Crenellation patterns for fatigue crack retardation in fuselage panels optimized via genetic algorithm

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Abstract

Crenellation is a promising technique to effectively improve the fatigue life of fuselage panels. It systematically varies the thickness of the fuselage skin at a constant structural weight. In the design of the crenellation patterns, the schemes of redistributing the skin material between different thickened and thinned regions can be innumerable. In order to select the optimum design from the huge searching space, a genetic algorithm was used in this study, which was coupled with FEM simulations used to predict the fatigue life of different crenellation designs. To accelerate the optimization process, a progressively refined searching approach and an old-individual-filtering technique were used. The suggested approach leads to both a reduced computational cost and improved solution quality.

1. Introduction

Laser-beam welding is a very promising technique to be widely applied in future fuselage construction. It not only enhances the production efficiency significantly (over 15 times faster than the traditional riveting technique [1]) but also helps to reduce the structural weight by getting rid of redundant materials at the riveted joints. However, the damage tolerance of the welded structure is inferior compared to the riveted structure [2], which confines its applications to certain parts of fuselage, where damage tolerance is not a critical design criterion. To further extend

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the application of LBW in fuselage construction, the concept of crenellation [3-6] was proposed in recent years, which can improve the fatigue resistance of the welded structure without increasing the structural weight.

The idea is to introduce a systematic thickness variation in the fuselage skin, where the mass variation in the thickened and thinned areas counterbalances each other. The fatigue life improvement due to the local thickening of fuselage skin will far outweigh the fatigue life loss in the local thinned region, which results in an overall fatigue life improvement. The effectiveness of crenellations depends on its geometry, which can be estimated from the stress intensity factor profile along the crack path obtained from the FEM modeling of the structure [3, 7]. It is very promising to perform a geometric optimization of crenellation pattern based on the FEM simulation to fully achieve the potential of the crenellation concept. This paper presents an approach to perform an automatic optimization of crenellation pattern by coupling the FEM simulation with a genetic algorithm (GA).

Fig. 1. (a) Flat and (b) crenellated integral structure with the same weight.

Genetic algorithm is very robust in finding the global optimum in large and complex searching space (e.g. high dimensional, discontinuous space with many local optima) [8, 9]. The simplicity of its rules which requires no analytical information about the problem also makes it very easy to implement [10]. Those characteristics make GA a very promising candidate for the task of geometric optimization in this work, which involve large amount of design variables. However, the population-based GA searching can take thousands of evaluations of individuals before converging to the global optimum, which also depends on the population size and the requirement of solutions quality. Thus, when GA is coupled with FEM simulation, the computational cost can be enormous. In order to keep it in a feasible level, a strategy of progressively refined searching similar to the work of Kim and Weck [11] combined with an old-individual filtering technique [12] was proposed in this study. The solution quality and computational cost of both progressively refined searching and direct searching are compared.

2. Proposed GA-FEM methodology

In this work, the fatigue life of crenellated panels with different geometries but identical weight is evaluated using FEM simulation. To focus on the sole effect of crenellation, stringers are not included in the FEM models whereas their sockets are preserved. The FEM model used is based on biaxial fatigue tests as described in the previous work of the author [13] and its accuracy in fatigue life was validated by experimental results as shown in [14]. The implementation of GA in the present optimization task is described in detail in following paragraphs.

2.1. Definition of the optimization problem

The optimization is based on the assumption that the crack starts at the root of the stringers, where favorable conditions for fatigue crack initiation have been developed during the welding process, such as high defects content and tensile residual stresses. The aim of the optimization is to maximize the number of cycles needed for the initiated crack to approach the adjacent stringers (from \( a_0 = 5 \) mm to \( a_f = 145 \) mm, Fig. 2). In the optimization the thickness of fuselage skin between those two stringers can vary freely within the following three constrains:

1. Inequality relation; the variation of thickness \( t \) is confined in the following range: \( 1.9 \text{ mm} < t < 4.15 \text{ mm} \).
2. Equality constraint; the crenellated panel should be equivalent in weight to a flat panel with a thickness \( t_{\text{flat}} = 2.9 \text{ mm} \).
3. Symmetrical constraint; the crenellation pattern should be symmetrical to the center line of each bay between two stringers since fatigue crack can initiate from either welding site.

Fig. 2. Assumed sites for fatigue crack initiation (red dots) and definition of the optimization problem.

2.2. Encoding scheme

As shown in Fig.3 the fuselage skin between the two stringers is subdivided into many sections. Due to the symmetrical constraint, only half of those sections need to be coded into the chromosome. Binary coding is used to represent the thickness of each section. In the example shown in Fig.3 every 3 alleles are translated into the thickness of one section, which can provide 8 different thickness variations bounded by inequality constraint as specified in 2.1. However, this direct translation of thicknesses from stochastically produced binary series can result in structures with various weights. To maintain a constant weight, a compensation factor is added to the directly translated thickness of each section. The corrected thickness is formulated by:

\[ t_{i,c} = t_{i,0} + \varepsilon = t_{i,0} + \left( \sum_{i=N} t_{i,0} - t_{\text{flat}} \cdot N \right) / N \]  

(1)

where, \( t_{i,0} \) is the thickness of i-th section directly translated from the chromosome, \( t_{i,c} \) is the corrected thickness of the i-th section considering the constant weight constraint, \( \varepsilon \) is the compensation factor, \( t_{\text{flat}} \) is the thickness of the flat panel with the same weight (\( t_{\text{flat}} = 2.9 \text{ mm} \) and \( N \) is the half of the number of sections. If the corrected thickness of one section violates the previously mentioned inequality constraint, its thickness will stay at the closest boundary of the valid range. The rest part of the compensation values for this section will be evenly distributed to all other sections. In this way, any chromosomes will always encode valid solutions satisfying both the equality and inequality constraints.

Fig. 3. The encoding of thickness values into a series of binary code.

2.3. Progressive refinement of the searching space and GA parameters used in each refined stage

To explore the possibility of reducing computational cost, we perform a progressive refinement of the searching space when running the optimization process. In the coarse searching, the region between two adjacent stringers is divided into 10 sections, the thickness of which can vary among 8 discrete values as shown in Fig.3. In the 1st refined searching, the same region is further divided into 20 sections. The best solution obtained from the coarse searching will be put into the initial population as seed. In the 2nd refined searching, the number of sections remains the same as 1st refined searching while the thickness can vary among 16 discrete values. The best solution from the
1st refined searching is then used as seed. As references, the direct 1st and 2nd refined searching without seeding are also performed.

Many previous researchers proposed optimum population size of GA showing proportional relation with the chromosome length [19, 20]. Goldberg [12] also suggested that in order to prevent the premature convergence sufficiently large population should be used. As result, based on the different chromosome lengths and requirements for solution accuracy in different stages of refined searching the following population sizes as listed in Table 1 are used.

<table>
<thead>
<tr>
<th>Stage of Searching</th>
<th>Chromosome Length</th>
<th>Population Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>coarse searching</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>1st refined searching</td>
<td>30</td>
<td>32</td>
</tr>
<tr>
<td>2nd refined searching</td>
<td>40</td>
<td>100</td>
</tr>
</tbody>
</table>

All other GA parameters are kept the same for all the GA optimizations. Tournament selection scheme with tournament size of 3 is used. The cross over rate is 0.5. The mutation rate is controlled at two levels: for an individual the probability of being selected for mutation is 0.2; for the selected individuals the mutation rate for each allele is 0.2.

2.4. The organization of the optimization process

![Flowchart of the GA-FEM coupled optimization process.](image)

The optimization process is schematically sketched in Fig.4. As shown in the flowchart, after starting the optimization process, the first generation is randomized with stochastically produced binary bitstrings of prescribed chromosome length. To maximize the initial diversity of the genotype, there are no duplicate individuals in the first generation. Then each binary string is decoded into series of thickness values of the corresponding crenellation pattern. Based on the decoded thicknesses the INP files of the template FEM model are edited accordingly and submitted to the Abaqus Standard solver. The fatigue life of each crenellation pattern is estimated based on the calculated ΔK profile and is assigned to the individual as its fitness value. After the evaluation, the genotype and fitness values of the individual are added to an archive. This archive is used to compare with the individuals of
subsequent generations before their evaluation. Those already evaluated individuals will directly copy fitness values from the archive. This old-individual-filtering technique ensures each genotype is evaluated only once. After the evaluation of the whole generation is finished, the DEAP module of Python is used to perform the selection, mutation and crossover operations, which will produce the new generation. The optimization loops will be stopped when the number of generations reaches 40 or if the no fitness improvement of the best individual is observed for 15 consecutive generations.

3. Results and discussion

3.1. Optimization results

The optimization results indicate a successful application of the constant-weight constraint – all the solutions provided by the optimization process have exactly the same structural weight. As shown in Fig. 5 the optimized crenellation patterns show the same trend of thickness variations: the thickness is the smallest close to the sockets of the stringers and increases stepwise towards the symmetrical line in the center. Generally those optimized solutions are expected to improve the fatigue life by about 10% compared to the initial design as suggested by Uz et al. [3]. Comparing the solutions obtained at different stages of refined searching, it was found that the greater the refinement of the searching space is, the better solution can be obtained. This is expected since the refinement of searching space provides larger degree of freedom in searching the optimum solution. At the same stage of refined searching, the seeded searching converged at better solutions than the unseeded searching.

![Fig. 5. Optimized geometries of crenellation patterns (the thickness values are summarized in Table 2) and the estimated fatigue life.](image)

### Table 2. Optimized thickness in different sections of the crenellation pattern

<table>
<thead>
<tr>
<th>No.</th>
<th>description</th>
<th>thickness of different sections [mm]</th>
<th>estimated fatigue life</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>initial design</td>
<td>1.9</td>
<td>2.5</td>
</tr>
<tr>
<td>2</td>
<td>10 sections 8 thickness levels</td>
<td>1.98</td>
<td>2.3</td>
</tr>
<tr>
<td>3</td>
<td>20 sections 8 thickness levels</td>
<td>1.9</td>
<td>2.23</td>
</tr>
<tr>
<td>4</td>
<td>20 sections 16 thickness levels + seed</td>
<td>1.9</td>
<td>2.15</td>
</tr>
<tr>
<td>5</td>
<td>20 sections 16 thickness levels + seed</td>
<td>1.9</td>
<td>2.03</td>
</tr>
</tbody>
</table>

The strategy to improve the fatigue resistance evolved in the optimization can be interpreted as follows. Firstly, the stepwise increase of thickness leads to a continuous retardation in the early half of fatigue crack growth as indicated by the $\Delta K$ profiles in Fig. 6. This is consistent with the observation of Lu et al. that the retardation zones.
of crenellations are always found at the increasing thickness steps [14]. As characterized by Paris Law, with increasing crack length and $\Delta K$, there is an accelerating increase of crack growth rate. This leads to the fact that the majority of fatigue life is spent at the first half of total length. As a result, a continuous retardation in this range is most effective in improving the fatigue life. During the GA optimization the increment at each thickness steps are also finely tuned, which theoretically provide nearly the largest resistance to fatigue crack growth under the previously mentioned constraints. As a result, it can be seen in Table 2 the thickness values at the same position of the panel are very close when results of different optimizations are compared.

![Graph of ΔK profile](image)

**Fig. 6.** Comparison of ΔK profile in flat panel and in crenellated panel after optimization at the stage of coarse searching.

### 3.2. Computational cost

Fig. 7 compares the change of solution quality with increasing computational cost (the number of evaluations) up to convergence in both the coarse and refined searching. In order to show the total computational cost in the approach of progressively refined searching, the curves of the coarse searching and the two subsequent seeded stages of refined searching are connected consecutively. It can be seen, fast converged coarse searching has already brought the major leap of fatigue life. Further refinement of the searching space only leads to limited improvement. Therefore a proper refinement of searching space is critical for a cost effective optimization.

![Graph of computational cost](image)

**Fig. 7.** The change of solution quality with increasing computational cost.
Compared to the direct refined searching without seeding, the progressively refined approach needed shorter computation time but converged to even better solutions. The fast evolution of solutions in the coarse searching stage is due to the smaller population size and shorter chromosome length, since the convergence time was found increased with both factors [15, 16]. Further saving of computational cost in the stages of refined searching probably comes from the altered convergence behavior due to the seeding.

4. Conclusions and outlook

In this study a GA-FEM coupled approach has been successfully applied in the optimization of the crenellation patterns in laser-beam-welded fuselage panels. The optimized designs are expected to have about 10% fatigue life improvement compared to the initial design that was developed based on experience. In order to reduce the computational cost for the optimization process, a progressively refined searching approach combined with an old-individual-filtering technique were used. This approach shows faster evolution of solutions, requires smaller computational cost and yet provides improved solution quality compared to the direct searching with the same degree of refinement of the searching space.

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References