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Application of Artificial Neural Networks in Design of Steel Production Path

Igor Grešovnik[1,2], Tadej Kodelja[1], Robert Vertnik[2,3], Bojan Senčič[3] Miha Kovačič[2,3] and Božidar Šarler[1,2,4]

Abstract: Artificial neural networks (ANNs) are employed as an alternative to physical modeling for calculation of the relations between the production path process parameters (melting of scrap steel and alloying, continuous casting, hydrogen removal, reheating, rolling, and cooling on a cooling bed) and the final product mechanical properties (elongation, tensile strength, yield stress, hardness after rolling, necking) of steel semi products. They provide a much faster technique of response evaluation complementary to physical modeling. The Štore Steel company process path for production of steel bars is used as an example for demonstrating the approach. The applied ANN is of a multilayer feedforward type with sigmoid activation function and supervised learning. The entire set of 123 process parameters has been reduced to 34 influential ones and 1879 data sets from the production line have been used for learning. The results of parametric studies performed on the ANN based model seem consistent with the expectations based on industrial experiences. However, further improvements in data acquisition and analytical procedures are envisaged in order to obtain a methodology, reliable enough for use in the everyday industrial practice. The methodology seems to be for the first time applied in the through process modeling of steel production.

Keywords: Through process modeling, computational intelligence, steel processing, mechanical properties, response approximation, feed forward artificial neural networks with back propagation.

[1] Centre of Excellence for Biosensors, Instrumentation and Process Control, Solkan, Slovenia. igor.gresovnik@cobik.si, tadej.kodelja@cobik.si, www.cobik.si
[2] University of Nova Gorica, Nova Gorica, Slovenia bozidar.sarler@ung.si, www.ung.si
[3] Štore Steel, Štore, Slovenia.
robert.vertnik@store-steel.si, bojan.sencic@store-steel.si,
miha.kovacic@store-steel.si, www.store-steel.si
[4] Corresponding author. Institute of Metals and Technology, Ljubljana, Slovenia

1 Introduction

Prediction of the final mechanical properties of the steel rods, based on the physics based numerical modeling of the whole process (through process modeling (TPM)) [Quested, Crumbach, and Hamerton (2006); Crumbach, Quested, and Hamerton (2006)], is extremely complicated due to the multi-scale and multi-phase character of the underlying physics as well as complicated material behavior. As an alternative approach to the physical modeling, the computational artificial intelligence approach, based on the neural networks (ANNs) is used in the present paper.

For several years, ANNs have been successfully used for second level process automation in a number of industries [Bhadeshia (1999)]. For example, in steel making industries, neural networks are already being used for predicting steel mechanical properties [Mukherjee and Singh (2009)], for thermal model of a ladle furnace [Sampaio, Braga, and Fujii (2007)], for rolling mills [Martinez, Protzel, Gramchow, and Sorgel (1994)], for heat transfer in continuous casting process [Bouhouche, Lahreche, and Bast (2008)], for predicting the mechanical properties of aluminum foil [Trčko and Šarler (2009)], etc.

One of the fields where it is additionally possible to exploit the neural networks is to predict important mechanical properties of steel, such as elongation, tensile strength, yield stress, hardness and necking on the basis of the composition, and other process parameters that define the complete process path from the steelmaking to the final semi-product.

The complete process path in steelworks Štore Steel, Slovenia [Store Steel d.d. (2012)] consists of six main individual process steps [Verlinden, Driver, and Samajdar (2007); Irwing (1993); Lenard (2007)]: steel making, continuous casting of steel, hydrogen removal, reheating, multiple stage rolling, and cooling on the cooling bed. Each of these processes can be modeled either by a physics based numerical model [Šarler, Vertnik, Saletić, Manojlović, and Cesar (2005); Vertnik and Šarler (2006); Vertnik and Šarler (2009); Hanoglu, Islam, and Šarler (2011); Lorbiecka, A.; Vertnik, R.; Gjerkeš, H.; Manojlović, G.; Cesar, J.; Šarler, B. (2009); Lorbiecka, A.; Šarler, B. (2010)] or by a computational intelligence approach such as for example the genetic programming [Kovačič and Šarler (2011); Kovačič and Šarler (2009)]. Output values of a process step can define the input values of the next process step in the path and thus act as input parameters (e.g. by defining initial or boundary conditions) in the model of that process. Another possibility, when using ANN, is to build an integrated model of the whole production path. We can model only outcomes after the last process step and relate them to the entire set of process parameters of the whole production path.

The main aim of this work is to explore the possibility of applying ANN for mod-

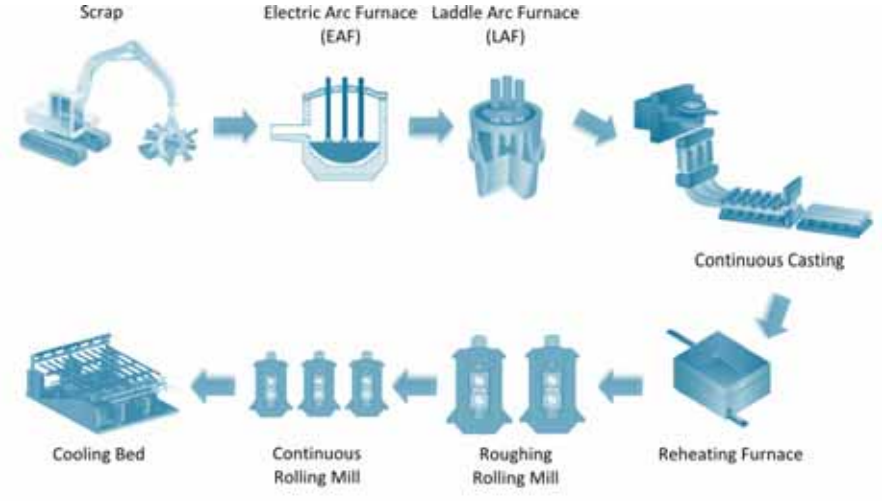

Figure 1: Steel manufacturing process in Štore Steel company.

eling the whole process path. The results of the ANN model are used for prediction of five mechanical properties of a steel semi-product in terms of a set of process parameters of the whole production path.

2 Steel manufacturing process and process parameters

The manufacturing of steel semi-products in Štore Steel company involves a series of subsequent process steps. First, the steel is melted from scrap in an electric arc furnace (EAF). When the molten steel reaches a foreseen temperature (around 1600 °C), it is poured into a preheated ladle (tapping) where it reaches the desired composition and temperature by adding the alloying elements. Once the specification of the steel is confirmed, the ladle is transported by a crane to the continuous casting device where the billets are manufactured. The cast billets are reheated in the reheating furnace and enter the rolling line, composed of the roughing and continuous rolling mill. Before the steel semi products leave the production path, they pass to the cooling bed. A scheme of complete process is shown in Figure 1.

There are 123 important parameters, divided into seven groups that define the complete process path (Table 1). Of these, 24 parameters define the steel grade, 12 parameters the 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 other hand, five basic mechanical properties characterize the output values of the product (Table 2).

Table 1: A complete list of process (input) parameters.

ID	PROCESS	PARAMETER		USED in ANN
1 – 24	Composition	Elements: C, Si, Mn, P, S, Cr, Mo, Ni, Al, Cu, Ti, V, W, Sn, As, Zr, Ca, Sb, B, N, O, H, Pb, Zn		24
25	Continuous casting of steel	Casting dimensions (140 x 140mm or 180 x 180mm)		
26		Casting temperature		1
27		Casting speed		1
28		Casting powder type		
29		Mould level depth		
30		Mould water flow		1
31		Mould inlet water temperature	Delta Temperature	1
32		Mould outlet water temperature		
33		Wreath spray water flow		1
34		Wreath spray water temperature		0
35		Spray cooling system 01 spray flow		1
36		Cooling water 01 temperature		1
37	Hydrogen removal	Time in the furnace		
38		Temperature in the furnace		
39	Biller reheating furnace	Conveyor speed		
40 – 42		Temperature in furnace Zone 1 – 3		3
43	Rolling mill	Input dimension (140 x 140 mm or 180 x 180 mm)		
44		Input temperature		
45		Number of rolling passes		
46 – 52		Entry rolling speed pass 1 – 7		
53 – 59		Radius of roll 1 – 7		
60 – 66		Roll gap 1 – 7		
67 – 73		Roll groove 1 – 7		
74	Continuous rolling mill	Input dimension		
75		Input temperature		
76		Entry or outlet rolling speed		
77 – 86		Roll 1 – 10 engagement yes/no		
87 – 96		Radius of roll 1 – 10		
97 – 106		Roll gap 1 – 10		
107 – 116		Roll groove 1 – 10		
117	Cooling bed	Product dimension – cross-section		
118		Product dimension – length		
119		Product temperature		
120		Distance between two products		
121		Number of bars in one spot		
122		Lifting apron (radiation shield) height		
123		Frequency of product moving		
123	**Process path input parameters ← Total → Training data for ANN**			**34**

3 Neural networks approximation module

In everyday industrial practice, the process design parameters have to be adapted quickly in order to produce the results that comply with the customer requirements

Table 2: A complete list of material properties (output values).

ID	TYPE	VALUES	USED in ANN
1	Mechanical properties of materials	Elongation (A)	1
2		Tensile strength (R_m)	1
3		Yield stress ($R_{p0,2}$)	1
4		Hardness after rolling (HB)	1
5		Necking (Z)	1
5	**Process path output values ← Total → Training data for ANN**		**5**

and productivity. The classical approach to optimization of process parameters, where the physics based simulators impose long computational times, can limit applicability of process optimization in industrial environment. The solution has been conceived in the form of ANN – based approximation of the system response [Belič (2006); Belič (2012)], which is calculated on the basis of a sampled response prepared in advance, either by runs of numerical model or by measurements performed on previous designs used. The optimization procedure that searches for optimum process design parameters, consistent with the requirements, can alternatively be performed much faster on the surrogate model, based on the approximated response [Grešovnik, Kodelja, Vertnik, and Šarler, (2012)], than on the physics based model.

In the current work, approximation of process path, based on the ANN is considered. A convenient characteristic of the approach is that approximation is 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, the trained network is used for all subsequent calculations of the approximated response as a function of input parameters.

An in-house approximation module has been developed, based on general purpose neural network libraries and extensive code base for development of technical applications [Grešovnik (2012)]. It features modular design, such that new underlying libraries can be easily utilized (open source libraries Aforge.Net [Aforge.net (2011)] and NeuronDotNet [NeuronDotNet (2011)] are currently used for ANNs). This also provides good flexibility in integration with other software, designing training strategies, filtering training data, verification of results, testing different network layouts, etc.

This is crucial when approximating behavior of material processing systems with a large number of process parameters. Data obtained from such systems is often inaccurate or even corrupted due to practical limitations and possible failures in acquisition procedures. Response sampling could not be planned in advance but is accommodated to production schedules in the factory. Therefore, the information

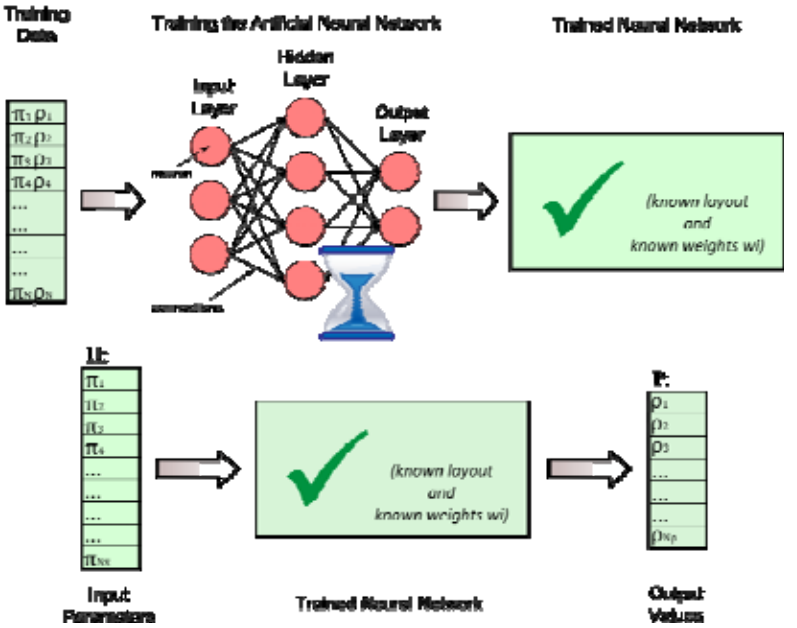

Figure 2: Approximation with neural networks: training of a network (top) and calculation of approximated response with a trained network (bottom).

available may be deficient in some regions of parameter space in order to obtain a good response approximation. Consequently, verification of the results plays an important role.

Both the Aforge and NeuronDotNet libraries offer a number of neural network algorithms that are convenient for various tasks. In Aforge, we can find backpropagation learning, delta learning, elastic learning, evolutionary learning, perceptron learning and Kohonen self-organizing map. In NeuronDotNet the backpropagation learning and Kohonen self-organizing map are implemented. With both Aforge and NeuronDotNet we have constructed feedforward backpropagation neural networks, which is a supervised learning method. In our case, architecture is such that every neuron from the input layer is connected to every neuron in the hidden layer and every neuron in the hidden layer is connected to every neuron in the output layer (Figure 3).

In Aforge, we used bipolar sigmoid activation function in all layers. This function is defined as

$$f(x) = \frac{2}{1+e^{-x}} - 1, \tag{1}$$

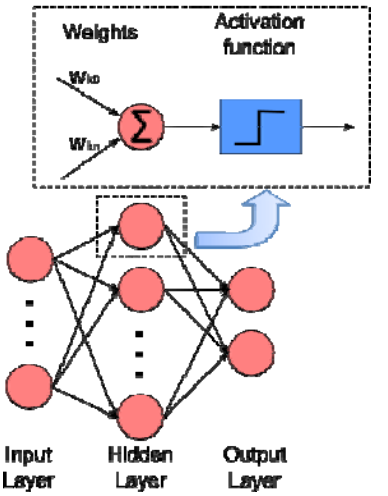

Figure 3: Feedforward backpropagation neural network scheme.

with output range from -1 to 1. In NeuronDotNet we used linear activation function in the first layer,

$$f(x) = x, \tag{2}$$

with range from -2 to 2, and sigmoid activation function, for all layers above with range from 0 to 1

$$f(x) = \frac{1}{1+e^{-x}}, \tag{3}$$

The learning procedure in both algorithms is divided in four basic steps (Figure 4). First we compute all outputs on the basis of training input parameters and with the current weights. Then we calculate the squared difference between the output calculated by the neural network and actual output from training data. Errors are propagated backwards. In the next step we compute correction to weights for each neuron in the network. In the last step we update the network with new values of weights for the next epoch.

4 Training the artificial neural network

The ANNs are in the present paper trained with the data from the complete steel production path in Štore Steel company. The process is completely defined with

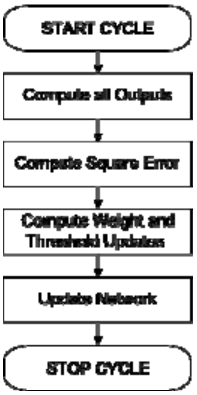

Figure 4: Algorithm for training one input-output sample in one epoch.

123 process parameters (Table 1), of which 34 are recognized as influential. 5 output values were considered.

Process data for steel bars for applications in the forging, spring and engineering industries were used. After separating the data belonging to two billet dimensions (140 mm and 180 mm) and after a suitable filtering to exclude the corrupted data, 1879 data sets for billet dimension 140 mm have been prepared. The data have been manually collected from different synchronized data bases of the plant. The main goal of the study is to train the ANN in order to be capable of predicting elongation, tensile strength, yield stress, hardness after rolling and necking, while changing the chemical composition and other process parameters accounted for in the training procedure. For the practical set-up of the relevant ANN, we used multilayer feedforward ANN with sigmoid activation function and supervised learning, implemented in our software module written in C-sharp. The datasets were stored in predefined JSON-based format and imported from the file before the training. The developed module allows checking the training and the verification errors during the training procedure. The procedure consists of five steps: reading the data from a file, data preparation, training, testing and prediction of unknown output values based on different combinations of 34 input parameters, listed in Table 1. During training, the state of the ANN is adjusted to the data sets with known output values. These comprise historical cases of steel production in the past. During training, the ANN response in training and verification points is checked in order to see how well it does at predicting known and unknown output values. Verification and training points used for testing are usually a subset of historical data. The verification points are randomly chosen from the datasets before training starts and are not used in the training procedure, while the training points are. When the error

on training points becomes smaller than the user specified tolerance, or when the number of training cycles reaches a specified number, the training stops. Different combinations of layouts and training parameters, decided on the basis of past experience [Belič (2006)], and some additional experimentation were tried. More than 20 trainings with both NeuronDotNet and Aforge libraries were performed. Good results were achieved by using ANN with one hidden layer containing 20-40 neurons. The learning rate that determines the learning speed was set to 0.3. Momentum that determines how much of the previous corrective term should be applied on in the current training was set to 0.6, and the maximum number of epochs was set to one hundred thousand. The training procedures were performed on a HP workstation HPDL380G7 with 12 Intel Xenon 2.0GHz processors, 24GB installed RAM. The trained neural network which gave us the best results was trained in approximately 18 hours with NeuroDotNet library and slightly more with Aforge.

5 Parametric studies

After the training of the ANN was done, the errors of the approximated outputs in verification sets were calculated. Some parametric studies were performed as well and the results were checked against practical industrial knowledge in order to validate the obtained approximation model.

The relative errors δ of the obtained approximation in all verification points were first calculated. These errors are a good indicator of accuracy of the obtained neural network-based approximation, and are defined for an arbitrary output quantity v as

$$\delta v_i = \left| \frac{v^{(m)}(\mathbf{p}_i) - v(\mathbf{p}_i)}{\max\limits_{j \in I_T} \left(v^{(m)}(\mathbf{p}_j) \right) - \min\limits_{j \in I_T} \left(v^{(m)}(\mathbf{p}_j) \right)} \right| ; \; i \in I_V , \tag{4}$$

where $v^{(m)}(\mathbf{p}_i)$ is the actual (measured) value of the output quantity v at the vector of input parameters $\mathbf{p}_i$, $v(\mathbf{p}_i)$ is the approximated value of this quantity at the same vector of parameters, and denominator contains the range of the considered quantity over all training sets. $\mathbf{p}_i$ is the vector of input parameters of the verification set i, in which the actual values of the output quantities are known, since verification sets are taken out of the data provided by industrial measurements. Dimension of the space of input parameters is in our case N_p=34. Index i is an element of the index set I_V that enumerates the verification points, with cardinality $|I_V| = N_V$. Index j is an element of the index set I_T that enumerates the training points, with cardinality $|I_T| = N_T$. Division by the range is performed for normalization and easier comparison of the results for different quantities that may typically differ by several orders of magnitude.

Verification points represent 5 % of the complete data provided for our test. There were N_M=1879 data sets provided from industrial measurements, of which N_V=94 were randomly selected as verification sets and were excluded from the training procedure. This preparation procedure is done automatically before the training starts.

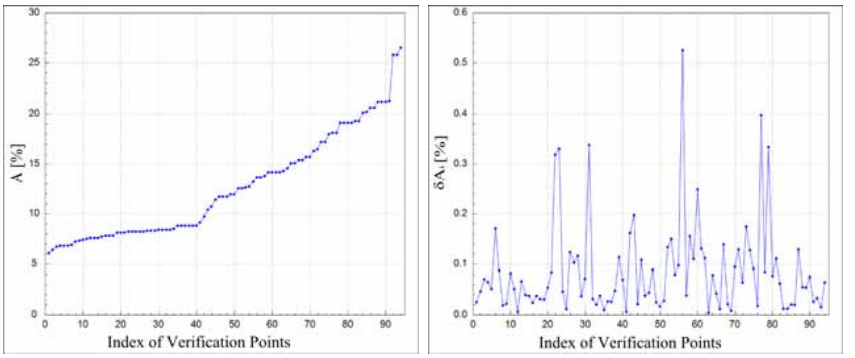

Figure 5: Approximation of elongation (A) in 94 verification points. Verification points are represented by dots. Left: real elongation values. Right: relative error calculated by Eq. 4. The verification points are ordered with respect to the magnitude of the elongation on both graphs.

The actual values of elongation in verification points and the relative error, calculated by Eq. 4 in these points, are shown in Figure 5. The maximum relative error in verification points for elongation is 0.6 %. Data sets in the figure were reordered in such a way that they are indexed by the growing value of elongation.

Real values for tensile strength in verification points and the relative error, calculated by Eq. 4 in these points, are shown in Figure 6. The maximum relative error in verification points for tensile strength is 0.7 %.

Real values for yield stress in verification points and the relative error, calculated by Eq. 4 in these points, are shown in Figure 7. The maximum relative error in verification points for yield stress is 0.4 %.

Real values for hardness after rolling in verification points and the relative error, calculated by Eq. 4 in these points, are shown in Figure 8. The maximum relative error in verification points for hardness after rolling is 0.5 %

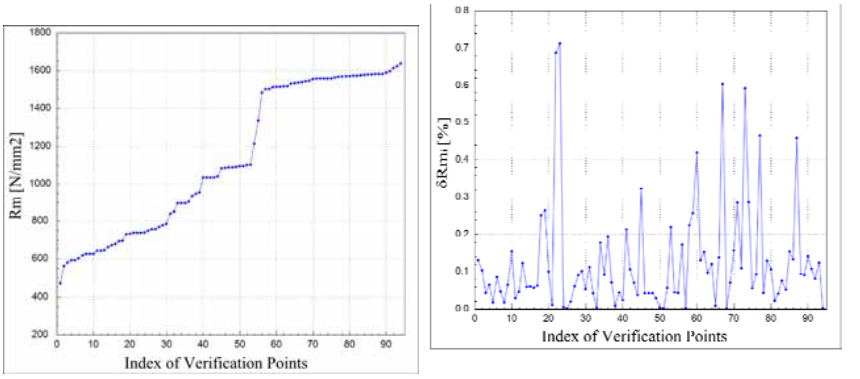

Figure 6: Approximation for tensile strength (R_m) in 94 verification points. Verification points are represented by dots. Left: real tensile strength values. Right: relative error in verification points.

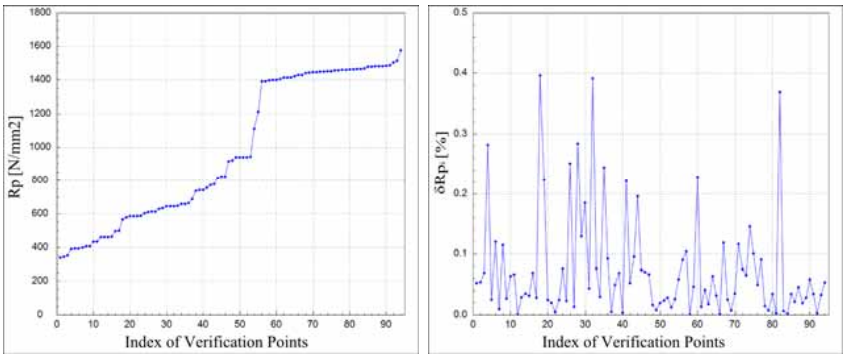

Figure 7: Approximation for yield stress ($R_{p0,2}$) in 94 verification points. Verification points are represented by dots. Left: real yield stress values. Right: relative error in verification points.

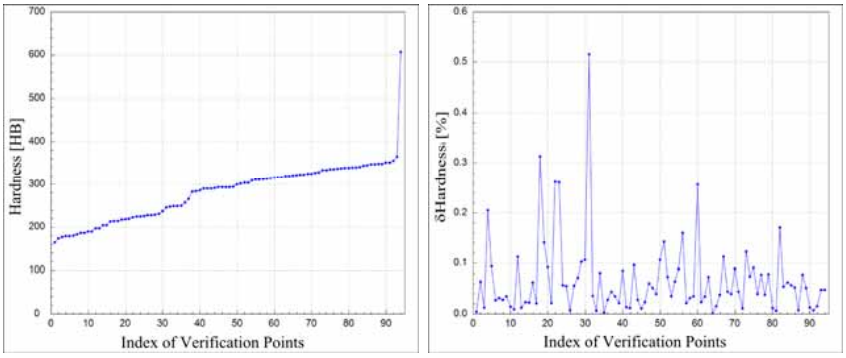

Figure 8: Approximation for hardness after rolling (Hardness) in 94 verification points. Verification points are represented by dots. Left: real hardness after rolling values. Right: a relative error in the verification points.

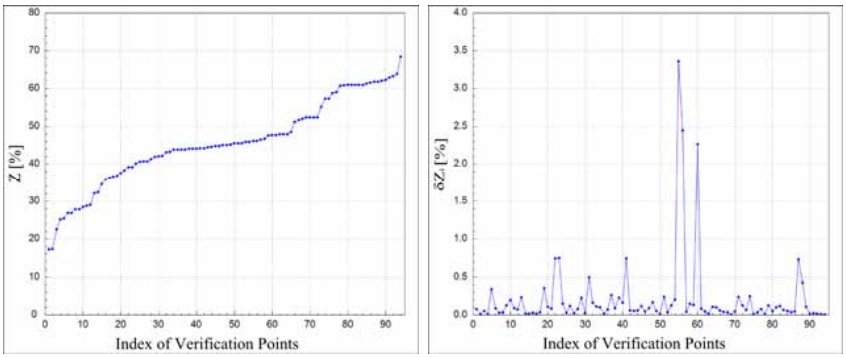

Figure 9: The approximation for necking (Z) in 94 verification points. Verification points are represented by dots. Left: real necking values. Right: a relative error in the verification points.

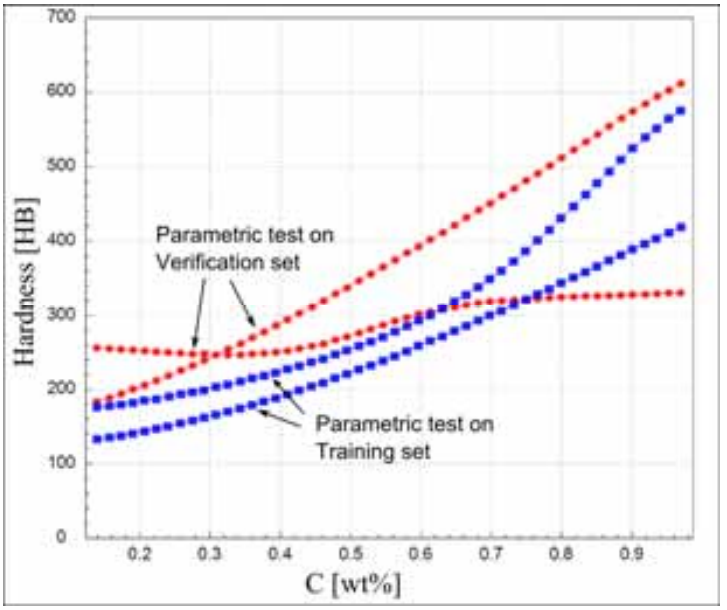

Figure 10: Steel hardness after rolling as a function of the carbon mass fraction, calculated by the ANN model on two verifications (line with dots) and two training sets (line with squares).

Finally, the real values for necking in verification points and the relative error, calculated by Eq. 4 in these points, are shown in Figure 9. The maximum relative error in verification points for necking is 3.4 %.

A comparison between the actual and the approximated response in a number of randomly selected verification points gives us an indication of the quality of the approximation. A problem that we notice is that the training sets are grouped in clusters in the space of input parameters. Each cluster corresponds to a specific steel grade. This means that the chosen verification points are usually relatively close to some other points from the training set that remain involved in the training procedure. Therefore, the accuracy of the approximation in these verification points is better than the actual average accuracy over the observed domain, which is affected by regions where the training points are scarcely distributed. In this case, we do not exactly know what happens with the approximation between the clusters, because we simply do not have enough information.

In the next study we randomly take 4 data sets from the entire data set. 2 sets were chosen among verification points and the other 2 from the training points. In each

chosen set we varied one input parameter, for example, concentration of Carbon (C), while the other parameters were fixed. The parameter was varied within the range defined by the minimum and the maximum value of that parameter over all data sets used in the training. These kind of tests help us find out how the change of one parameter, influences the output quantities of interest such as the elongation, the tensile strength, the yield stress, the hardness after rolling, and the necking. We performed these tests for all 34 input parameters. The influence of the concentration of element C on hardness after rolling is shown in Figure 10.

From the graph we can see that if we increase C concentration, hardness after rolling also increases. This trend is well known from metallurgical practice. It is expressed in the approximated response, whether the parametric tests are based on parameters taken from the verification of form the training set.

Next we perform a series of parametric tests where carbon mass fraction is varied and each parametric test is based on a vector of input parameters taken from a spatially related set. This set is constructed in such a way that the contained parameter vectors lie on the line connecting the two chosen endpoints $\mathbf{p}_I$ and $\mathbf{p}_F$ from the space of input parameters. The effects of variation of the carbon mass fraction are plotted around the constructed points (including the chosen endpoints). The intermediate input parameter vectors $\{\mathbf{p}_1, \mathbf{p}_2, \ldots \mathbf{p}_n\}$ are chosen equidistantly such that

$$\mathbf{p}_j = \mathbf{p}_I + (\mathbf{p}_F - \mathbf{p}_I)\frac{j}{n+1};\ j = 0,\ 1,\ 2,\ \ldots, n+1, \tag{5}$$

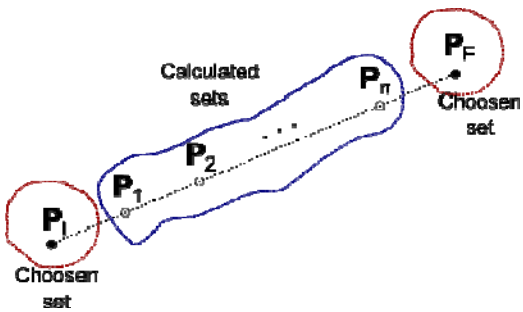

Figure 11: Points for parametric studies chosen on the line between the two points chosen from the training data.

where n is the number of the intermediate input vectors. The endpoints $\mathbf{p}_I$ and $\mathbf{p}_F$ are in our case taken from the data used for training the ANN. The arrangement of the input vectors is schematically shown in Figure 11.

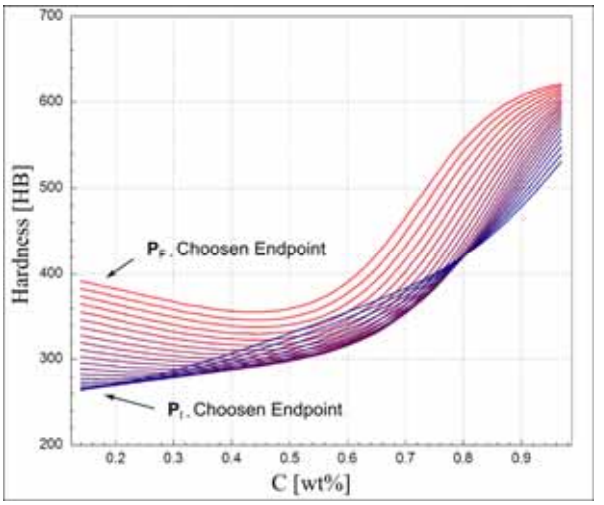

Figure 12: Steel hardness after rolling as a function of carbon mass fraction, calculated by the ANN model in 2 points from the training data, and for 18 other points on the line between them.

The influence of the carbon mass fraction on hardness is shown in Figure 12. In each of the curves in this figure, a single parameter (concentration of C in the present case) varies over the whole range of values, while other parameters are fixed and taken from one of the constructed parameter vectors $\mathbf{p}_j$.

In this test we can find out how smoothly the curves on the graph pass from the parameter vector $\mathbf{p}_I$ to $\mathbf{p}_F$. Because the parameter vectors $\mathbf{p}_j$ that lie between $\mathbf{p}_I$ and $\mathbf{p}_F$ were not included in the training, one could expect lower accuracy of the approximated response at these parameters.

In the next study we examine how uniformly the parametric space is covered by the training data. We first calculate for each vector of input parameters from the training set the smallest weighted Euclidean distance from this vector to any other input parameters vector from the training set. We define the weighted Euclidean distance d_l as:

$$
\begin{aligned}
d_l(\mathbf{x},\,\mathbf{y}) &= \sum_{k=1}^{N_p} \sqrt{w_k^2\,(x_k - y_k)^2}, \\
w_k &= \frac{1}{l_k}, \\
l_k &= \max_i (p_{ik}) - \min_i (p_{ik});\;\; i \in I_M,
\end{aligned}
\tag{6}
$$

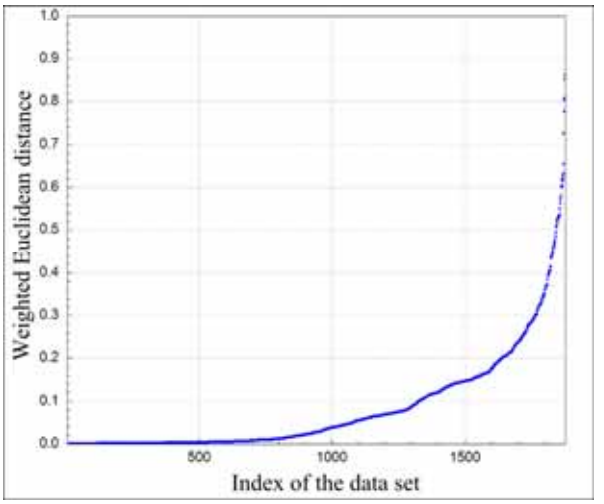

Figure 13: A minimum weighted Euclidean distance from the training point to the closest training point, calculated by Eq. 6.

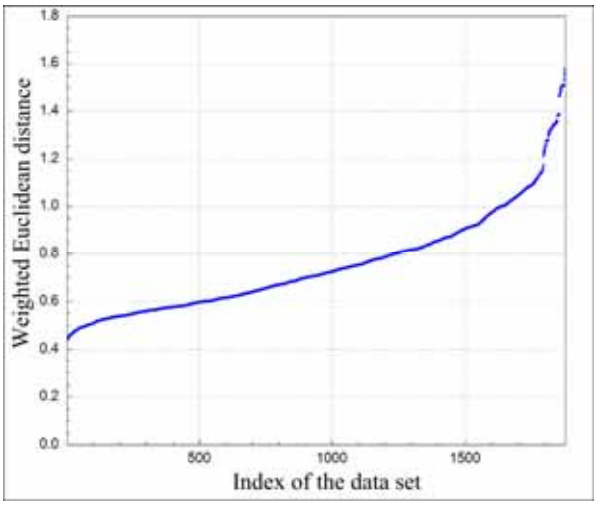

Figure 14: A minimum weighted Euclidean distance to the 35th closest training point.

where l_i represents the range of the corresponding input parameter over the complete measured data obtained from the industrial line, and $\mathbf{x}$ and $\mathbf{y}$ are arbitrary vectors in the space of input parameters and N_p is the dimension of the space. We denote by I_M the index set used to enumerate all data sets obtained form industrial measurements, thus p_{ik} represents the k-th element of the vector of input parameters $\mathbf{p}_i$.

Figure 13 and Figure 14 show the distribution of the training and the verification points according to their distances to the closest training point, and to the m-th closest training point, respectively. We use the value m=35, since this is one more than the number of process parameters and is equal to the minimal number of data-sets necessary for linear regression. Points on the graphs correspond to the provided data sets that are ordered by the distance to the m-th closest point. We can see from the graph that the distance to the closest points varies a lot, and a large portion of points do not have close neighbors. This indicates non-uniformity of the distribution of data points in the parameter space. This is expected, since the data were obtained from the actual industrial line. In steel production, a number of standardized steel qualities are used with narrowly defined chemical compositions, for which the process is adjusted according to expert knowledge, generated by the past experience. The clusters of data points are therefore formed around the parameter settings that are commonly in use.

6 Conclusion

An ANN – based approximation model for complete steel production process path was presented. A specially designed software framework has been developed for construction, validation and application of this kind of approximation models. The represented model was built on a basis of 34 process parameters that turn out to be influential. Five output values were modeled which represent important outcomes of the production process. Some parametric studies were performed to examine the accuracy of the approximation. The trends exhibited by the approximated response were consistent with the metallurgical knowledge, and the practical experience. However, the accuracy over the whole domain in the parametric space is not yet satisfactory for a reliable use in tuning and optimization of the process parameters. The accuracy varies over domain of interest due to the clustering of the sampling points contained in the data, captured from the industrial production line.

Further development will be directed towards the development of new methods for assessment of the quality of training data, and accuracy of the approximation. In particular, the meaningful ways of quantitative description of the multidimensional distribution of the training points in space have to be developed and used in optimal selection of verification points. The error estimators will be developed and

integrated with the optimization and other procedures where the approximate models will be utilized. On the other hand, the feedback regarding the critical influential factors is continually sent back to industry in order to improve the accuracy of measurements and consistency of conditions at points that critically affect repeatability of the process. In order to be industrially relevant and effective, ANN model should always be used with great care and with sufficient data. Physical models [Šarler, Vertnik, Lorbiecka, Vušanović, and Senčič, (2012); Šarler, Vertnik, and Mramor, (2012)] should also be developed in parallel and used wherever possible to supplement and validate the ANN models. This would allow also better and more versatile validation and interpretation of the results.

With the represented trained artificial intelligence TPM, the Štore Steel company obtained a basic model and particularly a new state-of-the-art methodology for estimation of the final product properties as a function of the process parameters. The developed methodology is particularly important, since it allows the optimization [Grešovnik, Kodelja, Vertnik, and Šarler, (2012)] of the whole production with respect to the productivity, quality, use of the resources, and the environmental impact in the outlook. The presented approach can be used in other industries as well.

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