APPLICATION AND EVALUATION OF META-MODEL ASSISTED OPTIMISATION STRATEGIES FOR GRIPPER ASSISTED FABRIC DRAPING IN COMPOSITE MANUFACTURING

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Abstract
With respect to their extraordinary weight-specific mechanical properties, continuous Fibre Reinforced Plastics (CoFRP) have drawn increasing attention for use in load bearing structures. Contrasting metals, manufacturing of CoFRPs components requires multiple steps, often including a draping process of textiles. To predict and optimise the manufacturing process, Finite-Element (FE) simulation methods are being developed along virtual process chains. For maximum part quality, draping process parameters need to be optimised, which requires numerous computationally expensive iterations. While efforts have been made for time-efficient process optimisation in metal forming, composite draping optimisation has is a comparably young discipline and still lacks time-efficient optimisation strategies. In this work, modelling strategies for time-efficient optimisation using computationally inexpensive meta-models are examined, which are used to guide the search for optima in the parameter space. The meta-models are trained by observations of FE-based draping simulations of an automotive part, thereby learning the relationship between variable gripper forces (input) and the resulting shear angles (output). Parametric model functions are compared against deep neural networks (DNN) as non-parametric models with respect to prediction accuracy. Best results are achieved using a DNN that predicts the shear angles of more than 24 000 fabric shell elements.

1. Introduction and Related Work

Continuous fibre reinforced plastics (CoFRP) are increasingly applied, in particular in the aerospace and automotive sector, due to their remarkable mechanical properties and low specific weight. In general, the mechanical performance of CoFRP components is mainly governed and adjusted by the component geometry and the material properties. For both, researchers have developed approaches for optimisation. For example, in [1] the shape of components is varied for improved performance, whilst in [2] the local material properties (e.g. stacking sequence or patch positioning) for a given geometry are optimised for improved performance.

However, not only optimum material usage is of interest, but also manufacturability needs to be ensured, possibly even optimised. In many cases CoFRP components require a forming process of a textile reinforcement, also known as "draping". One option to reflect manufacturing is the use of simplified, possibly even analytical relations, such as kinematic draping approaches for textile forming [3] or geodesic designs for filament winding. Typically these relations neglect the actual physical behaviour (e.g. material non-linearities, frictional effects or process conditions) and are thus of limited accuracy. Also, empirical design rules for manufacturable ply-stacks have been developed, as exemplarily

summarised in [4]. However, they can only serve as rough best practice guidelines and may not depict all possible manufacturing effects. In practice, process design by experience in conjunction with expensive trial and error approaches are still frequently encountered.

To overcome this, physics-based process simulations methods, e.g. Finite Element (FE) simulations, have been developed to identify and study the underlying physical mechanism of the process [5]. Thus, they offer remarkable potential for cost reduction: Since manufacturability can be assessed virtually, expensive test cycles in hardware can be reduced. Additionally, as variations of parameters in numerical models are comparably easy, they can be used to determine beneficial process parameters for e.g. maximum part quality or minimum cycle time. This procedure is usually referred to as virtual process optimisation.

In contrast to metals, forming simulation for textiles has yet a young history. While many researchers have focused on accurately describing the forming process, e.g. in [6] or [7], only few studies are available with respect to process optimisation. The authors of [8] for example optimise blank holder forces to avoid excessive distortions in the fabric. Additionally, the influence of process optimisation on the structural performance has been studied in [9]. Due to their highly non-linear nature, a simulation run can require considerable computation time, often many hours for larger numerical models. Thus, the computation time becomes impracticably cumbersome for iterative optimisation algorithms. Consequently, computation time is a limiting factor in process and part design strategies for CoFRP, and developing time-efficient methods is of utmost importance.
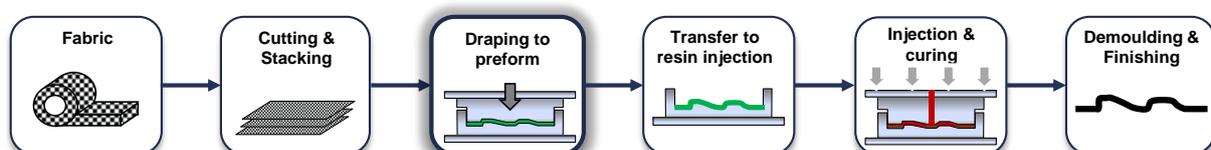
In the past, meta-models, also known as surrogate models, have been successfully applied to metal forming optimisation [10],[11]: Rather than solving a constitutive equation for the forming process, an easy-to-evaluate phenomenological relationship (meta-model) between input (process parameters) and observed output (part quality measure) is established ('trained'). Optimisation is subsequently performed on the meta-model in short time. However, selection and configuration of a suitable meta-model is a profound and challenging task: A priori it is unknown, which model function is most suitable for retrieving the underlying patterns within a given set of input-output-pairs.

Conventionally, meta-models are trained to predict a scalar part quality attribute (e.g. maximum strain) from given process parameters. This scalar is preselected by engineering knowledge and reflects the envisaged optimisation objective. In this work, typical 'single-scalar'-meta-model approaches are compared in regard of their predicitive capabilities. Additionally, a new, more complex modelling approach is evaluated, that predicts not only a single scalar but the forming result of more than 24 000 elements.

The paper is organised as follows: Section 2 and Section 3 give an overview over the considered forming simulation framework and the meta-modelling approach, respectively. An application example with different meta-modelling strategies is presented in Section 4, followed by a discussion and conclusion in Section 5.

2. Description of the Forming Process and Simulation Approach

Contrasting sheet metal parts, in many cases manufacturing of CoFRP components comprises multiple steps as shown in Figure 1.

Figure 1: Resin-injection process chain for CoFRP components (draping process is highlighted)

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Initially, plies of fabric are cut and stacked, whereby the initial fibre orientations are determined. The stack is then transferred to a press tool. When the punch is driven into the mould, the stack is formed to the three-dimensional preform with significantly altered fibre orientations and possibly further process-induced draping effects. Typically, a binder fixes the preform for subsequent transfer to the resin injection for infiltration and curing. After demoulding any finishing operations can take place.

This work focuses on the forming behaviour of woven fabrics. Macroscopically, these materials exhibit a high tensile modulus, whilst their bending and shear stiffness is comparably low. Thus, their primary deformation mechanism is in-plane shear, typically quantified by the shear angle γ. A visual impression of γ under pure shear assumption is given in Figure 2 (left). Typically the shear angle is employed to assess the component quality after forming: As with metals, fabrics cannot deform infinitely but pose a forming limit, the so-called locking angle γ^{lock}. Imposing further shear deformation increases the likelihood of forming defects such as wrinkles or textile folding as exemplarily shown in Figure 2 (right).

Figure 2: Schematic sketch of the assumed fabric deformation mechanism (left) and an example of wrinkling (right) [9]

Additionally, higher shear angles lead to higher compaction of adjacent fibre bundles (rovings) which impedes resin infiltration and may ultimately lead to inadmissible non-infiltrated regions, so called dry spots. Ultimately, since the fibre orientations usually reflect the load paths within a component any deviation (i.e. shear) from the intended orientation may have adverse effects [9]. Hence, it appears desirable to reduce these deviations to a minimum for optimum part performance.

One frequently used option to reduce the shear angle during draping for a given material and geometry is the use of grippers. They are distributed along the textile's perimeter and exert restraining forces during the process, which controls the local material draw-in. By variation of the number, positions and forces of the grippers, the process can be optimised to reach maximum part quality. The authors of [8] propose a two-stage optimisation approach: Starting with a uniform distribution of grippers, they successively remove grippers until only clusters in the most decisive regions remain. These are subsequently merged to form single grippers, whose restraining forces are optimised in a second step. The proposed optimisation procedure is successfully employed in [9] on an automotive structure, whereby the maximum absolute shear angle $\gamma_{max} = \max\left(|\underline{\gamma}|\right)$ is reduced by nearly 8 %.

3. Meta-Model Assisted Optimisation (MAO)

In general, optimisation tasks in engineering applications are of high dimensional and non-linear nature, in many cases even multi-modal, non-convex and/or non-differentiable (discrete optimisation). Often these conditions make gradient-based optimisation algorithms inadequate [13] and one may resort to derivative-free algorithms such as genetic algorithms (GA). GAs are based on evaluation, principled selection, mutation and combination of a population of candidate solutions and are frequently used in engineering optimisation. They tend to find a global optimum, yet this comes at the cost of a substantially increased number of function evaluations (i.e. simulation runs). This leverages the use of meta-models as a numerical efficient approximation for the resource-intensive simulation. Performing the optimisation on the meta-model allows to identify and exploit the most promising parameter regions.

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3.1. Meta-Modelling Approach

Engineering optimisation problems can often be cast to a parametric problem of which an optimum parameter combination is desired. Therefore, the FE simulation may be perceived as a function $\varphi_{\text{sim}} : C \mapsto A$, that maps from a parameter set $\underline{c} \in C$ to a predefined product attribute $\underline{a} \in A$. Meta-modeling now aims at determining a numerical efficient function $\mu_{\text{meta}} : C \mapsto A$ that approximates φ_{sim} in a certain subdomain $C_{\text{targ}} \subset C$. Formally, this results in $\mu_{\text{meta}} \approx \varphi_{\text{sim}} \forall \underline{c} \in C_{\text{targ}}$. It may be noted, that φ_{sim} can be evaluated (i.e. by simulation runs), but not explicitly formulated. Therefore, a detailed mathematical analysis (e.g. higher derivatives of φ_{sim}, ...) is well-nigh intractable, which makes 'classical' approximation techniques (e.g. Taylor series expansion) an unfeasible option. Thus, meta-modeling pursues a data-driven approximation of φ_{sim} from a data set of samples $D^n = \left\{ (\underline{c}, \underline{a})_1, \ldots, (\underline{c}, \underline{a})_n \right\}$ containing n observed function evaluations. The meta-model function μ_{meta} stems from a preselected function class $\mathcal{M}$. Commonly used function classes for meta-models are polynomials, splines, artificial neural networks (ANNs), support vector machines, decision trees or Gaussian Regression [14]. The choice of the function class is a critical step, as it determines the predictive capabilities of the model more than any other step. In this work, lower and higher order polynomials as well as shallow and deep neural networks are examined.

During the so-called training μ_{meta} is established as the function that minimises the error between the prediction of μ_{meta} and observed sampling data from D^n. In regression, the error is typically referred to as the loss L:

$$\mu_{\text{meta}} = \underset{\mu_{\text{meta}} \in \mathcal{M}}{\arg \min} [L(\mu_{\text{meta}}, D^n)] \tag{1}$$
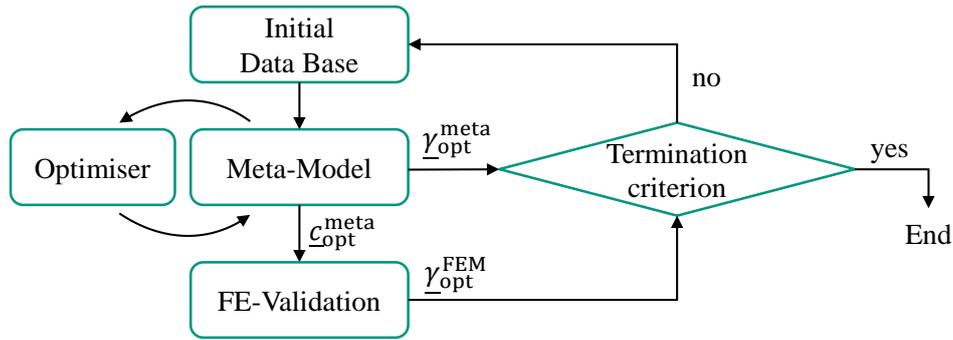
Assuming that the loss L is normally distributed around μ_{meta} results in minimizing the mean squared error (MSE), a typical error measure in regression problems and is also used in this work:

$$MSE = L(\mu_{\text{meta}}, D^n) = \frac{1}{n} \sqrt{\sum_i (\underline{\hat{a}}_i - \underline{a}_i)^2} \tag{2}$$

where $\underline{\hat{a}}_i = \mu_{\text{meta}}(\underline{c}_i)$, i.e. the meta-model prediction. Some techniques to further increase the predictive capabilities have been introduced in the literature, e.g. regularisation techniques, whose detailed presentation however is beyond the scope of this work.

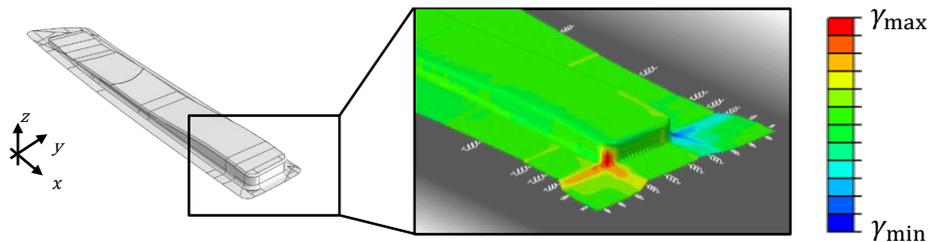### 3.2. Coupling Meta-Models and Optimisation Algorithms

The meta-model shall be used to guide the search for an optimum combination of process parameters $\underline{c}_{\text{opt}}$ yielding an optimum part quality measure $\underline{a}_{\text{opt}}$. For optimisation an objective function $f : \underline{a} \mapsto a_{\text{obj}}$ must be defined, that assesses the part quality by means of a single scalar value a_{obj}, that is sought to be minimised. In the case of fabric forming, the maximum shear deformation $a_{\text{obj}} = f(\underline{\gamma}) = \gamma_{\text{max}}$ is frequently used. For visualisation, the workflow is sketched in Figure 3. After training on an initial data base, the meta-model is able to make predictions on the objective function and optimisation can be performed on the meta-model. The proposed optimum solution is then validated by a simulation run and the results $f(\underline{\gamma}_{\text{opt}}^{\text{FEM}})$ and the meta-model prediction $f(\underline{\gamma}_{\text{opt}}^{\text{meta}})$ can be compared. If both match, then a global optimum is likely to be found. If not however, then the new FE solution is added as a further sample to the data base, the meta-model is retrained and optimisation started again. This cycle is repeated until convergence, whereby the predictive capabilities are gradually enhanced in the vicinity of potential optimum points and costly FE-simulations are concentrated on the most promising solutions. It may be noted, that the choice of a suitable meta-model function is crucial for optimisation success.

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Figure 3: Schematic workflow of meta-model assisted optimization (MAO) [12]

4. Application Example, Results and Discussion

In this work, forming of a car door reinforcement beam from [9] is taken as a practical example to evaluate different meta-model functions for their applicability. The beam is designed to distribute loads in case of side crash. It shows a complex shape with a twist, a global bent and a surrounding hem. Most decisive from a forming perspective are two protruding blent corners at one end of the beam with a depth of about 40 mm. The beam is formed from a rectangular stack of carbon fibre fabrics in one stroke using a single punch. To account for the envisaged load case (approximately Three-Point-Bending), the fibre orientations in the fabric are set to [0°/90°] prior to forming. An illustration of the part as well as an exemplary forming simulation result is given in Figure 4. As is readily seen, high shear deformations occur around the blent corners. Additionally, a total number of $n_c = 50$ grippers, have been introduced to control the shear deformations. They are modelled as springs, whose stiffness can be individually varied for optimisation. For maximum influence in the region of interest they are concentrated near the corners, cf. Figure 4.

Figure 4: Geometry of the car door beam and a simulation of the resulting shear angle distribution after gripper assisted forming. Grippers are modelled as springs. [9],[12]

Details on the simulation set-up including material data and along with a initial FE-based optimisation approach (i.e. without meta-models) can be found in [9]. Yet, the performance of the optimisation was not promising in respect of computation time: After 8 weeks the optimisation was terminated, leaving a data base with $n = 584$ simulation runs. In order to further explore the 50-dimensional parameter space with less numerical effort, MAO appears appealing.

As stated, the choice of the meta-model function is of crucial importance. The goal is to establish a model function μ_{meta} that predicts the forming result (e.g. $\gamma_{\max}$) from 50 individual spring stiffnesses $c_{1,...,50}$ of the grippers (i.e. $\mu_{\mathrm{meta}}: \underline{c} \in \mathbb{R}^{50 \times 1} \mapsto \gamma_{\max} \in \mathbb{R}$). In this study four model functions have been evaluated for their suitability in approximating the forming behaviour: Linear (LR) and Polynomial Regression (PR) up to degree 7, as well as shallow and a deep artificial neural networks, denoted by ANN and DNN, respectively. Training is performed on 90% of the available data (i.e. 526 samples), whilst 10 % are held back to test the predictive capabilities of the models on new, 'unseen' data. Details

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on data acquisition, training regime and the implementation in a MAO workflow are given in [12].

The first ANN takes the $n_c = 50$ individual spring rates and predicts the maximum and minimum shear angle $\gamma_{\min,\max}$, respectively. The network architecture consists of three fully connected layers as presented in Table 1. Additionally, a second, deep neural network (DNN) is configured, which predicts not just $\gamma_{\min,\max}$ but is trained to make a prediction of each shear angle $\gamma_{1\ldots24272}$ in the model, i.e. more than 24 000 elements. In contrast to conventional engineering meta-models, the DNN does not only predict a scalar value (i.e. $\gamma_{\min,\max}$), but is requested to learn the full forming result.
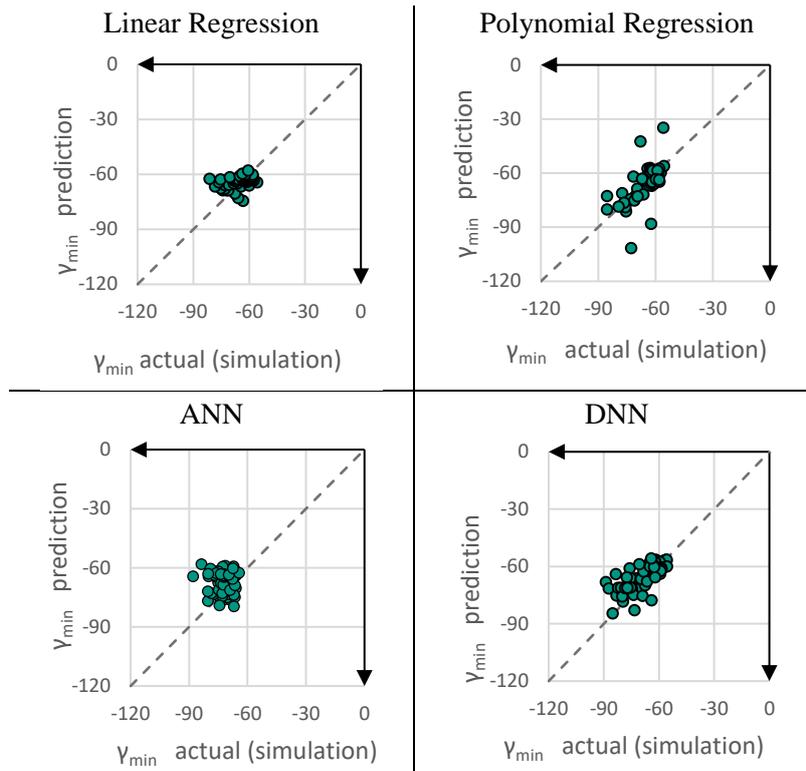
Table 1: Architecture of ANN and DNN,
PReLu denotes Parametric Rectified Linear Unit

No.	Input layer	Layer 1 neurons	Layer 1 activation	Layer 2 neurons	Layer 2 activation	Layer 3 neurons	Layer 3 activation	Layer 4 neurons	Layer 4 activation	Output layer
1	$\underline{c}$	50	Sigmoid	38	Sigmoid	1	Linear	-	-	1 $\gamma_{\min,\max}$
2		150	PReLu	1000	PReLu	5000	PReLu	12 000	Linear	24 272 γ_i

Table 2 presents some quality measures for the used meta-models on 58 held out test samples that are also used in [15]. Additionally, predicted-vs-actual plots are given in Figure 5. The closer the markers lie to the dashed line, the higher the accuracy. By evaluation it is seen, that LR is not able to make accurate predictions. Its plot loosely forms a horizontal line, indicating that it merely 'predicts' the average of the simulations. Similarly, the ANN also cannot make accurate predictions. For both models the coefficient of determination R^2 of about 0.4 and almost 0 is deemed insufficient. There is virtually no structure in the data, indicating inadequate model accuracy of the process dynamics. Better results are achieved for PR: Its R^2 is higher and also its markers are closer to the dashed line, however some physically implausible outliers with high absolute errors are observed. This may be seen as a sign of undesirable overfitting. Since they falsely predict low values, the optimiser is likely to converge to one of these outliers, resulting in a meaningless optimisation result. Best performance is found for the DNN: The highest R^2 and overall relatively low errors rates imply the most suitable recovery of the problem structure.

Table 2: Accuracy metrics of the meta-models. R^2 denotes the coefficient of determination, RAAE is the relative average absolute error, RMAE is the relative maximum absolute error

	LR	PR	ANN	DNN
R^2	0.391	0.616	-0.010	0.733
Max. abs. error	18.718	29.062	25.397	20.501
RAAE	1.150	1.103	1.362	1.006
RMAE	5.283	4.711	5.030	4.731

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Figure 5: Predicted-vs-Actual plots of the used meta-models

5. Discussion and Conclusion

Meta-model assisted optimisation offers great potential to reduce computation time in engineering applictions. However, selecting an appropriate model function class significantly influences its performance. This work evaluates four function classes for meta-models in high-dimensional production processes ranging from simple linear models to deep neural networks. The DNN reaches superior performance compared to conventional models, despite all models being trained on the same data base. It is assumed that the DNN can make maximum use of information supplied in the training data: Since it is trained on all available elements in the model rather than just a maximum value, it is able to learn relations between neighbouring elements. This gives additional internal structure in the network and significantly increases the predictive accuracy. Thus, it may be concluded that meta-models using DNNs can benefit greatly from presenting all available data rather than a preselected part quality measure. However, it must be noted, that this comes at the cost of increased training time: Training of the considered DNN amounts to tuning more than 350 million parameters, which takes about 5 hours on a modern work station. The DNN from this work is used for MAO in [12] and shows remarkable optimisation results. Also, a greatly reduced number of FE simulations during optimisation is found, which may compensate for the increased training effort. First studies also hint that DNNs are even able to learn physical effects from abstract training samples and extrapolate to real-world engineering problems [16]. Thus, DNNs show great potential for further application in part and process design of composites.

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