Sustainable Thermal Management of Passenger Cars using multi-fidelity AI-models

Patrick K.S. Vaudrevange [0000-0002-1528-6430],
Matthias Moullion [0009-0000-1417-0447],
Hendrik von Schöning [0009-0007-8807-0001],
Tobias Rößler [0009-0008-3820-999],
Frank Beutenmüller [0009-0000-3648-4519],
Victor Fäßler [0009-0000-6519-9098]

TWT GmbH Science & Innovation
Ernsthaldenstraße 15, 70565 Stuttgart

patrick.vaudrevange@twt-gmbh.de
matthias.moullion@twt-gmbh.de
hendrik.vonschoening@twt-gmbh.de
frank.beutenmueller@twt-gmbh.de
victor.faessler@twt-gmbh.de

Abstract: In the context of the introduction of electromobility, the importance of thermal management will continue to increase, especially in terms of sustainability. In vehicle development, thermal management is validated with both tests and simulations. Due to time constraints, simulations are often performed with simplified models (1D models). In special cases, however, complex and more accurate 3D CFD simulations are also used. Artificial intelligence is just establishing itself here, alongside testing and simulations, as the 3rd pillar in vehicle development. The use of neural networks is particularly well suited for complex problems where many simulations would be necessary to arrive at the optimum. By using AI surrogate models, simulation times are drastically reduced, and the accuracy of the results is increased. This not only makes the development process more economical, but also more sustainable.

1 Motivation

As the number of BEVs sold increases, it is becoming clear that availability of materials required for battery cells, such as lithium, will be critical [1] or at least a bottleneck [2], even with new battery technology like lithium iron phosphate and solid state. OEMs are therefore striving to maximize the efficiency of their vehicles so that the same range can be achieved with fewer battery cells. In addition to optimizing the powertrain efficiency the reduction of the c_W value and an optimization of the thermal management are promising measures [3].

Reducing the size of the cooling air inlet area in the front of the vehicle reduces the c_W value [4], but also influences the cooling performance of the vehicle radiators due to the lower cooling air mass flow. This is achieved with electrically controllable shutters, which are located in the front of the vehicle between the air intake and the radiator package. Optimum control can be implemented if the c_W value or drag performance and the cooling capacity of the vehicle radiators as a function of the vehicle speed, the shutter angle and the fan control are known. [5]

Experience from our projects has shown that for an acceptable number of grid points per degree of freedom, a map of several 100 to more than 2000 points may be required (Table 1). A CFD simulation of the complete vehicle can provide c_W values as well as air mass flows of the vehicle radiators, which can be converted into cooling power. However, the simulations are too complex to calculate the complete characteristic map.

Physically based 1D models allow calculations in acceptable time but cannot represent all flow phenomena and therefore show deviations of more than 25% (Figure 6) compared to CFD in some map ranges. The method presented in the following solves this problem by combining results from the 1D models with a limited number of results from CFD simulations and thus reduces the deviation in the entire map range to less than 10%.

The result is sustainable in a double sense, as it reduces both the energy consumption of a BEV and the need for time-consuming CFD simulations.

This work is structured as follows: In Section 2, we elaborate on the need of accurate thermal simulations in more detail and describe our approach of multi-fidelity AI surrogate models. Then, we briefly describe the setup of our thermal simulations in Section 3. Afterwards, the neural network's architecture and training are presented in Section 4. In Section 5, we present our results and, finally, Section 6 gives our conclusions.

2 Multi-fidelity surrogate models for thermal simulations

Precise thermal simulations are often very time-consuming. For example, a single, physical accurate CFD simulation for the described case can easily take one day. In addition, during the engineering process or for testing various configurations (like for different speeds of the vehicle) not a single thermal simulation is needed but many – for example, hundreds or even thousands. This renders traditional thermal simulations highly inefficient. Nevertheless, an optimal thermal management is of upmost importance. Examples include: the cooling of the electric motor to maximize the powertrain efficiency and continuous power [6] [7], the cooling of the battery cells to increase their lifetime, and the reduction of the vehicle's c_W value. Hence, thermal management has a large impact on the vehicle's sustainability [4]. Consequently, there is a strong need for faster thermal simulations without downgrading the precision of the results.

Surrogate models based on neural networks can help us out [8]. Once a neural network has been trained to predict the outcome of a thermal simulation, its evaluation only takes a little time. For example, in our case evaluating a trained neural network takes around 20-50 ms on a standard computer. Hence, comparing a CFD simulation with a trained neural network the speed-up is easily of the order 10^6. However, to train a neural network successfully, one needs enough training data. This training data can originate from simulations or from wind tunnel tests. Both cases are again time consuming and expensive. Hence, the question arises how to successfully train a surrogate neural network without investing too much time and resources into creating training data.

In this paper, we use the approach of multi-fidelity to train a precise thermal surrogate model. The multi-fidelity modelling method exploring abundant low-fidelity (LF) data and limited high-fidelity (HF) data is considered the potential method to effectively reduce the acquisition cost of labelled data [9] [10] [11]. As the name "multi-fidelity" suggests, this training is done stepwise. First, we pre-train a neural network using a lot of training data of low precision. This data has been created using fast physical based 1D simulations. Then, in a second training step, we continue the training of the pre-trained neural network using a few cases from precise CFD simulations, especially in those regions of the parameter space, where the results of the 1D simulations differ most from the results of the precise CFD simulations. In this way, we obtain a precise thermal surrogate AI-model without spending too much time and resources into creating training data. This method is also applicable to new battery technology like lithium iron phosphate and solid state.

In the following, we will describe the setup of our thermal simulation and the corresponding multi-fidelity surrogate model in more detail.

3 Setup of the thermal simulation

For the thermal management one needs to simulate the air mass flows at the coolant radiators. Therefore, we built our thermal models with COOL3D from Gamma Technologies. In this 3D tool, the air inlets above and below, the shutters top and bottom, radiators, fan and air outlets are modelled based on CAD data, as shown in the example in Figure 1. The model is then discretized to 1D. Pressure losses of the components are stored in maps. The model allows the air mass flow of the cooler to be calculated as a function of the vehicle speed, fan control and shutter control. In total we sample 2.688 points in this space, see Figure 2.

Parameter	Number of settings
Vehicle speed	7
Fan control	6
Shutter top	8
Shutter bottom	8
Total number of settings	2.688

Table 1: Parameter space for the 1D simulations

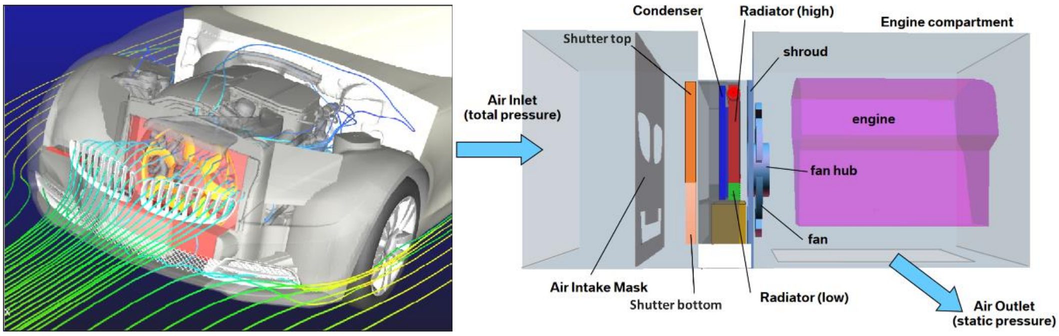

Figure 1: CFD and COOL-3D model of the vehicle front with shutter top and bottom. Right image: Green: radiator for the battery. Red: radiator for the electric motor [12].

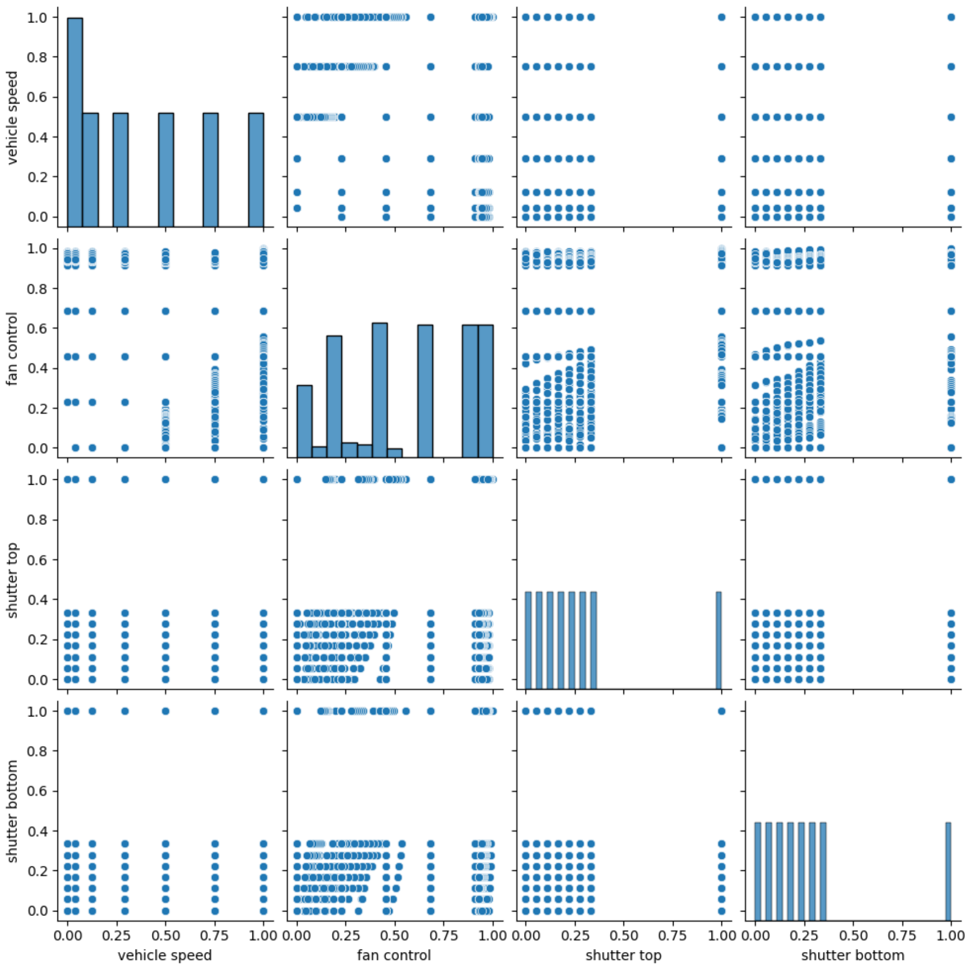

Figure 2: Pair-plot of (normalized) parameter space for the 1D simulations: the plots on the diagonal give histograms of the respective quantities, and the off-diagonal plots visualize the corresponding two dimensions as scatter-plots.

4 Multi-fidelity surrogate model

We use two surrogate models, one for the radiators of the electric motor and one for the battery, respectively. On a technical side, our surrogate models are based on neural networks of the following network architecture:

- input layer with 4 neurons corresponding to the four parameters: vehicle speed, fan control, shutter top, shutter bottom,
- 4 hidden (dense) layers with x neurons each and tanh activation function, where $x = 20$ for the radiator of the electric motor and $x = 9$ for the radiator of the battery, respectively,
- 2500 training epochs with callbacks: early stopping and reduce learning rate on plateau,
- 80% training data, 10% validation data, and 10% test data,

- optimizer: Adam,
- activation function of output layer: sigmoid,
- loss function: mean squared error.

For both cases, i.e., radiator of the electric motor and radiator of the battery, the architecture has been identified to be especially suitable by scanning over various configurations. In the following, we briefly describe the two-step procedure to obtain the multi-fidelity surrogate AI models for our use case.

4.1 Pre-training with low-precision data

In the first step, we pre-train the neural networks for the air mass flows at the radiator of the electric motor and at the radiator of the battery using the results of the 1D simulations only. Here, we take 80% to train the neural network, 10 % for validation (i.e., to adopt the learning rate and to identify over-fitting), and the final 10 % are used as test data in order to see how our models generalize to previously unseen data.

The resulting losses read:

- for the surrogate model for the radiator of the electric motor:
    - using all data: $1.616 \cdot 10^{-5}$
    - using the test data: $2.885 \cdot 10^{-5}$
- for the surrogate model for the radiator of the battery
    - using all data: $3.881 \cdot 10^{-5}$
    - using the test data: $4.482 \cdot 10^{-5}$

Hence, the surrogate models generalize very well on the test data. Further details will be discussed in Section 7.

4.2 Final training with high-precision data

In the second step, the CFD data (consisting of only 57 CFD simulations) is used to specialize the pre-trained neural networks to reproduce the more precise CFD simulations. Before doing so, we compute the losses of both pre-trained models on the respective CFD data, resulting in the following losses:

- for the surrogate model for the radiator of the electric motor:
    - using all CFD data: $90.201 \cdot 10^{-5}$
- for the surrogate model for the radiator of the battery
    - using all CFD data: $985.776 \cdot 10^{-5}$

Consequently, we see that the pre-trained models as such do not generalize well to the CFD data, as expected. For the electric motor the loss increased by a factor 50, while for the battery the loss increased even more: by a factor 250.

Hence, we specialize the pre-trained models using either various fractions of the CFD data or all CFD data (i.e., 1/3, 2/3, or all data) and train for at most 5000 additional training epochs (using an “early stopping callback” that ends training if the accuracy of the validation set is not improving for a certain number of epochs). The results are given in Table 1 and discussed in the next section in more detail.

Model	**Loss of model “Radiator for electric motor”**	**Loss of model “Radiator for battery”**
Base surrogate model	$90 \cdot 10^{-5}$	$99 \cdot 10^{-4}$
specialized using 1/3 CFD data	$37 \cdot 10^{-5}$	$69 \cdot 10^{-4}$
specialized using 2/3 CFD data	$33 \cdot 10^{-5}$	$8 \cdot 10^{-4}$
specialized using all CFD data	$7 \cdot 10^{-5}$	$4 \cdot 10^{-4}$

Table 1: Losses of the various models evaluated on the CFD data for both radiators (electric motor and battery): the base surrogate models have been trained using only data from 1D simulations, while the specialized surrogate models originate from the respective base models with continued training using 33%, 66% or 100% of the CFD data.

5 Results

Our base surrogate models for the air mass flows at the radiators for the electric motor and the battery, respectively, reproduce the results from the 1D simulation to very high accuracies, see Figure 3. If one applies these base surrogate models to the results from the CFD simulations, one sees larger deviations, see

Figure 4. This outcome is expected, since the CFD simulations are physically more accurate than the 1D simulations. The discrepancy is especially large for the radiator of the battery, where many results from CFD simulations differ by more than 20 % from the 1D results.

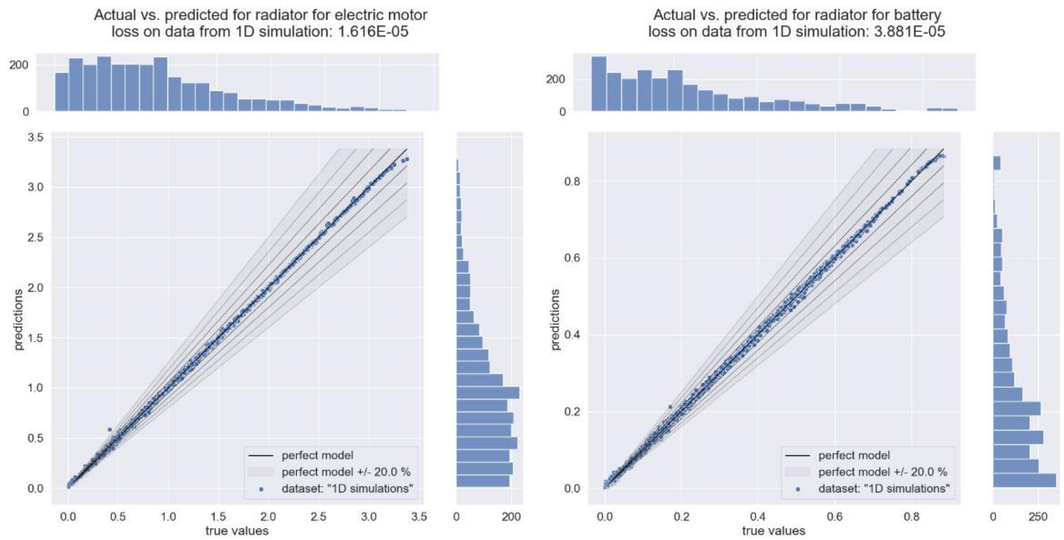

Figure 3: The base surrogate models (trained using data from 1D simulations) reproduce the results from the 1D simulations to a very high accuracy.

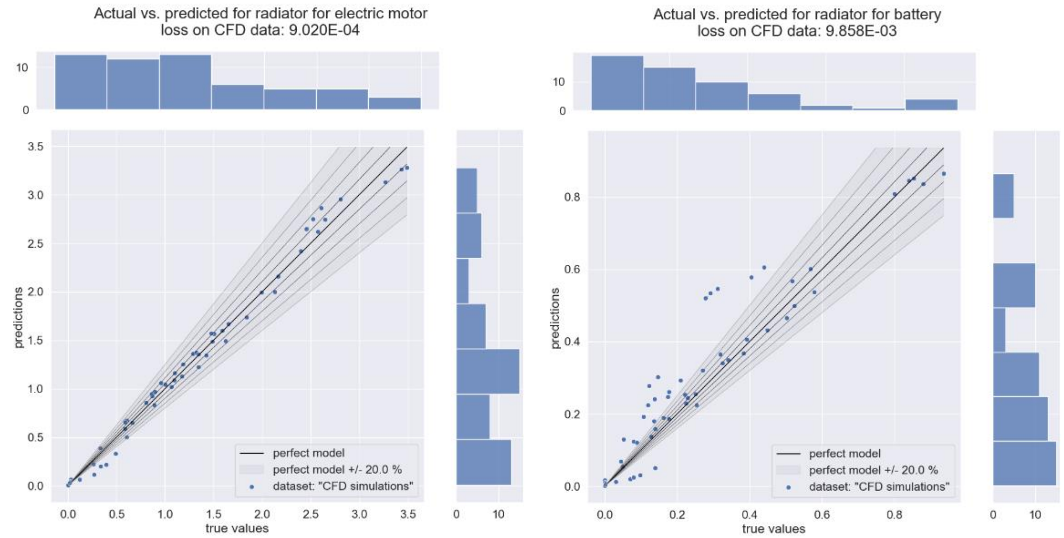

Figure 4: The base surrogate models (trained using data from 1D simulations) cannot reproduce the CFD results. This result is expected, as it is known that CFD simulations are more accurate than 1D simulations.

In addition, we plot histograms of the differences between the predictions of the base surrogate models and the values computed using the CFD simulations. In Figure 5, we show the differences for the air mass flow at the radiator for the electric motor (normalized to the range from 0 to 1). Here, the differences range up to 0.07. On the other hand, the histogram Figure 6 shows that for the battery radiator the corresponding base surrogate model yields differences that range up to 0.25 from the CFD results. This confirms our interpretation of Figure 4 that the CFD simulation is rather similar to the 1D simulation for the radiator of the electric motor but very different for the radiator of the battery.

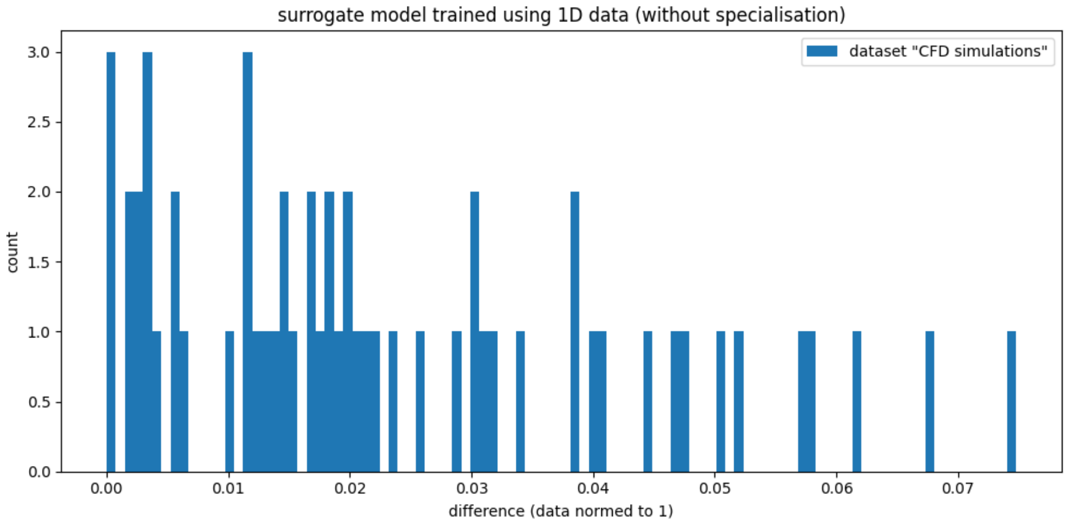

Figure 5: Histogram of absolute errors in the (normalized) air mass flow at the electric motor radiator. Here, the base surrogate model has been evaluated on the full set of CFD data, showing that the CFD results can differ (up to 7% for the normalized data) from the results of 1D simulations.

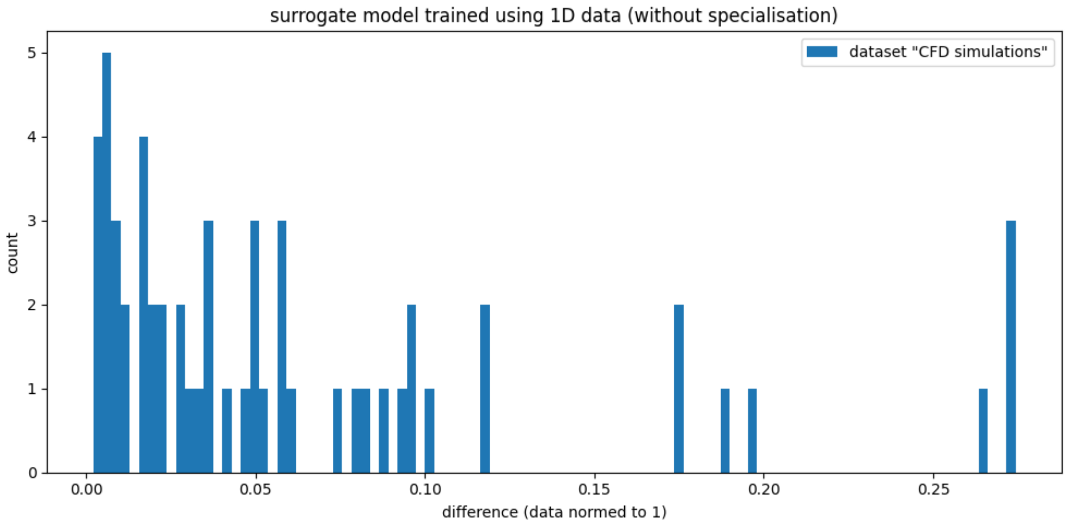

Figure 6: Histogram of absolute errors in the (normalized) air mass flow at the battery radiator. Here, the base surrogate model has been evaluated on the full set of CFD data, showing that the CFD results can differ quite drastically (up to 25% for the normalized data) from the results of 1D simulations.

5.1 Air mass flow at the radiator for the electric motor

After continuing training of the base surrogate model for the air mass flow at the radiator for the electric motor using CFD data, the absolute errors from Figure 6 decrease step-by-step when using more and more CFD data. Using all CFD data, the final multi-fidelity surrogate model is in excellent agreement with the results from simulations, see Figure 7.

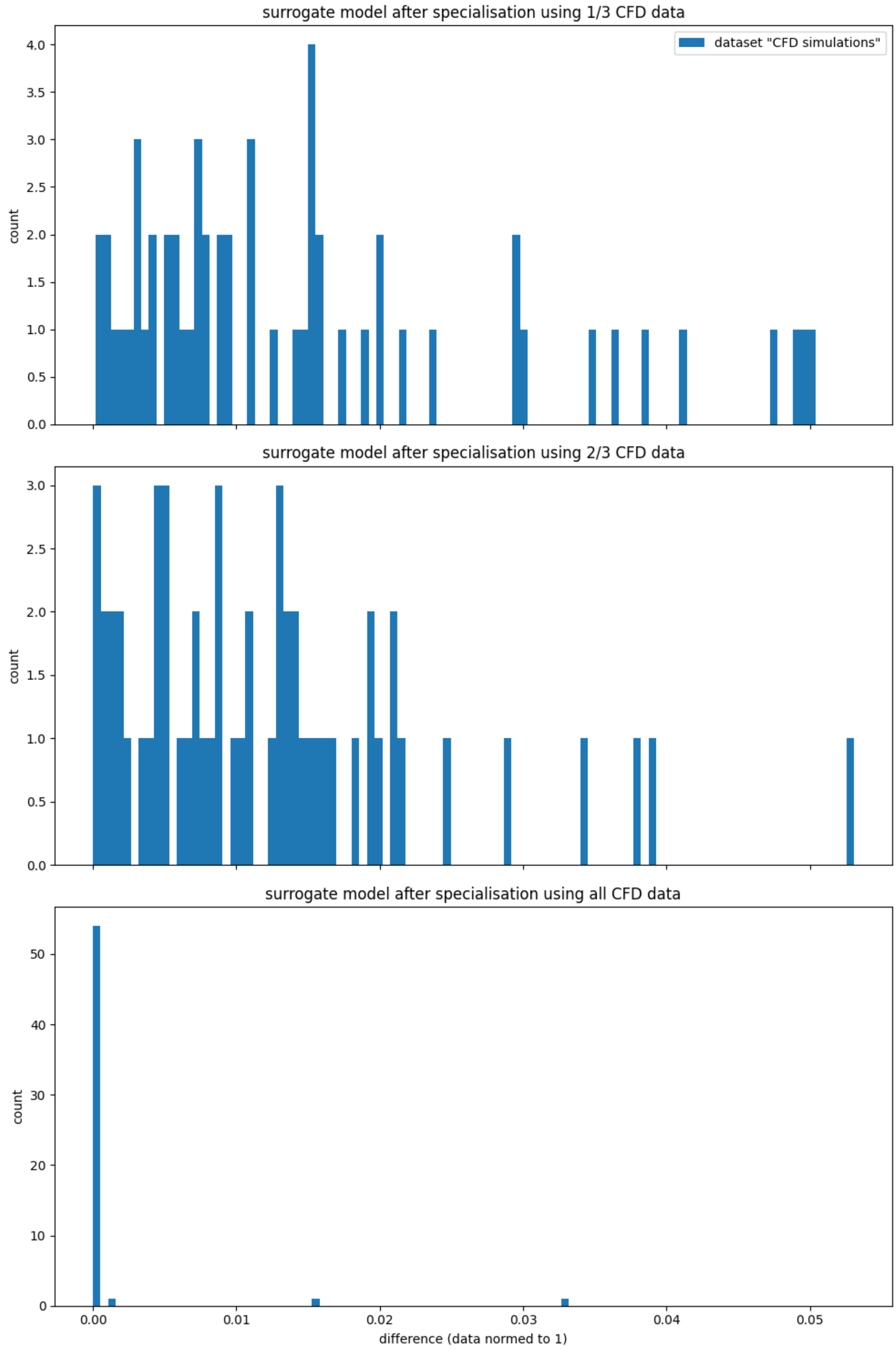

Figure 7: Histograms of absolute errors in the (normalized) air mass flow at the electric motor radiator. From top to bottom: the base surrogate model has been specialized using 33%, 66%, and 100% of the CFD data. In each case, the model has been evaluated on the full set of CFD data.

5.2 Air mass flow at the radiator for the battery

Repeating these steps for the surrogate model of the air mass flow at the radiator for the battery, we obtain Figure 8. This is a dramatic improvement compared to Figure 7, illustrating the strength of the multi-fidelity approach for thermal management.

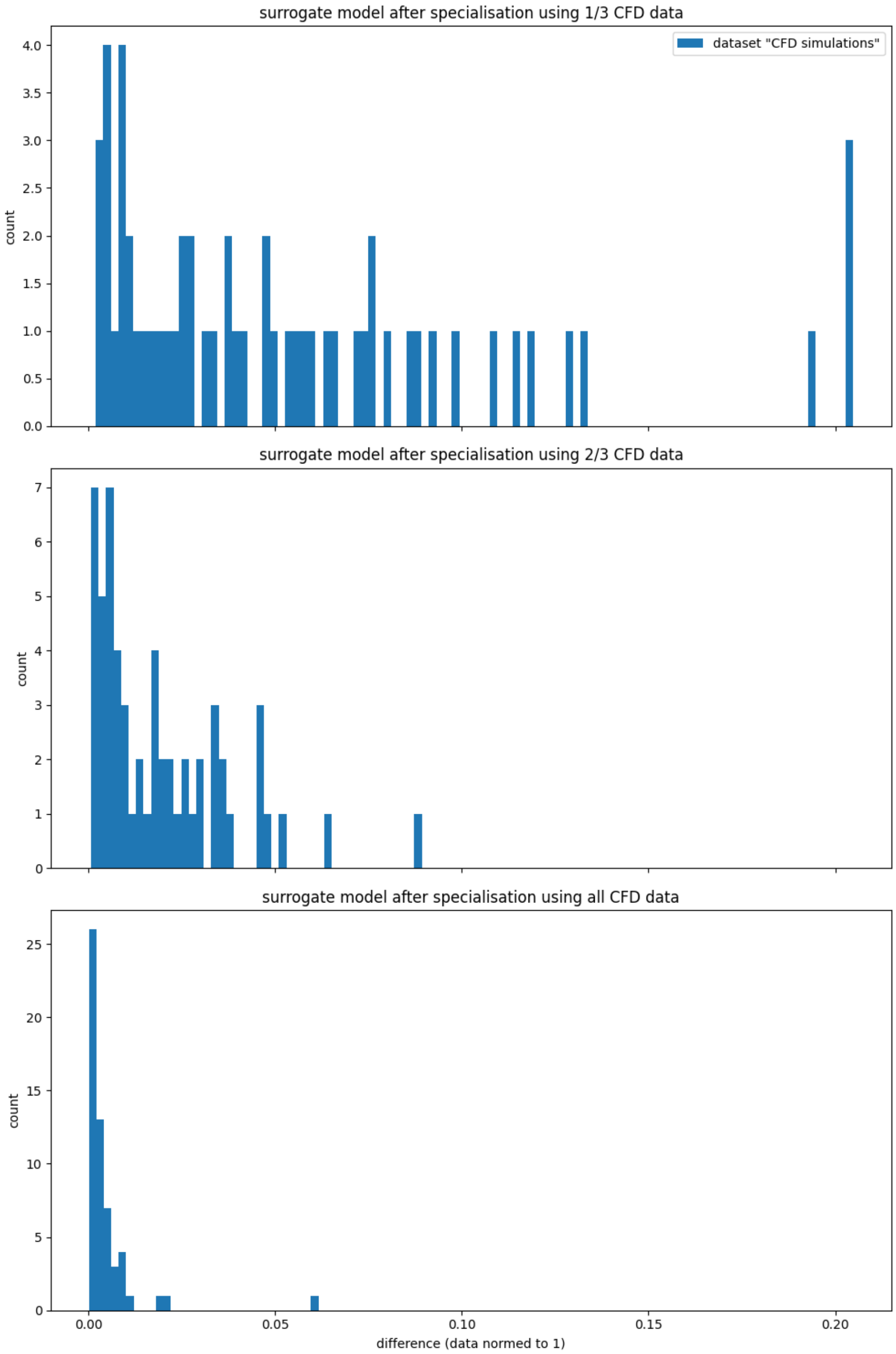

Figure 8: Histograms of absolute errors in the (normalized) air mass flow at the battery radiator. From top to bottom: the base surrogate model has been specialized using 33%, 66%, and 100% of the CFD data. In each case, the model has been evaluated on the full set of CFD data.

6 Conclusions

The results from chapter 5 show that with the presented method the accuracy of the cooling air characteristic maps can be significantly increased compared to the physical 1D results. With a deviation of less than 5%, the cooling performance can be predicted very well, which at the same time allows an optimal control of the active shutters and fan in terms of minimizing the energy demand. The methodology can be applied to any problem. It is particularly promising in areas where complex physical processes are to be predicted in real time.

The following areas of application are conceivable:

- The most accurate control of a complex system
- Monitoring of a component with warning of a failure
- Prediction of state variables and reduction of sensors

If CFD simulations are not available or too complex, the method can also use results from measurements [13]. This can be useful if phenomena occur which are very difficult to represent in a CFD simulation. In the example presented, this would be the case when the blades of the shutters bend at high speed.

The method can thus be a supplement to the CFD and 1D models used so far, combining the advantages of both models.

7 Reference list

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