Nonlinear Models Provide Better Control of Annealed Brass Strip Microstructure

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Nonlinear modeling is a good method to relate chemical composition and process variables of annealing brass with the resulting grain size.

The microstructure of brass is highly sensitive to annealing conditions and chemical composition. Small variations in annealing temperature or line speed result in significant variations in mechanical properties, as well as grain size. Because microstructure and mechanical properties are influenced by a large number of variables, it is difficult for operators to determine how to anneal strip of different thicknesses and compositions to achieve a specified grain size.

The relationship between brass composition, annealing process variables, and resulting microstructure is complicated. Development of sufficiently accurate, reliable physical models for this heat treatment is not feasible, partly because the phenomena taking place in the process are not well understood. However, empirical or semi-empirical modeling does not require knowledge of these phenomena; measurement of variables of interest is sufficient. Conventional methods of empirical modeling are linear statistical techniques. However, nothing in nature, particularly in materials science, is very linear. Nonlinear modeling is often a better alternative.

Research conducted at the Aurubis Zutphen plant illustrates how nonlinear modeling is an efficient approach for relating composition and process variables of annealing with resulting grain size. Nonlinear models were developed entirely from production data, and were implemented in suitable software for use by plant operators.


Fig. 1 — *Aurubis brass-strip plant in Zutphen, Netherlands.*

Introduction

Brasses are used in various applications including architecture, radiators, pipes, valves, and musical instruments, as well as for decorative purposes. Brasses are alloys of copper and zinc (up to 40%), and sometimes contain other alloying elements in small amounts. Different material properties of brass are important depending on the application. In many situations, hardness and tensile strength are the most crucial, while electrical and thermal conductivities are important in others. Hardness or microstructure requirements are often achieved using a continuous annealing process after cold rolling. Final hardness depends on material composition, annealing process variables, and strip thickness.

Production process

The first step in the brass production process is melting in a furnace. The melt is shifted to a holding furnace, after which strip is produced by continuous casting. After cooling, strip undergoes flattening and milling of top and bottom surfaces, followed by break-down rolling. Intermediate annealing is done in either a strand annealer or batch annealer. After annealing, the strip is rolled to desired thickness in a four-high, five-stand rolling mill. Rolled strip is continuously annealed in a vertical furnace (strand annealer), which is the subject of this article.

The annealing furnace consists of a horizontal chamber for preheating, followed by a long vertical chamber with four zones, each having four variable-speed fans to improve convection. The strip passes through the furnace to a quench tank where the temperature drops to around 30°C. Temperature in all the four zones of the vertical part of the furnace are usually kept the same, but fan speeds are often different. After quenching, the strip is pickled, brushed, and rinsed before coiling. Final operations consist of rolling to temper and slitting, or just slitting (annealed to temper).

Process guidance and control

Different production processes have different characteristics: different objectives, variables, kinds of constraints, and different materials undergoing changes. The process might be batch, continuous, or fed-batch. However, different processes have some common features in process development. Production of a product specifies what process to use and what raw materials should be used to satisfy some conditions, typically upper and lower limits.

For several types of production processes, product (or material) properties, production rate, raw material consumption, energy consumption, emissions, etc. can be considered to be consequences of the process for process development purposes. These depend on variations in composition, process, and dimensions. The objective of process guidance is to determine the best values of process variables. This is so the consequences are within desired limits, and preferably, a production economic variable (e.g., production rate, raw material consumption, energy efficiency, purity, number of defects, emissions, etc.) is maximized or minimized. The problem is similar for a variety of processes from a mathematical modeling point of view.

Nonlinear modeling

Industry has taken advantage of the benefits of using of nonlinear modeling for more than 15 years[1, 2]. Various industries successfully use it for process development. Nonlinear modeling is used for many processes and materials in several sectors of process industries including metals, polymers, ceramics, concrete, biotechnology, power generation, pulp and paper, semiconductor processing, water treatment, chemical production, etc. Even so, awareness of the technique is still very limited.

Nonlinear modeling is defined as empirical or semi-empirical modeling, which takes at least some nonlinearities into account. Nonlinear models can be static or dynamic, and modeling can be performed in many ways. Simpler methods include polynomial regression and linear regression with nonlinear terms. Nonlinear regression is useful in some situations, but the form of nonlinearities has to be specified in these older techniques. Newer techniques of nonlinear modeling are based on free-form nonlinearities, including a series of basis functions, splines, kernel regression, feed-forward neural networks, etc. Feed-forward neural networks are a set of efficient tools for nonlinear modeling, particularly because of their universal approximation capability[3].

Why nonlinear modeling?

Mathematical models represent knowledge of quantitative effects of relevant variables in a concise, precise form. They can be used instead of experimentation if they are sufficiently reliable. Mathematical models also enable carrying out various kinds of calculations (such as optimization), which can be used to determine suitable values of process variables. Mathematical modeling can be performed in various ways, depending on different situations.

Physical modeling cannot be used in many situations, and where it is possible, it computes the output more slowly than empirical or semi-empirical models. Also, development of physical models is time consuming, the models involve assumptions and simplifications, and physical modeling is more expensive than nonlinear modeling. Thus, empirical modeling is often a better alternative when suitable data is available.

Traditional empirical modeling is based on linear statistical techniques. However, nothing in nature is absolutely linear, so it helps to take nonlinearities into account rather than ignore them. If the range of variables is small, linear techniques are sometimes sufficient. New techniques of nonlinear modeling based on feed-forward neural networks enables approximating nonlinearities without specifying in detail which nonlinearties to account for. They allow for free-form nonlinearities, unlike linear and nonlinear regression methods.

Production data

Microstructure is studied as a part of quality control (Fig. 2). Some microstructures are viewed in polarized light

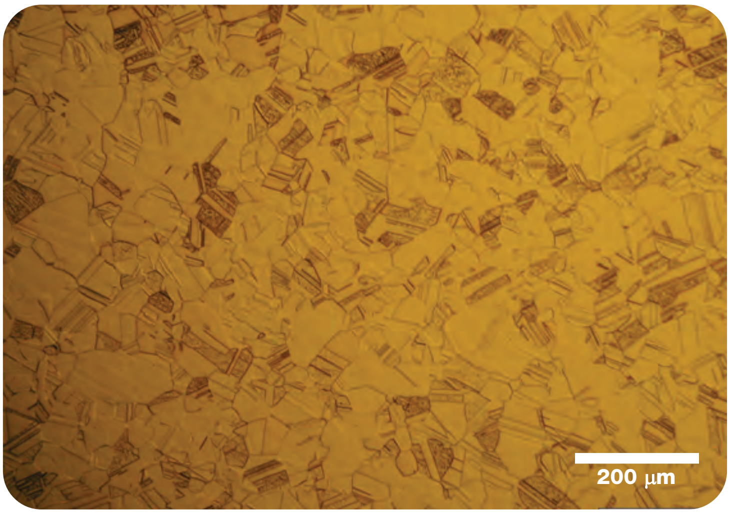


Fig. 2 — *Grains of an annealed brass strip seen under an optical microscope.*

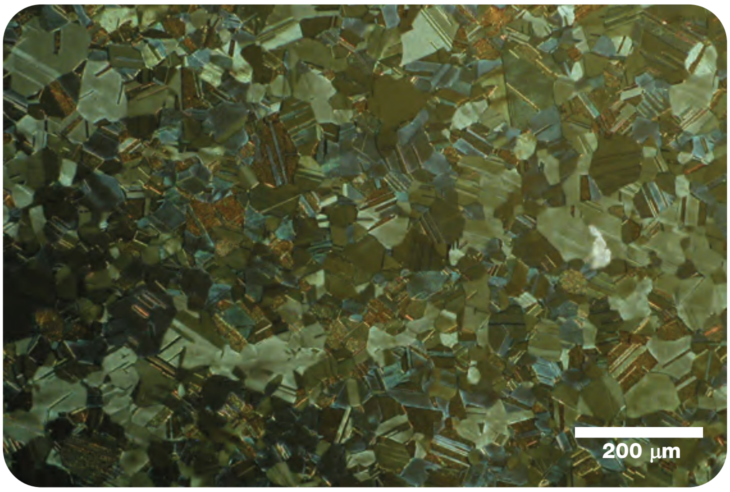


Fig. 3 — *Microstructure of an annealed strip seen under polarized light.*

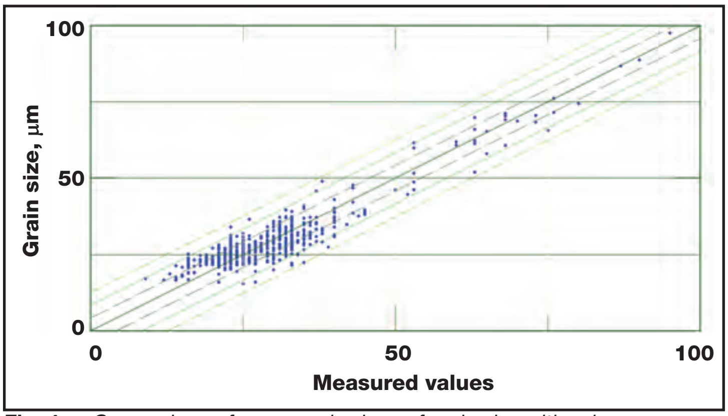


Fig. 4 — *Comparison of measured values of grain size with values predicted by nonlinear model on production data.*

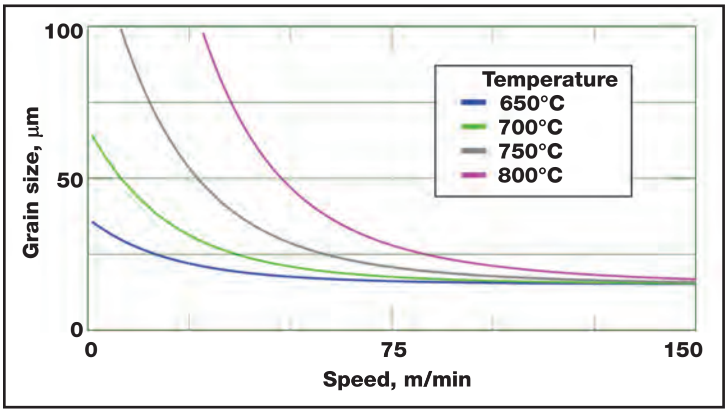


Fig. 5 — *Effect of speed on average grain size for different annealing temperatures in the vertical zones, keeping other input variables constant.*

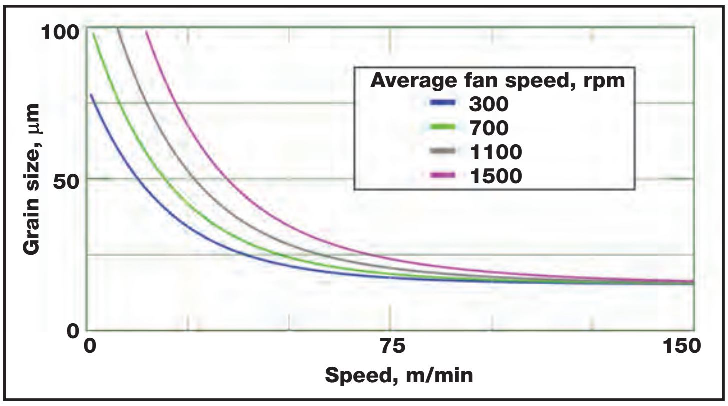
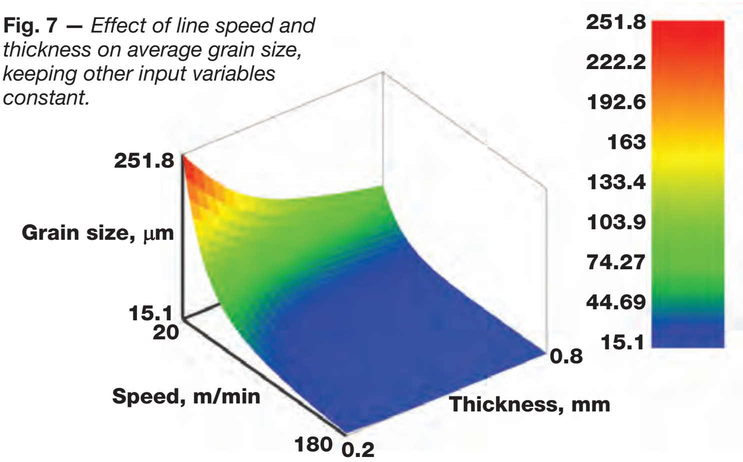


Fig. 6 — *Effect of speed on average grain size for different average fan speeds in the vertical zone, keeping other input variables constant.*

Fig. 7 — *Effect of line speed and thickness on average grain size, keeping other input variables constant.*



(Fig. 3), which results in a lot of valuable data. As mentioned previously, nonlinear modeling requires experimental or production data. For this work, normal production data gathered over about one year was used. Data contained more than 50 columns for different variables, including brass composition, annealing process variables (temperatures, line speed, and fan speeds), strip thickness, hardness, and average grain size after annealing. Data was preprocessed, analyzed, and cleaned before developing the final nonlinear models using the NLS 020 software.

Nonlinear models of the average grain size

Nonlinear models developed for Aurubis were in the form of feed-forward neural networks with sigmoidal activation functions. The quality of the nonlinear model of grain size was quite good considering it was developed from plain production data, and measurements of grain size were done manually, making them subjective to some extent. The nonlinear model showed correct effects of input variables, and the correlation coefficient was above 86%. The standard deviation of the prediction error was about 4.2 μm. Figure 4 shows a comparison of predicted and measured values of average grain size.

Nonlinear models were implemented in software suitable for use in metals industries. Models were tested by Aurubis and found to be quite good and useful. It is now possible to predict grain size and hardness of annealed strip before annealing begins, and operators can make changes to line speed, oven temperature, and fan speed if the predicted hardness is far from the desired value.

Figure 5 shows the effect of speed on average grain size for different annealing temperatures in the furnace vertical zones, keeping other input variables constant, for a certain composition of brass. At higher speeds, temperature has a small effect, while at lower speeds, temperature makes a big difference. Similarly, as seen in Fig. 6, fan speed has a small effect on grain size at higher speeds, but has a large effect at lower speeds. This kind of cross-term effects of pairs of variables is often visible better from surface plots like that shown in Fig. 7, which shows the effect of line speed and thickness on grain size. ❍

References

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