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Meta-Model Based on Artificial Neural Networks for Tooth Root Stress Analysis of Micro-Gears

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Abstract

Micro-transmissions, consisting of micro-gears with a module <200µm, are used in manifold industrial applications, e.g. the medical industry. Due to the technological limits of their manufacturing processes, micro-gears show large shape deviations compared to their size, which significantly influence their lifetime. Thus, for micro-gears a model has been developed to enable a prognosis of their lifetime based on areal measurements of the gear geometry, finite elements simulations as well as lifetime experiments. To significantly reduce the amount of experiments, existing prior knowledge is additionally used as input to the lifetime model by means of Bayesian statistics.

To enable a time-efficient application of the model for industrial series production, in this article the application of a machine learning approach based on artificial neural networks is investigated.

The uncertainty of the model is evaluated according to the principles of the Guide to the Expression of Uncertainty in Measurement (GUM).

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Keywords: metrology; machine learning; uncertainty

1. Motivation

Micro-transmissions are used in many industrial applications e.g. in the field of medical engineering for minimal invasive surgery equipment or in the field of industrial automation for hexapod actuators. The main components of micro-transmissions are gears with a module <200µm, which are defined as micro-gears [1]. Micro-gears are often produced as steel spur gears by the means of hobbing and tempering to resist the high loads in most industry applications. Due to the technological limitations of the production process, final grinding is not possible for micro-gears. This leads to significantly larger shape deviations in relation to their dimensions compared to conventional gears. This can ultimately result in an impaired rolling motion function under load. The lifetime, which is the most important functional characteristic of micro gears, is negatively influenced by this. It is mainly impaired by tooth root breakage. Hence, it is crucial to understand how the geometric shape deviations of micro-gears are related to their lifetime. For micro-gears, standard methods such as particularly load capacity calculation according to ISO standard 6336 [2] are very imprecise. Thus, in previous research for micro-gears an elaborate model was developed which enables to quantitatively specify the relationship between the shape deviations and the lifetime for specific micro-gears [3,4]. To parametrize the model for a respective type of micro-gears, areal measurements of the entire gear geometries of a couple of gear pairs are conducted and the tooth root stresses of the gear pairs are simulated by means of finite element (FE) simulations based on the measured gear geometries.

However, a disadvantage of the existing model is that the calculation time of the FE simulations is more than a day, even using high-performance computation facilities [4]. Because of this the existing model is not yet applicable for a real-time evaluation of measured micro-gears in production processes, e.g. for an individual pairing of gears [5]. Thus, in this article an approach is investigated to model the relationship between the measured shape deviations of a gear to the tooth root stresses in

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a simplified meta-model. The meta-model is established using a machine learning approach based on an artificial neural network (ANN). Additionally, the uncertainty of the ANN meta-model is evaluated.

This article is structured as follows. After a description of the state of the art (Ch. 2), the meta-model and its uncertainty evaluation are presented in Ch. 3 and demonstrated in Ch. 4 with an exemplary application. Ch. 5 concludes with a summary and outlook.

2. State of the art

The most common method for the evaluation of the gear reliability is the load capacity calculation according to ISO standard 6336 [2]. Considering only assumed tolerances instead of the measured 3D geometry of the gears, ISO standard 6336 is imprecise for micro-gears due to their larger shape deviations in relation to their dimensions, as experimentally demonstrated by Braykoff [6] and Haefner [4]. This general issue is addressed by the approaches of Brecher et al. [7], Beck et al. [8] and Haefner & Lanza [3,4] modelling the rolling motion of measured gears under load by means of finite element analysis. Haefner & Lanza apply FE analysis to model and predict the lifetime of micro-gears dependant on the measured shape deviations. In this approach, the areal geometry of each tooth of a gear pair is measured. From the areal measurement data, B-spline representations are generated and the tooth root stresses at each tooth are evaluated by means of FE simulations. The simulation data are correlated with the failure times in lifetime experiments of the measured gear pairs to set up the lifetime model (cf. Fig. 1). In addition, in this approach for the modelled relationship the uncertainty is evaluated according to the principles of the Guide to the Expression of Uncertainty in Measurement (GUM) [9].

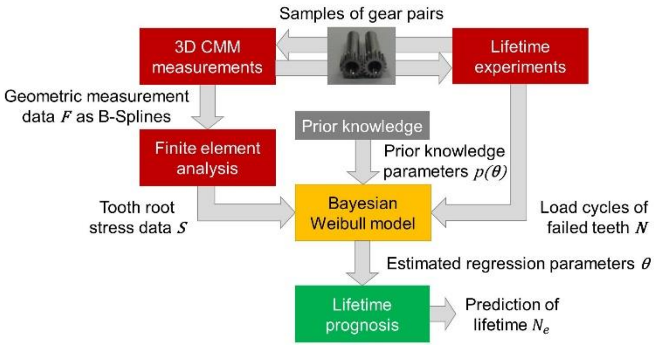

Fig. 1. Model for the lifetime prediction of micro gears dependant on measured shape deviations by means of FE simulations [3]

Machine learning methods provide the possibility to model relationships for the purposes of classification and regression based on a set of existing data [10]. Machine learning algorithms can mainly be divided into the subcategories of supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning and active learning [11]. Supervised learning uses pairs of input and output data to learn about the functional relationship. Potential machine learning methods for supervised learning are e.g. artificial neural networks or support vector machines [11, 12].

Artificial neural networks are inspired by biological neural networks and can be used to model complex relationships between inputs and outputs [13]. This is based on so called perceptrons, each creating an output x_k from n inputs x_{ki}:

$$x_k = f\left(\sum_{i=1}^{n}(w_{ki}x_{ki}) + \theta_k\right), \qquad i = 1\ldots n \tag{1}$$

A network of such perceptrons is designed, using the outputs of some perceptrons as the input of other perceptrons. The activation function f can be selected e.g. as a sigmoid, logistic or hyperbolic tangent function. To cope with non-linear, separable problems typically at least one hidden layer of perceptrons is added [13]. After designing the ANN, the weights w_{ki} and biases θ_k of the perceptrons are to be parametrized by learning from existing data sets. A typical approach is to set up a loss function measuring how well the network predicts the outputs of the test data set. After this training phase, the ANN model can be applied and validated with further input data.

If an ANN is applied to model and quantitatively predict the value of an output variable, it defines a regression problem. In this case the uncertainty of the output value based on the inputs and the model can be evaluated. There are various approaches evaluating the uncertainty of ANN by specifying confidence intervals of an output variable [14-21]. An approach which is consistent with the general GUM principles of uncertainty evaluation is the application of the simulative Monte Carlo method according to GUM Supplement 1 [22] to the ANN, as investigated e.g. by Coral et al. [21].

As a conclusion of the state of the art, currently there is no research approach enabling a real-time analysis of the tooth root stresses of micro-gears dependant on their measured geometries. Machine learning approaches such as ANN, however, provide the potential to model this relationship based on existing data sets, which can serve this purpose.

3. Research approach

3.1. Artificial neural network model

In the following, a meta-model is presented which relates the measured shape deviations of micro-gears with tooth root stresses at the respective teeth. The model approximates the complex relationship of the FE simulation model defined in [3,4] to enable the prediction of the tooth root stress of a specific micro-gear type.

As illustrated in Fig. 2, every model, in general, is characterized by the degree of theory richness and the degree of data richness. While mechanist models, such as the elaborate FE model of micro-gears according to Haefner & Lanza [3,4], have a very high degree of theory richness, data-rich models, such as statistical or machine learning regression models (e.g. ANN) have the potential to learn from existing data sets. Often the main benefit of data-rich models is to detect relationships which have not been obvious due to a limited availability of theory-rich models. The requirement for this is an adequate

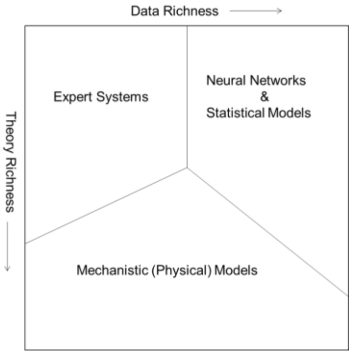

Fig. 2. Modelling techniques in relation to theory and data richness (structure adapted from [23])

amount of data. Yet, if a powerful theory-rich model, such as the micro-gear FE simulation, is available, this can be used to generate a high amount of data to establish a data-rich model, like the meta-model in this research approach.

The developed meta-model is based on an artificial neural network. The modelling of the artificial neural network for the tooth root stress as output variable starts with the determination of relevant input variables. For the ANN model, the available B-Spline representations of the measured micro-gears, as described in [3,4], are pre-evaluated. Based on the general approach of Stöbener et al. [24] a best-fit plane of the deviations of the nominal gear geometry is generated according to the least-square principle for the data points on the B-Spline surfaces of the tooth flanks (cf. Fig. 3). Similarly, also for the deviations at the tooth roots a best-fit plane is generated.

From the two best-fit planes of the flank and the tooth root deviations, the following nine characteristics are evaluated:

- areal profile slope deviation of flank $f_{H,\alpha}$
- areal helix slope deviation of flank $f_{H,\beta}$
- areal pitch deviation r_0
- areal form deviation of flank $f_{f,surface}$
- areal total deviation of flank $f_{surface}$
- areal profile slope deviation of tooth root $f_{r,H,\alpha}$
- areal helix slope deviation of tooth root $f_{r,H,\beta}$
- areal form deviation of tooth root $f_{r,f,surface}$
- areal total deviation of tooth root $f_{r,surface}$

The nine pre-evaluated gear characteristics serve as inputs for the ANN model.

In the next step, a data set for the training of the ANN is to be generated. To obtain the output values of the tooth root stresses for the training data sets, finite element simulations with the FE model according to [3,4] are to be conducted based on measurements of the gear geometry and the resulting B-Spline representations for each tooth of a reasonable amount of gear pair specimens. To obtain the input values for the training data set, the aforementioned best-fit planes at the flanks and tooth roots have to be determined and the nine gear characteristics have to be evaluated for each tooth.

Next, the artificial neural network is trained with the test data sets of the input and output variables. By means of this, the weights w_{ki} and biases θ_k of all perceptrons according to Equation (1) are determined [13]. The training of the ANN is executed by means of well-established backpropagation algorithms [23].

After that, the parametrized ANN meta-model can finally be applied to predict the tooth root stresses for measured teeth in real-time. For this, only the nine defined gear characteristics have to be pre-evaluated, in advance.

Fig. 4 demonstrates the design of the resulting ANN meta-model.

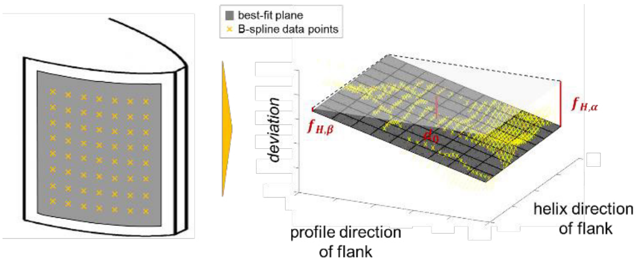

Fig. 3. Modelling techniques in relation to theory and data richness (structure adapted from [23])

3.2. Uncertainty evaluation of artificial neural network model

To evaluate the uncertainty of the established artificial neural network model, in this research approach the Monte Carlo method according to GUM Supplement 1 [22] is used. The Monte Carlo approach uses a large number of sample values for each input variable of the model, according to [22] at least 1 million. These are sampled from the distributions of the input variables. Then, random combinations of the input values are selected and propagated through the artificial neural network model.

There are two general types of uncertainties related to an ANN model: the measurement uncertainties of the inputs of the ANN and the uncertainty of the ANN model itself. The model uncertainty is related to the variation of potential realizations of the ANN model depending on the training data. To consider both, in this research approach the Monte Carlo method is adapted for suitable application with regard to the ANN model in the following way. Thus, to quantify the model uncertainty of the ANN, 1000 different combinations of training data sets are generated. The combinations of training data sets, each with the same amount of data, are randomly selected from the available data for training and validation. As a result from this, 1000 different realizations of the ANN model are generated.

To also consider the measurement uncertainties of the input values, for each of the input characteristics of the ANN, a PDF is determined. Based on these PDFs, for each validation data set, 1000 combinations of input values are randomly generated. Then, by applying the Monte Carlo method, all of these are propagated through each of the 1000 realizations of the ANN model. Thus, for each validation data set, 1 million realizations of output values are generated and the empirical probability density function (PDF) of the tooth root stress is evaluated for the uncertainty evaluation.

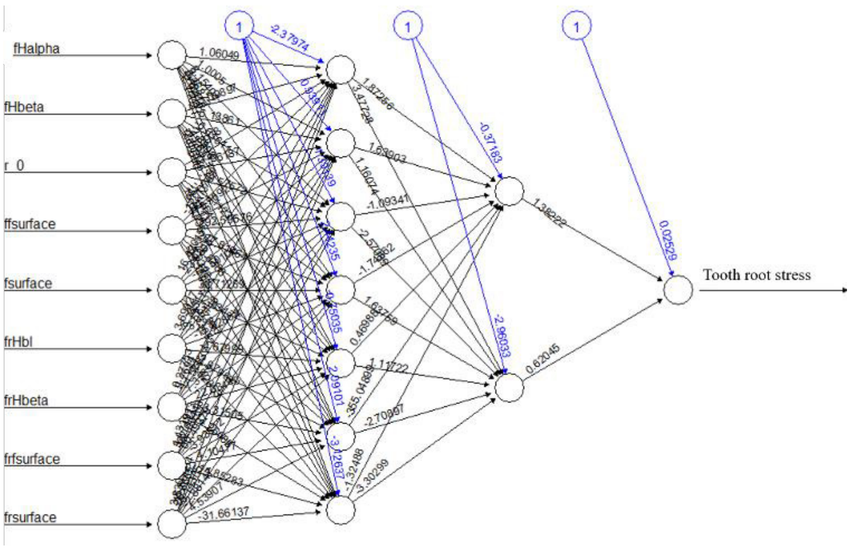

Fig. 4. Artificial neural network with two hidden layers as a meta-model of the tooth root stress based on the geometry characteristics of micro gears

From this, for each validation data set the smallest 95% confidence interval is determined according to GUM Supplement 1 to characterize the uncertainty limits of the estimated tooth root stress for the ANN. In this case, the coverage factor according to the GUM [9] is $k = 2$. For a general estimation of the uncertainty interval of the ANN model the average of the uncertainty intervals for the different validation data set is calculated.

4. Application

The method for the generation of an ANN meta-model and the evaluation of its uncertainty, as described in Ch. 3, was exemplarily applied to an industrial micro-gear type with a module of 200µm and 31 teeth (cf. Fig. 5).

In order to generate a data set for the training of the ANN, for 12 gear pairs (24 gears) the 3D geometry of each of the 31 teeth was measured with the tactile CMM Zeiss F25 and for each gear the B-Spline representations were generated with a MATLAB program. Then, a full rotation of each gear pair operation with a torque of 340mNm was simulated, conducting a FE analysis by means the software ABAQUS as described in [3,4]. Thus, altogether 12*2*31=744 values of the tooth root stresses at the respective teeth were determined. The considered test data were the same as in [3,4]. These serve as output values of the ANN meta-model within its training. In order to add the conditions of a gear without any geometrical deviations as a reference point of the ANN model, a FE simulation with

Fig. 5. Exemplary micro-gear with module of 200µm and 31 teeth [3,4]

the nominal gear geometry is also evaluated. For a high weighting of this reference of the ANN, this type of training data set was considered 744 times within the training. Thus, in total there are 1488 training data sets.

Moreover, for each of the measured 744 teeth, the values of the nine gear characteristics, defined in Ch. 3 are determined from the geometrical 3D data. The calculation is executed by means of a MATLAB program. For the 744 data sets of the nominal geometry, the nine gear deviation characteristics are all zero. These together serve as input values of the ANN meta-model in the training.

The ANN was implemented using the statistical software R and its graphical user interface RStudio with the package "neuralnet" [25]. This package is very flexible and uses an extension of generalized linear models with multi-layer perceptrons in the context of regression analyses. The package also allows the application of various well-established ANN training algorithms like traditional backpropagation and resilient backpropagation with or without weight backtracking [11,13,25]. Moreover, particularly, also the amount of layers, the amount of perceptrons per layer and the activation function f of the ANN can be varied.

With the designed R program, the ANN meta-model was trained by means of the aforementioned data sets of the 1488 input-output-combinations. The training was performed considering different ANN configurations. In particular, the network structure defined by the amounts of layers and perceptrons, the activation function as well as the type of the backpropagation algorithm were systematically varied. Regarding the network structure previous experiments showed that more than two hidden layer of the ANN lead to insufficient results for the defined problem. The two network configurations "first layer: 5 perceptrons/second layer: 3 perceptrons" (5,3) and first layer: 7 perceptrons/second layer: 2 perceptrons" (7,2) were analysed. Fig. 4 exemplarily shows the network structure with the (7,2) configuration. For the activation function f, a logistic or hyperbolic tangent function were considered, which are defined as:

Logistic: $f(x) = \frac{1}{1-e^{-x}}$ (2)

Hyperbolic tangent: $f(x) = \tanh(x) = 1 - \frac{2}{e^{2x}+1}$ (3)

With regard to the training algorithm, resilient backpropagation was considered with and without weight backtracking, defined by the R algorithms "RPROP+" respectively "RPROP−" [26,27].

To evaluate the quality of the ANN meta-model, validation data sets from another 2 gear pairs (4 gears) with altogether 2*2*31=124 teeth were additionally generated according to the same procedure as describes above for the training data sets.

For the input data of each of the n=124 validation data sets, the input data of the nine geometrical characteristics were inserted into the ANN meta-model and the predicted output value of the tooth root stress $S_{ANN,i}$ were determined in each case. $S_{ANN,i}$ can be compared to the actual tooth root stress $S_{FEM,i}$ given by the elaborate FE model. As a metric for the quality of the ANN meta-model the average deviation $\bar{d}$ was calculated:

$$\bar{d} = \sqrt{\frac{\sum_{i=1}^{n}(S_{ANN,i} - S_{i,FEM})^2}{n}} \times 100\% \qquad i = 1 \ldots n \qquad (4)$$

The results of the evaluations of the average deviation $\bar{d}$ for the considered options of the ANN meta-model are stated in Table 1. As the evaluations show, a good quality of the ANN meta-model can be achieved. Particularly the configuration with the network structure (5,3) with logistic activation function and the backpropagation algorithm RPROP+ has only an average deviation of $\bar{d} = 11.8\%$.

Table 1: Average deviation $\bar{d}$ for the options of the ANN meta-model

Activation function	Logistic		Hyperbolic tangent	
Network structure	(5,3)	(7,2)	(5,3)	(7,2)
RPROP+	**11.8%**	12.8%	21.0%	17.9%
RPROP−	12.7%	16.3%	13.3%	15.0%

To evaluate the uncertainty of the model for this preferred model configuration, the Monte Carlo method was applied according to Ch. 3.2. First, 1000 different realizations of the ANN model were generated. For this, 1000 combinations of training data sets were randomly selected by partially substituting some of the 744 measured training data sets by 62 of the validation data sets mentioned before.

For each of the remaining 62 validation data sets, the Monte Carlo method was applied by propagating 1000 combinations of input values through each of the 1000 realizations of the ANN model. To randomly generate the input values, regarding the PDFs of all 9 input characteristics of the ANN a normal distribution can be assumed. Based on the previous research in [3,4], it can be estimated that the standard uncertainties for the measurement uncertainty of the input characteristics are: 0,364µm for $f_{H,\alpha}$ and $f_{r,H,\alpha}$, 0,824µm for $f_{H,\beta}$ and $f_{r,H,\beta}$, 0,202µm for r_0, and 0,300µm for $f_{f,surface}$, $f_{surface}$, $f_{r,f,surface}$ and $f_{r,surface}$. Thus, for all 62 validation data sets, the PDF of the tooth root stress is obtained based on 1 million output values if the ANN model. Fig. 6 exemplarily visualizes the output PDF for the validation data set with mean equals 0 for all PDFs of the 9 input characteristics.

The PDF of the tooth root stress using the FE analysis was calculated in accordance with the GUM principle of the propagation of uncertainty [3,4]. The uncertainty analysis considers both the standard uncertainties of the inputs to the FE analysis and the standard uncertainty of the discretization the FE mesh. The standard uncertainty of the inputs to the FE analysis comprises the standard uncertainties of the measurements of the geometrical characteristics of the, of the material characteristics as well the conditions during the rolling motion of the gears (e.g. temperature changes) and is evaluated according to the Monte Carlo method [22] using a latin hypercube sampling design [3,4]. The uncertainty of the discretization is calculated by means of a comparison with a reference FE analysis [3,4].

From the PDFs determined according to the ANN model and the FE model, the uncertainty intervals of the tooth root stress for both models can be calculated and compared. Under the assumption that the PDFs are normally distributed the uncertainty intervals are determined as 95% confidence intervals (coverage factor $k = 2$). The results of these intervals are stated in Table 2. For the ANN model, the limits are calculated by averaging the 62 validation data sets. From these results it can be concluded that the width of the uncertainty interval for the ANN model is approximately 5.5 times larger than the uncertainty

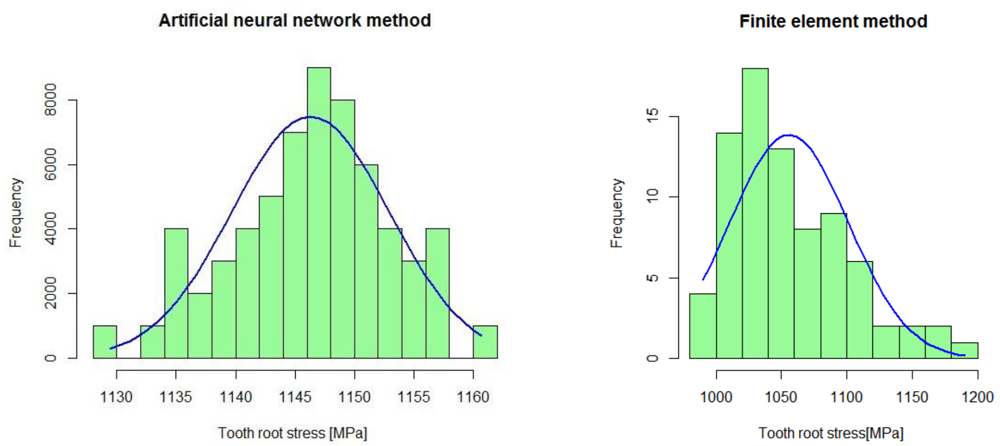

Fig. 6. PDF of the tooth root stress for the ANN model and FE model (PDF representation of the FE model according to [3])

interval for the FE model. Thus, this increase of uncertainty of the model is the trade-off of the capability of the ANN model for real-time evaluation.

One reason for the higher uncertainty of the ANN model is that as inputs of the ANN only the 9 aggregated characteristics of the best-fit planes are considered instead of a direct evaluation of the 3D geometry of the micro-gears. Because of this, the information density of the input data is reduced. Thus, a potential approach for improvement of the ANN model in future research is the direct application of machine learning techniques based on the 3D geometry of the micro-gears as input of the model. A promising approach for this, for instance, can be the use of Deep Convolutional Neural Networks.

Table 2: Uncertainty intervals of the ANN model and the FE model

95% confidence interval	Lower limit	Mean	Upper limit
ANN model	639.22	1146.30	1653.38
FE model	990.01	1055.82	1170.13

5. Summary and outlook

In this article an extension for the function-oriented evaluation of micro-gear measurement based on the approach of Haefner & Lanza [3,4] was described. In order to reduce the computational effort for the calculation of the tooth root stress, the relationship between the measured geometrical gear characteristics and the tooth root stress was modelled by means of an ANN meta-model. Based on the Monte Carlo method according to GUM Supplement 1 the uncertainty of the ANN model was evaluated. The calculation of the tooth root stress and the uncertainty evaluation were demonstrated for exemplary industrial micro-gears.

Potential further research can be conducted to directly evaluate the 3D geometry of the micro-gears with machine learning techniques (e.g. associated to Deep Convolutional Neural Networks) instead of pre-analysing the geometry based on a best-fit plane.

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