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# Dreaming neural networks for adaptive polishing

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**Abstract**
Mechanical polishing is an important step within the process chain of manufacturing workpieces with high requirements regarding the surface quality, e.g. for optical components. The resulting surface quality depends on several parameters, e.g. the process parameters, the workpiece material, the initial surface roughness and the tool condition. Thus, finding process parameters that lead to the desired surface roughness can be regarded as a complex optimization problem. For this purpose, an artificial neural network (ANN) has been designed and trained with data from polishing experiments. Using a dreaming network approach, the ANN has been enabled to suggest appropriate process parameters under consideration of the initial roughness of the workpiece and the tool condition. The validation experiments showed that the process parameters suggested by the neural network led in 72% to the target roughness within a standard deviation.

Process planning; Deep learning; Neural network; Mechanical polishing; Control loop

## 1. Introduction and Motivation

Polishing is crucial for finishing high quality surfaces and the final roughness of a workpiece. Applications can be found in the automotive and the medical industry as well as in optics [1]. Mechanically abrasive polishing processes with bonded grain, which is embedded in the polishing tool, remove material of the surface by scoring, micro-chipping abrasive grains. The polishing tool with bonded grains can be flexible or rigid. In polishing with flexible tools, concave or convex shaped elements with narrow radius can be polished, too (Figure 1).

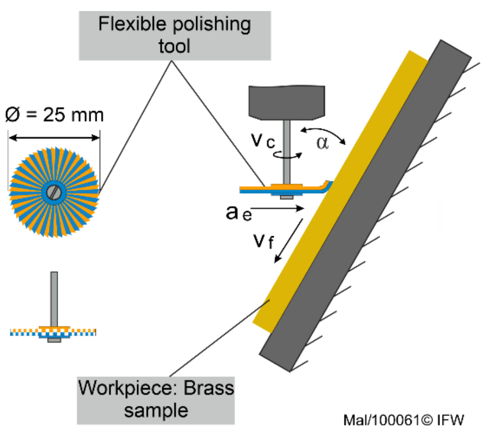


**Figure 1.** Flexible polishing tool with bonded grain and process kinematics for polishing, adapted from [7]

Since polishing levels roughness peaks from prior processes, the resulting surface quality depends not only on the workpiece material, the polishing tool and process parameters, but also on the initial roughness of the workpiece. Thus, it is important to consider these factors in process planning. In order to achieve a desired surface roughness under given conditions, process parameters like cutting speed, feed rate, cutting depth, inclination angle and polishing repetition must be determined [2]. In polishing, the applied radial force affects strongly the material removal. Force-controlled approaches for process control take the contact pressure between the tool and the workpiece into account [4, 5]. While these approaches control the process conditions rather than the result, Denkena et al. [6] introduced an adaptive planning procedure based on the feedback from quality control. They found that the cutting speed and the feed rate have the highest effect on the roughness. However, the modelling of the surface roughness as a function of process parameters was difficult, due to the high variance of the process outcome. Furthermore, time-variant parameters, e.g. tool wear, were excluded from their study.

Polishing operations with flexible tools are still often carried out manually, despite the existence of some automation approaches [3]. Efficient process planning of polishing becomes increasingly important by decreasing batch sizes and a higher level of individualization. Since experimental process planning is time consuming and cost intensive, a feedback of quality controlling has the potential to improve process planning continuously and enables self-optimization. Some studies intended to optimize the polishing process, e.g. the process planning based on fuzzy theory and case-based reasoning [7] or using machine learning to detect the stopping time by robot-assisted polishing using multiple sensor monitoring [9]. Especially, artificial neural networks (ANN) enable to consider highly non-linear correlations in manufacturing [9].

ANNs consist of a collection of connected neurons [10]. Traditionally, an (artificial) neuron/perceptron is defined as a scalar product of an input and a weight vector passed on to an activation function [11] to produce an output (or activation). Combining an input vector with several neurons yields a so-called layer and connecting the outcome of a layer to further layers leads to a neural network. An architecture with several hidden layers is called deep neural network [7]. Such a network is usually optimized by gradient descent on an output error using backpropagation. Neural networks are function approximators and can learn any mapping from an input to an output space. Dreaming networks refer to the generation of images that produce desired activations in a trained neural network. The term indicates a collection of related approaches already starting in the 80s [12]. The key idea is to perform a forward propagation of input data in a classification network. Outcome is a decision of an object category. When the label is swapped to another category, the error can be back propagated through the network. Whereas in the learning phase, the weights of the network are modified to correct the error (backpropagation), the weights are kept unchanged in the operation phase. Instead, the error is propagated and overlaid with the input image. The effect is a modified input image maintaining the characteristics of the input image with subtle modifications of textual components. The modification drives the image towards the selected object category.

**2. Approach**

This study aims for a self-optimizing process planning of polishing with flexible tools. The approach is based on a dreaming ANN that suggests process parameters to achieve the desired roughness while considering the initial roughness and the tool condition. Since neural networks are general function approximators, an approach would be to train a ANN in such a fashion that the initial tool condition, the initial and desired roughness are used as input variables and the process parameters are the predicted output variables. Unfortunately, this approach does not work well, since the process parameters are highly correlated and several process parameter combinations can lead to similar desired results, e.g. feed rate and cutting speed or the amount of repetitions are highly correlated and redundant. Therefore, the modification of one parameter can be compensated by another parameter to obtain a similar quality, causing a singularity. For this reason, we followed a different approach: The process parameters, initial tool condition and initial roughness are used as input for an ANN to predict the output roughness as regression network. Since the overall goal is to optimize the required process parameters for a desired target roughness, a dreaming network approach is now applied. The method is based on six main steps:

1. Preparation: Train standard neural network for roughness prediction
2. Optimization: Initialize start parameters, set initial configuration
3. Predict roughness, compute error between predicted and desired roughness
4. Backpropagate error through network, without weight update (dreaming framework)
5. Update the process parameters and go to 3
6. Repeat until the predicted roughness is close enough to the desired roughness

Finally, the actual achieved roughness after polishing with the suggested process parameters is used to update the ANN. In this way, the ANN will be optimized and can improve its accuracy of prediction (Figure 2).

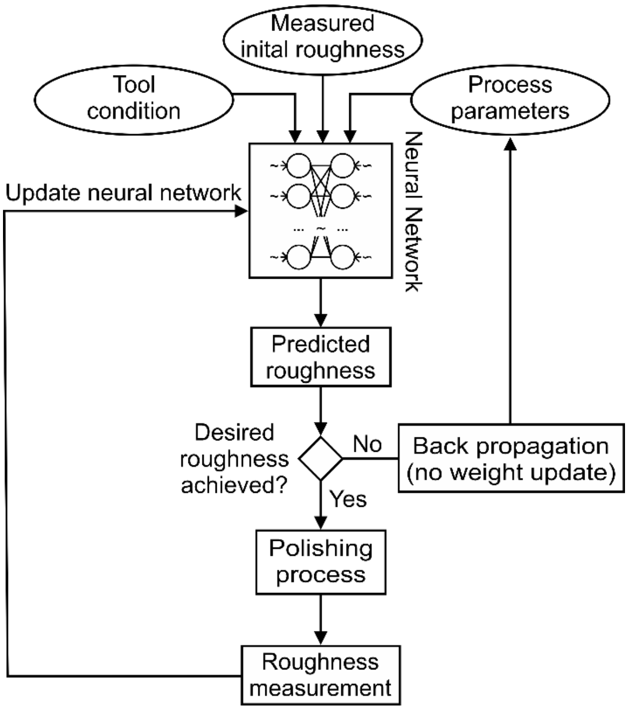


**Figure 2.** Approach for self-optimizing process planning of polishing processes using a dreaming neural network

**3. Experimental investigation**

***3.1. Experimental setup***

To train the ANN, 139 experiments were conducted with different process parameter combinations according to Table 1. All experiments were conducted on a Sauer Ultrasonic 10 using flexible polishing tools with medium-grained size silicon carbide and polyurethane bonding (EVE Ernst Vetter GmbH). A brass plate (Ms58, 80 x 80 x 10 mm) was used as workpiece. Each sample was polished on eight different areas. The length of all of these polishing paths was kept constant to 35 mm. The experimental parameters in the polishing process can be separated firstly in variable parameters as process parameters: cutting speed $v_c$, feed rate $v_f$, inclination angle $\alpha$ and cutting depth $a_e$. Secondly in constant parameters, such as the measured initial roughness, the desired roughness and the current tool condition (Table 1).

**Table 1** Variations of experimental input parameters

| **Process variable** | **Symbol** | **Unit** | **Range** |
|---|---|---|---|
| Cutting speed | $v_c$ | m/s | 5 – 15 |
| Feed rate | $v_f$ | mm/min | 100 – 500 |
| Inclination angle | $\alpha$ | Degree | 30 – 60 |
| Cutting depth | $a_e$ | mm | 0.6 – 2 |
| Initial roughness | $Ra_i$ | - | non, coarse and fine ground |
| Polishing repetition | $N_p$ | - | 1 – 10 |
| Tool condition: Number of processes | $N_w$ | - | 0 – 26 |
| Tool condition: Duration of use | $T_w$ | s | 0 – 316 |

The surface of samples were characterized before and after the polishing by tactile measurements. Perthometer S6P from Mahr GmbH was used for this purpose. A measuring tip with a geometry of 2 µm / 90° was applied. The profile measurments were conducted at a speed of 0.1 mm/s. The roughness values were determined according to EN ISO 13565. Due to its high importance in industry, the arithmetic mean deviation Ra was chosen as primary measuring value. Five adjacent lines with a same length according to the standard were measured in the same direction as the feed direction. Then, the mean value and standard deviation were calculated.

### *3.2. Setup of the neural network*

For this study, an ANN with eight input values was set up. Each input value was fed in a fully connected regression ANN with ten hidden and one output neuron (the predicted output roughness). The standard Adam optimizer [13] was used to train the final ANN. Due to the limited amount of training data and the risk of overfitting, the ANN was kept reasonable small with low number of layers. To avoid any artificial bias or misconception, the training data was not extended with a data augmentation technique. A shallow 3-layer neural network was programed with one input and output layer. The input size was eight dimensional and the prediction is a one dimensional value (the predicted roughness). The number of dreaming iterations was set constantly to five. Since the start configuration of the optimization could be randomly selected, a simple RANSAC approach was used [14] to find a suited model hypothesis.

## 4. Result and Discussion

After training the ANN with the above mentioned 139 experiments, eleven validation experiments were conducted (divided into three groups), aiming to reduce the surface roughness by 50%, 30% and 15%. Based on the given constant parameters, the process parameters were derived by the dreaming network approach. For this purpose, the ANN predicts the process parameters as outcome for a given starting set of variable parameters (Table 2).

**Table 2** Validation experiments

| **Input (Constants)** | | | | | |
|---|---|---|---|---|---|
| Exp. No. | Roughness (Ra in µm) | | | Tool Condition | |
| | Reduction | Initial | Target | $N_w$ (-) | $T_w$ (s) |
| 1 | 50% | 1.69 | 0.85 | 24 | 328 |
| 2 | | 1.54 | 0.77 | 26 | 248 |
| 3 | | 1.42 | 0.71 | 0 | 0 |
| 4 | 30% | 1.30 | 0.91 | 0 | 0 |
| 5 | | 1.29 | 0.90 | 26 | 248 |
| 6 | | 1.27 | 0.89 | 0 | 0 |
| 7 | | 1.27 | 0.89 | 5 | 32 |
| 8 | 15% | 1.21 | 1.03 | 0 | 0 |
| 9 | | 1.16 | 0.99 | 18 | 234 |
| 10 | | 1.16 | 0.99 | 0 | 0 |
| 11 | | 1.10 | 0.94 | 28 | 177 |
| **Predicted parameters (Variables)** | | | | | |
| Exp. No. | $v_c$ (m/s) | $\alpha$ (°) | $v_f$ (mm/min) | $a_e$ (mm) | $N_p$ (-) |
| 1 | 14.71 | 60.00 | 99.95 | 0.6 | 3 |
| 2 | 11.83 | 30.67 | 39.32 | 0.6 | 3 |
| 3 | 8.83 | 46.17 | 498.82 | 0.8 | 4 |
| 4 | 12.04 | 45.46 | 499.52 | 0.7 | 1 |
| 5 | 14.54 | 30.46 | 499.53 | 1.5 | 3 |
| 6 | 9.52 | 30.48 | 299.51 | 1.5 | 5 |
| 7 | 5.11 | 29.89 | 400.06 | 0.6 | 3 |
| 8 | 5.02 | 44.97 | 499.95 | 0.6 | 1 |
| 9 | 9.88 | 30.12 | 299.85 | 2.0 | 5 |
| 10 | 14.73 | 30.27 | 100.01 | 1.7 | 3 |
| 11 | 10.05 | 30.55 | 495.86 | 1.4 | 1 |

The results of the validation experiments are depicted separately for each group in Figure 3. It can be seen that in case of eight experiments, the target roughness could be achieved within the standard deviation of the roughness measurement.

In two out of three experiments, which the target roughness could not be reached, the surfaces were polished by a new and unused polishing tool. An unused polishing tool shows depending on other process parameters an unreproducible and a non-uniform performance. This could be the reason why the desired roughness was not achieved with the predicted parameters by ANN in these two experiments.

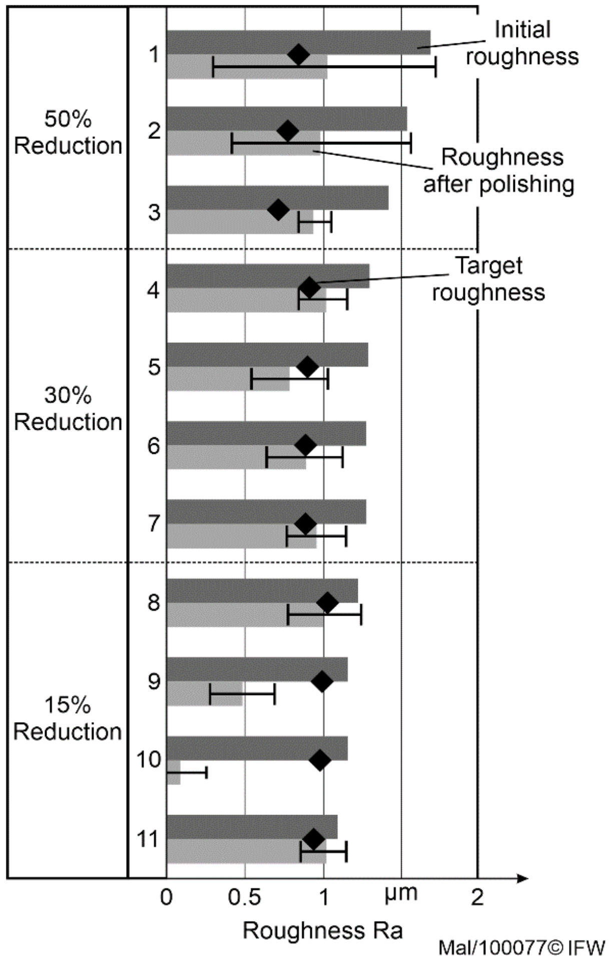


**Figure 3.** Results of the validation experiments

As shown in Figure 3, the measurement deviation is too large for experiment 1 and 2. It can be recognized, that the measuring deviation decreases with reduction of the initial roughness. In Figure 4 shows it in detail for training experiments, where the total measurement deviation of Ra for each measurement is depicted with respect to the different ranges of initial roughness and regardless of process parameters. The Ra profile represents just one line of the topography of a surface. However, the surface can have a non-even position or scratchs. Thus, Ra will be differnet for different measurement positions. Similarly, it cannot be assured, that the exact measurement position before polishing will be taken for measuring after the polishing. This is the reason of the large deviation for the measurements. Since the overall surface quality is important for the polishing process, a surface-referencing parameter like $S_a$ should also be taken into account for evaluation.

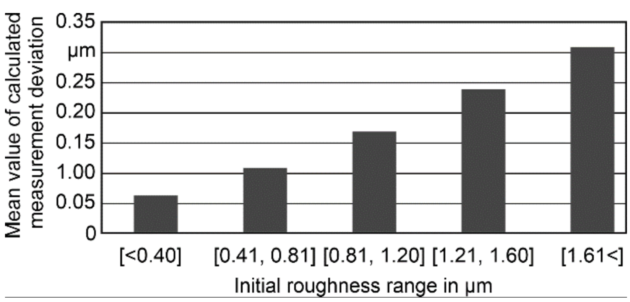


**Figure 4.** Measurment deviation regarding Initial raughness

## 5. Conclusion and outlook

In this article, we presented a dreaming neural network to predict process parameters for polishing with flexible polishing tools under consideration of the initial workpiece roughness and the tool condition. Despite the stochastic nature of the polishing process, the target roughness within a deviation could be achieved in 72% of the conducted validation experiments. In future research, the database will be increased to investigate the training behavior of the ANN more in detail. Moreover, we plan to train the ANN directly with results of a fast optical in-line measuring system to estimate the surface roughness instead of tactile roughness values.


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## References


[1] Cheung CF, Ho LT, Charlton P, Kong LB, To S, Lee WB. Analysis of surface generation in the ultraprecision of freeform surfaces, J Eng Manuf, 2010; 224(1):59–73.

[2] G. Wang, Y. Wang, J. Zhao, and G. Chen, Process optimization of the serial-parallel hybrid polishing machine tool based on artificial neural network and genetic algorithm, *J Intell Manuf*, vol. **23**, no. 3, pp. 365–374, 2012.

[3] Feng-yun L, Tian-sheng L. Development of a robot system for complex surfaces polishing based on CL data. *Int J Adv Manuf Technol* 2005;26(9):1132–1137.

[4] Feng D, Yuwen S, Huapeng D. Investigations on the automatic precision polishing of curved surfaces using a five-axis machining centre. *Int J Adv Manuf Technol* 2014:72(9-12):1625–1637.

[5] Chaves-Jacob J, Linares JM, Sprauel JM. Control of the contact force in a pre-polishing operation of free-form surfaces realised with a 5-axis CNC machine. *CIRP Annals* 2015;64(1):309–312.

[6] Denkena B, Dittrich MA, Nguyen HN, Technological CAD/CAM chain for automated polishing of geometrically complex workpieces. *Procedia CIRP* 2017; 65:32–37.

[7] Wang G, Zhou X, Liu J, Zhu P, Zhou H. Polishing process planning based on fuzzy theory and case-based reasoning. *Int J Adv Manuf Technol* 2017:90(1-4):907–915.

[8] Segreto T, Teti R. Machine learning for in-process end-point detection in robot-assisted polishing using multiple sensor monitoring. *Int J Adv Manuf Technol* 2019;52(2):611.

[9] Wang J, Ma Y, Zhang L, Gao RX, Wu D. Deep learning for smart manufacturing: Methods and applications. *J Manuf Syst* 2018;48:144-156.

[10] Kearns M, Vazirani UV. 1994. An Introduction to Computational Learning Theory. MIT Press;1994. *ACM Trans. Graph* 2018;37(4):128:1-128:15.

[11] Raiko T, Valpola H, LeCun Y. Deep Learning Made Easier by Linear Transformations in Perceptrons. *In Conference on AI and Statistics (JMLR W&CP)* 2012;22:924–932.

[12] Lewis JP. Creation by refinement: a creativity paradigm for gradient descent learning networks IEEE Int Conf. on Neural Networks 1988.

[13] Diederik P. Kingma and Jimmy Lei Ba. Adam : A method for stochastic optimization. 2014. arXiv. *ICLR*:1412.6980v9

[14] Martin A. Fischler und Robert C. Bolles: Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography. 1981; *Commun ACM* 1981.24:381-395