

An Approach for Adaptive Parameter Setting in Manufacturing Processes

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Abstract: In traditional manufacturing processes the selection of appropriate process parameters can be a difficult task which relies on rule-based schemes, expertise and domain knowledge of highly skilled workers. Usually the parameter settings remain the same for one production lot, if an acceptable quality is reached. However, each part processed has its own history and slightly different properties. Individual parameter settings for each part can further increase the quality and reduce scrap. Machine learning methods offer the opportunity to generate models based on experimental data, which predict optimal parameters depending on the state of the produced part and its manufacturing conditions. In this paper, we present an approach for selecting variables, building and evaluating models for adaptive parameter settings in manufacturing processes and the application to a real-world use case.

1 INTRODUCTION

Product and process quality is playing an increasingly important role in the competitive success of manufacturing companies (Robinson and Malhotra 2005). As a consequence, this trend forces manufacturing companies to further improve their production (Wuest et al., 2014).

In general, quality is defined as the degree to which a commodity meets the requirements of the customer (DIN EN ISO 9001:2015). In this context, customers are not only the users of final products; they can also be other companies in a supply chain network. When a company is a supplier of components, which serve as assembly parts in a final product, then important quality requirements are dimensions of parts, which have to be within predefined tolerances. There exist International Tolerance Grades of industrial processes, which identify what tolerances a given process can produce for a given dimension (ISO 286-1:2010). If an industrial process is more precise, less scrap is produced or even a higher tolerance class can be achieved and the produced components can generate more profit for the company.

The appropriate and prompt selection of process parameters in manufacturing processes plays a significant role to ensure the quality of the product, to

reduce the machining cost and to increase the productivity of the process (Pawar and Rao, 2013). In practice, the adjustment of process parameters to get dimensions of a produced part in predefined tolerances can be a difficult task. Traditional control systems rely on rule-based schemes, expertise and domain knowledge of highly skilled workers or on trial and error. Furthermore, modern manufacturing processes are becoming more and more complex and modelling every aspect of a process in a rule- and expert-based system is getting challenging or even impossible.

The phase of parameter adjustment consumes precious production time where scrap parts are processed. Once an acceptable setting of parameters is obtained, it is common to remain it unchanged for the whole production lot. However, each part processed has its own history and slightly different properties. Individual parameter settings for each part can further increase the quality and reduce scrap. Machine learning (ML) methods offer the opportunity to generate models based on experimental data, which automatically predict optimal parameters depending on the state of the produced part and its manufacturing conditions.

This paper contributes to the application of ML methods for parameter setting in manufacturing processes and addresses the following research ques-

tions:

- How can ML methods be integrated in a framework for adaptive parameter setting?
- Which ML methods are suitable in models for adaptive parameters settings?
- Which accuracy can be reached when predicting quality measures and is this accuracy sufficient for practical applications?

We provide the related work to this topic in Section 2 and present the methodology of the developed approach in Section 3. Afterwards, we apply and evaluate our approach in a use case based on real-world manufacturing data in Section 4. Concluding remarks follow in the final Section 5.

2 RELATED WORK

There exist literature of parameter optimization and parameter setting for different kinds of manufacturing processes.

For the injection moulding process there are different approaches. A common design method to reduce the amount of simulation runs and to consider interaction effects of parameters is the Taguchi method (Oliaei et al., 2016; Tian et al., 2017). It is used to find a better initial point for the optimization and to reduce time for solving the problem. For the optimisation of a multi-objective problem a combination of Response Surface Methodology (RSM) and non-dominated sorting genetic algorithm II (NSGA II) is used (Park and Nguyen, 2014; Tian et al., 2017). The function generated out of the RSM is optimized with the NSGA II. As initial values for the first iteration of the genetic algorithm it is possible to use results from the Taguchi method or to generate random values within a set range. Oliaei et al., (2016) used an Artificial Neural Networks (ANN) with the learning algorithm of back-propagation to optimize the quality. In their work, they compared the results of the Taguchi method with the results of the ANN. In both methods the same sample set was used. The results show that there is a slight difference between them.

In Additive Manufacturing unsuitable process parameters influence the quality of 3D printed parts adversely. There exist various approaches to use Machine Learning to choose optimal process parameters for different technologies in 3D printing (Fused Deposition Modeling, Selective Laser Melting or Sintering). The most popular method used is Artificial Neural Networks (ANN) (Collins et al., (2014), Ding et al., (2016)) which performs good due

to the provided flexibility. Although comparisons show that in some cases regression is only slightly worse (Xiong et al., (2014), Mohamed et al., 2016).

Cook et al., (2000) develop an ANN to model the relationship between process operating parameters and a critical strength parameter in a particleboard manufacturing process. Then a genetic algorithm is applied to determine the process parameter values, which result in desired levels of the strength parameter.

Park and Kim (1998) present a review on artificial intelligence approach which attempt to automatically adapt and optimize the CNC machining parameters based on sensor information in real time. Again ANN is the dominating method in this field of application.

Venkata Rao and Kalyankar (2013) present an approach for process parameter optimization in a multi-pass turning operation. They developed a teaching-learning-based optimization algorithm, which outperforms other optimization methods in their multi-objective and single-objective examples. It is stated that this algorithm can be easily modified for parameter optimization of other manufacturing processes, such as casting, forming and welding.

An approach for estimating control parameters of a plasma nitriding process is presented in Kommenda et al., (2015). They solve inverse optimization problems to find good combinations of parameters such that desired product qualities can be fulfilled simultaneously.

As already slight variations of the product state during production can lead to costly and time-consuming rework or even scrap, Wuest et al., (2014) suggest an approach based on recording of the individual product's state along the entire production process. Whereas condition monitoring is mostly focused on a single manufacturing process, monitoring of the whole manufacturing programme has to be further investigated (Choudhary et al., 2009). Wuest et al., (2014) suggest a combination of cluster analysis and support vector machines (SVM) to achieve the goal of improved quality monitoring. They provide a theoretical example to illustrate the potential of the approach, but the application to a real-life manufacturing process is missing.

This paper applies the concept of tracking the individual product state to predict quality relevant requirements of finished manufactured parts. As the considered target variables are numeric (e.g. dimensions of the part), instead of classification (e.g. good and bad parts), methods for regression are chosen. Furthermore, the developed approach is evaluated on data from a real-life industrial environment.

3 METHODOLOGY

In this section, an approach for the setting of process parameters of a manufacturing process is developed. The setting of the process parameter is adaptive for each produced part depending on its properties and previous manufacturing conditions. First, the collection of the necessary process and product data is presented. Then the basic concept of the parameter setting is introduced. Based on this concept the next steps are data pre-processing, the selection of a suitable machine learning model and its evaluation based on different criteria.

3.1 Data Collection

We consider a multi-stage manufacturing process, consisting of N consecutive steps (Figure 1). In each step a physical transformation of the product is performed, so that, starting from the raw material in step 1, the final product is finished in step N . The approach, which is developed in this section, refers to parts of one specific product type. If there are multiple product types in the manufacturing system, it is possible to apply this approach to each type separately.

The basic idea is to record all relevant product and process variables of each manufactured part. Due to variations in material properties and manufacturing conditions (e.g. machine and tool conditions, environmental conditions, influence of human workers) each part will be characterised by individual values of the variables, which describe the life cycle of the part during the manufacturing process. This concept is introduced by Wuest et al., (2011) as product state based view.

In our approach, it is important to distinguish between independent and dependent variables. Some of the product and process variables, like the type of raw material or the adjustment of process parameters, can be manually selected and are not influenced by other recorded variables. Other variables, like quality relevant properties of the part, depend on the values of multiple variables, although the precise relationships are not known in practice.

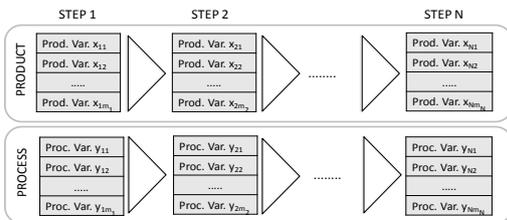


Figure 1: Product and Process Variables.

3.2 Basic Concept

The final objective is to determine appropriate, adaptive parameter settings of the last production step for a specific part based on its manufacturing life cycle to fulfil the quality requirements. The selection of multiple process parameters is likely to deliver a manifold of solutions whereas the fulfilment of multiple quality requirements won't be feasible in general. Therefore, we restrict our approach to the determination of one process parameter of the last production step (u), in order to fulfil a single relevant quality requirement (z). The considered process parameter belongs to the independent process variables of step N and the quality requirement is part of the dependent product variables of step N . In our approach, we take only numeric quality measures into account, like critical dimensions or the weight of the part.

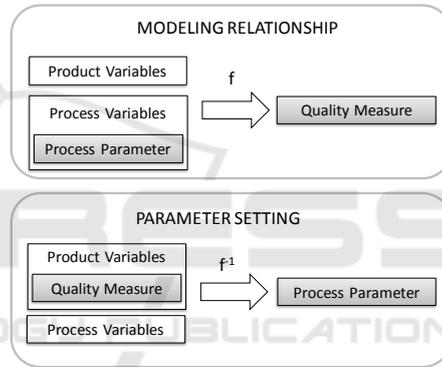


Figure 2: Basic Concept.

To achieve this goal, we suggest a two-step approach (see Figure 2). First, we model the relationship between the quality measure and relevant product and process variables, including the selected process parameter, by a function f .

$$\hat{z} = f(x_{ij}, y_{ij}, u) \tag{1}$$

This function enables the prediction of the relevant quality measure (\hat{z}) based on the life cycle of an individual part. Then we calculate, if possible, the inverse function of f . This inverse function f^{-1} enables us to set a predefined optimal value for the quality measure and to estimate the necessary process parameter (\hat{u}) under consideration of the actual product and process variables of a specific part.

$$\hat{u} = f^{-1}(x_{ij}, y_{ij}, z) \tag{2}$$

If f is no bijective function, Eq. (1) has to be solved

implicitly, for example by using Newton's method. However, in this case, multiple solutions can exist.

3.3 Data Pre-processing

There are some data pre-processing needed, in order that we are able to apply regression models in the first step of our approach. If there are nominal variables in the set of the recorded product and process variables, they have to be replaced by binary attributes (dummy coding). A nominal variable with m levels has to be transformed in $m-1$ dummy variables with 0 and 1 as possible values.

The second point, which has to be checked, is the collinearity of attributes, since it reduces the accuracy of the regression model. It is likely that some of the recorded product and process variables are correlated. For example, if the height of the part is measured after each process step, i.e. N times, then these N variables are presumably more or less correlated. Here not only correlation between two attributes has to be considered, also multicollinearity has to be detected. A way to assess multicollinearity is to compute variance inflation factors (VIF). The smallest possible value for VIF is 1, which indicates no collinearity. Attributes with VIF values that exceed 5 or 10 should be dropped from the regression analysis (James et al., 2013).

In some cases, it can be useful to create new features based on the recorded process and product variables to increase the accuracy of the applied machine learning model. Using domain knowledge of experienced workers of the considered manufacturing process can help in feature engineering as well as in the selection of relevant variables.

3.4 Model and Variable Selection

For modelling the relationship between product and process variables and the quality measure, regression models and artificial neural networks (ANN) are applied.

ANN are a flexible and widely spread method for modelling complex relationships (Widrow et al., 1994). A multi-layered architecture is built up from one or more hidden layers placed between an input and an output layer. Each layer consists of several highly interconnected processing units, called neurons, which sum weighted inputs and apply an activation function for generating the output. The weights are determined by training the neural network with the goal to minimize the error between the actual and predicted output values. Then a separate test set of data is used to estimate the network's performance

on new data. After all, the neural network serves as a function that maps input values (product and process variables) to output values (quality measures). Although ANN deliver good models for prediction, regression models are more transparent and easier to interpret when applying them in the practice of manufacturing companies.

When we choose a regression model, we first have to answer the question, which variables from the set of the recorded product and process variables of the whole manufacturing process have the biggest influence on the quality measure and therefore should be used for modelling. From the point of view of the practitioners in the companies, it is desirable to get a model with a good accuracy, which only depends on a few variables. This configuration would reduce the cost and time for measuring and recording a huge amount of data from the production process. However, using too few variables will lead to bias and the inclusion of too many of them is likely to cause overfitting. A variety of methods for selecting variables is available (Miller, 2002; James et al., 2013), such as

- Best subset selection
- Forward selection
- Backward elimination

Best subset selection fits a model to each combination of possible numbers of prediction variables. If there are p prediction variables, then 2^p models are trained and the best of them is selected. Because of the computational effort, the application is only possible, if p is not too high. Otherwise, stepwise methods, like forward selection and backward elimination, are alternatives, which only explore a restricted set of combinations. Forward selection starts with the best model containing only one variable and increases the number of variables in each step by one. Conversely, backward selection starts with all possible prediction variables and reduces the number in each step by one.

Regardless of the applied method for variable selection, performance measures for the comparison of different models are necessary in order to pick out the best model (Murtaugh, 2010). Different techniques for model evaluation are introduced in the next subsection 3.4.

If linear regression is not adequate to generate models with good performance, the linearity assumption can be relaxed by introducing polynomial terms or generalized additive models. The selection of the applied function types can be motivated by known physical relationships of product and process variables.

3.5 Model Evaluation and Parameter Setting

Different models based on different sets of prediction variables have to be compared in order to select the best one. Residual Sum of Squares (RSS) and R^2 are not suitable measures because they are based on the training data and are getting better, when the number of prediction variables increases. For model selection, the test error has to be estimated directly (e.g. by cross-validation) or indirectly (by adjusting the training error to account for the bias due to overfitting). In the first case, mean squared error (MSE) or root mean squared error (RMSE) can be applied. In the second case, the following criteria can be used: Akaike information criterion (AIC), Bayesian information criterion (BIC), C_p value and Adjusted R^2 (James et al., 2013).

One of these criteria or the cross-validation error can be applied for model selection in order to get a linear regression model f based on a selected set of process and product variables or a neural net with an optimal number of neurons in the hidden layer. In variable selection, it must be observed that the process parameter u , which has to be adjusted for each individual part, is included in the set of selected prediction variables. By calculating the inverse function f^{-1} of the linear function and inserting the optimal value of the quality measure z and the individual product and process variables of a part, an estimation \hat{u} for the parameter setting is yield.

4 CASE STUDY

In this section, the developed approach is applied to a real-world production process in metal processing industry, which consists of three production steps. The whole workflow for parameter setting was implemented in R, an open-source software for statistical computing. In the next subsection, we describe the data, which was recorded in a manufacturing company. There exist two relevant quality measures of the finished part, so the approach is applied twice and the results are reported in the following sections.

4.1 Experimental Data

In an experiment, the data of 200 produced parts and the associated process data were recorded. Together with experts of the involved production processes, relevant variables have been selected. Table 1 shows

the number of the analysed variables of each production step. According to Figure 1, the following notation is used:

- x_{ij} : j -th product variables of step i
- y_{ij} : j -th process variable of step i

Product variables include, for instance, the dimensions of the part after each process step and its weight. Important process variables are temperatures, pressures and forces.

Both product variables of step 3 are important quality measures, namely the height ($z_1 = x_{31}$) and the diameter ($z_2 = x_{32}$) of the part. One of the process variables of step 3 ($u = y_{31}$) is the process parameter which should be determined individually for each part produced. With the exception of y_{23} , all product and process variables are numeric. Since y_{23} is a nominal attribute with 5 different levels, it is replaced by four binary attributes ($y_{231}, y_{232}, y_{233}, y_{234}$), such as proposed in section 3.2.

Table 1: Number of Product and Process Variables.

Variables	Step 1	Step 2	Step 3	Total
Product Variables	6	6	2	14
Process Variables	4	4	2	10
Total	10	10	4	24

4.2 Results for Quality Measure 1

Here the first quality measure, the height of the finished part $z_1 = x_{31}$, is used as response variable in a linear regression model. In this model, the second quality measure x_{32} has to be excluded from the analysis, because it is not available in advance when using the regression model for prediction.

The calculation of VIF, using the R package “car”, reveals that there is just one process variable with a VIF higher than 10 ($VIF(x_{16}) = 12.16$). After the elimination of this variable, the VIF are calculated again with the result that the maximum value is 7.56. So this reduced data set is used for building the regression model.

Since the number of variables is relatively small in our application, best subset selection can be applied for model selection. For this purpose we use the “regsubsets” function from the R-package “leaps”. Representative for the evaluation of the criteria mentioned in Section 3.4, Figure 3 displays the results of adjusted R^2 .

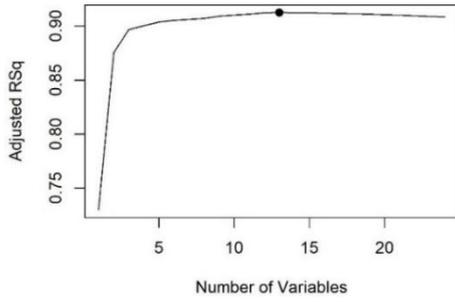


Figure 3: Adjusted R squared for Linear Regression Models.

Although the optimal number of variables varies from 5 to 13, all criteria reach good values with just a view number of variables. A closer look at adjusted R^2 reveals, that already 3 variables achieve a result that is close to the optimal value.

Additionally, 10-fold cross-validation was applied to best subset selection, to get a better estimation of the test error. Figure 4 displays the comparison of test and training error depending on the number of prediction variables. This evaluation indicates also that 3 to 5 variables are a good choice for the regression model.

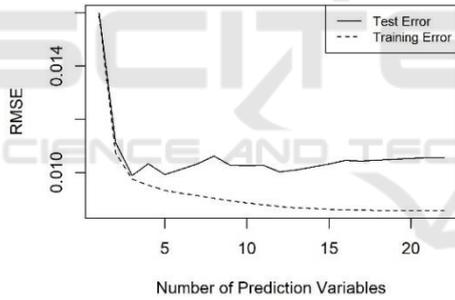


Figure 4: Cross-validation of Linear Regression Models for Quality Measure 1.

Table 2: Comparison of Linear Regression Models for Quality Measure 1.

Number of Variables	3	4	5	8
Variables	u x_{21} y_{231}	u x_{21} y_{231} y_{32}	u x_{11} x_{21} y_{231} y_{32}	u x_{14} x_{21} $y_{231}, y_{232}, y_{233}, y_{234}$ y_{32}
Adjusted R^2	0.897	0.900	0.904	0.907
RMSE	0.00977	0.00958	0.00939	0.00914

Now the linear regression model is trained on the whole dataset in order to obtain models with 3, 4, 5 and 8 variables. Table 2 compares the values of adjusted R^2 and RMSE for these models and reveals

that all of these models lead to similar good results. In all of the models the process parameter u , the product variable x_{21} and the dummy coded process variable y_{231} are selected.

The formula obtained by linear regression for estimating quality measure 1 as a function of three prediction variables is:

$$\hat{z}_1 = \hat{x}_{31} = f(u, x_{21}, y_{231}) = 18.477 + 0.772x_{21} - 0.289u - 0.012y_{231} \quad (3)$$

Therefore, we can see that the quality measure increases when x_{21} increases and it decreases, when the process parameter u increases or the binary variable y_{231} has the value 1. The experts of the manufacturing company confirm these relationships, although for them it was surprising, that a linear function with only three variables can provide good estimates for this quality measure. Figure 5 provides a graphical comparison of actual and predicted values of the quality measure.

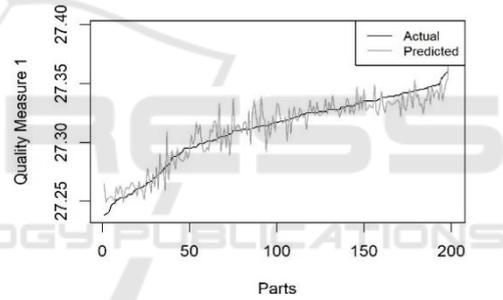


Figure 5: Actual vs. Predicted Values for Quality Measure 1 using Linear Regression.

In order to be able to better assess the results, it is important to know that the optimal value for the quality measure is 27.29 and the accepted tolerance is 0.06. Partly, there exist quite large deviations from the optimal value, which is the consequence of the rather large variations of possible parameters (in comparison to serial operation) in the experiment to get better insights in the relationships of product and process variables. However, the deviation of predicted values to actual values is less than the tolerance.

Calculating the inverse function of f and inserting the optimal value for the quality measure in Eq. (3) yields a function for the process parameter:

$$\begin{aligned} z_1 = 27.29 &\Rightarrow \\ \hat{u} &= -30.495 + 2.671x_{21} - 0.042y_{231} \end{aligned} \quad (4)$$

This equation can be applied to estimate the process

parameter u of step 3 individually for each part, just by inserting one product variable and one process variable of step 2.

For the purpose of benchmarking the results from linear regression models, we also apply ANN for regression. This is done by the “neuralnet” function of the “neuralnet” package in R. We select a neural net with one hidden layer and apply 10-fold cross-validation to get the optimal number of neurons in this hidden layer, using a range from 1 to 15. Figure 6 shows the training and test error as a function of the number of neurons in the hidden layer, with a minimum test error for four neurons. The training errors of neural networks are comparable to the training errors for linear regression models (see Figure 4), but the test errors for ANN are significantly higher. One reason for this could be the small number of datasets for training the neural net. So already models with three neurons tend to overfit the training data and lead to relatively high test errors.

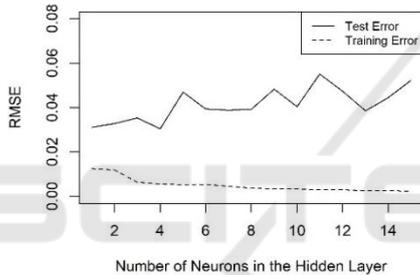


Figure 6: Cross-validation of Neural Networks for Quality Measure 1.

When the neural net with four neurons in the hidden layer is trained on the whole dataset, the following performance is obtained:

$$\begin{aligned} Adjusted R^2 &= 0.967 \\ RMSE &= 0.00517 \end{aligned} \tag{5}$$

These values outperform the good results from linear regression (see Table 2), however it is important to note that the performance of the neural net on new data is considerably worse than for linear regression. Further drawbacks of neural nets in this application is the number of variables applied (and the associated measuring effort) and the impossibility to calculate an inverse function, which is required for Eq. (2).

4.3 Results for Quality Measure 2

Now the same approach is applied to quality measure 2, the diameter of the finished part. Again the reduced dataset without the product variable x_{16} , due to its multicollinearity detected by calculating VIF, is used.

Only the response variable x_{31} is replaced by x_{32} .

However, the first results are not very promising. Training a linear regression model on the whole dataset using all variables delivers adjusted R^2 of only 0.07. A neural net can increase this value at 0.2, which is also too less for practical applications. At this point, feature engineering is necessary to improve the results. A detailed analysis revealed that it is favourable to replace the diameter in step 3 as response variable by the change of the diameter from step 2 to step 3: $z_2 = d_2 = x_{32} - x_{22}$. Additionally we introduced the change of the diameter from step 1 to step 2 as a new feature $d_1 = x_{22} - x_{12}$ and excluded the diameter x_{22} from the analysis for the sake of collinearity.

First, best subset selection for linear regression models in combination with a 10-fold cross-validation is applied for model selection (Figure 7). Also for the change of the diameter, a small number of variables (2 – 5) is sufficient for a good predictive model. In Table 3 linear models, which are trained on the full data set with 2, 3, 4 and 5 variables, are compared. Adjusted R^2 is nearly equally excellent for all these models. For parameter setting, the first model is not suitable, because the process parameter u is not used for prediction. Selection of three variables for prediction of the change in diameter yields the function

$$\begin{aligned} \hat{z}_2 = \hat{d}_2 = f(u, x_{12}, d_1) &= \\ &= 45.982 - 1.054x_{12} + 0.009u - 0.972d_1 \end{aligned} \tag{6}$$

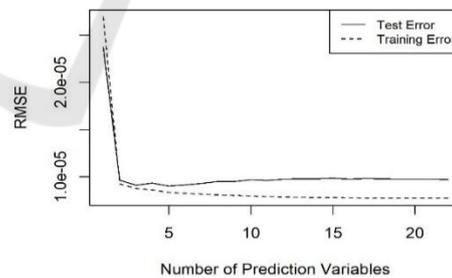


Figure 7: Cross-validation of Linear Regression Models for Change in Diameter.

Table 3: Comparison of Models for Change in Diameter.

Number of Variables	2	3	4	5
Variables	d_1 x_{12}	u d_1 x_{12}	u d_1 x_{12} x_{13}	u d_1 x_{12} x_{13} y_{32}
Adjusted R^2	0.974	0.975	0.976	0.976
RMSE	0.00304	0.00296	0.00294	0.00290

Figure 8 shows the comparison of actual and predicted values for the change in diameter. The accepted tolerance for this diameter is 0.012 and the optimal value is 44.043, which can be applied for calculating estimates of the necessary process parameter for individual parts:

$$\begin{aligned} x_{22} + d_2 &= 44.043 \Rightarrow \\ \hat{u} &= -215.44 + 117.11x_{12} + 108d_1 - 111.11x_{22} \end{aligned} \quad (7)$$

Also for this quality measure we train a neural net with one hidden layer and select the optimal number of neurons with a 10-fold cross-validation. Here three neurons lead to the minimum test error in the studied range from 1 to 15 (see Figur). The performance of the neural net, trained on the whole data set, can be assessed by the following measures:

$$\begin{aligned} \text{Adjusted } R^2 &= 0.976 \\ \text{RMSE} &= 0.00275 \end{aligned} \quad (8)$$

Adjusted R^2 is roughly equal than the value for linear regression models and RMSE is slightly better (see Table 3). Taking into account the higher test error for ANN (Figur) and the drawbacks already discussed for quality measure 1, also for quality measure 2 the linear regression model should be preferred.

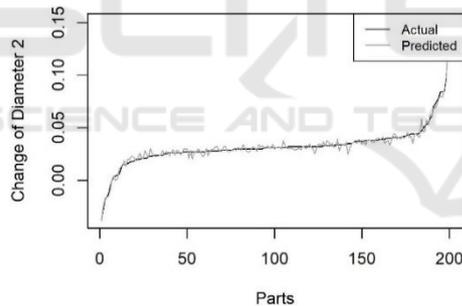


Figure 8: Actual vs. Predicted Values for Change in Diameter.

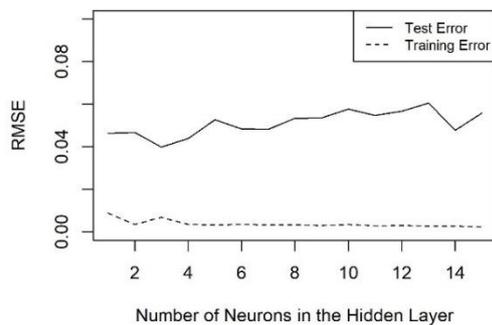


Figure 9: Cross-validation of Neural Networks for Change in Diameter.

5 CONCLUSIONS

In this article, we present an approach for parameter setting in manufacturing processes. The parameter adjustment is adaptive to the properties and history of each individual part. In the first step the relationship between multiple input variables and a relevant quality measure is investigated. Then this relationship is used to calculate estimates for a specific process parameter in order to get optimal quality measures. The results of the case study, based on real-world manufacturing data, show that even simple linear regression models with a few product and process variables provide good estimates for quality measures and can be applied for parameter setting. We also train neural nets to get a benchmark for the linear regression models. The results reveal that neural nets outperform linear regression on the training data, but application on the test data shows a significantly higher test error. Recording more data for training and testing could be favourable for neural networks.

In further research, we want to extend the approach to multiple quality measures, which are weighted in an objective function. In order to investigate the scalability of the presented approach, we plan to apply it in a long-term study on a larger data set of the considered real-world use case. To evaluate the generality of our approach we intend the application in other manufacturing processes as well.

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REFERENCES

- Barz, Christiane, and Rainer Kolisch. 2014. “Hierarchical Multi-skill Resource Assignment in the Telecommunications Industry.” *Production and Operations Management* 23 (3): 489–503. doi:10.1111/poms.12053.
- Choudhary, A. K., J. A. Harding, and M. K. Tiwari. 2009. “Data mining in manufacturing: A review based on the kind of knowledge.” *Journal of Intelligent Manufacturing* 20 (5): 501–21. doi:10.1007/s10845-008-0145-x.
- Collins, P. C., C. V. Haden, I. Ghamarian, B. J. Hayes, T. Ales, G. Penso, V. Dixit, and G. Harlow. 2014. “Progress Toward an Integration of Process–Structure–Property–Performance Models for “Three-Dimensional

- (3-D) Printing” of Titanium Alloys.” *JOM* 66 (7): 1299–1309. doi:10.1007/s11837-014-1007-y.
- Cook, D. F., C. T. Ragsdale, and R. L. Major. 2000. “Combining a neural network with a genetic algorithm for process parameter optimization.” *Engineering Applications of Artificial Intelligence* 13 (4): 391–96. doi:10.1016/S0952-1976(00)00021-X.
- Quality management systems - Fundamentals and vocabulary (ISO 9000:2015). DIN EN ISO 9001:2015. 2015.
- Ding, Donghong, Chen Shen, Zengxi Pan, Dominic Cuiuri, Huijun Li, Nathan Larkin, and Stephen van Duin. 2016. “Towards an automated robotic arc-welding-based additive manufacturing system from CAD to finished part.” *Computer-Aided Design* 73: 66–75.
- Geometrical product specifications (GPS) — ISO code system for tolerances on linear sizes. ISO 286-1:2010. 2010.
- James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2013. *An introduction to statistical learning: With applications in R*. Springer texts in statistics 103. New York: Springer.
- Kommenda, M., B. Burlacu, R. Holecek, A. Gebeshuber, and M. Affenzeller. 2015. “Heat treatment process parameter estimation using heuristic optimization algorithms.” In *Proceedings of the European Modeling and Simulation Symposium*, edited by M Affenzeller, Bruzzone, Jimenez, Longo, Merkurjev, and Zhang, 222–27.
- Miller, Alan J. 2002. *Subset selection in regression*. 2nd ed. Monographs on statistics and applied probability 95. Boca Raton: Chapman & Hall/CRC.
- Mohamed, Omar A., Syed H. Masood, and Jahar L. Bhowmik. 2016. “Investigation of dynamic elastic deformation of parts processed by fused deposition modeling additive manufacturing.” *Advances in Production Engineering & Management* 11 (3): 227–38. doi:10.14743/apem2016.3.223.
- Murtaugh, Paul A. 2010. “Methods of variable selection in regression modeling.” *Communications in Statistics - Simulation and Computation* 27 (3): 711–34. doi:10.1080/03610919808813505.
- Oliaei, Erfan, Behzad S. Heidari, Seyed M. Davachi, Mozghan Bahrami, Saeed Davoodi, Iman Hejazi, and Javad Seyfi. 2016. “Warping and Shrinkage Optimization of Injection-Molded Plastic Spoon Parts for Biodegradable Polymers Using Taguchi, ANOVA and Artificial Neural Network Methods.” *Journal of Materials Science & Technology* 32 (8): 710–20. doi:10.1016/j.jmst.2016.05.010.
- Park, Hong S., and Trung T. Nguyen. 2014. “Optimization of injection molding process for car fender in consideration of energy efficiency and product quality.” *Journal of Computational Design and Engineering* 1 (4): 256–65. doi:10.7315/JCDE.2014.025.
- Park, Kyung S., and Soung H. Kim. 1998. “Artificial intelligence approaches to determination of CNC machining parameters in manufacturing: A review.” *Artificial Intelligence in Engineering* 12 (1-2): 127–34. doi:10.1016/S0954-1810(97)00011-3.
- Pawar, P. J., and R. V. Rao. 2013. “Parameter optimization of machining processes using teaching–learning-based optimization algorithm.” *The International Journal of Advanced Manufacturing Technology* 67 (5): 995–1006. doi:10.1007/s00170-012-4524-2.
- Robinson, Carol J., and Manoj K. Malhotra. 2005. “Defining the concept of supply chain quality management and its relevance to academic and industrial practice.” *International Journal of Production Economics* 96 (3): 315–37. doi:10.1016/j.ijpe.2004.06.055.
- Tian, Maosheng, Xiaoyun Gong, Ling Yin, Haizhou Li, Wuyi Ming, Zhen Zhang, and Jihong Chen. 2017. “Multi-objective optimization of injection molding process parameters in two stages for multiple quality characteristics and energy efficiency using Taguchi method and NSGA-II.” *The International Journal of Advanced Manufacturing Technology* 89 (1-4): 241–54. doi:10.1007/s00170-016-9065-7.
- Venkata Rao, R., and V. D. Kalyankar. 2013. “Multi-pass turning process parameter optimization using teaching–learning-based optimization algorithm.” *Scientia Iranica* 20 (3): 967–74. doi:10.1016/j.scient.2013.01.002.
- Widrow, Bernard, David E. Rumelhart, and Michael A. Lehr. 1994. “Neural networks: Applications in industry, business and science.” *Communications of the ACM* 37 (3): 93–105. doi:10.1145/175247.175257.
- Wuest, Thorsten, Christopher Irgens, and Klaus-Dieter Thoben. 2014. “An approach to monitoring quality in manufacturing using supervised machine learning on product state data.” *Journal of Intelligent Manufacturing* 25 (5): 1167–80. doi:10.1007/s10845-013-0761-y.
- Wuest, Thorsten, Dieter Klein, and Klaus-Dieter Thoben. 2011. “State of steel products in industrial production processes.” *Procedia Engineering* 10: 2220–25.
- Xiong, Jun, Guangjun Zhang, Jianwen Hu, and Lin Wu. 2014. “Bead geometry prediction for robotic GMAW-based rapid manufacturing through a neural network and a second-order regression analysis.” *Journal of Intelligent Manufacturing* 25 (1): 157–63. doi:10.1007/s10845-012-0682-1.