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Assessing the influence of DMLS production process factors on fatigue resistance of Maraging steel MS1 in the finite life domain using ANN prediction abilities

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Abstract

Analysis-of-variance (ANOVA) is a standard statistic method for assessment of the influence of various factors on fatigue resistance in the finite life domain. However, the previous research has shown that this method was not capable to determine with sufficient confidence if the build orientation, the thickness of allowance for machining, and the position in the production chamber affect fatigue resistance of Maraging steel MS1 products made by direct metal laser sintering (DMLS) technology. To contribute to a better understanding of the subject, the results of fatigue test experiments were used for training four types of artificial neural networks (ANN) for fatigue resistance assessment in the finite life domain. Each ANN had different structure of inputs, which corresponded to a different combination of the factors of DMLS production process. The differences between the predictive abilities of the ANN were attributed to influences of the respective factors on the fatigue resistance of the material in the finite life domain. The approach was verified by the agreement with the conclusive results of ANOVA analyses. Furthermore, in the cases when ANOVA does not lead to a clear result, the analyses of the predictive ability of the ANNs strongly suggest that build orientation and thickness of allowance do not influence. Conversely, the position of a part in production chamber does affect the fatigue resistance in the finite life domain of Maraging steel MS1 produced by DMLS technology.

Keywords

Additive manufacturing, DMLS, Fatigue behaviour, Artificial neural networks

Introduction

The key advantage of additive manufacturing (AM) technologies for mechanical designers is their ability to manufacture functionally graded parts[1] and products with internal open spaces[2], which enables topology optimization of product shape[3] and, consequently, design of lightweight components[4] and products with shape-integrated functionality[5]. Direct Metal Laser Sintering (DMLS), as the AM technology capable of manufacturing metal products, is increasingly used to implement the advantages of AM in automotive and aerospace industry. Mechanical components and structures in these applications are subjected to dynamic loads and fatigue, which often represents a critical aspect in design of these products. This problem may be addressed by improving product design[6] and by better understanding of fatigue resistance of materials produced by DMLS[7].

The AM principle of layerwise building from melted powder particles creates more inhomogeneities in the microstructure of DMLS products than it is the case with traditional technologies[8]. The fundamental importance of the inhomogeneities for mechanical properties of materials was a motivation for concern and extensive studies of materials produced by DMLS. The majority of the research was focused on numerical[9] and experimental studies of the influence of the DMLS process parameters[10], as well as the post-processing procedures[11], to static tensile strength and surface quality[12] of AM products. Few papers deal with fatigue behaviour of AM materials, and these are mainly focused to light metals, dealing with influence of microstructure[13] and heat treatment[14] on fatigue resistance of aluminium alloys, as well as with general fatigue behaviour[15], high-cycle fatigue[16], influence of build orientation[17] and notch effects[18] on fatigue resistance of titanium alloys.

For these reasons, the authors of this paper in recent years turned their attention to the fatigue behaviour of steel materials produced by DMLS. Within the course of the Horizon 2020 project "Advanced design rules for optimal dynamic properties of additive manufacturing products (A_MADAM)"[19] they carried out a systematic experimental campaign with the aim to determine which production conditions and post-processing procedures have substantial influence on fatigue resistance of maraging steel MS1[20,21] (in further text abbreviated just as MS1) and the stainless steel PH1[22]. A comparison of the results of fatigue tests obtained for the two steel materials is presented in the literature[23]. The experimental campaign was devised using the Design-of-Experiment approach and the results were analysed using the Analysis-of-Variance (ANOVA) methodology[24]. The results of the research established the influence of post-processing procedures and their order on the fatigue resistance of the MS1 produced by DMLS[21], as well as the influence of build orientation, post-processing procedures and their order on the fatigue resistance of the stainless steel PH1 produced by DMLS[22]. However, the application of ANOVA methodology to the experimental results could not confirm the influence of build orientation and the thickness of allowance for machining on the fatigue resistance of MS1 produced by DMLS[21]. While the result is yet to be published and discussed, the ANOVA analysis was also not able to confirm the influence of position of a sample in production chamber with respect to inert gas flow on the fatigue resistance of the MS1 produced by DMLS. In principle, the ANOVA methodology may only confirm the existence of influence of certain factors to the observed data. On the other hand, the inability of the ANOVA method to state such influence does not necessarily mean that it does not exist, but that further studies may be needed and may perhaps confirm this effect. However, considering the high costs of DMLS technology and long duration of the fatigue tests, other methods for studying the already available experimental data are worthy of research.

While ANOVA may be nonlinear across factor levels, it is linear in parameters, and it is considered to be a special case of linear regression[25]. On the other hand, fatigue resistance is a highly nonlinear phenomenon, which is confirmed to be influenced by several complex factors such as material microstructure and surface quality[26], which, in the case of DMLS technology, depend on multitude of production conditions and post-processing procedures. The complexity of the factors and their multi-level interactions motivated the authors of this paper to try to use artificial neural networks (abbreviated as ANNs, and ANN in singular) to better understand the influence of individual factors on the fatigue resistance in the finite life domain of MS1 produced by DMLS.

ANNs are machine learning computing systems capable of developing complex relationships between input and output quantities, open to handling different types of inputs, such as continuous, discrete and fuzzy variables. Their ability to grasp complex dependencies between the inputs and outputs was already successfully used for studies of dimensional stability[27], thermo-mechanical internal stresses[28] and mechanical properties[29] of AM products. The aspects of production processes such as scanning strategies[30] and material consumption[31] were also subjects of ANN-based investigations. ANNs were also used for prediction of fatigue life of composite materials[32], but despite the complexity of fatigue and the DMLS technology, the application of ANNs for studies of fatigue behaviour of DMLS products started only recently. The initial step in that direction was a study of high-cycle fatigue of stainless steel[33] that used ANNs trained on datasets describing production process parameters and post-processing procedures. The obtained results motivated further research of application of ANNs and other machine learning methods[34], including propositions of a two-phases methodology for in-situ prediction of fatigue life[35]. This study gave way to a potential roadmap to establish a data-driven evaluation platform that would use a large number of experimental data, arising from tests on miniature specimens[36], in order to reduce production costs. A recent study[37] has shown that ANNs trained by support vector machine (SVM) method were able to achieve coefficients of determination between the predicted and experimental fatigue lives of Ti-6Al-4V alloy as high as 0.99.

The research presented in this paper *does not* use ANNs to provide superior predictions of fatigue life of materials produced by DMLS in comparison with standard methods, as it was the case with the research efforts presented above[32-37]. Instead, it uses ANNs only as a complementary tool, which enables better understanding of the influence of production factors on the fatigue resistance in finite life domain that standard methods cannot clearly resolve. It is important to notice that the production factors, whose influence on the fatigue resistance in finite life domain is the subject of the study, are the *inputs* of the used ANNs, and *not their outputs*, as it is the case in majority of the studies that use ANNs. This fact reflects on the methodology used in the paper, since subject of the study are *the differences between the predictive abilities of different ANNs* and *not the predictive abilities of individual ANNs*. The authors believe that the approach, which may be extended to other applications, is a useful novelty, as they are not aware of any similar study in the existing scientific literature.

Experiments

The experimental data used in this study represent a part of the results of the experimental campaign performed within the A_MADAM[19] project. The project, among the other activities, comprises a systematic study of the fatigue behaviour of AM steels (Maraging steel MS1, Stainless steel PH1 and Maraging stainless steel CX). The part of the results that is published is briefly mentioned in the introduction, and the subject of the study in this paper concerns the results of fatigue testing of samples made from MS1 using DMLS technology. Maraging steel MS1 is a tool steel especially designed for AM with chemical composition that corresponds to DIN 1.2709 or ASTM 18Ni300 steel. The details of the chemical composition and the relevant mechanical properties of the material are given in the references[20,21]. After AM production, the MS1 parts are subjected to heat treatment by simple thermal age-hardening that leads to excellent hardness and strength, which makes MS1 an optimal choice for tooling applications. The intensive dynamic loads to which tools are exposed in exploitation raise interest for studies of fatigue behaviour of MS1.

Fatigue testing was performed according to the ISO 1143 standard[38], which specifies the experimental method for fatigue testing of metallic materials using bending of rotating bars. The specifications describe the accuracy of the testing apparatus, the testing procedure and presentation of the fatigue testing results. The standard, as well as the references[20-23], describe also in details the shape, dimensions and preparation of the samples, which consist of two mounting heads and a gage between them. During a test, a sample rotates under a constant bending moment over the gage. As a consequence, the sample undergoes cyclic symmetric loading ($R = -1$, zero mean stress) with frequency equal to the rotation speed, and the loading conditions generate fatigue load at the sample gage. Test is carried out until the sample breaks (“failure”) or until a pre-determined number of loading cycles is achieved without failure of the sample (“run-out”). The run-out criterion in this research was set to be 10^7 cycles without failure, which is usual for fatigue testing of steels[20]. The experimental data that describe a test are the maximal bending stress at the sample gage (denoted as S), and, in the case of failure, the number of cycles until the break of the sample (denoted as N). The other details of the implementation of the testing procedure (such as description of the control of dimensions and surface quality of the samples, the machine and the loading conditions used for testing) may be found in the references[20,21].

According to the experimental plan used in the project, the samples were divided into 16 sets. The samples of each individual set were manufactured under the same production conditions and, after the production, treated by the same post-processing procedures. The differences between production conditions (build orientation and position of the samples in production chamber) and post-processing procedures (the order and application of heat treatment and surface treatment procedures) enabled study of those factors on the fatigue behaviour of the MS1 manufactured by DMLS. The details of the manufacturing and post-processing procedures used for production of the samples (such as production machine and production parameter settings) are also presented in references[20,21].

The production conditions and post-processing procedures for each of the sample sets are presented in the Table 1 that uses the coded conventions defined in the A_MADAM project. The first two columns of the Table 1 contain the numeric and alphanumeric codes of the sets, and the third column represents the number of the samples in the respective sample set. According to the coding system used in the project and this paper, each sample set has a unique short (numeric) and long (alphanumeric) code, where the numeric code is useful for simple referencing of a sample set, while the alphanumeric code is useful because it describes the manufacturing conditions and post-processing procedures used for each of the sets.

Numeric code	**Alphanumeric code**	**Size**	**Production**		**Post-process**	
			Orient.	**Pos. (x)**	**Heat (Yes)**	**Machining (mm allowance)**
1	Vx.STM	10	|			0.5
2	Hx.STM	10	—			0.5
3	Sx.STM	10	/			0.5
4	Vx.ST3	15	—			3
5	Hx.ST3	10	/			3
6	Sx.ST3	10	|			3
7	Vx.ST1	10	|			1
8	Vx.ST2	10	|			2
9	Vx.ST4	10	|			4
10	Vx.SNN	15	|		No	No
11	Vx.SMN	10	|		No	0.5
12	Vx.STN	15	|			No
13	Vx.MSN	15	|		No	0.5
14	VU.TMS	15	|	U		0.5
15	VM.TMS	15	|	M		0.5
16	VD.TMS	15	|	D		0.5

Table 1: Sample sets that were subject of the standard fatigue tests

The alphanumeric code consists of five symbols divided in two groups separated by a dot. The first group of the symbols represents production conditions, and the second group of the symbols represent the post-processing conditions.

The sample sets were manufactured under the production conditions described in the fourth and the fifth columns of the Table 1:

- orientation of the longitudinal axis of the samples during manufacturing process (building orientation), described in the fourth column of the Table 1, which was either vertical (represented by "|"), horizontal (represented by "—") or made an angle of 45^0 with the horizontal (represented by "/") (Figure 1 left); the build orientation is coded by the first symbol of the alphanumeric code by letter "V" for vertical, letter “H” for horizontal and letter “S” for slanted orientation of the sample axis;

- position of the samples in the production chamber with respect to the inert gas flow (used to remove the burnt particles created during the laser sintering process) which may be upstream, midstream, downstream (Figure 1 right) or undefined; due to their mass, the inert gas flow cannot remove all the burnt particles from the production chamber. Since the burnt particles may be incorporated into a manufactured sample and act as material defects and sources of initial cracks, the samples manufactured in downstream positions may have lower fatigue resistance. The position of the samples of a set in the production chamber is coded by the second symbol of the alphanumeric code, which may be “U” for the upstream positions, “M” for the midstream positions, “D” for downstream positions and “x” for undefined positions; the undefined position means that the samples of the set were manufactured in positions with different categories (as it usually occurs with products in industry), or that different parts of samples were placed in different zones with respect to the inert gas flow (e.g. samples with horizontal axis oriented along the gas stream); the positions of the samples are indicated in the Table 1, where the code “x” was considered as default value and was omitted;

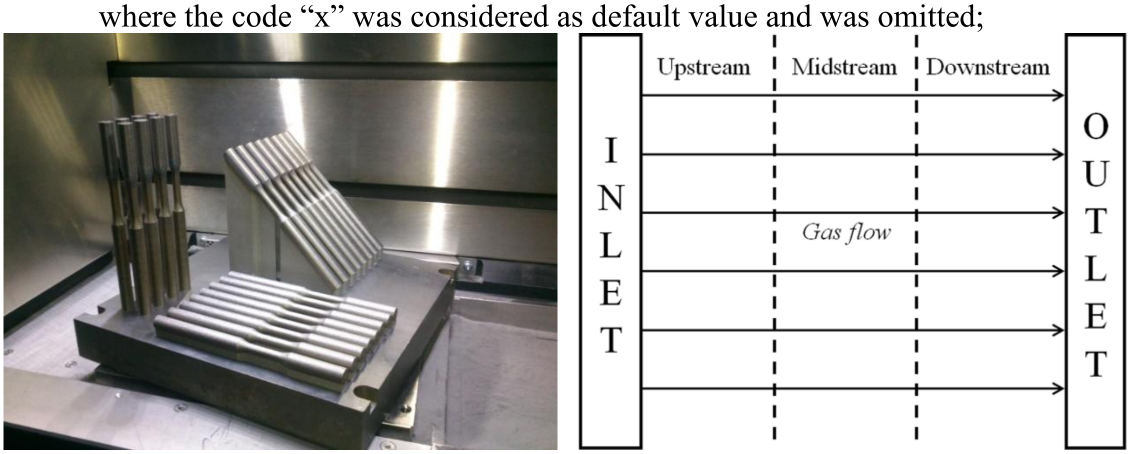

**Figure 1: Build orientations of the samples (left)
and the definition of the classes of positions within the production chamber (right)**

Due to the internal inhomogeneities, the influence of the post-processing procedures (and in particular of their order) on the fatigue response of steel manufactured by DMLS may be different than it is the case with steels manufactured by traditional technologies[21,22]. The post-processing procedures consisted of combinations of shot-peening, machining and heat treatment in variable orders. All the sample sets underwent shot-peening using stainless steel spherical shots with 400 μm diameter under a flow pressure of 5 bar. Table 1 also shows if a sample set underwent heat treatment and machining to improve surface quality. The heat treatment was carried out according to the specifications by the supplier of the powder material, as described in references[20,21]. The application of a certain post-processing procedure and their order are described by the second part of the alphanumeric code of the set, as the ending triplet of symbols represents the actual sequence of the three post-processing stages by the respective codes:

- “S” for micro-shot peening
- “T” for heat treatment;

- "M","1","2","3" and "4" represent machining, where the number indicates the thickness of the layer of material removed during machining (in millimetres); such samples are produced with the respective allowance and reached the dimensions specified by the ISO 1143 after removal of the material; the code "M" stands for allowance of 0.5 mm;
- "N" specifies that a post-processing step is not performed;

The post-processing procedures (without any indication of the order, unlike in the alphanumeric codes) are listed in the sixth (heat-treatment) and seventh (machining) column of Table 1. To increase the clarity of the table data, the value "Yes" was considered as the default value of the sixth column and was omitted.

Models and results

This chapter introduces the methods for prediction of fatigue resistance in the finite life domain used in the study presented in this paper. The basic aim of a method for prediction of fatigue resistance in the finite life domain is to predict the number of cycles to fatigue N based on a given bending stress S and other inputs. The difference between different prediction methods are those other inputs and mathematical models that utilize the input data to calculate the predictions. The predictive abilities of different methods are compared by calculation of statistical indicators that measure the difference between the predictions of the respective models and the experimental data, where better performance of a method is indicated by lower mean absolute error (MAE), lower mean absolute percentage error (MAPE), higher correlation coefficient (r) and higher coefficient of determination (R^2).

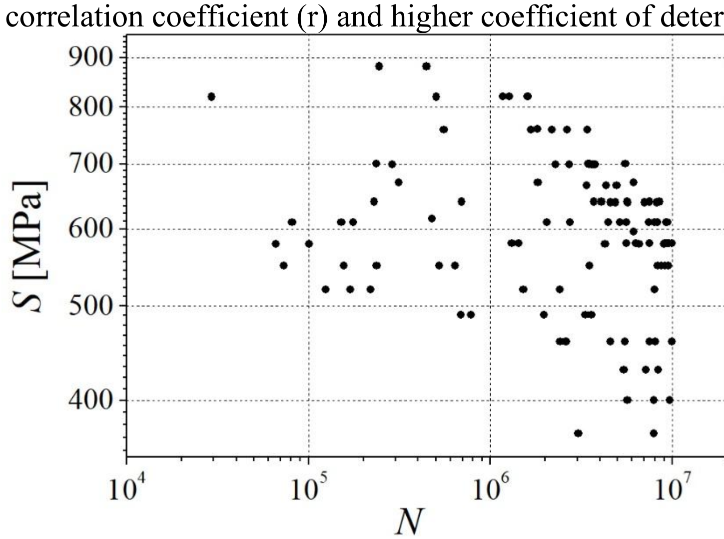

Figure 2: Experimental results of fatigue testing in the finite life domain

The analysis of the fatigue behaviour in the finite life domain presented in this study considers only the samples that underwent failure during the tests described in the previous chapter. During the experiments, 112 samples (out of 195 tested from all 16 sets) underwent failure, thus providing the data about both the number of cycles to failure N and the maximal bending stress S. Those experimental results are presented in the Figure 2. The data about the maximal bending stress S of the remaining 83 samples ("run-outs") are relevant for the fatigue behaviour in infinite life domain.

The obtained results were subject of the studies presented in the literature[20,21], which were based on prediction methods specified by the ISO 12107[39] standard, both in the finite and infinite life domain. In the research presented in this paper, the authors investigated the potentials of application of ANN to the same experimental results. As applicability of the ANN rises with the number of input data, the authors decided to focus on the fatigue resistance in the finite life domain. Since the problems met by previous research[20,21] motivated the study presented in this paper, some of its results will be briefly presented here to serve as a reference point for the results of the research presented here.

Standard methods

According to International Standard ISO 12107[39], the fatigue resistance of a material in the finite life domain may be represented by the S-N curve (or the S-N relationship), which uses a linear mathematical model of the form

$$x = b - ay \tag{1}$$

where $x = \log(N)$ and $y = S$ or $y = \log(S)$, whichever gives better plot linearity, and a and b are constants obtained by fitting of the experimental results; in the equation (1), log represents logarithm for base ten.

The simplest ("brute-force") approach to application of the ISO 12107 standard method would be to represent all the obtained experimental results using *a common S-N curve*. By performing the linear regression analysis of dependence of $x = \log(N)$ on $y = \log(S)$ using all the experimental results presented in the Figure 2, one obtains the constants $b = 11.69$ and $a = 1.92$, with MAE = 0.474, MAPE = 7.986%, r = 0.244 and $R^2 = 0.059$. The low value of correlation coefficient r quantifies the visible scattering of the experimental results that may be observed in Figure 2, and the low value of coefficient of determination R^2 indicates that only around 6% of the variation of the dependent variable (log N) in this set may be explained by the variation of the independent variable (log S). Therefore, the method that would predict number of cycles to failure N in dependence *only* on the stress amplitude S using the model (1) and the data presented in Figure 2 would have poor performance, and it is not used in practice. The poor performance of the "brute-force" approach indicates that the variations of the observed results are not random, and that, besides the bending stress S, the production conditions and post-processing procedures influence fatigue behaviour of the samples in finite life domain.

Set ID	*b*	*a*	Set ID	*b*	*a*
1	23.564	6.043	9	21.664	5.323
2	24.311	6.237	10	38.988	12.177
3	20.712	4.981	11	30.201	9.065
4	29.868	8.282	12	42.087	13.444
5	30.174	8.335	13	28.688	8.261
6	27.465	7.361	14	42.174	13.029
7	18.970	4.424	15	56.619	18.079
8	20.932	5.056	16	44.619	13.635

Table 2: Coefficients of determined S-N curves

For these reasons, the usual approach to application of the ISO 12107 standard model consists in determination of *a set of S-N curves*, where each of the S-N curves correspond to a specific combination of production conditions and post-processing conditions. In this case, it led to the determination of a S-N curve for each of sample sets listed in the Table 1. The S-N curves for each of the sixteen sample sets were determined according to specifications of ISO 12107, considering 4-8 stress levels for a set, with two tests at each level. The stress levels were selected to cover a broad range from 10^4-10^5 lifecycles to obtaining runouts for each of the sets. The constants *a* and *b*, determined by linear regression of experimental results for each of the sets are given in the Table 2, and the statistical indicators of the difference between the predictions of the model (1) using experimental results for individual sets are given in the Table 3. The obtained results show strong correlation between the measured and predicted fatigue lives, as well as high explanatory power of the method. In other words, a model that consists of 16 equations of type (1) provides a successful prediction of the fatigue life of MS1 produced by DMLS in the finite life domain.

Set ID	R^2	r	MAE	MAPE
1	0.991	0.995	0.016	0.242%
2	0.985	0.992	0.018	0.261%
3	0.995	0.998	0.011	0.16%
4	0.827	0.91	0.159	2.46%
5	0.899	0.948	0.119	1.837%
6	0.845	0.919	0.173	2.777%
7	0.785	0.886	0.097	1.456%
8	0.951	0.975	0.043	0.64%
9	0.942	0.971	0.057	0.872%
10	0.845	0.919	0.276	4.547%
11	0.880	0.938	0.212	3.377%
12	0.673	0.821	0.271	4.997%
13	0.946	0.973	0.128	2.079%
14	0.911	0.954	0.153	2.682%
15	0.975	0.987	0.075	1.154%
16	0.765	0.875	0.182	2.938%

Table 3: Results of statistical analysis

In order to assess the influence of individual factors (production conditions or post-processing conditions) on the fatigue behaviour, the differences between the experimental results and the predictions of S-N curves presented by the Table 2 were subjected to the ANOVA[20,21]. In essence, the ANOVA is able to reject the so-called null hypothesis, which means that differences between fatigue resistances observed for different levels of a factor are occurring randomly. One way to quantify validity of the null hypothesis is calculation of the quantity called "*p*-value" which, in the simplest case, represents a probability that the Fisher's ratio (ratio between the variations of fatigue strength between sets and variations of the fatigue strength within sets) due to random variations is higher than the value observed by analysis of experimental data. If p is smaller than the significance value α (probability of rejecting the null-hypothesis when it is true, usually set as 0.05), then the null-hypothesis may be rejected. The rejection of the null hypothesis indicates that the different levels of the factor are causing the observed differences between fatigue resistances, i.e., that the factor influences the fatigue behaviour. However, if p is higher than the significance value α, ANOVA is not able to reject the null hypothesis, and the influence of the factor on the fatigue behaviour in finite life domain *may not be assessed*. As mentioned in the introduction, the application of the ANOVA methodology to the data presented in Figure 2 and Table 2 was able to confirm the influence of the post-processing procedures ($p \approx 3 \cdot 10^{-5}$ for heat treatment, $p \approx 1 \cdot 10^{-5}$ for machining and $p \approx 1 \cdot 10^{-6}$ for interaction of the two factors in two-factors analysis of results of testing sets 1-13) and their order ($p \approx 0.038$ for the order of shot-peening and machining for one-factor analysis of testing sets 11 and 13) on the fatigue behaviour of MS1. However, it was not able to assess the influences of the build orientation ($p \approx 0.65$ and $p \approx 0.28$ for interaction with thickness for allowance for two-factor analysis of results of testing sets 1-9), the thickness of allowance for machining ($p \approx 0.05$ for two-factor analysis of results of testing sets 1-9, and $p \approx 0.19$ for one-factor analysis of testing sets 1-9), and the position of a sample in the production chamber ($p \approx 0.51$ for one-factor analysis of testing sets 14-16). The details of the ANOVA methodology, the obtained results and interpretation are given in the references[20,21].

ANN models

As explained in the introduction, ANNs represent a possible choice for description of a such a complex phenomenon as fatigue. A good ANN for description of fatigue life should predict the number of cycles to failure N with sufficient prediction ability, using as inputs the bending stress S and the data about the relevant production conditions and post-processing procedures.

The approach presented in this paper uses ANNs to assess the influence of the factors of interest (production conditions and post-processing procedure) to fatigue resistance of MS1 in finite life domain. The main idea of the approach is based on the fact that predictive abilities of different ANNs depend on their design, including selection of their inputs. Therefore, if a factor is relevant for fatigue behaviour of studied material, then the ANNs that have the factor as one of the inputs will have higher predictive abilities of fatigue life than the ANNs that do not consider that factor. Vice versa, if a factor is not relevant for fatigue behaviour of the studied material, then the predictive abilities of ANNs that have that factor as one of the inputs will be similar to the predictive abilities of the ANNs that do not consider that factor.

With the described aim were designed four feedforward ANNs. The output of the ANNs described the number of cycles to failure N using $x = \log(N)$. The differences between them were different structures of the input layers (i.e., the input data) and the consequential structures of the hidden layers. The concept of the design of the structures of the input layers was governed by the following requests:

- D.1. The inputs of the ANNs comprise numeric value of stress amplitude S and descriptors of some of the factors of interest;
- D.2. The complexity of structures of input layers is gradually increasing, so that the input structure of a more complex ANN has the input structures of the less complex ANNs as subsets;
- D.3. The difference between the ANNs with subsequent level of complexity comprises description of only one of the factors of interest, so the difference between predictive abilities of the ANNs may be attributed to the influence of that factor;
- D.4. Two of the ANNs with lower complexities (hereinafter referred to as ANN#1 and ANN#2) have as inputs the factors for which ANOVA has confirmed their influence on the fatigue resistance of the samples. The difference between the prediction abilities of ANN#1 and ANN#2 is used to check the validity of the approach used in this study.
- D.5. The other two ANNs, with higher complexities (hereinafter referred to as ANN#3 and ANN#4), apart from the abovementioned inputs, have as additional inputs the factors which effect was not possible to determine using ANOVA. The differences

between the prediction abilities of the two ANNs with lower complexity and the two ANNs with higher complexity are the potential sources of information for assessments that ANOVA was not able to provide.

With the described concept, the input structures of the ANNs are designed as follows:

1) ANN#1 predicts fatigue life of a sample in the finite life domain on the basis of *applied load and post-processing methods used after sample production*. Since all samples for study of fatigue behaviour are post-processed by shot peening, two binary variables are introduced in order to describe the application (or absence) of the corresponding type of post-processing method (one binary variable to describe the application of machining, and the other to describe the application of heat treatment). The input datasets of ANN#1 consist of these two binary variables and experimentally determined $y = \log(S)$. Therefore, the neural network ANN#1 has 3 input nodes.
2) ANN#2 predicts fatigue life of a sample in the finite life domain on the basis of the applied load, performed post-processing methods *and the order of their application*. To prepare the qualitative data for the ANN model, all the studied combinations of post-processing methods were first represented by one categorical variable, and then, using dummy encoding, that categorical variable was transformed into five binary variables which were used as neural network inputs along with the experimentally determined $y = \log(S)$. Therefore, the neural network ANN#2 has 6 input nodes.
3) ANN#3 assumes existence of the influence of sample position in the production chamber with respect to gas flow on fatigue behaviour, and that, therefore, this factor should be used for prediction of fatigue life in the finite life domain. For estimation of the fatigue life of a sample, *besides the position of the sample*, this ANN uses data about the applied load, the performed post-processing methods and the order of their application. To prepare the qualitative data for this ANN, all combinations of post-processing methods and all categories of sample positions were first represented by two categorical variables, and then, using dummy encoding, these variables were transformed into eight binary variables, which were, along with experimentally determined $y = \log(S)$, used as neural network inputs. Therefore, the neural network ANN#3 has 9 input nodes.
4) ANN#4 predicts fatigue life of a sample in the finite life domain on the basis of *applied load, performed post-processing methods and all the known production conditions*, therefore build orientation, sample position in the chamber and thickness of allowance for manufacturing. In the process of data preparation for neural network modelling, all combinations of post-processing methods, all categories of sample positions and all build orientations were represented by three categorical variables, which were further transformed by dummy encoding into ten binary variables. These binary variables, along with the value of allowance for manufacturing and the experimentally determined $y = \log(S)$ were used as ANN#4 input data. Thus, the ANN#4 has 12 input nodes.

It may be noted that the difference between the predictions of ANN#1 and ANN#2 may be attributed to the possible influence of the order of the post-processing steps. The difference between the predictions of ANN#2 and ANN#3 may be related to the possible effect of the position of a sample in the production chamber. Finally, the difference between the predictions of ANN#3 and ANN#4 may be related to the possible influences of build orientation and thickness of allowance for machining.

The concept of the structure of the ANNs' inputs presented above restricted their design, and the structure of ANNs described above is not the only solution that satisfies the requests D.1–D.5, but there are no many choices as it may seem at the first glance. The structures of the input of ANN#1 and ANN#2 are essentially completely determined by these requests because the description of the order of the post-processing procedures (described by ANN#2) may not be introduced before introduction of the post-processing procedures (described by ANN#1). Therefore, the only input factors which order may be changed while simultaneously satisfying requests D.4 and D.5 are the descriptions of position of a sample in production chamber with respect to inert gas flow, build orientation and thickness of allowance for machining. However, the results obtaining by variation of the order of inclusion of production process factors into input layer structure of ANNs led to the same conclusions about the influence of the factors as the ANNs described above, and the obtained numerical results will not be presented in this paper.

The structure of an ANN depends also on the amount of data that may be used for its training and verification. The limited amount of the input data (112 points presented in the Figure 2) brings the danger of "overtraining" of an ANN, and, therefore, attention should be dedicated to the process of design of the ANNs. The number of the hidden layers of networks and the activation functions of the ANNs were determined through the process of hyperparameter tuning[40], which enables definition of the architecture of the ANN with the desired level of generalization. The hyperparameter tuning method balances between the opposing requests for better approximation of complex relationships between the inputs and outputs (which requires increase of the number of ANN nodes) and the reduction of the risk of ANN overtraining (which requires decrease of the number of ANN nodes). This maximizes the accuracy of predictions on unknown datasets, hence the datasets that are not used in the process of the ANN training. During the neural network training process, Adam optimization algorithm[41] with learning rate $\alpha = 0.001$, exponential decay rate for first moment estimates $\beta_1 = 0.9$, exponential decay rate for second moments estimates $\beta_2 = 0.999$, and zero-value $\varepsilon = 10^{-8}$ was used to update the network parameters.

The ANNs were developed using the datasets that consisted of values $y = \log(S)$, $x = \log(N)$, the data describing production conditions, and the data describing the applied post-processing procedure for each of the samples that underwent failure during the fatigue testing. A total of 92 datasets were used for network training, whereas 20 datasets (close to 20% of total) were used for validation of the developed neural networks. The collections of datasets for training and validation were formed randomly, but with restriction that both collections had to contain samples from all sets under the study. In addition, the process of network training was repeated using different training and validation datasets to check the stability of the obtained results.

ANN	ANN#1	ANN#2	ANN#3	ANN#4
Input	3	6	9	12
Hidden	5	5	5	8
Output	1	1	1	1

Table 4: Number of the neurons in the layers of the developed ANNs

The ANNs obtained by the described procedure had one hidden layer of neurons. The activation function of the neuron in the output layer is linear (also known as “identity”) function, whereas the activation functions of the neurons in the input and hidden layers are of the rectified linear unit (ReLU) type. The optimal number of nodes in the hidden layer is presented in the Table 4, along with the number of nodes in the input and output layers.

Results of prediction of fatigue life obtained by the developed ANN are compared to the experimentally obtained data. The validity of the models is estimated by statistical analyses of differences between the experimental and predicted results for all 112 datasets using the same statistic indicators as in the case of models based on the standard linear regression. Since ANN models are trained on 92 out of 112 datasets, the results of statistical analyses are also presented separately for training and validation datasets. The Table 5 presents these results along the results of predictions obtained (for the same datasets), using the common S-N curve and the set of 16 S-N curves, as discussed in the previous section.

Analysis and discussion

By the concept of the study, the influence of the production conditions and post-processing procedures on the fatigue behaviour of MS1 produced by DMLS will be studied by comparison of the predictive abilities of different ANNs. Nevertheless, further comments will also be made about the comparison of the prediction abilities of the ANNs and methods based on ISO 12107 standard.

	Model	**Common**	**Set of**	**ANN**			
Indicator	**Dataset**	**S-N**	**S-N**	**#1**	**#2**	**#3**	**#4**
R^2	All data	0.06	0.90	0.68	0.83	0.89	0.90
	Training	0.07	0.91	0.70	0.83	0.89	0.91
	Validation	0.02	0.85	0.58	0.80	0.86	0.86
r	All	0.24	0.95	0.83	0.91	0.94	0.95
	Training	0.25	0.96	0.84	0.91	0.94	0.95
	Validation	0.19	0.93	0.77	0.90	0.93	0.93
MAE	All data	0.47	0.15	0.26	0.20	0.16	0.15
	Training	0.46	0.13	0.25	0.19	0.15	0.14
	Validation	0.52	0.20	0.31	0.24	0.19	0.20
MAPE	All data	7.99%	2.39%	4.28%	3.21%	2.55%	2.42%
	Training	7.79%	2.19%	4.07%	3.05%	2.42%	2.24%
	Validation	8.87%	3.29%	5.28%	3.97%	3.15%	3.24%

Table 5: Comparison of predictive abilities of different models for fatigue behaviour prediction

The comparison of the predictive abilities of the ANN#1 (which has the lowest prediction ability of all the ANNs) and the common S-N curve shows that adding explanatory variables describing the parameters of the post-processing procedure results in a profoundly higher explanatory power (more than tenfold increase of coefficient of determination R^2, e.g., from 0.06 to 0.68 for all data). Prediction accuracy is also significantly enhanced (more than three times higher correlation coefficient r, e.g., from 0.24 to 0.83 for all data), which further confirms the established knowledge that the fatigue behaviour of DMLS products is strongly affected by the applied post-processing methods[21]. The introduction of description of the order of the post-processing further contributes to clear increase of the predictive ability of ANN#2 (R^2 increases from 0.68 to 0.83 for all data, which means that the part of variation of the dependent variable that cannot be explained by the variations of input variables, $1–R^2$, decreased almost twice, from 0.32 to 0.17) in comparison with ANN#1. This outcome confirms that the order of post-processing steps does influence the fatigue resistance of DMLS products[21].

The agreement between the results obtained by comparison between the predictive abilities of the common S-N curve, ANN#1 and ANN#2, on one side, and the results of previous research[21] on the other side, verifies the approach to the analysis of the influence of the studied factors on the fatigue resistance developed in this paper. In other words, the ANN approach confirms that the influence of a factor is significant when ANOVA leads to the same conclusion. Such an outcome encourages further application of the ANN approach to additional cases, when ANOVA was not able to establish the significance of the studied factor (i.e.: was unable to reject the null hypothesis), which was the primary goal of the present study.

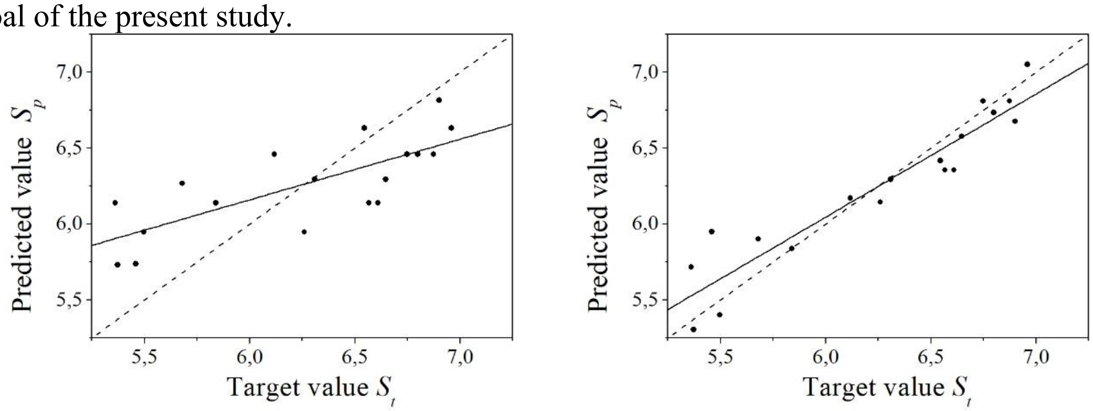

Figure 3: Experimental (target) values and results of prediction by ANN#2 (left) and ANN#3 (right) for samples with defined positions with respect to inert gas flow

The inclusion of the position of a sample in the production chamber with respect to inert gas flow as additional explanatory variable increases the prediction ability of the ANN. This conclusion is suggested by higher values of the coefficient of determination R^2 and correlation coefficients r for predictions of the ANN#3 network in comparison with their values for ANN#2. The Table 5 shows that R^2 values increase from 0.80 to 0.86 in validation dataset, and from 0.83 to 0.89 for the training dataset and all data. In other words, the variation of the dependent variable that cannot be explained by variation of input variables, $1–R^2$, is reduced by one third, from 0.17 to 0.11, by introduction of the position of a sample in production chamber as input variable. The result is of particular interest and worthy of further analysis, because it suggests that the position of the samples in production chamber has influence on the fatigue resistance in the finite life domain of the MS1 produced by DMLS, which ANOVA was not able to prove.

To further study the difference between the predictions of the ANN#2 and ANN#3 (and thus the influence of the position of a sample to its fatigue resistance), the authors compared predictions of the two ANNs for a subset of the experimental data that consisted only of the samples with defined positions, which underwent failure during fatigue testing. As Table 1 shows, only 45 samples were manufactured with defined positions with respect to the inert gas flow, and only 18 of them underwent failure during testing. The experimental results and predictions of ANN#2 and ANN#3 for those 18 samples are shown in Figure 3. The dotted lines indicate the target of the prediction (i.e.: equal values for experimental results and predictions), whereas the full lines represent the actual dependences between the predictions and the experimental results obtained by linear regression. The statistical indicators of differences between the experimental results and predictions are given in the Table 6. Both the Figure 3 and Table 6 clearly show that the ANN#3 has much higher predictive ability than the ANN#2 for the samples with known position in production chamber, thus indicating that the position of a sample with respect to the inert gas flow influences its fatigue resistance in the finite life domain.

Model	R^2	r	MAE	MAPE
ANN#2	0.52	0.76	0.35	5.68
ANN#3	0.88	0.94	0.14	2.34

Table 6: Comparison of prediction capabilities of ANN#2 and ANN#3 for samples with defined positions with respect to inert gas flow

Further analysis of the results in Table 5 clearly shows that the predictive ability of ANN#4 is not significantly better than predictive ability of ANN#3, because the coefficient of determination R^2 for training set if 0.86 for both ANNs, while it increases from 0.89 to 0.91 and 0.90 for training dataset and all data, respectively. With more accurate calculations of the values, the increase of coefficient of determination from ANN#3 to ANN#4 is five times smaller (0.012) than the increase of the predictive ability from ANN#2 to ANN#3 (0.058). This observation suggests that the build orientation and thicknesses of allowance for machining larger than 0.5 mm do not influence the fatigue resistance of MS1 manufactured by DMLS, thus providing a quantitative support to similar claims and potential explanations made in references[21].

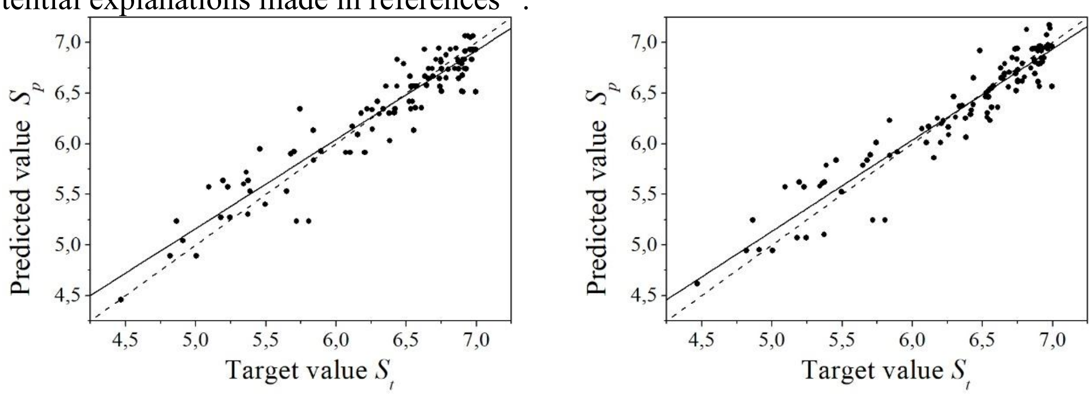

Figure 4: Experimental (target) values and results of prediction by ANN#3 (left) and the set of S-N curves (right)

The predictive ability of the ANNs may be compared also to the predictive ability of the set of S-N curves. Figure 4 presents a comparison between the experimental results (which serve as target values) and predictions by ANN#3 and the set of S-N curves. Like in Figure 3, the dotted lines indicate the target of the prediction (i.e.: equal values for experimental results and predictions), whereas the full lines represent the dependences between the predictions and experimental results obtained by linear regression. Both Figure 3 and Table 5 indicate that the ANN#3 and the set of 16 S-N curves have similar prediction abilities.

The inability of the developed ANNs to have higher prediction ability than the set of S-N curves shows that the limited set of input data prevents development of an ANN with sufficiently complex structure to overcome predictive ability of the set of S-N curves. If considerably more input data were available, the hyperparameter tuning procedure could lead to ANNs with more hidden layers, which might have higher prediction abilities than those of the ANNs studied in the paper. However, creation of new experimental data would also lead to considerably higher costs for production and testing of additional samples. Nevertheless, as explained in the introduction, the goal of the research presented in this paper was not to develop an ANN that would be regarded as a superior prediction tool. The subject here was to compare prediction abilities of *different ANNs* developed using *the same datasets*, with the aim of understanding better the influence of certain production conditions and post-processing procedures on the fatigue behaviour. This study introduces *the use of ANNs as a complementary tool to assess the significance of potentially relevant factors for fatigue behaviour*.

Conclusion

In this paper is presented a novel approach to assess the influence of production conditions and post-processing procedures on the fatigue resistance of the MS1 in the finite life domain. The approach aims at compensating for the lack of ANOVA methodology to assess the influences in some cases. In particular, this study is related to the inability of ANOVA to assess the influence of build orientation, of the thickness of allowance for machining, and of the position in the production chamber, on the fatigue resistance of MS1 produced by DMLS technology.

With this aim, four different ANNs for prediction of the fatigue life of MS samples in finite life domain were designed. The complexity of the input structure of the ANNs was incremental: the predictions of the ANN#1 were based on the applied load and post-processing procedures used after sample production; the predictions of the ANN#2 also included the order of application of post-processing procedures; the predictions of the ANN#3 further included the position of a sample in the production chamber; finally, predictions by ANN#4 included build orientation and thickness of allowance for manufacturing. The four ANNs were trained on 92 datasets and validated on 20 datasets. The processes of training and validation were repeated to check for stability of the results. The differences between the predictions of the ANNs and experimental data, quantified by standard statistic descriptors, were used to measure the predictive abilities of the ANN. Since the basic difference between the ANNs is the structure of their inputs, i.e., the production conditions and post-processing conditions used to calculate their predictions, the differences between the predictive abilities of the ANNs were attributed to the significance of the influence of the respective DMLS production process factors.

The approach was verified by comparison of its results to the ANOVA results for the cases where ANOVA gave well definite answers. Much higher values of coefficient of determination R^2 and correlation coefficient r of the ANN#1 in comparison with a common S-N curve indicate that post-processing procedures influence fatigue behaviour of MS1 in finite life domain. Furthermore, considerably higher values of coefficient of determination R^2 and correlation coefficient r of ANN#2 in comparison with ANN#1 shows that the order of the post-processing procedures also influences the fatigue behaviour of MS1. Both conclusions agree with the previously published results of the ANOVA, which verifies the approach presented in the paper.

The most important result of application of the ANN in the presented research is the assessment of the influence of the factors whose relevance for the fatigue response of MS1 produced by DMLS cannot be determined by ANOVA. Higher values of coefficient of determination R^2 and correlation coefficient r of ANN#3 in comparison with ANN#2 indicates that the position of a sample in the production chamber with respect to the inert gas flow has some influence on fatigue behaviour of MS1 in finite life domain. On the other hand, essentially the same values of coefficient of determination R^2 and correlation coefficient r of ANN#4 in comparison with ANN#3 suggest that the build orientation and thicknesses of allowance for machining higher than 0.5 mm do not influence fatigue behaviour of MS1 in finite life domain.

The obtained results are of practical importance for reduction of high costs of experimental studies of fatigue behaviour of MS1 produced by DMLS. Besides, they bring useful directions for development of computational tools for prediction of fatigue life in finite life domain of MS1 produced by DMLS.

It is also important that the approach presented in the paper may be applied to other materials, and even generalized to many other cases when ANOVA does not give definite answers concerning the influence of certain factors, even beyond the fields of materials and engineering.

The drawback of the approach arises from the application of the ANNs as the computational tool: the approach may establish the influence of a certain factor on the output quantity, but it does not reveal the nature of that influence or the analytic relationship between the factor and the output quantity. However, it is also the case with majority of statistic methods, and with the ANOVA in particular.

Finally, while the approach presented in this paper uses ANNs an alternative way to look at the experimental data already analysed by statistical methods, it still remains limited to the information contained in that data. For that reason, the research presented in this paper does not address some important aspects of fatigue, such as influence of the mean stress to fatigue resistance, because testing according to the ISO-1143 standard, which used to obtain the experimental data used in this study and previously analysed by ANOVA methodology[20,21], comprises only loading with $R = -1$. While this conclusion definitely means that further research is necessary to understand better fatigue behaviour of MS1, it is not particularly related to the methodology proposed and studied in this paper.

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