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Optimisation of manufacturing process parameters using deep neural networks as surrogate models

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Abstract

Optimisation of manufacturing process parameters requires resource-intensive search in a high-dimensional parameter space. In some cases, physics-based simulations can replace actual experiments. But they are computationally expensive to evaluate. Surrogate-based optimisation uses a simplified model to guide the search for optimised parameter combinations, where the surrogate model is iteratively improved with new observations. This work applies surrogate-based optimisation to a composite textile draping process. Numerical experiments are conducted with a Finite Element (FE) simulation model. The surrogate model, a deep artificial neural network, is trained to predict the shear angle of more than 24,000 textile elements. Predicting detailed process results instead of a single performance scalar improves the model quality, as more relevant data from every experiment can be used for training. For the textile draping case, the approach is shown to reduce the number of resource-intensive FE simulations required to find optimised parameter configurations. It also improves on the best-known overall solution.

Keywords: Artificial intelligence in manufacturing; Modelling, Simulation and Optimisation; Process Parameter Optimisation; Machine Learning; Deep Learning; Composite Textile Draping

1. Introduction

Most manufacturing processes require careful parametrization to achieve optimal operations in terms of cost, quality and time. The number of considered process parameters can range between less than ten and many hundred parameters. Current approaches to parameter optimisation for production processes require many expensive trial experiments. In some cases, physically precise simulation models, e.g. based on the Finite Element (FE) method, can substitute actual experiments. However, FE simulations often require hours or even days of computation. In this work, we reduce the number of trial experiments (simulations) by the use of surrogate-based optimisation (SBO).

Prior work uses surrogate models (sometimes called metamodels) to predict an overall performance scalar or low-dimensional process features only. This limits the usable information gained from every experiment. Since experiments are costly, it is beneficial to make detailed sensory observations or simulation results available to the surrogate model. In this work, a deep artificial neural network (ANN) is used for the surrogate model. For the considered use case, the draping of composite textiles, the ANN takes a 50-dimensional process parameter set and predicts the shear angles of over 24,000 composite fabric elements.

The paper is organized as follows. The state of the art and the considered use case are introduced in Section 2 and Section 3. Section 4 gives details about model training and parameter optimisation for SBO. The approach is applied to the composite textile draping use case in Section 5 with results discussed in Section 6. The paper concludes in Section 7 with a summary and future outlook.

2. Related Work

2.1. Surrogate-Based Optimisation

Optimisation problems in engineering, such as design- and parameter-optimisation problems, are often high-dimensional, highly non-linear and even non-convex. Global derivative-free optimisation methods [1] can find good solutions under such conditions. But they require many expensive evaluations in the form of physical or simulated experiments. Physically motivated

models, such as Finite Element (FE) analysis and Computational Fluid Dynamics (CFD) simulations predict physical behaviour with high precision. But these simulations come at the price of long computation times.

Surrogate approximations (meta-models) are easy-to-evaluate approximations of high-fidelity models [2–4]. Common surrogate model choices are polynomials, splines, stochastic processes, kernel smoothing, radial basis functions, artificial neural networks and decision trees [2]. The surrogate model can be used to select optimised candidate solutions with reduced computational effort. However, since the surrogate model introduces a bias, the selected solutions may in effect not contain the optimum solution [5]. Surrogate-based optimisation (SBO) [6,7] tries to eliminate the bias of the surrogate model by iteratively improving the surrogate model with new experimental (simulated) evidence for the previously selected candidate solutions.

2.2. *Model-Based Optimisation of Manufacturing Process Parameters*

The recent work [8] gives an overview on model-driven process parameter optimisation. In [9], artificial neural networks are combined with a genetic optimisation algorithm to find improved process parameters. The authors of [10] apply this technique to the optimisation of an injection molding process. [11] introduce surrogate-based optimisation in the injection molding process optimisation. In [12], the authors use expected improvement to select candidate solutions in a surrogate-based optimisation approach. The authors of [13] introduce Model-Based Self-Optimisation (MBSO). They propose to equip machines with reasoning capabilities so that they can adapt parameters automatically to changed external conditions and objectives. However, they assume a fixed process model for the optimisation. This goes in contrast to surrogate-based optimisation where the process model is iteratively improved with new observations.

2.3. *Optimisation of Material Forming Processes*

Material forming processes, such as sheet metal forming, are widely applied in the automotive and aerospace industry to manufacture shell structures, e.g. for lightweight applications. With the advent of FE-techniques, many authors have made efforts to accurately simulate the forming process and use surrogate techniques to determine an optimum process design without unwanted defects, such as cracking, wrinkling or inadmissible springback of the formed part [14]. Typical process parameters for optimisation are blank holder forces, the inital blank shape, tool load paths (e.g. force/pressure over time) and the die shape [15–17]. More recently, simulation approaches for forming of composite materials, also referred to as draping, have drawn attention [18–20]. To account for the multi-step-nature of composite manufacturing, virtual process chains including the simulation of resin infiltration and curing are proposed [21,22]. Apart from the inherently anisotropic complex material behaviour, infiltration and curing significantly complicates the prediction of manufacturing defects and makes optimisation a challenging task [23].

3. Use Case: Process Parameter Optimisation for Composite Textile Draping

Continuous Fibre Reinforced Plastics (CoFRP) are increasingly used for load bearing structures, especially in aerospace and automotive applications. However, their superior material properties (e.g. the high strength- and modulus-to-weight ratio) come at a higher cost, not only caused by the higher material prices but also by the effort required to build up a stable manufacturing process with the required quality.

Figure 1 shows a common process chain from raw material to finished CoFRP components: Plies of fabric material are cut and stacked, which initially determines the fibre orientations of the part. The ply stack is then transferred to a press tool. As the tool closes, the ply stack is formed to a three-dimensional preform. Typically, an adhesive binder material is applied between the plies, which stabilizes the preform for demoulding and subsequent handling. The preform is then transferred to a resin injection tool for infiltration and curing. Finally, the part is demoulded and possible finishing operations are performed. Process parameters need to be optimised at each stage of the process chain for maximum throughput and part quality. This work focuses on optimising the draping process.

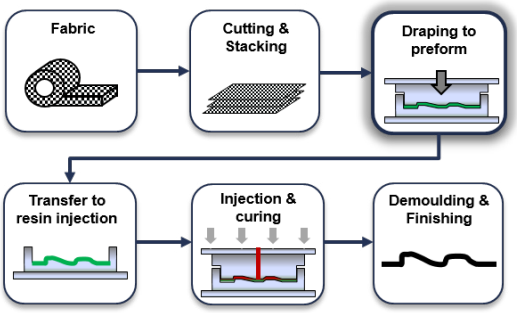


Fig. 1. Process chain for Continuous Fibre Reinforced Plastics (CoFRP) manufacturing. The draping process considered in this work is highlighted.

Woven fabric has a low shear and bending stiffness compared to the high tensile stiffness. This makes in-plane shear the predominant deformation mechanism during forming. The shear deformation is quantified by the shear angle γ as shown in Figure 2.[1] Similar to metals, woven fabrics cannot be deformed indefinitely. The shearing limit of the fabric is characterised by the locking angle γ^{lock}. Shearing beyond γ^{lock} may result in draping defects, such as wrinkles or textile foldings. These have to be avoided. Since the fibre orientations usually reflect the load path, deviations can severely compromise the part's structural performance. An example for wrinkling is shown in Figure 3. Additionally, a higher shear angle reduces the permeability for resin infiltration and may lead to non-infiltrated regions, so-called dry spots [23].

3.1. *Draping of a car door reinforcement beam*

The CoFRP component examined in this study is a car door reinforcement beam, which is designed to withstand side crash

[1]The forming literature refers to this shear angle as γ_{12} to distinguish the in-plane shear deformations from out-of-plane deformations. The subscript $_{12}$ is dropped here for readability.

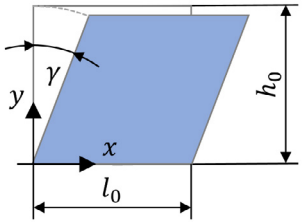


Fig. 2. Visualisation of shear deformation and the the shear angle γ.

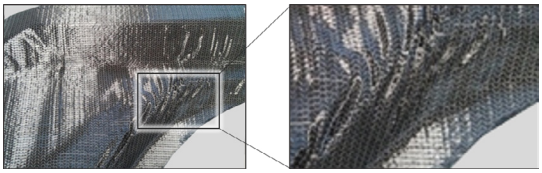
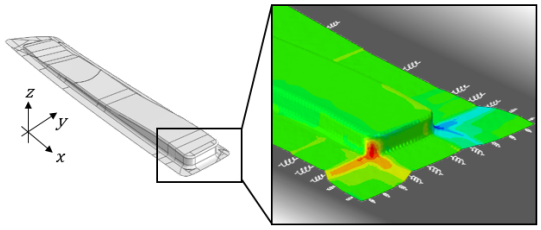


Fig. 3. Example of excessive shear deformation leading to wrinkling [23].



a) b)

Fig. 4. Visualisation of the car door reinforcement beam: a) geometry of the component b) qualitative plot of the forming results. Red and blue regions mark areas of high shear angles. Springs indicate the position of attached grippers.

loads. The beam is about 1220mm long and 220mm wide. Additionally, it is surrounded by a hem for joining with adjacent parts during assembly. From a forming point of view, the most decisive geometric features are two protruding filleted corners at one end of the beam, as can be seen in Figure 4 a). The protrusions are approximately rectangular and flatten out towards the opposite end of the beam. This leads to two areas with concentrations of high shear angles (cf. Figure 4 b)), which are prone to the occurrence of draping defects and hence require special attention.

The beam consists of three stacked layers of carbon fibre fabric, which are oriented at $0°/90°$ with respect to the x-axis in Figure 4 a). The draping tool is closed in a single stroke. To control the draping process and to reduce the maximum shear angle, 50 grippers have been distributed along the fabric's circumference. They locally restrain the material draw-in into the mould and thereby control the draping result (i.e. local shear angles). In the simulation the grippers are modelled as springs with a stiffness between 0 N/mm and 25 N/mm. In accordance with the findings from [24], the grippers have been concentrated near the corners of the beam, where the highest shear angles occur for a fabric with $0°/90°$ orientation. The forming simulation is performed using the commercial FE-tool ABAQUS. Details on the simulation approach, the applied material models and the simulation setup can be found in [23].

3.2. Initial Draping Parameter Optimisation

In practice, adjusting and optimising a manufacturing process in terms of machine parameters (e.g. tool temperature, press forces, gripper strategy) is often done by costly "trial-and-error"-experiments until a defect-free part is manufactured. This approach relies on the experience of engineers and is unlikely to reach a global optimum if the number of parameters is large. The parameters for the trial experiments can be selected with a gradient-free optimisation method. We call this the *direct optimisation method* as it requires no surrogate model. As outlined in Section 2, physics-based models have been developed to simulate the detailed process behaviour. This allows for easier assessment of parameters prior to any testing with actual hardware.

In a previous study [23], the FE-based draping simulation was coupled with an evolutionary algorithm from the open-source toolkit DAKOTA [25]. Starting with an initial population of solutions, evolutionary algorithms use selection, mutation and recombination of the most promising candidate solutions to iteratively improve on a predefined objective function. In [23], 14 individuals per generation were used with a cross-over factor and a mutation factor of 0.8 and 0.08, respectively. The objective function for the initial optimisation was the minimum of the maximum absolute shear angle of all elements in the FE-model $\gamma_{\max} = \max_j |\gamma_j|$, where j is the index of the composite textile elements. However, the computational performance was not convincing: Due to the highly non-linear nature of process simulations, FE simulation can quickly become computationally expensive. This holds in particular for manufacturing simulations of fibrous materials, which exhibit a strongly non-linear and anisotropic material behaviour and pose severe challenges to accurately grasp the contact behaviour between the fabric plies. In our case, a single simulation run required on average about 3 hours of computation on a workstation with 28 CPU cores. The direct optimisation approach was terminated after more than eight weeks of computation and 584 completed draping simulations. The maximum absolute shear angle $\gamma_{\max}$ was reduced with the direct optimisation approach from about 65° for the initial solution to $\gamma_{max}^{\text{direct}} = 60.0°$. Note that this result stays above the shear locking angle of $\gamma^{lock} = 54.4°$ of the composite textile.

4. Surrogate-based Optimisation of Production Process Parameters

For the purposes of parameter optimisation, a production process can be seen as a function $\boldsymbol{\pi} : C \rightarrow A$, which maps process parameter configurations $\boldsymbol{c} \in C$ to product attributes $\boldsymbol{a} \in A$. The data set $D^k = \{(\boldsymbol{c}^n, \boldsymbol{a}^n) \,|\, n = 1, \ldots, k\}$ contains k observed input-output relations sampled from $\boldsymbol{\pi}$. The space of possible observation data sets is denoted as $\mathcal{D}$. Training a surrogate model can be seen as selecting a model $\boldsymbol{\mu} : C \rightarrow A$ from the model class $\mathcal{M}$ based on the observations. This is often cast as the solution to an optimisation problem [26]. The model selection function $\tau_{\mathcal{M}} : \mathcal{D} \rightarrow \mathcal{M}$ is defined as follows:

$$\boldsymbol{\mu}^k = \tau_{\mathcal{M}}(D^k) = \underset{\boldsymbol{\mu} \in \mathcal{M}}{\arg\min} \Big[f(\boldsymbol{\mu}, D^k) + h(\boldsymbol{\mu}, k) \Big] \tag{1}$$

The fitness function $f : \mathcal{M} \times \mathcal{D} \rightarrow \mathbb{R}$ evaluates how well the model predictions match the observations. But a model with a good fit could simply reproduce the training data D^k by heart without capturing the underlying structure. The regularization h is added to prevent overfitting the model to the data [27]. It usually penalizes the model complexity vis-à-vis the size of the

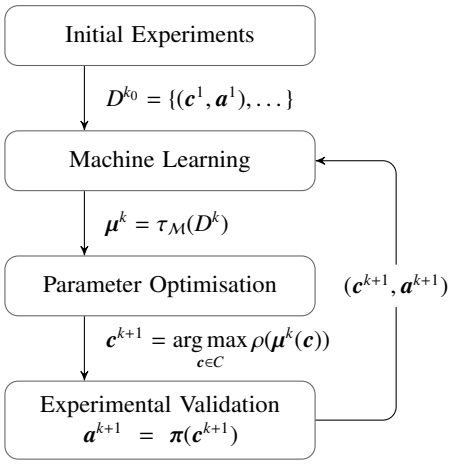


Fig. 5. Surrogate-based optimisation of production process parameters.

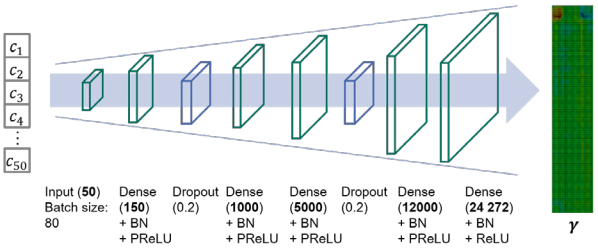


Fig. 6. Architecture of the deep neural network used to predict the shear angles of composite draping $\boldsymbol{\gamma}$ from the gripper stiffnesses $\boldsymbol{c}$. Neurons in a deep ANN are arranged into layers. We densely connect adjacent layers. BN stands for Batch Normalization, PReLU stands for (Parametric) Rectified Linear Unit.

training data, for example in terms of the number of (non-zero) parameters, information entropy, or the model smoothness.

Parametric models have a fixed set of parameters. Choosing the model according to (1) amounts to tuning the parameters within the bounds defined by the model class $\mathcal{M}$. Non-parametric models, for example interpolation methods [28,29], have no fixed set of parameters. Artificial Neural Networks (ANN) are commonly seen as non-parametric models as well, even though they do have a fixed number of parameters. However, so-called deep ANN may contain many thousands for neurons [30]. Before training, the parameters governing each neuron's behaviour and their relations have no a-priori meaning with respect to the process $\boldsymbol{\pi}$ they shall emulate.

The merit function $\rho : A \to \mathbb{R}$ maps product attributes to a scalar performance indicator. The overall objective is to find an optimal parameter configuration $\boldsymbol{c}^* = \arg\max_{\boldsymbol{c}\in C} \rho(\boldsymbol{\pi}(\boldsymbol{c}))$. But, since evaluations of $\boldsymbol{\pi}$ are time- and resource-intensive, the optimisation is performed over the surrogate model.

$$\boldsymbol{c}^{k+1} = \arg\max_{\boldsymbol{c}\in C} \rho(\boldsymbol{\mu}^k(\boldsymbol{c})) \tag{2}$$

The new parameter configuration $\boldsymbol{c}^{k+1}$ is experimentally validated on the actual process $\boldsymbol{a}^{k+1} = \boldsymbol{\pi}(\boldsymbol{c}^{k+1})$ (a physically accurate FE simulation in our case) and the results are added to the data set D^{k+1}. Then, an updated surrogate model is computed for the next iteration. The underlying assumption is that, starting with a number of initial samples k_0, iteratively applying (2) converges $\boldsymbol{\pi}(\boldsymbol{c}^k) \to \boldsymbol{\pi}(\boldsymbol{c}^*)$. (There may be several optimal solutions in the configuration space. The goal is to converge to any one of them.) The main difference of our approach compared to previous work [4] is that the surrogate model is trained to predict the observed product attributes and not the performance scalar given by the merit function. This is made possible by machine learning techniques that allow the training of large-scale models. See Figure 5 for an overview of the approach.

5. Applying Surrogate-Based Optimisation to the Composite Textile Draping Use Case

The initial data set contains $k_0 = 584$ FE simulations of the composite textile draping process from Section 3. The input parameter configurations of the initial data set (each containing 50 spring stiffness parameters) were selected by the initial genetic optimisation process described in Section 3.2. Initially, 'classical' regression approaches such as linear and polynomial regression as well as a simple ANN were evaluated for their capacity in predicting the maximum absolute shear angle $\gamma_{\max} = \max_j |\gamma_j|$ from the spring stiffness configuration $\boldsymbol{c}$. However, those methods were not able to accurately model the process and led to inaccurate predictions of $\gamma_{\max}$. This hints at a highly non-linear process π that can not be learned from just 584 samples or that requires a more flexible surrogate model class.

Instead of predicting $\gamma_{\max}$ only, a deep ANN was trained to predict the shear angle of all 24,000 composite fabric elements. See [30] for a recent overview of deep ANN and their training. By predicting all 24,000 shear angles, the training can use more information from each training example. It also enables the network to learn relations between neighbouring elements of the composite textile. Figure 6 shows the architecture of the deep ANN. Note that it includes no convolutional layers commonly used in image recognition [31]. Convolutional layers are suited for finding common patterns independent of their position in an image. Also, each convolution decreases the size of the layers in the ANN architecture. But in this case, the cell position on the composite fabric is highly relevant and we gradually increase the size of the network layers instead of reducing them. The network requires the training of more than 350 million model parameters. As the number of model parameters is much bigger than the size of the training data set, measures were taken to reduce the effects of overfitting: The use of mini-batches for training (with batches of 80 randomly selected samples), dropout layers in the architecture of the neural network and early stopping according to a separate test set with a random selection of 10% of the initial experiment results.

The neural network surrogate model is highly non-convex. We therefore avoid gradient-based methods for the parameter optimisation as they could converge to local minima. Instead, we use Differential Evolution (DE), a stochastic genetic algorithm for global optimisation [32]. DE starts with an initial population of randomly generated solutions. The population is updated in each optimisation epoch. Bad solutions are discarded and good solutions are combined via genetic crossover to form new solutions. This explores the parameter spaces while gradually moving towards an optimum solution. DE requires comparatively many model evaluations. On the other hand, the neural network model is comparably fast to evaluate (about 250ms on our hardware).

The optimisation goal is to reduce the maximum absolute shear angle. The merit function is therefore $\rho(\boldsymbol{\gamma}) = -\max_k |\gamma_k|$. Optimizing ρ was however found to be problematic for the DE

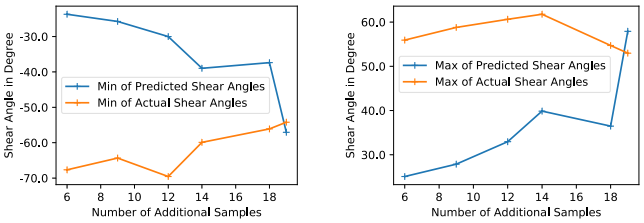


Fig. 7. Predicted and actual maximum and minimum shear angle for the selected configurations in each iteration of the SBO approach.

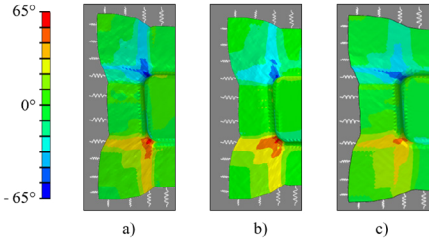


Fig. 8. Plot of the shear angle distribution a) before optimisation, b) best result after direct optimisation, c) after SBO with the deep ANN surrogate model.

algorithm. Suppose a situation with two local clusters of high shear angles as shown in Figure 4. If the left cluster contains the highest shear angle, then all improvements to the right cluster are at first invisible to the optimisation. So the DE algorithm evaluates all spring stiffnesses with respect to one relevant composite material cell only. But the position of this relevant cell can jump between clusters of high shear angles. To overcome this problem, we devised an approximation of the merit function that takes more into account than just the maximum shear angle. In general, for an m-dimensional vector $\boldsymbol{x}$, the p-norm is defined as $\|\boldsymbol{x}\|_p = \left(\sum_{i=1}^{m} |x_i|^p\right)^{1/p}$. The p-norm covers the maximum norm ($p = \infty$), the sum of absolute values ($p = 1$) and the Euclidean norm ($p = 2$) as special cases. We selected the approximate merit function $\bar{\rho}(\boldsymbol{\gamma}) = -\|\gamma\|_4$. It was empirically found to be a good tradeoff between penalizing the maximum absolute shear angle and the suppression of high shear angles in general.

The results of our SBO approach applied to the composite textile draping use case are shown in Figure 7. Initially, the discrepancy of the maximum absolute shear angle predicted by the surrogate model for an optimised parameter configuration compared to the FE simulation amounts to over 40°! By incrementally enriching the data set with the new observations, the model predictions improve around the last parameter configuration. After only 19 iterations, the SBO approach finds a parameter configuration that outperforms the previously best known result. Specifically, our method reduced the maximum shear angle from $\gamma_{max}^{\text{direct}} = 60.0°$, the result of the direct optimisation method from previous work, to $\gamma_{max}^{\text{SBO}} = 54.2°$. This reduction was achieved by extending the deformed zone over a wider area, thereby avoiding local overshearing. Figure 8 gives a visual impression of the shear angle distribution across the composite textile in the relevant area.

6. Discussion

The results of the proposed SBO approach using deep ANN achieves a considerable improvement of the shear angle distribution after iteratively adding 19 additional draping simulations to the training data. Note that our solution is the first to drop below the shear locking angle of $\gamma^{lock} = 54.4°$ for the composite textile. This is a prerequisite for using the part design as a car door reinforcement beam. The solution was obtained from numerical simulation only. Some small adjustments for a physical realisation of the process are expected due to small differences of the numerical simulation. The overall approach for parameter optimisation remains the same also for physical experiments.

Also it may be noted, that predicting 24,000 elements led to better accuracy than predicting just a single scalar value. This comes however at the cost of increased training effort for the larger net: In this work, training the final ANN required about 10 hours. On the other hand, the number of required finite element simulations was drastically reduced as the direct optimisation method did not achieve similar results even after more than eight weeks of computation.

In our case, the initial training data set was not sampled according to a Design of Experiments (DoE) method [33] and was instead generated during the evolution of the direct optimisation approach from [23]. Our analyses show that the training data contains clusters of similar process parameters and also regions in the parameter space where data samples are sparse. If the global optimum lies in a region with no initial samples, then the SBO approach might never sample from this region and may converge to a local optimum.

7. Summary and Future Outlook

This work examined the optimisation of a composite textile draping process. A surrogate-based optimisation method based on deep artificial neural networks was proposed to guide the exploration of the 50-dimensional parameter space. The selected candidate solutions were evaluated via Finite Element simulations and added to the training data to iteratively improve the model accuracy near the perceived optimum solution. Predicting the shear angles of all 24,000 composite textile elements performed better than simpler models that predict a scalar performance value only. After only 20 model updates, a parameter combination was found that surpasses the previous best solution from direct optimisation.

It may be noted, that the process parameters in the initial training data were not sampled according to a DoE but were generated during the course of a previous optimisation effort without the use of a surrogate model. We expect a further reduction in the required effort by a principled selection of the initial samples, e.g. based on latin hyper cubes [34]. Another aspect for future research is the impact of the size of the initial training data set on surrogate-based optimisation. Certainly, with more training data, the accuracy of the prediction increases. But this in turn requires more effort before switching to the iterative surrogate-based optimisation. A criterion for a suitable tradeoff is desirable.

Another open research question is the choice of candidate parameter configurations for the optimisation for a given surrogate model. The choice between sampling the predicted optimum and sampling in a region with less empirical evidence (high uncertainty) is known as the exploration/exploitation tradeoff in the literature [35,36]. It can be resolved by the introduction of prior assumptions and an explicit treatment of the model uncertainty.

Deep artificial neural networks show great potential for fur-

ther application in part and process design when enough training data is available. As shown in [37], convolutional neural networks (CNN) are able to learn system dynamics from data and predict physical effects in real-world engineering problems. We expect an improvement in the sample complexity of the learning task by considering interlinked surrogate models at different scales [38]. For composite textile draping, the fabrics cells from the finite element simulation are a natural candidate for a submodel at a small scale. The regularity of the cells can then be exploited for the model at the meso or macro scale. With respect to the use case of composite textile draping, such developments could lead to generalised models that can be applied to different part designs. Ultimately, this could enable a tool for engineers to evaluate the impact of design decision on the composite manufacturing process already at an early stage.

Acknowledgments

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