HOW TO OPTIMIZE THE DESIGN OF A CAR-BODY-STRUCTURE BY USING MACHINE LEARNING

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ABSTRACT –
The future of the automotive industry is electric. Guaranteeing the perfect match between sustainability and performance is our challenge. A feature which plays a crucial role in this challenge is the weight of the car. Lighter structures mean higher battery autonomy, as well as lower production costs for the company. At the same time, weight reduction can lead to the deterioration of the car functional properties. Standard vehicle development projects are still driven by trial-and error methods. Based on experience, car body designers propose tentative configurations of the structure, which are then tested by the simulation team. Inevitably, multiple configurations need to be tested before a satisfactory design is reached. Moreover, due to time constraints, only few configurations can be analysed, which limits our understanding of the problem and ignores potentially better solutions. Artificial Intelligence (AI) and Machine Learning (ML) techniques offer new ways to push our boundaries. They are based on the idea that we do not need complex and time-consuming models to identify patterns in the behaviour of a structure. The method developed in the context of this work uses this principle to maximize the stiffness and comfort behaviour of a car while minimizing its weight. Based on a machine learning approach known as Proper Generalized Decomposition method (PGD), the tool self-learns how to approximate the solution of a complex problem depending on a set of design parameters (material/geometry properties of car components). It consists of three main phases. First, it parametrizes the model. Next, with only one computation, it automatically computes a parametric solution which contains the results for every possible combination of predefined design variables. This parametric solution is then used to perform fast optimization analysis. All results are uploaded to an interactive app, where users, both technical and nontechnical, can explore in real-time how changes in the design variables affect the car performance and make decision accordingly, thus drastically reducing the repetitive iterations in the development process and improving the quality of the final solution.

TECHNICAL PAPER –

1. INTRODUCTION

The automotive design process is complex and time-consuming, requiring collaboration between engineers from different areas of expertise to predict and optimize every aspect of the product. Meeting numerous targets and regulations while keeping up with the fast-paced global market adds further challenges. To remain competitive, automotive companies must improve development efficiency by reducing time-to-market and production costs without compromising quality. Simulation-based studies are crucial in the early design phase, but the extensive computational requirements of detailed vehicle models make them impractical for exploring the entire design space. Consequently, the industry often relies on a trial-and-error approach, leading to potential issues and resource waste. To address these limitations, this work proposes to enhance standard simulations with Machine Learning (ML) methods to optimize the automotive design process and achieve better outcomes.

An innovative methodology is introduced to assess the noise and vibration (NVH) performance of car-body structures. NVH simulation engineering plays a critical role in ensuring that the product meets noise and vibration criteria, thereby improving comfort, quality, and customer satisfaction. This target is highly influenced by the global static and dynamic stiffness of the vehicle body structure, making it extremely sensitive to changes in design parameters. To address this challenge, the proposed approach extends a physics-informed machine learning technique known as Proper Generalized Decomposition (PGD) to solve parametrically the dynamic and static analysis of a structure characterized by material and/or geometric design variables. The main idea is to construct a parametric FE model of the structure and then employ the PGD-based parametric solver. This technique effectively reduces the dimensionality of complex models with only one offline computation, enabling the identification of behavioral patterns within the structure. By utilizing the proposed method, engineers can develop predictive models capable of rapidly evaluating multiple design configurations, facilitating the identification of optimal choices that meet NVH requirements. Employing this methodology allows engineers to navigate the design space more efficiently, enabling early-stage decision-making and minimizing the risk of encountering design challenges in later stages. Next challenge is to allow an easy interaction of the methodology with BETA pre- and post-process software, such that a user-friendly frontend interface can be used by engineers in daily activities.

The proposed method was developed in the context of the doctoral thesis “Static and dynamic global stiffness analysis for automotive pre-design”, one of the 15 projects implemented in the context of the Pro-TechTion programme (Industrial decision-making on complex Production Technologies supported by simulaTion-based engineering), funded by the European Union’s EU Framework Programme for Research and Innovation Horizon 2020 (more info at: https://www.lacan.upc.edu/ProTechTion/). The thesis was supervised by the Universitat Politècnica de Catalunya (UPC) and Swansea University (SU), in collaboration with the automotive company SEAT S.A. as industrial partner. The project is currently in a “Proof of Concept” stage at SEAT, such that it can be included in the current SEAT workflow.

2. THE METHODOLOGY

The mathematical details of the proposed method are extensively described in the referenced publications (1-3). From a conceptual point of view, the method consists of three phases (pre-process, ML solver, post-process), which are described in the following three subsections.

2.1. Pre-process

The pre-process starts with the preparation of a parametrized FE model of the BiW structure. In this work, this is done by means of the ANSA-BETA pre-processor software, which contains a powerful *Optimization Task Tool* able to organize the set-up of an optimization study. The first step consists of defining the design variables (DVs) and their ranges of variation. If geometric parameters are considered, they are defined by means of the morphing tool available in ANSA, which allows to manage the shape changes. The Design Variables are also able to control any other ANSA entity or ANSA card, through the respective ANSA parameters. Based on the DVs definition, the tool can generate a Design of Experiment (DoE) containing all the possible combinations of the parametric values of interest. Once the experiments are defined, the FE output solver files are generated in the desired commercial software, which in this work is MSC-Nastran. By using a special Nastran language (DMAP), all the input files generated by the DoE study are run such that the input quantities of the underlying problems (in this case the mass and stiffness matrices) are just assembled and stored, without solving any static or dynamic problem. The stored files are then uploaded into an in-house code and expressed in the PGD format as explained in (3).

2.2. Machine Learning solver
The machine learning solver utilized in this study is an extended version of the Proper Generalized Decomposition (PGD) method (4), specifically designed for analysing the static and dynamic global stiffness of a Body-in-White (BIW) structure. To tackle the parametric static problem, the solver incorporates the Inertia Relief method, which determines the equilibrium state of an unconstrained structure. In parallel, the dynamic problem is solved by performing a parametric modal analysis to compute vibration modes and natural frequencies, ensuring that relevant targets are met.
The solver is fed with parametric input derived from the pre-processing stage. Acting as a black-box for the end user, the algorithm approximates the solution through a single offline computation. This resulting parametric solution, known as a surrogate model, captures the behaviour of a standard simulation model with sufficient accuracy. Moreover, it allows real-time evaluation of the problem's solution for any combination of the predefined parameters. A notable advantage of this method is its reliance on the governing equations and physics of the problem, enabling the construction of a robust and reliable model without the need for extensive training data. Specifically, the method requires only an initial sampling of the input data (rather than the solution itself). This effectively reduces the computational cost of the pre-process phase, as no full-order simulation must be run. Moreover, it reduces the uncertainty arising from sampling choices, alleviating the burden on the user to make intricate decisions regarding data sampling and calibration of the machine learning model's parameters.

2.3. Post-process
The obtained parametric solution can be easily post-processed in order to perform efficient optimization studies. Moreover, all the results can be uploaded to a standalone interactive app which was developed in the context of this work, where users, both technical and non-technical, can explore in real-time how changes in the design variables affect the car performance. This tool can be used as support by the structural designers for the decision-making process already during the preliminary phase of the design process, thus drastically reducing the repetitive iterations in the development process and improving the quality of the final solution.

3. NUMERICAL EXAMPLE

The proposed method is tested on a simplified BiW structure. Fig. 3.1 shows the geometry and the mesh discretization of the model, which is formed by 3819 nodes. Isoparametric triangular and quadrilateral elements based on the Mindlin-Reissner shell are used.

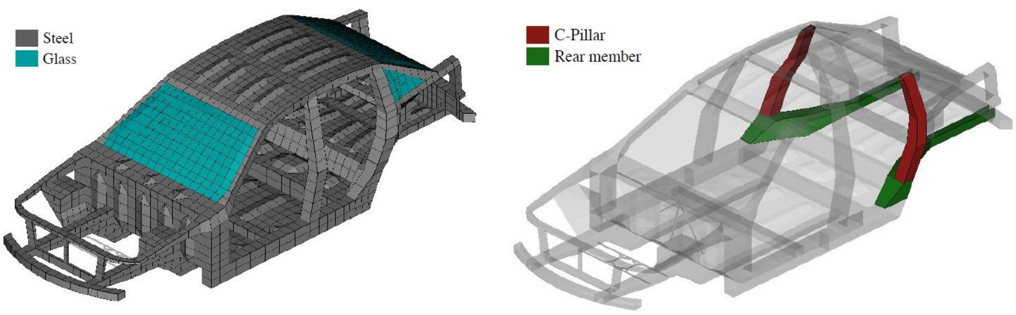

Fig. 3.1. Geometry and mesh properties of the BiW structure (left). The two car components highlighted (right) are characterized by parametric properties, that is the thickness and the cross section of each one of the components.

All the car components are characterized by isotropic linear elastic materials (MAT1 in MSC-Nastran). In this example, four parameters are introduced as design variables of the problem, which are the thickness and the cross sections of the C-pillars and the rear long members shown in the right picture of Fig. 3.1. Table 3.1 summarizes the DVs definition. Each of the four parametric spaces is discretized by means of nine equidistant nodes, which means that the total number of parametric combinations is given by $m_{tot} = 9^4 = 6{,}561$ different configurations.

Table 3.1. Design variables

	IDs	Component	Type	Current Value	Min	Max	Step
Geometry	μ_1	C-pillar	h, w	0	-20	20	5
	μ_2	Rear long member	h, w	0	-10	10	2.5
Material	μ_3	C-pillar	t	1.4	1.0	1.8	0.1
	μ_4	Rear long member	t	0.9	0.5	1.3	0.1

*h: section height; w: section width; t: element thickness (values are in millimetres).

The solver requires a sampling of the input data (mass and stiffness matrices) for each combination. To do that, a list with all the 6,561 parametric combinations can be uploaded into the ANSA optimization tool. Then, a Design of Experiments (DoE) study can be set up which automatically generates the input files in the format of the desired commercial software, which in this work is MSC-Nastran. All the input files generated by the DoE study are run such that the mass and stiffness matrices are just assembled and stored, without solving any static or dynamic problem. The stored files are then uploaded into an in-house code and expressed in the parametric format required by the PGD method (1-3).

The parametric global static and dynamic stiffness analysis is then performed by means of a PGD-based methodology to optimize the NVH performance of the BiW structure. Two quantities of interest (QoIs) are obtained in a parametric format:

- the Equivalent Torsional Stiffness (ETS): to assess the static stiffness of the BiW;
- the natural frequency of the first torsional mode: to assess the dynamic stiffness of the BiW.

The accuracy of the method is measured by comparing the two quantities of interest (ETS and torsional frequency) with the corresponding full-order results, which resulted into a maximum relative error in the order of 10^3. It is important to mention that the PGD results were obtained by performing only one offline computation for the static and dynamic problems and then particularizing the results for any parametric combination in real-time. On the contrary, a total of 13,122 full-order simulations (6,561 for the static and 6,561 for the dynamic case) were needed to sample the results by means of standard methods.

In order to show the potential of the proposed methodology, a multiobjective optimization analysis is performed. The goal is to find the optimal combinations of the parameters such that the ETS and torsional frequency are maximized while the mass of the two parametric car components is minimized. Three objective functions are defined as:

$$\begin{cases} g_1(\boldsymbol{\mu}) & = M(\mu_1,\mu_2,\mu_3,\mu_4), \\ g_2(\boldsymbol{\mu}) & = \mathrm{ETS}(\mu_1,\mu_2,\mu_3,\mu_4), \\ g_3(\boldsymbol{\mu}) & = f_t(\mu_1,\mu_2,\mu_3,\mu_4). \end{cases}$$

where $M(\mu_1, \mu_2, \mu_3, \mu_4)$ represents the total mass of the C-pillars and the rear long members, depending on their variable geometries and thickness. Clearly, this quantity is strictly related to the production cost. ETS($\mu_1, \mu_2, \mu_3, \mu_4$) and $f_t(\mu_1, \mu_2, \mu_3, \mu_4)$ are the parametric static and dynamic output, respectively, obtained by means of the proposed PGD-based algorithm. The explicit dependency of the three functions on the parameters permits to easily compute the Pareto front (Fig. 3.2) of the multiple objective functions by means of a genetic algorithm (GA). The cloud of sampled points in the plot represents the mass and ETS coordinates corresponding to each of the 6,561 parametric combinations considered initially. The optimisation study allows to drastically reduce the number of configurations which would be considered by the designers in the final decision-making process.

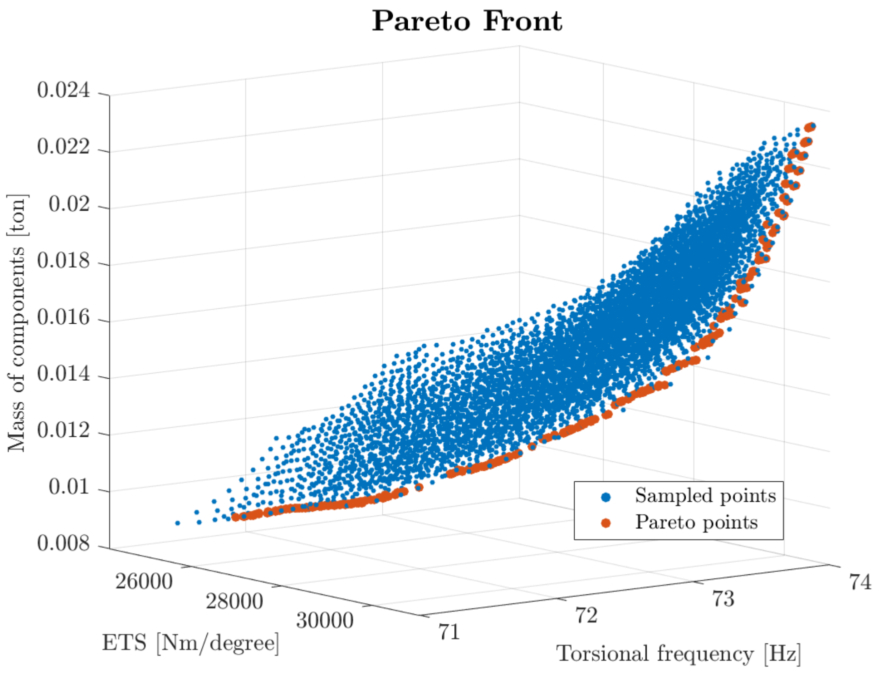

Fig. 3.2. Multi-objective optimization showing the Pareto front as a function of the objectives.

Finally, a graphical interface app was developed by using the Matlab App Designer software, providing an interactive visualization of the results, such that the designers can check in real-time the effects of variables on the global static and dynamic behavior of the BiW structure. The developed app is just an example of the potential of this method. In fact, the information contained in the app could be modified and adapted to the needs of the specific problem, representing the kind of support that the industry urgently needs to optimize the development process.

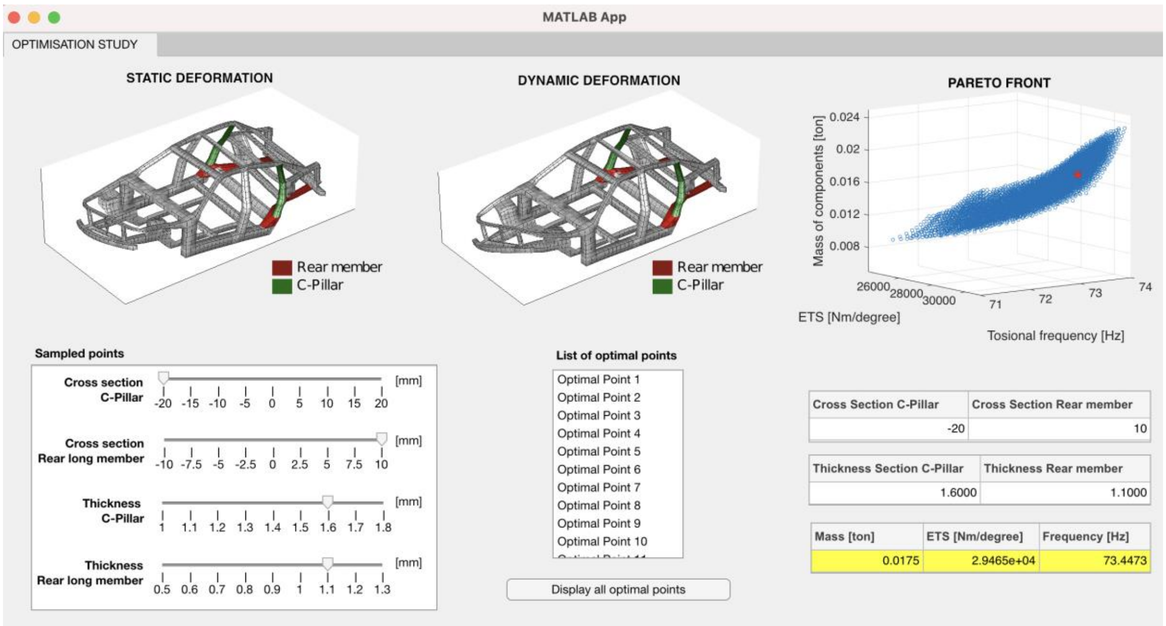

Fig. 3.3. Graphical interface of the developed PGD-NVH app for the static and dynamic analyses.

4. CONCLUSION & CHALLENGES

The proposed ML technique, based on the PGD method, allows to efficiently explore an arbitrary large design space, and perform real-time sensitivity analysis with respect to the different design parameters. The key idea behind the method is to invest an initial affordable computational effort, already during the preliminary phase of the design process, to build an accurate surrogate model of the problem. The obtained reduced model is then used to perform efficient optimization studies and real-time evaluations, which empowers the designers during the intricate decision-making process.

Currently, the authors are working on scaling up the methodology and test it on real industrial models. Moreover, one of the main objectives is to encapsulate the whole technique in a tool which can be easily used by our engineers. To reach this goal, one possibility is to couple the proposed ML-solver with BETA pre- and pot-process software.

At this purpose, the next purpose is to create a BETA-based graphical interface which can perform the following three steps:

1. Pre-process (coupled with BETA-ANSA):
    - To parametrize a model (entities and/or geometric morphing)
    - To set up a DOE analysis (in order to generate the input decks in the desired FE software format)

2. In-house machine learning solver:
    - Call in-house PGD-based toolbox (written in Python language) to solve the parametric problem and generate a surrogate model
    - Convert the results into an ANSA-META readable format

3. Post-process (coupled with BETA-META):
    - Visualize the parametric results in ANSA-META (e.g., parametric curve plots, heatmaps, deformations, etc.)

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