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Multi-response optimization design of tailor-welded blank (TWB) thin-walled structures using Taguchi-based gray relational analysis

Fengxiang Xu[a,b,*], Suo Zhang[a,b], Kunying Wu[a,b], Zhinan Dong[a,b]

[a] Hubei Key Laboratory of Advanced Technology of Automotive Components, Wuhan University of Technology, Wuhan 430070, China
[b] Hubei Collaborative Innovation Center for Automotive Components Technology, Wuhan University of Technology, Wuhan 430070, China

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A B S T R A C T

In order to further improve crashworthiness and reduce weight, tailor-welded blanks (TWBs) have been widely applied in auto-body design. In this paper, the discrete optimization design of TWBs structures with top-hat thin-walled section subjected to front dynamic impact is performed by using Taguchi-based gray relational analysis. Material grades and thicknesses with three levels are taken as discrete design variables. The total energy absorption (*EA*), the total weight (*Mass*) and the peak crashing force (F_{max}) are chosen as optimization indicators. Considering the uncertain weight ratio of responses, four different cases would be analyzed. In order to determine the optimal parameter combination more accurately and eliminate errors from range analysis, the analysis of variance (ANOVA) would be performed. The optimized results demonstrate that it is feasible to increase the crashworthiness of TWBs by increasing the gray correlation of the structure. Compared to initial structure, case 1 ($w(F_{max})$:$w(EA)$:$w(Mass)$ = 1/3:1/3:1/3) has the largest improvement among the four cases, i.e., the F_{max} and the *Mass* are reduced by 29.3% and 2.7%, respectively, while the *EA* is increased by 3.5%. The discrete optimization method with only 27 iterations is a low computing cost or cost-effective and provides some guidance for some similar structural design. More comprehensive studies are essential to optimize performance of multi-components with more discrete variables.

1. Introduction

Lightweight design of the vehicle is a significant important aspect when the indispensable requirements such as stiffness, strength, crashworthiness and NVH, etc have been satisfied. Generally, there are three main ways to achieve lightweight. The first is from the light material such as widely-applied high strength steel (HSS) [1], magnesium [2,3], and composite materials [4,5], etc. The second is from the manufacturing technologies such as tailor welded blank (TWB) [6–8], and hot thermoforming [9], etc. And the third is from the structural optimization design such as functional gradient structure [10–13], novel section structures [14–17], topological optimization structures [18,19], and some advanced optimization methods for its [20,21], etc. Those lightweight ways have been widely conducted to reduce weight and improve corresponding performance [22].

Among those ways, TWBs are defined as effective energy-absorbing structures with different materials or thicknesses welded together to form an integral component through the laser welding process [23]. This processing can be achieved due to the advantages of laser welding technology such as the narrow welds width, short welding processing time, high productivity, and no secondary treatment, etc [24].

Based on abovementioned advantages of TWB processing technology, many researchers have studied the formability and solder joint distribution of TWB. For example, Chan et al. [25] performed a formability analysis concerning the mechanical characteristics of the weld zones of TWBs made of cold rolled steel sheets with different thicknesses. They analyzed the effect of the thickness ratios on the forming limit diagram (FLD) for TWBs. Xu [26] numerically compared the modeling strategies of the weld line under quasi-static and dynamic events, and proposed a novel method with crossover scheme. Gaied et al. [27] proposed a new method to overcome the formability of TWB and was able to accurately predict the unique characteristics for TWB formation early in the design process.

Apart from the forming of TWBs, their crashworthiness performance is also one of the most important cases, which reduces injury risk for passengers. Therefore, it is essential to study the crashworthiness of TWB structures for improving the safety. Song et al. [28] investigated the crashworthiness of three different types of TWB with hat-shaped section and concluded that the optimized TWB tubes could improve energy absorption and enhance the reliability. Xu et al. [29] carried out

* Corresponding author at: Hubei Key Laboratory of Advanced Technology of Automotive Components, Wuhan University of Technology, Wuhan 430070, China.
E-mail address: xufx@whut.edu.cn (F. Xu).

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multi-objective optimization design of a multi-component TWB structure that involved both the B-pillar and inner door system subjected to a side impact. Zhu et al. [30] proposed an integrated approach using finite element analysis, an artificial neural network (ANN), and a genetic algorithm (GA) for the optimization design of an inner door panel with a TWB structure to reduce weight reduction and improve crashworthiness.

There are also a great number of researchers to investigate optimization algorithms in discrete space. Those advanced optimization algorithm combined with finite element analysis can reduce the number of experiment tests and save a lot of time compared with traditional optimization algorithm to a considerable extent. Important crucial experiments combinations which could comprehensively reflect situation of various factors were conduct by using Taguchi orthogonal table [31,32]. However, a single Taguchi analysis only applies to mono-objective optimization, which greatly limits its use. At the same time, there are increasingly attentions to gray correlation due to the outstanding application of its in multi-objectives. Eskandari et al. [33] simultaneously optimized surface roughness, tool wear and volume of material by using gray relational analysis, and finally obtained the best cutting parameters. Cai et al. [34] studied multi-responses optimization of S-rail extracted from the frontal body to improve its crashworthiness by using gray relational analysis, and the proposed method reduced the peak collision force to 26.81% as well as increased the corresponding specific energy absorber by 176.06%. Most researchers used gray analysis alone for multi-objective optimization without considering the robustness of the system, let alone combine it with Taguchi analysis.

Regarding the design variables of TWB, the main and obvious feature is the discrete such as the material grades and even material types, etc. To the author's best knowledge, the crashworthiness optimization design of TWB structures considering discrete variables was seldom reported, to say nothing of Taguchi-based gray relational analysis for it.

In this paper, Taguchi-based gray relational analysis would be further performed to multi-response optimization design of TWB thin-walled structures under crashing event. Firstly, a finite element model (FEM) about TWB crashing verified by physical experiment is constructed to simulate actual collision behavior. Then, orthogonal experiments are carried out by changing design variables with different thicknesses and material combinations based on Taguchi orthogonal array. Furthermore, analysis of Taguchi method, gray relational analysis and analysis of variance are applied into optimization design of HSS TWBs thin-walled structures. Finally, the optimal results obtained from which significant effect factors and optimal level combinations are presented. The optimum results demonstrate that the optimized structure can reduce the weight and improve the crashworthiness to a certain extent, and provide some guidance for some similar structural design.

2. Design procedure of TWB structures

With regard to TWB structures, the inherent properties of the structure have a relatively large effect on energy absorption and lightweight, especially thickness and material grade. Material grades and thicknesses of base materials fabricated into TWB structures are based on a series of constant discrete values. Therefore, the discrete optimization design problem can be defined as determining the optimal values of the some discrete design parameters in order to obtain maximum or minimum of objective functions or responses. To our best knowledge, Taguchi method is one of the most popular discrete optimization methods applied in engineering problems, but it's limited by a problem with a single quality characteristic. To analyze and solve a problem with multiple responses, the Taguchi-based gray relational analysis is considered an effective method [35,36]. Hence, it is crucial that discrete optimization algorithm based on Taguchi-based gray relational analysis is investigated. In this study, the procedure of discrete optimization design for TWB structures is showed in Fig. 1.

2.1. Taguchi method

Taguchi method takes signal to noise ratios (S/N ratios) as the characteristic values of the responses to measure the current values deviating from the desired values [31,32]. The quality characteristic in the analysis of the S/N ratios is divided into the-larger-the-better type characteristic (Eq. (1)), the-smaller-the-better type characteristic (Eq. (2)) and nominal-the-better type characteristic.

$$x_i(k) = -10\lg\left(\frac{1}{y_i^2(k)}\right) \quad \text{For the}-\text{larger}-\text{the}-\text{better response} \tag{1}$$

$$x_i(k) = -10\lg(y_i^2(k)) \quad \text{For the}-\text{smaller}-\text{the}-\text{better response} \tag{2}$$

where “the-larger-the-better” means that the greater the value of the response, the better the collision system, such as total absorbed energy and specific energy absorption, etc. $y_i(k)$ is the original experimental data or responses for kth response at ith trial, $x_i(k)$ is the value of S/N ratios for kth response at ith trial.

2.2. Gray relational method

Gray relational analysis (GRA) is a measurement method in gray system theory that analyzes the degree of relation for different datasets in a discrete space [33]. It is based on the gray relational coefficient between sample dataset and ideal dataset, and then uses the gray correlation to rank order of relation among factors or responses. The original responses about S/N ratios should be linearly normalized in the range of 0–1 (called the normalization of S/N ratios). Thus, according to the different characteristics of the dataset, GRA has different normalization formulas illustrated in Eqs. (3)–(5) [35,36].

$$x_i'(k) = \frac{x_i(k) - \min x(k)}{\max x(k) - \min x(k)} \quad \text{For the}-\text{larger}-\text{the}-\text{better response} \tag{3}$$

$$x_i'(k) = 1 - \frac{x_i(k) - \min x(k)}{\max x(k) - \min x(k)} \quad \text{For the}-\text{smaller}-\text{the}-\text{better response} \tag{4}$$

$$x_i'(k) = 1 - \frac{|x_i(k) - x_0(k)|}{\max x(k) - x_0(k)} \quad \text{For the}-\text{nominal}-\text{the}-\text{best response} \tag{5}$$

where min $x(k)$ is the minimum original experimental data or simulation data for kth response at all trials, max $x(k)$ is the maximum original experimental data or simulation data for kth response at all trials, $x_0(k)$ is the nominal for kth response, $x_i(k)$ is normalized value for kth response at ith trial, i is the number of trials. In this paper, k is 1, 2 or 3 indicating $F_{\max}$, EA and $Mass$, respectively.

Thus, the gray relational coefficient could be further calculated as follows:

$$\xi_i(k) = \frac{\min_k\left(\min_i |x_i(0) - x_i'(k)|\right) + \rho \max_k\left(\max_i |x_i(0) - x_i'(k)|\right)}{|x_i(0) - x_i'(k)| + \rho \max_k\left(\max_i |x_i(0) - x_i'(k)|\right)} \tag{6}$$

where $x_i(0)$ is ideal value at ith trial, ρ is resolution coefficient ($\rho \in [0, 1]$), the smaller the ρ,the greater the resolution is. In this experiment, the ρ value is set as 0.5 and the reference data for the ideal value is taken as 1.

For a practical engineering system, different performance responses have different effects on the system. The different effects on performance can be transformed by using Eq. (7) with diverse weight ratios.

$$\gamma_i(m) = \sum_{k=1}^{n} \omega_k \xi_i(k); \quad \sum_{k=1}^{n} \omega_k = 1 \tag{7}$$