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Influence of the tape number on the optimized structural performance of locally reinforced composite structures

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Micro Abstract
For lightweight applications, a combination of discontinuous and continuous fiber reinforced polymers is aspired, where position, geometry and orientation of the reinforcing continuous fiber tape needs to be optimized. Therefore, the proposed approach combines an evolutionary algorithm with a structural simulation in the FE software Abaqus. With this method, the influence of different tape numbers on the optimized tape design as well as on the final structural performance is demonstrated.

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Introduction

Optimization tools are often part of the product development process, where problem specific strategies are necessary to find the best solution. A commonly used optimization objective is to achieve highest performance in terms of maximum stiffness, while using a minimum of material. To fully exploit the excellent weight-specific stiffness of composite materials, however, the high anisotropy of this material needs to be suitably considered in optimization strategies.

In this work, an optimization strategy is proposed to determine an optimal patch design for continuous-discontinuous fiber reinforced composites. In such hybrid composite structures, continuous fiber patches are used to reinforce long-fiber composites and, thus, to maximise the weight-specific stiffness within a tolerable frame of time- and cost-efficient manufacturing. The proposed approach comprises an evolutionary algorithm (EA) in combination with the finite element (FE) software Abaqus. Evolutionary algorithms are generally suitable to solve Black Box optimization problems very efficiently. Another advantage of the presented approach is the use of parallel computation, which can be utilized for the computationally expensive FE calculations. The capability of EA to solve composite related FE problems has been proven with the optimization of a laminate stacking sequence [1]. Furthermore, an EA has been used in [2] to optimize a draping process. The application of an EA to optimize for a patch optimization problem has been demonstrated by the author [3]. For the presented patch optimization problem, the influence of the number of used patches on the final result will be demonstrated.Put the First Section Title Here

1 Optimization Problem Definition

In order to maximize the part stiffness, the optimization objective is the minimization of the compliance. Therefore, the displacement at a reference point is measured. A minimum of patches should be used, which is why the minimization of the tape length is used as second objective. Besides the optimization objectives, a number of manufacturing constraints should be considered to achieve a producible solution. Constraints are, for example, distances to boundaries, maximum total patch length and patch width.

Four optimization parameters are required to characterize the patch (Figure 1): length (L), orientation (α) and position (X, Y). For all patches the position is specified by the X and Y coordinate of the corner of a patch, as shown in Figure 1. Patch width (W) is kept constant during the optimization. Also, the z-position is well known, because the patch is always on the part surface.

To demonstrate the influence of the part number on the optimization problem, the total number of patches is varied between the optimization runs.

Therefore, the optimization problem is described as follows:

$$Min\, f_1(\underline{y}) = Min\ displacement\,(\underline{y})$$

$$Min\ \ f_2(\underline{y}) = Min\ patch\ size\,(\underline{y})$$

are the objective functions, while the vector of design variables is

$$\underline{y} = (L, X, Y, \alpha)$$

Since an EA is used to solve this optimization problem, the objective functions fitness 1 (f1) and fitness 2 (f2) are treated equivalent, hence no weighting is necessary. The number of patches is a main subject of the analysis, and is therefore set to NP = [1, 2, 3].

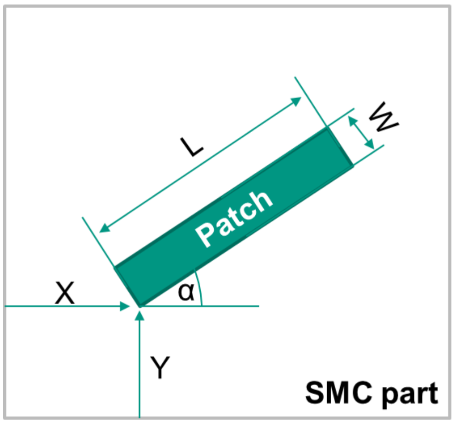

Figure 1: Representation of the optimization parameter

2 Evolutionary Algorithm

The applied evolutionary algorithm consists of three major phases: selection, recombination and mutation. Figure 2 (left) shows the workflow of EA. First, an initial population μ0 is created. In this context a population is a set of design variable vectors y. The size of the initial population depends on the optimization problem. For the patch optimization problem the initial population is set to μ0 = 100 for all patch configurations. The design variables, y, for the initial population are set randomly. The fitness calculation step for each individual consist of a draping simulation, followed by a structural simulation (compare figure 2 right).

After the fitness calculations are completed for the initial population, new offspring have to be developed; therefore, a recombination step is necessary. In the proposed algorithm, a multi-point parameterized binary crossover operator is used. The purpose of the crossover step is to create new design variables, y, based on the existing solutions. Thereby two existing solutions are used to form two new design variables. The crossover operator is performed for each design variable individually. The mutation step, which takes place after the crossover, is essential to maintain diversity in the population. For the creation of a new population μi the fitness values for parents and offspring are compared.

The entire optimization process will continue until either a given number n of iterations or a convergence criteria is reached. In this case an approach consisting of three indicator numbers is used. The first number is the difference between the both extreme points on the front and is used to indicate the expansion of the front. The second metric is describes the distribution of the solutions along the current front. To rate the changes from iteration to iteration the number of rejected solutions is used as third convergence criterion. The number of necessary iterations is very problem sensitive, and for the examples given n is set to 50.

To conduct the evolutionary algorithm, the open source software toolkit Dakota is used [4].

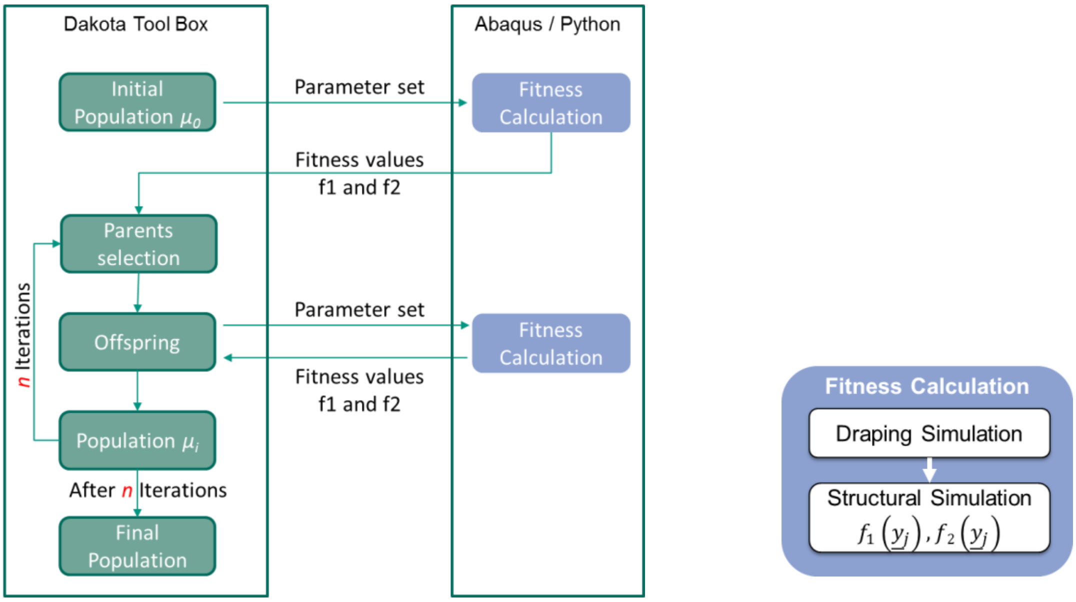

Figure 2: Workflow of the optimization process (left), fitness determination step (right)

3 Results

A sheet structure with a line load is used as the main application example for the patch optimization. All degrees of freedom are fixed at side A, while a line load is applied at B, with the load conditions presented in Figure 3. The fitness values for each individual are the displacement at the loading side A (fitness 1) and the patch size (fitness 2) respectively. The algorithm setup is the same for all optimization runs, except the number of patches, which has been set according to NP = [1, 2, 3] (see Figure4).

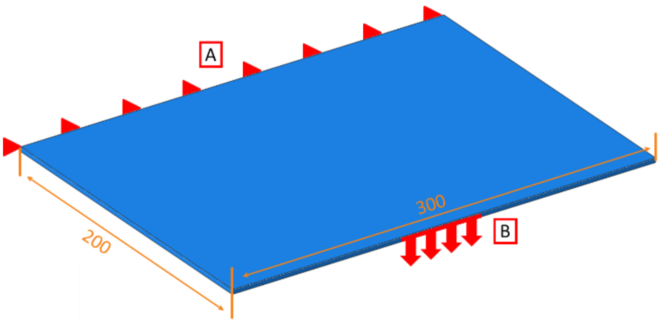

Figure 3: Load conditions for the reference model

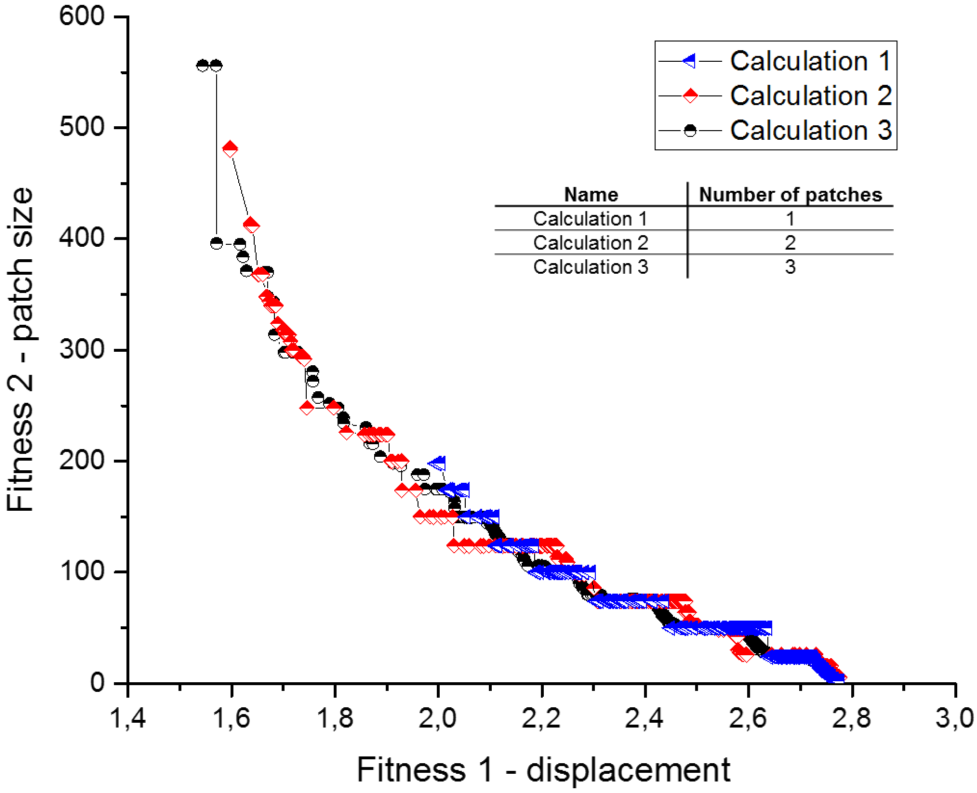

Figure 4: Comparison of the final Pareto fronts for the different patch setups

The final Pareto optimal sets for the different patch number configurations are shown in Figure 4. The resulting curves show similarities in fitness ranges that could be covered by all patch configurations. These similar results are caused by multiple patch solutions, with one long patch and one or two patches with the defined minimum patch length. The longest patch is located in a similar position, as for the calculation with fewer patches (Figure 6).

Figure 5 (left) shows the intermediate results for the three-patch optimization run. This figure shows that there are more possible patch configurations in the area of smaller patch dimensions. Furthermore, Figure 5 (right) shows that it takes up to 30 generations until a solution with maximum patch length as well as a minimum for fitness 2 (patch size) is reached. The reason for this is that based on geometrical restrictions solutions with smaller patches are more likely to arise.

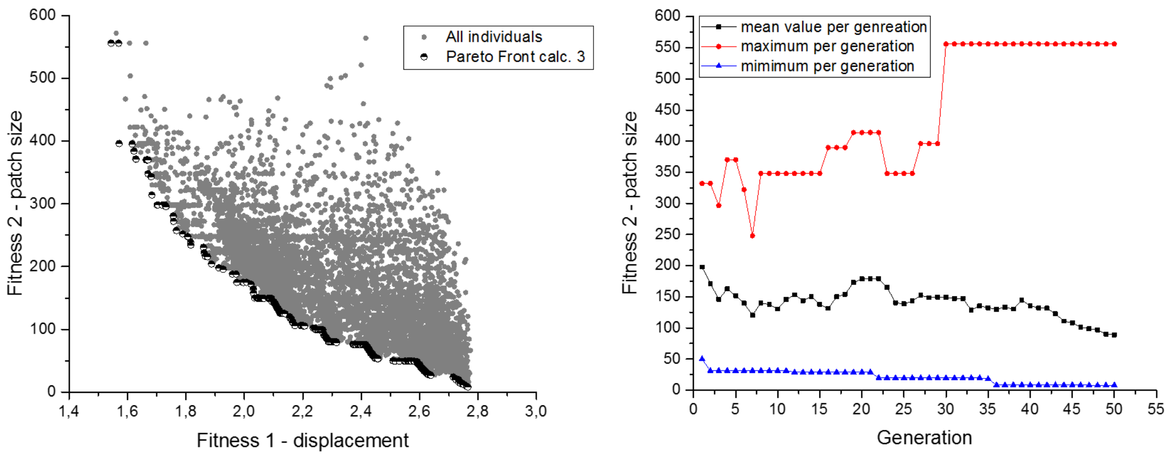

Figure 5: Final results with intermediate solutions as representation of the search space (left), and development of fitness 2 over the generations (right), both results are for calculation 3

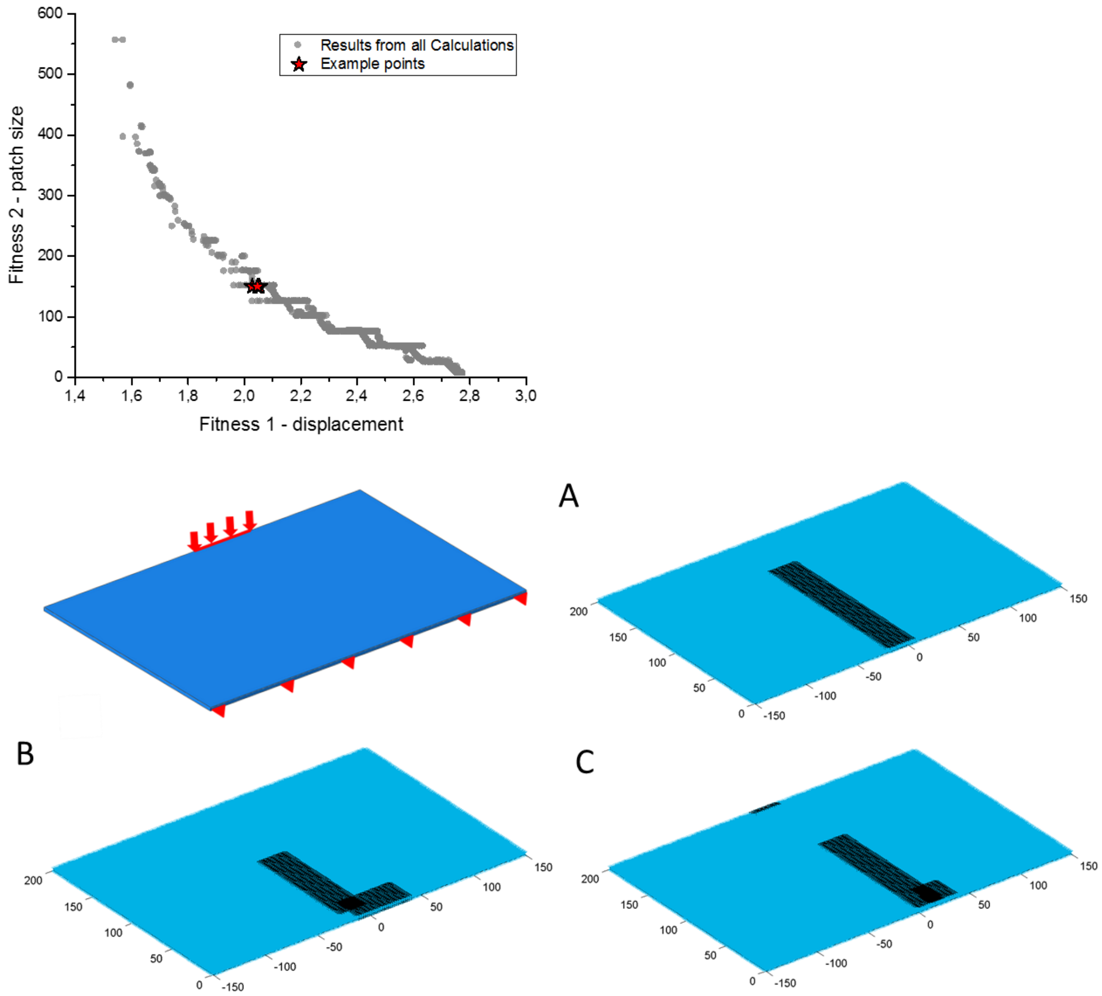

Figure 6: Comparison of results from calculation 1 (A), calculation 2 (B) and calculation 3 (C)

Conclusions

The results showed that the multi objective patch optimization problem can be solved with an evolutionary algorithm. Therefore, an example has been used for which the results could be determined analytically.

With different optimization setups, regarding the number of patches, the influence on the optimization results has been demonstrated. The distribution of the possible solutions within the search space has been demonstrated with the example of the three-patch optimization run. Using the example of fitness 2, the comparison of mean, minimum and maximum values per generation showed the convergence behavior, as well as the spread within the search space.

Acknowledgements

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