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

D4.5 Verification of the optimized model with high fidelity simulations for a fully electric SUV/city car and final report on the framework performance.

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Project Details

PROJECT TITLE	Upscaling product development simulation capabilities exploiting artificial intelligence for electrified vehicles
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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 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 crashmodelling. 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

PARTICIPANT Nº	PARTICIPANT ORGANISATION NAME	COUNTRY
1 (Coordinator)	**IDIADA AUTOMOTIVE TECHNOLOGY SA (IDIADA),**	Spain
2	VOLVO PERSONVAGNAR AB (Volvo Cars)	Sweden
3	VOLKSWAGEN AG (VW)	Germany
4	CENTRO RICERCHE FIAT SCPA (CRF)	Italy
5	ESI GROUP (ESI GROUP)	France
6	ENGYS LTD (ENGYS LTD)	United Kingdom
7	Kompetenzzentrum - Das Virtuelle Fahrzeug, Forschungsgesellschaft mbH (VIF)	Austria
8	VRIJE UNIVERSITEIT BRUSSEL (VUB)	Belgium
9	ECOLE NATIONALE SUPERIEURE D'ARTS ET METIERS (ENSAM PARISTECH)	France
10	ALGORITHMICA TECHNOLOGIES GMBH (ALGORITHMICA)	Germany
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Document Details

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DELIVERABLE Nº	4.5
DELIVERABLE TITLE	Verification of the optimized model with high fidelity simulations for a fully electric SUV/city car and final report on the framework performance.
NAME OF LEAD PARTNERS FOR THIS DELIVERABLE	Volvo Cars
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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	28/04/2022	Collection of all results	Guglielmo Minelli (VOL)

Disclaimer

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1. Executive Summary

After an optimal solution to the reduced order model has been found in task 4.4, a high-fidelity simulation (CFD) will be run, including an adjoint part that shows the sensitivity on aerodynamic drag from changing the geometry. The results from the reduced order model and the CFD simulation will be compared. Furthermore, the adjoint results are mapped to the geometrical input parameters, yielding a sensitivity on aerodynamic drag from changing the input parameters around the optimized point. If the high-fidelity simulation results are close to the modeled results when comparing aerodynamic drag, lift and cooling flow or heat rejection and the adjoint sensitivities mapped to the input parameters are small, the task is complete. If the results differ or the adjoint sensitivities are high, the simulation will be added to the reduced order model and the results from tasks 4.2-4.4 will be updated before running task 4.5 again.
The comparison has been performed for both cases to different extents. Both cases show potentials and limits of the method.

Two main content deviations are taking place in this final step:

- The adjoint verification step has been overlooked. The exchange of data to train the ML was very large, therefore the partners decided to reduce to the minimum the collected data. Collecting adjoint results for each simulation would noticeably increase the data exchange and the speed of the project. Moreover, the use of the adjoint is not always beneficial when the parameters are constrained. The sensitivity on aerodynamic drag can still be very large, even near the extreme of the parameters' geometrical boundaries. Nevertheless, the partners recognize that this area has a large, unfolded potential to pursue in further research actions.
- The results are only compared at the end of the WP. There is not sufficient time to recursively train the ML surrogate model on newly introduced, and more accurate high-fidelity simulations. Nevertheless, the workflow and the software are ready for such an implementation. All partners think that this point has also a large potential, but it would require further future research to exploit and fine tune the above-mentioned implementation.

The impact of the deviations is small with regards to the success of the project. The two deviations consist of possible future implementation, being a further step into the already big workflow that has been setup. WP4 shows that the utilization of ML technique applied to aerodynamics is viable, even when commercial and non-simplified geometries are used. The milestone of the workflow implementation and the analysis of the result shows the potential and the limits of this research work, regardless of the deviations.

2. Electric SUV

In this section, a comparison between the optimum results found using the ML surrogate model for a SUV (Volvo XC40) is compared to CFD simulations. This is done to verify the accuracy of the workflow, to understand its limit, and to plan for further research actions in the future.

2.1. Comparison between ML optimized result and CFD

The results collected in D4.4 are now compared with CFD simulations results to verify the accuracy of the usage of a ML surrogate model for optimization.
The minimum Cd value already present in the database (db), used for training the ML model, is Cd = 0.2948, therefore it would be ideal that the optimization procedure could find a lower Cd case. After the optimization loop, selected cases are run in CFD to ensure this comparison. Table 1 shows the method used for the optimizer and the drag comparison between the surrogate model and CFD. What is visible is that the prediction is highly accurate for the first two cases, and it degrades when the optimizer predicts a very low Cd case. Probably, going toward the boundaries of the search space, and in this case to the lowest Cd value, the model has difficulties predicting accurate values.

Table 1: Comparison between ML surrogate model and CFD results. Volvo XC40

Method	Cd (CFD)	Cd (optimum ML)	Cd error (%)
GA + linear reg. O(2)	0.3079	0.3069	0.33
Grid search + lin reg. O(2)	0.3083	0.3058	0.79
GA + Kriging	0.3193	0.2909	8.88

A better analysis of the prediction trend of the surrogate model is performed in the next chapter using the city car db.

3. Electric City Car

In this section, a comparison between the optimum results found using the ML surrogate model for a city car (Fiat 500e) is compared to CFD simulation. This is done to verify the accuracy of the workflow, to understand its limit, and to plan for further research action in the future.

3.1. Comparison between ML optimized result and CFD

For this car model different optimizer have been tested. The minimum Cd value already present in the database (db) used for training the ML model is Cd = 0.2801. The results are in line with what was found in the previous section. Table 2 shows that an increasing prediction error comes with a decreasing predicted Cd (using the ML surrogate model). As described before, the performance of the predictor degrades moving toward the boundary of the search space, therefore toward very low Cd values.

Table 2: Comparison between ML surrogate model and CFD results. Fiat 500e.

Method	Cd (CFD)	Cd (optimum ML)	Cd error (%)
GA + linear reg. O(2)	0.285	0.266	6.21
GA + Kriging	0.280	0.271	3.20
GA + Kriging anisotropic	0.281	0.274	2.38
GA + Radial basis function	0.279	0.276	1.02

For this case a deeper analysis of the trend of the prediction is also performed. The main goal here is to verify that the predictor can give a good indication of the direction to implement further optimizations. In other words, it is done to verify that the predictor can be trusted in terms of trends. Table 3 collects the drag coefficients and mass flow rate history of the optimization procedure. For selected cases, CFD simulations are also run to verify and plot the prediction trend.

Table 3: Optimization history for trend verification. Fiat 500e.

# generation	Cd (predicted)	Mass flow (predicted)	Cd (CFD)	Mass flow (CFD)
0	0.287	0.897	0.288	0.900
2	0.281	0.877	0.288	0.877
4	0.279	0.873	0.285	0.877
5	0.278	0.869	0.283	0.871
10	0.275	0.882	0.283	0.888
13	0.274	0.878	0.281	0.886
16	0.273	0.892	0.281	0.893
63	0.271	0.879	0.281	0.882
999	0.271	0.875	0.280	0.879

Figure 1 shows a plot extrapolated from Table 3. The trend is successfully predicted by the surrogate model for both Cd and mass flow rate. As mentioned before, going toward lower Cd value the error between CFD and predicted values is larger.

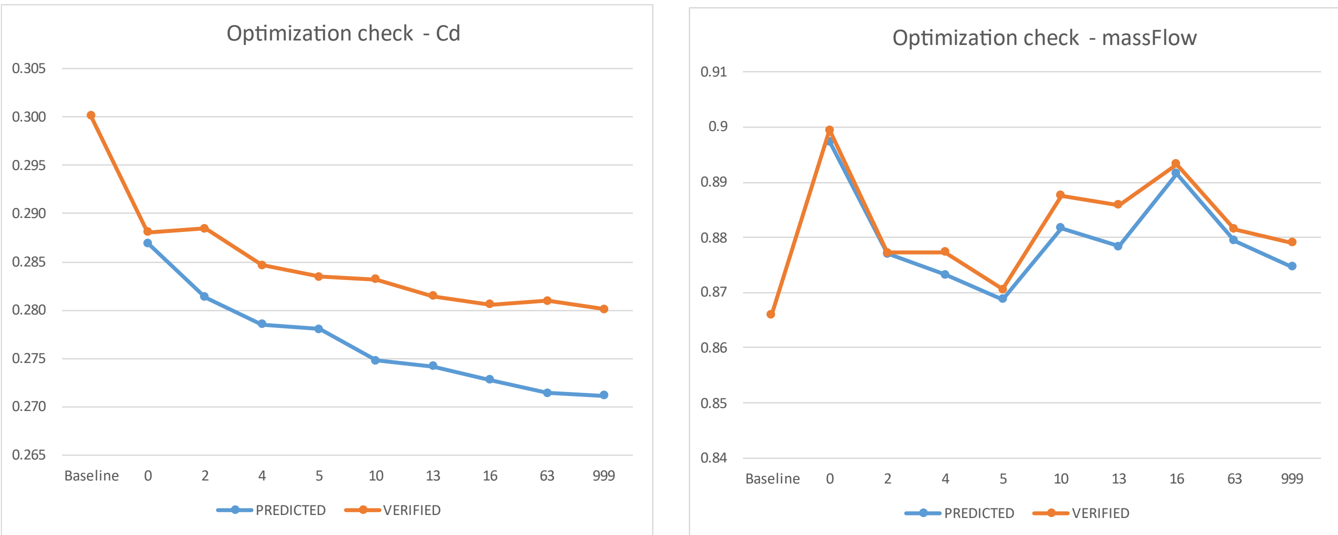

Figure 1: Prediction trend for Cd (left) and mass flow (right)

In Figure 2, an animation of the evolution of the geometrical feature is reported for the selected generations described before.

Figure 2: An animation of the geometry evolution through the optimization procedure. Fiat 500e.

4. Conclusion

Regarding in specific WP4.5 it has been shown that the ML predictor, can be trusted for giving indications based on trends when considering optimizations, but it is still too stiff to be considered for accurate absolute values predictions. The work has also shown a limit of the predictor going toward the boundary of the optimized variable, Cd in this case. Having an increasing error (CFD-prediction) with decreasing Cd values.

Considering a broader picture, WP4 has shown the viability of using ML techniques on real and non-simplified car geometry for aerodynamic optimization. The process is defined by the following milestones:

- It started with the selection of the models from the three OEMs
- The selection of the parameters to be morphed
- The implementation of an elaborate workflow to automate the creation of large CFD databases
- The training of ML tools on the created databases
- The optimization of the car models using the surrogate ML model
- The verification of the optimized data

The work has been carried out in a successful way, showing the advantages, the potentials, and the limit of the created ML tool. Starting from the latter, the work shows that, having parameters to optimize stiffens the work, the databases are limited to themselves, not taking advantage of transferable learning features. A parameter free ML environment would be the basis for the continuation of this research. Concerning potentials, the two deviations described in the executive summary represent future improvements that can be worked on top of the present implemented workflow. Therefore, introducing the potential of adjoint simulations and the implementation of a continuous learning tools that update itself with every new high-fidelity simulation are natural future steps for the project. Regarding the advantages, it has been shown that ML is mature enough to be applicable for CFD optimization and scalable for very complicated geometries.

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Project partners:

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