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Machine-Learning-Based Modelling of Electric Powertrain Noise Control Treatments

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Abstract

Encapsulation of electric powertrains is a booming topic with the electrification of vehicles. It is an efficient way of reducing noise radiated by the machines even in later stages of the design and without altering the electromagnetic performance. However, it is still difficult to define the best possible treatment. The locations, thicknesses and material compositions need to be optimized within given constraints to reach maximum noise reduction while keeping added mass and cost at minimum. In this paper, a methodology to design the encapsulation based on numerical vibro-acoustic simulations is presented. In a first step, the covered areas are identified through post-processing of a finite element acoustic radiation model of the bare powertrain. In a second step, a design of experiment is performed to assess the influence of various cover parameters on the acoustic radiation results. This second step can be hugely computationally expensive as the number of required virtual experiments increases exponentially with the number of treated regions and parameters for each treated region. In this chapter, we present a physics-based reduced-order model to overcome this difficulty and do design of experiments in a much more affordable manner. It is then enriched with machine learning to provide finer tuning of the treatment definition. This would allow the final designer to iterate between treatment strategy in the matter of seconds, paving the road for an advanced optimization algorithm. The accuracy of the presented models is detailed.

Introduction

Radiated noise reduction of powertrains is an important topic for carmakers and suppliers involved in electric powertrain developments. The design of the electric powertrain is a complex task where many factors need to be taken into account, such as mechanical and thermal performance, integration in the vehicle, interactions with other components, structural strength and durability, and reliability, noise and vibration. All this needs to be performed while ensuring the best possible efficiency to ensure adequate range for the electric vehicle. This also means that different engineering teams can be working together to achieve all of these goals. To assess the NVH performance of the powertrain the full powertrain design needs to be advanced enough to create virtual or real prototypes to simulate or test. Hence it is often the case that problems related to NVH performance are identified in later stages of the design process when the design cannot be changed. An efficient way to improve the NVH performance, without affecting the functional properties of the powertrain, is by adding acoustic insulation materials, or noise control treatments, which usually consist of multiple layers of different materials, such as porous and solid layers.

The regions where acoustic treatments can be applied are usually given as constraints from the powertrain designers or by the integrators. These parts of the exterior surface of the powertrain are called the target regions in this paper. The treatment must be optimized for each one of these regions, potentially independently from each other. We can use multiple layers, and choose from multiple material types, properties and thicknesses for each layer. Very fast, the number of configurations combining all those parameters becomes so enormous that it is simply not feasible in practice. A method for helping designers finding a good treatment without spending weeks or months on running virtual experiments would be therefore very beneficial.

In the next sections we define how such a problem can be tackled and solved with high efficiency. This process involves Actran, a finite element software suite for acoustic simulations, reduced order modeling that is based on principles of acoustic radiation physics, and machine learning to equip the reduced order model with more flexibility. We will show that the developed complex workflow can reduce the simulation time for virtual experiments by several orders of magnitude. The demonstrated model creation takes only days, involving model preparation, runs and machine learning model training. Even though the model implements some simplification on the physics-based reduced order modeling, and includes also machine learning techniques, the achieved accuracy remains high, with R^2 metrics of 0.995 for the shown example case and virtual test data.

In the end, the model generated can provide the acoustic treatment efficiency for any combination of acoustic treatment parameters in a matter of seconds using a very simple and efficient user interface.

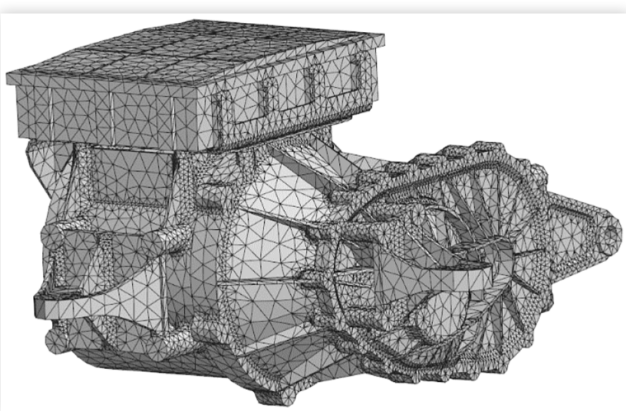
Numerical Model of Radiation

Acoustic radiated power of a vibrating structure could be simply approximated based on the ERP (estimated radiated power) value. This is air impedance times structure velocity squared & integrated on the outer surface of the vibrating powertrain. However, this approximation is usually not precise enough and proper modelling of the acoustic propagation in free field is necessary. This can be achieved by finite element numerical modeling. Fluid-structure coupling in radiation in free field can be considered as weak: the retroaction of the radiated pressure waves on the vibration of the structure itself is negligible. Therefore, the vibration of the structure can be transmitted to the surrounding air and the acoustic wave propagation in free field can be simulated independently. In such simulation framework, volume finite elements model the near field, and non-reflecting boundary conditions are applied on their outer skin. The non-reflecting boundary conditions can be achieved by, for example, infinite elements or perfectly matching layers [1].

Bare model

The structural finite element model of the electric powertrain is shown in Figure 1. It will provide vibration level on its outer skin as a boundary condition for the acoustic simulation. The acoustic radiation finite element model is automatically meshed and set up based on the structure model. For the current example the resulting model has a mean mesh size of ~10 mm of quadratic finite elements, the near field mesh is half wavelength thick (based on the minimum frequency), and infinite elements of order 10 are employed. This is the bare model, a model without any noise control treatments (encapsulation).

FIGURE 1 Structure finite element model of the electric powertrain

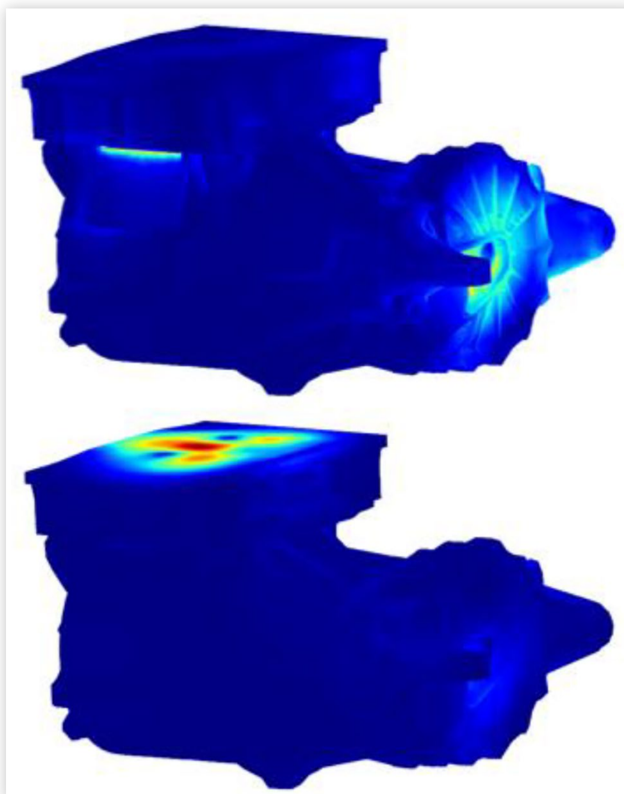


Once structure vibrations from electromagnetic forces are obtained and output on the structure mesh, the vibration can be automatically mapped on the acoustic model and propagated in free field. The fluid pressure at any point of space can be retrieved, and radiated power can also be computed. We study the radiated noise from 900Hz to 1400Hz in this paper to illustrate our methodology. There is no specific limitation inherent to the process preventing us to apply it to higher or lower frequency range.

Target Regions for Noise Control Treatment

Parts of the external surface of the powertrain where acoustic treatments can be applied are constrained by the design (connected parts, mountings, available space in the surrounding). In addition to these constrains, the radiation of the powertrain without any treatments can also help us identify promising positions for noise treatment by plotting the acoustic intensity [W/m^2] on the structural model. This acoustic intensity plot is shown in Figure 2 at two frequencies

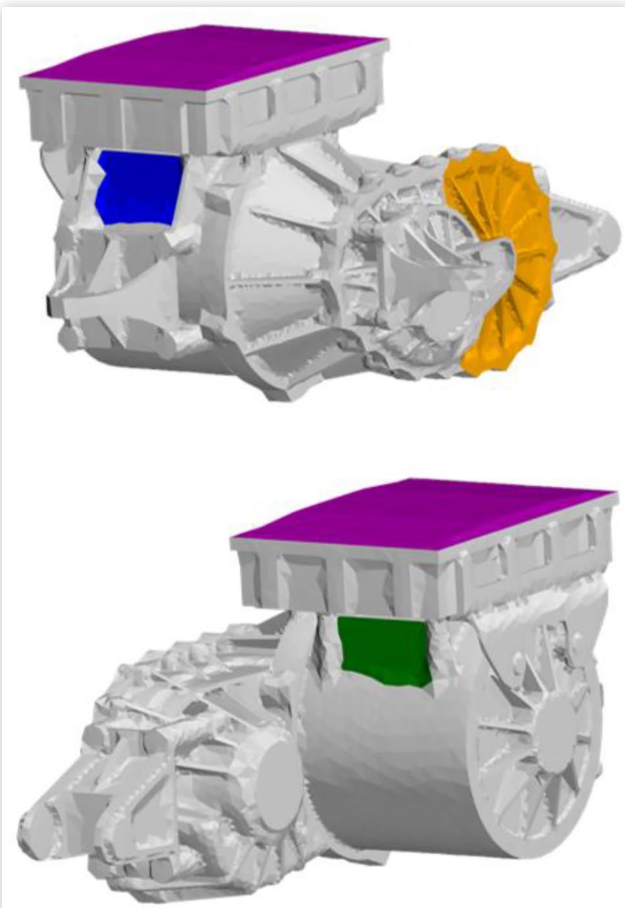
FIGURE 2 Intensity maps at 920, 960 on top and bottom, respectively, for illustration purpose. Based on this map and design constraints, one can decide the regions for possible noise control treatment application.



for illustration purpose. Based on this and some design constraints, we identify 4 target regions as shown in Figure 3. These regions will be fixed, but we can decide if any placement is applied on each region, and if so, what it should be made of.

To define our design space, we also fix the number of layers of the treatment. In this study the noise control treatment will be made of two layers, as it is very typical in these applications: the first layer is made of a porous material and the second (usually thinner) layer is of a solid, heavy material. This is often referred to as composite trim treatment. These two layers can be simply thought of as a spring-mass-damper system, where stiffness and structure damping are given by the porous material and the supported mass is the heavy layer. This system ensures insulation & absorption effects between the structure vibration and the imposed velocity of the surrounding air. It is assumed these effects do not alter notably the structure modes and the vibrations of the powertrain.

FIGURE 3 Target regions. Gray region is kept bare, no noise control treatment is applied there. There are four regions which can be treated. Violet region is region 1. Green region is region 2. Blue region is region 3. Orange region is region 4. Area of the regions in m^2: 1.370 (untreated), 0.1008 (region 1), 0.007690 (region 2), 0.009895 (region 3), 0.05526 (region 4).

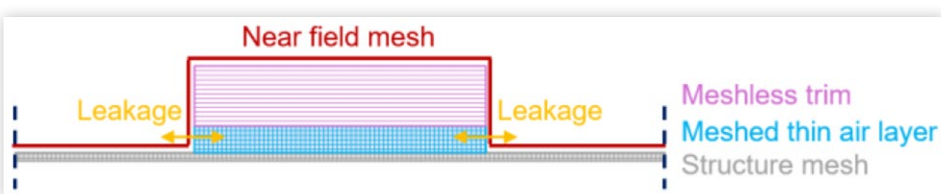


Meshless Modelling of Noise Control Treatments

In order to make the modelling process efficient, and save significant amount of engineering time, a meshless representation of the composite trim is implemented [1, 2]. This allows for quick and flexible changes of the layer thicknesses and material properties. In practice the treatments are not continuously glued to the engine, first because of this is often not possible, and second because this would not be advantageous from a thermal performance point of view. A small air layer can be therefore present between the treatments and the structure, and it is important to model it in the acoustic simulation to account for possible leakage effects.

In a first step, thin air layers are created on the target regions, which are meshed with acoustic finite elements and then the meshless composite trims are applied on top of them. Then the finite element model for the acoustic radiation (both the near field mesh and the far field mesh) is set up automatically. Once such a setup is complete, it can be reused for all the possible treatments thanks to the meshless representation: changing the thickness of a layer of the acoustic treatment is performed through a parameter and not the finite element mesh. The meshless approach allows us to be flexible on the number of layers and the layer thicknesses while keeping the same radiation finite element model. In this study the number of layers of the treatment is fixed to 2. If one target region is not treated, then the meshless trim material can be defined as air. A schematic for the model at one treated region is shown in Figure 4.

FIGURE 4 Modelling the noise control treatment at one target region. The meshless approach allows us to be flexible on the number of layers and the layer thicknesses while keeping the same radiation finite element model. In this study the number of layers of the treatment is fixed to 2. The near field mesh is created automatically, as well as the far field mesh (not shown).



DOE with Physics-Based Reduced Order Model

Number of Simulations Needed for a Full Factorial Design

The goal is to be able to investigate the effect of different noise control treatments on the radiated acoustic power. The target regions are fixed, as well as the number of layers of the treatments (2 layers). But the objective is to allow designers to select freely the layer thicknesses and some material properties on the target regions independently.

Let us take the following example. We would like to change the thickness of both the porous layer and the heavy layer, and we also want to change the porosity of the porous layer and the density of the heavy layer. These are the target parameters of the acoustic treatment. If we want to run a full factorial design of experiments (DOE), with 4 values for each of these properties, then for one target region we would have 256 samples: 4 porous thickness x 4 porous porosity x 4 heavy layer thickness x 4 heavy layer density.

However, we have 4 target regions, and if we would like to be able to change any of the treatment properties on these 4 regions independently, then the number of samples we need to have is:

$$N = 256^4 = 4.29\ \text{billion} \quad (1)$$

Please note that here the number 4 in the exponential refers to the number of treated regions. And it appears in the exponential as we would like to treat each region independently. If that was not the case, and we allowed the regions having strictly the same treatment, this exponential dependance of the number of samples on the number of regions would not occur.

Even though the simulation model is highly optimized and can be run in a few minutes on a HPC cluster node, it is absolutely not feasible to run these many simulations to generate the virtual samples. Even if more efficient sampling technique is chosen, the required runs will not be decreased by several orders of magnitude.

The motivation behind the physics-based reduced order model (ROM), presented in this paper, is to make such DOEs possible by populating the full design space with high accuracy from affordable number of simulation runs.

Radiated Power Computation from Contributions

The objective of creating a reduced order model is to recover the total radiated power as the sum of the contributions from the untreated (bare) part and the 4 treated regions. These contributions, however, need to account for both main and cross effects to be accurate. Main effect is related to the power generated by the velocity field of a vibrating region on the pressure field that the vibration induces, while the rest of the structure is not vibrating. Cross effects are related to the power radiated or absorbed by the vibration of one region A in the pressure field already generated by another region B, while all other regions (either A or B) of the structure are not vibrating. This can be elegantly defined in a finite element framework using multiple back transformations of the factorized system matrix and assemble each contribution to recover the full system.

The degree-of-freedom of an acoustic finite element model is pressure, but velocity can be derived from the pressure and one can compute the intensity purely from the velocity field. The intensity field can then be integrated on a closed surface to get the radiated power [3]. For the case of two regions, this may be written as the quadratic product:

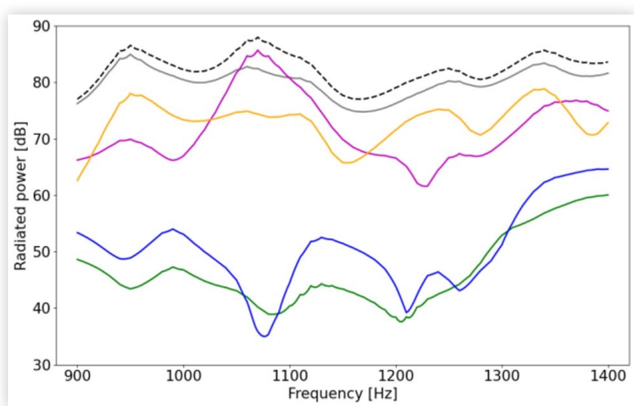
$$rP(\omega) = \begin{bmatrix} \tilde{v}_1 & \tilde{v}_2 \end{bmatrix} \begin{bmatrix} C_{11}(\omega) & C_{12}(\omega) \\ C_{21}(\omega) & C_{22}(\omega) \end{bmatrix} \begin{bmatrix} \tilde{v}_1 \\ \tilde{v}_2 \end{bmatrix} = \tilde{\boldsymbol{v}}^T \boldsymbol{C}(\omega) \tilde{\boldsymbol{v}} \quad (2)$$

Here rP is the total radiated power, $\tilde{v}_1$ and $\tilde{v}_2$ are arbitrarily chosen, constant reference values of the velocity fields of regions 1 and 2, respectively, on the surface of radiating object. The (radiating) velocity field $\boldsymbol{v}_1$ of region 1, for example, is $\boldsymbol{v}_1 = \tilde{v}_1 \boldsymbol{v}_{1s}$, with $\tilde{v}_1$ being a reference value. The entries of $\tilde{\boldsymbol{v}}$ can be chosen to be one. In this way the vibration of a region can be deactivated by setting the corresponding entry of $\tilde{\boldsymbol{v}}$ to zero, and activated by setting it back to unity. Finally, the entries of the symmetric matrix $\boldsymbol{C}$ are the contribution terms, taking into account the velocity field and its reference value from the excitation, scaled with pressure-velocity conversion values, and integrated over the surface of region. With more regions involved the size of the matrix gets bigger and we need to make sure to compute all the necessary main and cross contributions.

The radiated power that we can compute from the entries of the contribution matrix $\boldsymbol{C}$ is (and has to be) exactly the same as the radiated power computed in a classic radiation acoustic simulation.

Computing contributions of different regions to the radiated power also helps us study whether applying treatments on these regions can be effective. In Figure 5 the radiated power of the bare model, without any treatments on

FIGURE 5 Total radiated power (dashed line) versus main contribution of the bare region (grey), region 1 (violet), region 2 (green), region 3 (blue) and region 4 (orange). DOE with physics-based reduced order model



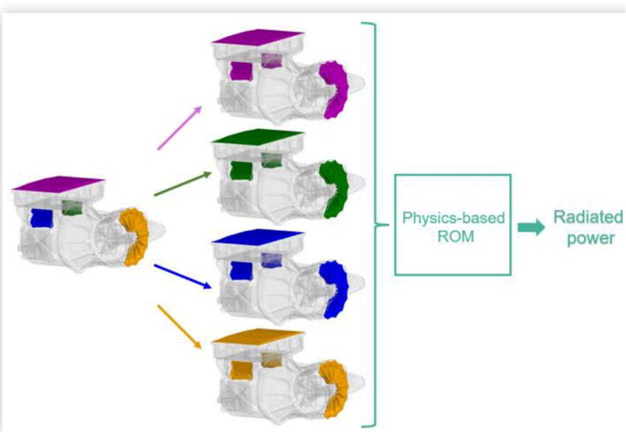
the regions, are shown by the dashed line. The excitation is the vibration of the powertrain due to given electromagnetic forces, the same as used everywhere in this paper. There we can also see the (main) contributions of the untreated region, and the four target regions (without treatments) to the radiated power. It is clear from this figure that the untreated region radiates the most power, as it is also the largest in area. Still, there is room for attenuating the total radiated power by acoustic treatment application, especially on the regions 1 and 4 (violet and orange curves in Figure 5).

Physics-Based Reduced-Order Model

The radiated power contributions can be used to estimate the total radiated power of a powertrain covered by different treatments on different regions. An approximate contribution matrix can be compiled based on base contribution matrices. These base contribution matrices are related to homogeneously treated powertrains, i.e. powertrains covered on every region by one of the treatments form the original encapsulation. Once this compilation of the estimate contribution matrix is finished, the radiated power can be simply computed based on the entries of the matrix. In other words, we can efficiently approximate, based on physical principles, the radiated power of a heterogeneously treated powertrain from results of homogeneously treated powertrains. A schematic for the ROM is shown in Figure 6 and illustration of the accuracy is shown in Figure 8.

Therefore, it is enough to run simulations and generate virtual samples for powertrains covered by the same treatments at all the regions. Following our examples with 256 possible treatments on one region, it is then enough to run only 256 simulations to populate the full factorial design samples, as many as given by Eq. (1). It is needless to say that *reducing the number of simulation runs by 7 orders of magnitude* in this example makes the approach extremely powerful. It is the exponential in Eq. (1) that is eliminated by the ROM. The more target regions we have, the more significant the reduction is.

FIGURE 6 A schematic of the Reduced Order Model (ROM)



Variable and Fixed Parameters of the Treatments

In the current study we chose the following *variable parameters* and their limit values:

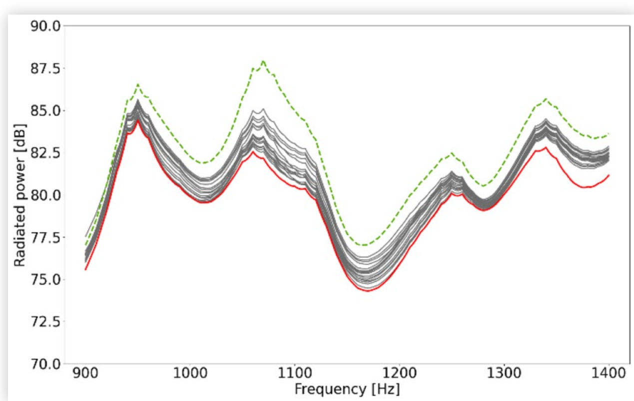
- Heavy layer thickness: 1-2 mm
- Porous layer thickness: 10-25 mm
- Heavy layer density: 1400-2200 kg/m^3
- Porous layer porosity: 0.75-0.85

Other parameters of the porous layer and heavy layer such as flow resistivity, density, tortuosity, damping, Young modulus are defined.

First, the potential attenuation of such treatment needs to be evaluated. For this, 16 simulations, combining the extreme values of the parameters are calculated. The same treatments are applied at once on every target region. The resulting curves, together with the bare result for comparison, are shown in Figure 7. It can be seen that a few dB power difference can be obtained with the chosen parameter ranges. There is a significant variability in the results from different treatments, especially between 940 and 1250 Hz and above 1340 Hz. There is also a curve (red line in the figure) that indicates the radiated power in case the 4 target regions are perfectly treated: no vibration is transmitted to the surrounding air and there is perfect absorption. The gray curves with applied treatments can get close to this perfectly attenuated situation, especially in the frequency region below 1300 Hz. This justifies the search for an optimal acoustic treatment.

It is worth noting that the most efficient treatment is not always the thickest one. The porous and heavy layer composite trim has resonant frequencies. Close to a resonant frequency, the layout trim with thicker porous layer can be less efficient as a layout with thinner layer. We have simulated some layout with different layer thicknesses and with fixed material properties in a simpler model setup. We found that as the porous

FIGURE 7 Radiated power of the bare powertrain (dashed green line) and powertrains with treatments of variable parameter extremities (gray lines). The red line shows the radiated power with the 4 target regions perfectly treated, as the maximal achievable target.



layer gets thicker a resonance frequency appears in the studied frequency range, with 25 mm porous and 1 mm heavy layer, at it is at 1070 Hz. This also makes finding the optimal acoustic treatment challenging.

Validation of the Physics-Based Reduced-Order Model

Demonstration of the physics-based reduced-order model is given based one treatment with random variable parameters. These are the following:

- Porous layer thicknesses: 22.03, 11.16, 10.06, 10.32 mm
- Heavy layer thicknesses: 1.109, 1.116, 1.0444, 1.245 mm
- Porous porosity: 0.7587, 0.7725, 0.8441, 0.8137
- Solid layer density: 2162, 1998, 2160, 1874 kg/m^3

The true versus estimated results are shown in Figure 8. The root mean squared error (RMSE) is [4]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\left(rP_{true,i} - rP_{predicted,i}\right)^2}{M}} = 2.843e^{-6} \qquad (3)$$

and the coefficient of determination (R^2) is [4]:

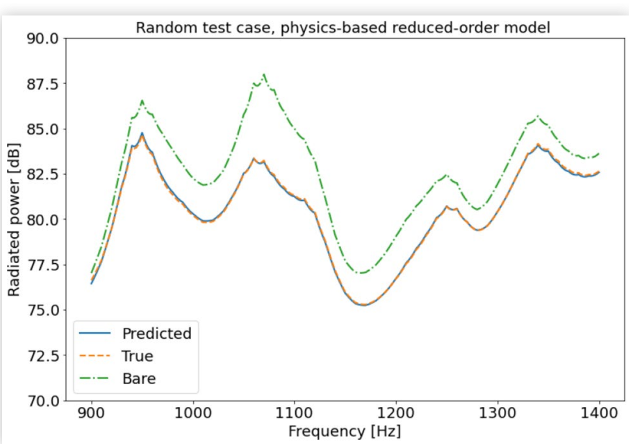
$$R^2 = 1 - \frac{\sum_{i=1}^{M}\left(rP_{true,i} - rP_{predicted,i}\right)^2}{\sum_{i=1}^{M}\left(rP_{true,i} - rP_{mean}\right)^2} = 0.9980 \qquad (4)$$

Here $rP_{true,i}$ is the true (or exact) value of the radiated power at the i^{th} solution frequency, $rP_{predicted,i}$ is the predicted value of the radiated power at the i^{th} solution frequency, and rP_{mean} is the mean value of the radiated power on the studied frequency range. The solution frequency at i=1 is 900Hz, the frequency step is 2 Hz, and the solution frequency at i=M=251 is 1400Hz. Radiated power values are substituted in Watt.

These indicators, and corresponding good correlations, are obtained for cases where the acoustic treatments are different on the regions (heterogeneously treated powertrain). If the treatments are the same on all the regions, the radiated power result from the ROM is exact.

The accuracy of the method is estimated to be sufficient to allow its usage for defining optimal treatments. Based on the 256 simulations (around 1h per calculation), the effect of any treatment configuration (among 4 billion possibilities) can be calculated in a few seconds.

FIGURE 8 Radiated power from the physics-based reduced-order model. Random layer thicknesses and material properties were chosen for the treatments and the true solution was estimated based on results of powertrains with homogeneous acoustic treatments



Implementing Machine Learning

Motivation in Machine Learning Implementation

The ROM presented in the previous section is very efficient in making DOE studies possible with an affordable number of simulation runs. It is however still restricted to the chosen discretization of the target parameters. So, one cannot fine tune the acoustic treatment properties, but can only see the effects of changing a few (4 in this example) values for each target parameter.

Therefore, a machine learning model can be trained so that target parameters (treatment properties such as porous and heavy layer thicknesses, porous porosity, heavy layer density) can take any value within the range of validity of the model. This would also make it possible to include the model in a constrained parameter optimization algorithm to find a good balance between achieved noise attenuation and added mass or cost.

Machine Learning Model Training and Selection

The machine learning model was trained first on the 256 full factorial samples of the design space. The following regression models have been trained using Scikit-learn, a machine learning library for the Python programming language [5]:

- ElasticNet (with different alpha and L1 ratios)
- Support Vector (with poly and rbf kernels, and different regularization parameters)
- Gradient Boosting (with different learning rates and number of estimators)
- Random Forrest (with different number of estimators, with and without bootstrapping)
- Gaussian Process, (with radial basis function - RBF, RationalQuadratic, and Matern kernels)
- RBF Interpolator (with linear, thin plate spline, cubic, quintic, multiquadric, inverse multiquadric, inverse quadratic, and gaussian kernels)

5-fold cross validation was used to choose the best parameters for the models. Finally, RBF Interpolator with inverse quadratic kernel was chosen based on its high accuracy, fast training time and the lightweight final model.

The effect of the encapsulation is frequency dependent. The machine learning algorithm is trained for each frequency independently. All the calculation frequencies are considered in this training set, no frequency interpolation or extrapolation has been used.

Validation of the Machine Learning Enriched Physics-Based Reduced-Order Model

30 test cases have been created with randomly chosen material properties and layer thicknesses, in the validity of the model, different on each region, to test the performance of the whole workflow. The root mean squared error (RMSE) and the coefficient of determination (R^2), averaged on the 30 test cases, were 4.839e-6 and 0.9922, respectively.

Finally, the effect of sampling on the performance of the trained model was also studied. The model was trained based on 256 samples created by Latin hypercube sampling. The selected model was RBF Interpolator with cubic kernel. (Note that with the full factorial sampling the best model was the RBF Interpolator with inverse quadratic kernel). The root mean squared error (RMSE) and the coefficient of determination (R^2), averaged on the 30 test cases with the newly trained ML model, were 4.037e-6 and 0.9948, respectively. It is interesting to note that the best RBF Interpolator is different when considering two different sampling methods of the design space. Still the differences are limited with a R^2 above 0.99 in each case.

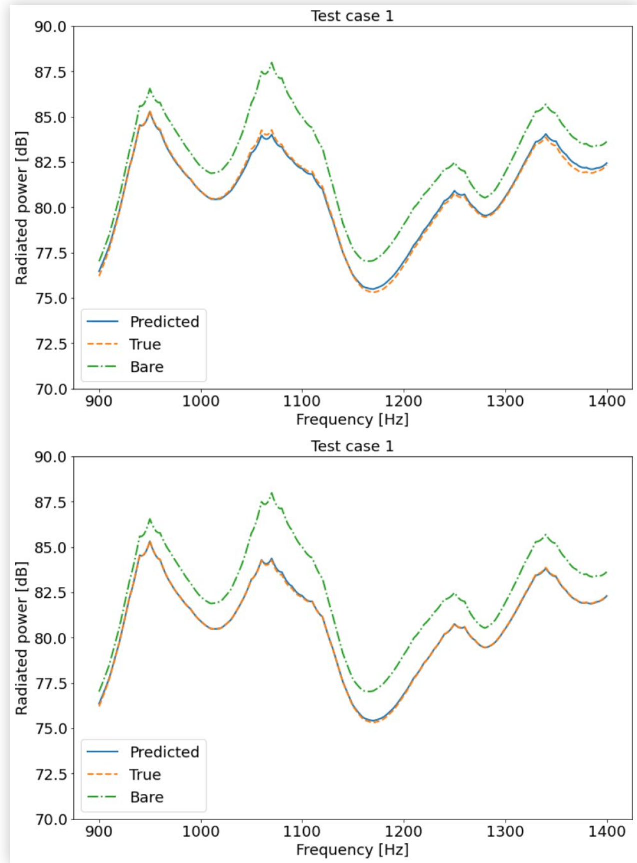
Figure 9 shows a comparison of true versus predicted radiated power curves for the model trained on the full factorial samples (top) and for the one trained with the Latin hypercube samples (boot) on one of the 30 test cases to show graphically the good correlation between predicted and true solutions. The radiated power of the powertrain without any noise control treatment is also shown in the figure to show the efficiency of the treatments.

On the computation time perspective, the physics-based reduced-order model and machine learning can be performed on a single (powerful) machine in around 30 hours. This really enables this kind of methodology to product design and is not restricted to advanced method department anymore.

Numerical Optimization Outlook

Having a fast and reliable reduced-order model makes it possible to do parametric optimization of the noise control treatments. It is beyond the scope of this paper to perform this optimization, but an outlook is given below of what could be done as next steps.

FIGURE 9 Illustration of radiated power prediction accuracy on a test data with random layer thicknesses and material properties, different on each target regions. Top: model trained with full factorial samples. Bottom: model trained with Latin hypercube sampling. Results without any treatments (bare) are also shown for comparison.



We would need to search for optimum parameters of the treatments for each region: thicknesses of the porous and solid layers, porosity of the porous and mass density of the heavy layer. As the validity of the machine learning model is bounded by the limit values of the material parameters, the optimization should be constrained by inequality constrains.

The target of the optimization would be naturally the minimization of the radiated power. As a scalar value is usually to be optimized, a good candidate would be the overall sound power level (OSWL). Besides, we would need to keep an eye on the added mass (or cost) by the applied treatment. The objective is to minimize the radiated noise with a minimum added noise control treatment material.

As there are 4 target regions, each having 4 variable parameters, the constrained optimization needs to be searched for in a 16-dimensional space. Performing a multi-objective optimization would be preferable with a pareto front of optimal solutions. This would very well guide the decision making in the final treatments, to balance between the gain (noise reduction) and cost (extra added material).

Conclusions

In this paper a novel methodology for finding optimal noise control treatment properties to reduce the radiated noise of powertrains was presented. The methodology started with finding regions of the powertrain where treatment can be beneficial to apply. These depend both on design constraints and a simulated intensity field (element contribution) around the vibrating structure. Once the target regions were identified, we defined the acoustic treatment to be made of two layers, a porous one and a heavy one, as typical in these kinds of applications. But this is not a limitation of the method, the number of layers can be arbitrary. Then some variable parameters of these layers (their thicknesses and some of their material properties, namely the porosity of the porous layer and the density of the heavy layer) were selected. These parameters were the target of the optimization. After these preliminary steps, the reduced-order model creation was discussed. The model is not a black box data-driven model, but it is based on physical principles. It was shown that the ROM approximates the exact radiated power solution very precisely. The developed ROM, however, can only be used to populate a full factorial DOE in a very efficient way. We went then further by training a machine learning model to get rid of the limitations of the coarse discretization of the parameter space of the original resolution for the DOE. In this way a (data-driven) ML model powered our physics-based ROM to reach a model that can be run very fast (almost instantaneous) and can be the bases of optimization algorithm. The results of the ML enriched ROM were also validated against independent numerical simulations with random variable parameters and a very good performance was achieved. Finally, we made some outlooks for further possible applications in the developed reduced-order model for numerical optimization of the noise control treatments. The presented method can be automated, leading to an easy-to-use tool for designers to assess maximum excepted effects of noise control treatments help them finding an optimal setup.

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Definitions/Abbreviations

DOE - Design of experiments

FEM - Finite Element Method

HPC - High performance computing

OSWL - Overall sound power level

RBF - Radial Basis Functions

ROM - Reduced order model

RMSE - Root mean squared error

$\mathbf{R_2}$ - Coefficient of determination

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