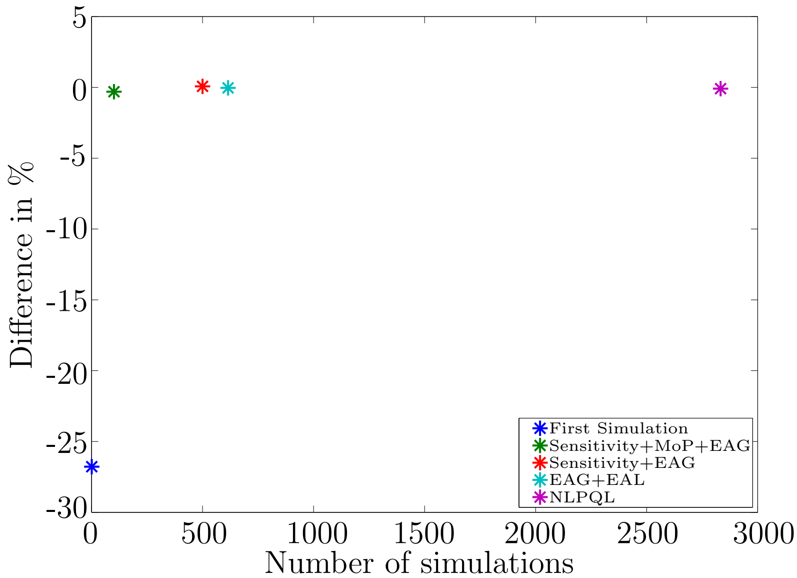

Figure 7: Average difference in percent between measurement and simulations and number of simulations by the different methods to reach this value

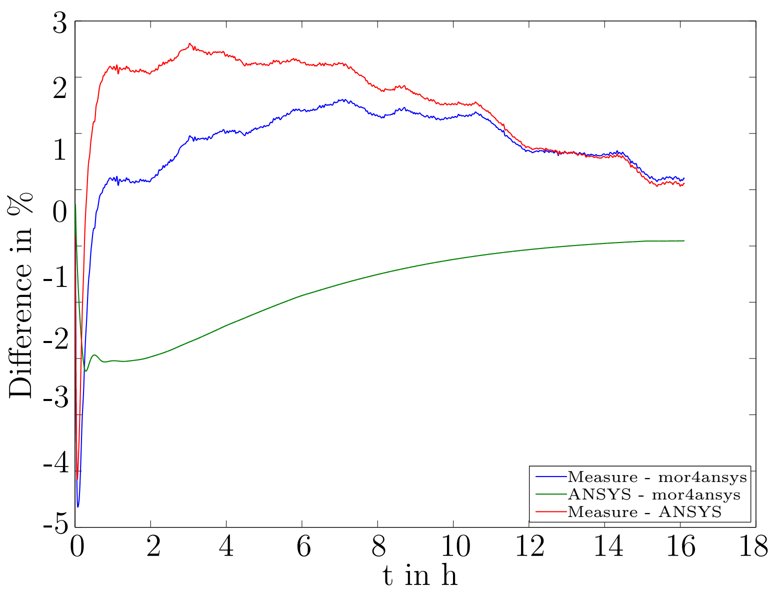

Figure 8: Differences in percent between the measurement and the MOR-model and the FEM-model and the MOR-model for the heat up process

5 System simulation and feedback control of the calibration bench

A PI feedback control was designed using the MOR-model and implemented in the calibration bench. A new measurement to compare the controller operation was carried out and compared again with the simulated response to assess the proposed method. Additionally, the step response of the heat up process from fig. 3 was used to identify a transfer-function-model by means of the Matlab System Identification Toolbox as well. This model was also simulated with the PI feedback control from the MOR-model and compared with the measurement too. These curves are shown in fig. 9. The difference in percent between the two simulated curves and the measurement are shown in fig. 10.

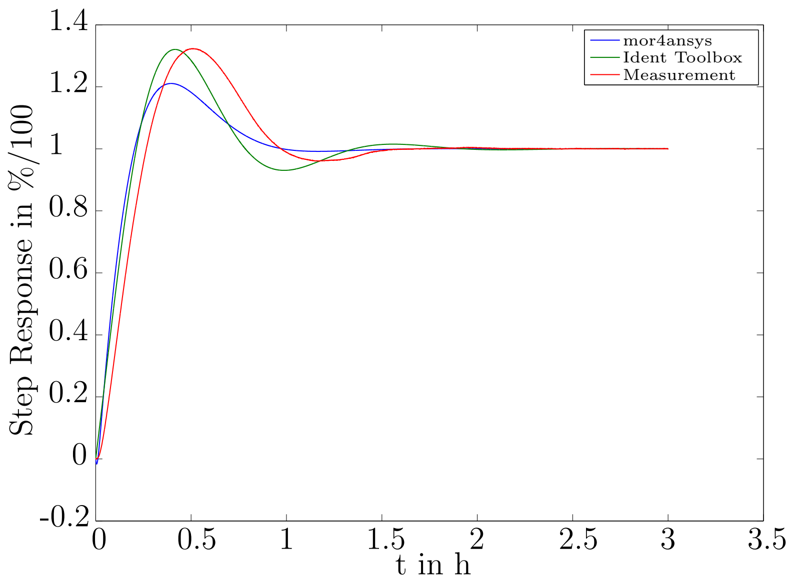

Figure 9: Temperature step response for the reduced model and the measured control loop of the calibration bench

Both methods of system simulations show similar modelling errors. The proposed method can be used, although the error of the MOR-model is bigger than the identified model with the Ident toolbox, because the designed feedback control fulfils appropriate his work. The model order reduction with mor4ansys after a sensitivity analysis and optimization with optiSLang has the advantage that it does not require a measurement for the characterization of the most influence parameters on the system response and would be allow to design a feedback control without the existence of a real device, also in the virtual design phase (dashed line fig. 2). Likewise, it be also allow the system order reduction of most complicated FEM-models with more inputs and more outputs or the reduction of slower systems, in which a measurement for a system identification would be longer.

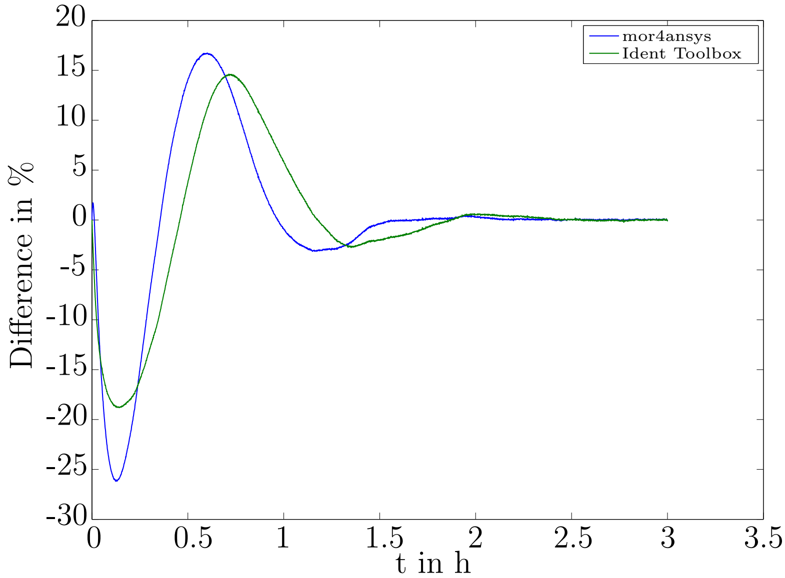

Figure 10: Difference in percent between measurement and simulation with the reduced and the identified model

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