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Fundamentals of a recommendation system for the aluminum extrusion process based on data-driven modeling

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Abstract:

The aluminum profile extrusion process is briefly characterized in the paper, together with the presentation of historical, automatically recorded data. The initial selection of the important, widely understood, process parameters was made using statistical methods such as correlation analysis for continuous and categorical (discrete) variables and 'inverse' ANOVA and Kruskal–Wallis methods. These selected process variables were used as inputs for MLP-type neural models with two main product defects as the numerical outputs with values 0 and 1. A multi-variant development program was applied for the neural networks and the best neural models were utilized for finding the characteristic influence of the process parameters on the product quality. The final result of the research is the basis of a recommendation system for the significant process parameters that uses a combination of information from previous cases and neural models.

Keywords: aluminum extrusion, advisory system, product defects, data mining, neural networks

1. Introduction

The extrusion process is one of the most popular and effective manufacturing technologies for a large variety of aluminum profiles. It is a process in which complex mechanical, thermal and surface phenomena take place. Its implementation requires specialized machinery and tooling. The process itself must be strictly controlled to prevent product defects, the most common of which are various surface defects (especially scratches) and deviations from the assumed geometry. These issues are widely described in the professional literature, where there are guidelines for product and tooling design, as well as setting the process parameters (Aluminum Extruders Council, 2018, p. 200; ASM International, 2005; Bauser et al., 2006; Laue & Stenger, 1981; Lesniak & Libura, 2007; Pilar Noriega & Rauwendaal, 2010; Sheppard, 1999; Zasadziński et al., 2004; Zhu et al., 2012). In practice, however, such defects appear and are associated with various types of losses for the company. Their causes are often hidden and may be related to incorrect settings of the process parameters, the tooling design and quality and human errors occurring at various stages of the preparation and running of the process.

Modern manufacturing systems ensure the measurement and recording of the most important parameters. Such databases can be used to obtain useful knowl-

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edge about the processes, including the impact of their parameters on the quality of the product. There are currently many examples of data mining and data-driven modeling applications for diagnostics and optimization of manufacturing processes in the literature. They apply to both discrete processes (typical for such industries as machine-building, automotive, electrical, aircraft) as well as continuous, i.e. processing (chemical, fuel, food, pharmaceutical, etc.); some of them are quoted and characterized in (Köksal et al., 2011; Perzyk et al. 2014; Qin, 2012). Nevertheless, the authors of this article are not aware of the applications of this type of tool in the control and diagnostics of aluminum extrusion processes.

A more systematic approach to data-driven modeling of production processes can be found in (Stanley, n.d.; Kapadia et al., 2007), where the types of models and process failure management issues are discussed. The possibilities of using advanced data-driven process modeling have increased significantly in the current era of industrial development known as Industry 4.0. In an excellent recently published review paper (Silva Peres et al., 2020), the current state and the possibilities of using artificial intelligence in the manufacturing industry are comprehensively presented.

In a cooperating production plant, a project is being carried out to create an advisory system aimed at indicating the optimal parameters of the process and tooling to reduce the formation of defects in aluminum profiles made by the direct extrusion method. This article describes how to build the foundations of such a system and presents the main results obtained.

2. Quality issues in the extrusion process

Defects of aluminum profiles related to the extrusion process can occur at three stages of the process (Fourmann, 2017): during extrusion, after extrusion (related to metallurgy) and after anodizing. Some defects (such as dents, bend & twist, scratches) may also occur as a result of improper handling, storage or transportation of the profiles (Prakash et al., 2021). Despite the great importance of the direct extrusion process of aluminum alloys, a uniform classification of product defects has not yet been developed and widely accepted (Raimundo & Canuto, 2019).

In the cooperating plant, the quality management procedures distinguish 34 types of defects. However, the adopted classification, apart from defects resulting from the extrusion process, also includes other defects, e.g. failure to meet the size of the ordered product batch, and also differentiates the same defect depending on the place of its detection: in production or in the store.

In the group of defects directly related to the manufacturing process, the largest share are surface defects and shape defects. In the first group, defects such as die lines, blisters, tearing, excessive surface roughness and pitting are detected. The second group includes the following: dimensional variation, lack of rectitude, waving, angle variation, flatness variation, twisting, dents, broken walls. It is worth noting, however, that only information about the entire class of defects, e.g. surface or dimensional, is stored in the plant's databases, without distinguishing between their specific forms. Therefore, it should be expected that the advisory system based on such a database will indicate several different parameters responsible for the defect of a given class.

3. Industrial data characteristics and preparation

The original database contained around 66,000 records, each of which contained various types of information related to one ingot. This information included the values of over 100 variables related to product, tooling, machine and process parameters as well as several identifying variables. Some variables are of a numerical type (e.g. dimensions, speeds, temperatures, etc.), others are categorical (e.g. product defect code, mold type, operator's name). All these data hereinafter referred to as "historical", were acquired and saved over a period of 3 months, selected by the cooperating plant as representative from the point of view of the product assortment, the tooling used, and the level of defective products.

Figure 1 shows a diagram illustrating the frequency of occurrence of particular types of defects. Surface and dimensional defects are clearly distinguishable, and therefore further research was focused on them. Importantly, the defect cases accounted for a small fraction of the total production. For this reason, specially prepared data sets were adopted for the creation of models in which all records with a given defect were supplemented with randomly selected records without defects so that their number of the last ones would be twice the number of the former. Only records with no empty cells for all selected variables (see above) were included in the database. The two data sets, corresponding to the two defect types, contained approximately 5,000 records each.

The main steps in creating a database for neural modeling and the recommendation system, according to data preparation methodology (Grzegorzewski & Kochański, 2019), are described below.

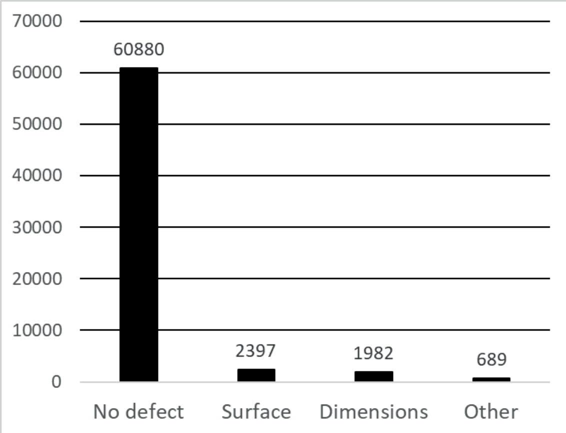

Fig. 1. Occurrences of defect types in the original database

3.1. Cleaning the data

After initial cleanup of the data by removing variables (columns) with constant or mostly empty values, the correlation analysis between potential input variables, i.e. related to product and process parameters was made. The correlations were determined between all pairs of variables expressed in real numbers and separately between all pairs of categorical variables (nominal and/or ordinal). For the numerical variables, Pearson and Kruskal–Wallis analyses were made. For categorical variables, the analysis of correlation was carried out with the use of contingency tables, and the Cramér's V statistic was adopted as the measure of the degree of correlation. Each pair showing a high value of a correlation coefficient was carefully analyzed and an individual decision was made. At this stage, one numerical variable was detected having identical values with another variable and was eliminated from further analysis. However, the results of correlation analysis were utilized again after the significance analysis of all variables presented further (section 3.2). The resulting number of input variables at this stage was 53.

3.2. Preliminary analysis of the significance of product and process parameters

Significance analysis was performed separately for continuous numerical and categorical parameters. As the type of defect is expressed by categorical values (surface, dimensions, no defect), the significance analysis of numerical parameters was performed using one-way ANOVA with defect type as input (level) and given parameter as output; this approach can be called 'inverse ANOVA'. Due to very different statistical distributions of parameter values, the Kruskal–Wallis analysis was also used in the 'inverse' version. The relative significance of the variables was defined as F-ANOVA statistics (H statistics in K–W) divided by the maximum value among those found for all variables. Of course, such an 'inverted' treatment of inputs and outputs only means that we can check whether a given parameter had significantly different values in the group of cases with a defect compared to cases without a defect. If this differentiation is small compared to other parameters, then the omission of a given parameter in the neural model is justified from a practical point of view.

Figure 2 shows the results for the dimensional type defects. The "average" curve does not show a clear cut-off of significant parameters from the others. Therefore the limit value of 20% was intuitively adopted as reasonable, allowing, on the one hand, to reduce the number of parameters for further analysis, and on the other hand, to retain all potentially significant parameters. It should be noted that the relative significance values obtained from both analyzes (ANOVA and K–W) significantly differ for some parameters. Adoption of this cut-off level ensured that none of the significance for the discarded parameters was greater than 20%.

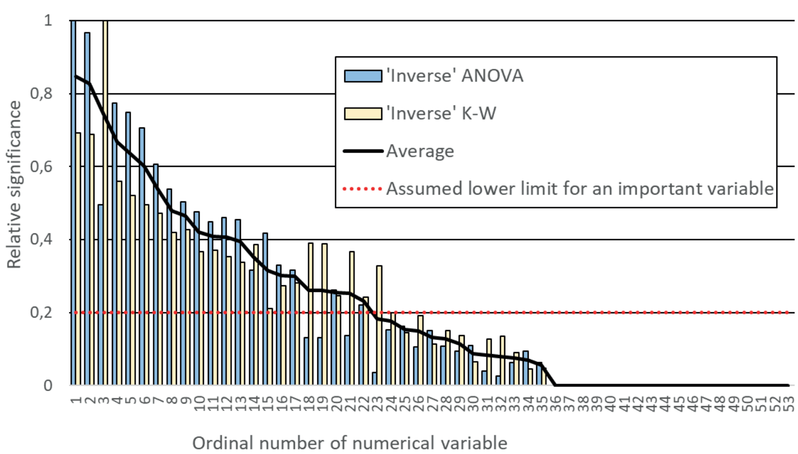

Fig. 2. Relative significances of potential numerical input variables (product and process parameters)

For categorical parameters, the significance analysis was performed using the contingency table approach in such a way that one of the variables was the occurrence of a given defect, and the other was a given input variable. The Cramér's *V* statistic was adopted as a measure of the significance level of a given input parameter and, as in the case of numerical variables, its normalized values were adopted as a measure of relative significance. Figure 3 shows the results for the dimensional type defects. Variables with a clearly low relative significance were omitted in further analysis.

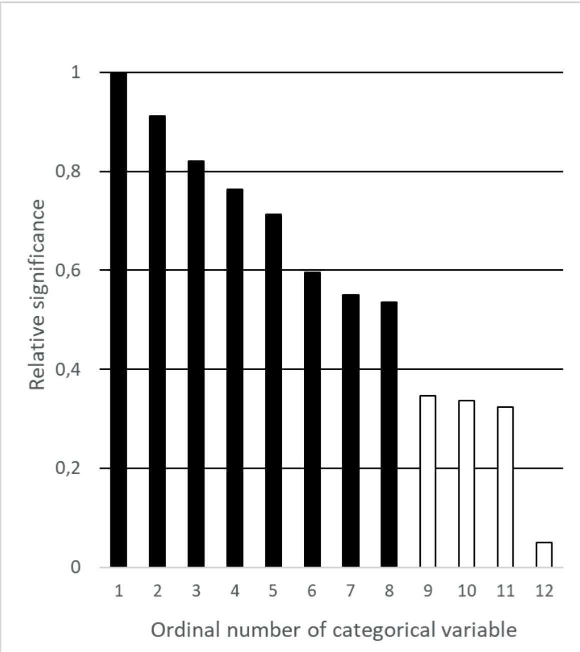

Fig. 3. Relative significances of potential categorical input variables (product and process parameters) based on Cramér's V statistics; the variables marked in light grey have been rejected

At this stage, pairs of variables with a significant degree of correlation (see section 3.1) were carefully analyzed and an individual decision was made to either:
- replace several variables with a single 'substitute' variable, being combination of their values (e.g. adopting average cooling intensity from several independent fans, replacing the number of runs for a given die by the ratio of this value to the total number of hours of its operation);
- leave the correlated variables.

As a result of the above analyses, the final numbers of input variables for neural modeling were:
- for surface defects: 15 variables (8 numerical and 7 categorical),
- for dimensional defects: 17 variables (10 numerical and 7 categorical).

4. Neural modeling

The aim of the neural models developed in this project was to use them to find significant relationships between product, tooling, and process parameters and the tendency to the occurrence of two selected types of defects. The choice of artificial neural networks was dictated by their widely recognized advantages over other types of data-driven models, including the modeling of manufacturing processes.

4.1. ANNs construction, training and assessment

As part of the project, MLP neural networks were adopted due to the positive experiences of many authors in similar applications (see e.g. Perzyk & Kochański, 2003; Perzyk et al., 2005, 2008) and publications cited therein). The dependent variable is the occurrence of a product defect, so it is essentially a categorical type variable. Due to the nature of the network output signals expressed by a continuous activation, it was decided to treat this variable as numerical, assuming the values in the database equal 0 (no defect) or 1 (defect occurrence). A logistic activation function was adopted for the output neurons to ensure that results in this particular range were obtained. According to many recommendations, the hyperbolic tangent was adopted as the activation function for internal neurons.

The neural networks were created using the efficient training algorithm from Dell Statistica software, assuming the default random division of data records (training 70%, 15% testing, 15% validation), one hidden layer, and a random selection of the number of hidden layer neurons between 8 and 25 (Statistica's default for this data). 500 ANNs were created, from which the 5 best networks were selected for further analysis. The selection was made based on the criterion of the maximum product of the network quality calculated for each of these subsets (network quality was defined as the linear correlation coefficient between the actual values and those obtained from the network). These best networks contained between 16 and 25 hidden neurons.

The quality levels of the selected networks were high, usually 0.94–0.95 for the training subsets for both types of defects, above 0.9 for the testing and validation subsets in the case of surface defects, and over 0.87 for the testing and validation subsets in the case of dimensional defects. In Figure 4, a typical distribution of the predicted values are shown together with the real values. It can be observed that the overwhelming majority (of total about 5,000 records) of network responses were very close to 0 or 1, which indicates their tendency to clearly indicate the presence or absence of a defect (with a small number of errors, affecting the network quality values given above).

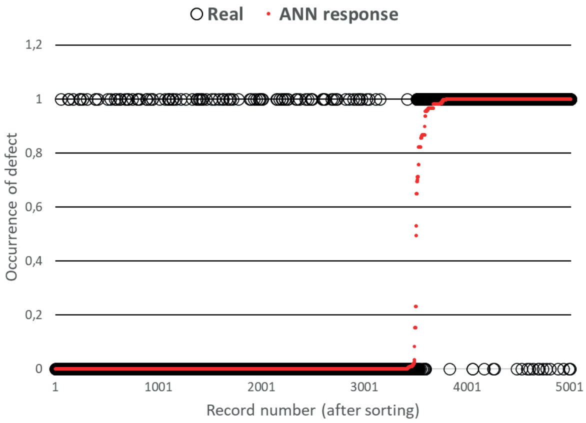

Fig. 4. An example of a typical neural network response (one of the 5 selected networks for the surface defect)

In order to assess the reliability of the predictions of neural networks, their responses were rounded to the values 0 and 1, and then the prediction consistency of the selected 5 best networks was evaluated. The agreement of predictions for all 5 networks calculated for all real values was in 89% cases for the surface defect and 79% for the dimensional defect. In order to assess the reliability of network predictions for completely new combinations of input data values, analogous indices of compliance of the selected 5 best networks were calculated for 5,000 records with randomly selected values. The results were as follows: the agreement was in 27% for the surface defect and 33% for the dimensional defect. These large prediction inconsistencies for different networks call into question the usefulness of neural networks for recommending process settings and tooling design for new products.

Further analysis revealed the cause of this neural network behavior. In the data used to create the neural networks, quite numerous identical records were present. Hence, high network quality indices were also obtained for validating data, which contained a significant fraction of records similar to those in the training data. Some test neural networks were constructed for the data prepared in such a way that the validation records did not appear in the data used for training. The summary of these tests can be presented in the form of correlation coefficients between the predictions obtained from all the 5 networks which could be used as a measure of agreement between networks which indicates their reliability. For the surface defect, the correlation coefficient was 0.86 for all real records, 0.28 for completely new random combination of input values and 0.52 for validating records (being also 'new' for the neural network). This means that the reliability of the predictions of the neural network for new data is significantly better if the input data were also obtained within certain conditions, i.e. excluding some combinations of values appearing in the randomly obtained data that the network was unable to learn. This conclusion was crucial in using neural networks in the developed recommendation system.

4.2. Knowledge extraction from ANNs

The first purpose of using a neural network to recommend process parameters in tooling construction is to identify the main causes of product defects in order to minimize the likelihood of their occurrence. There are various methods of determining the relative significances of input variables of the neural model from the point of view of the degree of their influence on the output. The most popular and relatively simple method takes the measure of the significance of the variable, the increase of the neural network error as a result of blocking a given input at a constant level, i.e. replacing the actual values in the training set with certain constant values, e.g. averages. However, in the case of discrete input variables, where one variable is replaced by several variables (the number of which corresponds to the number of possible values of that variable), the applicability of this approach is questionable. The authors of the article conducted several tests with the use of specially prepared artificial and real data sets using the Dell Statistica software that utilizes the input significance calculation based on the above principle. It turned out that it significantly overestimates the significance of discrete variables, typically by 1.5–2.5 times. This prompted the authors to abandon this approach as a tool used to determine the most defect-influencing product, tooling, and process parameters.

Taking into account the conclusions from the reliability testing of neural networks (section 4.1), the following methodology for obtaining knowledge about the influence of various types of parameters on the tendency to defects was adopted.

The magnitude and direction of the influence of one input variable on the output generally depends on the current values of the other variables. The values of the output, found for a specific level of the considered input variable for different values of the remaining variables, can be considered as some random set of the output values, for which statistical analysis, including ANOVA, can be used. By applying several levels of the input variable under consideration, important information about its possible influence on the output (defect tendency) can be obtained. For categorical inputs, all values appearing in the data were used, while for numerical inputs, continuous values were converted into one of 10 equally spaced intervals (levels). The levels of a continuous variable should be numerous enough to reflect its effect on the dependent variable. When the character of the dependence between variables is unknown, especially when non-monotonic influence of a given input should be taken into account, 10 levels is a reasonable value. For monotonic dependencies usually smaller numbers are satisfactory (e.g. Perzyk et al. 2014).

In order to obtain more reliable neural model responses (see section 4.1) it was decided to adopt the following combinations of the remaining input variables:
- appearing in the historical data (used for the network training);
- randomly generated, but only those for which all top 5 networks gave consistent responses;
- for comparison, calculations were also made for all random values (5000), i.e. including those for which the predictions of the network were inconsistent.

In Figures 5–13 examples of the results obtained from the best five neural models are presented in the form of graphs showing the average network predictions vs input levels. It can be noticed that all three variants of the values of the remaining variables give qualitatively similar predictions. However, significantly larger differences between the five networks are observed when all random records were used for the remaining variables (compared with those obtained for the real, historical values).

a) b) c)

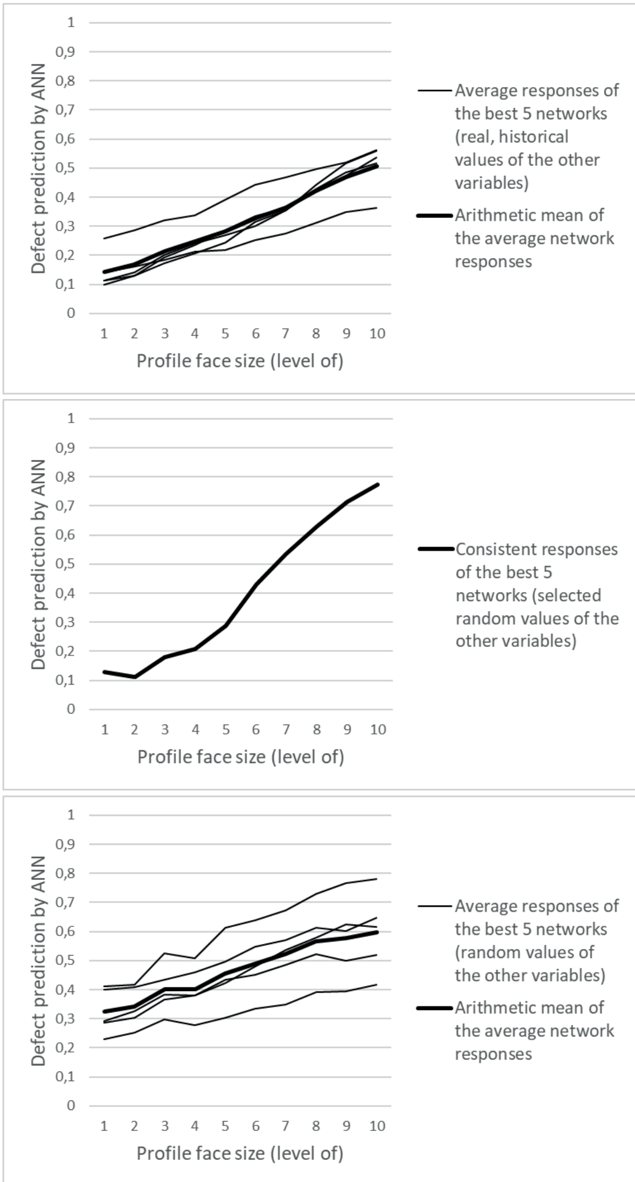

Fig. 5. Example of surface defect predictions vs level of a numerical variable characterizing the product, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values

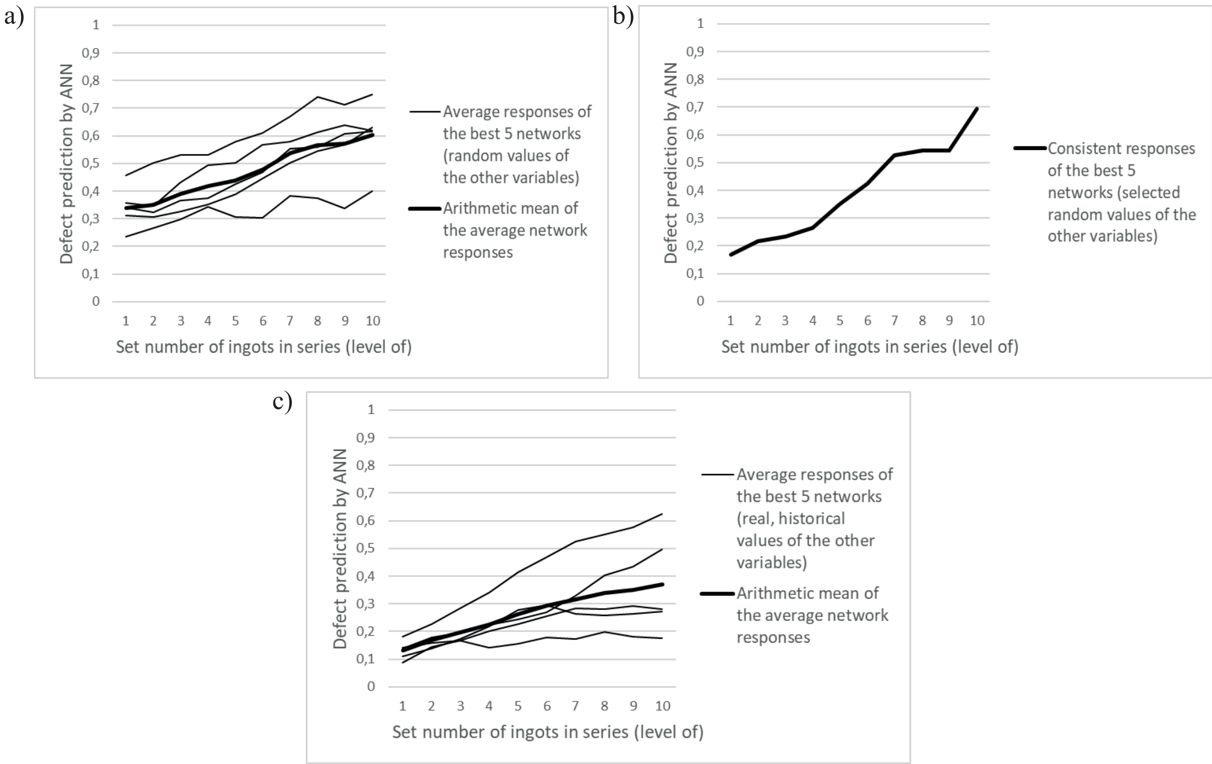

Fig. 6. Example of surface defect predictions vs level of a numerical variable characterizing operational conditions, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values

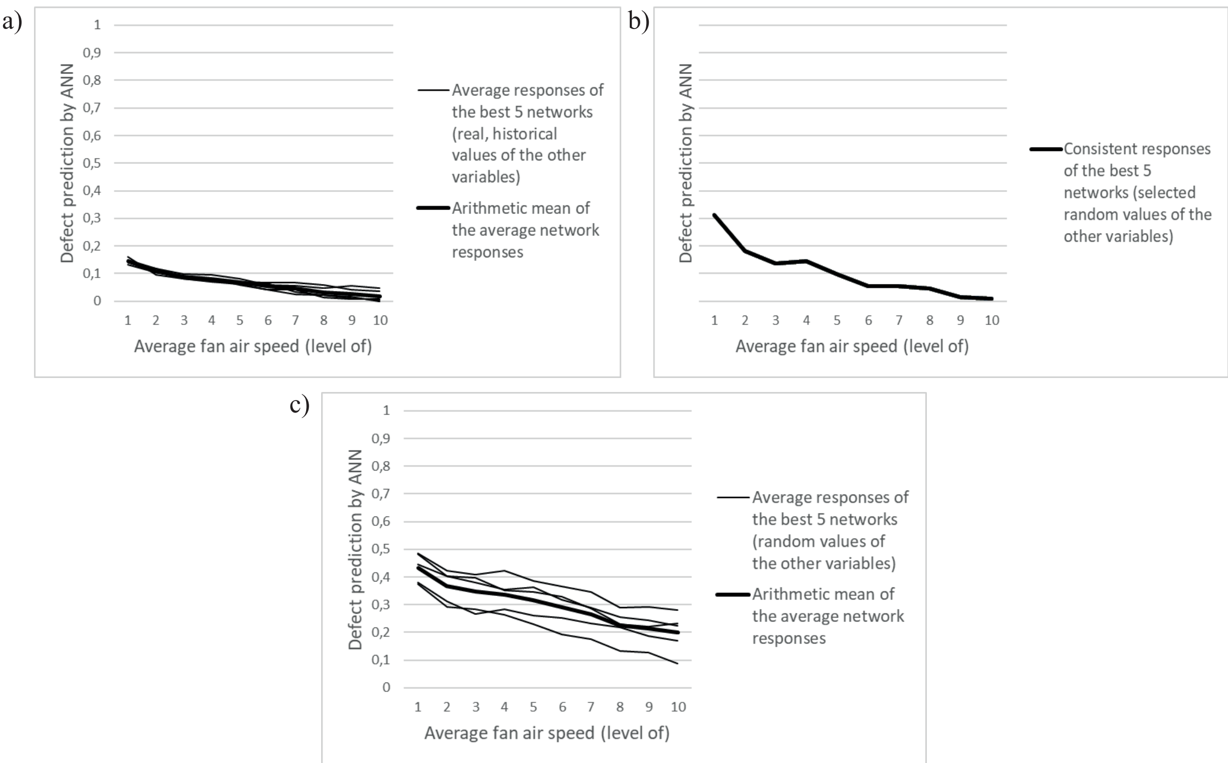

Fig. 7. Example of dimensional defect predictions vs level of a numerical variable characterizing machine settings, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values

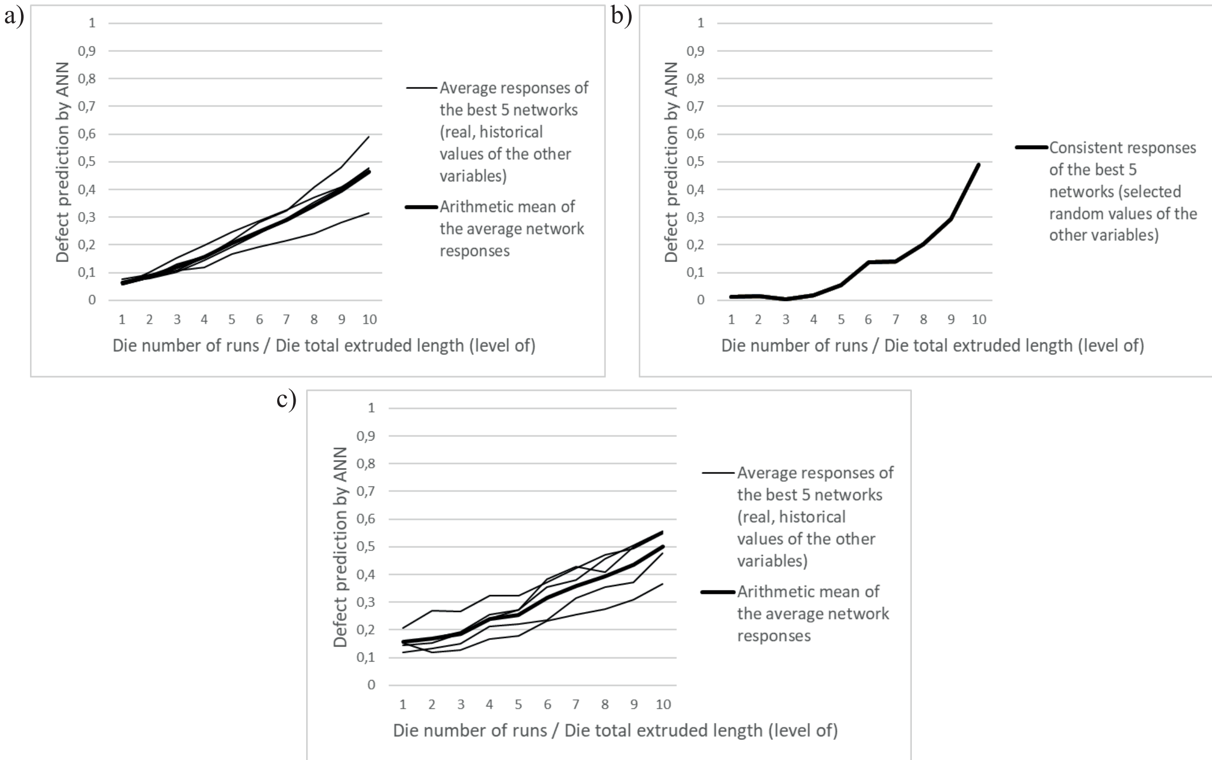

Fig. 8. Example of dimensional defect predictions vs level of a numerical variable characterizing die operation, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values. This is an example of one of the most influencing numerical parameters, with apparent nonlinearity

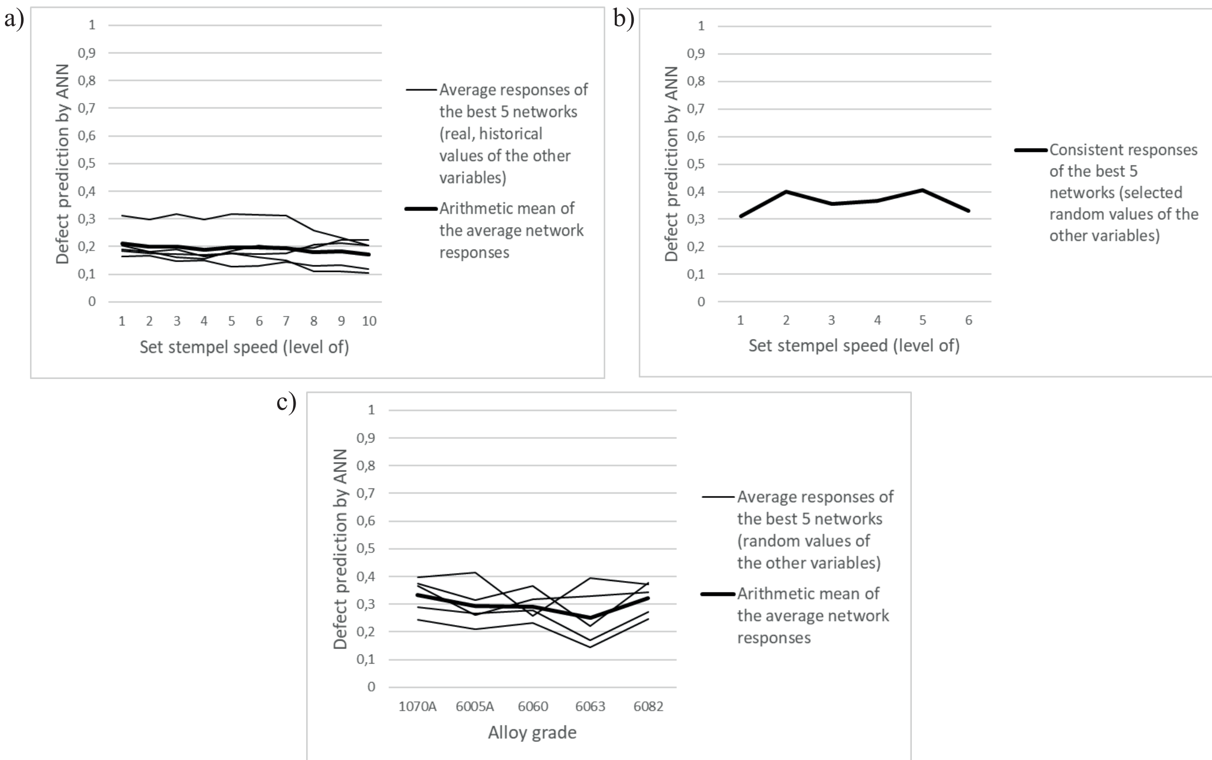

Fig. 9. Example of dimensional defect predictions vs level of a numerical variable characterizing die operation, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values. This is an example of one of a non-influencing numerical parameters

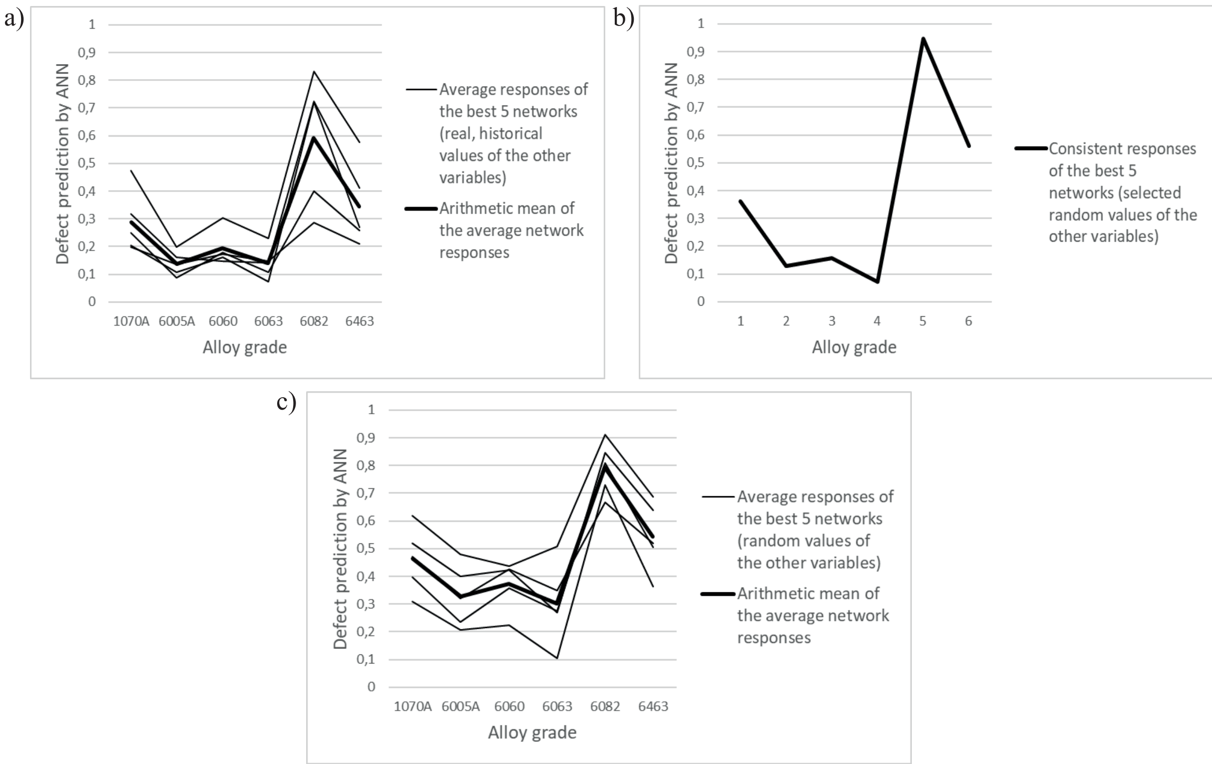

Fig. 10. Example of surface defect predictions vs level of a categorical variable characterizing the product, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values. This is an example of one of the most influencing categorical parameters

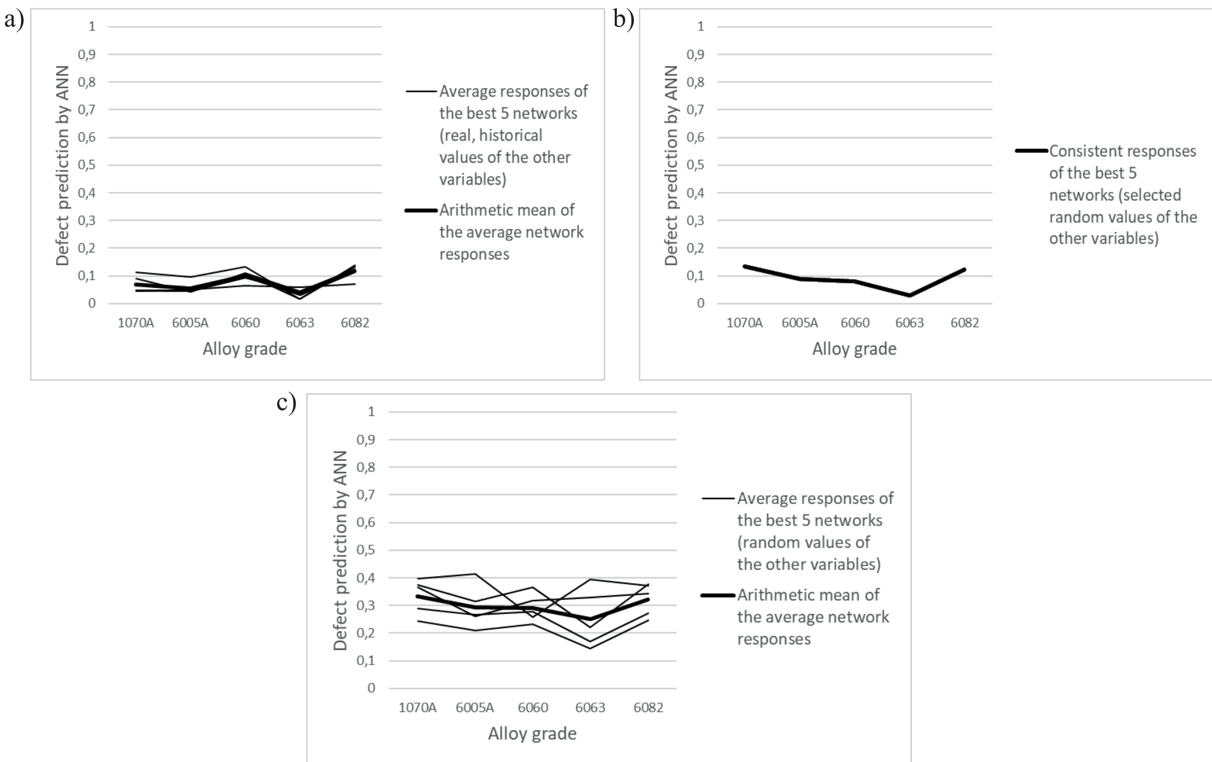

Fig. 11. Example of dimensional defect predictions vs level of a categorical variable characterizing the product, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values. This is an example of one of the non-influencing categorical parameters whereas this same parameter (alloy grade) was much influencing the surface defects (see Fig. 10)

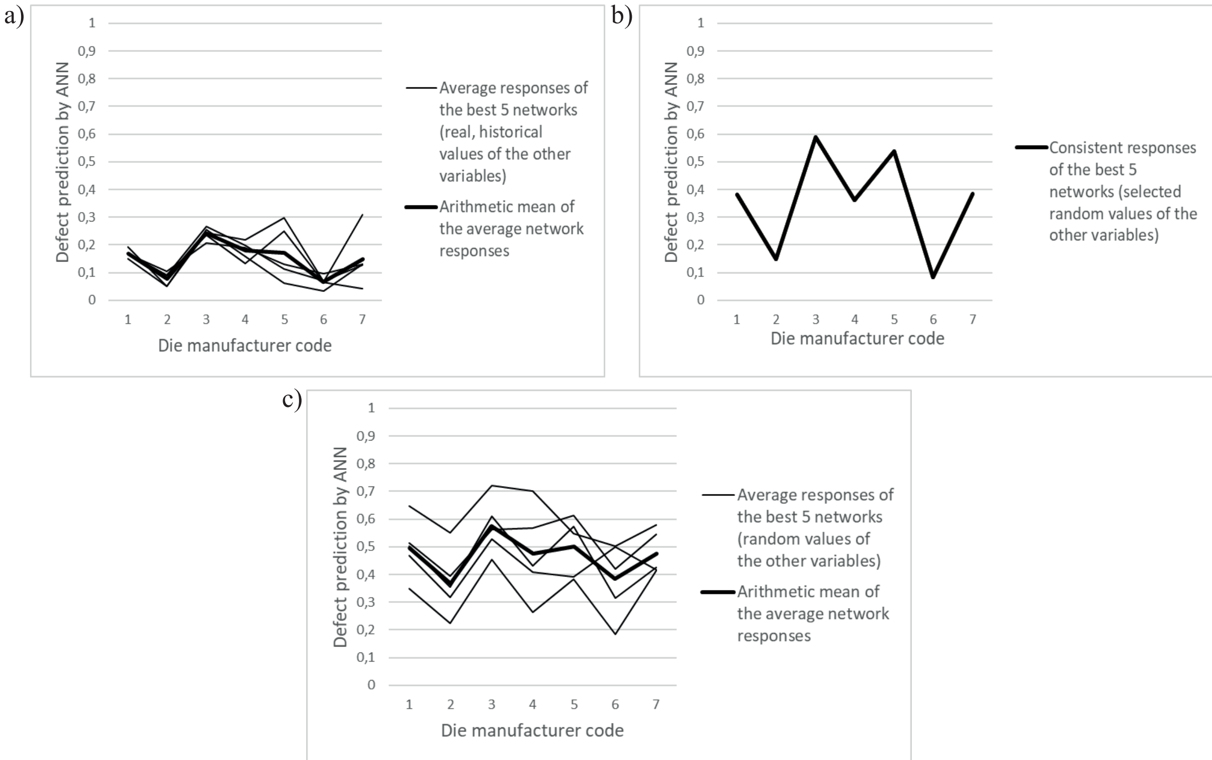

Fig. 12. Example of surface defect predictions vs level of a categorical variable characterizing the die, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values

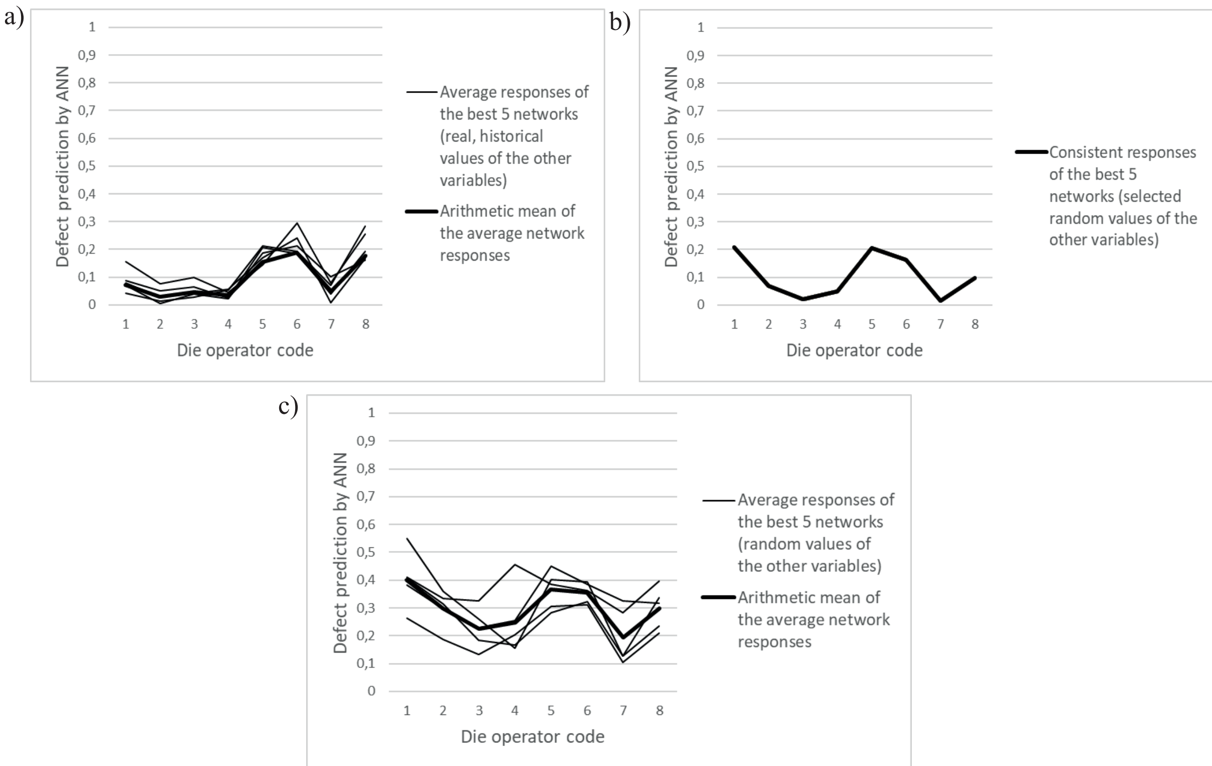

Fig. 13. Example of dimensional defect predictions vs level of a categorical variable characterizing the human factors, obtained for the remaining variables: a) appearing in the historical data (used for the network training); b) randomly generated, but only those for which all 5 networks gave consistent responses; c) all random values

Figures 14 and 15 show the comparisons of two quantities characterizing the magnitude of the impact of individual variables on the predicted defects. It can be seen that some input variables clearly stand out, and this is confirmed for all 3 variants of interrogating the neural network. Additionally, it can be noticed that the consistent predictions for the remaining random-valued variables give impact values greater than for the real, historical values.

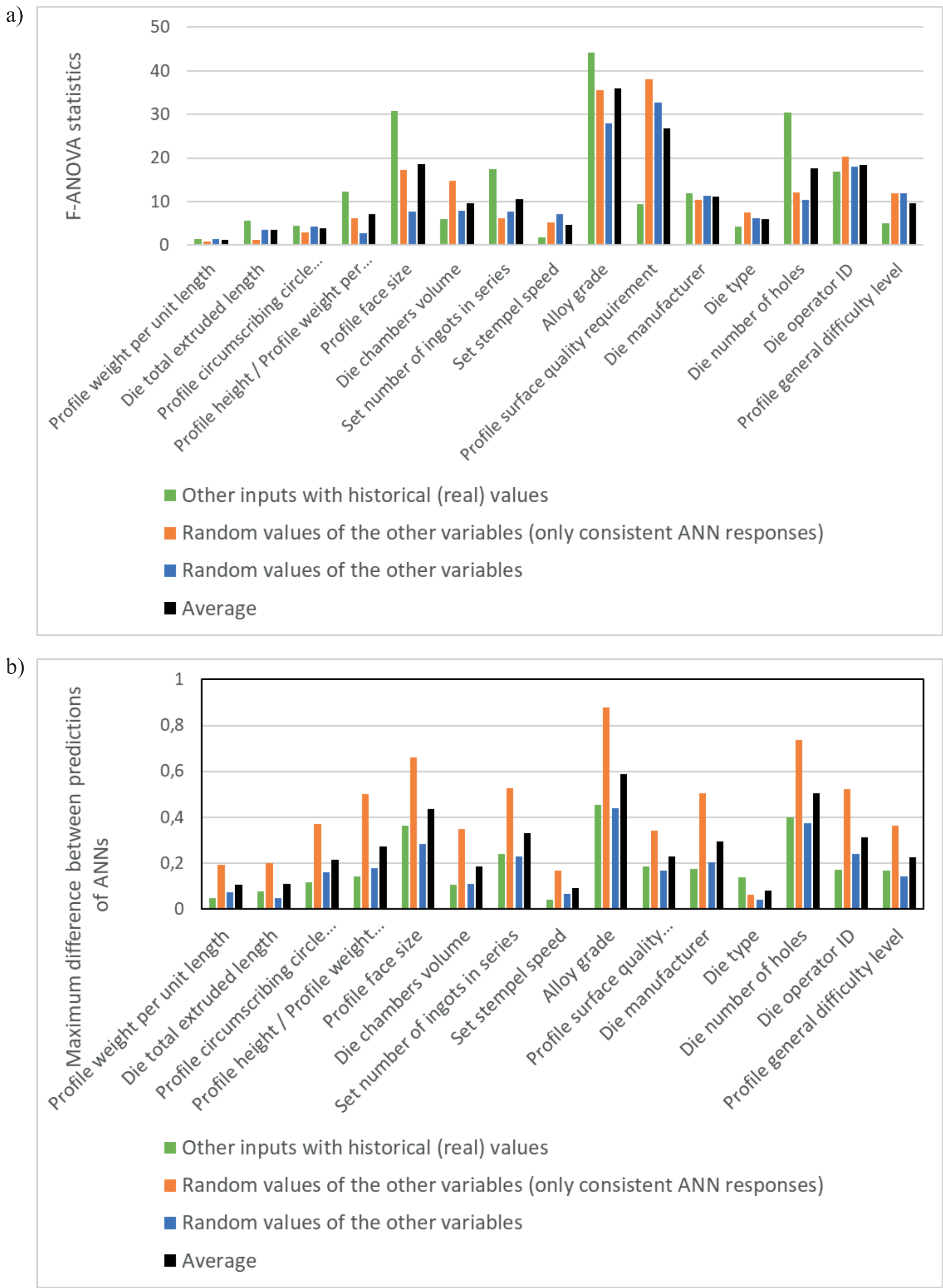

Fig. 14. Comparison of the impact of input values on the predicted average occurrence of the surface defects: a) F-ANOVA statistics calculated for the network predictions; b) the maximum difference between average predictions of the five networks due to extreme change of the given parameter

a)

b)

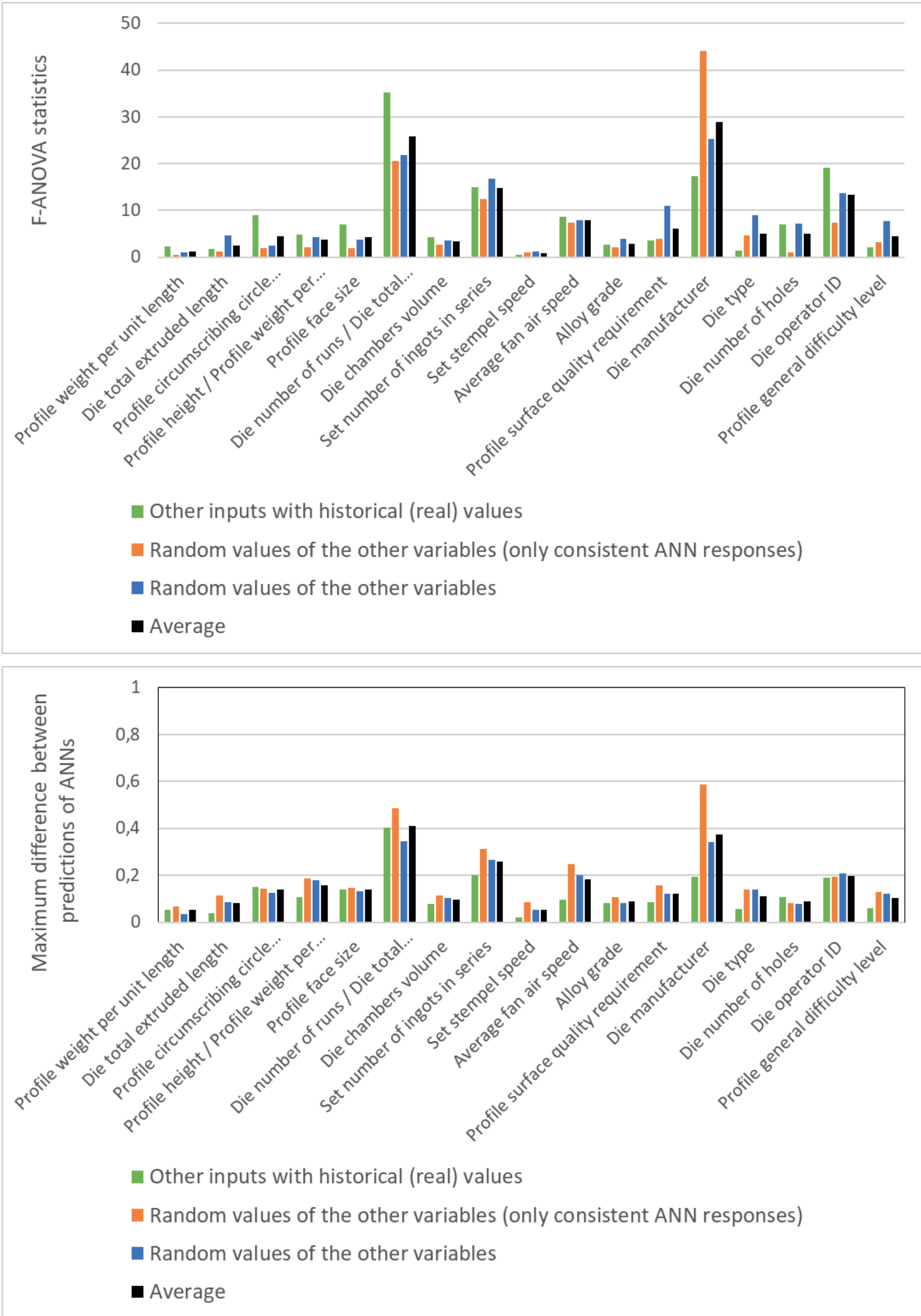

Fig. 15. Comparison of the impact of input values on the predicted average occurrence of the dimensional defects: a) F-ANOVA statistics calculated for the network predictions; b) the maximum difference between average predictions of the five networks

5. Idea of the recommendation system

The results of modeling with neural networks described in the previous chapter allowed the determination of the most important factors influencing the formation of defects as well as the strength and direction of this influence. This information is summarized in Tables 1–4. They can serve as recommendations for the design and operation of dies and the setting of some process parameters and its organization.

Table 1. Semi-quantitative strength and direction of the influence of numerical (continuous) variables on the tendency to produce surface defects

Names of numerical (continuous) variables	Profile circumscribing circle diameter / Profile weight per unit length	Profile height / Profile weight per unit length	Profile face size	Set number of ingots in series
Strength and direction of influence	↑	↓	↑↑	↑↑
Best	0.013	0.172	0	3
Worst	0.267	0.003	612	382

Table 2. Semi-quantitative strength and direction of the influence of categorical (discrete) variables on the tendency to produce surface defects

Categorical (discrete) variables	Alloy grade	Profile surface quality requirement	Die manufacturer code	Die number of holes	Die operator code	Profile general difficulty level
Strength of influence	***	*	**	***	**	*
Best	6063	raw	6	1	6	X – impossible
	6005A	to be anodized	2	6	8	C – difficult
	6060	to be lacquered	7	2	3	B – normal
	1070A	important surface quality	4	3	4	A – easy
	6463	no treatment	1	10	1	D – very difficult
	6082		5	8	5	
			3	4	7	
Worst				5	2	

Table 3. Semi-quantitative strength and direction of influence of numerical (continuous) variables on the tendency to produce dimensional defects

Numerical (continuous) variables	Profile circumscribing circle diameter / Profile weight per unit length	Profile height / Profile weight per unit length	Profile face size [mm]	Die number of runs / Die total extruded length	Set number of ingots in series	Average fan air speed [m/s]
Strength and direction of influence	↑	↓	↑	↑↑↑	↑↑	↓↓
Best	0.013	0.172	0	0.00012	3	59.8
Worst	0.267	0.003	612	0.01	382	0

Table 4. Semi-quantitative strength and direction of influence of categorical (discrete) variables on the tendency to produce dimensional defects

Categorical (discrete) variables	Die manufacturercode	Die operator code
Strength of influence	**	**
Best	6	6
	2	8
	7	3
	4	4
	1	1
	5	5
	3	7
Worst		2

Each of the parameters appearing in Tables 1–4 can be assigned to one of the following three groups:
– related to the product, are not subject to change;
– related to tooling (die);
– related to the extrusion process.

The advisory system should support two basic types of tasks carried out in the plant. The first is the launch of a new product, where decisions are made about the design and supplier of the die. The second task is the selection of parameters for a new or continued (already running) process.

The idea of the advisory system is to utilize the historical cases in the database. In both tasks, the limited number of parameters having a significant impact on the formation of defects makes it realistic to find cases similar to the new one in the database. In the first task (starting a new product) the similarity is based only on the group of the product-related parameters, whereas the similarity should take into account both product-related and tooling-related parameters in the second task.

The system should search for good cases (without defects), for which the parameters used for matching were at the same or more 'dangerous' level than those of the new or modified process. This can be done by using the information provided in the lower cells of the tables. If finding such historical cases turns out to be impossible, then the selection of the safest parameters should be followed, as presented in Tables 1–4.

6. Summary, conclusions and further work

The development of the basis for the recommendation system for the aluminum extrusion process was carried out in several basic stages. They included the initial selection of significant variables using statistical methods, then the construction and evaluation of neural models, and finally their use to create tables of the impact of product, tooling and process parameters on selected profile defects. One of the achievements of this work is finding ways to use neural models to avoid their inherent imperfections and limitations. The target recommendation system should be developed by taking into account the comments on the reliability of the predictions of neural models presented in section 4.1.

The obtained results should allow the construction of a practical recommendation system for the extrusion process, using the existing records stored in the database and the results of neural modeling summarized in Tables 1–4, as described in section 5. This approach seems to provide the most reliable and secure system. It should be expected that the consistent application of the system's recommendations will allow for a significant overall reduction in the number of defective products. Its implementation will be the subject of further work.

Also envisaged is the testing of the use of neural models to predict the effects of changes in some parameters, including simultaneous changes to several of them. However, their use should be limited to cases where all neural networks give consistent results.

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