

A New Data-Driven Design Method for Thin-Walled Vehicular Structures Under Crash Loading

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ABSTRACT

A new design methodology based on data mining theory has been proposed and used in the vehicle crashworthiness design. The method allows exploring the big dataset of crash simulations to discover the underlying complicated relationships between response and design variables, and derive design rules based on the structural response to make decisions towards the component design. An S-shaped beam is used as an example to demonstrate the performance of this method. A large amount of simulations are conducted and the results form a big dataset. The dataset is then mined to build a decision tree. Based on the decision tree, the interrelationship among the geometric design variables are revealed, and then the design rules are derived to produce the design cases with good energy absorbing capacity. The accuracy of this method is verified by comparing the data mining model prediction and simulation data. The result indicates that the data mining based methodology could overcome the weakness of traditional design method, i.e. lack of capability in information discovery from big datasets.

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INTRODUCTION

Thin-walled structures, including beams and columns play an essential role in vehicle crashworthiness by absorbing impact kinematic energy effectively and efficiently [1, 2, 3]. To be in compliance with the regulatory and non-regulatory requirements for crash safety, these structures must meet all service load requirements, and must deform plastically in a short period of time (milliseconds) within a limited crush space to absorb the crash energy in a controllable manner. Due to the highly nonlinear nature of the problem, Computer-aided Engineering (CAE) (e.g. numerical simulations based on finite element (FE) method) have been adopted as a powerful tool and widely used for mechanical system analysis and evaluation. [4, 5].

In the design phase of a complicated mechanical system such as a vehicle using CAE methodologies, big datasets are generated since a large number of simulations are carried out to verify the design. Based on the design datasets, two design techniques, namely (1) meta modeling and (2) optimization approaches are traditionally used [6, 7]. Meta models are linear or nonlinear functions to predict system performance as a function of design variables. Examples of meta modeling techniques include RSM (Response Surface Methodology), Kriging (namely Gaussian process regression), Radial Basis Functions (RBF), Extended Radial Basis Functions (E-RBF), Artificial Neural Network and Support Vector Regression (SVR), etc. [2, 3, 8, 9]. Optimization based approaches are implemented through

iterations. Subjected to the design constraints, the initial design “evolves” towards the optimum through iterations. Commonly used optimization techniques include Genetic Algorithm (GA), Simulated Annealing (SA), Evolutionary Algorithm (EA), and Particle Swarm Optimization (PSO) [10, 11, 12]. Both techniques have been widely applied in the vehicle structure design, for example, uncertainty optimization of thin-walled beam [8], multi-objective optimization of foam-filled thin-wall tube for vehicle lateral impact [9].

However, both techniques have numerous limitations [6]. These approaches cannot reveal the interrelationship/coupling effect among different design variables implied in the simulation datasets. Since in the vehicular components, design variables have coupling effect and cannot be deemed as independent. Some design variables are “parents” whose values could influence “children” variables and then overall behavior of the component. In the design practice, the “parents” variables must be determined first and then followed by the “children” variables. Such intrinsic coupling effect of design variables is complicated and usually implicit and “hidden” in the vast amount of simulation data. Without this knowledge, it would be difficult to generate reasonable design and decision making rules (i.e. work flows) to tune each individual variable in the right sequence. To overcome these drawbacks, a novel methodology is greatly demanded to discover the desired relationships by exploring the large amount of

design data. With this knowledge obtained, design rules can be generated to make righteous decisions from the top-down direction as to be explored and demonstrated in this study.

According to these functional requirements, the proposed design methodology is based on data mining theory [6, 13], which is developed for exploration and analysis, by automatic or semiautomatic means, of large quantities of data to discover meaningful patterns and rules. The data mining tool enables designers to filter large amount of data, discover hidden data, reveal new relations and patterns, and extract anticipative and useful information implied in big datasets.

Data mining algorithms, such as clustering and decision trees have been used in the design of numerous products. For example, the fuzzy rough set based variable screening method was used to distinguish the key variables for the vehicle body NVH analysis in order to obtain the minimum body weight [14]. Classification technique was applied to discover the coupling effect of key parameters in the head to study the mechanism of brain injury subject to air shock loading [13]. Recently, this approach was employed by the authors to vehicle system safety design, to reveal the relationship and design rule at the system-component level [6]. Based on this work, the present study further extends the approach to the detailed design of a crashworthy component. A thin-walled energy absorbing structure in passenger cars (namely S-beam) serves as a good example for demonstration of exploration and analysis of the results below.

METHOD

The objective of this study is to explore the interrelationship of design variables and establish the design rules by applying the newly developed data-driven method in the vehicular thin-walled structure design. Workflow of this method is shown in Figure 1.

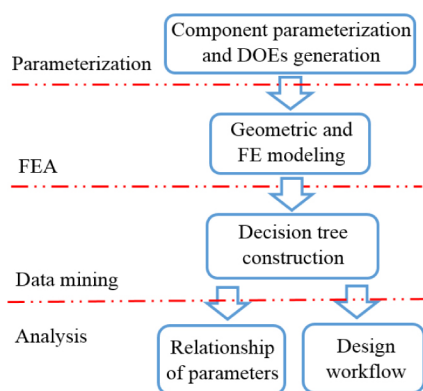


Figure 1. Workflow of the data mining-based design method for vehicular S-shaped beams

In the first step, the structure to be designed, an S-shaped beam, was parameterized. The profile was described by a number of geometric parameters, and the range of the values of these parameters were also determined [15, 16]. Based on the relevant safety regulations [17], the crash speed was assumed to be constant. Therefore, speed was not

considered as a design variable. To consider different combinations of these parameters, a large number of DOEs (Design of Experiments) were generated. Each DOE represents a case with a certain combination of design variables and the population of DOEs forms a design space.

Then the geometric model for each DOE was built using a CAD software and converted to finite elements using a mesh tool. Simulations were conducted on all DOEs and the results formed a big dataset.

In the next step, the simulation results dataset was mined through a data mining software to discover the relationship among design variables and their influence on the results. Likewise, all of DOEs were classified as three groups, namely good (g), intermediate (m) and poor (p) designs, in terms of their energy absorbing performance. A tree like structure (termed as Decision Tree [18]) was generated by the software to determine a decision making rule or workflow to link the key geometric parameters and design results. In this way, the variables leading to good design sets can be determined in the right sequence.

COMPONENT PARAMETERIZATION AND GEOMETRY MODELING

The fully parameterized S-beam model is shown in Figure 2. The total length of the beam is 1000 mm. Geometric parameters, including upper segment length (UL) and radius (UR), slope segment angle (AN), bottom segment radius (DR), height (H), the tube cross-section length (CL) and thickness (T) are design variables. Points **r** and **f** are two center points at the ends. Points **a**–**d** are the transition points between different segments of this beam.

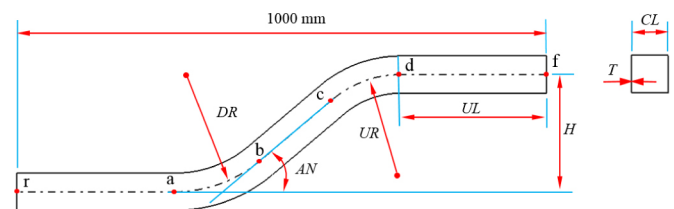


Figure 2. Parameterization of an S-shaped beam

Similar to other methods based on design space like optimization approaches, data mining methods are not sensitive to the selection of initial design. The initial geometric parameters were set in an arbitrary way when generating the design space. The geometric constraints were set and improved based on the previous literatures [15, 16], which achieves a full parameterization for the structure and describes its profile in sufficient detail. Therefore, these geometric parameters were selected in the current study as design variables. The geometric constraints are $H - (UR + DR) \cdot (1 - \cos(AN)) > 0$ in the vertical direction, which makes the length of segment **bc** larger than zero, and $1000 - (UL + H \tan(AN) + (UR + DR) \cdot \tan(AN/2)) > 0$ in the horizontal direction, which guarantees the length of segment **ra** longer than zero, respectively. The range of design variables are as