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Adequate Method Selection for Quantifying Verbal Knowledge in Context of Composite Manufacturing

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Abstract. With this contribution, the quantification of verbal knowledge is being discussed. This quantification is particularly necessary in composite structural design, as mechanical, economical and technical aspects are strongly intertwined. Hence, modelling technical and economical aspects becomes relevant in context of structural design optimization of composites. With this paper, the decision on whether to utilize machine learning or fuzzy inference systems is clarified in case complex composite manufacturing techniques such as braiding are in light.

Keywords. Structural design optimization, modelling of manufacturing effort, vector optimization, composite manufacturing and design

Introduction

In design of composite structures, structural performance, hence stiffness and strength w.r.t. mass, are evidently linked with manufacturing. One of the most obvious links is given by the orientation of carbon fibers, where conflicts of manufacturability and light-weighting arise. However, there are many more parameters, yielding different outcomes in terms of manufacturing cost and light-weight metrics such as stiffness and strength per mass ratio.

As for lifting most of the inherent light-weight potential of composites, it is key, to strike optimal compromise in-between multiple criteria such as manufacturing cost, being as lightweight as possible and carbon footprint over product life span for instance. Evidently, these criteria are quite likely to conflict, which is why a numerical procedure for deriving optimal composite designs is key. In order to realize this, each aspect of the design process is to be captured via models. Therefore, aside from structural mechanics models, the technical aspects are to be modelled as well.

Particularly, design associated costs and production metrics like scrap rate are essential, but rather challenging to model. In case simulating the whole manufacturing process considering all relevant steps and allow a certain depth in complexity is not always feasible in light of composite structures. Therefore, capturing these aspects via neural nets or fuzzy systems is ideal for many reasons. This research work focuses on how to capture, model and predict responses being vague in nature and, in that sense, associated with soft computing. Moreover, a brief discussion on why a certain technique shall be acquired is realized as well.

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1. Literature review

It is evidently the case, that in engineering multiple disciplines ought to be considered. Hofer, Sturm and Wehrle [1], for instance did recently show how aside from mechanics, uncertainties arising from load variations do have an imprint on actual design. Broading this understanding, it becomes obvious, how important the consideration of all relevant disciplines is.

In product design, aside from mechanics, manufacturing of course contributes a lot. This is case, as manufacturing as a technical discipline does influence material properties and – in many cases – residual stress state. This is highlighted by M. Jabbari, I. Baran et al. [2], where a clear link of manufacturing to mechanical quantities like deformation and stress has been drawn. However, there is more, as manufacturing is also strongly linked to economical aspects like lead time or costs. Particularly the latter, is of high relevance when it comes to composite design (see [3] for instance). With former research work of the author like [4] and [5], it has been shown, how structural design optimization might be used in order to balance conflicting criteria like for instance light-weight design and cost. However, in order to do so, manufacturing in terms of economical aspects is to be captured.

There are basically three different approaches for modelling manufacturing in context of optimization. First, one could directly abstract the problem in hand, by using analytics; like Henderson et al. [6] or Ghiasi et al [7]. This is by the most efficient and robust way of considering manufacturing aspects. However, this method is limited to processes allowing for a certain simplification. Secondly, one could directly simulate manufacturing as for instance realized by Picket, Sirtatas and Erber in [8]. Of course, this approach yields the most accurate predictions of process times, costs and serves best as basis for deriving material properties like stiffness and strength. However, this approach also comes along with great efforts results in time consuming modelling and simulation phases, where – on top – thorough tests, so as to characterize key parameters, shall be performed prior to any simulation. So, summing up, this approach might be difficult to be set-up within an industrial frame. For this reason, the third approach might be the one of choice; namely soft computing. Soft computing comprising all methods, that model the underlying nature of the problem via methods being opposed to sharp analytical or numerical ones (see [9]). So as to name a few; neural computing, evolutionary strategies or fuzzy logic shall be mentioned here. This third branch is of light in this paper as well. For more literature in this context, please consult [10].

2. Problem description

With this section, the problem in hand will be described.

2.1. Multidisciplinary vector optimization

Obviously, economical and technical criteria – manufacturing cost, time and quality – may conflict with each other and with mechanical design metrics such as strength or being as lightweight as feasible. Nowadays, structural optimization becomes more and more relevant in many industry disciplines, as by utilizing algorithms, optimal compromises are to be found.

Yet, in order to deploy an optimization strategy allowing to find an optimal compromise in-between technical (e.g. manufacturing quality), economical (e.g. manufacturing costs) and mechanical (e.g. stiffness), each discipline has to be modelled at first. This does therefore yield problems being of multi-disciplinary nature as depicted with figure 1. Secondly, the underlying optimization problem then does necessitate the minimization of a vector of criteria as given by equation set (1),

$$\min\{\vec{f}(\vec{x})|\vec{g}(\vec{x}) \leq 0\} \quad \vec{x} \in \mathrm{X}^{n_{DV}} = \{\forall x_i \in \mathbb{R}: x_i^l \leq x_i \leq x_i^u\} \tag{1}$$

where $\vec{f}$, $\vec{g}$ and $\vec{x}$ are the vector of criteria, in-equality constraints and design variables. Please note, that one seeks for an argument $\vec{x}$ minimizing the vector of criteria (mass, cost, time), while fullfilling all in-equality constraints (e.g. stiffness and/or strength requirements) and side constraints, i.e. being within the lower $\vec{x}^l$ and upper bound $\vec{x}^u$.

With figure 2 an example of vector optimization result is given, where the black line indicate the pareto frontier as a set of optimal compromises derived via gradient-based vector optimization [5] and the dots are results derived via the genetic algorithm NSGA-II.

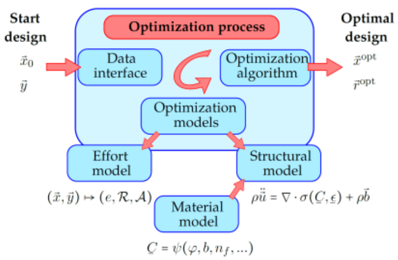


Figure 1. Multidisciplinary of optimization problem.

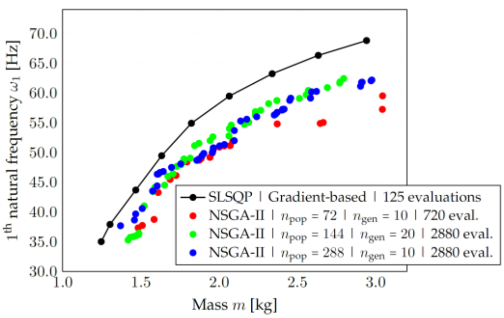


Figure 2. Exemplary result of vector optimization in-between natural frequency and mass [4].

2.2. Manufacturing and quantification through manufacturing effort

The following gathering of figures (figure 3 to 6), provides an overview on some of the key elements making efficient and goal-oriented manufacturing demanding. One of the most obvious aspects is the handling of scrap, as half-goods are to be manufactured. So for instance, within tape laying, the orientation of fibers is linked to scrap and in cost of cost-driven design vice versa (see figure 3).

In the frame of composite design numerical design optimization shall ideally be utilized in order to dose each of the many parameters being involved so as to balance overall criteria such as costs, mass, stiffness and alike. However, in doing so, one has to acknowledge, that these parameters such as fiber orientation, thickness of each ply, patch region, geometry and number of different plies (layers) are not only linked to mechanics, but to economical implications and restrictions due to manufacturing. This becomes clear, when considering (figure 4) that two neighboring plies shall ideally share the same orientation allowing continuous manufacturing and proper load transmission (even for half-goods prior to curing). Figure 5 depicts two aspects, one being the patches in terms of number and size and, secondly, how plies shall be dropped. Last but not least, figure 6 displays how, in general, the two dimensions complexity of lengthwise geometry and complexity of profile geometry do limit each other or in other words cause high manufacturing efforts.

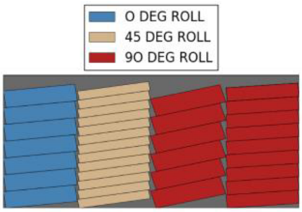


Figure 3. Tape lay-out for scrap consideration.

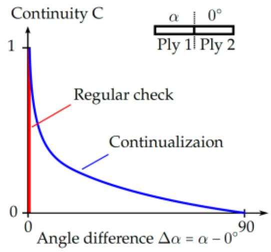


Figure 4. Judging continuity.

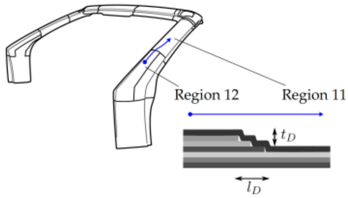


Figure 5. Ply drop-off zones.

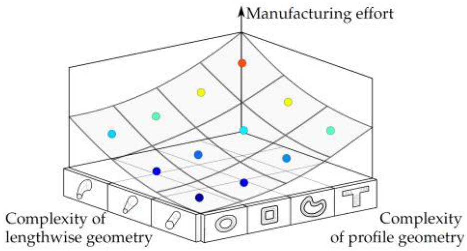


Figure 6. Complexity of braiding.

Based on the idea of having not only restrictions but mutual dependencies, the definition of effort as a measure of manufacturing complexity and rise in costs, has proved to be ideal. On top, this may also be understood as a generalization, since effort does not depend on industry (e.g. cost-driven automotive versus performance-driven aerospace), country (e.g. local tax schemes) or company (e.g. global player with many sites and capacities versus small sized with tight bounds on investment and limited available capacities). In this work, the manufacturing technique shall be braiding. However, the underlying math may be applied to others – such as tape laying [5] – as well.

3. Modelling manufacturing effort

3.1. Knowledge engineering

Prior to any actual modelling or predicting of manufacturing effort, the underlying mechanisms have to be understood. For realizing this, knowledge engineering serves as methodology. With figure 7, a general process flow from deriving knowledge from manufacturing experts and literature down into the knowledge base (KB) for being able to judge and predict manufacturing effort in real world examples. Figure 8 provides more insight, as it makes transparent, that a sequence of interviews basically allows to define the knowledge base. For more details on this process, the reader may be redirected to published work [5].

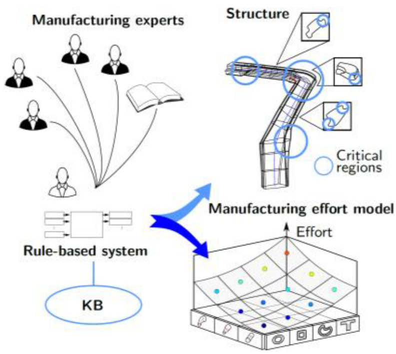


Figure 7. Flow of knowledge engineering.

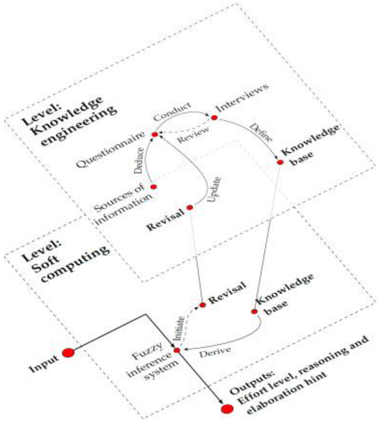


Figure 8. Level of knowledge engineering.

3.2. Approach via machine learning

With the prior discussed methodology of knowledge engineering, a thorough knowledge base may be deduced, which could be transferred into model being rule-based with ease. However, the deduction of such a base may be regarded as cumbersome. For this reason, an alternative approach may be followed. One could simply gather data and utilize machine learning so as to derive a manufacturing effort model. In order to do so, one shall first inspect the data in hand. By following this, one seeks for uniform statistical distribution, probing for data in all relevant regions and cross correlation. For achieving comparability, standard implementations for both methods have been considered. In case of machine learning, python´s module *tensorflow* was considered.

3.3. Approach via fuzzy inference system

In case one already has successfully derived a knowledge basis (see section 3.1), the transformation into a fuzzy inference system or fuzzy rule-based system is straight forward, as one already has the rules, ranges and all parameters are linked. Figure 9 depicts the fuzzy inference system as deployed in this work. It shall be noted, that one may incorporate fuzzy inference system within each other (see three FIS within box) or incorporate known analytics as well with ease. This is mainly due to the fact, that the fuzzy arithmetic is that close to human perception and understanding of physics.

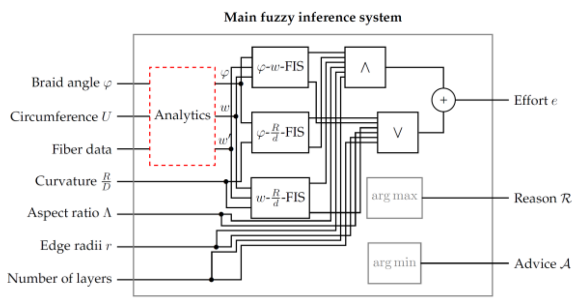


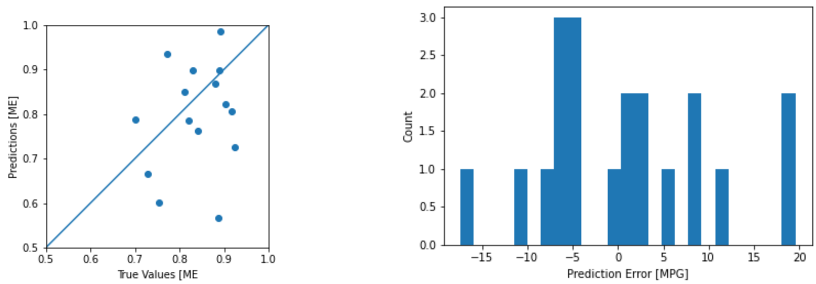
Figure 9. Fuzzy inference system of composite manufacturing [4].

4. Contrasting both approaches

4.1. General discussion

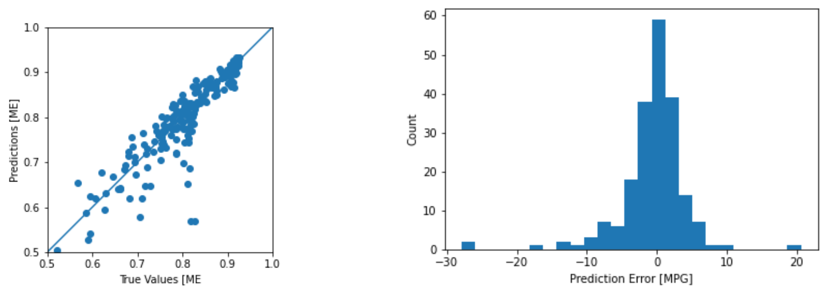
With this section, both above discussed approaches are contrasted. First, the numerical effort and prediction quality shall be assessed. For fuzzy inference systems, predictions based on a certain knowledge base are as accurate as the knowledge base is. Following this, they may be regarded perfectly accurate. However, it is key to any prediction, that the knowledge base is holistic enough for predicting all scenarios in light.

For machine learning, the exact same applies. Yet, as a weighted sequence of layers of neurons predict responses, their adaption in terms of weights (training) is in most cases more costly. This is mainly due to the fact, that the underlying math via projection type, variable links and nature is not considered. Exactly this element makes machine learning that general as well, as it may be deployed in any case where sufficient data is available with ease. On the contrary, one has to ensure, that one has enough data so as to train the model. This is visualized with the following sets of figures ranging from figure 10 to 12 and where each figure is divided into one subfigure providing response quality and the other a error histogram. In this specific case of composite preform braiding, the amount of data was pinned down to well above 5,000 sample points and ideally as close as possible to 10,000.



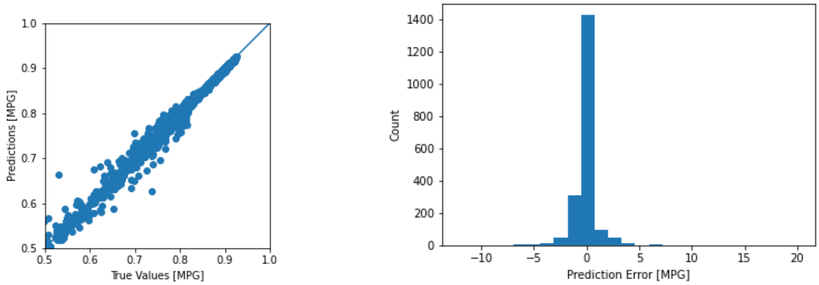
(a) Response quality **(b)** Prediction error histogram

Figure 10. Quality of neural net with 100 data points in total.



(a) Response quality **(b)** Prediction error histogram

Figure 11. Quality of neural net with 1,000 data points in total.



(a) Response quality **(b)** Prediction error histogram

Figure 12. Quality of neural net with 10,000 data points in total.

At this point, it shall be emphasized, that the more accurate prediction of fuzzy inference systems for a given knowledge base, comes with a huge effort; namely knowledge engineering. Therefore, in case one is able to gather 10,000 sample points for a given braiding process, machine learning is certainly superior. Nonetheless, one has to ensure, that all relevant links in-between design variables and projections to relevant criteria are observable by this data set.

The knowledge base comes along with another advantage. This advantage is visualized with figure 13. One can for instance use the underlying arithmetic to not only calculate the direct response, here, effort e, but moreover provide reasoning $\mathcal{R}$ why this level of effort has been predicted and an elaboration advice $\mathcal{A}$ on what to alter in order to improve the situation.

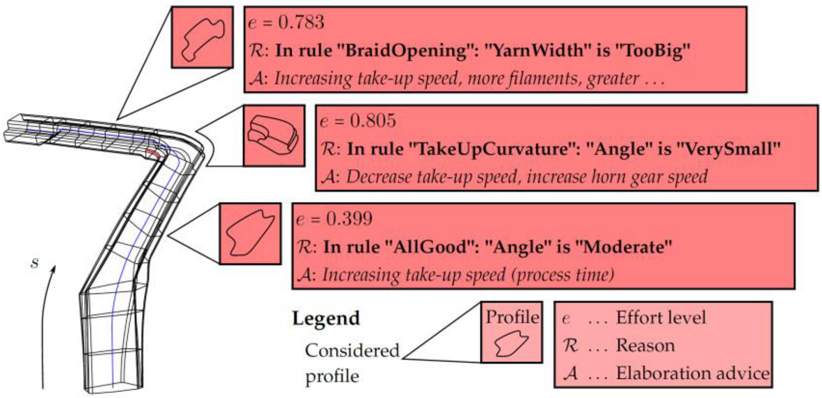


Figure 13. Reasoning and elaboration advices provided by fuzzy inference system.

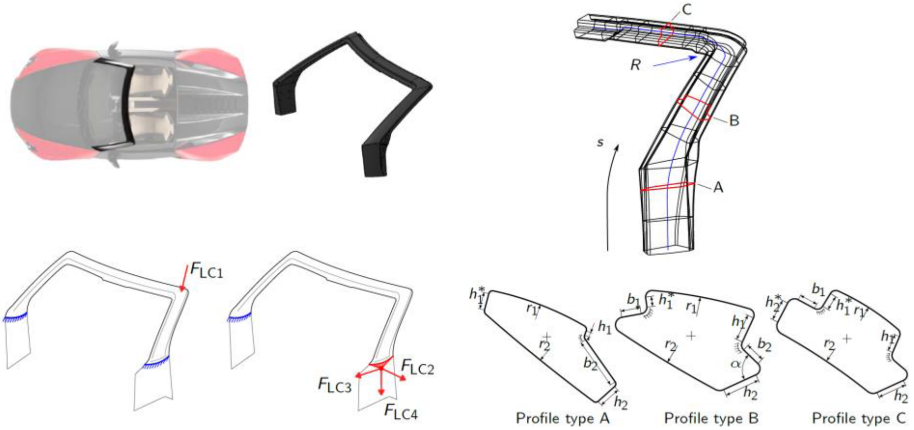
On top, there are many more soft computing methods. However, the two representatives being investigated herewith, do each represent a sub-class; namely with extensive knowledge engineering or without. A comprehensive overview on both approaches is given with table 1.

Table 1. Contrasting both approaches.

	Machine Learning (ML)	Fuzzy Inference Systems (FIS)
Advantages	• No complex knowledge engineering • Feedback on quality through comparison of training and verification set	• Accurate with few data • Information may be gathered via interviews • Reasoning for data is inherent (knowledge base)
Disadvantages	• In general, a lot of data needed • Curse of dimensionality (i.e. the more parameters exponentially more data is needed)	• Cumbersome gathering of information (knowledge engineering) • A certain creativity is needed so as to interpret data (deducing rules etc.)

4.2. Effect on vector optimization result

As an exemplary structure, an automotive A pillar shall be optimized. The problem is sketched with figure 14, where sub-figure (a) of figure 14 provides the mechanical abstraction into the four load cases (LC 1 – roof crush in and LC 2-4 – stiffness describing driving dynamics). Sub-figure (b) of figure 14 depicts the parameterized model of the A pillar.



(a) Mechanical abstration **(b)** Parameterization

Figure 14. Problem description of A pillar.

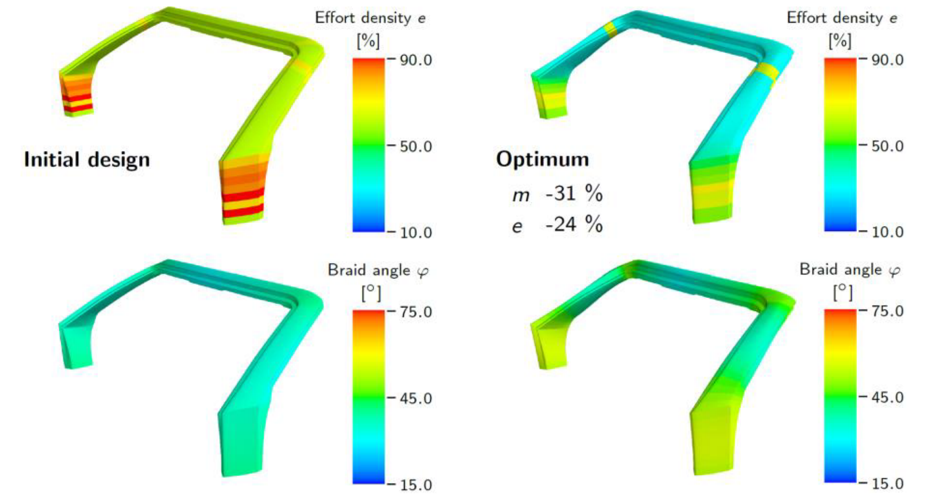
In this example, the mass (criteria 1) and manufacturing effort (criteria 2) shall be minimized simultaneously. While doing so, the requirements towards stiffness (in-equality constraints 1-4) and strength (remaining in-equality constraints) are fulfilled throughout.

Figure 15 depicts how the A pillar transitions from initial design via sub-figure (a) towards the optimal variant sub-figure (b). In order to minimize mass and manufacturing effort simultaneously, the cross section, number of layers and fiber orientation (e.g. braiding angle φ) is dosed in an optimal fashion along the A pillar profile.

In order to contrast the two approaches, the vector optimization is performed with both. Table 2 summarizes the findings. It shall be observed, that both yield the more or less same results, where the effort prediction via machine learning has a slightly greater effort level and needs 5 more iterations.

Table 2. Contrasting both approaches in terms of vector optimization.

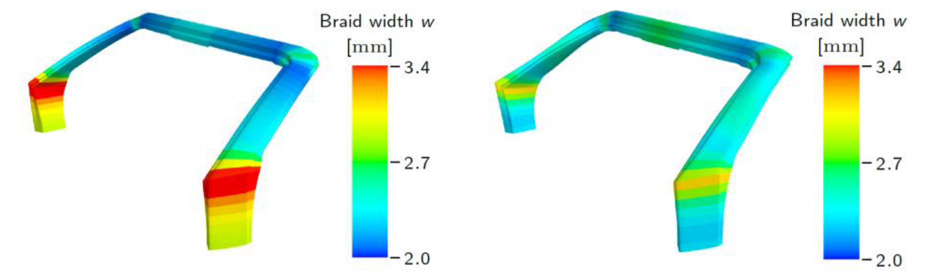
	Machine Learning (ML)	Fuzzy Inference Systems (FIS)
Criteria	• e of 43.5% • m of 5.9kg	• e of 41.2% • m of 5.9kg
Optimization Quantities	• 19 iterations • Feasible optima – constraints fulfilled and (local) optimality given	• 14 iterations • Feasible optima – constraints fulfilled and (local) optimality given



(a) Initial design **(b)** Optimum

Figure 15. Vector optimization of an automotive structure (A pillar of a convertible).

The sub-sequent figure 16 depicts the braiding width for the two cases. For the initial case, the braiding width succeeds 3.0mm (red regions), thereby clearly indicating, that the preform would open in this case. After convergence of the optimization, the braiding width relaxes to moderate values.



(a) Initial design **(b)** Optimum

Figure 16. Detailed investigation of both designs in terms of braid width.

5. Conclusion

With this work, the modelling of soft criteria arising from either economics or technics like costs or manufacturing time and/or quality has been discussed. Two of the most representative soft computing methodologies have been contrasted; machine learning and fuzzy inference systems.

It has been shown, that – in order to achieve the necessary accuracy – by far greater sample sizes are needed if machine learning is pursuit. On the contrary, fuzzy inference systems are as accurate as their knowledge bases describes the physics of interest. The advantage is, that only a few interviews are sufficient so as to derive a knowledge base. This accuracy and efficiency, however comes with the costs of great efforts in pre and post processing of interviews. On top, a certain creativity – in understanding and probing the problem – is needed for instance when generalized rules are to be deduced.

Last but not least, both modelled have been used within a vector optimization of an automotive A pillar. Mass and manufacturing effort were simultaneously optimized, while all constraints determined via strength and stiffness ought to be fulfilled throughout the optimization run.

Again, both methods were contrasted. The difference between both methods were judged to be marginal, even though, the vector optimization based on manufacturing effort model formed via the fuzzy inference system was slightly more performant.

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