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TOPMOST STEEL PRODUCTION DESIGN BASED ON THROUGH PROCESS MODELLING WITH ARTIFICIAL NEURAL NETWORKS

PROJEKTIRANJE PROIZVODNJE VRHUNSKIH JEKEL NA PODLAGI MODELIRANJA SKOZI PROCES Z UMETNIMI NEVRONSKIMI MREŽAMI

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Application of artificial neural networks for modeling of a complete process path in a steel production – from the scrap steel to the material properties of semi products – is presented. The described approach is introduced as an alternative to physics based through process modeling, with the advantage of lower complexity of the software and much lower computing times for calculating the influence of a specific settings of the process parameters. This new approach can be beneficially used in designing the production process. This is clearly demonstrated by estimating the influence of 34 alloying elements and process parameters of 6 process steps on 5 final mechanical properties of spring steel (elongation, tensile strength, yield stress, hardness after rolling and necking), based on 1879 recorded data sets from the production line in Štore Steel company. The ANN used is of a multilayer feedforward type with sigmoid activation function and supervised learning. An important feature of this approach is its dependence on accurate and sufficient data, acquired from the modeled process. Therefore, special care must be devoted to validation of the obtained model and error estimation. The reliability and other characteristics of the available data can vary to a great extent in real industrial practice, therefore analysis of the models is a highly customized task that has to be performed on a case to case basis. A flexible and easily extensible software base has been developed in the scope of the described work in order to adequately support research, development and practical application of this kind of models.

Keywords: steel production, mechanical properties of steel, artificial neural networks, response approximation, feed forward networks with back propagation

Predstavimo uporabo umetnih nevronskih mrež za modeliranje celotne procesne poti izdelave jeklenih polizdelkov – od rene do snovnih lastnosti polizdelkov. Opisani pristop je vpeljan kot alternativa fizikalnemu modeliranju skozi proces s prednostjo manjše kompleksnosti programske opreme ter bistveno manjšimi računskimi časi za izračun vpliva specifične nastavitve procesnih parametrov. Takšen pristop se lahko s pridom uporablja pri načrtovanju proizvodnega procesa. To je nazorno prikazano pri oceni vpliva 34 legirnih elementov in procesnih parametrov 6 procesnih korakov na 5 končnih snovnih lastnosti vzmetnega jekla (raztezek, natezna trdnost, meja tečenja, trdota po valjanju in skrček), na podlagi 1879 zabeleženih podatkovnih setov iz proizvodne linije podjetja Štore Steel. Uporabljena je usmerjena nevronska mreža s sigmasto aktivacijsko funkcijo in nadzorovanim učenjem. Pomembna značilnost tega pristopa je njegova odvisnost od pravilnih in zadostnih podatkov, pridobljenih iz procesa. Zato se je potrebno posebej posvetiti validaciji pridobljenega modela in oceni napak. Zanesljivost in ostale značilnosti razpoložljivih podatkov, pridobljenih iz realnih industrijskih procesov, se običajno zelo razlikujejo, zato je analiza takšnih modelov zelo specifična in mora biti narejena od primera do primera. V ta namen je bila izdelana fleksibilna in enostavno razširljiva programska oprema, ki omogoča primerno podporo raziskavam, razvoju in praktični uporabi tovrstnih modelov.

Ključne besede: izdelava jekla, mehanske lastnosti jekla, umetne nevronske mreže, aproksimacija odziva, nevronske mreže s povratnim razširjanjem napak

1 INTRODUCTION

Controlling the final mechanical properties of products or semi products is very important for steel production companies. This is a difficult task because there are a number of sequentially connected processes where the output of one process is an input to the next one. Different physics based numerical models can be used to predict the outcomes, but their development can be very complicated and time consuming.[1,2] Artificial neural networks (ANN) based models[3,4] can be used as an alternative to these physics based numerical models. Over the last years, ANNs have been successfully used across an extraordinary range of problem domains. Examples can be found in almost all fields of industry as well as in research areas that show promise for the future.[5] ANNs are already being used in steel production industries in modeling of blast furnace,[6] continuous casting, steel rolling,[7] etc. The first use of ANN in modeling of the entire production path (also referred to as "through process modeling") has been demonstrated for production of aluminum foil in[8]. Furthermore, a preliminary study[9] was made for complete steel production path, while in this study, additional parametric studies and sensitivity tests were added. The main drawback of

ANN models over physics based models is the fact that they can be used based on the specific training data only, and do not allow generalization to different production plants. Only the developed methodology is transferable.

In the present paper, we study the possibility of using ANN-based models as a comprehensive decision support tool in steel production. We explore the prediction of important mechanical properties of steel (elongation, tensile strength, flow limit, hardness and shrinkage) based on values of influential process parameters that determine the complete steel production path. The steel manufacturing process in the Štore Steel company and the respective available data were considered[10] as a basis for the present study. The manufacturing process path consists of six individual processes:[11,12] steel making, continuous casting of steel, hydrogen removal, reheating, multiple stage rolling, and cooling on the cooling bed. Each of these processes can be independently modeled by a physics based numerical model.[13–21] The state of the steel (shape, microstructure) of an individual process influences the downstream processing (subsequent processes in the process chain) and thus act as a part of input data (e.g. defining initial or boundary conditions) in the model of that process. This is schematically represented in **Figure 1**. In the current work we use another approach where an ANN is used to build a complete model of the whole production chain. We model the outcomes after the last process step and relate them to process parameters defining all processes involved in the production path. After the model is built, we can explore the effect of variation of process parameters to the final material properties, e,g. by changing process parameters independently in parametric and sensitivity tests and observing model outputs.

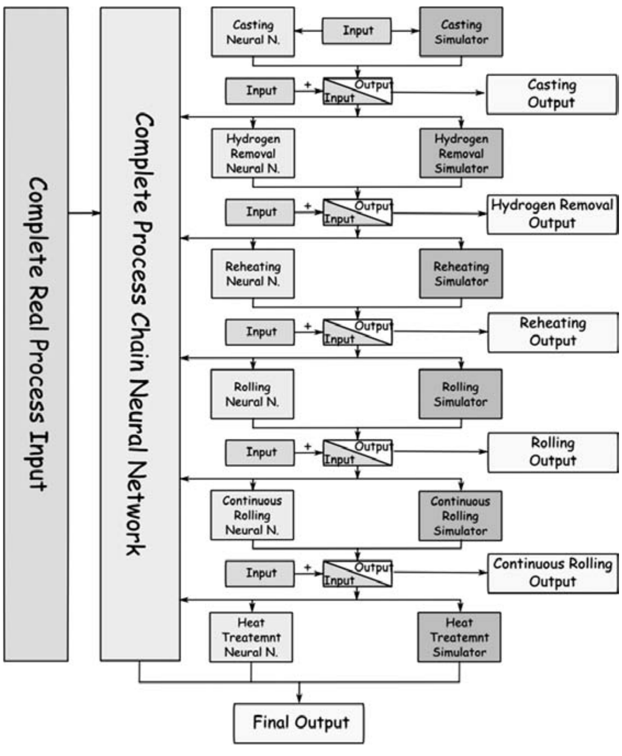

Figure 1: Steel manufacturing process modeling strategy
Slika 1: Strategija modeliranja procesa izdelave

2 MODELING SOFTWARE

A software for construction and use of ANN-based models has been developed in the scope of this work. The software was designed to match the challenges and requirements met when solving this kind of problems. In particular, it has to provide good flexibility in designing training strategies, filtering training data, verification of results, testing different network layouts, integration with other software, etc. This is crucial when approximating behavior of steel processing systems with large number of processing parameters. Data obtained from such systems is often inaccurate or even corrupted due to practical limitations in acquisition procedures. Response sampling can not be planned in advance but is accommodated to production schedules in the factory, therefore information available may be deficient in some regions of parameter space in order to obtain good response approximation and therefore verification of results plays an important role. The software platform has been elaborated in[22,23].

The Aforge.Net library is used as ANN framework.[24] A convenient characteristics of neural networks is that approximation can be performed in two separate stages (**Figure 2**). In the training stage, the network is trained by using the sampled response (either measured or calculated by a numerical model). In the approximation stage, trained network is used for all subsequent calculations of approximated response at arbitrary values of input parameters. This gives the neural networks an important advantage over other modeling techniques, since the second stage if very fast as compared to the first stage. The software takes full advantage of this feature by separating these stages. This is especially

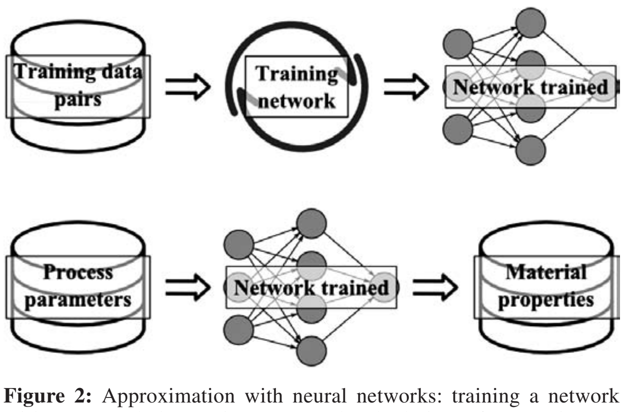

Figure 2: Approximation with neural networks: training a network with presented data pairs (top) and calculation of approximated response with trained network (bottom)
Slika 2: Aproksimacija z nevronskimi mrežami: učenje mreže na podlagi podatkovnih parov (zgoraj) in izračun aproksimiranega odziva z naučeno mrežo (spodaj)

important when performing extensive analyses of the considered process on the basis of the developed ANN models, or when incorporating the models in automatic optimization procedures.[25,26]

3 CONSTRUCTION OF THE ANN-BASED PROCESS MODEL

In the considered production setup from the Štore Steel company, the complete process is defined by 123 influential parameters (**Table 1**). There are 24 parameters defining the steel grade, 12 process parameters defining the continuous casting, 2 parameters the hydrogen removal, 4 parameters the reheating furnace, 31 parameters the rolling mill, 43 parameters the continuous rolling mill, and 7 parameters the cooling bed. On the output side, five mechanical properties of the final product are observed and represent the output values of the model (**Table 2**).

Table 1: Process parameters (input)
Tabela 1: Procesni parametri (vhod)

Processes / properties	Number of parameters
Composition	24
Continuous casting of steel	12
Hydrogen removal	2
Billet reheating furnace	4
Rolling mill	31
Continuous rolling mill	43
Cooling bed	7
Total	123

Table 2: Material properties (output)
Tabela 2: Snovne lastnosti (izhod)

Final mechanical properties	Elongation (A)
	Tensile strength (R_m)
	Yield stress ($R_{p0.2}$)
	Hardness after rolling (HB)
	Necking (Z)

For construction of the models, data was manually collected from different databases representing production of the steelwork in year 2011. Data was first separated for two billet dimensions (140 mm and 180 mm) which undergo considerably different process parameters. In addition, the data had to be filtered by applying a number of specially designed criteria in order to exclude corrupted data and overshoots. After these procedures, a total of 1879 data sets for dimension 140 mm have been prepared and used in the training procedure.

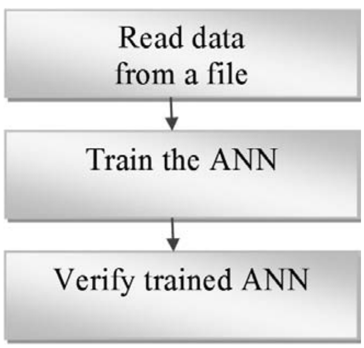

Figure 3: Training and verification procedure for model construction
Slika 3: Proces učenja in verifikacije pri izdelavi modela

This data was randomly divided into disjoint training and verification sets. Training data was then used in training a feed forward neural network with sigmoid activation function, in which we iteratively minimize error of the model on this data by the back propagation algorithm. After the convergence was achieved, the model was validated on the verification set that was not involved in the training, in order to estimate its accuracy (**Figure 3**).

A number of training procedures with different ANN architectures and training parameters have been performed in order to find the best settings. **Figure 4** shows convergence of maximum relative training errors for 15 different ANN settings.

Optimal settings (listed in **Table 3**) were identified by the convergence curve that reaches the lowest error at the end of the training procedure.

Table 3: ANN training and architecture settings
Tabela 3: Nastavitve učenja in arhitekture umetne nevronske mreže

Training parameters	
Learning rate	0.4
Momentum	0.6
Alpha value	1.0
Architecture	
Neurons in input layer	34
Neurons in 1st hidden layer	25
Neurons in output layer	5

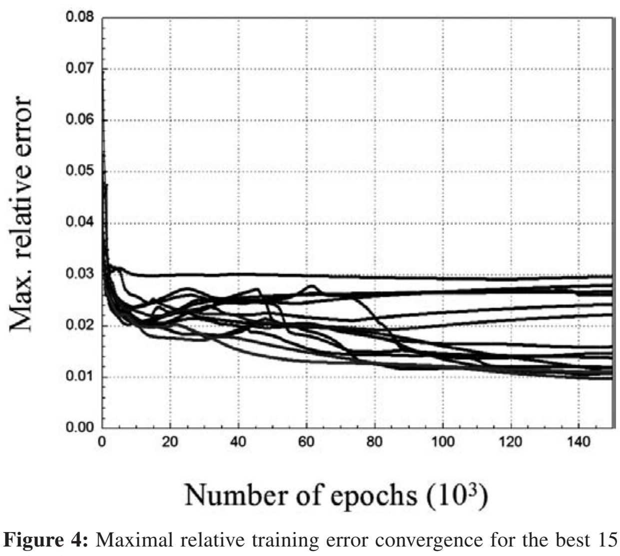

Figure 4: Maximal relative training error convergence for the best 15 trained ANNs
Slika 4: Največja relativna napaka konvergence napake učenja za 15 najboljših umetnih nevronskih mrež

In order to build the final model, we trained the ANN with optimal architecture and training parameters from **Table 3**. The maximum number of epochs was set to 10^5. Training procedures were performed on the HP ProLiant DL 380 G7 workstation with 2 six core 3.47 GHz Intel Xenon X5690 processors (6*256 kB L2 and 12 MB L3 cache), with 24GB installed RAM. Trained neural network which gave us the best results was trained in approximately 13 hours. A remark should be given here, that training of ANN is indeed a cumbersome and CPU time consuming task, typically on the same order of a computational cost of a physics based model. However, when the ANN is trained, the use of it is typically several orders of magnitude faster than executing the physical model.

4 RESULTS

The training procedure results in the artificial intelligence model that relates the modeled output values **v** to the input parameters **p**:

$$\mathbf{v} = \mathbf{v}(\mathbf{p}) \tag{1}$$

In the present context, **v** contains mechanical properties from **Table 2** and **p** contains process parameters from **Table 1**.

The obtained model can be used for a detailed study of response of final mechanical properties on variation of process parameters, which gives operators a better insight into the process and can be used as a valuable decision support tool. This is endorsed by low computational times necessary to evaluate a single response once the model is built, which are around 10^{-3} s in our case.

For illustration, we show dependence of hardness on carbon fraction around different points in the space of model input parameters (**Figure 5**). We have randomly selected 5 sets of parameters (points in the parameter space) from the training data. Then we varied the parameter of interest (in our case the carbon mass fraction), while the other parameters remained fixed. The parameter was varied from the minimum to the maximum value attained by that parameter within the training data.

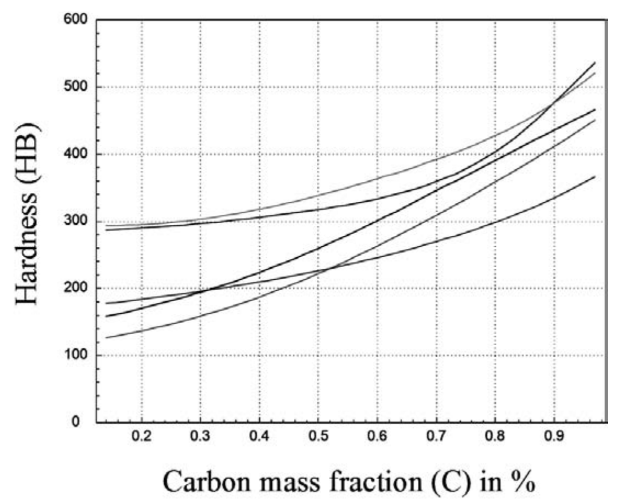

Figure 5: Steel hardness after rolling as a function of the carbon mass fraction, calculated by the ANN model on five training sets
Slika 5: Trdota jekla po valjanju kot funkcija masnega deleža ogljika, izračunana z umetno nevronsko mrežo na petih učnih množicah

It can be seen from **Figure 5** that hardness generally increases with increasing carbon mass fraction, which is in line with the well-established metallurgical knowledge. This is observed for different fixed combinations of other parameters, while the precise form of the relation varies significantly with the values of other parameters of the model. Since influences of individual parameters are highly correlated, it is important for some purposes to study behavior over larger range of process settings. This facilitates to obtain a deeper insight in the process. The described approach employing ANN-based models is ideal for such purpose due to the short calculation times and exhaustiveness of information that is provided by such models.

In another illustrative example, we take a different point of view. Instead of focusing on influence of individual parameters, we try to obtain a broader picture of the comparative influence of different parameters on the observed outcomes. We first chose a set from the training data sets close to the center of the interval containing the measured data. We denote the vector of input parameters of this set by $p_c = p_i$. We then varied one by one each component of the vector (i.e. the particular composition or process parameter) while the others were held fixed, and observed how the modeled quantities change as result of this variation. More precisely, we considered the following function of one variable:

$$\begin{aligned} &u_{ij}(t) = v_i(p_{c1}, p_{c2}, \ldots, p_{cj-1}, t, p_{cj+1}, \ldots, p_c) \\ &i = 1, \ldots N_v,\ j = 1, \ldots, N_p \end{aligned} \tag{2}$$

where N_p is the number of model parameters and N_v is the number of output quantities of the model. Each element of the parameter vector p_c was varied over the whole interval that the given parameter attained in the provided industrial data. The variations were then calculated for each output value (denoted by index i in equation (2) and for each parameter (index j in equation (2) and used as a measure of influence of the specific

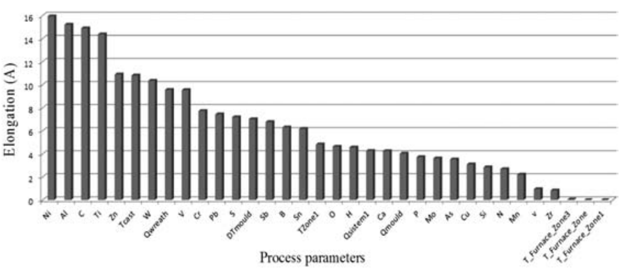

Figure 6: Influence of process parameters on changes in elongation (A), ordered from the most influential one on the left, to the least influential one on the right
Slika 6: Vplivi procesnih parametrov na spremembe v elongaciji (A), urejeni od najbolj vplivnih na levi do najmanj vplivnih na desni

parameter. The results are shown in **Figures 6** to **10** and are for each parameter calculated by:

$$\Delta u_{ij}(t) = \left(\max u_{ij}(t) - \min u_{ij}(t)\right) \tag{3}$$

where $\max u_{ij}(t)$ and $\min u_{ij}(t)$ represents maximum and minimum influence of j-th parameter on i-th output value.

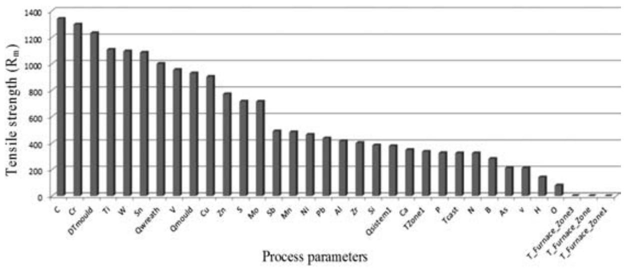

Figure 7: Influence of process parameters on changes in tensile strength (R_m)
Slika 7: Vplivi procesnih parametrov na natezno trdnost (R_m)

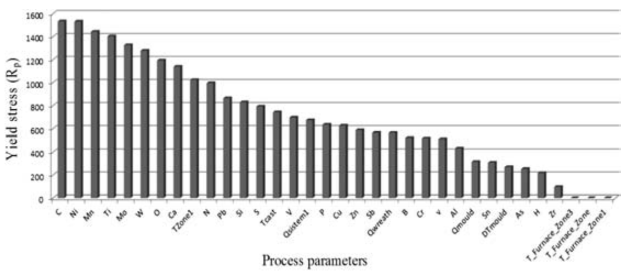

Figure 8: Influence of process parameters on changes in yield stress (R_p)
Slika 8: Vplivi procesnih parametrov na mejo tečenja (R_p)

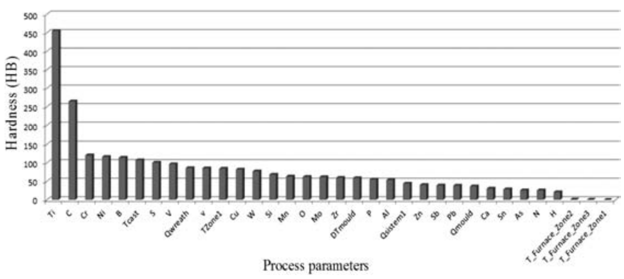

Figure 9: Influence of process parameters on changes in hardness after rolling (HB)
Slika 9: Vplivi procesnih parametrov na spremembe trdote po valjanju (HB)

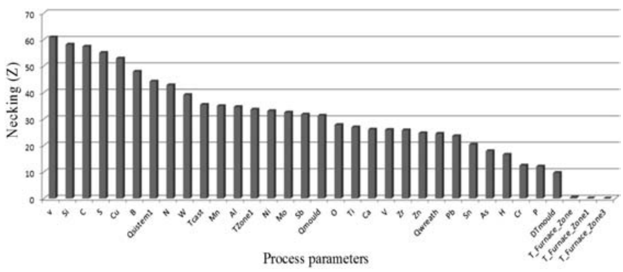

Figure 10: Influence of process parameters on changes in necking (Z)
Slika 10: Vplivi procesnih parametrov na spremembe vratu tečenja (Z)

Table 4 shows 3 most influential parameters for each material property. From the available parameters that we use for training the ANN (**Figures 6** to **10**), different elements of the composition of the material are the most influential for all five properties. Process parameters do not have major influence. The most important parameters obtained from the present ANN response are temperature of the liquid steel (Tcast) for elongation and hardness after rolling, temperature difference in the mould (Dtmould) for tensile strength, cooling water temperature in zone 1 (TZone1) for yield stress and cooling water flow rate in first spray system (Qsistem1) for necking. Obviously, the response of the model is not entirely expected. This indicates that the represented methodology should be used with care and finally judged by engineering expert knowledge. It is however true, that in the present model, several important process parameters are missing due to the lack of data acquisition in the plant (particularly for rolling), since a new rolling mill has been installed recently.

Table 4: The 3 most influential parameters for each mechanical property
Tabela 4: Trije najbolj vplivni parametri za posamično mehansko lastnost

	Elongation (A)	Tensile strength (R_m)	Yield stress (R_p)	Hardness after rolling (HB)	Necking (Z)
1	Ni	C	C	Ti	V
2	Al	Cr	Ni	C	Si
3	Ti	Delta temperature in the mould	Mn	Ni	C

5 CONCLUSIONS

ANN have been used to model a complete production path in a steelwork. The developed methodology is essentially a black box modeling approach. Outcomes of the process can be predicted for arbitrary combination of process parameters without directly considering the physical background of the modeled process, but are instead relying on information about previous realizations of the process. As an example, a model of production line in the Štore Steel company was studied, reduced to 34 influential process parameters and with 5 observed properties of the final product. Several combinations of models that will include even less influential parameters will be studied in the future.

A significant advantage of the approach, as compared to the physics based numerical models, is much lower complexity of the model. There is no need to calibrate the model in order to compensate for physical simplifications and inaccurate knowledge of model constants, since the model is based on the realistic data gained from the actual process. Once the model is built, evaluation times are extremely short, in the order of a millisecond, compared to several hours or even days that would be necessary for state-of-the-art physics based models of the same process. This represents a great advantage in tasks where large number of evaluations are required, such as automatic optimization of process parameters or detailed parametric studies.[22,23] This kind of modeling has therefore a great potential to enable better insight and understanding of industrial processing, as well as to serve as a powerful decision support tool. This potential was indicated in the present paper by clearly presenting influence on individual process parameters on the outcomes.

The drawback of the approach is its dependence on reliable and abundant data that is sometimes hard to obtain. Great attention must be paid to estimation of accuracy of the model in imperfect conditions with regard to the available data.[9] This will remain the main focus of future research, where influence of various factors on model accuracy will be studied which will eventually lead to procedures for reliable prediction of error bounds, which is crucial for industrial use. This will incorporate arrangements where controlled acquisition of training data is possible, e.g. by using physics based models. In this context, a large portion of work is devoted to building a flexible, modular and scalable software base to support such work. Finally, it should be noted, that the presented methodology stimulated more careful and complete data acquisition of the process parameters in Štore Steel company, needed for continuation of the present work and for better process repeatability as such.

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