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Optimization of laminated structures considering manufacturing efforts

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1. Abstract
In many cases, structural design optimization highlights great weight saving potentials, but yet, engineers may face difficulties unlocking these potentials, since further economical and technical constraints need to be obeyed. This especially holds for the optimization of composites, because manufacturing techniques often not only imprint limits onto realizable parameter configurations for a given design, but furthermore differ considerably in the associated manufacturing effort level for different parameter configurations. This work mitigates this issue of inchoate designs, by introducing a method capable of quantifying expert knowledge regarding manufacturing effort at early design phases and, thereby, leveraging the optimization's significance by introducing technical aspects into the optimization responses. The method will be introduced and displayed at length and thereafter be presented for a structural design optimization task.
2. Keywords: Composite design optimization, quantification of manufacturing effort, considering efforts associated with the prepreg lamination technology, ply waste algorithm.

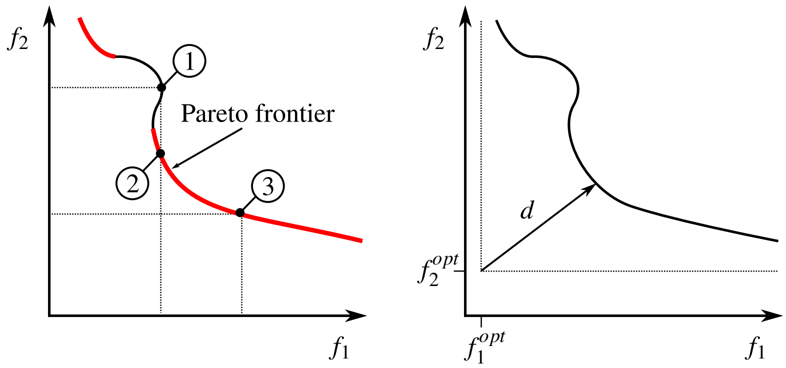
3. Introduction and literature review
It is evident, that structural optimization can solely bring forth designs comprising aspects, which are explicitly modeled and being incorporated into the optimization process. In this regard, the designs derived via structural optimization, are only as relevant as the underlying optimization models are holistic. This especially holds for structural design optimization of composites, where given manufacturing processes impinge not only on whether or not derived optima are technically realizable, but further determine associated levels of manufacturing effort and, in that consequence, also the products final manufacturing cost. This marks the importance of capturing manufacturing aspects - specifically those leading to efforts - in tandem with structural mechanics, when optimizing composite structures, designated to actually be build with moderate or even low manufacturing effort. For this sake, a method facilitating the modeling of verbal expert knowledge for any given knowledge domain - herein apparently manufacturing effort - will be introduced and displayed for an exemplary optimization task. The introduction of this method will be given in chapter 5, followed by chapter 6, where the simultaneous mass and effort optimization will be displayed. Prior, to that, the general formulation of a vector optimization task is being introduced. The paper will be topped off by summarizing the conducted work, discussing the key results and sketching prospective research work. Next, a brief overview of literature addressing the demand for holistic structural design optimization models, i.e. optimization models including further aspects beside those stemming from structural mechanics, will be given.

Wang and Costin [1] used analytical manufacturing constraints for capturing restrictions associated with the hand prepreg lay-up process. By doing so, they where able to show the importance of these technical aspects within the structural optimization. Similar to this research work, many researchers incorporated technical aspects via sharp bound based on analytical equations such as Henderson et al. [2] and many more. Pillai, Beris and Dhurijati [3] used soft computing approaches so as to model the operating of an autoclave. The knowledge-based system they derived is able to predict the curing of thick composite laminates and served as a source of inspiration for the approach displayed in this paper.

4. General definition of the optimization task
With Eq.(1) the optimization task is stated in its general form, where f, $\mathbf{g}$, $\mathbf{x}$ and χ are the objective, vector of inequality constraints, vector of design variables and design space respectively. More information regarding optimization can be found in [4].

$$\min_{\mathbf{x}\in\chi}\{f(\mathbf{x})\,|\,\mathbf{g}(\mathbf{x})\leq\mathbf{0}\} \tag{1}$$

In the later solved optimization problem, the manufacturing effort e will be defined as one objective beside mass m. Thus, this leads to a multi-objective problem - or also referred to as vector optimization task. Since mass and manufacturing effort are conflicting goals, a so-called pareto frontier will emerge, as being exemplary displayed in sub-figure 1a. In this work gradient-based algorithms will be used, for which reason, both objectives need to be condensed to one single objective for obtaining one pareto optimal solution, i.e. one point on the pareto frontier. For that purpose, the following general norm as a distance to a fictitious design point, being composed of extremal pareto optimal values is being defined and given with Eq.(2). It is further displayed in sub-figure 1b.



(a) Pareto optimality (b) Norm approach

Figure 1: Pareto frontier and vector norm definition for gradient-based optimization

$$f = d(f_1, ..., f_{n_f}) = \|f_i - f_i^{\mathrm{opt}}\|_q \quad i \in \{1, ..., n_f\} \tag{2}$$

Inserting the two objectives - mass m and manufacturing effort e - into the euclidean norm, i.e. $q = 2$ in Eq.(2), leads to the objective definition as used herein. Note that ξ_i represent the weight factor for mass ($i = m$) and effort ($i = e$).

$$f = \sqrt{\xi_m (m - m^{\mathrm{opt}})^2 + \xi_e (e - e^{\mathrm{opt}})^2} \tag{3}$$

5. Modeling manufacturing effort based on verbal expert knowledge

This chapter aims to give a brief outline on how expert knowledge is modeled. Obviously, the challenge in hand, is the quantification of verbal information; or more precisely, the transformation of verbal expert knowledge into a knowledge domain expressed in algorithm-close rule networks.

5.1. Quantification of verbal expert knowledge

At first, the knowledge domain of the manufacturing effort model needs to be acquired. A knowledge domain can be comprehended as a gathering of information for a given field and is most commonly expressible in a sequence of inference logic rules. Because verbal knowledge, and in that consequence inherently qualitative information, needs be gathered, evaluated and processed, the so called fuzzy logic will be used. This theory is founded by Zadeh [5] and, among other features, enables the handling of imprecise and qualitative information. It is owned to this qualitative modeling approach, why it is also referred to as soft computing [6]. Herein, the knowledge domain is defined by human expertise concerning manufacturing effort associated to the prepreg technology. In [7], the authors discuss the process of how a knowledge domain can be derived at length. The demonstration technology therein is braiding. This also highlights the general nature of the proposed approach.

5.2. Generating the rule network

With figure 2 an overview of the derived fuzzy inference system (FIS) is given. As depicted, the input parameters are the curvature, ply number, wastage, ply-drop-offs, continuity and radii. These inputs do not have to be passed by the user; instead they are fetched from the finite element analysis (FEA) input deck automatically. So, for instance, the continuity requirement is evaluated based on a neighborhood search for each ply and the check whether or not plies do continue into their neighbors. The rule network computes, based on these input parameters, the effort level for that given design configuration. This is done by evaluating each implemented rule of the knowledge domain by checking, which verbal variable is active (antecedent) thereafter the degree of fulfillment for each rule (implication). The final output is then obtained by summing up active rules (aggregation).

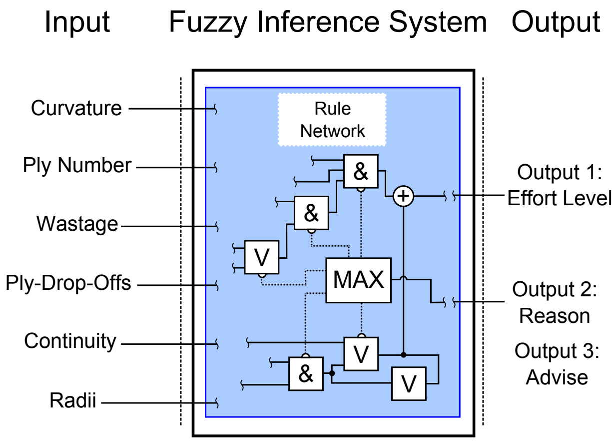


Figure 2: The prepreg manufacturing effort model based on the fuzzy inference system

The output can be expanded, when each implication value is being cross-checked with the knowledge domain, since this reveals the reason for the output. This reason supports the optimizer in verifying one specific output by making it plausible within the post-processing or by re-consulting an expert. Another feature of the knowledge domain can be unlocked, when the implication and antecedent values are inspected. This combination provides insight on how the design can further be improved, because one gets insight on which rule was active and moreover which verbal variable did trigger it the most. This latter can be understood as an elaboration advise and is highlighted as the output number three in figure 2.

5.3. Modeling ply wastage

As can be seen in figure 2 one input parameter for the manufacturing effort model is the play wastage. This ply wastage is determined by the ply's geometry, thus width and length for square patches, the orientation of the ply and available rolls, i.e. orientation and width of the prepreg roll from which the ply will be cut. For that purpose a wastage algorithm has been developed in python. An exemplary results of this algorithm is shown next. One can

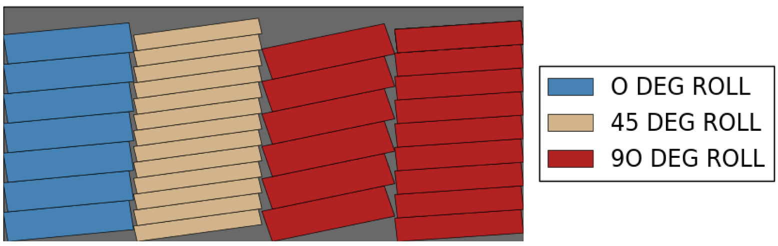


Figure 3: Ply wastage for given lay-up illustrated in gray

see in figure 3 how the wastage (depicted in gray) is computed for four different ply bundles. These bundles are of orientation 7°, 35°, 75° and 85° and are therefore cut from the rolls of 0°, 45° and both latter ones from 90° orientation.

5.4. Preparing the rule network for the subsequent optimization

Prior to the optimization on responses from both models - hence, finite element and manufacturing effort model - the effort model's condition needs to be leveraged to a higher level, by introducing relaxation schemes, e.g. interpolation or meta-modeling for discrete variables and parameters such as ply number or continuity. This guarantees efficient and robust gradient-based optimization runs resulting in fast convergence. Figure 4 provides an example, where the continuity check is relaxed for two neighboring plies (θ and 0°). The plot displays the regular check for angle difference $\Delta\theta = \theta - 0°$ as a red singleton and the relaxed one in blue. The relaxation in this case has been realized via $C = 1 - \frac{\Delta\theta}{90}^{0.2}$ and clearly improves the models behavior in terms of differentiability and continuity in the derivatives in light of gradient-based optimization.

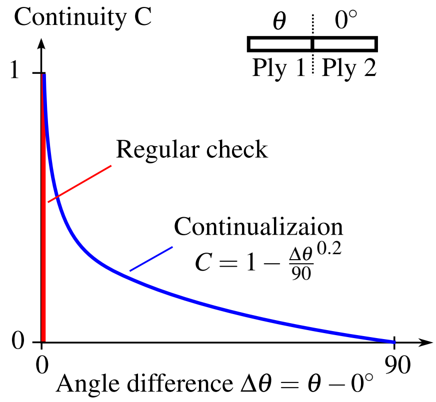


Figure 4: Demonstration of the continualization for two given plies

6. Optimizing an automotive A pillar considering manufacturing efforts

For the purpose of demonstrating the derived approach, the following example of an automotive A pillar of the convertible *Roding Roadster R1* is defined and optimized. The load cases are derived from a roof crush test according to FMVSS 216a and driving dynamics requirements addressing the structure's stiffness. They are illustrated in figure 5. Along the lengthwise extrusion axis, the A pillar has been fully parametrized in its geometry, so as to allow the optimization algorithm to vary not only curvature and length properties of the extrusion axis but also all profile dimensions.

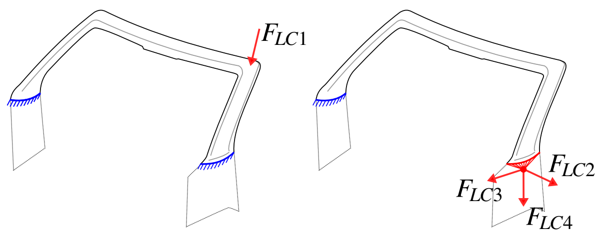


Figure 5: Illustration of the load cases for the A pillar structure [7]

The optimization task can be stated as follows,

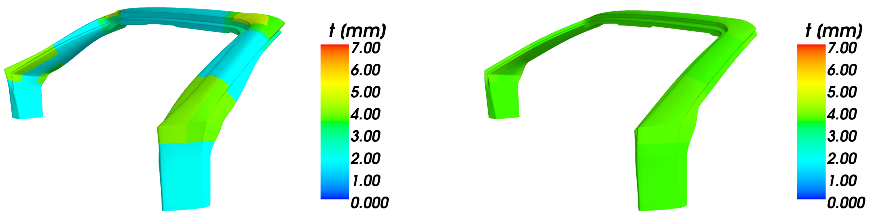
$$\min_{\mathbf{x}\in\chi} \{ f(\mathbf{x}) \,|\, \mathbf{g}(\mathbf{x}) \leq \mathbf{0} \} \tag{4}$$

where

$$\begin{aligned}
f(\mathbf{x}) &= d(m,e) \\
\mathbf{g}(\mathbf{x}) &= g_i = \frac{\mathtt{FI}_i}{0.9} - 1 \qquad \forall i \in \{1,\dots,n_{\mathrm{Secs}}\} \\
&\ g_{1+n_{\mathrm{Secs}}} = \frac{u_{\mathrm{LC1}}}{u_{\mathrm{Intrusion}}} - 1 \\
&\ g_{2+n_{\mathrm{Secs}}} = \frac{K_{\mathrm{LC2}}}{K_{\mathrm{min},1}} - 1 \\
&\ g_{3+n_{\mathrm{Secs}}} = \frac{K_{\mathrm{LC3}}}{K_{\mathrm{min},2}} - 1 \\
&\ g_{4+n_{\mathrm{Secs}}} = \frac{K_{\mathrm{LC4}}}{K_{\mathrm{min},3}} - 1 \\
\mathbf{x} &= \left[\mathbf{x}_{\mathrm{Profile}},\ \mathbf{x}_{\mathrm{Extrusion}},\ \mathbf{x}_{\mathrm{Orientations}},\ \mathbf{x}_{\mathrm{Thicknesses}}\right]^T
\end{aligned}$$

define the objective and constraint functions. As stated, the objective is set to d as defined with Eq.(2) and displayed in sub-figure 1b.

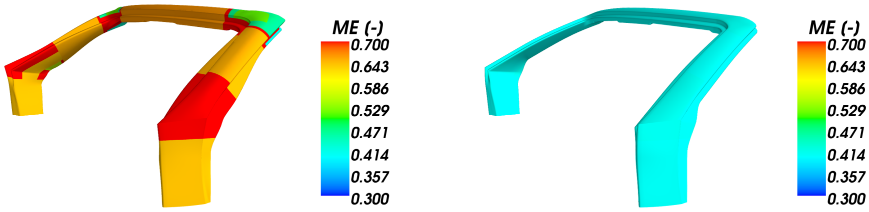
Prior to directly solving the optimization task given with Eq.(4), the two extremal solutions, i.e. minimal mass m^{opt} and minimal effort e^{opt}, need to be found by minimizing $f = m$ and $f = e$ respectively. Obviously, the constraints as defined in Eq.(4) are imposed throughout the individual minimization of mass and effort as well.
With the following two sub-figures the two extrema of the pareto frontier are given. In sub-figure 6a the thickness distribution for the minimal mass solution is given, whereas the sub-figure 6b depicts the one of the minimal effort design. Both designs can be made plausible, considering that the left design is characterized by maximizing bending stiffness resulting into a blown up A pillar design and on the contrary, that the left, thus minimal effort, is showing neat patch geometries, and therefore rectangularly shaped, for minimizing the ply wastage.



(a) Mass optimal solution (b) Effort optimal solution

Figure 6: Thickness plotted for both extremal solutions, thus mass and effort minima

In addition to the thickness distribution, one can also visualize the associate manufacturing effort level and its origin. This is achieved by plotting the manufacturing effort density, which is being computed for each ply region, leading to the final effort level via an integration scheme. Figure 7 depicts again both extremal solutions, but now the manufacturing effort density is plotted for minimal mass (sub-figure 7a) and minimal effort (sub-figure 7b)



(a) Mass optimal solution (b) Effort optimal solution

Figure 7: Manufacturing effort density plotted for both extremal solutions, thus mass and effort minima

As the objective in the defined optimization task Eq.(4) is set as the distance to the fictitious combination of both extremal optima of the pareto frontier the solution represents a compromise. The engineer could define different weights ξ_i for shifting the compromise in favour of mass ($i = m$) or effort ($i = e$). Here, both weights have been set to one. With figure 8 the compromise solution is illustrated. Due to its relative position within the minimal mass and effort design it can be stated, that this solutions indeed strikes a compromise.

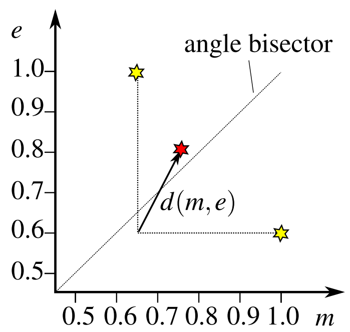


Figure 8: Optimal compromise (red start) struck in-between the two mass and effort (yellow stars are individual optima)

7. Summary and outlook

It has been shown, that the integration of technical aspects via soft computing has been proven to be a viable approach. By doing so, the optimization process can be enriched through information regarding manufacturing effort, thereby increasing the optimization's significance. The optimization evinces a greater significance, since derived optima not only satisfy structural requirements, but also honor technical constraints arising from the chosen manufacturing process. Moreover, the modeling of manufacturing effort enabled the optimization to meet an optimal compromise by simultaneously maximizing structural efficiency and minimizing effort.

Because of the fact, that in [7] the presented approach has been applied for braiding and herein for the prepreg lay-up process, it can be concluded that this technique is of general nature and can in that consequence be applied for various manufacturing processes.

It also has been shown, that the manufacturing effort model not only computes the effort level for a given design, but also provides reasoning about the determined effort level. This supports the engineer in the post-processing of the optimization in a manner, that effort levels can be verified.

8. Acknowledgements

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9. References

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