Achieving ultra-high speeds of polypropylene buffering for stranded loose tubes using nonlinear modelling

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Abstract

Doubling the line speed is a task. It is usually not easy to increase line speeds by even 20% without adversely affecting the excess fiber length. When we try to increase the line speed by 100%, it becomes difficult to keep excess length, mechanical properties and shrinkage within acceptable limits. These properties depend on several variables including line speed, tension, cooling water temperature, etc. These relations are not very simple and some variables including line speed have clearly nonlinear effects.

Therefore, linear statistical techniques are not very efficient for modelling extrusion processes. Developing phenomenological models is not feasible, since the phenomena in shrinkage of the polymer under tension and adhesion with primary coated optic fibers are not well understood. Even when feasible, phenomenological models require a lot of assumptions and simplifications, and therefore tend to predict the consequences of the process less accurately.

Nonlinear modelling is the only suitable approach. It does not require any major assumptions or simplifications. Nonlinear models have been used for improving the productivity of a large variety of processes in several industrial sectors, including optic fiber cables. This work demonstrates how nonlinear models of excess fiber length, shrinkage and elongation at break of dry polypropylene tubes allowed us to increase the line speed on a buffering line.

Keywords: Extrusion, nonlinear modelling, polypropylene, excess fiber length, elongation at break, tensile modulus, shrinkage, optic fiber cables

1. Introduction

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

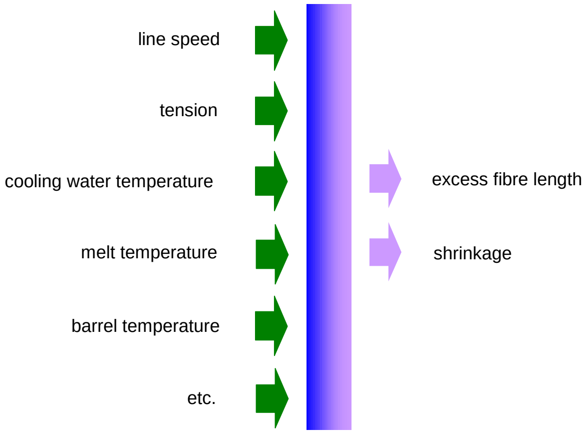

Figure 1. A schematic diagram for the modeling of extrusion of dry tubes for optical fiber cables

For optic fiber cables, a small increase in the line speed substantially improves the production economics. In comparison, the cost and effort in carrying out a few experiments and developing nonlinear models from the experimental data are small. This work demonstrates how nonlinear models of excess fiber length and shrinkage of dry polypropylene tubes allowed us to increase the line speed on a buffering line. The same methodology can be used to improve the production economics of various kinds of extrusion processes in the telecommunication cable as well as power cable industry.

In this work, feed-forward neural network models (Figure 2) were developed based on experimental data with process variables as inputs. The nonlinearities are clearly visible from the neural network model. This is a typical situation where the conventional linear statistical techniques are not effective

2. 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 feed-forward 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.

Nonlinear modeling can be carried out with a variety of methods. The older methods include linear regression with nonlinear terms, polynomial regression and nonlinear regression. These have several limitations. The newer methods include feed-forward neural networks, kernel regression, multivariate splines, etc. which do not require a priori knowledge of the nonlinearities in the relations.

Feed-forward neural networks have the so-called universal approximation capability [1] which make them particularly suitable for most function approximation tasks we come across in engineering and in process industries. The user does not need to know the type and severity of nonlinearities while developing the models. In other words, we have free-form nonlinearities in feed-forward neural network models.

Feed-forward 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 [2]. Neural networks have been in use in process industries for about twenty years [3]. The multilayer perceptron, a kind of a feed-forward neural network, is the most common one. Most neural network applications in industries [4-15] are based on them.

In a feed-forward neural network of the kind shown in Figure 2, the output of each neuron i in the feed-forward neural network is usually given by

$$z_i = \sigma\left(\sum_{j=0}^{N} w_{ij} x_j\right) \qquad (1)$$

where σ is called the activation function, and is usually the logistic sigmoid, given by

$$\sigma(a) = \frac{1}{1+e^{-a}} \qquad (2)$$

The incoming signals to the neuron are xj, and wij are the weights for each connection from the incoming signals to the ith neuron. The wi0 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 very many years back. Today, most people use good optimization methods [16] instead

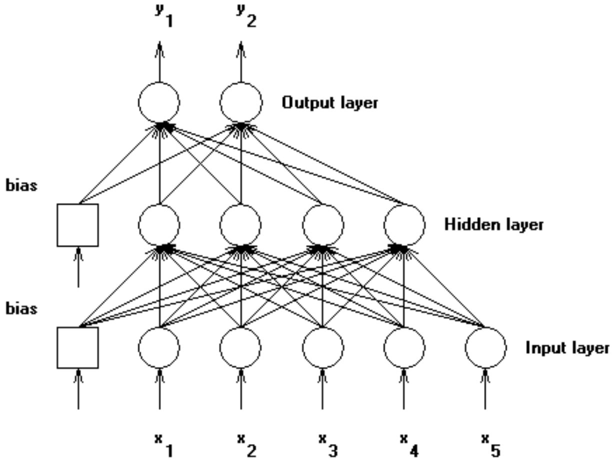

Figure 2. A typical feed-forward neural network for use as a nonlinear model

3. Secondary coating line

The high-speed secondary coating line OEL 40 (Figure 3) 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.

There have been several key innovations in the field of clinching concept. Those will ensure proper product properties even at high speeds.

Figure 3. Secondary coating line with clinching concept

4. Experimentation

For carrying out this process development task of increasing the line speed, it would be desirable to carry out about 19 experiments. This work was partly also meant for better understanding of the process, so 27 experiments were carried out with different values of the independent variables. For example, the line speed was varied between 250 and 850 m/s since the normal production speed for dry polypropylene tubes is 200 to 300 m/min. Cooling water temperature was varied between 15 ºC and 40 ºC. Fiber tension was varied between 100 and 200 cN.

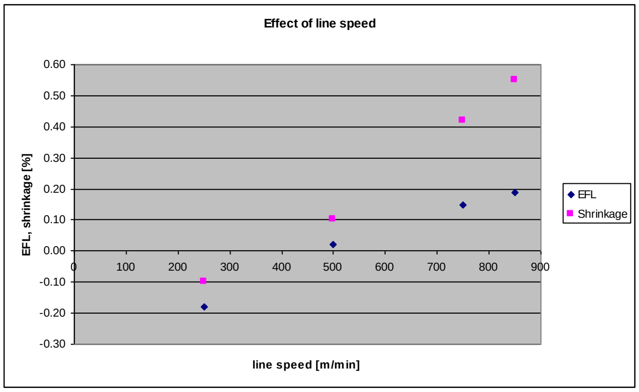

Figure 4. Effect of line speed on EFL and shrinkage while keeping other variables constant, as seen from the raw experimental data

Excess fiber length (EFL) was measured from 40-meter samples instantaneously after the processing. 40-meter sample was placed on the table and 5-meter sample was cut out in the middle of the sample. Before cutting both ends were locked in order to prevent any fiber movement then fibers were pulled out and the length of the fibers was compared to the length of the tube. Shrinkage of the tube (2 m sample) was measured after heat treatment for 60 minutes at 80 ºC in an oven. The recorded values are averages of measurements from 5 samples. Excess fiber length requires the difference of similar large values, and therefore negative values of excess length are not very accurate. That, however, has not been a problem because there was very good variation in excess length in the experiments. Shrinkage measurements also require the difference of similar large numbers, but that has not been a problem. Shrinkage measurements have shown good repeatability..

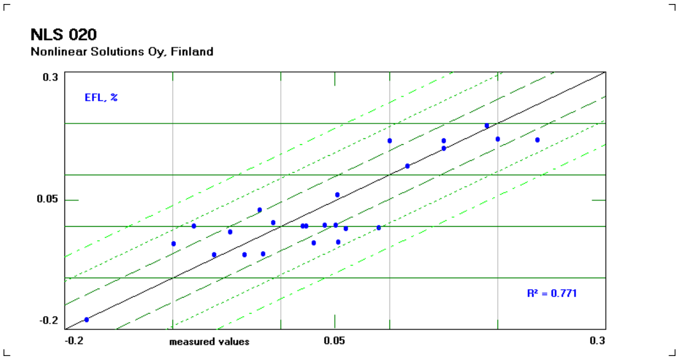

Figure 5. A comparison of measured values with the values predicted by the nonlinear model of excess fibre length

The data set for nonlinear modelling consisted of a total of 27 observations. Two observations of EFL and five observations of shrinkage were either measured or recorded incorrectly and were removed from the data set. Fortunately, the amount of data was more than sufficient for the development of nonlinear models, so the loss of these observations did not cause any harm

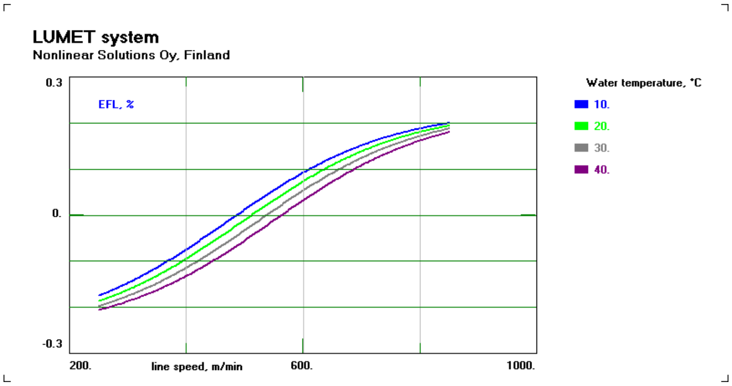

Figure 6. A plot of excess fiber length as a function of line speed at different cooling water temperatures, keeping other independent variables constant

5. Results

A number of nonlinear models for excess fiber length were attempted from the data set consisting of 25 observations. Most of the better models showed moderate correlation coefficients, typically around 75%. From several such models, one model was then selected for use. The rms error (roughly speaking the standard deviation of prediction errors) for excess length was 0.04689, with maximum error of 0.09119. This corresponds to a correlation coefficient of 0.7706.

The statistical characteristics of the nonlinear model for excess length were as follows.

rms err : 0.04689

mean |err| : 0.03773

max |err| : 0.09119

Correlation : 0.7706

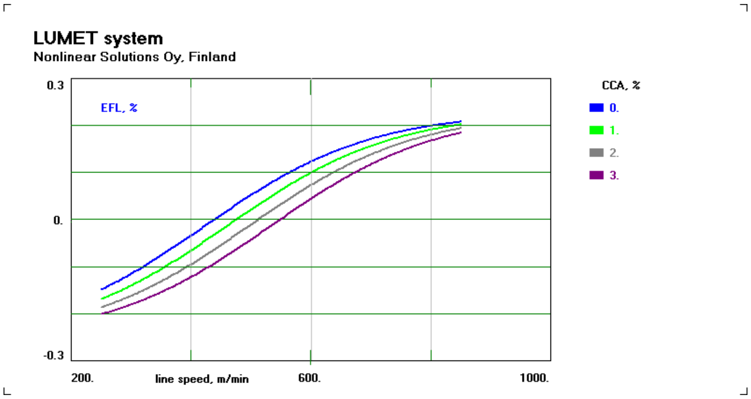

Figure 7. A plot of excess fibre length as a function of line speed for different values of CCA, keeping other independent variables constant

Figure 5 shows a comparison of measured values with the values predicted by the nonlinear model of excess fiber length. It can be seen that there is a moderately small prediction error in most cases. These models were then implemented in a software system called LUMET system which allows the user to work with nonlinear models without dealing with the complicated equations. It was then easy to plot the effects of independent variables on excess length and shrinkage.

Figure 6 shows a plot of excess fiber length as a function of line speed at different cooling water temperatures, keeping other independent variables constant. Lower water temperatures lead to higher excess lengths. Figure 7 shows a plot of excess fiber length as a function of line speed for different values of CCA, keeping other independent variables constant. Higher values of CCA reduce the excess length.

For shrinkage also, a number of nonlinear models were attempted from the data set consisting of 22 observations. Most of the better models showed good correlation coefficients, typically above 95%. From several such models, one model was then selected for use. The rms error for shrinkage was 0.04125, with maximum error of 0.1064. This corresponds to a correlation coefficient of 0.9619.

Figure 8 shows a comparison of measured values with the values predicted by the nonlinear model of shrinkage. It can be seen that there is a fairly small prediction error in most cases.

The statistical characteristics of the nonlinear model for shrinkage were as follows.

rms err : 0.04126

mean |err| : 0.03027

max |err| : 0.1064

Correlation : 0.9619

Figure 9 shows a plot of excess fiber length as a function of line speed for different values of water temperature, keeping other independent variables constant. Higher water temperatures lead to lower shrinkage. Figure 10 shows a plot of shrinkage as a function of line speed for different values of CCA, keeping other independent variables constant. Higher CCA leads to lower shrinkage. Figure 11 shows a plot of shrinkage as a function of fiber tension for different values of line speed, keeping other independent variables constant. Increasing fiber tension first reduces the shrinkage and then at higher values, the shrinkage is again higher. Higher line speeds lead to higher shrinkage.

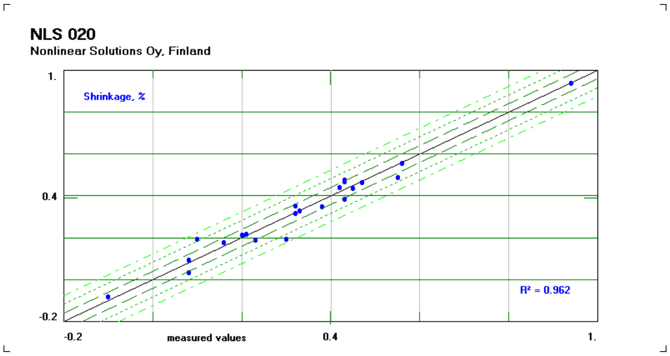

Figure 8. A comparison of measured values with the values predicted by the nonlinear model of shrinkage

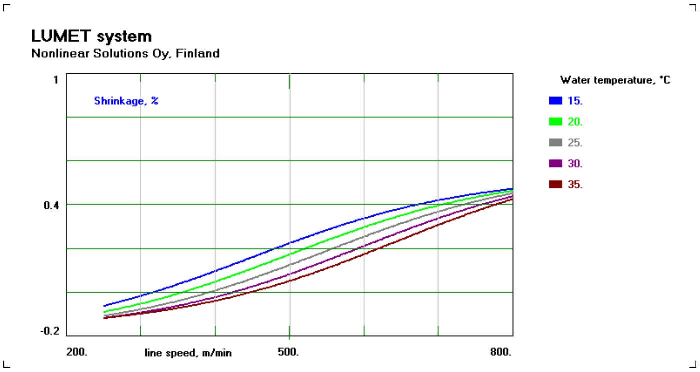

Figure 9. A plot of excess fibre length as a function of line speed for different values of water temperature, keeping other independent variables constant

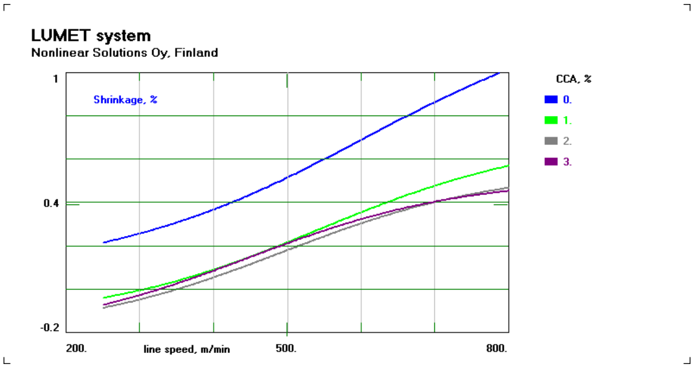

Figure 10. A plot of shrinkage as a function of line speed for different values of CCA, keeping other independent variables constant

With the nonlinear models implemented in the LUMET system, it is now easy to determine better operating conditions. For example, we can find higher line speeds such that excess fibre length and shrinkage will remain within specified limits, both below 0.1 %

6. Buffer material

The polypropylene especially selected for this work has proven to be rather robust. The dry buffer tubes manufactured on the secondary coating line had a nominal inside and outside diameter of 1.6 and 2.2mm respectively and to achieve EFL and shrinkage levels of less than 0.1% at a production above 600m/min is very encouraging.

Using an extrusion temperature profile of 195-230-230-230/230 °C, it was possible to vary the draw down ratio drastically from 4 to 20. The relatively high draw down capability of this polypropylene on a secondary coating line makes the process optimization relatively easy. Also the start-up procedures were smooth and the melt strength enables extremely high line speeds.

The tensile and elongation properties of all the buffer tubes made during the development of the models were measured both at a Borealis laboratory and at Emtelle UK Ltd.

We measured according to the requirements of a relatively new specification EN 60794-5-20 (1W) where 100 mm long samples were conditioned for two hours at 23 °C and using the 50 mm distance between the grips, we testing using a speed of 50 mm/min. The elongation at break results reached the equipment limitation of 603% without the samples breaking on one apparatus, and on the other, the samples were taken to break giving elongation values of between 903-1257%. The tensile strength at yield values were between 21.7-34.8MPa and at break between 26-35MPa

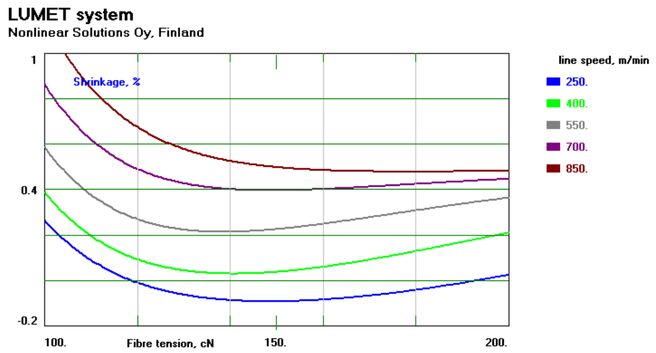

Figure 11. A plot of shrinkage as a function of fibre tension for different values of line speed, keeping other independent variables constant.

7. Conclusions

Nonlinear models have been used for improving the productivity of a large variety of processes in several industrial sectors, including optic fiber cables. For optic fiber cables, a small increase in the line speed substantially improves the production economics. In comparison, the cost and effort in carrying out a few experiments and developing nonlinear models from the experimental data are small. This work demonstrates how nonlinear models of excess fiber length and shrinkage of dry polypropylene tubes allowed us to increase the line speed on a buffering line. The same methodology can be used to improve the production economics of various kinds of extrusion processes in the telecommunication cable as well as power cable industry.

It is usually not easy to increase line speeds significantly without adversely affecting the excess fiber length. Doubling the line speed is a big step. Excess fiber length depends on several variables including line speed, tension, speed of the clincher caterpillar, cooling water temperature, distance to the capstan, etc. These relations are not very simple and some variables like line speed have clearly nonlinear effects.

It was clearly shown that when the target is to improve the production efficiency remarkably it is very important to optimize both machinery concept and raw material properties. This can be combined with process modelling which creates solid base for future process development.

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Mikko Lahti received the degree of M. Sc. in Chemical Engineering in 1991 and the degree of Dr. Tech. in Polymer Technology in 1996. Before joining Nextrom in 1997 he worked as Research Scientist in European Joint Research Center in Milan. From 1997 to 2006 he held nine years various positions in Nextrom's product management being actively involved with process development for fiber optic cables. Then he joined Maillefer Extrusion Oy in 2006 as Extrusion Development Manager responsible for the development of the extrusion processes for different cable applications. Currently as R&D director he is responsible for R&D in Maillefer Group. Mikko has over fifteen years experience working on cable industry. His work has ranged across R&D, product management, product development, process development and material science.

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