Testing for Welding, Joining or Additive Manufacturing Applications

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Transferability of ANN-generated parameter sets from welding tracks to 3D-geometries in Directed Energy Deposition

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Abstract: Directed energy deposition (DED) has been in industrial use as a coating process for many years. Modern applications include the repair of existing components and additive manufacturing. The main advantages of DED are high deposition rates and low energy input. However, the process is influenced by a variety of parameters affecting the component quality. Artificial neural networks (ANNs) offer the possibility of mapping complex processes such as DED. They can serve as a tool for predicting optimal process parameters and quality characteristics. Previous research only refers to weld beads: a transferability to additively manufactured three-dimensional components has not been investigated. In the context of this work, an ANN is generated based on 86 weld beads. Quality categories (poor, medium, and good) are chosen as target variables to combine several quality features. The applicability of this categorization compared to conventional characteristics is discussed in detail. The ANN predicts the quality category of weld beads with an average accuracy of 81.5%. Two randomly generated parameter sets predicted as "good" by the network are then used to build tracks, coatings, walls, and cubes. It is shown that ANN trained with weld beads are suitable for complex parameter predictions in a limited way.

Keywords: additive manufacturing; artificial neural network; DED; quality assurance; welding parameter.

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1 Introduction

In recent years, an increasing number of applications for metal-based additive manufacturing have been developed. Apart from technologies that use a powder bed, directed energy deposition (DED) is meanwhile established in the industry. This process enables a high deposition rate by melting metal powders or wires with focused thermal energy while being deposited. This way, a material can be added to substrates and existing surfaces [1], components can be repaired [2], and structures can be built for additive manufacturing [3]. In the powder-based process, 3D structures are built using a combination of a nozzle-blown powder and a laser. Single weld beads are deposited onto each other in a series of layers to create customized components. The bead shapes are mainly influenced by the process parameters such as laser power, scan speed, and powder feed rate. Depending on the machine that is used, other parameters such as spot diameter, focus distance, and shield- as well as carrier-gas-flow are also of importance. Furthermore, build strategy, cooling time, and preheating of the substrate influence the welding process. All mentioned aspects must be considered and adjusted based on the used machine and material to provide the best combination for additive manufacturing.

One material that is widely used in DED is the nickel-based alloy Inconel 718. It is characterized by a high corrosion resistance at high temperatures (up to 1000 °C). Thus, it can be used to produce parts for gas turbines and turbochargers as well as highly stressed components in aerospace [4]. Despite its high potential, up until now, only a few studies have investigated the influence of process parameters on geometries produced with Inconel 718. A study by Corbin et al. [5] deals with the influence of the parameters such as laser power, powder feed rate, working distance, and substrate preheating on the geometry of a weld bead. This study concludes that laser power has the greatest influence on bead width, and that working distance has the greatest influence on bead height as well as the angle of repose. In addition, substrate preheating was found to increase the effects of varying laser power on bead height and width. By applying linear regression, the data were used to create empirical models to predict weld bead geometry. Kistler et al. [6] investigated the effect of the same parameters on the microstructure, fusion zone morphology, and hardness of a weld bead. Microstructure, hardness, and geometry of the fusion zone were considered as quality characteristics. It was shown that laser power and scan speed have a linear effect on the width and area of the melt zone. In this case, the greatest effect was achieved by the laser power. Preheating the substrates increased the width of the fusion zone and resulted in more uniform hardness throughout the welding process. Bax et al. [7] dealt with the significance of laser power, powder feed rate, and scan speed on weld beads as well. For this purpose, specific process parameter maps were created based on experimental tests and a semi-empirical correlation from findings in the literature. It can be shown that some correlations are valid regardless of machines and materials, but not everything is generally transferable. It is pointed out that the evaluation of individual beads is the prerequisite for high-quality coatings and 3D structures.

For the evaluation of weld beads, bead width and bead height, as well as burn-in depth, are usually considered. Several investigations deal with the dependencies of these target variables. In general, there are two main approaches: Statistical design of experiments (DoE) and the application of artificial neural networks (ANNs).

Graf et al. [8] used a full factorial experimental design to describe the influence of the parameters such as laser power, spot diameter, scan speed, and powder feed rate on both the bead width and height. It was demonstrated that laser power has the most significant effect on bead width. By contrast, scan speed and powder feed rate were shown to have a statistically significant influence on the bead height. The prognosis based on the empirical model indicates that, especially with regard to the bead width, there is still potential for optimization. Similar research was performed by Ermurat et al. [9] using the Taguchi optimization method. Laser focus distance, working distance, feed gas flow rate, and scan speed were varied to apply minimally dimensioned weld beads. Again, it was shown that significant influences on the bead geometry, in this case, mainly the laser focus distance, can be identified using DoE. Jinoop et al. [10] used the DoE approach as a full factorial experimental design to investigate the influence of process parameters on the geometry and quality of thin-walled buildups. Limit values for laser energy and powder feed rate, both per unit length, were determined. By evaluating the observed effects, an optimal process window for a defect-free buildup could be identified.

These publications show that the focus of the statistical experimental design is to identify the influence of process parameters on defined target variables to increase the process knowledge. By contrast, when using neural networks, the focus is on predicting the target variable as accurately as possible based on input data. Since this is a black box approach, the effects of individual input parameters are usually not determined. Song et al. [11] compared both tools for the prediction of geometric characteristics in DED and concluded that the use of statistical DoE is appropriate if the prediction does not require a high degree of accuracy, and in addition, low costs have to be considered. Neural networks are advantageous when the data points are not based on a statistical experimental design, and accuracy requirements are comparably high. The predictive ability of neural networks has already been extensively studied, as shown by the following publications. Saqib et al. [12] investigated the influence of laser power, scan speed, powder feed rate, focal length, and focus position on the weld geometry for P420 fine-grain structural steel. The predictive abilities of the analysis of variance and a neural network were compared. This work shows that the best match between the predicted and actual values is achieved by the neural network. An accuracy of 96.3% between predicted and experimentally determined validation data was achieved. The 32 data points used during the experiment were generated by a central composite design. A similar approach was taken by Mondal et al. [13], who also compared the analysis of variance to neural networks. The material used was a nickel-based alloy. Based on a Taguchi plan, nine experimental points were generated to predict the bead width and the penetration depth. The prediction performance of the neural network was 95.3% for the bead width and 96.9% for the penetration depth. Within the context of another publication, the bead height could be predicted with an accuracy of 72% [14]. Guo et al. [15] investigated the influence of laser power, scan speed, and powder feed rate on the geometry and hardness of a weld bead. Based on a 3^4 experimental design, 81 experimental data points were generated using a cobalt alloy. Contrary to other research, the neural network was designed to predict optimal process parameters. For this purpose, bead geometry and hardness were used as inputs, whereas laser power, scan speed, and powder feed rate served as outputs of the network. The trained neural network achieved a predictive accuracy of around 90%. Moreover, Feenstra et al. [16] used ANN to determine the process window in DED, regardless of the material. For this purpose, 297 beads consisting of three different materials (Inconel 265, 316L, and Hastelloy X) were produced. The results are used to visualize relationships between volumetric energy density and the energy required to melt a given amount of added powder.

The principal approach for the application of ANN is mostly identical. The existing database is divided up into datasets for training, validation, and testing. Initially, all weights of the neurons as well as all biases are set randomly. In every training iteration, the network calculates output values based on the training inputs. The error between those values and the actual training output values is determined, and neuron weights and biases are updated to decrease the error. During training, weights and biases are constantly optimized until a certain termination criterion is met. Hyperparameters such as network topology, learning rate, and number of epochs can be adjusted using the validation data. When the optimal hyperparameters are found and the training is completed, the network accuracy is finally validated using test data that was not used during training. The described learning procedure is known as supervised learning. Here, in addition to the input data, the provision of output data is of particular importance [17]. On the one hand, neural networks can be trained to predict numerical values, such as bead width and bead height. On the other hand, for classification tasks, different weld bead categories can be determined.

The state-of-the-art shows that with ANN, the prediction of process windows in DED related to bead height and bead width works reliably. Transferability from predicted values of weld beads to three-dimensional additive structures has not yet been investigated. In addition, an evaluation of when the respective target values are suitable for practical applications is missing. One possibility to implement this is a categorization system based on optical quality assessment. In production, manufactured components are often divided up into the categories “good” and “poor” to identify rejects. Weld beads can be categorized with the same principle. The machine operator usually tests different parameter combinations and classifies the weld beads based on practical experience. For the additive buildup, beads rated as “good” are selected and used to create 3D structures. This procedure is mimicked in this work by using ANN. The results of the networks are validated by a buildup of different geometries. The aim is to test whether ANN that has been trained on weld beads can specify suitable parameter sets for complex geometries.

2 Experimental approach

2.1 Material

The nickel alloy Inconel 718 was used both as the substrate and the powder material. The dimensions of the substrate plate are $300 \times 300 \times 10$ mm³.

2.2 Experimental setup

All experiments were carried out using a TRUMPF TruLaser Cell 7020 with three translational and two rotational axes and a 2 kW Yb:YAG disk laser with a wavelength of 1030 nm. The mounted ring jet nozzle has an ideal working distance of 9 mm to the substrate.

First, to provide a database for the neural network, 86 weld beads were deposited. After that, the network was trained to predict the bead quality based on the given process parameters. To evaluate the transferability of the network predictions within the welding process, additional beads, as well as coatings, walls, and cubes, were deposited with new promising parameter sets proposed by the ANN.

The parameters for the 86 initial weld beads were selected based on the process window shown in Table 1. Accordingly, laser power P, scan speed v, powder feed rate $\dot{m}$, and working distance w were varied. For this purpose, a full factorial test plan based on the process limits was applied and expanded by additional randomly chosen points.

Next, the weld beads were visually assessed and categorized into the categories “good”, “medium”, and “poor”. Figure 1 provides an explanation of this categorization.

3 Design of the ANN

Training and evaluation of the ANN was carried out using the programming language Python in combination with the machine learning program library PyTorch. Before being fed into the network, the input data were normalized to ensure an even distribution and a uniform range of values. Apart from that, the data were divided up into training, validation,

Table 1: Process window.

	Lower limit	Upper limit
Laser power, P	200 W	1000 W
Scan speed, v	200 mm min^{-1}	1000 mm min^{-1}
Powder feed rate, $\dot{m}$	3.5 g min^{-1}	21 g min^{-1}
Working distance, w	7 mm	11 mm

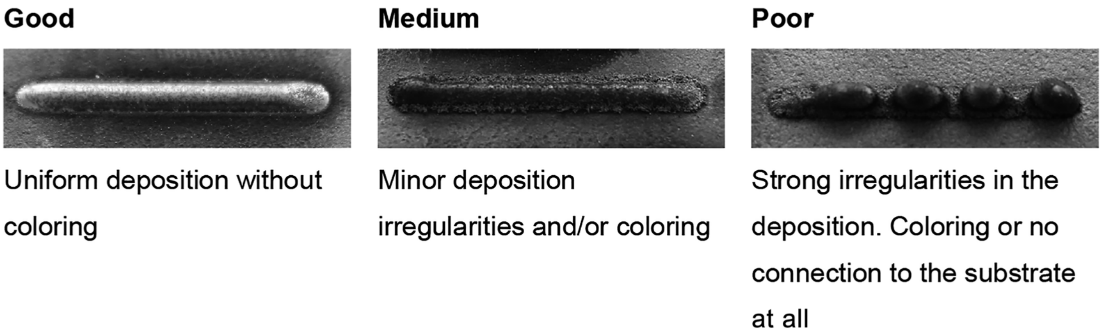

Figure 1: Categorization of welding beads.

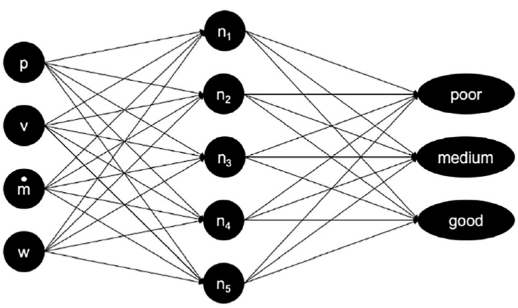

Figure 2: Topology of the ANN.

and test data to prepare for the training phase and to ensure a proper evaluation of the prediction accuracy. In this study, a percentage ratio of 70/10/20 was chosen, resulting in 60 beads in the training set, 9 beads in the validation set, and 17 beads in the test set. The parameter sets of four values, according to Table 1, were used as input, whereas the quality category of the weld bead represented the output value (good, medium, and poor). By trial-and-error method, the number of neurons in the hidden layer was set to five. The topology of the neural network is visualized in Figure 2.

The simple and widespread ReLU (rectified linear unit) function was chosen as the activation function of the neurons. It determines if and how a neuron passes on an incoming signal. The ReLU function sets the output as the given input if it is positive. Otherwise, the output is set to 0 [18]. With cross-entropy loss, a common loss function suitable for classification tasks was applied during training to calculate the error of the respective quality prediction. For this purpose, the ideal probability distribution of each class, for example, [1, 0, 0] if the example belongs to the first class, and the actual probability distribution with numbers between 0 and 1, for example, [0.7, 0.2, 0.1] are compared and processed. Moreover, the Adam optimizer was used as the optimization algorithm to update the weights and biases of the neurons as it is fast and applicable for simple classification tasks [19].

3.1 Transferability on other geometries

Two new randomly generated parameter combinations that had been classified as “good” by the ANN were used to build up more complex geometries. This was done to examine the transferability of such parameter sets on coatings, walls, and cubes. The respective buildup strategies of these geometries are shown in Figure 3.

For the walls, the scan direction was changed after every layer. While building up the cubes, the layer pattern was rotated by 90° after every layer to vary the starting points and to improve the inner structure of the cube. The values of both parameter sets are listed in Table 2.

4 Results and discussion

4.1 Process window and database

All 86 weld beads are shown in Figure 4. Since these beads serve as the basis for the neural network, the aim should be

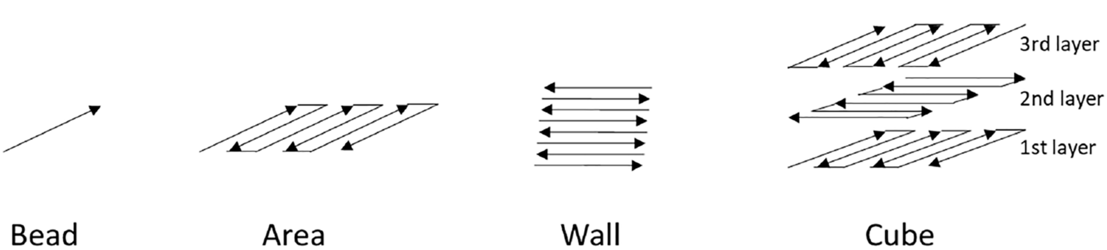

Figure 3: Buildup strategies of the geometries.

Table 2: Predicted parameters.

	Parameter $P_{1,prog}$	Parameter $P_{2,prog}$
Laser power, P	850 W	730 W
Scan speed, v	600 mm min^{-1}	900 mm min^{-1}
Powder mass flow, $\dot{m}$	7 g min^{-1}	3.5 g min^{-1}
Working distance, w	11 mm	9 mm
Overlap, O	50%	30%

to achieve a relatively even distribution among the categories good, medium, and poor. A total of 31 good, 26 medium, and 29 poor beads were generated. Of the poor beads, 11 did not show sufficient attachment to the substrate.

In the literature, the process window for welding beads using DED has already been extensively studied. The comparison with the beads generated in this work confirms the previous findings. So far, the existing research has mostly concentrated on findings regarding the extent to which the parameters affect the bead height, bead width, and penetration. These target parameters are usually considered separately from each other. For example, Corbin [5] and Graf [8] showed that laser power affects the bead width especially. This relationship is due to a larger melt pool if the power input increases. In the case of bead height, the powder feed rate has a significant effect [8]. The more powder is available for the melting process, the higher the structure of the individual beads. However, it should be noted that there is an interaction with the laser power: if there is not enough energy to melt the powder, in some cases, no sufficient melt pool can be created on the substrate. Thus, bonding of the bead is prevented. These findings are necessary for the basic process understanding. However, it is difficult to estimate a process window without any information about when a bead is well or poorly suited for practical applications. In particular, a combined consideration of all target variables to provide a suitable process window for the user is not available.

One way of combining the target variables is categorizing the beads. In practice, the operator often makes an experience-based decision about whether a weld bead is "good" or not. Generally, various factors can be included in this evaluation. In the context of this work, a visual assessment was carried out to indicate whether a welding bead is suitable for further applications. Here, the geometric shape and tarnish colors, which generally indicate an excessive energy input, were considered (Figure 1). A correlation of three optical weld bead categories to the four varied process parameters is shown in Figure 5.

Thus, it appears that laser power has a decisive influence on the categorization. Good beads could only be generated from about 400 W upward, and a low energy input led to poor bead quality. It is also clear that if the laser power input is too high, the beads tend to receive worse ratings. However, there is no clear limit to this effect. Rather, it is strongly related to the scan speed and the powder feed rate. This can be explained by the correlation between energy input and the powder mass to be melted (Figure 5).

Within the scope of this work, it has been shown that an energy per unit length of at least 25 kJ m^{-1} usually produces good beads. This confirms the observations known from prior experiments [5]. Furthermore, it can be stated that a visual assessment gives a good representation of the combination of bead height and bead width. The powder feed rate also has a clear influence on the evaluation of beads. The assumption that too much powder does not ensure a good application is confirmed. A powder feed rate of 3.5 g·min^{-1} to 10.5 g·min^{-1} tends to yield favorable results. However, especially with higher powder flow rates, the quality of the bead depends on other factors, such as the laser power or the energy per unit

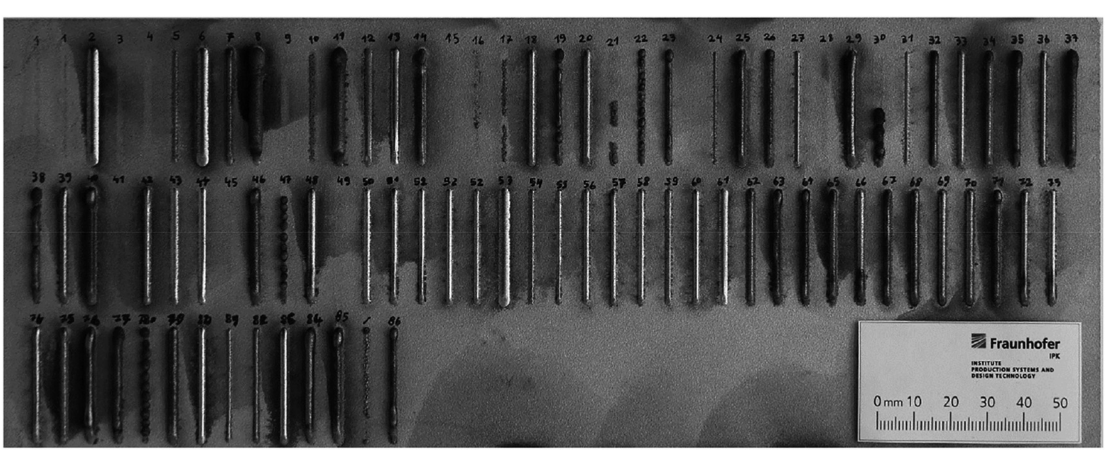

Figure 4: Overview of all welding beads.

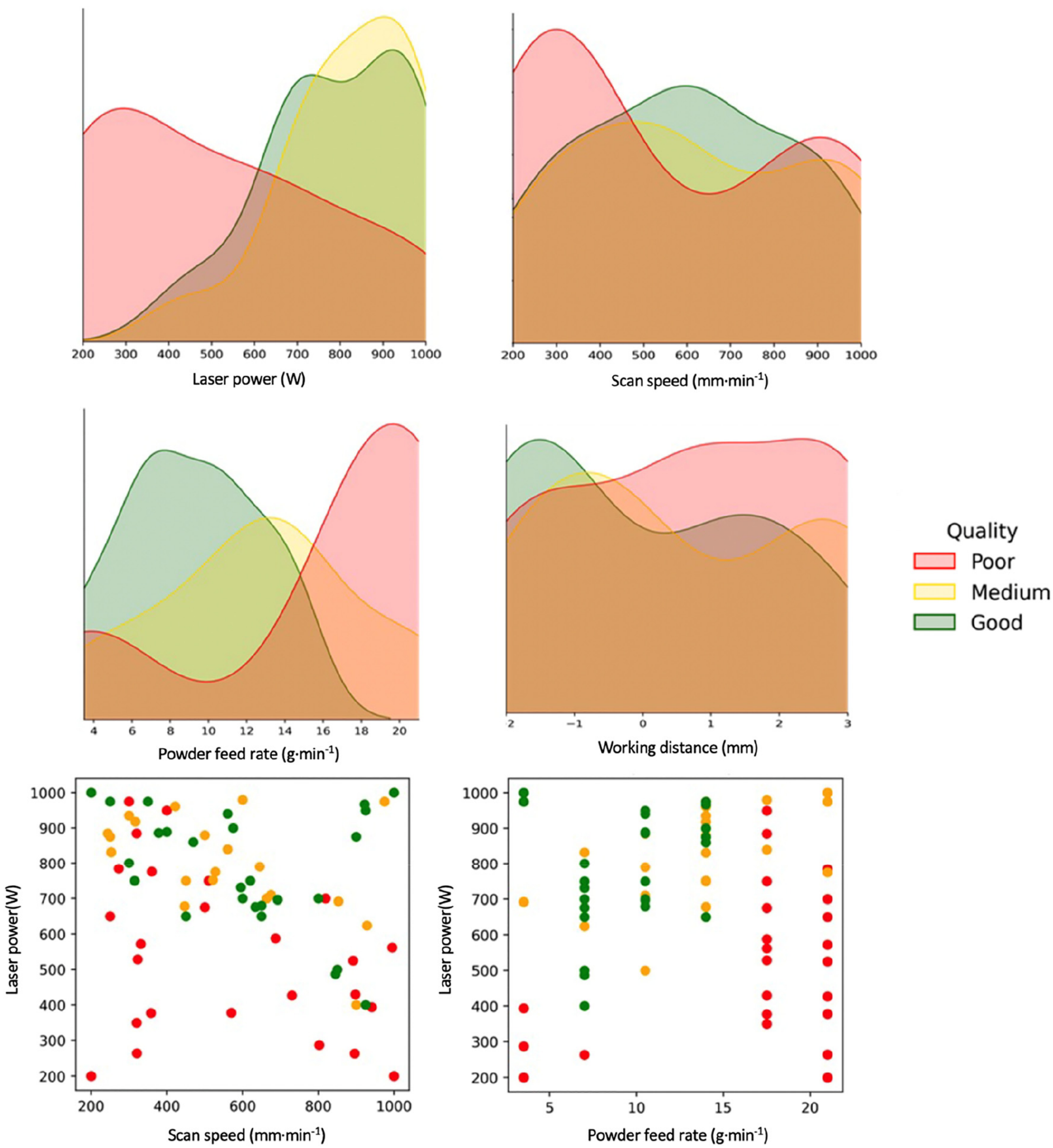

Figure 5: Correlation between single parameters and categorization.

length. Nevertheless, it is generally true that higher powder quantities lead to smaller melt pools, since the introduced powder attenuates the effective laser power, as Bax [7] showed in his investigations. The scan speed has a direct effect on the bead quality as well. Once more, the justification is based on the energy per unit length. For instance, if the scan speed is too low, excessive heat input occurs locally. Furthermore, velocities that are too high result in poor beads. With an unfavorable scan speed, the welding beads either get too voluminous or too smooth. In contrast to the work of Corbin [5], no significant influences on the bead height and thus ultimately on the optical quality evaluation could be detected regarding the working distance. This can be observed by the fact that all quality categories are arbitrarily represented over the entire varied spectrum of the parameter. The different observations are likely attributable to the additional factor of powder feed rate, which was considered in this work. It exerts a greater influence on the buildup of the bead than the working distance and the associated influence on the powder flow. However, based on Corbin's findings, it is assumed that the factor can still influence the additive buildup.

In summary, it was shown that the categorization of weld beads reflects the process knowledge that exists to date. Process parameters declared as significant based on prior experiments are also highly relevant for an optical quality evaluation. Thus, using categorical quality classes as the output of an ANN can be considered reasonable. Furthermore, it becomes clear that the process window is limited by the process parameters. At the same time, the three quality classes must tend to be equally represented in the data set to create a balanced input for the ANN. If one category is overrepresented in the training data, the network learns that the probability of this very category is higher and the prediction accuracy of the network in a real application scenario decreases. In addition, the parameter combinations should not be too narrow to avoid the network from receiving duplicate information for almost the same data point. Thus, it can be concluded that only a limited number of data points are available when using ANN in DED. Generally, it can be assumed that such a limited database, as often also found in the literature, is too small to ensure a high informative value of the network.

4.2 Results of the ANN

In the first step, an ANN was created and trained according to the specifications. After the training was completed, the prediction accuracy was evaluated. For the evaluation, it was considered that the accuracy of the network depended on the random composition of the training and test data set. For this reason, the mean accuracy value over several runs was determined. After 20 runs, the mean prediction accuracy on the test data was 81.5%. Thus, approximately 14 out of 17 beads were categorized correctly on average. All incorrect categorizations were off by just one category. The individual accuracies of the runs are shown in Figure 6.

The ANN trained within the scope of this work reached an average accuracy of 81.5% regarding the bead quality based on four input variables, such as laser power, scan speed, powder feed rate, and working distance. The predictive accuracy is significantly lower than that in similar use cases in the literature. There are several reasons for this.

First, it should be noted that previous studies always chose numeric characteristics to perform regressions with ANN. For instance, most researchers predicted bead height and bead width. Predictions of quantitative characteristics of welding beads are usually easier to make because the target values are distributed in a small range. Qualitative assessments, as performed in the present work, are not always unambiguous. Different operators may already have divergent opinions about whether a welding bead is too narrow or too flat for a specific application. Therefore, their quality evaluation might vary between “good” and “sufficient” or “sufficient” and “poor”. Making a clear assessment is difficult even for experienced operators. Accordingly, the error potential in a corresponding prediction by an ANN is also high.

Another reason for the strongly deviating results of prediction accuracy in the different runs is the limited amount of data. In the studies regarding the applicability of ANN in DED, the findings are generally based on a very small database. Often, data were obtained based on a statistical experimental design and then evaluated by an ANN. The added value compared to statistical evaluation, for example, by ANOVA or regression analysis, is not apparent here. With a systematic data composition, the ANN recognizes, depending on the topology, a very similar mathematical model to the one generated by statistic evaluations. In addition, the creation of a model via ANN has two disadvantages: The mathematical model is not visible, since ANN function as a black box. Only the result is presented, but not the calculation path. aTherefore, the impact of individual parameters cannot be assessed. Accordingly, statistical models offer the essential advantage of generating the process knowledge. Feenstra et al. already pointed out the difficulties regarding the accuracy of neural networks [16]. Despite having a nominal target size, the bead

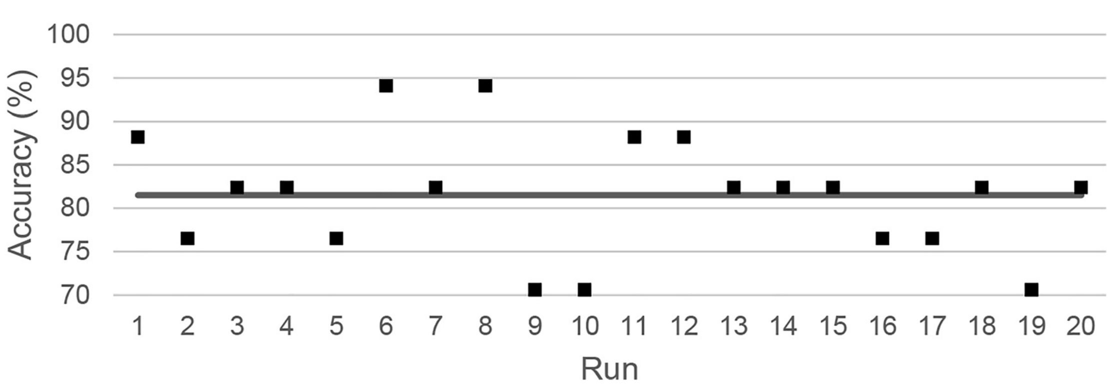

Figure 6: Accuracy of the ANN at 20 runs.

width could only be predicted with an accuracy of 72–78%. The reasons were seen on the one hand in the number of data points and on the other hand in the complexity of the parameters and their interactions with each other. This can be confirmed by the findings in the present work. Furthermore, Song et al. [11] compared the predictive capabilities of statistical DoE and ANN and concluded that the use of DoE is justified, especially if the accuracy of the prediction does not need to be very high and the system has to be designed cost-effectively. By contrast, the use of ANN is reasonable if the accuracy requirements are high, and if the database is not based solely on a statistical experimental design. This can be confirmed by the present work. The data basis was also initially built based on a full factorial experimental design, but only through the extension by random experimental points, the ANN could be trained properly. Especially for categorization, it must be considered that enough data points from all different categories are available during the training. The data basis is decisive for the informative value of the network. Conducted experiments show that the accuracy is about 20% higher if an even distribution of categories in the training data is ensured. This finding can also be applied to quantitative target variables: If the numerical values of the target variable are too close together in the training data, it is difficult for the network to correctly predict outliers in practical application.

The importance of the data basis can be extrapolated from the accuracy distribution in Figure 6. All networks were trained and tested with the same topology on the same database. However, the data points for training and testing were randomly selected in each case. This has an enormous influence on the accuracy of the neural network. Runs showing correct predictions for almost all beads were observed. Nevertheless, the capability of the network is limited. If irregularities occur in the process, the probability is high that the network will not be able to identify them. For this reason, a general estimate of the capability of a network is only possible if different runs are evaluated, and if an average value is calculated. If the accuracy is too low, optimization measures must be taken regarding network topology, boundary conditions of the network, and data basis.

4.3 Transferability to complex geometries

Beads, coatings, walls, and cubes were created based on the new parameter combinations predicted as “good” by the ANN. The results are shown in Figure 7.

The results show that a parameter set cannot be transferred to different geometries without further adjustment. Although both parameter combinations predicted as “good” work well for beads, it must be considered for coatings that the overlap factor is added as an unknown influence. In the present case, this parameter was chosen freely based on previous findings. It is known that a desirable overlap ratio is between 30 and 50%. Depending on the bead geometry, it must be varied accordingly within this interval. Due to the missing information in the training data, quality predictions for coatings or other geometries, such as cuboids, are difficult.

In the present case, however, it was shown that with the selected overlap ratio, the parameter sets can be transferred to coatings. This depends on, among other things, the fact that the shape of the bead is decisive for good coatings. Bax et al. have shown this already in their research [7]. The predicted beads have a uniform structure with good substrate connection and without tarnish. It can be observed that the bead height of the parameter $P_{2,prog}$ is significantly lower than that of $P_{1,prog}$. The bead height is especially important in additive manufacturing. This can be observed well for the geometries such as wall and cube. The walls are judged from sufficient to poor.

In the case of $P_{2,prog}$, the insufficient bead height is reflected in the wall structure. With 40 welded layers, a height of 7 mm was achieved. It can be concluded that the parameter set is not suitable for building wall structures. By contrast, $P_{1,prog}$ yields more favorable results. An additive structure with 40 layers achieved a wall height of 20 mm. In the optical quality evaluation, however, it is only classified as “medium”: The buildup shows a wavy contour and strong powder adhesion. Accordingly, an ideal wall buildup could not be achieved with any of the parameter sets predicted as “good” and suitable for beads by the ANN. The optimal parameter set for a wall structure depends on various factors. In particular, the laser energy and the powder feed rate per unit length are decisive, as shown in the work by Song et al. [11].

They stated that these factors ideally range from 105 kJ m^{-1} to 210 kJ m^{-1} and 4 g m^{-1} to 12.5 g m^{-1}, respectively, for an ideal buildup of thin walls using Inconel 718 material. Such specific findings are generally not easily transferable. Especially, the laser beam systems and the materials used play an important role [7]. However, the values certainly provide an orientation range. In the case of the predicted parameter sets of this work, the laser energy introduced per unit length is significantly lower. In detail, a laser power of 85 kJ/m is introduced with $P_{1,prog}$ and about 49 kJ/m with $P_{2,prog}$. This is well below the optimum range. Thus, it can be concluded that the energy introduced is too low for an optimum wall structure. The powder feed per unit length, by contrast, shows that the predicted parameters of 13.3 g·min^{-1}

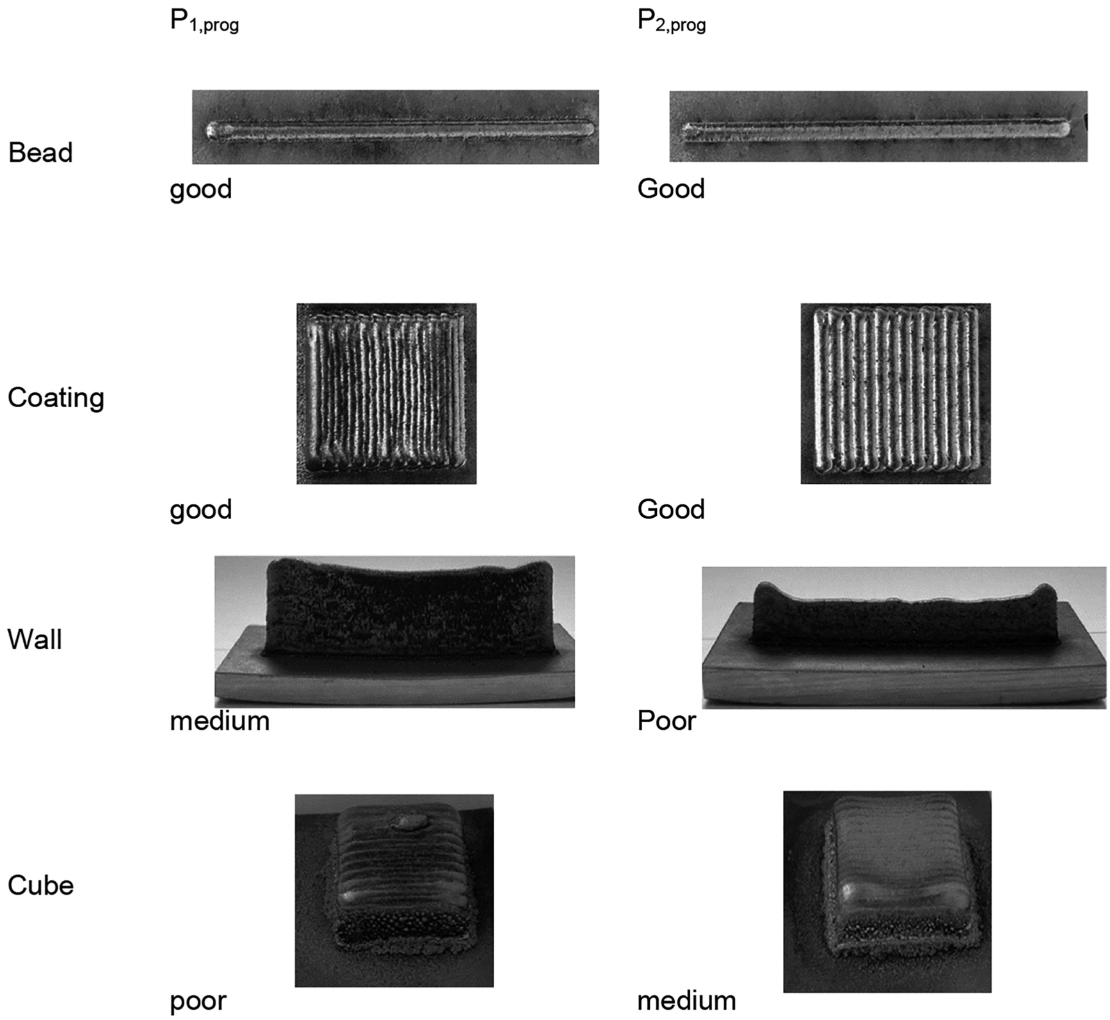

Figure 7: Transferability of the predicted parameters to complex geometries.

($P_{1,prog}$) and 5.48 g·min^{-1} ($P_{2,prog}$) are within or close to the defined optimum parameters. This factor describes whether sufficient powder is available for the ideal buildup. In particular, it plays an essential role in the appearance of a weld bead. Therefore, it can be explained that the powder feeds per unit length show a better match with the optimum range than the combination of laser power and scan speed. It can also be deduced well as to why the thin-walled structure could not be successfully implemented. For future developments, it is therefore conceivable to provide such additional information to the network as an additional input.

The buildups of the cubes show similar results: an optimum structure was not achieved with either of the two parameter sets. In the case of cube 1, an excessive amount of energy and thus an excessive amount of heat is introduced. This leads to strong tarnish and shape deviation. Regarding the number of layers, it can be observed that a significantly higher application rate is achieved with a lower number of layers. Cube 1 was buildup with 20 layers and reached a height of 16 mm. By contrast, cube 2 was deposited with 40 layers and has a height of only 10 mm. In addition, cube 2 also shows significant elevations at the corner points. This can be explained mainly by the buildup strategy. In the present investigations, the pattern was rotated by 90° for every new layer. It is advisable to build frames between layers to avoid strong shape deviations, especially at the corner points. Generally, it is important to bear in mind that with complex components, an optimum buildup strategy tailored to the geometry is necessary for achieving satisfactory results in practice. In addition, cooling times and preheating and postheating of the substrate play a decisive role in a successful buildup. However, the ANN cannot take any of this information into account for classification tasks.

In conclusion, the prediction of welding parameters for additive manufacturing by DED based solely on welding beads does not work consistently. In additive manufacturing, the beads are no longer buildup on a flat surface of the substrate but are strongly influenced by the shapes of the previous beads and layers. In this case, the buildup strategy plays a decisive role to compensate for such unevenness. To apply ANN successfully, the networks require more information. However, it must be considered that for any additional information as input, the number of required data points increases accordingly.

5 Conclusions

In this work, the prediction ability of an ANN that was trained with welding beads was tested on different geometries. To generate training data for the network, weld beads were deposited and then classified into quality categories. Two new random parameter sets classified as "good" by the trained ANN were then transferred to more complex geometries. The following conclusions can be drawn:

– ANN that are trained with welding beads can be applied for parameter prediction in DED in a limited way. Process understanding of bead deposition can be increased, and an optimal process window can be identified. However, the process conditions for coatings and especially for Additive Manufacturing (AM) applications are significantly more complex, so that transferability is only possible to a limited extent. Nevertheless, the knowledge of optimized weld bead parameters is an important prerequisite for a stable and economical process. It is therefore recommended to investigate beads through DoE to identify significant influences. Based on this knowledge, AI methods can be used to efficiently implement quality assurance in DED. For instance, quality-relevant characteristics such as mechanical properties can be predicted to reduce downstream inspections.
– The selection of an optimal buildup strategy is a major challenge in additive manufacturing and thus, an obstacle to the use of ANN. A variety of possible approaches are used with consideration for the geometry and requirements for the mechanical characteristic values. The ANN in their present form trained with currently available data sets are not able to master this complexity.
– One possibility to deal with the complexity of coatings and AM applications and thus to better train the ANN is to extend the data basis. Up to now, beads have always been used as the data basis in the literature. A new approach would be to use coatings or cubes. This way, for instance, parameters such as overlap ratio and cooling times could serve as an additional input for the ANN.
– Furthermore, it is possible to generate measurement data during the process and feed that information to the ANN. Today, many DED machines already have basic sensor systems for process monitoring. For example, the average temperature or melt pool size could contain important information to significantly improve quality assessments by ANN even for complex geometries.

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