A Comparative Design Study of Topologically Dissimilar Automotive Structures

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Abstract. Automotive body structure design is critical to meet various design requirements primarily based on the engineer's experience. One of the critical automotive body components is the frame that supports the hood, which withstands many static, dynamic, and local impact loads. In the current design process, designers improve upon previous-generation designs to meet updated targets. However, this process diminishes the possibility of adapting design ideas from other models. Consequently, there is a trend to start with topology optimization and then optimize for size. However, a smooth transition between meshes produced by topology optimization and parametric CAD does not exist. The uniqueness of each design and nonuniform parameters make it difficult to compare multiple designs and extract useful feature information. The proposed methods use the existing dataset of hood frames with parameterized CAD geometries. It is aimed at guiding designers for a new hood frame. Hood frames vary in shape (ribs, pocket features, and layout) and size (dimensions of shapes and features). Conventional designs of experiments cannot be used since the designs contain different geometric features, layouts, and parameterization schemes. The research proposes a non-uniform parametric study using a pseudo-design of experiments to provide guidance. It uses an experiment design for parameter reduction, and parameter correlation and then runs finite element analysis (FEA) for a given set of loads. The response data generated from this FEA is processed and analyzed using multiple pseudo-experiment design methods to make predictions on the ideal features to be used in a design. Each method can be used separately to perform comparative studies in understanding the effect of features in dissimilar structures.

Keywords: automotive hood design, design of experiments, structural optimization, pseudo-DOE
DOI: https://doi.org/10.14733/cadaps.2024.374-391

1 INTRODUCTION

Structural optimization has proven to be an important tool in the design process. The objective of the optimization can vary based on the individual component (or set of components) of interest for various boundary conditions. The optimization method is commonly utilized to design engineering structures. The optimization techniques most widely used in various industrial fields for structural optimization generally can be placed into two categories: parametric optimization and non-parametric optimization. In parametric optimization, the parametric variables defining a geometric model are used as design variables. For example, key parameters or dimensions defining a geometry can be used as parameters in an optimization process to achieve the desired objective. In non-parametric optimization, an initial design space of the geometry is defined, and the optimization process either removes mass without changing the node locations in the mesh (topology optimization) or directly manipulates the node locations (shape optimization) to achieve the desired objective. Prior to the use of topology optimization (TO), parametric methods used an ad-hoc initial geometry and experimented with various parametric schemes to optimize for a given objective.

The rapid development of the topology optimization [4] and the availability of commercial tools offers the possibility to find load paths from which to derive conceptual designs as starting point [2, 24, 25]. However, the applicability of topology optimization to the product design process is limited primarily due to the monolithic structures obtained and the disconnect between finite element meshes and parametric CAD. While there is ongoing research in the use of topology optimization tools for product design and development (e.g., for automotive structures) [16, 35, 3, 37], the number of parameters and features variations makes this a daunting task. To perform a parametric optimization on designs that vary in both shape and size, it is necessary to explore variations of the design of experiments (DOE), response surface method (RSM), machine learning (ML), or combinations of them.

1.1 Research Scope

Most automotive body structural components (e.g., A-pillar, B-pillar, hood frames, door panels, etc.) are made from welded stamped sheet metal. The design of these components involves multiple, and often conflicting, objectives involving manufacturability, light-weighting, and structural integrity under several different operating (or static) and crash conditions. Prior to the advent of modern simulation and optimization methods, designs were done by trial and error which were then followed by physical testing. However, advances in computing capabilities and the development of methods in design and optimization have helped produce better designs while reducing time and cost.

Although the focus of this paper is on hood frames, the methods presented are generalizable to other components. Hoods consist primarily of a skin (exterior styling surface) and a support frame that provides the required stiffness, as shown in Figure 1. Two macro-level features found on all hood frames are patterns of ribs and pockets (or cut-outs); the former presumably aligned with load directions and the latter to reduce weight. The advent of TO embedded in FEA programs opened the possibility of generating shapes consistent with load paths. In theory, one can say that TO can give us feature shapes and patterns (conceptual design), and then size optimization can be done by any parametric optimization method, such as GA or DOE. The advantage afforded by this approach is that shape is produced analytically instead of using some ad-hoc feature pattern. However, the practicality of this approach is limited by several factors. First, TO produces solids, while many automotive components are hollow (e.g., pillars are typically double hat sections). Second, TO results are generally not manufacturable by mass production processes. Third, TO results are meshes and not solid or surface models that can be parameterized for input to size optimization programs. It would require a considerable amount of manual work to featurize and parameterize such models. Also, this is a sequential process: optimize shape first, then size. Based on the above observations, this research focuses on investigating alternative approaches.

Parametric optimization of automotive hoods requires independent parameters (inputs) and outputs (termed responses in DOE and objective function in optimization). The base surfaces are derived from the outer styling surfaces and are not a load-bearing member. The frame on the other hand is a structural member, made of feature patterns, that is impacted by various load cases. The primary goal for a hood is to meet load and crash requirements with minimum weight. Figure 2 shows examples of hood models with different features and the corresponding sample parameters (P1, P2, and P3) [29]. However, the study of multiple designs with unique features and parameters cannot be incorporated because they are different and cannot be compared. This nature of the parameters, coupled with the large quantities, makes it non-uniform which cannot be represented accurately using conventional experiment design methods.

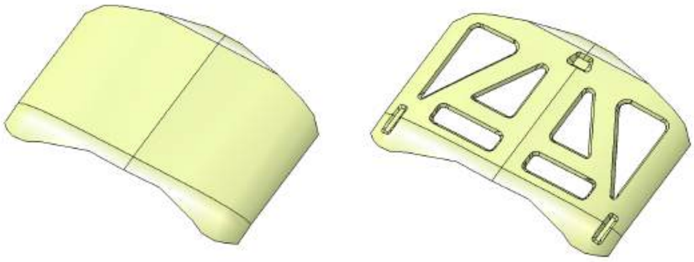


Figure 1: Hood Skin (left), Hood Frame (right).

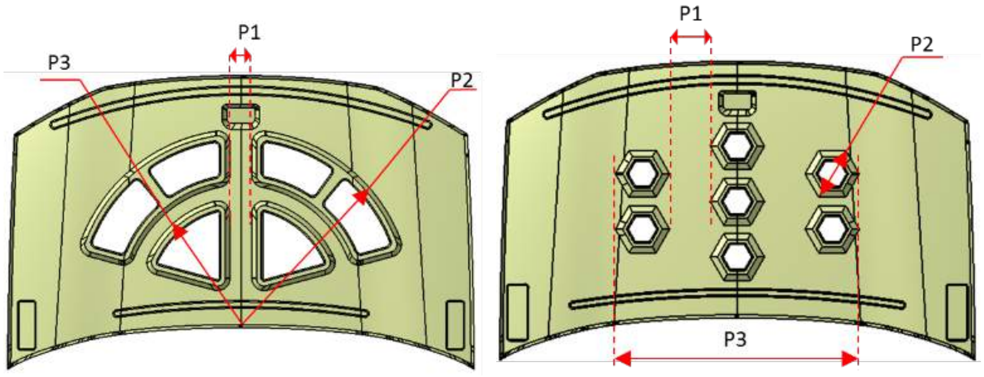


Figure 2: Examples of hood models with different features [29].

This research aims to propose and compare a set of structural optimization workflows for automotive hood frames for component efficiency and practicality. As discussed earlier, there does not exist a single optimization technique that can handle a combination of multiple objectives, load cases, constraints, parameters, etc. Hence, a hybrid scheme of DOE techniques (or *unconventional DOE methods*) has been used to solve such a complex problem. Depending on designer preference, the *three* methods presented can be used separately or together. The end goal is not to provide a final detailed design, but instead, it is to provide the designer with a tool to compare starter designs that have different geometry and topology. The frameworks developed in this research can also be adapted to any automotive structural component that uses a parameterized feature-based design approach.

2 LITERATURE REVIEW

Design optimization has been a very challenging research issue in the field of engineering design, which requires not only a lot of experience and knowledge but also some appropriate scientific approaches. In the traditional approach, designers usually adjust the design parameters manually to assist the product optimization. However, it is relatively complicated, time-consuming, and cannot be executed automatically [33].

Design optimization problems are usually categorized into *parametric* and *non-parametric* optimizations [34]. Parametric optimization is a method that works with a fixed set of predefined parameters. These parameters are used to determine the optimal solution for a given optimization problem. The main feature of a sizing problem is that the domain of the design model and state variables are known a priori and is fixed throughout the process.

Non-parametric optimization method solves the optimization problem without any predefined geometric design parameters. This means that no assumptions of parameter values are required to perform the optimization. Only the objective function and constraints are required to optimize a given problem. Typically, a certain number of constraints are applied to limit the search space for the optimization and keep it within a manageable size. *Shape* and *Topology* optimizations are the most common forms of non-parametric optimizations. However, since this research is on developing a pseudo-DoE method, the focus will largely remain on parametric (or *size*) optimization.

In most design problems, the number of unknown variables is more than the relations among them, which means that there are many feasible solutions. A design optimization problem needs to find the values of independent design variables to maximize/minimize design objectives without violating any constraint. In most design problems, there are more unknown variables than the number of relations amongst them, causing it to be under-constrained. This also means that there are many feasible outcomes to the optimization problem. Most parametric problems can be solved using mathematical, sampling methods, and evolutionary methods. A few larger, more complex problems, require additional capabilities that are outside the capabilities of these optimization methods.

Parametric programming has been used to solve optimization problems where the design variables are implicit functions of certain parameters that represent unknown problem data [31]. The main advantage of using parametric optimization is that the optimal design variables and corresponding objectives are obtained as explicit functions of the unknown parameters. This removes the need for evaluating objective functions for every change in the unknown parameter [23]. Choi and Kim [6] describe various shape design parameterization methods in their monograph. They are compatible with CAD systems and allow high computational efficiency.

Many researchers studied different linear and non-linear instances of parametric optimization. Acevado et al. [1] developed a multiparametric algorithm for engineering problems under uncertainty. The study by Leverenz et al. [17] seems to be the first to introduce parametric optimization into multidisciplinary design optimization (MDO). The sub-gradient algorithm uses the Multi-Parametric Toolbox (MPT) [12]. Additional details on various numerical methods for engineering design problems have been presented in [19], [11, 36, 8].

Design of experiments (DOE) is a sampling method that uses a statistical approach to effectively sample a design space with the factorial combination of design parameter values [9]. DOE technique is based on the concept of simultaneous variation of factor levels in order to build forecasting models for relevant outputs [21]. An additional advantage is that DOE principles can be implemented in a well-defined and relatively low number of experiments [22]. It is one of the most important methodologies for researchers dealing with experiments in practical applications, and its tools are incorporated in many statistical software packages that ease calculation and interpretation of results.

The long simulation times and computational expenses that accompany these high-fidelity models limit the number of designs that may be tested [5]. Since the parameterization scheme has a huge influence on the optimization process, knowing which designs to test can be challenging without an understanding of how each design variable influences the results. While engineering experience can help with this, the application of the method is limited when the designs are dissimilar and feature patterns vary.

Evolutionary design systems are loosely based on the Neo-Darwinian model of evolution through natural selection. A wide variety of evolutionary algorithms (EA) exist with very similar overall evolutionary processes [13, 32, 10, 15]. These have emerged as powerful tools for finding optimum solutions to complex optimization problems. EAs have been used extensively to obtain optimal designs and overcome the computational drawbacks of traditional mathematical optimization methods [39]. However, the above methods require a lot of performance evaluations performed by computation-intensive simulation, especially for complex designs, which may lead to lower iterative optimization efficiency and higher cost [7].

However, in order to use parametric optimization methods, designers need considerable knowledge and experience in selecting proper parameters for complex geometries and features. The optimization of the designs is strongly influenced by the parameterization scheme.

Although these optimization methods have shown exceptional capabilities in solving a design problem, either for size **OR** for shape, most methods usually fail due to the presence of a large number of non-uniform parameters and feature variations involved in designing an automotive component. It also fails to provide solutions that will enable a concurrent optimization of shape **AND** size.

The inability to handle multiple objectives, load cases, constraints, and a large number of parameters calls for a new approach that may include variations of traditional methods or a combination of those techniques to generate new and improved designs. The method and examples of its application to several dissimilar design problems will be described to demonstrate the validity and practical utility of the methods proposed here in the following sections.

3 OVERVIEW OF RESEARCH METHODS

In this research, the focus is on integrating the use of non-uniform parametric study for design exploration to gain valuable insights from past designs to make valuable suggestions to the designer. It is necessary to use unconventional methods to compare the performance of topologically different designs. The authors have published in the past details on CAD model generation (from skins and features) [14, 26] and also generated the performance data for each model [29]. This paper discusses the next step in using the performance dataset - processing the results for the non-uniform parametric models and obtaining the correlation between various features on the hood frame. The proposed method uses data sets of the parameterized geometric CAD models and their corresponding finite element analysis (FEA) for a given set of loads. Based on designer preference, three variations of DOE are proposed: 1) analyze for a specific hood skin, 2) analyze for a larger set that includes features from multiple hood frames at the same time, 3) analyze based on specific hood attributes (area, curvature, etc.) instead of individual feature parameters. The proposed methods enable concurrent *shape and size* optimizations of topologically dissimilar automotive frames. Figure 3 shows the workflow for the three proposed methods. Although the three methods appear parallel to each other in the workflow, each method can be used separately using the same input data generated in the previous stage. Details on the methods for generating the CAD and FEA datasets, performing parameter sensitivity study, and data analysis methods are discussed in the following sections.

4 DATA CURATION

A study conducted on combinations of 10 mass production hood skins and 10 frame feature patterns found the number of key design parameters in the range of 5 - 35. It was found that not all the parameters had the same influence on the responses (in this case: deflections and maximum von-mises stress) - a few parameters were dominant than the others. Given the large number of factors and variety of hood features, it is not meaningful to construct response surfaces to optimize the frame designs. Studies were performed on various models, which include cross-combinations of the base surfaces and feature patterns.

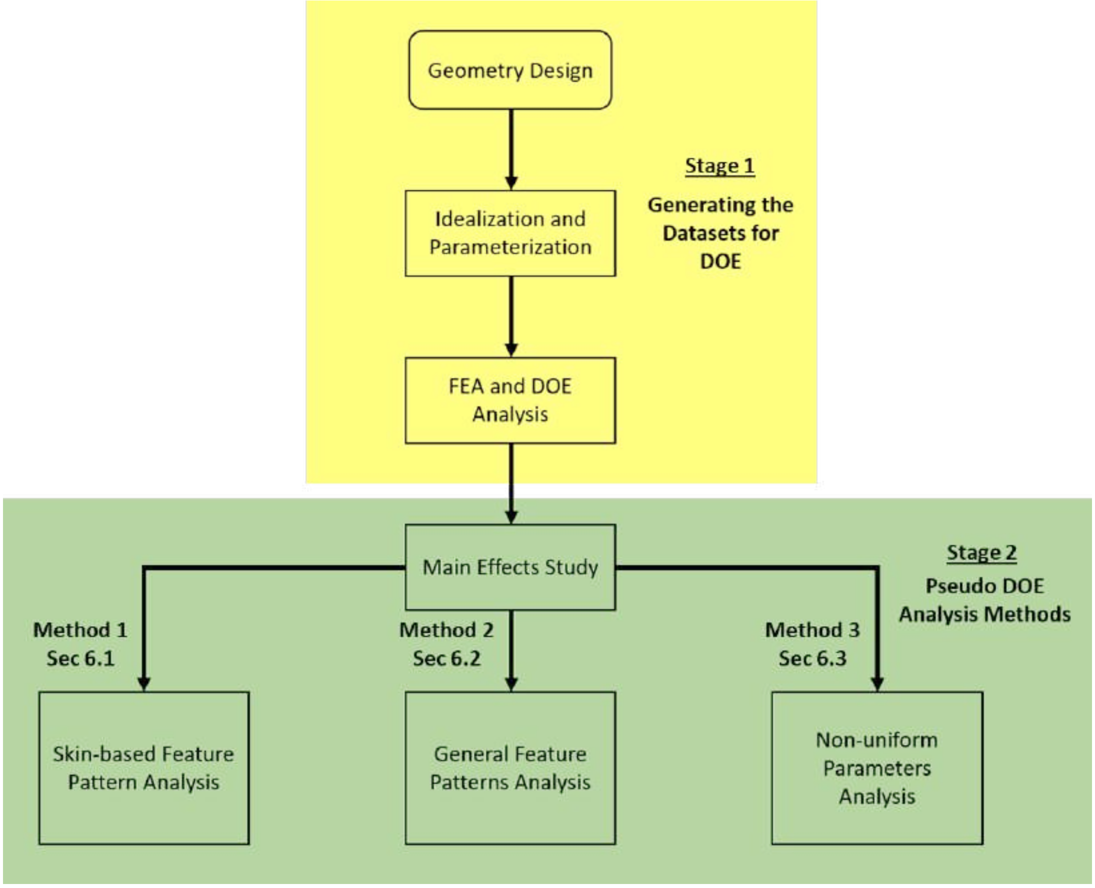


Figure 3: Workflow for comparative study.

To generate a large dataset of geometries, the 10 feature patterns were combined with all 10 skins to produce a total of 100 shape variants. These base geometries generated are shown as a "Mix and Match" matrix in Fig. 4. Certain features like hood locks and hinge flats are standard features in every design and were not changed or modified in this process.

Generating a large amount of CAD models of complex, industry-grade engineering parts, is challenging. An automated data generation pipeline was used for automotive hoods in CATIA v5, which results in a large set of variants of hoods that are geometrically valid, manufacturable, exhibit sufficient variability, and have functional properties comparable to real-world designs. In [29, 26, 27, 28], the authors provide a detailed description of the CAD data generation, as well as validation and post-processing of generated 3-D models and corresponding performance metrics. The data set is available from [30, 38] together with a detailed description of data types, data generation, and the organization of the repository. A summary of generating the datasets are described below.

4.1 CAD Data Generation

To automate the process of acquiring a large amount of CAD data sets, a feature-based design approach is chosen that is fast and robust. Automotive hood frames must meet several structural requirements, such

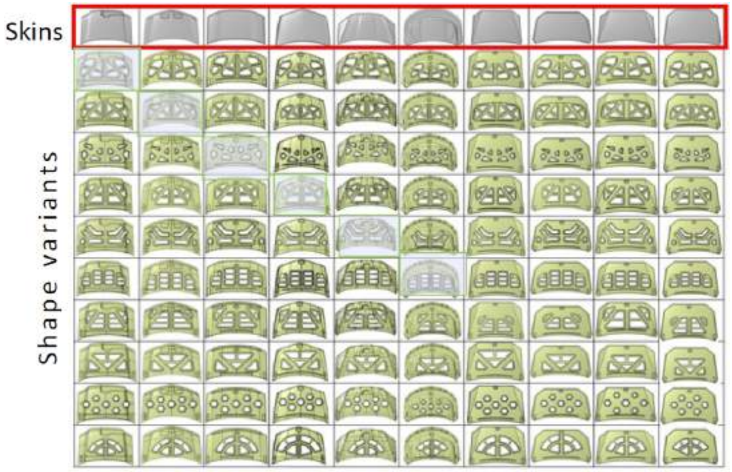


Figure 4: Results from mix and match of feature patterns and skins [20].

as maximum hood lift or twist deflections, and the ability to withstand pedestrian and frontal impact. The structure of the hood frame is made from sheet metal stamped components, and desirable properties of the component are achieved by adding features. For example, to add stiffness ribs and channels are created, while light weighting is achieved by creating cutouts or pockets. The specifications of the hood skin (like size, aspect ratio, etc.) constrain the design of the frame structure and the placement of features. For generating large sets of geometries, features or a set of features (pattern) are parameterized and parameter values are chosen such that a feature does not fail during automatic generation [27].

Parameter values describing the placement and characteristics of feature patterns were generated using a sampling scheme and stored in a design table [26]. Examples of design variations generated by varying parameter values are shown in Fig. 5. In the first design, compound features at the front corners are toggled off while in the other two designs, the sizes of features are varied.

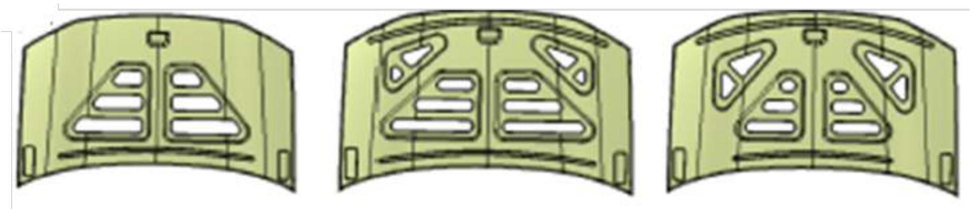


Figure 5: Example of design variants.

Once the base shapes are established using the mix-and-match approach, the design parameter of each shape is varied to produce 100 variants. This helps to generate a large amount of geometries that show sufficient variability. The workflow starts with the base component, which is an idealized hood skin, on which the various features are created and assembled. Features on the skin are then instantiated using a macro, which reads parameter values from the design table and executes the modeling steps necessary to generate the features. This method allows the generation of large data sets containing the shape variations shown in Fig. 4.

Using this method the total number of CAD models created with the presented library of features was M = A x B x C, where M is the total number of designs, A is the number of pocket feature patterns (11), B is the number of base surfaces (10), and C is the number of design variants for each surface (100). Therefore, the total number of generated geometric designs was M = 11,000. Of these, 10,478 were successfully generated while 522 designs failed during the CAD process. The geometries generated in CAD are converted to STL surface meshes via a custom script. Fig. 6 shows examples of CAD models generated using the mix and match method.

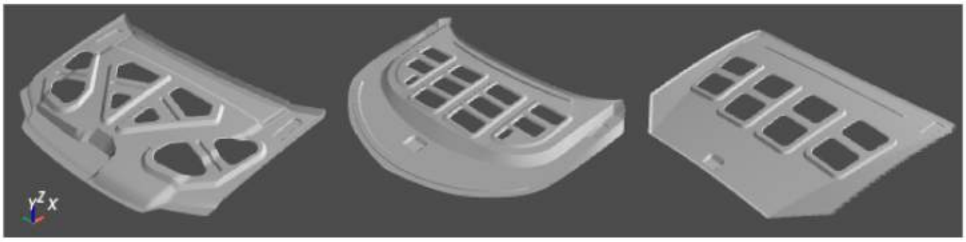


Figure 6: Example of hood geometries generated [38].

Finite Element Model Standardization and Setup

The performance values associated with each geometry was obtained using finite element analysis (FEA). The analysis was performed using Ansys Workbench R19.1. FEA was performed for hood lift and twist cases. Overall stiffness for hood lift and hood twist load cases during driving conditions is an important structural requirement when designing car hood frames. A load case correlation study was performed prior to generating the performance data [29], [27], [18]. It was found that a high correlation between the performance values for both load cases existed. Hence, only the results from one of the load cases (hood lift) was considered for further studies. The obtained performance values are maximum equivalent (von-mises) stress [MPa], maximum directional (z-axis) deformation [mm], and geometry mass [kg].

A uniform setup of boundary conditions (loads and supports, Fig. 7(a)) was established in order to standardize the automatic setup of thousands of models. Boundary conditions remained consistent between various FEA models with respect to fixture locations and loads (Fig. 7(b)).

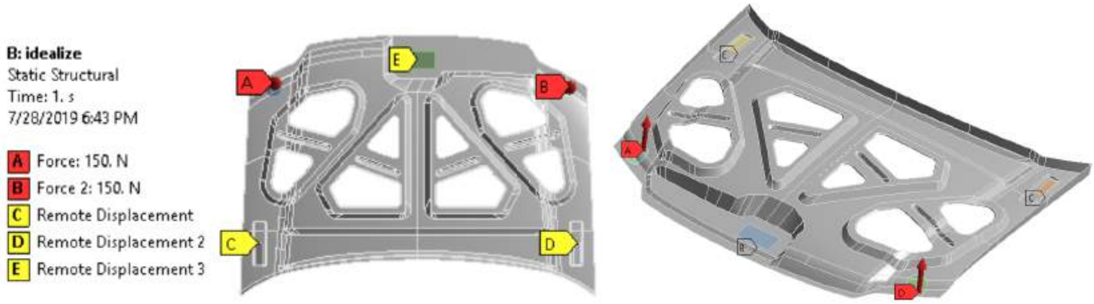


Figure 7: Boundary conditions for FEA. Location of boundary conditions for hood frame FEA (Left). (b) The direction of the applied loads, red markers indicate a force of 150 N and yellow markers indicate a remote displacement (Right).

A study was performed to understand the effect of common features (pocket features in particular) in the hood models. It was found that pocket feature patterns dominated the performance of the hood in comparison to other features. Further, varying the pocket feature patterns introduced sufficient variation in the performance of the data set. Hence other features like weld beads, adhesive locations, etc. were left out of the design.

5 PARAMETRIC SENSITIVITY STUDY

In DOE, it is important to filter out parameters that have no significant effect on responses. Having too many parameters might significantly increase the time of analysis and yield no added benefit. The most efficient method to reduce the number of parameters is using a parametric sensitivity analysis. The main procedure for parameter reduction is to use the response variable over the entire dataset and then find the main effect for all parameters. Since the number of parameters is relatively large on any hood frame model, only the linear effects are considered. Figure 8 shows a Pareto chart for parameter sensitivity. Parameters with longer bars have a larger influence on the response variable (e.g. deformation), and are important parameters

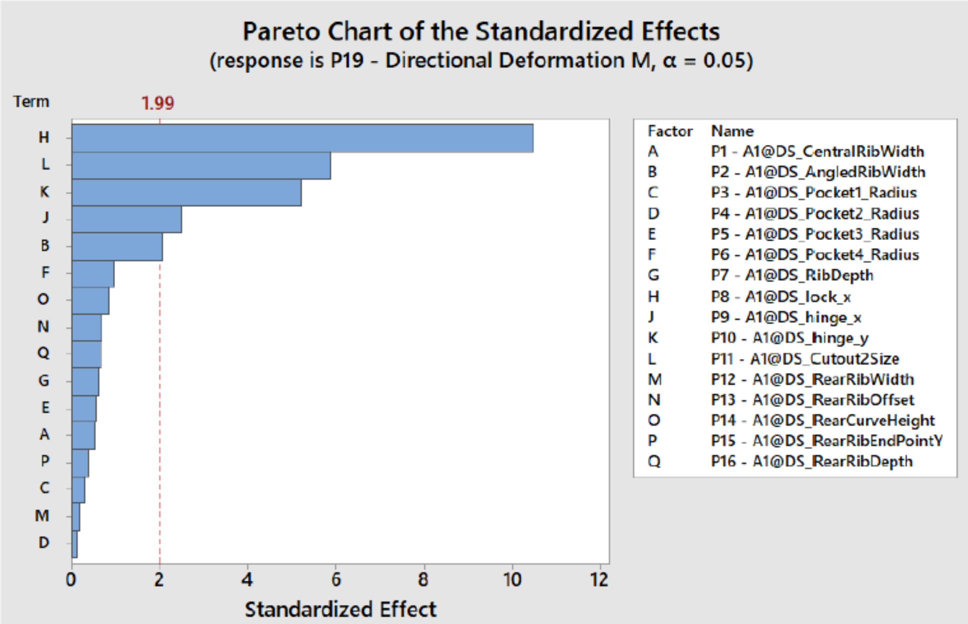


Figure 8: Pareto chart for sensitivity study on a hood frame [18].

In the example considered, the five most significant parameters are *DS_ lock_ x*, *DS_ Cutout2Size*, *DS_ hinge_ y*, *DS_ hing_ x*, and *DS_ AngledRibWidth*. These parameters were retained in the next steps (as the reduced parameter set) while other parameters were discarded. In the parametric sensitivity study of all the parameters, only linear effects were considered, but for the reduced parameter set, the number of parameters is less enough to do the interaction analysis among each other (second-order analysis). The reason for doing the sensitivity analysis for reduced parameters is that the interaction between parameters was not considered in the initial analysis for full parameter sets. The results from the reduced parameter set can be used to further reduce the number of parameters if required. Fig. 9 shows the main effect analysis for the reduced parameter sets.

6 UNCONVENTIONAL DOE METHODS FOR DATA ANALYSIS

As mentioned, performance data is generated using DOE to determine the design (combination of skin and feature pattern) with the highest frequency of occurrence in the analysis based on its performance. A conven-

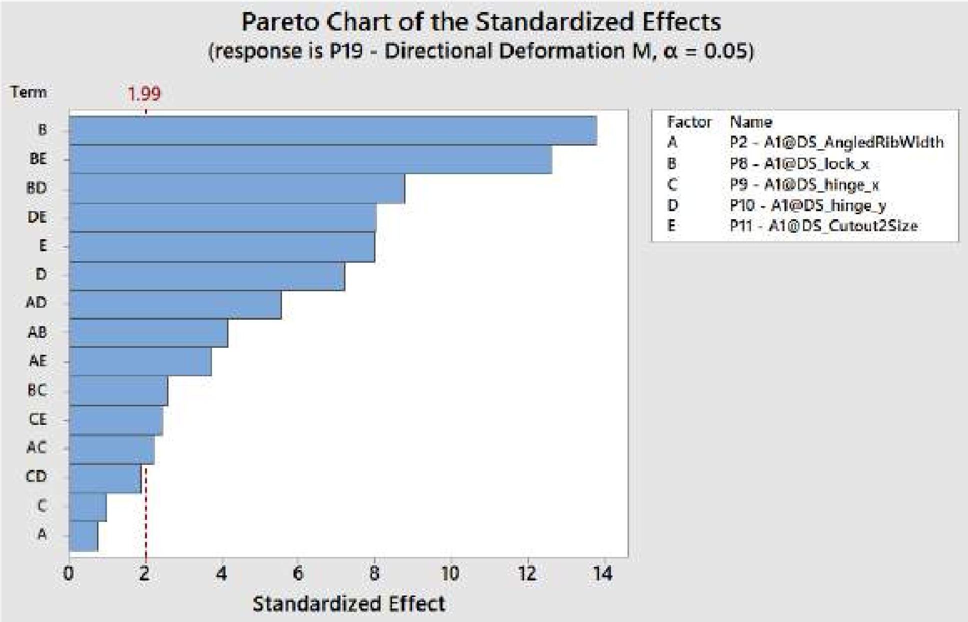


Figure 9: Pareto chart for sensitivity study on the reduced parameter set [18].

tional DOE cannot be used since the dataset contains different geometric features, feature layouts (feature patterns), and parameterization schemes. Hence three pseudo DOE methods were devised that can be used to compare designs:

- Method I: Partitioned Dataset - Best feature pattern for a given skin
- Method II: Aggregated Dataset - Dominant feature pattern across all skins
- Method III: Generalized feature attributes on the aggregated dataset

In *Method I*, only information on one skin model is used for the design study. It provides designers with information on the feature pattern with the highest occurrence frequency for a given skin surface. However, this would mean the method must be repeated for each skin separately. The second method (*Method II*) combines the performance for all skin and feature patterns. The outcome of this method is to find the top one or two feature patterns (or dominant feature patterns) that contribute to the best performance regardless of skin geometry. The third method (*Method III*) is a non-uniform parameter analysis and is the most significant method for evaluating performance among various hood models. In this method, all skin data points are collected together, and the evaluations are done based on important attributes (of skins and feature patterns) instead of size parameters - which provides a *cause & effect* evaluation. Based on the parametric sensitivity study, only the reduced parameter sets were used for the first and the second methods. Each model has around 15 total input parameters; hence, reducing the number of parameters saves a significant amount of time. The three methods (*I, II, and III*) presented have advantages and limits based on the features or designs of interest to compare and study.

6.1 Method 1: Partitioned Dataset - Best Feature Pattern for a Given Skin

Method 1 evaluates the models by considering one skin at a time. Each skin has 11 feature/pocket patterns, and the objective is to find the most suitable pocket pattern for a given input skin. For each hood (shape variant), there are 100 geometric variants (size variants), bringing the total number of data points to 1100 (100x11). The response variable considered here is the product of directional deformation (z-axis) and mass. Table 1 shows the performance values and the response variables for various feature patterns and the corresponding size variants for a given skin, sorted in ascending order based on the response variable. Lowering the value of this response variable will help generate the stiffest model with the least mass. Additional response variables can also be used based on desired criteria. The top 100 results can then be used to determine each feature pattern's frequency. The feature pattern with the most occurrences is considered the most suitable pocket pattern for the given skin.

Table 1: Subset of performance values for various pocket patterns for a given skin

pocket	z-deformation [mm]	vM stress [MPa]	mass [kg]	response ($\partial * m$)
PTRN1 - SZ07	4.66	169.40	14.60	67.99
PTRN1 - SZ18	4.67	177.00	14.66	68.38
PTRN1 - SZ17	4.77	168.45	14.40	68.71
PTRN1 - SZ09	4.71	172.33	14.61	68.84
PTRN3 - SZ16	5.22	162.62	14.70	76.79
PTRN3 - SZ24	5.24	162.33	14.67	76.82
PTRN3 - SZ01	5.24	163.21	14.69	77.02

Table 2 shows the results for SKIN 1. After sorting the results based on the response parameter, it can be found that PTRN1 is the most common pattern, occurring a total of 37 times out of 100, followed by PTRN5 which occurs 31 times. No other feature pattern has the same frequency of occurrence in the top 100. Based on these results, it can be determined that either PTRN 1 or PTRN5 is the most suitable pattern for SKIN 1. The same method can be applied to additional skin surfaces. Table 3 shows the results of method 1 applied to various skin surfaces.

Table 2: Results from Method I - top 3 pocket patterns based on frequency of occurrence

pocket	frequency of occurrence in top 100
PTRN1	37
PTRN5	31
PTRN2	12
PTRN4	11
Total	91

Based on the requirements, a different response variable can be used to determine the most frequently occurring pocket pattern for a given skin. The primary goal of the method is to figure out the existence of one feature pattern that performs the best (based on the response variable) on a given skin. However, its practicality is limited because it is specific to only one skin geometry. It does not guide finding the most suitable feature pattern in a more general case. Moreover, if the initial skins change, results from Method 1 may not be accurate and will provide minimal to no guidance to designers.

Table 3: Results for all skins using Method I

skin	suitable pocket	CAD model	skin	suitable pocket)	CAD model
SKIN1	PTRN1		SKIN6	PTRN4	
SKIN2	PTRN6		SKIN7	PTRN6	
SKIN3	PTRN6		SKIN8	PTRN4	
SKIN4	PTRN6		SKIN9	PTRN5	
SKIN5	PTRN6		SKIN10	PTRN10	

6.2 Method II: Aggregated Dataset - Dominant Feature Pattern Across All Skins

The aggregated dataset for all skins and feature patterns (Method 2) focuses on obtaining the design with the highest frequency of occurrence based on responses from the combinations of all skins and feature patterns. While overcoming some of the most critical limitations of Method I, this method helps find the pocket pattern with the best performance while looking at all the skins simultaneously. In other words, a more reasonable way to get the optimal feature pattern for all skins is to evaluate them based on all the available data.

Before the performance data from all the skins can be combined, it is important to normalize all the data points. Every skin has different parameters like surface area, aspect ratio, curvatures, individual size parameters, etc. Hence, without normalization, combining the results directly does not provide meaningful results. The response variables are normalized using intrinsic normalization:

Normalized deflection: $\partial_R = \partial_i/\partial_m ax$
Normalized mass: $m_R = m_i/max_{skin}$

After normalization, the response variables (or variables) take a value between 0 and 1, making them non-dimensional ratios. The non-dimensional values can then be used across all skins, either directly to compare individual response variables or as a composite objective ($\partial_R * m_R$).

The total number of data points, after the normalization, is 11,000 - 10 skins and 11 feature patterns, with 100 design variants in each. The next step is to sort all the response parameters in ascending order. Since the aggregated data is very large, one could look at the frequency of the feature pattern occurrence in the top 5 - 10 %. Table 4 shows the frequency of occurrence of various patterns in the top 5%.

Based on the results in Table 4, in the top 5% results, both PTRN 5 and PTRN 6 have the most occurrences. As per the outcomes from method II, PTRN5 and PTRN6 occur the most number of times in the aggregated dataset. For SKIN1, both methods I and II indicate that PTRN5 as a suitable or favorable pocket pattern overall. Figure 10 shows the PTRN5 feature on SKIN1.

Table 4: Results from Method II - frequency of occurrence in the top 5%

pocket	count	frequency of occurrence in top 5%
PTRN6	195	33.80%
PTRN5	193	33.45%
PTRN11	189	32.75%
Total	577	

Figure 10: PTRN5 on SKIN1 [18].

6.3 Method III: Generalized Feature Attributes on Aggregated Dataset

Both method 1 and method 2 used the same reduced parameter sets. If all skins and pocket patterns can be described with the same set of attributes across the board (Method 3), it enables the use of traditional DOE or Response Surface. Unique attributes from skins and feature patterns can be extracted which serve as input parameters to DOE. In addition, the response surface is used in Method 3 to determine the performance of the hood models. The data points for all the skins are analyzed together. The main goal is to obtain reasonable results for hood performance and performing analysis using generalized attributes which can reduce the uncertainty and error to certain extent. The attributes extracted for the skin and pocket patterns are:

- Skin Attributes:
  - Aspect Ratio
  - Axial Curvature
  - Transversal Curvature
- Pocket Pattern Attributes:
  - Pattern Type
  - Feature Depth
- Complex Parameter:
  - Net Area (of skin and pocket pattern together)

In Method 3, three skin attributes (aspect ratio, axial and transversal curvatures), two pocket pattern attributes (pattern type and feature depth), and the net area serve as the input parameters. The total number of input parameters are six and the response variable is the product of directional deformation (z-axis) and the mass ($\partial_R * m_R$). While all the attributes are numeric, the only non-numeric attribute (pattern type) is categorized as shown in Table 5. Table 6 shows an example of the input and output variables used in this method.

Table 5: Pocket pattern types

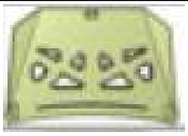
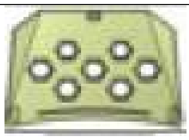
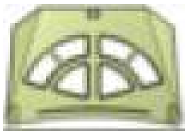
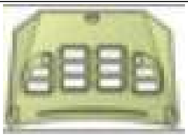
radial	mixed	circular	sectored	orthogonal
				

Table 6: Sample input and output data

pattern type	aspect ratio	area (mm^2)	def. [mm]	mass [kg]	response ($\partial * m$)
Orthogonal	1.34	441425.69	5.23	14.66	76.71
Circular	1.50	421801.80	5.22	14.70	76.79
Orthogonal	1.22	390178.79	5.24	14.67	76.82
Mixed	1.89	466212.89	5.24	14.69	77.02

In method 3 the response surfaces are used to predict the values of output parameters. As mentioned before, results from method 1 and method 2 only focuses on finding the frequency of occurrence of various pocket patterns given a skin surface, based on the existing data points. These results may not always guarantee the most suitable pocket pattern because it is possible that not all parameter values are *optimal*. The response surface can be further explored for obtaining an optimal design. It can also be used to determine the main effects and sensitivities of the input variables independent of specific feature pattern. The input parameters are set as continuous except for the pattern type, which is set as a discrete variable. A sample response surface for the aspect ratio, net area, and the response variable are shown in Fig. 11.

The goal of this method is to find a pocket pattern or a skin that has the best performance based on the changes to the input parameters. There is no data point in the response surface which has the exact same value as optimal input parameters. The closes data point was determined by using an *L1 norm* as shown below:

$$\sum_i \frac{(|y_c| - |y_o|)_i}{(|y_o|)_i}$$

where, y_c, y_o are sample and optimal values of attribute i respectively

The optimized response surface can be used to obtain suitable values for attributes that can then be used to generate a corresponding CAD geometry. Table 7 lists a subset of the attributes obtained from the response surface(s) and the corresponding CAD geometry for PTRN10.

7 CONCLUSIONS AND FUTURE WORK

In this research, a comparative study of structural optimization methods was performed to rate hood frame geometries with respect to their structural performance. The proposed methods include a pseudo-design

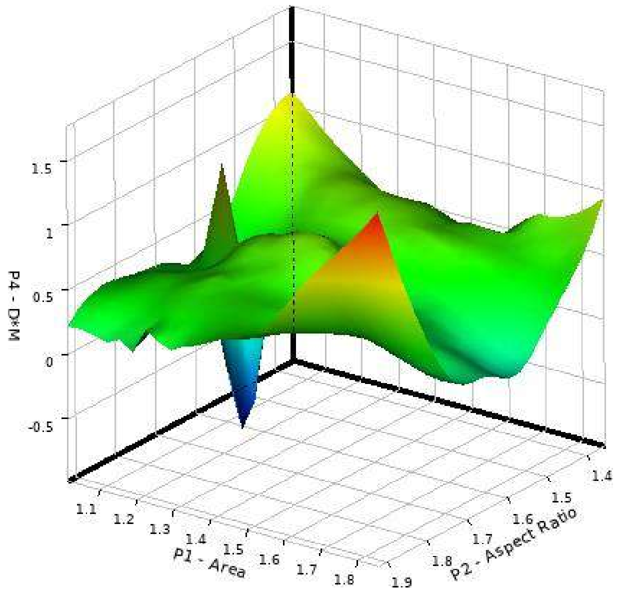
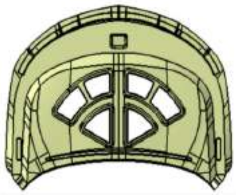


Figure 11: Response surface for two input parameters (aspect ratio and area) and the response variable [18].

Table 7: Example result from Method III

pattern type	aspect ratio	area (mm^2)	def. [mm]	mass [kg]	response ($\partial * m$)
Orthogonal	1.52	490013.69	4.79	13.78	66.00



of experiments and a response surface method. The uniqueness of hood frame designs and the presence of nonuniform parameters make it difficult to draw direct comparisons between two or more designs. The methods proposed in this research fill this gap by introducing three approaches to using a non-uniform parametric study with pseudo-DOE in order to make valuable suggestions to the designer. It uses a streamlined approach for processing FEA results for hood models with dissimilar topology and obtaining the correlation between various pocket features and the skins. The final evaluation/suggestion is based on the response variables of interest to the designer. In other words, the research is focused on rating the goodness/or not, of feature patterns for an input skin surface.

The goal of Methods 1, 2, and 3 is to find the pocket pattern with the highest frequency of occurrence based on the response variable. Method 1 focuses on finding an optimal pocket pattern for a specific skin, and Method 2 is a comprehensive method that combines all skins together to find the most suitable pocket pattern amongst all skins and pocket patterns. Method 3 is a unique method in this study because it uses generalized skin and pocket pattern attributes instead of geometric design parameters.

To make better use of the results from the proposed methods, they can be used directly or indirectly in the current design process. In the indirect method, designers can choose to use the dominant pocket patterns (irrespective of skin geometry) obtained from method II, as a starter design. While, these methods can be directly integrated into the design process by using the skin attributes correlated to the pattern attributes, as shown in method III. ML algorithms can also be used to overcome the limitations of method III in terms of adding additional attributes and establishing a relationship between them.

Future work would include the introduction of additional studies for filtering the parameters and including non-dimensional/non-design parameters. There is a need to investigate supervised learning methods to train ML algorithms to correlate hood shape and size attributes to performance. That would allow evaluation of new skin-frame combinations not contained in the current hood data set of 10,0000 designs. Additional methods and algorithms for machine learning can also be investigated to improve the efficiency of the output.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the technical and financial support received from Honda Development and Manufacturing America LLC.

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