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Upscaling **P**roduct development **S**imulation **C**apabilities exploiting **A**rtificial inte**L**ligence for **E**lectrified vehicles

D2.4 Validated tool to handle and rationalize aerodynamic data from heterogeneous sources

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Project Details

The UPSCALE Project

The UPSCALE (Upscaling Product development Simulation Capabilities exploiting Artificial inteLligence for Electrified vehicles) goal is demonstrating the feasibility of using AI enhanced CAE methods in EV development processes, such as vehicle aerodynamics, battery thermal modelling and crash simulation, and leading the deployment of AI tools for other CAE applications. UPSCALE is the first EU-project that has the specific goal to integrate artificial intelligence (AI) methods directly into traditional physics-based Computer Aided Engineering (CAE)-software and –methods. These CAE-tools are currently being used to develop road transportation not only in Europe but worldwide. The current focus of the project is to apply AI-methods to reduce the development time and increase the performance of electric vehicles (EVs) which are required by the automotive industry to reduce global emission levels. High performance computing (HPC) and CAE-software and –methods play a decisive role in the vehicle development process. In order to make a significant impact on the development process, the two most HPC intensive CAE-applications have been chosen as use cases for the project: vehicle aero-thermal and crash modelling. When considering total automotive HPC usage, approximately 20% is used for aero/thermal simulations and up to 50% of HPC resources are utilized for crash simulations. By improving the effectiveness of these two areas, great increases in efficiency will lead to a 20% reduction of product time to market. Other novel modelling approaches such as reduced order modelling will be coupled to the AI improved CAE-software and -methods to further reduce simulation time and ease the application of optimization tools needed to improve product quality. Through the combined effort of universities, research laboratories, European automotive OEMs, software companies and an AI-SME specialized in machine learning (ML), the UPSCALE project will provide a unique and effective environment to produce novel AI-based CAE-software solutions to improve European automotive competiveness.

The UpScale Consortium

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Document Details

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Revision History

The following table describes the main changes done in the document since it was created:

REVISION	DATE	DESCRIPTION	AUTHOR (ORGANIZATION)
0	19/10/2021	Initial version	Carsten Othmer (VW)
1	03/11/2021	Review of the draft	Luca Miretti (CRF)
2	04/11/2021	Final revision	Enric Aramburu (IDIADA)

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1. Executive Summary

The purpose of this activity is to develop a numerical tool that is capable of handling heterogeneous aerodynamic data, i.e. data that is coming from different sources with different degrees of fidelity, and to combine it into a predictive model with higher accuracy as compared to a model stemming from single-fidelity data only. To that end, we applied the recently developed methodology for multi-fidelity data fusion [1], which was investigated also in deliverable D4.2, to a combination of low-fidelity (Reynolds-Averaged Navier-Stokes, RANS) and high-fidelity (Detached-Eddy-Simulations, DES) simulations of the UPSCALE limousine test case (see deliverable D4.1). It is shown that adding RANS simulations as low-fidelity input can indeed improve a predictive model based purely on DES snapshots. In the investigated case, however, the improvement is even bigger when replacing the RANS data by a low-order model of the DES data itself, thus confirming the procedure outlined in D4.2.

This deliverable does not deviate from the plan regarding to its content or delivery time.

2. Available Data

In principle, sources of aerodynamic data employable for building a heterogeneous predictive model are wind tunnel measurements with different vehicle scales, road tests, as well as steady and unsteady numerical simulations of varying fidelities. A certain degree of data consistency is, however, required to combine the different fidelities into a single model. In the investigated case of predicting the effect of geometric variations, this requirement translates into a *geometric* consistency among the different sources: one has to make sure that all geometric variants can be represented within a common design space, i.e. with the chosen geometric parameters. According to the experience of the three vehicle OEMs of UPSCALE, this requirement can usually not be met between hardware experiments like wind tunnel measurements or road tests on the one hand and simulations on the other. As hardware tests take place in a later stage of the vehicle development process, their geometries do, in general, not correspond in all details to the ones that were simulated during the purely virtual development phase. And the few simulations that are run accompanying the hardware-based development are not enough to build a decent surrogate model. As a result, from a practitioner's point of view, we are left with numerical simulations of different fidelities as data sources for multi-fidelity models.

Therefore, we decided to use a combination of DES and RANS simulations to investigate the possible benefit from multi-fidelity modelling and wanted to know in particular if adding an appreciable number of RANS snapshots as low-fidelity data to rather coarsely sampled DES computations, which are todays' standard fidelity in automotive aerodynamics, can improve the accuracy of a drag prediction model that is based solely on DES data. The chosen test case is the UPSCALE limousine: the Volkswagen Jetta Hybrid (see D4.1) parameterized with 12 design variables.

The 301 RANS snapshots employed for training were the same as in D4.2: the baseline geometry of the Jetta plus 300 samples following a Sobol sequence. They were run for 4000 iterations with Helyx®, and the drag coefficient was averaged over the last 1000. Mesh sizes were around 52M cells.

With Helyx® in DES mode, we created in total 125 snapshots: the baseline geometry plus 74 samples that follow *the same* Sobol sequence as the RANS snapshots. For these 75 variants, which were used for training, we therefore have both DES and RANS data. In addition, we ran 50 DES samples following a Latin Hypercube that were set aside as test data. The DES cases ran for 4 physical seconds, and the last 1.5 seconds were averaged to obtain the drag coefficient. In order to reduce the computational budget to an affordable amount, we chose a meshing setup that resulted in cell counts of about 60M.

Fig. 1 depicts the correlation plot for the 75 training samples between the RANS and DES drag coefficients. Surprisingly, they are rather uncorrelated. We will look into the possible reasons for this poor correlation further down in this report. For the time being, we just note that given this lack of correlation, it is apparently not straightforward at all to make good use of the RANS data to improve a single-fidelity DES model and requires a robust multi-fidelity modelling strategy.

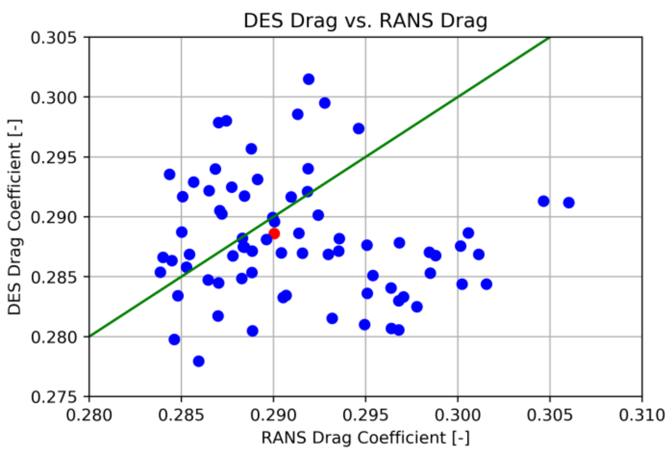

Figure 1: Scatter plot for the drag coefficients of the 75 training samples obtained by DES and RANS, respectively. The green line corresponds to the identity, and the red dot marks the baseline geometry.

3. Multi-fidelity Modelling Results

Building upon the positive experience from D4.2, where we tested the multi-fidelity modelling approach from Romor et al. [1] – albeit in a different setting, we teamed up again with the authors of this method and employed it here. In essence, the method consists of a concatenation of different single-fidelity models: the first model is built upon low-fidelity input only and makes a prediction of correspondingly poor quality, while the second takes the output of the low-fidelity model AND the high-fidelity data as input to make a high-fidelity prediction. It is possible to add more models to this hierarchy to accommodate for more than two fidelities. For a detailed description and possible augmentations we refer to [1].

In total, we created four surrogate models:

i. A 12-dimensional single-fidelity Kriging-model based solely on the 75 DES training snaphots as a reference (“DES” in Fig. 2).

ii. A multi-fidelity model using the 75 DES training snapshots as high-fidelity and the 301 RANS snapshots as low-fidelity data (“MF-DES-RANS”), following the procedure of [1].

iii. A single-fidelity Kriging-model based on the one-dimensional Active Subspace [2] of the DES training data (“AS”). The Active Subspace method is a dimensionality reduction method that – in its simplest form of application – identifies the one direction in parameter space along which the objective function exhibits the largest variation. This direction is a linear combination of the original parameters and is then used as the single design variable for the surrogate.

iv. A second multi-fidelity model according to [1], again with the DES training data as high-fidelity input, but in contrast to model (i) with the output of model (iii) as the low-fidelity data (“MF-DES-AS”).

The accuracy of the models is evaluated by the R2-score obtained for the 50 DES test data points. In order to assess how much the results change when the test dataset is perturbed a bit, a leave-one-out cross-validation on the test data is performed and shown in Fig. 2. Given the coarse sampling of 75 snapshots in a 12-dimensional design space, the poor R2-score of 0.816 of the single-fidelity DES model (i) does not come as a surprise. It is roughly on a par with the 1-dimensional AS model (iii), which usually indicates insufficient samplings. However, the important findings are:

a. The multi-fidelity method operating on DES and RANS data (model ii) does improve the single-fidelity accuracy, despite the observed poor correlation between the RANS and DES drag data: the R2-score increases by ~5% to 0.854. With respect to the spread of the R2-score across the different folds, this increase is marginal only, but statistically significant. We can thus conclude that the multi-fidelity modelling approach works as expected.

b. The most accurate model, and on top with the smallest spread across the folds, is the multi-fidelity model (iv), which does not rely on RANS data at all, but purely on the DES snapshots – used, however, in a multi-fidelity approach. The R2-score increases by 9% as compared to the reference model (i). It is the same order of improvement that was observed in D4.2, where a similar approach was used for lack of a separate source of low-fidelity data.

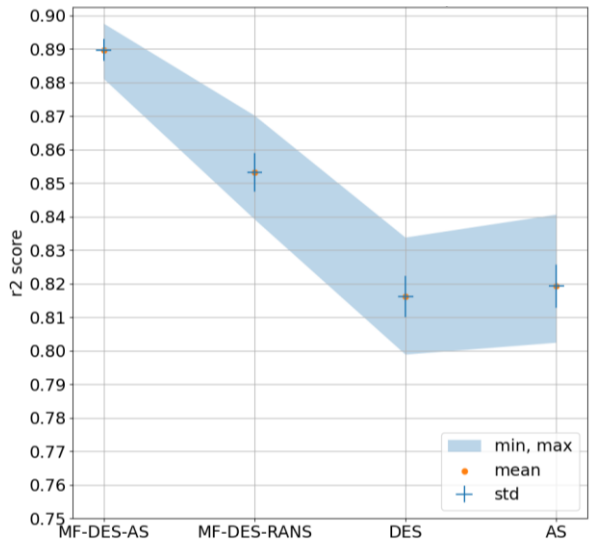

Figure 2: The R2-scores of the different surrogate models as obtained by a leave-one-out cross-validation, along with their standard deviation and minimum and maximum values across the folds.

That the purely DES-based multi-fidelity model (iv) outperforms the combined DES/RANS model (ii) can be attributed to the poor correlation between our RANS and DES results. For completeness, we looked into the reason for this lack of correlation: Fig. 3 (left) shows the contributions of the 12 parameters to the direction of highest variation in the objective function, as determined by the Active Subspace method. For both the 75 DES training samples and their RANS counterparts, the parameter with the dominant influence is no. 1 – the elevation angle of the rear spoiler ("PARAM-spoiler-Y-angle", see D4.1). DES and RANS disagree, however, on the effect of this one parameter on the drag coefficient (Fig. 3, right): while the DES computations predict a decrease in drag for increasing spoiler angles, the opposite is true for the RANS computations. With the effect of the dominant parameter being predicted contrarily by RANS and DES, it almost comes as a surprise that the multi-fidelity method combining these two data sources can benefit at all. It certainly speaks for the robustness of this approach, but also calls for higher data coherence among the heterogeneous sources in future applications of this method.

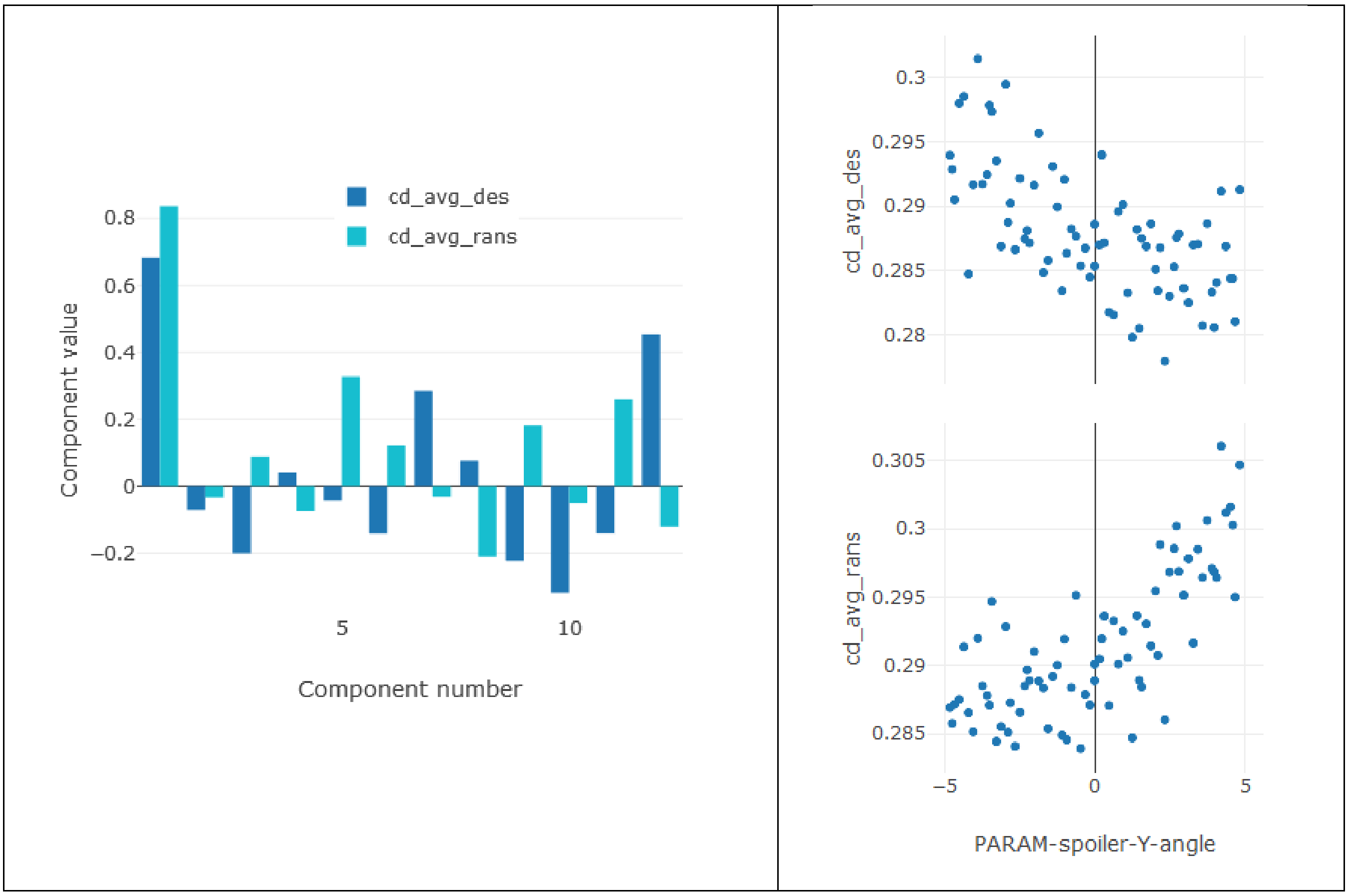

Figure 3: The contributions of the 12 original parameters to the direction of highest drag variation in the design space for both RANS and DES (i.e. the "first eigenvector" in the nomenclature of the Active Subspace method, left), and the drag coefficient as a function of the dominant parameter "PARAM-spoiler-Y-angle" (right, top: DES, bottom: RANS).

4. Conclusions

In collaboration with F. Romor, M. Tezzele and G. Rozza from SISSA (Trieste), we successfully applied their multi-fidelity modelling approach to the UPSCALE limousine test case. Two multi-fidelity models for the vehicle drag coefficient were created, which both use the DES computations as high-fidelity data, but differ in the source of the low-fidelity data: one model employs RANS computations while the other relies on a one-dimensional model of the DES data obtained by the Active Subspace method.

Both models outperformed the single-fidelity DES model, which confirms the validity of the approach for industrial test cases of this kind. Due to a poor correlation of the computed drag coefficients between RANS and DES, the accuracy improvements of the combined RANS/DES model are, however, only minor. It is questionable if – for this particular test case – the additional effort for the 301 RANS computations (corresponding to roughly 30 additional DES simulations) pays off as compared to a hypothetical single-fidelity model upgraded by 30 more DES samples. But for cases with a better correlation among the heterogeneous sources this will probably be the case.

In the investigated case, the highest accuracy can be achieved when removing the reliance on RANS data entirely in the second multi-fidelity model. It has the additional advantage of coming at no extra computational cost – apart from the modelling effort itself, which is negligible compared to the aerodynamic computations. This confirms the observation made in deliverable D4.2 and qualifies this approach as the most promising for actual applications in the vehicle development process.

5. Acknowledgement

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Project partners:

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6. References

1. Romor, F., Tezzele, M., Rozza, G., Multi-fidelity data fusion for the approximation of scalar functions with low intrinsic dimensionality through active subspaces, *Proc. Appl. Math. Mech.*, Vol. 20, Issue S1, 2021, https://doi.org/10.1002/pamm.202000349.
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