ARTIFICIAL INTELLIGENCE TECHNIQUES FOR IMPROVING CYLINDRICAL SHRINK-FIT SHAFT-HUB COUPLINGS

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ABSTRACT

Due to the continuous progress in information technology, complex problems of machine elements can be investigated using numerical methods. The focus of these investigations and optimizations often aims to reduce the stresses that occur or to increase the forces and torques that can be transmitted. Interference fit connections are an essential machine element for drive technology applications and are characterized by their economical fabrication. The transmission of external loads over a large contact surface between the shaft and hub makes it less vulnerable to impact loads. These advantages contrast with disadvantages such as the limited transmittable power, the risk of friction fatigue, and stress peaks at the hub edges, which can lead to undesirable and sudden failure, especially in the case of brittle hub materials. Analytical approaches already exist for optimizing these connections, which are expensive, time-consuming, and complex, so a high degree of expert knowledge is required to apply these methods in practice successfully. This paper presents a novel method using the example of optimizing the pressure distribution in the interface of a shrink-fit connection.

Keywords: Design engineering, Artificial intelligence, Optimisation, Industrial design

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1 INTRODUCTION

The shaft-hub connection is one of the main machine components used in machines that transmit power within drive systems. The transmission of power and torque between the shaft and hub can be frictional, positive, or material. Cylindrical interference fit connections (frictional locking) or keyed connections (positive locking) are often used. They can convey considerable torque, have significant economic benefits, and are easy to manufacture (Kollmann, 1981). Regardless of the type of shaft-hub connection, complex, time-consuming, and primarily iterative optimizations are necessary to meet today's power density, material utilization, and mass reduction requirements. Geometry changes are often made to optimize stresses (1st principal stress, joint pressure, notch effect), which requires expensive simulation tools to perform finite element analyses and expert knowledge. These are often inaccessible due to the high costs and the necessary expertise, especially for small and medium-sized enterprises (SMEs). Due to the time needed, significant expenses for specialized workers persist regardless of the company's size and resource availability. Additionally, shaft-hub connections have many uses in mechanical engineering, including turbopumps and engine applications for aviation. In the past 20 years, relatively few works have been inquisitive in investigating interference fit connections with solid shafts. It is valid for (elastic)-plastic interference design but not general interference fits (Glöggler, 2003; Heydt, 2012; Schwämmle, 2010; Smetana, 2001). In gear design, interference fits are frequently employed to secure couplings, pinions, and other shaft components (Blacha, 2009; Leidich, 2008). Typically, the fatigue strength controls the strength of the related shaft-hub connections and fractures the shaft or hub as a result of overloading (Leergaard Pedersen, 2022). Due to brittle materials or excessive radial and tangential stresses caused by stiffness jumps or external loads, the connection may then fail. The artificial intelligence (AI)-powered automated shaft-hub connection design can produce a user-friendly, less complex, and more time-efficient optimization, as shown in (Dausch *et al.*, 2022). Nevertheless, there still needs to be more performance due to the dependency on iterative and, therefore, still time-consuming finite element (FE) simulations. For this reason, the present article will introduce an optimization methodology for interference fit connections independent of finite element simulations because of its artificial neural network (ANN), which uses existing results as training data. It is an optimization of stresses and strains by changing the macro or micro geometry of the interference fit connection. This research on interference connections can also be used for shrink-fits (as we show in this paper) and for press-fits and combined shrink-press-fits. We only need the correct training data. The structure of the research is as follows. The problem and the objectives are described in Section 2. Section 3 contains simple optimization methods and already existing artificial intelligence AI-optimization methods. Section 4 presents the integration of artificial intelligence to shrink-fit connections using training data from existing finite element optimizations. In Section 5, the conclusions and optimum outcomes are presented.

2 RESEARCH PROBLEM AND OBJECTIVES

The interference fit connections attach two mechanical parts: a hub (outer part) and a hollow or solid shaft (inner part). Interference fits can be divided into two different types. The first type is with the press-fit connections, which are assembled by forcing the shaft into the bore of the hub. In contrast, the second type is the shrink-fit connections which are assembled using thermal expansion when heating the hub and cooling the shaft with liquid nitrogen. Both have the same problem of stress peaks at the hub edges because of the geometry-conditioned stiffness jump. Because of this reason, this article will present the research based on a shrink-fit connection with a solid shaft. However, the procedure can also be applied to press-fits following the same application on the shrink fits and connects with hollow shafts. As outlined in (Falter *et al.*, 2022), cylindrical shrink fit's analytical design (according to (DIN 7190-1, 2017a)), is based on a shrink fit with a shaft and hub that are the same length and are radially and axially symmetrical. As a result, it is assumed that radial and tangential loads are distributed consistently, and no axial stress occurs, or what is known as a planar stress condition. For this assumption, the constant pressure profile at the interstice of the connection is made.

The shaft and hub have no pressure profile with the same length. Analytical calculation formulae can be used to carry out the pressure profile under the simplifying assumption of a plane stress condition. However, a constant pressure profile on a shaft-hub connection does not reflect actual practice because the shaft and hub are usually of different lengths. It can lead to the aforementioned unavoidable jump in stiffness at the hub's edges. These excessive stiffness jumps initially cause stress peaks with different

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consequences, such as material failure (brittle materials), unintentional plasticizing (low-strength materials), or reduced joint fatigue strength. Previous studies, such as (Wagner and Binz, 2011), (Falter *et al.*, 2022) and (Dausch *et al.*, 2022), have produced several strategies based on geometry and material for optimizing shrink-fits. Due to their incredible complexity and lack of generic computation methodologies, these approaches are unsuitable for widespread use (Pedersen, 2016). These methodologies are time-consuming, and they frequently merely represent approximative iterative solutions. The key research question is how artificial intelligence might optimize the pressure within the shaft-hub connection for shrink fits without using finite element analyses. This research presents a new way to implement component optimization independently of iterative finite element analyses. Using existing optimization results in artificial neural networks (ANN) and machine learning (ML) methods is possible. This method, which can be used for a wide variety of optimization purposes on shaft-hub connections or other components, is presented using the example of stress optimization on cylindrical shrink-fit connections. As a result, this study offers a possibility for AI-supported optimization approach that reduces the complexity, is less time-consuming and improves the optimization result.

3 STATE OF THE RESEARCH

3.1 Optimization of stress for shrink-fit connections

Numerous studies have been conducted to optimize the stress on cylindrical press connections. There are simple approaches to geometrically adapting the hub edge to reduce radial stress peaks in the area of the hub edges (Kollmann, 1981; Zhang *et al.*, 2000; Blacha, 2009). However, computational analyses have revealed that the stress peak's root cause is due to the geometrically induced increase in stiffness in the vicinity of the hub edges, which is displaced using simple optimization approaches in the longitudinal direction as in Figure 1 (Dausch *et al.*, 2022). This assumption does not apply to all design optimizations and typically occurs with chamfers. For additively manufactured hubs, there is the possibility of integrating stiffness-reducing structures to optimize the stiffness specifically and, thus, the state of stress (Kröger *et al.*, 2018).

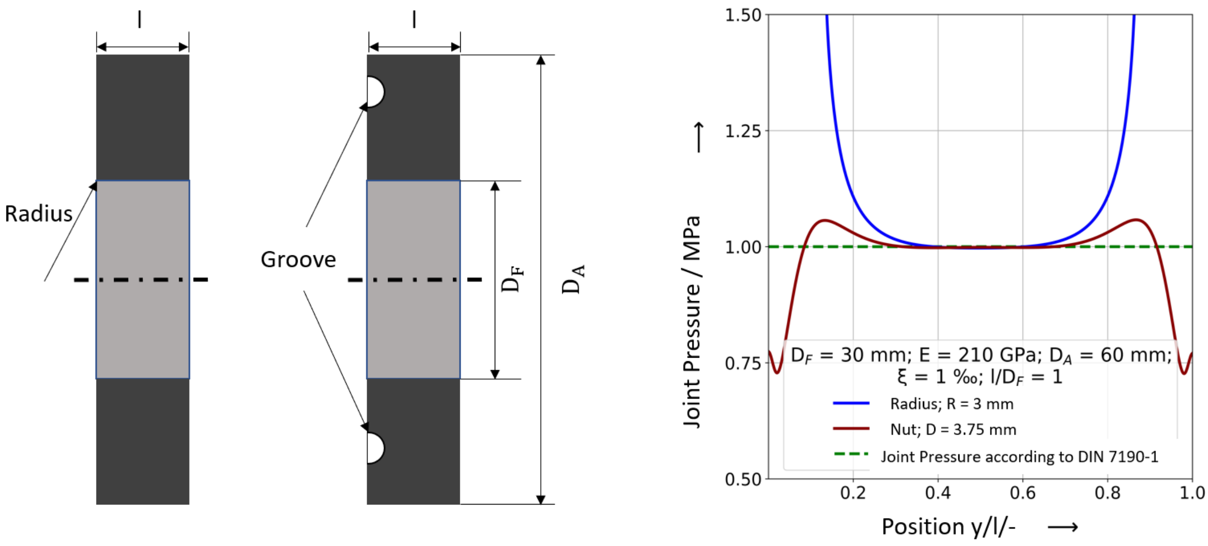

Figure 1. Simple optimization options based on (Falter et al., 2022) (left) and associated, numerically determined joint pressure curves (right)

(DIN7190-1, 2017b; DIN7190-2, 2017) specifies the design of cylindrical interference fits and thus also for shrink-fits discussed here. Either elastic-plastic or linear-elastic designs are possible. In industrial practice, linear elastic shrink fits are typically preferred due to a lack of experimental validation (Falter *et al.*, 2023; Kröger and Binz, 2020). The transmission of forces and torques with this kind of connection relies on a frictional connection. It is made possible by a geometric interference between the shaft's outside diameter and the hub's internal diameter (Kollmann, 1981). When this impact of interference after joining is removed, elastic deformations lead to triaxial stress (Leidich, 2008). The radial and tangential stress over the interface inside the shrink-fit connection is not proportionate under that stress setting. In the interstice region of the connection, the radial stress

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equals the pressure within the interface and decreases toward the exterior. A tangential tension is produced by the hub's elastic expansion as well. The joint is primarily pressured by shear forces caused by friction in the axial direction (Dausch *et al.*, 2022; Leidich, 2008).
Zhang (Zhang *et al.*, 2000) used FE method to research interference fit. The old design approach based on the thick-wall cylinder theory has some drawbacks, as demonstrated by their studies of interference fits in ring gear-wheel connections. Lame's equations did not produce satisfactory answers for the interference deformations and stresses. The reason for this is the problem's intricate geometry, which features a narrow ring on a hollow, stepped shaft that extends undefined, substantial distances. He has developed safety factors, which offer a fresh approach to assessing the effectiveness of interference fits.
A process for brittle hub materials, such as monolithic ceramics, ceramic-metal composite materials, and cast iron (Wagner and Binz, 2021; Wagner and Binz, 2011), was developed initially, with which the joint pressure can be optimized by locally adapting the interference. This process is also essential for hubs made of hardened steel for press connections that are subjected to high loads and may be plastically stressed to use the material potential better, while the hubs are stressed evenly without critical stress peaks. With this process, the local adjustment of the geometric interference creates a contoured shaft seat that can be produced using conventional CNC turning. This approach is an excellent way to reduce failure-critical stresses in conventionally manufactured hubs as in Figure 2, but it is time-consuming and requires a high level of expert knowledge (Krautter and Binz, 2015).

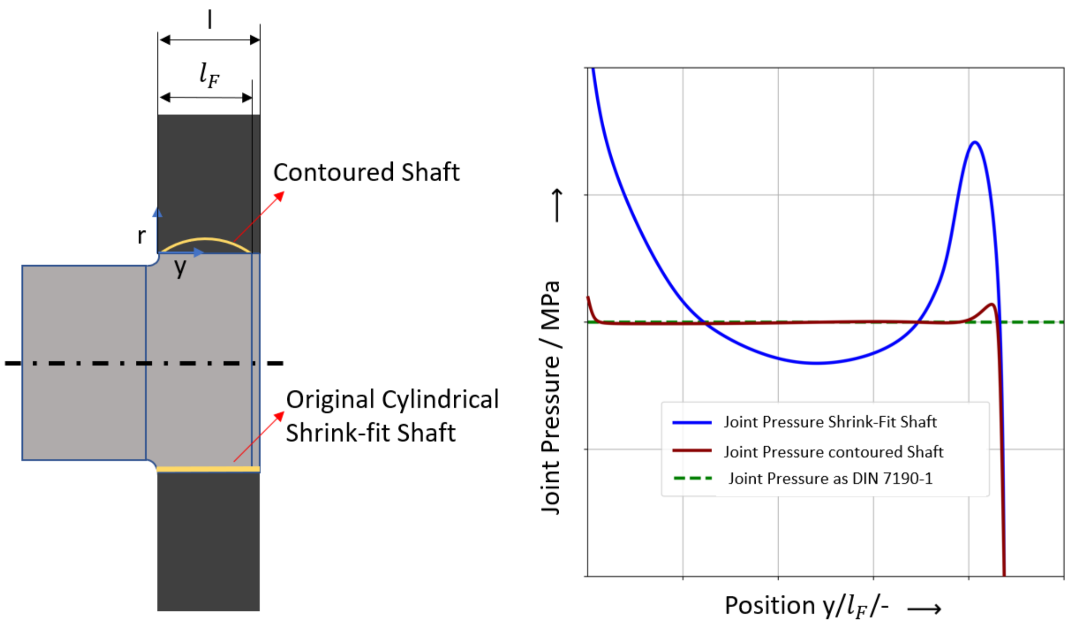

Figure 2. Qualitative, exaggerated representation of a possible contour (left) and exemplary joint pressure profile (right) following (Falter et al., 2022)

The procedure developed by (Blacha, 2009) initially provides a separate simulation of the shaft and hub, with the respective contact surfaces subjected to the desired pressure profile. The resultant deformations on the hub and shaft are combined with applying the contour needed for the compression profile on the hub or shaft. However, Blacha's (Blacha, 2009) approach initially did not consider any stresses in the interface of the connection caused by friction, so Blacha introduced an additional linear boundary condition. However, Krautter (Krautter and Binz, 2015) showed that the frictional forces in the interface of the connection show a non-linear progression. To take this into account, Krautter uses a complex thermomechanical simulation (Wagner and Binz, 2021). So far, contouring can only be used to optimize the joint pressure (radial stress) so that tangential and axial stresses can only be influenced indirectly. In addition, the procedure requires expert knowledge and is complex and time-consuming. With the method presented in Section 4, it will be possible to optimize any stress in a time-efficient manner.

3.2 Artificial intelligence methods

There are different understandings of the term artificial intelligence (AI) and its meaning, some of which need to be differentiated. The term is often already used for automated processes, but artificial

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intelligence instead includes the ability to imitate human thinking and actions and to understand complex relationships (Montague, 1999).
Figure 3 gives an overview of the sub-areas of the term artificial intelligence. In order to perform stress or geometry optimization, machine learning can be divided into unsupervised, supervised, and reinforcement learning (Womack, 2020). Unsupervised learning is often used to identify relationships in existing data sets. In supervised learning, training data link input and output variables and enables the best possible prediction based on the training data by explicating underlying patterns. Reinforcement learning is an agent-based process in which the agent awards a reward for actions previously taken. This method aims to maximize the reward function's value and find the optimal result (Skansi, 2018; Dausch *et al*., 2022; Montague, 1999).

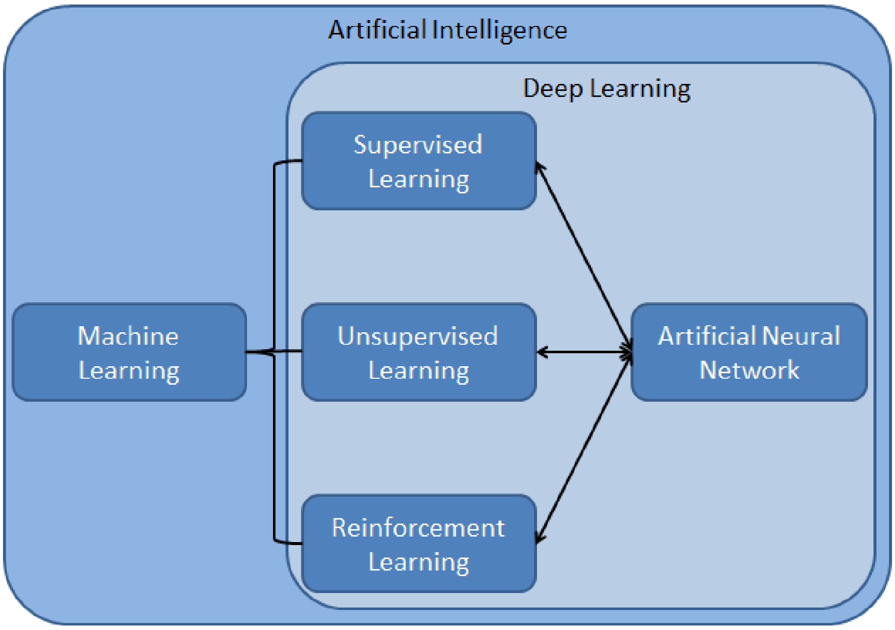

Figure 3. Sub-areas based on Artificial Intelligence in accordance to (Dausch et al., 2022; Falter et al., 2022)

3.3 Artificial intelligence methods to optimize shaft-hub connections

The research aims to replace complex analytical and numerical optimization processes with machine learning methods (ML) and, if necessary, artificial neural networks (ANN) to become independent of complex, time-consuming, and iterative finite element analyses. A first approach to the stress optimization of shrink-fit connections was developed with the help of reinforcement learning. This optimization method aims to automatically optimize stresses, such as joint pressure or tangential stress, to a target value by manipulating the contour of the shaft, i.e., the local interference. (Dausch *et al*., 2022).
Reinforcement learning forms an agent-based optimization environment, with the agent independently executing an action "$\mathbf{a_t}$" for a state "$\mathbf{z_t}$" to influence the target variable in the simulation environment. The action "$\mathbf{a_t}$" is rewarded (approaching the target value) or punished (deviating from the target value) based on a defined evaluation function "$\mathbf{b_t}$" (see Figure 4). With the help of Bellmann's principle of optimality, the so-called quality value (Q value) can be calculated for each executed combination of state "$\mathbf{z_t}$" and action "$\mathbf{a_t}$" (cf. Equation 1) (Montague, 1999).

$$Q(z_t, a_t) \leftarrow Q(z_t, a_t) + \alpha \cdot \left[b_{t+1} + y \cdot \max_a Q(z_{t+1}, a) - Q(z_t, a_t) \right] \quad \text{(Dausch } et\ al.\text{, 2022)} \quad (1)$$

The Q-values are stored in a table whose tabular structure allows these values to be assigned to a unique combination of n states z1 to zn (rows) and m capable actions a1 to am (columns). The agent thus independently learns the difference between good and wrong actions over the iterations so that the algorithm's performance increases with the number of iterations executed (Dausch *et al*., 2022).

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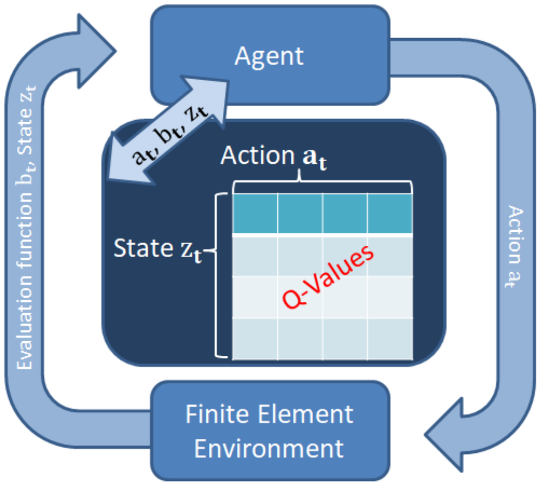

Figure 4. Flowchart for Q-learning based on reinforcement learning following (Dausch et al., 2022)

3.4 Conclusion and demand of further research

For most existing methods for optimizing shrink-fit connections, the disadvantages still outweigh the advantages. Simple changes to the macro geometry, as shown in section 3.1, usually cannot produce an improvement. With the reinforcement learning based optimization method, as shown in section 3.3, improving the quality of the optimization results and simplifying the process is possible. However, the performance of the optimization process still needs to improve because of its coupling with the finite element environment (cf. Figure 4). In order to eliminate this disadvantage in the future, further research should be done by replacing the finite element environment with an artificial neural network, as already stated above in section 2.

4 OPTIMIZATION INDEPENDENT OF FINITE ELEMENT ANALYSES

Optimizations on many machine components, e.g., axles, shafts, and shaft-hub connections, are often recurring, so that past and future results can serve as a data basis for an artificial neural network. In addition, many geometric elements are standardized, such as undercuts, grooves or shaft shoulders. Artificial neural networks can therefore be used to provide efficient support for component optimization, in that the artificial neural network finds the optimal solution for the application based on its experience from the training data sets without having to rely on complex finite element analyses. The following chapters, 4.1 and 4.2, describe how such an approach can be structured using the possibilities of artificial intelligence, how it works, and how artificial neural network training can be applied for this purpose.

4.1 Structure and functions of artificial intelligence approach

The idea of using machine learning (ML) is to use existing simulation data for predicting stress peaks in the shrink fits connection. The structure of ML is summarized in Figure 5 below. The shaft and hub geometry, material, and loadings of each design are represented by several parameters or variables we use to define these designs. There should be enough of these designs to cover the variety of potential designs we anticipate (Sutton and Barto, 2018). After that, we simulate these designs using Ansys to have finite element (FE) results and determine the desired performance standards. The several variables that can be utilized to describe the product design in each run of the FE simulation serves as the model's inputs. These parameters describe the geometry of the designs, the material qualities, the loading scenarios, and any unique characteristics that set the designs apart from one another.

Figure 5. Data extraction and machine learning training (Womack, 2020)

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Many alternative ML techniques could be used to fit such training data for various objectives. A range of ML methods, including deep learning, is available in powerful open-source libraries and paid software that can be employed in the above-described ML models for product creation. Depending on the shaft and hub connection such as press fits or shrink fits, these algorithms change. Deep learning is one of the most potent families of these algorithms for building ML models. It has been used to solve the issue of part design based on the outcomes of physics-based simulation. As part of deep learning, the approach presented here uses an artificial neural network (ANN) supplemented by supervised learning to train the simulation results obtained using FE simulations. The ANN consists of several layers of neurons. The input data is further processed within the networked layers of artificial neurons via several invisible layers - so-called hidden layers - and output in the output layer. With the feedforward approach, networking is only possible at the next higher layer. However, feedback to lower layers could also be made possible with feedback loops (Womack, 2020).

In order to create a computational model, the neural network method was inspired by the human brain's nerve cells (neurons). The input signal is processed by the neuron cell before being transferred to the other neuron. Artificial neurons were created and developed for deep neural network computational models based on this core notion. In this model, a single neuron receives input, adds weight, and then passes the weighted total to an activation function. The neurons in the hidden layers of the model use these activation functions, such as sigmoid, linear, or hyperbolic tangent functions, to produce the desired output. The computation in neurons in a neural network is based on bias, weight, and activation function. The network's activation function acts as a mathematical gate between the current input neuron and the subsequent neurons that exit. Figure 6 shows the structure of the artificial neural network with $\boldsymbol{n}$ layers. Within each artificial neuron, the input data $\boldsymbol{x_j}$ are converted with weighting factors $\boldsymbol{w_j}$ into a transfer function $\sum f(\boldsymbol{x_j}, \boldsymbol{w_j})$, within which the network output $\boldsymbol{y_j}$ is determined as the sum of the weighted input data as in equation 2 (Falter et al., 2022).

$$y_j = \sum_{j=1}^{n} x_j . w_j \tag{2}$$

The activation function Φ, which is often defined as a step function, decides on the further processing of the network input $\boldsymbol{y_j}$ within the neuron. In addition, the activation function Φ can be used to form a non-linearity between the input and output variables, which was previously not possible with the transfer function.

For the reliable results of ANN, it is first necessary for the essential neurons to be created, linked to one another, and weighted when it is created. The ANN created in this way can thus carry out stress optimizations independently of an FE analysis but will initially fail to deliver good results since weightings, links, and functions are not optimally selected.

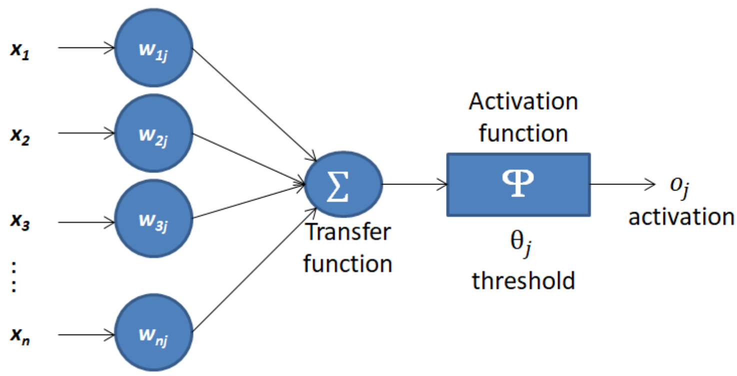

Figure 6. Schematic structure of an artificial neural network (Womack, 2020; Falter et al., 2022)

By training the network, optimization of the artificial neural network in and of itself, the quality of the outputs, and eventually, the performance of the optimization strategy is substantially enhanced (Womack, 2020).

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4.2 Training the artificial neural network

The training of artificial neural networks is of great importance for the quality of the results and the algorithm's performance. The initially created ANN can have incorrect weightings, links, threshold values, etc., which can be eliminated with the help of various learning methods. The training aims to remove existing connections and neurons or add new ones. In addition, the learning methods are used to improve weights, threshold values, and output functions. The three approaches of machine learning – unsupervised, supervised, or reinforcement learning – can be used for this. Which approach is used in individual cases depends on the available data? Only input patterns are specified when training with unsupervised learning, which must be available in a correspondingly high number to train the network. Reinforcement learning uses an agent-based function, similar to that described in Section 3.2, to find an optimal solution for any input data. This approach requires a lot of computing power and is time-consuming since the agent must first find its way around its environment to generate the necessary data. Supervised learning is particularly suitable for optimizing cylindrical shrink-fit interference connections, in which output data is also made available for each input data set. In supervised learning, the target data (training data) can be directly compared with the actual data (the result of the ANN). This procedure is also referred to as backpropagation, whereby the error function is calculated from the target/actual comparison at the level of the output layer. There are also different approaches for the error function, with the mean square error proven itself.

Figure 7 shows an abstract of the data contained in the training data set for the application presented. With the diversity of the training data, the applicability of the ANN can be extended to different use cases. All parameters present in the training dataset can be used later as an optimization target. For example, the slip, the principal stresses, or other measurable or calculable variables can be defined as an optimization target. The prerequisite remains that this variable was part of the learning process.

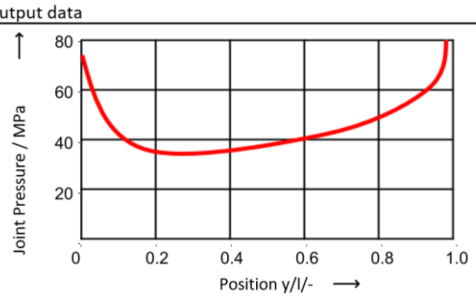
Dataset	Input Data	Value	Unit	Output data
1	Hub length	10	-	
	Shaft dia	0	-	
	Young's Modulus	210	GPa	
	Gap Radius	10	mm	
	Hub length/Gap Diameter	0.5	-	
	uPSC = xi*Gap radius /1000	0.015		
	xi	1.5	‰	
	...	...	...	
i	...	...	...	...

Figure 7. Abstract of a training data set following (Falter et al., 2022)

4.3 Results of optimization

On the way to the optimization result, training data is first automatically generated in a FE simulation environment (here: Ansys Workbench) in a specified parameter field. For ML optimization, the tool needs necessary amount of data to be trained. Ansys workbench in our case helps in achieving the necessary simulation results which can be later used by the ML model for optimization. The parameter field is manipulated automatically using a python script so that training data is generated within reasonable limits defined by the user, which can be used to train the ANN (see Section 4.2 of this article). The simulations required to generate the training data are automatically initialized, calculated, and evaluated using so-called workbench journal files with defined parameters.

The more training data available to the ANN, the more exact optimization results can be determined fully automatically and FE-independently for any application. In order to validate the optimization process, shrink-fit connections should be considered and then measured according to the simulated results. With this measurement method before and after the joining process, the hub expansion can be determined, which indirectly allows conclusions about the prevailing joint pressure, provided that exact material parameters are available. Figure 8 illustrates the result of the approach presented as an example. It can be seen that with the optimization method, the joint pressure curve, which occurs according to (DIN7190-1, 2017b), can be achieved with only minor deviations. Using AI as a solution strategy for shrink-fit optimization enables direct optimization of the failure-critical primary stress and the previously optimized joint pressure, offering the user a significant value-added benefit. This added

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value is distinguished, particularly by greater efficiency attained through automatization and by understanding the relationships between nearby sectors. In this case, learning is accomplished by linking numerical calculations' stress results with the interstice's associated geometric change.

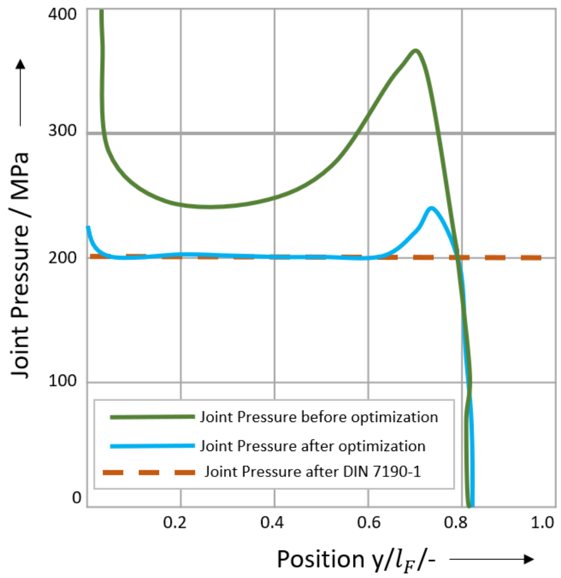

Figure 8. Result of the joint pressure optimized with the presented artificial neural network according to (Falter et al., 2022)

The above-described optimization procedure was finally employed to shrink fits to Figure 1 with straightforward geometry. However, as the algorithm has gone through more rounds, it has gained experience. As a result, a change in the stress profile might be seen. Since there is no direct way to quantify the pressure within the interstice, a tried-and-true indirect method was employed to validate the data obtained. The diameter growth of the hub during the experiment and the numerical simulation are compared using this indirect method. Additionally, a detailed depiction of the materials utilized is necessary for this comparison.

5 SUMMARY AND OUTLOOK

Increases in the power of drive systems require optimizing individual components such as shafts, hubs, or entire assemblies due to the associated increased stress. The complexity of such optimization processes and the associated effort continue to increase. This article describes a procedure with which the necessary expenses and complexity can be reduced and carried out fully automatically and FE-independent in the future. It leads to a significant reduction in the required optimization time. This timesaving represents a significant success factor for using such optimization methods. Future investigations should examine the required training data, as this is still a high expenditure of time.

Additionally, the problem of the provided procedure's generalizability needs to be resolved. Using AI as a solution strategy for contour optimization enables direct optimization of the failure-critical primary stress and optimized joint pressure, offering the user a significant value-added benefit. A user interface design for industrial use should also be encouraged because it permits use by inexperienced individuals.

These remaining issues can be resolved by the RL-based optimization technique discussed in Section 4. Because the developed algorithm is easily adaptable to any shrink-fit geometries as shown in Figure 9, the complexity of the user's work is decreased. The graph shows different iterations to be accommodated in optimizing the joint pressure. The peak value of the simulation has a stopping criterion, which concludes with the 95% and 105% of the DIN 7190 calculated value. The iterations here are compared between the simulation results and calculated joint pressure. Implementing RL into the FE-based optimization of a shrink fit offers the option that contouring can generate stress profiles along the interstice. The user merely needs to specify the desired interference and the geometry to be optimized. Additionally, any stress, such as the tangential stress, which is essential for the failure of the shrink fit, can be used as an optimization parameter in place of the joint's pressure, resulting in better material utilization.

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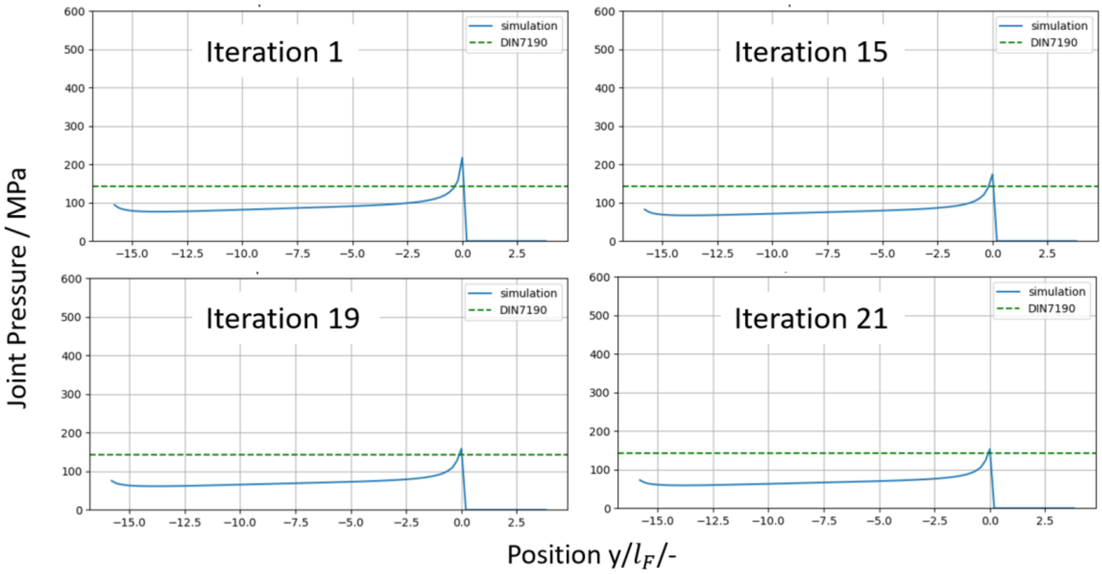

Figure 9. Joint pressure optimized with several iterations to improve the predictions

It will steadily lessen the level of expertise necessary to identify solutions, enabling designers to do such optimization with little effort. Future neural networks may also be expanded to include optimization based on reinforcement learning, which enters the realm of deep artificial intelligence. The neural network can assist in determining the optimal action within a continuous solution space in that usage case, further enhancing the optimization outcomes. The optimization algorithm is flexible enough to be modified for various uses besides this one.

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