

Chapter 7

Artificial Neural Network and Its Application in Steel Industry

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ABSTRACT

The recent developments in computational intelligence has enhances the applicability of empirical modelling in different areas particularly in the area of machine learning. These new approaches are based on analysing the data about a system, in particular finding connections between the system state variables (input, internal and output variables) without having precise knowledge about the physical behaviour of the system. These data driven methods explain advances on conventional empirical modelling and include contributions from many overlapping fields like Artificial Intelligence (AI), Computational Intelligence (CI), Soft Computing (SC), Machine Learning (ML), Intelligent Data Analysis (IDA), and Data Mining (DM). The most popular computational intelligence techniques used in process modelling of steel industry includes neural networks, fuzzy rule-based systems, genetic algorithms as well as approaches to model integration. This chapter describes mainly the application of Artificial Neural Network (ANN) in steel industry. ANN has extensively used in improving and controlling different processes of steel industry like steel making, casting and rolling which lead to indirect energy savings through reduced product rejects, improved productivity and reduced down time. The efficiency of artificial neural network tool in handling steel plant processes has been discussed in detail. ANN based models are found to be very potential to handle very complex, dynamic and non-linear problems.

1. INTRODUCTION

The combination of properties in various steel grades ensures its applicability in different areas. Strength, toughness, ductility, formability, weldability, corrosion resistance and surface quality are all important properties, depending on the application. The performance of steel can be defined as the balance between these properties while remaining cost-effective. So as per the requirements or applications, the

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demanding features of steel sheets in the market are high formability, adequate strength, excellent dent resistance, adequate workability, good welding properties and excellent surface finish. Many researchers have attempted to find an optimum balance of properties (requirements) using ANN and other soft computing tools (S. Datta (2006), S. Datta (2007), S. Datta (2004), S. Dey (2009), A. Sinha (2013), S K Ghosh (2005), S K Ghosh (2009), P Das (2009), S. Ganguly (2007), S. Ganguly (2009), A. Mukhopadhyay (2005), I Mohanty (2008)).

The recent trend in automotive industry is use of multi-phase, high strength innovative material with excellent surface quality. In order to compete with today's market steel companies are putting their effort in developing new products and improving the process, yield and product quality with optimum energy and cost. This is only possible by significantly optimizing and controlling the process. Computational methods based models will be able to help the production process to achieve its market demands and product quality posed by the customers. In modern manufacturing plants the data that characterize the plant process is collected automatically through sensors, PLCs, etc and stored in large databases or data warehouses. Data mining tools can be utilized to extract interesting and useful information in the manufacturing process. Neural network based models are extremely useful in such circumstances, not only in the study of processes but wherever the complexity of the problem is massive and dynamic in nature and at the same time it is very difficult to develop a first principle based model (Bhadeshia, 1999; H. K. D. H. Bhadeshia, 2008). Several attempts have already been made in this direction (Z. Guo (2004), S. M. K. Hosseini(2004), P. Korczak (1998), J. Kusiak (2002), J. Larkiola(1998), H. Monajati (2010), S. K. Ghosh (2008), Gladman T (1975), L. A. Dobrzański (2005), P. Das (2007), C. Dumortier (1998), V. Narayan (1999), S. Datta (2006), A. Mukhopadhyay (2005), S.B. Singh (1998), I Mohanty, 2011, 2014; G Majumdar, 2010, Sbarbaro-Hofer, D. (2002), L Rokach (2008)). It is not surprising that numerous attempts have been made to use neural network modelling to deal with complex properties such as fatigue (H. Fujii, 1996; T. Goswami, 1996; J. M. Schooling, 1999; T. Svensson, 2004), toughness (H. K. D. H. Bhadeshia, 1995 ;T. Cool, 1997; S. H. Lalam; D, 2000. Dunne, 2004), corrosion resistance (J. Cai, 1999) and creep rupture life (M. Evans, 1999; F. Brun, 1999; D. Cole, 2000; Y. S. Yoo, 2002).

Artificial neural network (ANN) has been established as a potential tool in steel industries in prediction of properties and design of alloys. It has been used successfully to control the mill process for achieving target properties with available steel composition and mill constraints by capturing the complex interactions among them (Martinetz, 1995; Döll, 1999, M.J. Willis, 1992; Andreas Draeger, 1995). Various models have been developed for different parts of the rolling mill to control like furnace model, deformation model, roll-force model, mill set up calculation model, run-out-table cooling model, mechanical property prediction model and deformation and joining process model. Different kinds of optimization models are available like draft scheduling, roll force ratio distribution, etc. A few physical models have been developed to predict phase transformation and mechanical property. Each model has been developed with a particular aim which is localized to that part of the mill.

This chapter gives an idea regarding the application of ANN in steel industry in key areas related to design of structural steels and alloys including composition–process–property correlation, control and optimization. First part of this chapter gives a detail overview of ANN. Second part describes the applications in the area of mechanical property prediction, modelling strength of TMCP HSLA steel, optimisation of tensile properties to facilitate new product development and accretion of yield strength accuracy in skin pass mill. These sections aim to establish the potential of ANN in capturing the com-

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