AI-Supported Material Simulation of Forming Processes

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ABSTRACT

Realistic material simulation is becoming increasingly important in the mapping of forming processes. The more accurate the material data and models are, the better the match between the simulation and the results of the production process will be. Thus, AI methods are also increasingly used in material simulation, which leads to further improvement of the simulation results.

The paper demonstrates the use of AI in the form of neural networks for the simulation of phase transformation processes in steels during cooling from the forming heat. In this context, new possibilities arise compared to the usual use of CCT diagrams: On the one hand, the influence of changes in chemical analysis and austenitization condition can be gleaned. On the other hand, temperature-time histories with variable cooling rates can be better understood. The results significantly improve the representation of the forming process in simulation programs. Two application examples show the influence on the development of microstructures in long products.

Keywords: AI methods, neural networks, material simulation, phase transformation, CCT diagrams, forming process

TRANSFORMATION BEHAVIOR OF STEELS DURING COOLING

During the course of production, all steel products undergo multiple temperature changes. The property changes associated with this result in part from the transformation of microstructure shares. In the past, the transformation behavior during cooling has already been examined for a number of steels. Results are illustrated in CCT diagrams from which the arising transformations and resulting microstructure formations for consistent alloy compositions at defined heating conditions can be gleaned as a function of time available for transformation. Various parameters aside from the pre-treatment condition are responsible for the formation and position of the phases in the CCT diagram. Among them are chemical composition, chemical and structural homogeneity, austenitization conditions, austenite grain size, cooling conditions as well as the share, type, composition, stability and distribution of the secondary phase. Forming in the austenite phase is another influencing factor (figure 1).

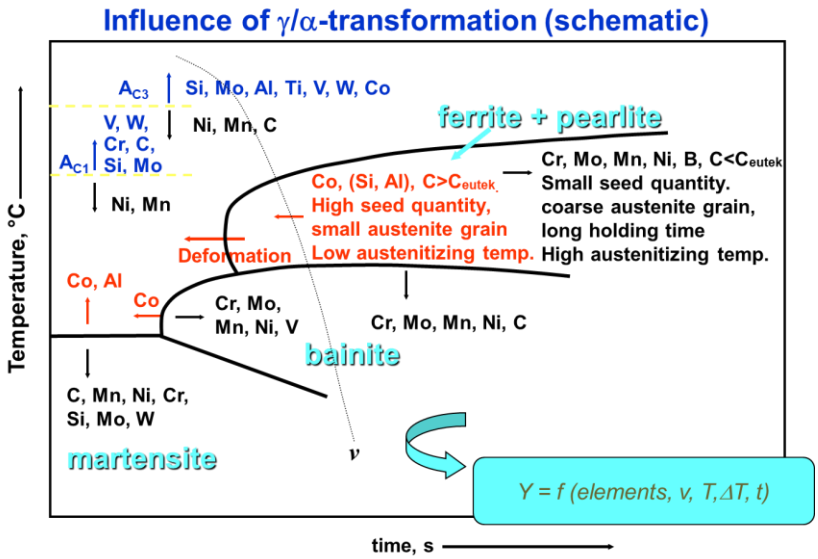

Figure 1: Parameters influencing phase formation depicted in a CCT diagram [1]

There are many diagrams on hand in literature describing the microstructure transformation of various steels during cooling after thermal treatment (CCT), welding, or forming. Accordingly, CCT diagrams are divided into four groups depending on the specific conditions of their recording (figure 2).

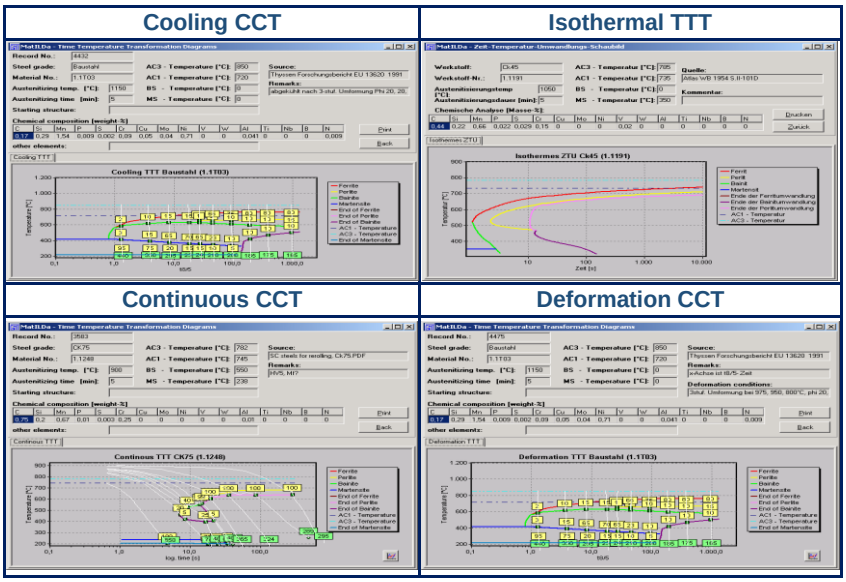

Figure 2: Example of different types of CCT diagrams

Schematics delineating phase shares and hardness as a function of cooling time between 800 °C and 500 °C are often given along with continuous CCT diagrams. These curves serve to interpolate the measured phase shares and present a comprehensive picture of the changes in phase distribution and hardness as a function of cooling time to the user. [2]

MODELLING OF PHASE TRANSFORMATION AND CALCULATION OF MICROSTRUCTURE SHARES

A disadvantage of CCT diagrams is that phase shares and hardness values are only valid for the conditions under which the respective diagram was recorded.

An extensive CCT data evaluation of over 4000 CCT diagrams allowed the determination of phase shares and hardness values resulting from cooling from the forming heat for selected steel groups on the basis of chemical analysis and austenitization temperature.

Due to the complexity of the technological parameters and material properties as input parameters and the resulting microstructure as output parameters in the feature space under examination, data mining (computer-assisted learning from data sets) was chosen as a method for modelling. Data mining methods such as neural networks allow an analysis of previously edited experimental data from large databases with the goal of detecting dependencies between the parameters. Advantages of such methods are:

- Extracting of previously unknown correlations between input and output parameters
- Description of non-linear correlations
- Identification and filtering of errors
- Short computing times and quick results

In order to configure the neural network, a suitable network architecture has to be determined on the basis of the task. This includes the number of hidden layers, the number of neurons per layer and the transfer functions of the respective layers. With regard to network architecture, the number of in- and output neurons is fixed due to the number of in- and output parameters. However, reliance on heuristic methods is necessary when choosing the number of neurons for the hidden layers. Generally, one should adhere to the rule of thumb “as complex as necessary and as simple as possible.” Figure 3 schematically outlines the structure of a neural network for predicting phase shares after cooling from the austenitization temperature.

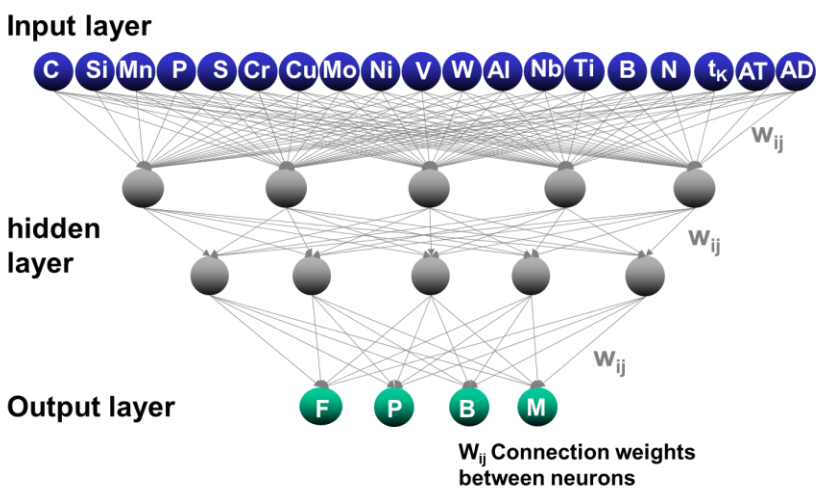

Figure 3: Structure of a multilayer perceptron for prediction of phase shares in steels [3]

Input parameters include chemical composition (C, Si, Mn, Cr, Mo etc. in mass-%), austenitization temperature (°C) and the logarithmized cooling time t8/5 (s).

Output parameters include the percentage of the microstructure shares ferrite, perlite, bainite and martensite as well as the start/end temperature of the phase transformation and the hardness HV according to Vickers. The data-based model has been parametrized for various steel groups in defined areas of analysis.

The application of neural networks so configured is useful in analyzing the influence of alloying elements in steels on microstructure formation. Figure 4 shows the influence of an altered carbon content on the formation of the individual phases for a 5115 steel.

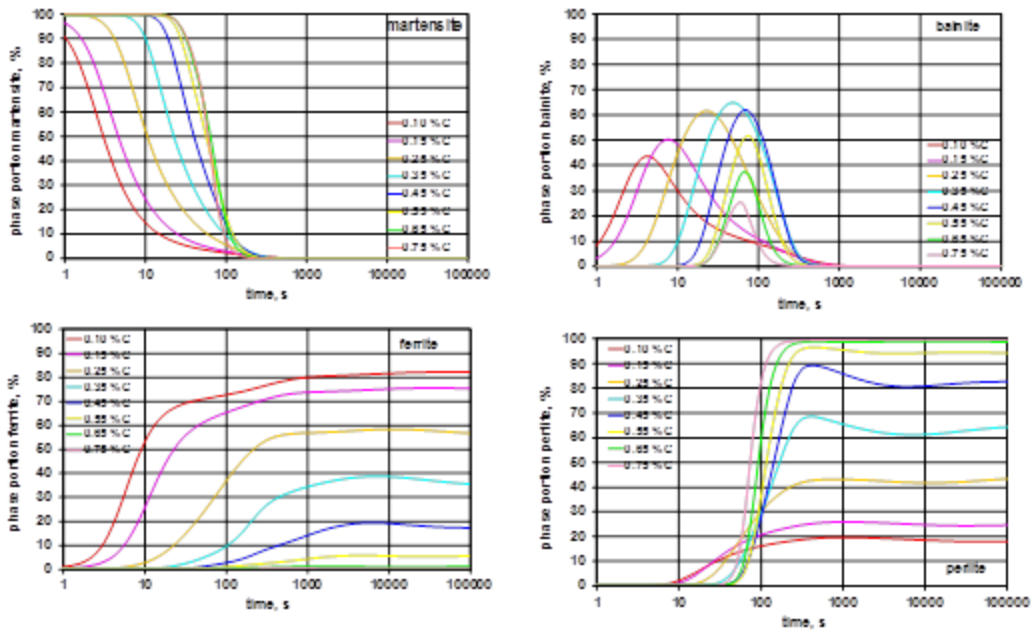

Figure 4: Analysis of the influence of carbon content on phase transformation kinetics for a 5115 steel x %C; 0.20 %Si; 1.00 %Mn; 0.80 %Cr; 0.03 %Cu; 0.02 %Ni; AT= 870 °C [3]

The sensitivity analysis of the input parameters of the neural network in relation to the output parameters offers several advantages:

- Quick optimization of steel compositions and production conditions without cost- and time-consuming laboratory and field experiments
- Identification of essential and non-essential parameters
- Shortening of test stages during development of new steels

The neural networks are visualized in the Material Information Link and Database MatILDa®. Figure 5 shows phase shares, transformation temperatures and hardness values for unalloyed carbon steels as well as a recalculated cooling CCT diagram.

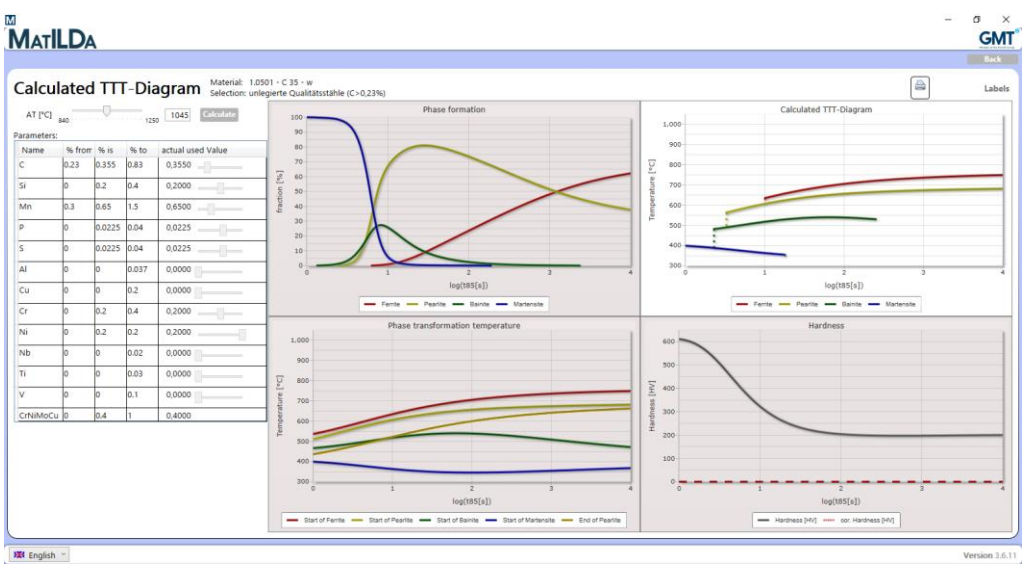

Figure 5: Visualization of parametrized neural network for carbon steels

This allows the user to easily check influences such as austenitization and chemical analysis and to compare changes due to alteration in chemical composition. Figure 6 illustrates this using the example of the same steel group as in figure 5 with an increase of C- and Mn-content.

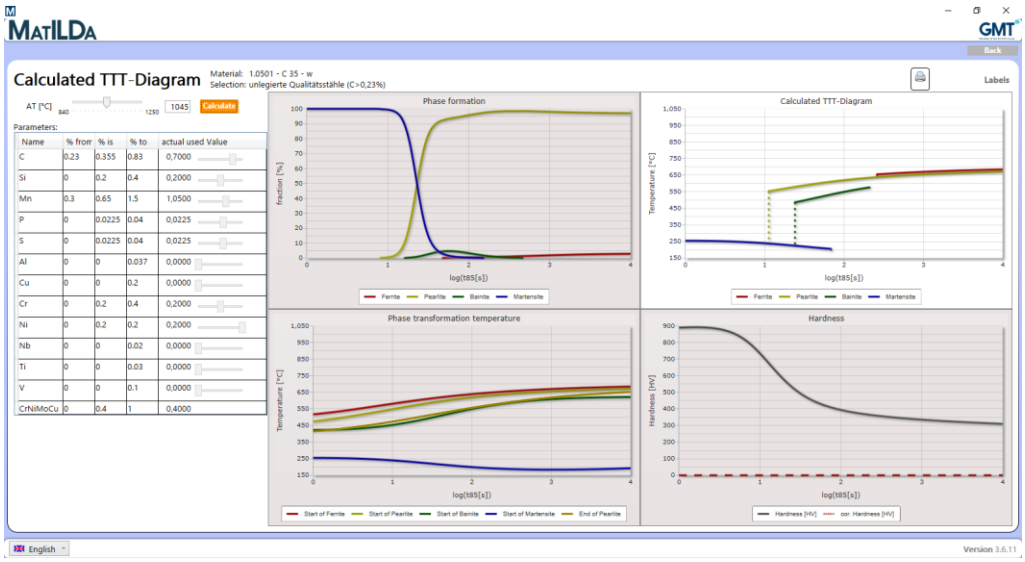

Figure 6: Visualization of parametrized neural network for carbon steels with altered chemical composition vis-à-vis figure 5

Furthermore, it is possible to readily estimate the resulting phase composition in the material during cooling at a constant cooling rate. Not only does the calculation algorithm permit continuous cooling processes; the incremental approach allows the user to simulate phase formation for discontinuous time-temperature-distribution at any point in time. Cooling processes with arbitrary time-temperature-distribution can be analyzed with the HT Viewer within MatILDa®. Figure 7 (left) shows such a random cooling process: After a period of rapid cooling the time-temperature curve levels out only for the cooling rate to accelerate again at about 400 °C.

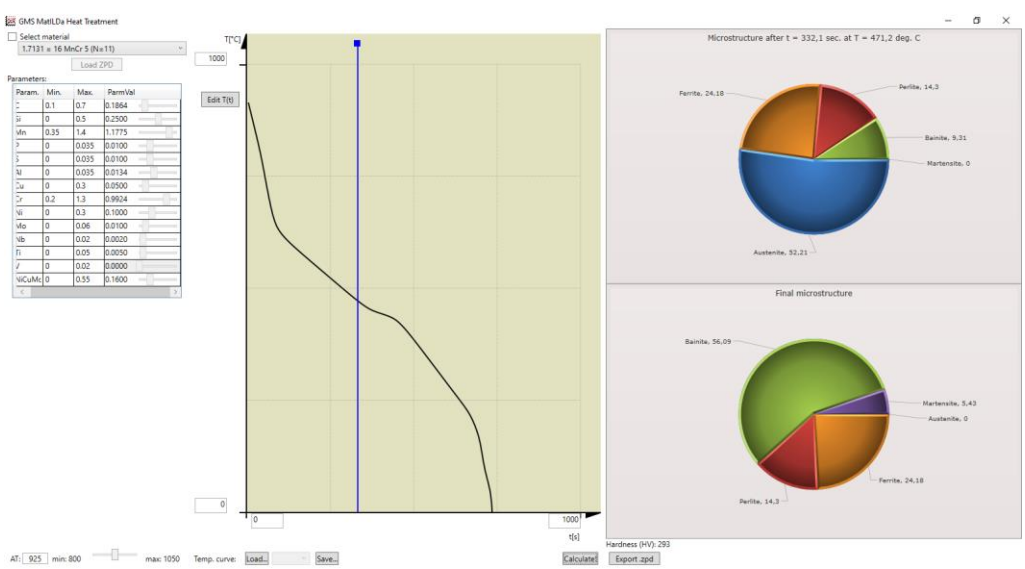

Figure 7: Defined discontinuous time-temperature-distribution and phase composition at room temperature (bottom pie chart) as well as selective intermediate temperature (top pie chart) for low alloyed steel

APPLICATION OF AI

Various forming and process simulation programs utilize the calculation library within the Material Database MatILDa® to predict, using neural networks, phase compositions of steels during and/or after cooling.

The use of a process model such as the Kocks Microstructure Simulator (KMS) offers two valuable advantages: It lends support in optimizing the process parameters, making it possible to perform a closer analysis of the direct influences of the rolling and cooling processes and their impact on the end product. Thus, the model's application helps reduce extensive rolling trials.

The following two examples illustrate microstructure formations in the production of long products using digital twins of the production processes in both mills as an advanced analysis and prediction tool. Prior simulation of forming and cooling processes was undertaken in order to achieve optimal final material properties. In comparing the two examples, this article presents a good overview of the advantages of simulation tools today using AI and how they complement and expand the customer's quality know-how.

The first example describes a thermo-mechanically processed Cr-alloyed spring steel at a state-of-the art bar mill, the second a processed welding material produced on an older type of wire rod mill in need of process optimization in order to be able to fulfil market requirements. In order to demonstrate the process and microstructure control of both production routes, the production results for both materials are put in comparison with the results modelled in a simulation program prior to the rolling procedure. [4]

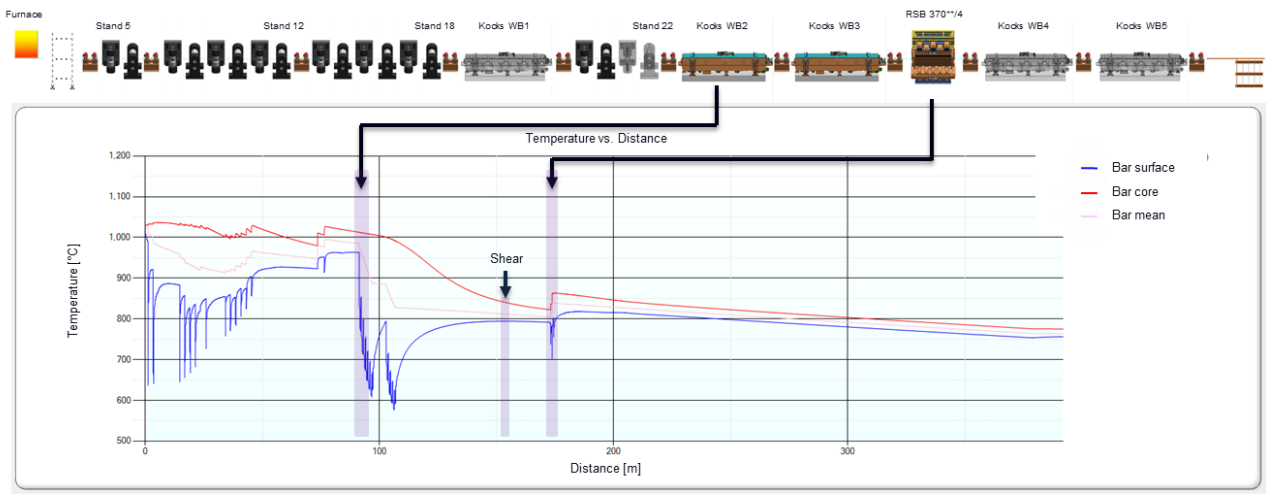

Figure 8: Layout of a state- of-the-art bar mill - Simulation of steel grade 5155

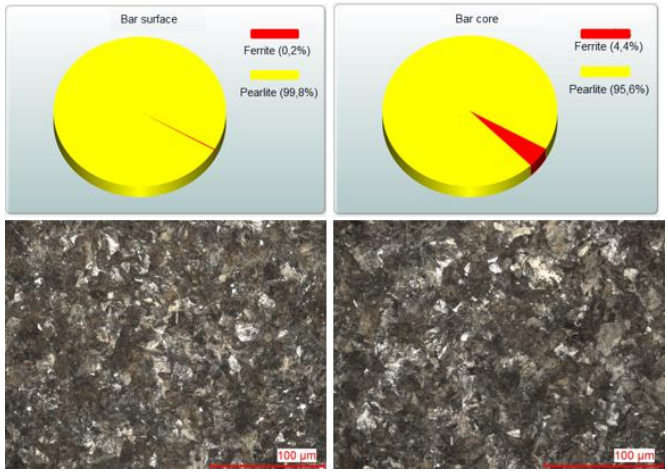

Figure 9 (a) and (b): Simulated (a) and real results (b) – top: 2 mm below surface, bottom: core, magnification 500x

Figure 8 shows the digital twin of a typical state-of-the-art bar mill layout including simulation of a low temperature rolled 5155 spring steel. The corresponding simulated and real results achieved regarding metallurgical properties are shown in figure 9. Both figures demonstrate the way in which such a process model aids the mill operator in precisely simulating and optimizing rolling processes – in combination with aspects relating to the material, such as transformation processes, resulting microstructure and mechanical properties – before they are applied under production conditions.

The second example of an MnSi-alloyed processed welding material illustrates how the application of the KMS benefits older types of production plants in particular by investigating and optimizing process parameters so that they are best equipped to fulfil market demands. Figure 10 shows the digital twin of the mill layout including process temperatures, while figure 11 presents the simulated results achieved in terms of microstructure evolution on this older type of wire rod mill.

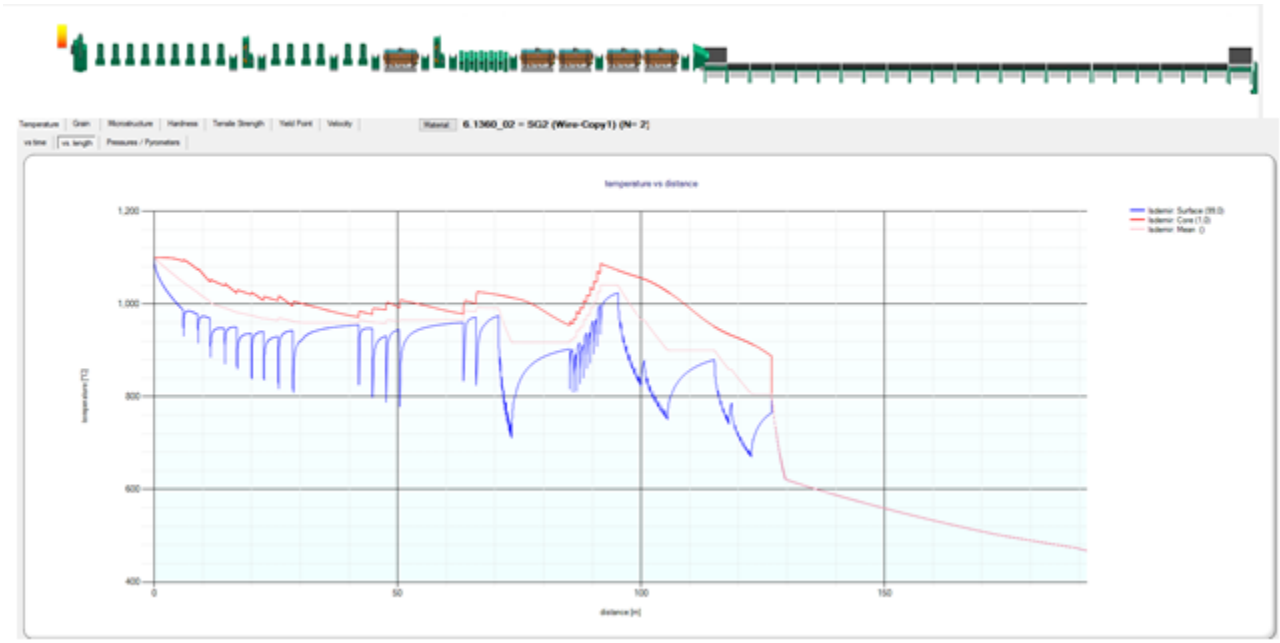

Figure 10: Layout an older type of wire rod mill - Simulation of MnSi-SG2 welding wire

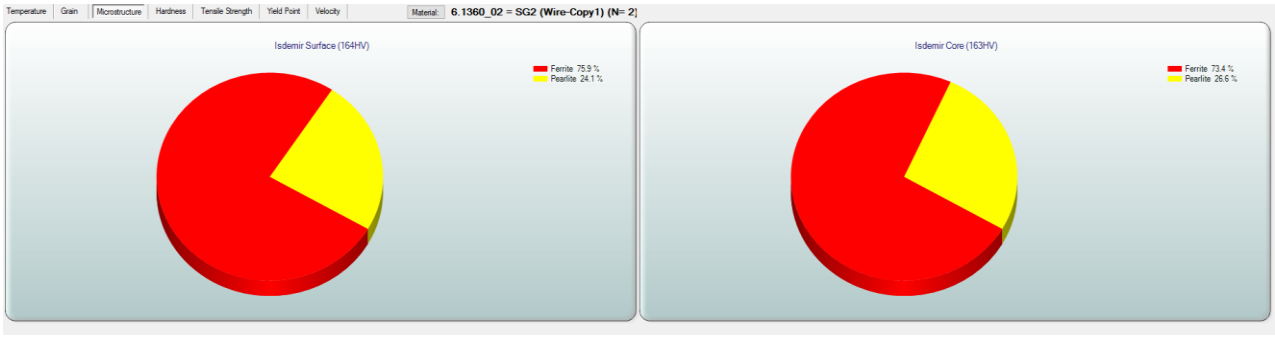

Figure 11: Simulated results of MnSi-SG2 welding wire

Welding wires are drawn down to a final diameter of 0.8 mm. This production route should be executed without any intermediate annealing which is why the purity of the steel is of vital importance. Low carbon content is the prerequisite for good weldability and tensile strength level. Accompanying elements like Cr, Cu, Ni, Mo, and N should be controlled and their quantity limited as otherwise tensile strength would increase undesirably and transformation would take longer. Consequently, depending on the length of the cooling conveyor and the time available for slow cooling, unwanted martensite portions may occur in the structure, especially in the overlapping loop regions. This creates problems in the subsequent

drawing process. In general, the microstructure of MnSi welding wire should be largely ferritic with minor shares of pearlite. Alongside a good tensile strength/toughness ratio, homogenous microstructure distribution and scale formation are important.

In order to produce a satisfactory end product, many factors ought to be taken into account from the manufacturing of the steel to the impact of forming and cooling in the mill itself. This is where process models and prediction tools play an increasingly important role in mapping mill layouts in the form of digital twins and in using simulation to optimize production routes.

CONCLUSIONS

This paper has demonstrated ways in which AI methods have the potential to significantly enhance rolling processes. In combination with realistic, physical material data stored in databases such as MatILDa®, neural networks continuously improve simulation software for the prediction of technological parameters. This has a direct effect on the end product in terms of technological properties and microstructure formation as the two examples have shown. The application of digital twinning software such as KMS further aids the tailoring of final product results by simulating mill configurations and resulting material properties.

REFERENCES

1. AIF-Forschungsbericht *„Modellierung und Laborsimulation der Gefügebildung von Stählen“*, TU Bergakademie Freiberg 2001
2. *Atlas zur Wärmebehandlung der Stähle Bd. 1 und 2*, Verlag Stahleisen mbH Düsseldorf 1961 und 1972
3. A. Doktorowski, *Datenbasierte Modellierung des Umwandlungsverhaltens bei Stählen*, Vortrag MetalNet-Treffen, Berlin 2004
4. M. Kruse, A. Fakih, M. Schuck, SEW 082, *“Advances in Equipment Design for Temperature-controlled Rolling and Comparison of Operational with Simulated Results through Thermo-mechanical Processing of Long Products“,* 90th AIKW Conference at Dresden 2022