



ACHIEVING BETTER VEHICLE NVH PERFORMANCE USING MSA AND RBDO METHODS

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Today's Presenter

Product Engineering Services

We are more than 3,000 engineers, designers, analysts, innovators, creative thinkers, and problem solvers, and believe human creativity combined with computer intelligence is the key to delivering pioneering solutions worldwide.

Our unique approach places simulation at the core of innovation – we apply our optimization technologies at the beginning of the design process and allow you to inform design direction from the beginning. This approach enables you to meet your performance targets fast with the optimum balance of weight and cost. We invented this design philosophy and call it 'Simulation-driven Design.'



Peter Benzie Senior Technical Specialist Altair Engineering

20 years of experience in the field of NVH simulation, specialising in Optimisation technologies.





Reducing Late Change

A common source of late change is where NVH issues are discovered late in a program during vehicle testing or even post launch.

Often this occurs on programs where the simulation has met the targets including vehicle level analysis. What could be happening?

Process Failure:

- Poor correlation.
- Simulation does not capture all error states.
- Insufficient testing to catch all issues.

What is being missed:

- Structural variability
- Loads variability
- Environmental variability





Understanding the potential effects of Variability

NVH Issues	Proto-1	Proto-2	Proto-3	Proto-4
Road NVH @75Hz	NOK	ОК	NOK	NOK
PT Shake @29Hz	ОК	NOK	NOK	ОК
Idle Boom at 45Hz	NOK	NOK	ОК	ОК
Suspension Squeak	ОК	ОК	ОК	NOK

WHAT is Variability in NVH Responses?

- Variability in NVH Responses multiple test of identical vehicles
- NVH problems are often 'Error States', which do not happen, or happen in the same ways on all vehicles
- Small design variation can lead to large changes in the NVH response



Slide 78 IVC Structure Borne Noise Workshop

Example of Test Variability



How should we compare Simulation Results with Test Data

Does the nominal simulation model do a good job in representing the response trends of the full population of possible results?

Does the traditional approach for vehicle performance assessment and development with very limited number of testing prototypes capture address all possible failure modes?

How can we take into account this variability (population) when setting targets and assessing the cost effectiveness of proposed countermeasures?







How should we compare Simulation Results with Test Data

A better way to set NVH targets is by level of customer satisfaction

Mean



Inadequate

Does not capture variations and hence population response



Capture variations and hence population response

+/-95% percentile



How can we include Variance in the Target Setting Process



A better way to achieve NVH targets by level of customer satisfaction

- · Vehicle performance assessment based on target setting for population performance
- Population matrix based on variance (+/-95 percentile) can be directly related to customer satisfaction
- Simulation driven MSA and RBDO provides a more robust and reliable way to sign-off on the design



HOW to Introduce Variability in Simulation Model



Traditional Analysis:

Single Sample based on the nominal design

Stochastic Analysis:

Perturb nominal design to create multiple samples that account for variations

Parametric Variables

- Geometry Parameters Variability
 - Panel thickness
 - Welds and connections
 - Material Properties, etc
- Connections Parameters Variability
 - Stiffness and damping of powertrain mounts
 - Stiffness and damping of suspension bushes
- Loads Variability
 - Imbalances in driveline system and phasing
 - Tire Forces due to flat spotting, etc





Example of Parametric Perturbation

Limitations of using perturbations in *parametric* variables

Perturbation Aspect	Limitations
Variability Content	 Limited availability, most common are panel gauges Other sources like <u>missing welds</u>, <u>assembly variations</u>, <u>etc</u> cannot be considered easily - <u>Not possible</u> to introduce all variation sources
Amount of Perturbation	Low - Few local variations around local design change
Range of Variation – NVH Responses	Low - Unable to get same level of variations as in tests
Computational Time	High - Each run involves <u>full FE models</u> for <u>several hours</u>

IS THERE AN ALTERNATE APPROACH TO OVERCOME THESE LIMITATIONS?



A new way is to introduce perturbations in component modes or modal parameters (non-parametric)

Significance of Modal Parameters

Modes or modal parameters depends on overall structural design and / or process

- Mass, stiffness and damping distribution
- Thickness
- Material Properties
- Sections
- Geometry and Construction
- Welding and connections
- Manufacturing and assembly variations

- Modal Parameters are the *Performance Parameters*
- Modal Parameters are the end result of the overall design and process
- Any variation in the any of the design parameters and / or the process has direct impact on these modal parameters

Any variation introduced in modal parameters is equivalent to introducing all possible variation sources in the product



Example of Non-Parametric Perturbation

Advantages of using perturbations in *non-parametric* variables

Perturbation Aspect	Advantages		
Variability Content	Any variation in modal parameters is indirectly considering all possible variation sources in vehicle		
Amount of Perturbation	 High - Possibility to introduce number of variations over broad range of parameter values 		
Range of Variation – NVH Responses	Broad - Response scatter is practical and similar to as observed in tests		
Computational Time	Low - Each run involves reduced CMS models for few minutes		



A new way is to introduce perturbations in component modes or modal parameters (non-parametric)

Modal Parameters Modifications in Reduced Models

- In reduced models from component mode synthesis (CMS), a finite element model of an elastic body is reduced to interface degrees of freedom and normal modes
- Possible to review and modify of these modal parameters

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NVH DIRECTOR WORKFLOW FOR MSA AND RBDO





Multi Sample Analysis



Achieving Better Design Using MSA and RBDO

Multiple Sample Analysis Design Sensitivity Analysis on Extreme Samples



Reliability Based Design Optimisation



Perturb Nominal Design and create response spread due to variations

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Filter the sensitive Variables for the extreme range of responses





Filter the sensitive Variables considering the uncertainties / variations

Accounting for Uncertainties and variabilities in Optimization

MSA and RBDO is the process to develop Reliable Designs for NVH



Multi Sample Analysis – Typical Application

- Full Vehicle Model
 - Extensive use of CMS SE reduced models
- Vehicle level loadcase such as RoadNoise (Tyre input)
- Introduce perturbations in:
 - Non-parametric variables (>10000)
 - Modal Frequencies (+/- 2%)
 - Modal Damping (+/- 10%)
 - Parametric variables (>500)
 - Connection Stiffness (+/- 20%)
 - Connection Damping (+/- 10%)
- Population Calculation: 500 Monte-carlo runs
 - (Latin Hypercube Method)
- Plotting the results from stochastic simulations showing spread of responses with +/- 95% and mean





Design Sensitivity Analysis



Achieving Better Design Using MSA and RBDO

Multiple Sample Analysis Design Sensitivity Analysis on Extreme Samples

Variable Filtering DOE / FIT

Reliability Based Design Optimisation



Perturb Nominal Design and create response spread due to variations

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Filter the sensitive Variables for the extreme range of responses



Filter the sensitive Variables considering the uncertainties / variations



Accounting for Uncertainties and variabilities in Optimization

MSA and RBDO is the process to develop Reliable Designs for NVH



Design Sensitivity Analysis – Typical Example

Design Sensitivity based on nominal and extreme samples

- Identify sensitive parameters for worst sample, best sample and nominal sample from MSA runs
- Get the list of sensitive parameters over the extreme range of response variation



Automatic generation of DSA solver decks for nominal, high and low runs is possible in Altair NVH Director



Variable Filtering – Typical Example

Design Variables Filtering using DOE / FIT

- Filter the design variables showing sensitivity to the spread or variations
- Run DOE / FIT for sensitive variables from DSA (Fractional Factorial and Least Square Regression) to evaluate effect of manipulating sensitive variables at different levels on responses
- Rank the effect of sensitive variables from DSA on output responses in hierarchical order using Pareto and/or Anova plots
- · Use of these reduced set of sensitive variables for RBDO





Reliability Based Design Optimisation



Achieving Better Design Using MSA and RBDO

Multiple Sample Analysis Design Sensitivity Analysis on Extreme Samples

Variable Filtering DOE / FIT Reliability Based Design Optimisation



Perturb Nominal Design and create response spread due to variations

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Filter the sensitive Variables for the extreme range of responses



Filter the sensitive Variables considering the uncertainties / variations



Accounting for Uncertainties and variabilities in Optimization

MSA and RBDO is the process to develop Reliable Designs for NVH



RBDO – Typical Example

Import Design Variables from DOE / FIT - Specify Objectives and Constraints, and submit RBDO run

iesion Results NVH-Utilities ×	IV Advance options	
	Number Of Evaluations : 200	
Des. Vars. Objective Constraint Display	System Reliability (%) : 98.0	
Define Design Variables	Robust Optimization : No	
	System Reliability Tol. : 0.1	
	On Failed Evaluation : Ignore failed evaluations	
Get Des, Vars.	Create RBDO jobs	Runs SRO HST BACT RUN

Review RBDO results in dedicated post processing tool - Automatic identification of optimised run numbers





RBDO – Typical Example

MSA can then be re-run with Optimized variables as the starting point.



Optimised



Achieving Better Design Using Deterministic Optimization

Traditional deterministic approach vs reliability-based design optimisation

Traditional

- Traditional approach will optimize nominal response only
- Does not account for variabilities and uncertainties
- Design Sensitivity varies with samples
- No clarity on for what percentage of population the optimized design from deterministic optimization will work
- High Probability of Failure

RBDO

- Population performance can be considered for setting the target and constraints (eg target 95 percentile performance)
- Define random design variables and/ or parameters (both on DESVAR)
 - Random Design Variables Mean Values are Optimized (e.g., thickness, etc)
 - Random Design Parameters Mean values are constant, but its variance is accounted for (e.g., Young's modulus of material, etc)
 - Design variables can be characterized using statistical distribution
- Optimisation will shift the mean and variations leading to a more reliable design – Less amplitude and less variation.





THANK YOU

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