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

Tadej Kodelja1, Igor Grešovnik1,2, Robert Vertnik2,3, Božidar Šarler1,2,4

1Center of Excellence BIK, Solkan, Slovenia
2University of Nova Gorica, Nova Gorica, Slovenia
3Store Steel d.o.o., Research, Store, Slovenia
4IMT, Ljubljana, Slovenia

bozidar.sarler@imt.si

Prejem rokopisa – received: 2013-06-14; sprejem za objavo – accepted for publication: 2013-07-03

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 Store 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

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 models3,4 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 in8. Furthermore, a preliminary study9 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 Store Steel company and the respective available data were considered as a basis for the present study. The manufacturing process path consists of six individual processes: 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. 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.

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.

The Aforge.Net library is used as ANN framework. 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 1:** Steel manufacturing process modeling strategy

**Figure 2:** Approximation with neural networks: training a network with presented data pairs (top) and calculation of approximated response with trained network (bottom)
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 Štor 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, 4 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)

<table>
<thead>
<tr>
<th>Processes / properties</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Composition</td>
<td>24</td>
</tr>
<tr>
<td>Continuous casting of steel</td>
<td>12</td>
</tr>
<tr>
<td>Hydrogen removal</td>
<td>4</td>
</tr>
<tr>
<td>Billet reheating furnace</td>
<td>2</td>
</tr>
<tr>
<td>Rolling mill</td>
<td>31</td>
</tr>
<tr>
<td>Continuous rolling mill</td>
<td>43</td>
</tr>
<tr>
<td>Cooling bed</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>123</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Final mechanical properties</th>
<th>Elongation (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tensile strength (Rm)</td>
</tr>
<tr>
<td></td>
<td>Yield stress (Rp0.2)</td>
</tr>
<tr>
<td></td>
<td>Hardness after rolling (HB)</td>
</tr>
<tr>
<td></td>
<td>Necking (Z)</td>
</tr>
</tbody>
</table>

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.

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 nevronске mreže

<table>
<thead>
<tr>
<th>Training parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning rate</td>
<td>0.4</td>
</tr>
<tr>
<td>Momentum</td>
<td>0.6</td>
</tr>
<tr>
<td>Alpha value</td>
<td>1.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Architecture</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Neurons in input layer</td>
<td>34</td>
</tr>
<tr>
<td>Neurons in 1st hidden layer</td>
<td>25</td>
</tr>
<tr>
<td>Neurons in output layer</td>
<td>5</td>
</tr>
</tbody>
</table>

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

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 $p$:

$$v = v(p)$$

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.

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 $p_c = p_c$. 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:

$$u_i(t) = v_{i_1}(p_{i_1}, p_{i_2}, \ldots, p_{i_j}, t, p_{j+1}, \ldots, p_{j+N_p})$$

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

\[ \Delta u_{ij}(t) = \left( \max u_{ij}(t) - \min u_{ij}(t) \right) \] (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.

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 paramet-
ers obtained from the present ANN response are tempe-
ration of the liquid steel (Tcast) for elongation and
hardness after rolling, temperature difference in the
mould (Dtmould) for tensile strength, cooling water tem-
perature 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 param-
eters 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>
<thead>
<tr>
<th>Elongation (A)</th>
<th>Tensile strength ((R_m))</th>
<th>Yield stress ( (R_p))</th>
<th>Hardness after rolling ((HB))</th>
<th>Necking ((Z))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Ni C C Ti V</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Al Cr Ni C Si</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Ti Delta temperature in the mould Mn Ni C</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 phy-
sical 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 pro-
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 simplifi-
cations 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,
Acknowledgment

The Centre of Excellence for Biosensors, Instrumentation and Process Control (COBIK) is an operation financed by the European Union, European Regional Development Fund and Republic of Slovenia, Ministry of Education, Science Culture and Sport. The financial support of COBIK, Slovenian Research Agency and Štore Steel company in the framework of the research program P2-0379 and the project L2-3651 is kindly acknowledged.

6 REFERENCES

12 J. G. Lenard, Primer on Flat Rolling, Elsevier, Amsterdam 2007
20 M. Kovačič, B. Šarler, Materials and Manufacturing Processes, 26 (2011), 464–474
21 M. Kovačič, B. Šarler, Materials and Manufacturing Processes, 24 (2009), 369–374