OPTIMIZATION OF SOUND PRESSURE AND VIBRATION LEVELS IN AUTOMOBILES AND RESPONSE PREDICTIONS USING DEEP NEURAL NETWORKS

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ABSTRACT –

The sound pressure level in the occupant cell is among the major components of driving comfort. An acceptable sound pressure level in the occupant area is a quality indicator of how well the car can reduce internal as well as external noises. A major contributor in reducing such noises is the choice of bushings and vibration absorption pads. One of the aims of this study was to implement a novel workflow to optimize the sound pressure levels and structure vibration levels in the occupant cell with a series of coupled optimization and DOE studies.

The newly proposed workflow not only tries to minimize the number of cycles but also allows the ability to fully understand the dependencies of components on the vehicle's overall response. This in turn improves the quality of engineering decisions made during the last-minute changes in the development cycle. NVH Console from BETA CAE Systems [1] was used to implement the frequency-based assembly in our workflow, which allowed us to find the optimal bush-stiffness parameters alongside running topometry optimization using Nastran's SOL200. Further, a targeted peak reduction technique was developed allowing the user to minimize multiple peaks from different responses with different weighting factors.

Further, utilizing the new workflow with NVH Console's fast response analysis, stiffness combinations and the corresponding responses were processed and used to train a deep neural network. This tool does not only assist the user approximate the peaks in responses but also their shifts across the frequency range, allowing them to take better decisions when it comes to choosing bushings of different stiffness coefficients.

1. OBJECTIVE AND IMPLEMENTATION

The absorber pads tend to add a lot of weight to the car when not optimized, which directly influences the fuel efficiency. An ideal design workflow therefore should address this multi-objective optimization problem. Moreover, a lot of time is spent calculating individual model matrices and solving the PDEs involved in the FEM process even for small changes in the model. High computational resource consuming tasks not only increases the cost of a project but also imposes limits on running DOEs for exploring the optimum response space.

The above two multi-objective problems are tackled with the new proposed workflow. For minimising the responses along with the weight of the absorber pads, the workflow combines the benefits of a topometry solver and simulated annealing optimization algorithm. Firstly, the panel with the most contribution to the overall responses was found. SOL200 was then used for optimizing the design of vibration absorber pads that helped reduce the SPL in the absorber material's active (frequency) range. To speedup finding the optimum bush-stiffness range, the bush that contributed the most in the SPL and vibration of panels were selected based on their strain energy by developing an energy evaluation tool. Further, to minimise the run time for each iteration of the simulated annealing optimization process, frequency-based assembly technique was implemented [2] using the NVH Console plugin from BETA CAE Systems.

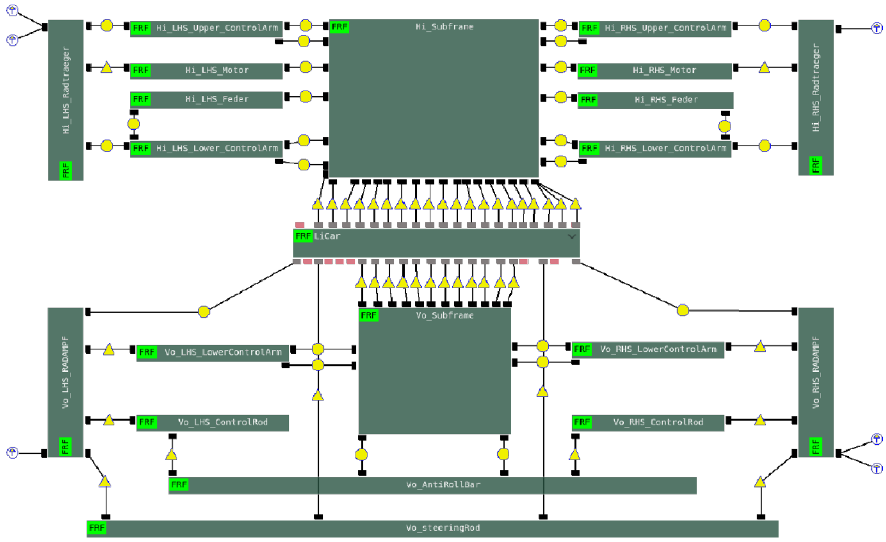

Figure 1 Frequency based assembly of the EDAG LightCar using NVH Console

With the run-time reduced and the top contributing bush selected, simulated annealing optimization algorithm was then implemented to explore the optimum bush stiffness range for attaining a minimum response space. To achieve an overall reduction in peaks, a weighted sum of peak values was fed to the optimiser. These weights help us prefer some peaks over the other when the optimiser seems to be stuck in a local minimum in the cold phase of the annealing optimisation process. The script also allows to change the peaks of interest in real time given the predefined optimiser constraints are not violated. The two solvers were then bridged with a series of scripts that updates the frequency-based assembly with the optimized pads and updates the component-level FRFs automatically.

The early sensitivity analysis stage of SOL200 and the fast FRA based bush-stiffness optimization results, in end effect, provides a large, labelled dataset. Wherein lies the relationships, for instance, between the bush-stiffness in each direction and the SPL or vibration response for the given structure grids. Similarly, relationship between the thickness of the VAP and its position on a panel and a structure response can also be extracted. For the course of this study, however only the relationship between bush-stiffness and the selected responses were extracted. To achieve this, special scripts were developed to extract the responses for a given frequency range for each bush-stiffness. TensorFlow Functional API [3] was then implemented to predict multiple response for a given set of bush stiffness.

2. RESULTS AND CONCLUSIONS

After two cycles through the new proposed workflow, a significant decrease in SPL and vibration responses are observed as shown in Figure 2. With the help of Principle Component Analysis [4] and some adjustments to the hyper-parameters and through DOEs on trainable parameters, an R2 of 0.97 was achieved. The trained neural network acts as a second order tensor which can accurately map the input bush stiffness combinations to the SPL and vibration responses solution space. With such high correlation achieved, the trained network was then integrated in a post-processing tool which helps the end user acquire the structure and acoustic responses for new bush-stiffness combinations. The response predictions are overlayed on the SPL and the 3D bubble plot showing with the bush parameters in Figure 3.

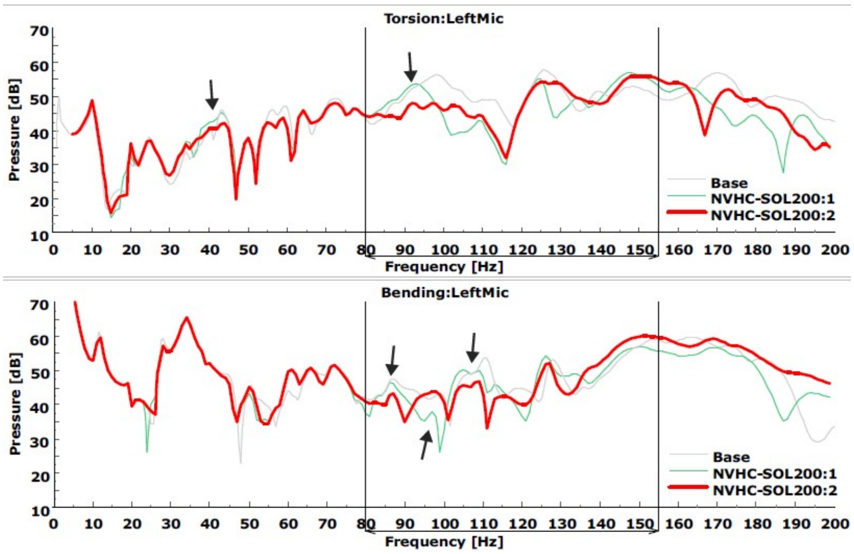

Figure 2: SPL after two cycles of the new workflow.

The stiffness-response post-processing tool helps visualise the approximate response for a given stiffness combination instantly, in-return saving a lot of time and hence the above-mentioned resources. On the same note, further post-processing tools were developed to help the user understand more about the model. The new workflow in end-effect allows to study the effects of individual components through quick what-if studies with the help of sub structuring. If a given component, for instance is bound to undergo multiple design changes, it can be treated as a substructure and its effects can be studied on an individual level. The newly integrated machine learning model further keeps getting improved after every new design cycle with new datasets.

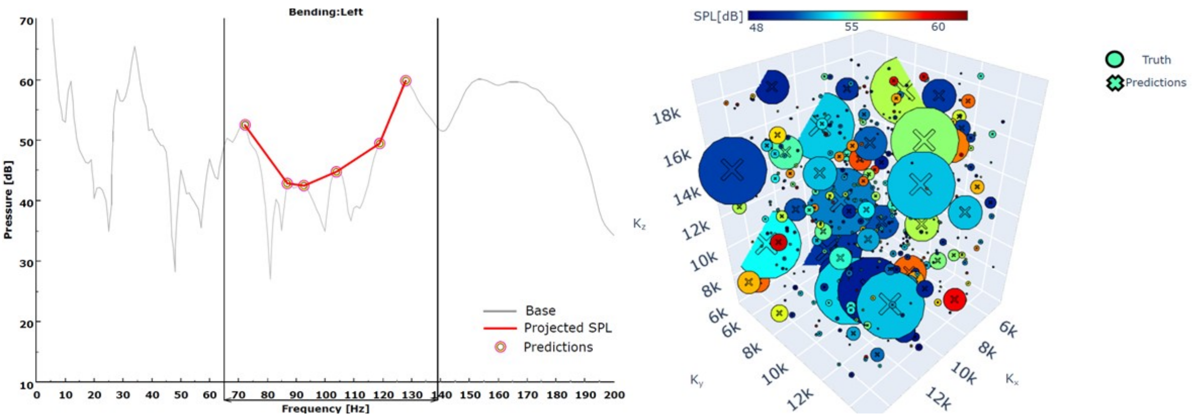

Figure 3: Response predictions overlayed with results from the simulation.

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