

# *Report on Modeling the Complete Process Path by an Artificial Neural Network*

## *Detailed Study*

Tadej Kodelja  
Igor Grešovnik

*Centre of Excellence for Biosensors, Instrumentation and Process Control*

*Revision 4, April 2013.*  
(revision 0: Nov. 2012)

**Warning:** This is a long document; please don't send it to a printer!



## **Contents:**

<b>1</b>	<b>Introduction.....</b>	<b>1</b>
<b>2</b>	<b>Process Parameters and Final Material Properties.....</b>	<b>3</b>
<b>3</b>	<b>ANN Module.....</b>	<b>5</b>
<b>4</b>	<b>Error Estimation .....</b>	<b>7</b>
<b>4.1</b>	<b>Elongation (A) .....</b>	<b>7</b>
4.1.1	Errors on training points .....	7
4.1.2	Errors on verification points .....	8
<b>4.2</b>	<b>Tensile Strength (<math>R_m</math>).....</b>	<b>8</b>
4.2.1	Errors on training points .....	8
4.2.2	Errors on verification points .....	9
<b>4.3</b>	<b>Yield Stress (<math>R_p</math>) .....</b>	<b>10</b>
4.3.1	Errors on training points .....	10
4.3.2	Errors on verification points .....	10
<b>4.4</b>	<b>Hardness After Rolling (HB).....</b>	<b>11</b>
4.4.1	Errors on training points .....	11
4.4.2	Errors on verification points .....	12
<b>4.5</b>	<b>Necking (Z) .....</b>	<b>12</b>
4.5.1	Errors on training points .....	12
4.5.2	Errors on verification points .....	13
<b>5</b>	<b>Parametric studies.....</b>	<b>14</b>
<b>5.1</b>	<b>Center Point.....</b>	<b>14</b>
5.1.1	Elongation (A) .....	14
5.1.2	Tensile Strength ( $R_m$ ).....	32
5.1.3	Yield Stress ( $R_p$ ) .....	49
5.1.4	Hardness After Rolling (HB) .....	66
5.1.5	Necking (Z).....	83
<b>5.2</b>	<b>Points on Line .....</b>	<b>101</b>
5.2.1	Elongation (A) .....	101
5.2.2	Tensile Strength ( $R_m$ ).....	118
5.2.3	Yield Stress ( $R_p$ ) .....	135
5.2.4	Hardness After Rolling (HB) .....	152
5.2.5	Necking (Z).....	169
<b>6</b>	<b>Sensitivity Tests .....</b>	<b>187</b>
<b>6.1</b>	<b>Elongation (A) .....</b>	<b>187</b>
<b>6.2</b>	<b>Tensile Strength (<math>R_m</math>).....</b>	<b>189</b>
<b>6.3</b>	<b>Yield Stress (<math>R_p</math>) .....</b>	<b>191</b>
<b>6.4</b>	<b>Hardness After Rolling (HB).....</b>	<b>193</b>
<b>6.5</b>	<b>Necking (Z) .....</b>	<b>195</b>

## 1 INTRODUCTION

For several years artificial neural networks have been successfully used for second level process automation in basic industries. One of the fields where it is possible to exploit neural networks is to predict five important mechanical properties of steel (elongation, tensile strength, flow limit, hardness and shrinkage) on the basis of their composition and other process parameters that define the complete processing path.

The complete steel manufacturing process in the Store Steel company [1] is schematically represented in Figure 1. There are 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 modeled either by a physics based numerical model or by an artificial neural network model. Output values of a process sometimes define the next process in the chain and thus act as input parameters (e.g. defining initial or boundary conditions) in the model of that process. Another possibility when using ANN is to build a common model of the whole production chain. In this case, we can model only outcomes after the last process and relate them to process parameters that can vary in the system.

The aim of this work is to explore the possibility of applying artificial neural networks to model the whole process chain. The resulting ANN models will be used for prediction of five mechanical properties for steel manufacturing process chain in terms of process parameters. In the scope of this work, procedures have been developed for building an ANN model of the process chain and for analyzing the model response. The concept has been demonstrated on the available data from the Štore Steel company.

The currently available data is not adequate for given complexity of the targeted models since it is not complete (not all influential parameters of the process are measured and stored), it contains errors, and the amount and spatial distribution of data are not adequate. Because of this, the models generated and analyzed here can not be considered accurate, reliable or correct. However, the applicability of the concept is demonstrated and the concept can be used in the future if adequate model data is provided. In the scope of further work, we intend to substantiate this claim on the cases where adequate data can be obtained by a numerical model suitable for generation of data that can be used to build ANN-based models. Currently, we have access to the continuous casting simulator that can be used for controlled acquisition of data for ANN-based modeling, and intend to use it to build the model of this process where errors can be estimated. Further steps are planned to link the JMatPro software for calculation of material properties with the simulator in order to build extended ANN-based casting models where chemical composition can also be varied. If this turns possible then such models will be used to study model requirements in terms of provided data, and to make estimations of how different kinds of data deficiencies influence model accuracy.