Application of Artificial Neural Networks in Design of Steel Production Path

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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 processing.

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

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)) [1]-[2], 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 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 spectra of industries [3]. For example, in steel making industries, neural networks are already being used for predicting steel mechanical properties after heat treatment [4], for thermal model of a ladle furnace [5], for rolling mills [6], for heat transfer in continuous casting process [7]-[8], 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 Store Steel, Slovenia [9] is schematically represented in Figure 1. It consists of six main individual process steps [10]-[11]: 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 [13]-[16] or by an ANN model. Output values of a process step might 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 and relate them to process parameters that can vary in the system in such a case.

The main aim of this work is to explore the possibility of applying ANN for computationally modeling the whole process path. The result of the ANN model will be used for prediction of five mechanical properties for steel manufacturing process path in terms of a set of process parameters.

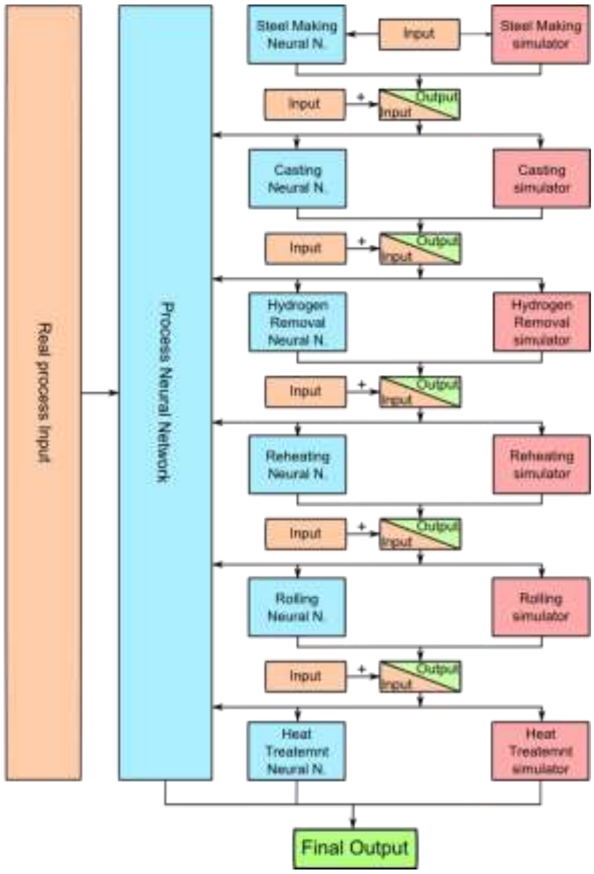


Figure 1: Steel manufacturing process modeling strategy by ANN

2 Steel manufacturing process and process parameters

The manufacturing of steel in Štore Steel company involves a series of process steps that follow one after another. First, the steel is melted from scrap in an electric arc furnace (EAF). EAF heats charged material by means of an electric arc.

When steel temperature is around 1600 ^{0}C the molten steel is then poured into a preheated ladle - this is called tapping. During tapping process lime, manganese, silicon, carbon and, if necessary and according to the type of steel that is being made, other alloying elements are added.

The ladle is then transported by a crane to the refining station, where more carbon, manganese, silicon and vanadium are added to achieve the specification of the steel grade being made. Argon gas bubbles flow through the ladle to help to remove any remaining impurities.

Once the specification of the steel is confirmed, the ladle is transported by the crane to the continuous casting device. Here, the ladle gate opens and the molten steel is allowed to flow in a controlled matter into a tundish. The steel afterwards flows from the tundish into a three strand billet caster. The steel billets are solidified and then cut to the desired length for further processing [12]-[15].

Once the appropriate billet grade is determined, the billet has to be reheated and is loaded into gas reheating furnace. The furnace is continually loaded. When one billet enters the furnace, another one that is now fully heated is rolled out, ready for the rolling process. The reheating furnace typically takes two to three hours to heat up the billets to the rolling temperature of 1260 ^{0}C. Gas burners in the furnace provide the heat and the hot exhaust gas is reused to preheat the incoming combustion air, minimizing the heat losses. The billets are moved through the furnace on a walking beam which lifts the entire furnace full of billets and moves them forward one step at a time.

Once heated to the appropriate temperature, the billet enters the continuous bar rolling line. Basically, the rolling line has two phases: the "roughing" stands or preliminary rolls, which do the initial rough shaping, and then the "finishing" stands which finally shape the steel to the appropriate shape. The square billet can pass through as many as eighteen sets of vertical and horizontal rolls with different grooves to reach its final shape. As the steel billet passes through each roll it speeds up since its cross-sectional area gets smaller, and the length gets longer.

Each of the rolls is technically designed not only to produce the correct size product, but to do it in a way that ensures the product quality and process productivity, by considering the limitations of the steel behavior, as well as of the equipment that controls and drives the rolls.

After the steel semi products leave the rolling line, they pass to the cooling bed. The bar on the cooling bed is cut to length with the flying shear, as it enters the bed. This ensures the fitting of the bar on the bed. Once on the cooling bed, the bar cools to a manageable state and it is then further processed with a cold shear, where it is cut to the customer required length. The product is then bundled and labeled to provide its unique identity. The complete process is shown in Figure 2.

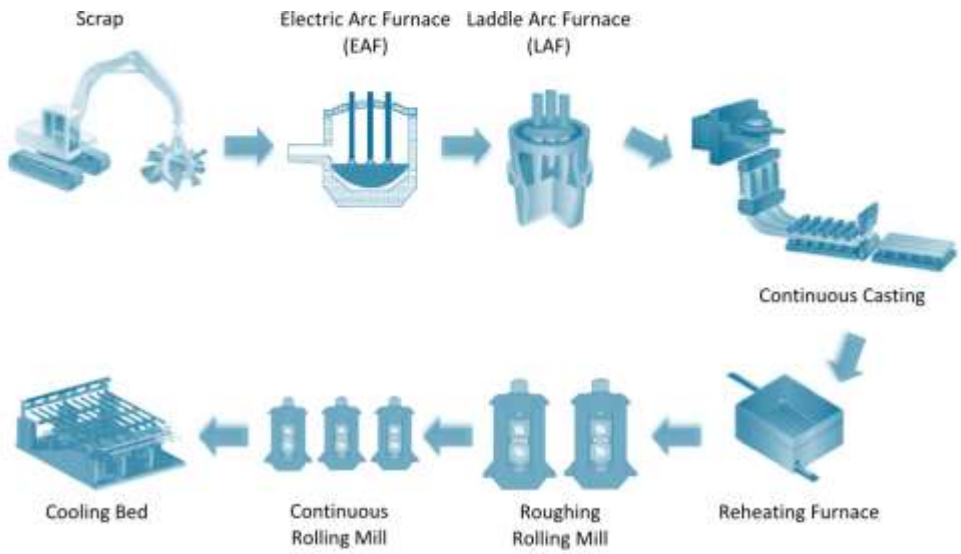


Figure 2: Steel manufacturing process in Store Steel company

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**

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**

3 Neural Networks Approximation Module

In several practical cases, the process design parameters have to be adapted quickly in order to produce the results that comply with the customer requirements. The classical approach to optimization of process parameters, where the physics based simulator can 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 ([21]-[22]), 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 [18].

In the current work, approximation of process path, based on the neural networks is considered. A convenient characteristic of neural networks is that approximation is performed in two separate stages (

Figure 3). 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 approximated response as a function of arbitrary values of input parameters.

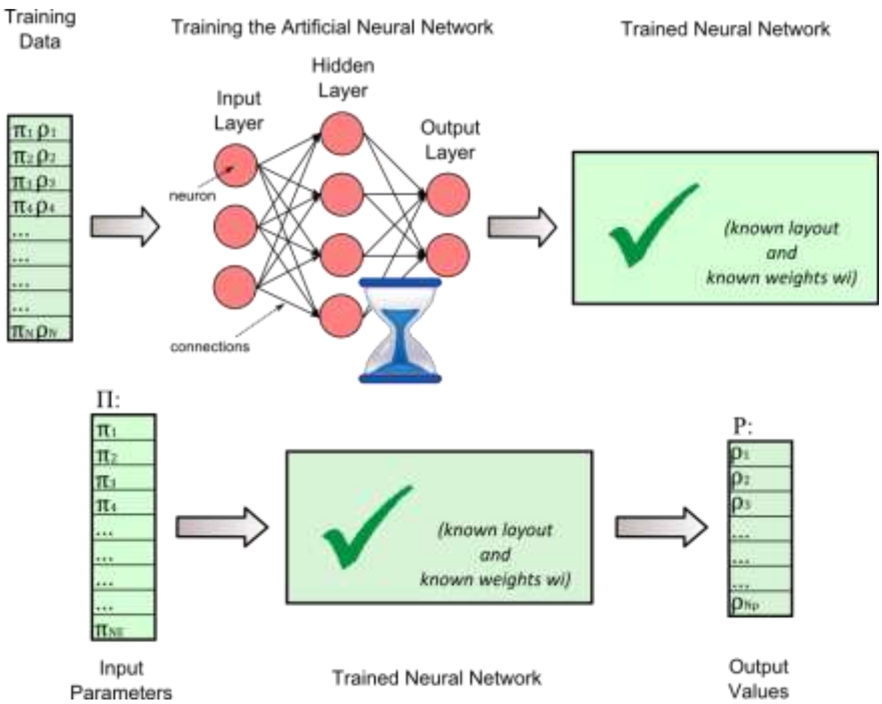


Figure 3: Approximation with neural networks: training of a network (top) and calculation of approximated response with a trained network (bottom).

An in-house approximation module has been developed, based on general purpose neural network libraries and extensive code base for development of technical applications [17]. It features modular design, such that the new underlying libraries can be easily utilized (open source libraries Aforge.Net [19] and NeuronDotNet [20] are currently used for ANNs). This also provides good flexibility in integration with the 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 processing parameters. Data obtained from such systems is often inaccurate or even corrupted due to practical limitations and possible failures in acquisition procedures. Response sampling can not be planned in advance but is accommodated to production schedules in the factory. Therefore, the information 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.

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 123 process parameters (Table 1), 34 influential input parameters. 5 output values were considered.

Process data for steel bars for applications in the forging, spring and engineering industries were used. After separating 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 to check 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 the 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 ([21]-[22]]) 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. Both libraries performed similarly in terms of final results, while NeuroDotNet was slightly faster. 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 100000. 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.

5 Parametric Studies

After the training of the neural network was done, the errors of the approximated outputs in verification sets were calculated, and some parametric studies were performed. The accuracy of the ANN and the dependences between the parameters have been verified through the parametric tests.

The relative errors of the obtained approximation in all verification points were checked in the first study. These errors are a good indicator of accuracy of the obtained neural network-based approximation, and are defined as follows:

$$\delta_{vi} = \left| \frac{v_{real}\left(\vec{p}_i\right) - v_{approx}\left(\vec{p}_i\right)}{v_{range}} \right|, \tag{1}$$

where $v_{real}\left(\vec{p}_i\right)$ is the actual value of the output quantity v in the verification point i, $v_{approx}\left(\vec{p}_i\right)$ is the approximated value of this quantity in the same point in parametric space, and v_{range} is the range of the considered quantity over all training sets. Division by v_{range} is performed for the normalization and easier comparison of the results for different quantities that may typically differ by several orders of magnitude. $\vec{p}_i$ is the vector of parameters, corresponding to the verification point *i*, in which the actual values of output quantities are known, since verification points are taken out of the provided data.

Verification points represent 5% of the complete data-set provided for our test. There were 1879 points with corresponding values of output quantities in the data-set, of which 94 were randomly selected as verification sets and were excluded from the training procedure. This preparation procedure is done automatically before the training starts.

The actual and the predicted values of elongation are shown in Figure 4. The maximum relative error in verification points for elongation is 0.6 %.

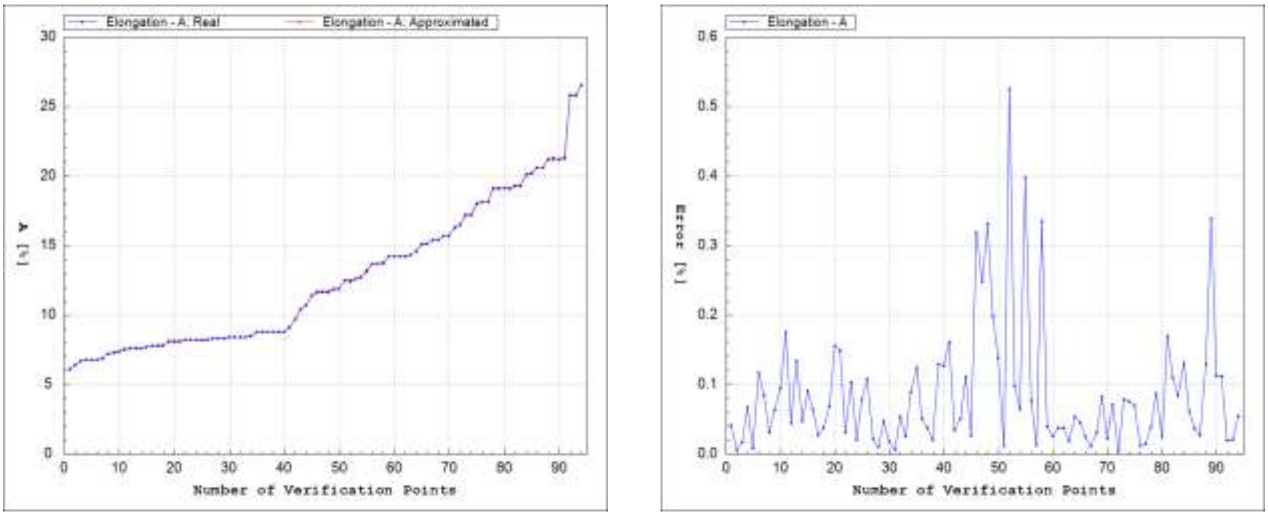


Figure 4: Approximation of elongation (A) in verification points. Left: comparison between actual and approximated values. Right: relative error in verification points. The verification points are ordered with respect to the magnitude of the elongation on both graphs.

Predicted and real values for tensile strength are shown in Figure 5. The maximum relative error in verification points for tensile strength is 0.7 %.

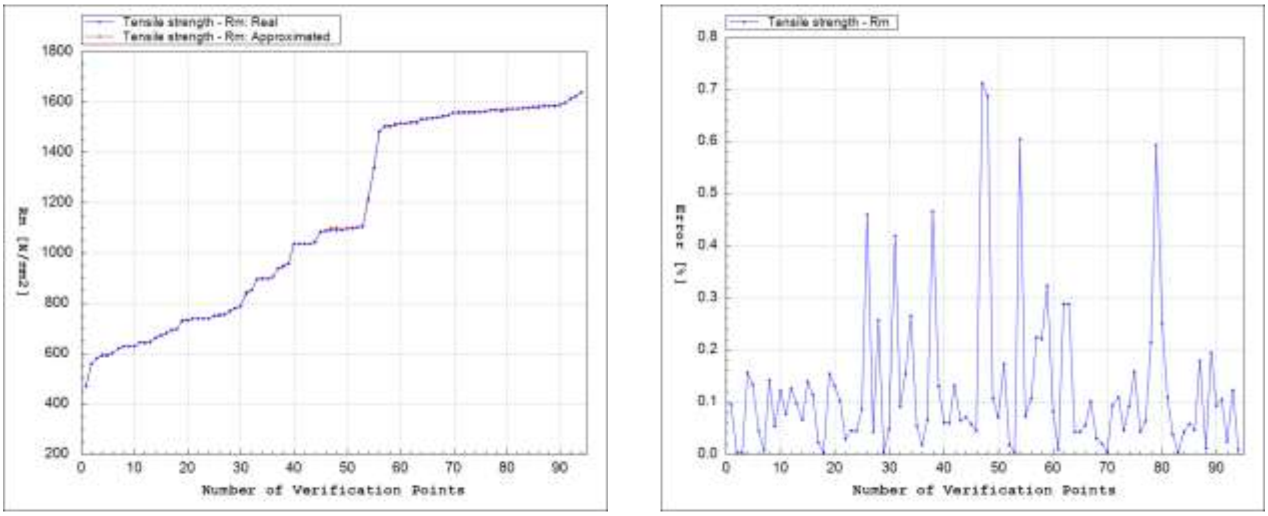


Figure 5: Approximation for tensile strength (R_m) in verification points. Left: comparison between actual and approximated values. Right: relative error in verification points.

Predicted and real values for yield stress are shown in Figure 6. The maximum relative error in verification points for yield stress is 0.4 %.

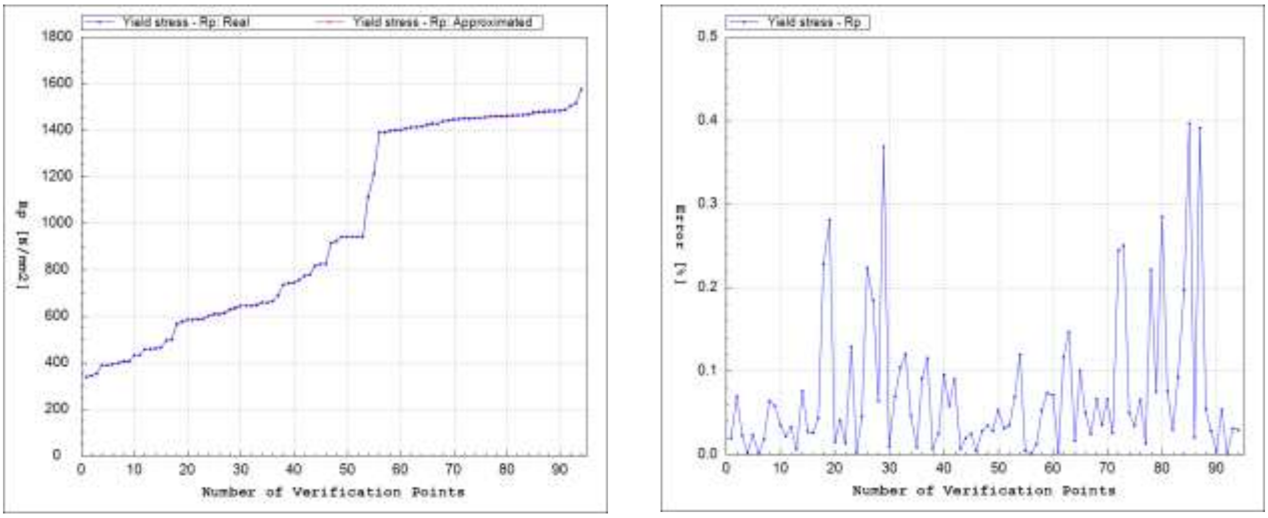


Figure 6: Approximation for yield stress ($R_{p0,2}$) in verification points. Left: comparison between actual and approximated values. Right: relative error in verification points.

Predicted and real values for hardness after rolling are shown in Figure 7. The maximum relative error in verification points for hardness after rolling is 0.5 %.

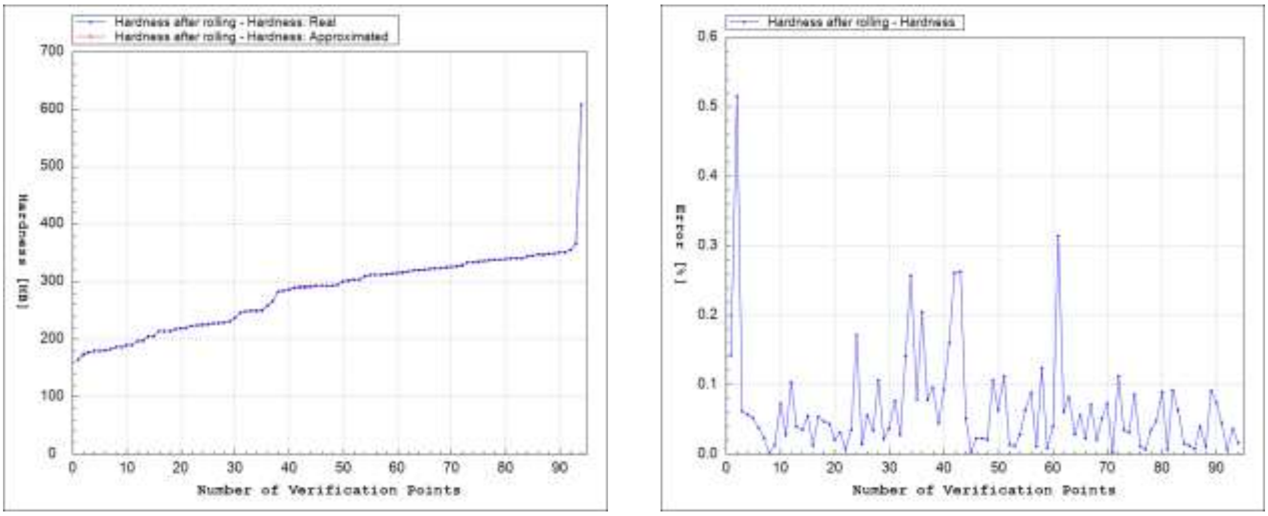
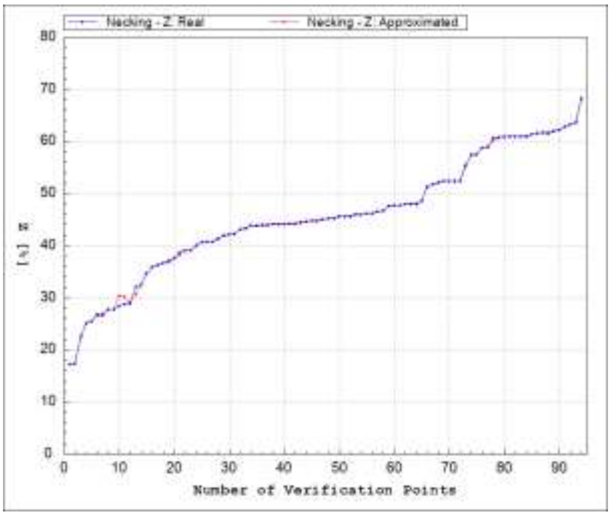


Figure 7: Approximation for hardness after rolling (Hardness) in verification points. Left: comparison between the actual and the approximated values. Right: a relative error in the verification points.

Finally, the predicted and real values for necking are shown in Figure 8. The maximum relative error in verification points for necking is 3.4 %.



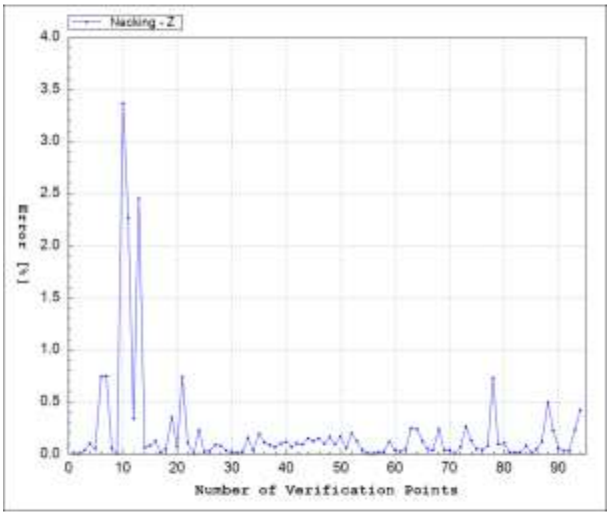


Figure 8: The approximation for necking (Z) in verification points. Left: comparison between the actual and the approximated points. Right: a relative error in the verification points.

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 data are grouped in clusters. This means that the chosen verification points are 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, 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. 2 sets were chosen among verification points and the other 2 from the training points. In each set chosen we varied one parameter, for example, concentration of 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, for example, element C, 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 9.

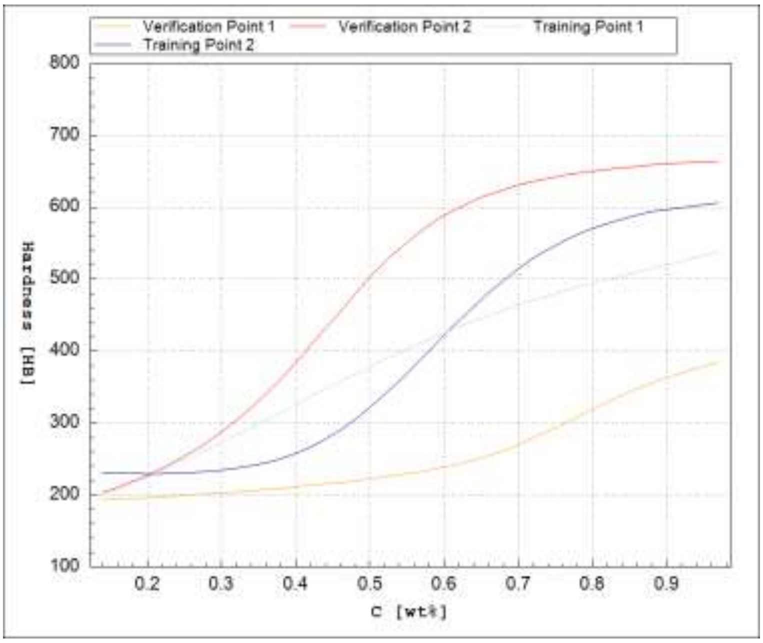


Figure 9: Steel hardness after rolling as a function of the carbon mass fraction, calculated by the ANN model on two verifications and two training sets.

From the graph we can see that if we increase carbon (C) concentration, hardness after rolling also increases. This trend is well known from metallurgical practice.

We chose two points ($\vec{r}_1$, $\vec{r}_2$) from the provided data-set, for which the corresponding data sets were included in training of the ANN in another parametric study. Then we took a certain number of equally spaced points on the line segment between these two points (including the chosen points). The effects of variation of certain parameters were plotted for all points. These intermediate points ($\vec{p}_1$, $\vec{p}_2$, …, $\vec{p}_n$) were calculated according to

$$\vec{p}_i = \vec{r}_1 + \left[\frac{\vec{r}_2 - \vec{r}_1}{n+1}\right], \qquad (2)$$

where n is the number of the intermediate points. The endpoints were included in the training of the ANN while the intermediate points were not. The arrangement of the points is schematically shown in Figure 10.

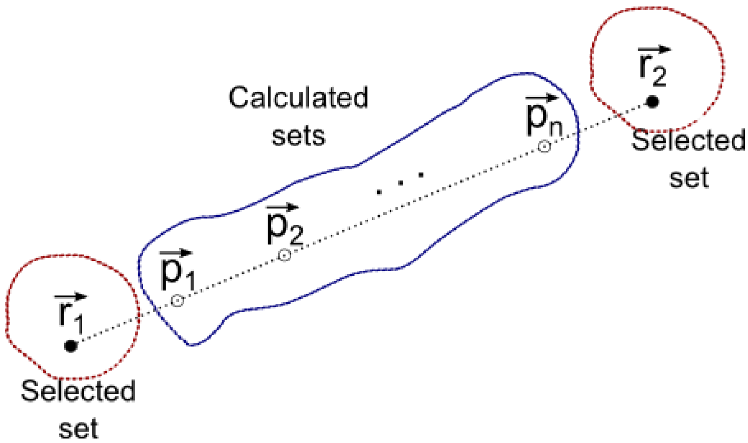


Figure 10: Points for parametric studies chosen on the line between the two points chosen from the training data.

In each of the points from Figure 10 we varied one parameter (concentration of C in this case) over the whole range of values, while other parameters remained unchanged. The influence on hardness is shown in Figure 11.

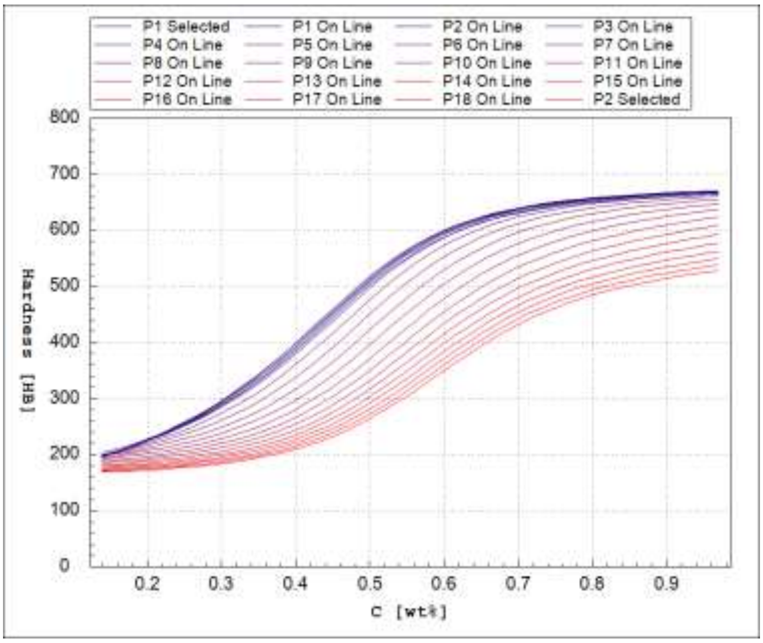


Figure 11: Steel hardness after rolling depends on carbon mass fraction, calculated by the ANN model in 2 points from the training data, and 18 other points on the line between them.

In this test we can find out how smoothly the curves on the graph pass from point $\vec{r_1}$ to $\vec{r_2}$. Because the points between $\vec{r_1}$ and $\vec{r_2}$ were not included in the training, one could expect lower accuracy of the approximated response in these points.

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

$$\begin{gathered} d_l\left(\vec{x},\vec{y}\right)=\sum w_i\left(\vec{x_i}-\vec{y_i}\right)^2, \\ w_i=\frac{1}{l_i}, \\ l_i=\max\left(x_i\right)-\min\left(x_i\right), \end{gathered} \tag{3}$$

where l_i represents the range of the corresponding parameter.

Figure 12 and Figure 13 show the distribution of the training and the verification points according to their distances to the closest training point, and to the $N+1$-st closest training point, where N is the number of the input parameters. Smaller blue points on the graph represent the training points, while the larger red points represent verification points. 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 shows a non-uniformity of the 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.

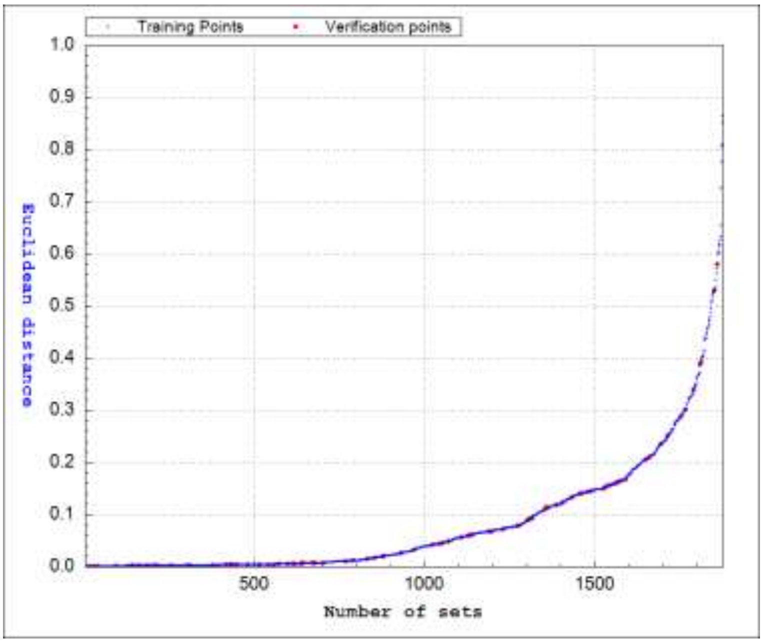


Figure 12: A minimum weighted Euclidean distance to the closest training point.

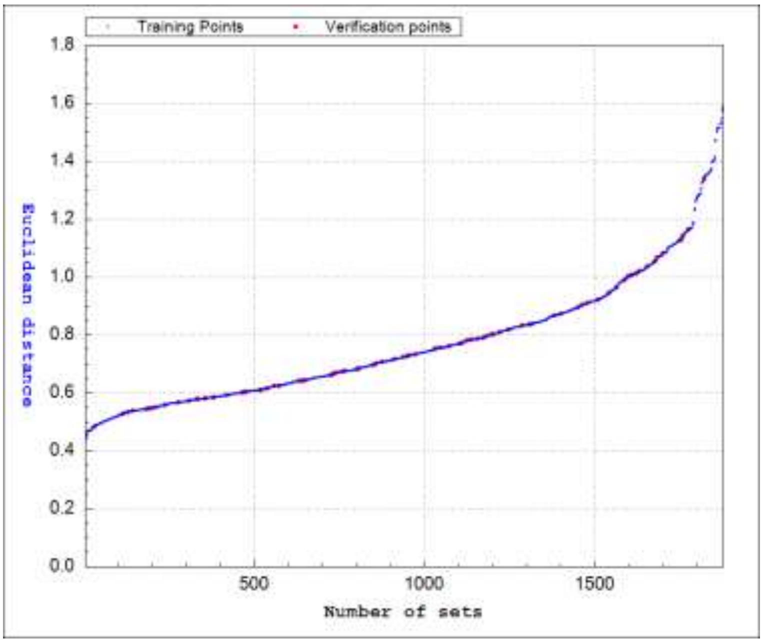


Figure 13: A minimum weighted Euclidean distance to the $N+1$-st closest training point.

6 Conclusions

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 presented 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 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.

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 of the whole production with respect to the productivity, quality, use of the resources, and the environmental impact in the perspective.

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