Nonlinear Modelling of Secondary Coating of OFCs from Experimental Data

Abstract

New techniques of nonlinear modelling have come up in the last ten twelve years which have opened up new possibilities in empirical process modelling. Secondary coating is a typical process which cannot be modelled adequately by physical modelling. The effects some of the process variables are clearly nonlinear, which makes it imperative for us to take into account the nonlinearities rather than ignore them. Neural network techniques are therefore more suitable for process modelling of secondary coating. Neural networks have been used in various process modelling applications in steel industries, pulp and paper industries, chemical industries, plastics industries, etc.

Introduction

Secondary coating is a plastics extrusion process, followed by controlled cooling and winding under tension (Figure 1). The properties of secondary coatings like excess fibre length depend to a large extent on the process variables and the material properties of the plastic. For a given product, the plastic material, the jelly, the external and internal diameters, and the number of optical fibres in it are fixed. The properties of the secondary coatings, then depend on the process variables, starting from tension on the optical fibres, extrusion variables, jelly temperature, cooling water temperature, line speed, capstan location, winding tension, etc.

In this work, feed-forward neural network models (Figure 2) were developed based on experimental data with process variables as inputs. The nonlinearities are visible in the neural network model (Figure 5). The neural networks used logistic sigmoid activation functions, and were found to be effective. This is a typical situation where the conventional linear statistical techniques are not effective.

Nonlinear modeling

There are hardly any processes in this world which are absolutely linear. It is therefore wise to treat the nonlinearities rather than ignore them. To treat the nonlinearities, one can use new techniques of nonlinear modelling, like artificial neural networks. The proponents of linear techniques draw on their simplicity and the possibility of adding nonlinear terms in linear regression. Often this is not done, and is not efficient even if it is done. Nature does not follow the simplicities that we try to fit it in, using common linear techniques.

Neural networks, on the other hand, have the so-called universal approximation capability which make them suitable for most function approximation tasks we come across in process industries. The user does not need to know the type and severity of nonlinearities while developing the models.

Artificial neural networks resemble structurally and to a smaller extent functionally the networks of neurons in biological systems. Like the networks of neurons in the brains, artificial neural networks also consist of neurons in layers directionally connected to others in the adjacent layers (see Figure 2).

There are many different types of neural networks, and some of them have practical uses in process industries [1]. Neural networks have been in use in process industries for about ten years. The multilayer perceptron, a kind of a feed-forward neural network, is the most common one. Most neural network applications in industries [2-6] are based on them. Nonlinear modelling can also be done in many other ways. The authors are not aware of very many applications of neural networks in plastics industries. Most of the work of the authors is confidential and is therefore not published.

The output of each neuron i in the feed-forward neural network is given by

$$z_i = \sigma\left(\sum_{j=0}^{N} w_{ij} x_j\right)$$

where the activation function is usually the logistic sigmoid, given by

$$\sigma(a) = \frac{1}{1+e^{-a}}$$

The incoming signals to the neuron are x_j, and w_{ij} are the weights for each connection from the incoming signals to the i^{th} neuron. The w_{i0} terms are called biases. This results in a set of algebraic equations which relate the input variables to the output variables. Thus, for each observation (a set of input and output variables), the outputs can be predicted from these equations based on a given set of weights. The training procedure aims at determining the weights which result in the smallest sum of squares of prediction errors.

There are a variety of training methods in use today. Back-propagation used to be the most common training method about ten years back. Today, most people use good optimisation methods instead.

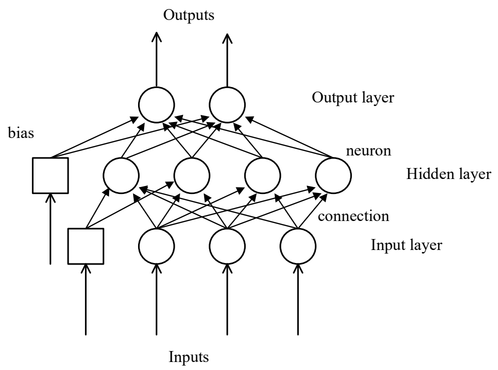

Figure 2. A typical feed-forward neural network

3. Secondary coating line OFC 40

The high-speed secondary coating line OFC 40 (Figure 1) is especially designed for loose tube production but it can be modified for fiber bundle or premises cable production thanks to its modularity. The line comprises multiple new innovations for high productivity and minimized scrap. Secondary coating is the first phase in the manufacturing process of fiber optic cables. The process is important in two ways. Stability and repeatability of the process together with high production speeds and flexibility of operation have been the key criteria in designing this line.

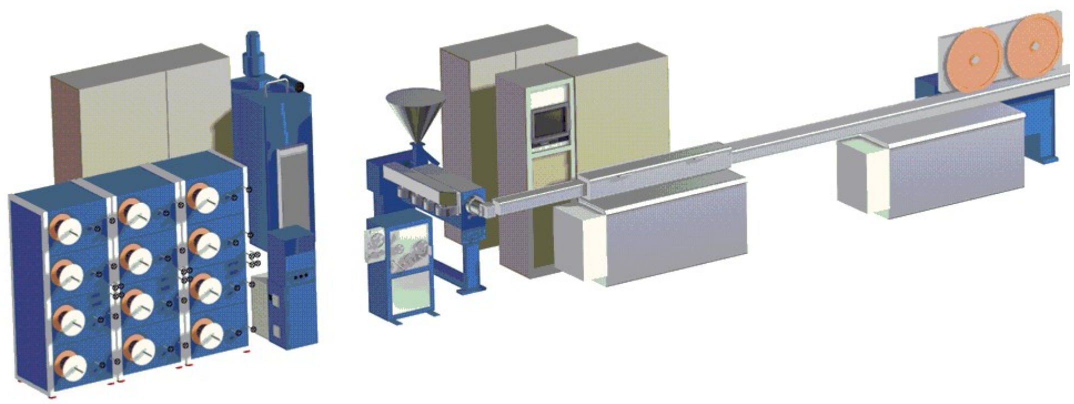

Figure 1. OFC lines are relatively well instrumented, huge amounts of data are logged and left unutilised or underutilised

4. Modeling of product properties

Neural network models have performed well in predicting product properties of various materials [1, 4-6] including material characteristics of pulp, paper, metals, plastics, cement, concrete, etc. These include variables like brightness and freeness of pulp, formation index of paper, mechanical properties of metals like tensile strength, yield strength, elongation, impact strength of plastics, and compressive strength of concrete.

One interesting example which describes such neural network modelling [5] is about compressive strength and compaction degree of concrete. By upgrading a linear model to a nonlinear model, the uncertainty in compressive strength reduces considerably. This reduction in uncertainty for a medium sized precast plant which makes 80 000 m^3 concrete can mean a saving of 700 000 mk of cement a year. Since most concrete plants don't even have linear models, the potential for saving is higher.

The rms error (roughly the standard deviation) of prediction of compressive strength with a linear regression model was 4.3 MPa while a neural network model resulted in a rms error of 2.4 MPa. Linear models for this purpose are anyway misleading because they show trends in only one direction implying that the maximum strength can be achieved with 100% water or with 100 % cement. In reality, the strength increases with water content upto a certain extent, and then reduces as concrete is watered down too much. Linear models do not describe this, but it is relatively easy for neural network models to do so.

5. Process guidance system

The nonlinear models can be cumbersome to use in the form of equations. For industrial use, it is important to make them easily accessible. A process guidance system has therefore been developed so that industries can utilise this technology without the need for nonlinear modelling experts. This system also allows us to see the characteristics of the models as described later in this section.

Several product properties of secondary coatings are important for the producers and the users. These properties include excess fibre length (difference between the lengths of the fibres and the tubes), dimensional accuracy (diameter, circularity) of the coatings, elasticity, etc. Excess fibre length was the first product property to be taken into account while developing the guidance system for secondary coating. Excess fibre length depends on several process variables, material characteristics of the coating material, and the dimensions of the coating (inner and outer diameters). Depending on the priorities and the needs of a given production unit, different input vectors can be implemented in the guidance system.

In the examples shown in the successive figures, five input variables are considered: pay-off tension, jelly hose temperature, line speed and cooling water temperature. Figure 3 shows a simple calculation predicting excess fibre length from these five variables.

It is easy to change the models, which may also have a different configuration. The system expects the models to be in files of a certain format. These files can be replaced to change the models. In future, the user will be able to pick the model of his choice at run time also.

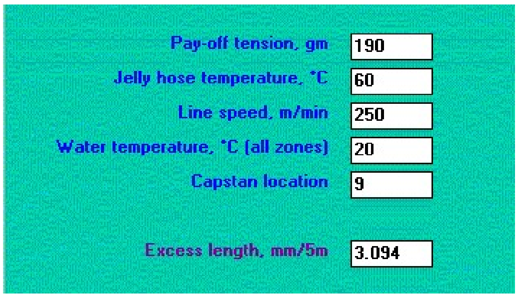

Figure 3. Excess fibre length predicted from five input variables in this model

Another window allows the user to see the effects of the input variables on the product property of interest. These plots also give a hint of how the performance can be improved. Figures 4 and 5 show the effects of line speed and water temperature on excess fibre length.

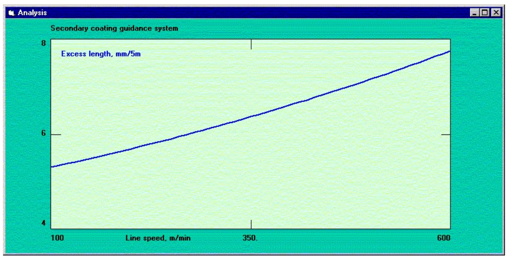

Figure 4. Effect of line speed on excess length according to the nonlinear model

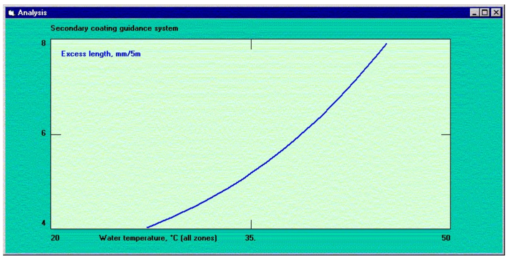

Figure 5. Effect of cooling water temperature on excess length

The guidance system also allows the user to calculate suitable process variables within specified limits with a single click of a mouse, in less than a second.

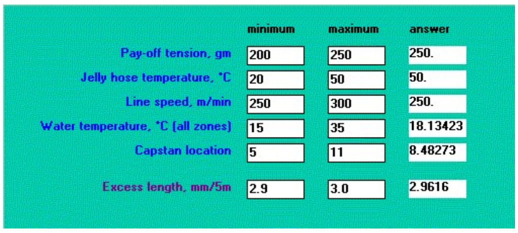

Figure 6. Finding good operating conditions using the nonlinear model

The models for this system were developed from experimental data. Experiments were carried out to measure the variables of interest, in the range of interest. This is, however, expensive, and production units cannot afford to carry out this kind of experiments. Nextrom has the facilities to carry out such experiments for its customers. In future, the requirements for experimentation will be reduced as much as possible. In parallel, model development will be made possible from normal production data. Such models will have a narrower range, but will nevertheless be useful for improving the performance of the secondary coating lines.