Application of data science in automotive design optimization for faster convergence

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Abstract:

The objectives of simulations during design process is to meet certain objectives, be it minimization of weight, maximization of strength, or having certain response values within some range. The simulations in Automotive design takes several phases and iterations consuming both cost and money. Though the optimization process based on blackbox surrogate models of finite element analysis as validation function has been around for some time, the adoption has been slower than what it should be due to lower confidence and also not having sufficient tools and technology. This paper provides a framework on optimization process using data science based surrogate models. The process involves identifying a baseline, design of experiments to generate initial samples, traditional finite analysis-based simulations, building surrogate models and the using genetic algorithms for optimization of stated objectives of response variables.

Keywords: Design of Experiments (DoE), Response Surface Modeling (RSM), Meta-Model, Surrogate models, Dimensionality Reduction, Multi Disciplinary Optimization (MDO)

1. Introduction

Computer aided engineering (CAE) has been a boon to automotive industry for decades now. Over the period, several computer applications have been developed for every stage in Automotive design. Numerous tools are available for CAD/modeling, pre-processing for solvers, to conduct simulations using Finite element analysis or computational fluid dynamics and then post-processors to visualize and understand the design outputs. These tools require special skills and it takes several hours for each simulation cycle. The automotive design involves thousands of simulations across various disciplines of design for each automobile and the typical concept to final design takes about 18 months or more.

While design process is streamlined over the years, the market conditions have changed enormously. Faster go-to-market on one hand and need for innovative design on the other hand are placing stress on the design cycles. Product development is becoming increasingly expensive because of regulatory compliances, testing and validation. These factors call for the review of current practices and innovations in design optimization process. The data science based surrogate models, also called as meta-model or response surface models (RSM) are used as validation functions to predict the response values for set of derived design parameter values during the optimization process.
2. Literature survey
The process for design optimization and in particular meta-model based optimization involves understanding steps involved such as Design of experiments (DoE), Finite element analysis, dimensionality reduction, Response surface model (RSM) and genetic algorithm (or other) based optimization techniques. For body-in-white (BIW) development as part of traditional automotive design requires several simulations for each discipline, such as Noise-Vibration-Harshness (NVH), Front crash, Rear crash, Dynamic stiffness etc.[1] There are several approaches available for DoE and the popular ones are Random, Latin Hyper Cube, Full factorial, adaptive design samples, Box-Behnken, Optimal design methods for RSM. While DoE is a first step in selecting the set of experiments to be carried out, any free or commercial Finite Element Analysis (FEA) tools can be used for simulations and obtain the corresponding values for one or multiple responses in each experiment.[2] During a panel discussions on “approximation methods”, many researchers observed that there is an important distinction between physical experiments or simulations.[3] Meta-model, being function of design parameter set evaluate the response value much faster. As an example one of the experiment showed that meta-model took 1 second to produce response value where the traditional FEA took 30 minutes to produce results for same input parameters[4]. These meta-models and associated qualitative or sensitivity analysis allow designers to gain insight into the characteristics of the product being designed or analysed[5]. In automotive design, several parameters are involved. The existence of parameters that are degenerative, redundant or even noisy could significantly hamper the performance and interpretability of models built for data containing such features.[6] Moreover dimensionality reduction, i.e. reducing the number of parameters reduces the number of samples as the design space to be covered stands reduced. Certain algorithms like Random Forest, XG Boost are commonly used to analyze the importance of parameters for a given response and have been found to be fairly successful as evidenced by researchers.[7][8] Some practices also involve the use of linear regression model coefficients.[9] The coefficients are obtained by iteratively solving the system of linear equations. However, since the nature of parameters and their influence vary by the problems to be solved, we suggest that parameter importance be obtained by multiple algorithms and then normalize importance scores. Robust rank aggregation method[10] proposed by R. Kolde et al. is one such method found useful in normalizing importance score. By placing a multi-disciplinary design optimization (MDO) within the development cycle, not only results in efficient BIW structure be developed, but a mass reduction otherwise unobtainable by traditional means may be achieved.[11]

3. Research problem and objectives
In most engineering simulations, the objective is to arrive at optimal parameter values to achieve the desired results – meaning, for example, arriving at minimum thickness (weight), material or shape of each component in the system under consideration. Unlike most research papers that focus on limited dimensions (design variables), the reality is that the variables involved are in large numbers. Each simulation takes several hours and is expensive.

The objectives of improvements in design process to meet the new demands should reduce cycle time and provide platform for automation. The current design systems for pre-processing, solvers and post-processing are all work in silos whereas most disciplines are interconnected. The data preparation and exchange of the intermediate results to next in line system is cumbersome. There are tools to automate some part of this process but still cycle times are longer than desired.

Traditional multidisciplinary optimization involving, for example, NVH, Durability, Stress or Crash or other disciplines involves several iterations. The vehicle parts involved in BIW analysis
are common to many disciplines and most common optimization done is for sheet thickness which will reduce weight of vehicle and thereby costs.

**Figure 1.** Design optimization

Assuming \( W_1 \) and \( W_2 \) are savings in each optimization process, as the same design parameters should meet both optimized designs, the actual savings would be limited by retaining the higher of the thickness for each common part. Thus the effective saving \( W \), can only be subset of the two savings i.e.

\[
(W_1 + W_2) - \sum (\Delta W_n)
\]

where \( W_n \) is delta weight of parts 1…n due to selection of higher of the 2 optimized thickness.

Objective of this is to put a framework around Design Optimization using the alternative concepts in the process. This shall limit the number of traditional simulations needed in automotive design process through

- scientific selection experiments (DoE),
- identification of sensitive parameters to reduce dimensions,
- developing surrogates to FEA analysis and
- using algorithms for optimization of design parameter combinations instead of multiple simulations

4. Methodology

**Framework**

Meta-model and optimization tools have been gaining importance. The elastic processing power of the cloud and advancements in data sciences have provided the opportunity to augment the design process through meta-models for responses and then optimizing the designs using these models. Wherever large number of simulations are involved, using the initial few sample design combinations and their responses, the meta-models can be built, and these models can then take the role of solvers reducing significant number of simulations. The new process would change to process as shown in figure 2:

**Figure 2.** Process change

The detail process looks like what is shown in figure 3 below:
Fig 3. Sampling and Modeling

Optimized designs are of good quality when the models from machine learning tools are built with least error. Larger the size of DoE, lesser is the model error but each simulation in solver is expensive and time consuming. Hence the challenge is to get good design space coverage with least number of samples to produce models with highest accuracy.

Design of Experiment – DoE is a selection of multiple design combinations wherein the design variable valuestake different values within the allowed values. These sample designs are then passed through traditional solvers along with their geometric parameters to get the response values for each design combination. Each simulation in solvers is computationally intensive and expensive. Advanced algorithms are used to achieve minimum samples requirement.

Sensitivity Analysis and Dimensionality reduction - As simulations are expensive, it is suggested to perform DoE in couple of iterations – first one to do sensitivity analysis for dimensionality reduction and then second DoE with reduced dimensions. Various quality insights similar to what is shown in figure 4 below can easily be obtained from underlying analytics.

Figure 4. Attributes
Meta-modeling – Several advanced algorithms and machine learning tools are now available to build fairly accurate surrogate models for linear or non-linear behavior of responses with respect to design variables. Dimensionally reduced models some time provide best results by reducing the noise. Metamodel concepts eliminates the designer bias and model parameter tuning requires adept skills in data science.

Optimization–It is a CPU intensive quick checks of combinations of design variable values that provide nearest designs meeting the objectives and constraints setup for design. Choice of algorithms is key to ensure best designs are uncovered by traversing through all possible zones in design space in a manner that converges faster to meet the objectives. Reducing the design variables to only those that are sensitive to set objectives is a big plus. When multi objectives are involved, the desired design can be selected from the designs on Pareto front (figure 5).

Unlike the output of solvers in traditional computer aided engineering (CAE), which is large data, this data science-based approach has an opportunity to store the information of all the current and past analysis. Statistical data analysis on this data in addition to insights from previous models will provide good inputs to designers. Augmented analytics now allows to merge human intelligence with machine learning to get most of the data produced in the process.

A simple sample experiment done following the above framework is presented below:

Objective:

1. Minimize the number of Spotwelds while retaining the strength at different locations within the given minimum constraints.
2. Reduce the number of recipes (samples/simulations) that are required to build surrogate model within 10% error for strength predictions and optimized designs.

Method adopted:

Latin Hypercube based DoE was used to get Spot pitch for 24 lines, spot counts at 25 clusters from within the constraints set for each.

- Using DoE and the range of values for spot pitch, we generated 50 samples.
- Traditional analysis methods were used to derive corresponding response values Lateral, Bending, Torsion and Spot weld counts.
- Sensitivity analysis conducted to analyze the critical parameters and correlations between the weld locations.
Meta model were built using various algorithm and the best one selected; the error observed was sub 3%.

- For the constraints set on parameter ranges, objectives of maximization of bending, lateral and torsion strengths and minimization of spot weld counts were set.
- Genetic algorithm used for optimization runs and provided the optimized designs.
- Results: In addition to effort and time saved for convergence, the 4% reduction in spot welds count per vehicle could mean savings in millions over product line lifetime (Table 1).

**Table 1. Convergence table.**

| Parameter                                      | Traditional Optimization | Metamodel based MDO |
|-----------------------------------------------|--------------------------|----------------------|
| Turnaround Timeline (days)                    | 530                      | 510                  |
| Efforts (man-hours)                           | 8                        | 3                    |
| # of Simulations runs on HPC Computer         | 80                       | 50                   |
| Easy to change the target responses (Global modes, global stiffness etc) | No                       | Yes                  |

There are now tools and utilities available to streamline all the steps. For DoE, sensitivity analysis, meta-modeling and optimization, we used Intuceo-Ex, a metamodel based optimization application.

The benefits of such framework are multitude:
- Faster convergence of optimized design and hence faster time to market
- Qualitative data analysis is possible throughout the optimization process
- Unlike in traditional simulations, the intermediate data is small, all results can be saved for continuous learning
- Multi-discipline multi-objective optimization is made easy
- Multiple functions of design process can be streamlined into one simplified design optimization process

5. Conclusion
The innovations in both methods and tools have been substantial to augment the traditional style of design with the meta-model, multi-objective and multi-discipline optimization methods. The ever-reducing design cycle time for automotive design to meet the time to market demands at reduced overall costs can be partially achieved by aligning the skill sets to the newer methods. As the MDO is based on meta-model, the framework can be used in multiple engineering problems where the simulations are involved or the observed behaviors of responses for changes in system parameters is available. Authors believe that further work can be carried out to tailor the presented framework and technologies to cover material and shape variations and new disciplines in optimization process.

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