HOW NONLINEAR MODELS HELP IMPROVE THE PRODUCTION ECONOMICS OF EXTRUSION PROCESSES

Extrusion is a common production process not only for plastics and rubber, but also for metals including copper and aluminium alloys, for food materials like spaghetti, and for no-slump concretes. Different extrusion processes have their differences, but there is a lot of physics and engineering in common to all of them [1]. Even the production objectives are similar. The production manager usually wants to maximise the production, often in terms of line speed. The operator has to keep the process variables within certain limits specified by the equipment and raw material suppliers. The customer wants particular product properties to be within specified limits.

The problem is to determine the best way of operating the process. This is a common process development problem. In mathematical terms, it is a straightforward constrained optimisation problem. If all the relevant variables could be related in the form of equations, the problem could be tackled. The most difficult task is to prepare these equations, or in other words, to develop mathematical models. This article attempts to introduce the concepts and fundamentals of nonlinear modelling, as applied to extrusion processes, and briefly describes a solution to the common problem based on nonlinear models.

The variables available to the operator include process variables like screw speed, temperatures of one or more zones, cooling water temperature, draw ratio, etc. Thus, there are several degrees of freedom available to influence the various consequences of the process (see Figure 1). The consequences of extrusion include production economic variables like production rate or line speed, raw material consumption, product properties like diameters, wall thickness, mechanical properties, surface properties, etc., and other intermediate variables like pressure, die swell, and molecular orientation.

Table 1 shows a list of possible variables (consequences of extrusion) for single layer pipes for which one can develop models. For multilayer or corrugated pipes, a few more dimension variables and pull off force can be added to the list. For loose tubes of optical fibres and for secondary coating of optical fibres, excess fibre length is one of the most important variables to be controlled. Figure 1 shows a small subset of consequences on the right hand side.

DIFFERENT KINDS OF VARIABLES

These consequences of extrusion depend on several factors such as process variables, feed characteristics and the geometry of the extruder. In fact, there are so many variables that will influence the final result of any process or a series of processes that we could never measure all of them. Some of these are disturbance variables – variables which will change on their own and so more or less beyond our control. If they are measured, their effects can often be counteracted by process variables. If they are not measured, they contribute to our ignorance of the process, which we conveniently label as stochasticity. In the case of extrusion, variations in the melt index of the feed granules is one such disturbance variable, which is usually not measured.

Because of this, any mathematical model will have a limited number of variables – a limited number of causes which are mathematically related to one or more consequences of the process. These variables are selected according to the objective of the model.

The models have certain input information, which we refer to as input variables, and the calculated or predicted results are referred to as output variables or dependent variables. A typical objective could be to maximise the production rate, in which case, production rate or line speed should be included as one output variable. In a mathematical model, the input variables should be causes which lead to consequences – the output variables. Additionally, the input variables should be independent variables, that is, variables that can vary independently of each other. In most cases, nonlinear models for each output variable should be developed separately.

To be able to influence the consequences, we need to know how our degrees of freedom and measured disturbances affect the consequences. This knowledge should be available from the mathematical model. In the case of the models in Figure 1, it has been decided that the operators will have the freedom to decide the values of only the four variables on the left. Line speed will be controlled to achieve a desired external diameter before cooling and shrinkage. This tells us the input variables that we should try to include in the model. The output variables should be the relevant consequences which we want to influence.

In the production of simple pipes, screw speed, temperatures of one or two zones, and cooling water temperature are usually included as input variables. These are usually measured. They have significant effects on several properties of the pipe including the weight per metre, external and internal diameters, eccentricity, ovality, shrinkage, impact strength, etc. These are also easily measured.

In cable insulation, screw speed, temperatures of one or two zones, cooling water temperature or crosslinking conditions are usually included as input variables. The output variables can be throughput, degree of crosslinking, external diameter, etc. Nonlinear modelling of the secondary coating of optical fibre cables has been reported in some detail [2]. The same principles apply to other processes such as injection moulding, blow moulding and melt spinning with somewhat different selections of input variables.

VARIOUS KINDS OF MATHEMATICAL MODELS

It is no simple task to develop mathematical models that relate these variables. Physical modelling is usually not useful for predicting material behaviour, and cannot be expected to relate process variables with most of the product properties. Empirical modelling is feasible when the relevant variables are measurable, as is usually the case with most extrusion processes. Conventional techniques of empirical modelling, however, are linear statistical techniques. These tend to have limitations because nothing in nature is very linear, and particularly so in materials science. It therefore makes sense to use better techniques which take nonlinearities into account.

External diameter
Internal diameter
Wall thickness
Shrinkage after 7 days (lengthwise)
Shrinkage after 7 days (diameter)
Shrinkage after heat treatment (lengthwise)
Shrinkage after heat treatment (diameter)
Eccentricity
Ovality
Weight per metre
Tensile strength (lengthwise)
Impact strength (lengthwise)
Impact strength (along the circumference)
Bursting pressure
Orientation
Production rate, m/min
Raw material consumption, kg/min
Power consumption, kW
Production cost, €/min
Value addition, €/min

Table 1. Consequences of extrusion of single layer pipes which can be influenced by tuning process variables.

Figure 1. A schematic diagram of models of three properties of extruded pipes and line speed using four process variables as inputs.

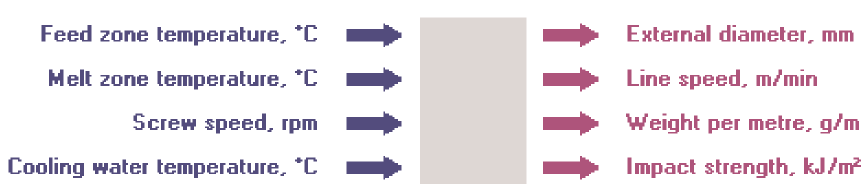
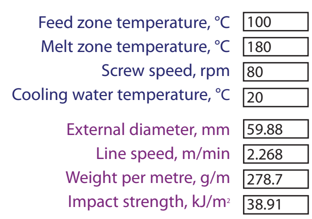


Figure 2. Nonlinear models predict line speed and three properties of extruded pipes from four process variables.



The optimum performance of an extrusion line can be determined by associating process variables with product properties using mathematical modelling based on the results of a small number of experiments. A. Bulsari of Nonlinear Solutions in Turku, Finland and M. Lahti of Maillefer Extrusion at Vantaa, also in Finland, describe the principles involved.

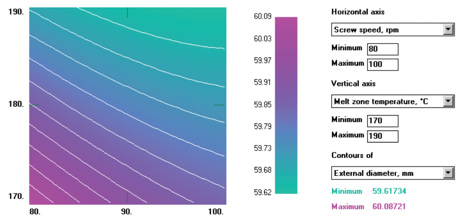


Figure 3. Contours of external diameter plotted by the LUMET system from the nonlinear model.

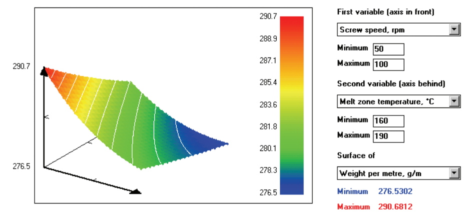


Figure 4. Surface plot and contours of weight per metre plotted by the LUMET system from the nonlinear model.

NONLINEAR MODELLING

Nonlinear modelling is empirical or semi-empirical modelling which takes at least some nonlinearities into account. The older techniques include polynomial regression, linear regression with nonlinear terms and nonlinear regression. These techniques have several disadvantages compared to the new techniques of nonlinear modelling which are based on free-form nonlinearities.

Among the new techniques, feed-forward neural networks have turned out to be particularly valuable in process modelling and for modelling of material behaviour [3,4]. Alongside these there are basis functions, multivariate splines and other techniques. Feed-forward neural networks have several features which make them better tools for nonlinear empirical modelling. Besides the universal approximation capability [5], it is usually possible to produce nonlinear models with some extrapolation capabilities with feed-forward neural networks.

Nonlinear modelling has been used succ essfully in several industrial sectors including plastics [6,7], metals [8,9,10,11], concrete [12], glass, power generation [13], pharmaceuticals [14], medicine, biotechnology, mineral wools [15], semiconductors [16] and food materials. Most of the referred articles illustrate situations where nonlinear models outperform linear models by a large margin, often an order of magnitude, and physical models are not feasible.

NONLINEAR MODELLING OF EXTRUSION PROCESSES

As already mentioned, empirical models can take various sets of input variables. One can restrict the modelling task to a single extruder and a single feed material, which leaves only process variables as candidates for input variables. Most of the nonlinear models of extrusion processes are of this kind, and require no more than about 20 experiments. Figures 1 and 2 include only process variables as input variables.

Production engineers cannot be expected to be familiar with the new techniques, let aside work with the unwieldy equations of the nonlinear models for constrained optimisation. Therefore a software tool has been developed for tuning this kind of nonlinear models from experimental data and for utilising the tuned model to determine the best operating conditions. Figure 2 shows models according to Figure 1 implemented in such a software package which allows simple use and tuning of nonlinear models. The tool has to go through minor customising for each set of variables that the user wants. The tuned nonlinear model contains valuable knowledge regarding the effects of input variables on the consequences in a concise and precise form – the information needed for optimised commercial production.

Figure 2 shows a typical LUMET system prediction screen. The user has fed in the values of the input variables, and the system predicts the consequences – the bottom four variables. It is easy to plot the effects of one or two input variables on the consequences. Figure 3 shows a plot of the external diameter according to screw speed and melt zone temperature. Similarly, surface plots can be used to show the effects of two input variables as in Figure 4, where the effect of screw speed and melt zone temperature on weight per metre is seen on a surface plot.

While it is useful to be able to predict the consequences of varying the input variables, what is of greater interest is the set of best values or most suitable values of those input variables. Sometimes one wants to determine only suitable operating conditions that will result in product properties within desired limits. It is easy to calculate such conditions in a LUMET system once the models of those properties are ready and implemented in the system. Figure 5 shows a calculation where the user has set upper and lower limits on the external diameter, feed zone temperature, melt temperature, cooling water temperature, and a lower limit on impact strength. The user wants to know how to produce the pipe while fulfilling these constraints.

This problem can have, and usually has, a vast number of solutions. In Figure 5, the software has found one solution which may not be very convenient from the point of view of the operator. One can now put a lower limit on screw speed to 70 or 80 RPM and see if it still finds a way to produce the pipe within specified limits, but much faster. Eventually, one can ask something which is impossible to achieve. In that case, the system looks for the best compromise. This is far more efficient than trial and error experimentation. Often one tries to achieve something that is not even possible. With nonlinear models, we would quickly know if we are aiming at the impossible.

EFFICIENT USE OF NONLINEAR MODELS

A bigger strength of having reliable models is that one has the opportunity to derive the maximum mileage out of the equipment. One would thus often like to optimise a variable in addition to ensuring that the product properties stay within specifications. That variable can be a production economic variable, or even a product property. One might want to minimise the weight per metre to minimise the raw material consumption. Or one might wish to claim that a pipe has a very high impact strength compared to others on the market.

Figure 6 illustrates such a calculation where the objective function is the line speed. This belongs to a general class of constrained optimisation problems [17]. In

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Figure 5. Determining process conditions which result in product properties within desired limits.

	minimum	maximum	answer
Feed zone temperature, °C	85	100	85.0
Melt zone temperature, °C	170	190	190.0
Screw speed, rpm			65.79971
Cooling water temperature, °C	15	21	19.22408
External diameter, mm	59.95	60.05	60.03
Line speed, m/min			1.9507
Weight per metre, g/m			280.0793
Impact strength, kJ/m²	40		40.9168

Figure 6. Determining process conditions which result in product properties within desired limits, and maximise one consequence of the process.

	minimum	maximum	answer
Feed zone temperature, °C	85	100	99.99906
Melt zone temperature, °C	170	190	170.322
Screw speed, rpm			84.11399
Cooling water temperature, °C	15	21	21.0
External diameter, mm	59.95	60.05	59.9916
Line speed, m/min	Maximum	found:	2.2758
Weight per metre, g/m			280.1022
Impact strength, kJ/m²	40		40.0

mathematical terms, this kind of optimisation problem is written as:

$$\underset{x \in R^n}{\text{maximise}} \quad F(x)$$

$$\text{subject to} \quad c_i(x) = 0, \text{ for } i = 1 \text{ to } m$$
$$\text{and} \quad ck(x) \geq 0, \text{ for } k = 1 \text{ to } p$$

In optimisation of extrusion processes, the inequality constraints are usually the limits on process variables and possibly also product properties, and are therefore simple inequalities in single variables. The problem can be rewritten more specifically as

$$\underset{x \in R^n}{\text{maximise}} \quad F(x)$$

$$\text{subject to} \quad x_k \geq a_k, \text{ for } k = 1 \text{ to } n+n'$$
$$\text{and} \quad x_k \leq b_k, \text{ for } k = 1 \text{ to } n+n'$$

where n is the number of process variables. The 2n' constraints pertaining to product properties come from typically n' product properties. These facilities have been implemented in LUMET systems, which allow the user to really stretch the limits of production economics. In certain applications like steel scrap melting, energy consumption should be minimised. In some other applications like extrusion, the production rate or line speed should be maximised while keeping the specified product properties within acceptable limits. In situations of competing chemical or biochemical reactions, selectivity should be maximised. In some situations, risks of product defects or production breaks should be minimised. If we have models of these variables to be minimised or maximised implemented in a LUMET system, it is relatively easy to perform the optimisation.

MORE ADVANCED ISSUES IN NONLINEAR MODELLING OF EXTRUSION

It is also possible to take geometry variables into account like thickness of profiles or diameters of the screw, barrel and the crosshead. It is further possible to include one or two characteristics of the feed material as input variables. When extruder variables are included in a nonlinear model, it becomes possible to determine the smallest size of an extruder that will serve the purpose.

CONCLUSIONS

Extra mileage can be derived by taking a little extra trouble. With about 20 experiments, nonlinear models of extrusion can be developed to work with four process variables. From these, production economics can be optimised within the limits of product properties as well as process variables. The procedure has been automated to a large extent through LUMET systems which are customised for each set of variables. The same can be done for injection moulding, blow moulding and spinning.

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EXTENDED HAUL OFFS ARE KINDER TO EXTRUDED PRODUCTS

Extra long belt versions of Gillard's heavy duty caterpillar haul offs have been produced in lengths of 1,500 or 1,800 mm with belt widths of 225 or 300 mm.

Gillard says that these longer belts enable higher tractive efforts to be achieved with considerably less clamping pressure on the extruded products avoiding distortion and damage, particularly to thin-wall products.

The new caterpillars also have an updated drive package with direct drive AC servo motors powering the belts. Two digital servo drives are used in master/slave configuration for optimum speed control.

The top belt is designed to 'float' over any lumps or bumps created during the start-up of the extrusion line. The entire top boom is suspended on two air cylinders at either end. This allows the belt to automatically raise and lower itself over the lumps while still maintaining an adequate grip on the extrusion.

www.gillard.co.uk

BATTENFELD AND CINCINNATI EXTRUSION UNDER ONE MANAGEMENT

The former SMS Group extrusion machinery subsidiaries Battenfeld Extrusion Group and Cincinnati Extrusion have been reorganised by private equity group Triton, which bought them early last year. Wolfgang Studener, long-standing managing director of Battenfeld Extrusionstechniks, has taken over the management of both groups of companies.

The aim of the reorganisation is to streamline the operations of the two companies – pipe and profile equipment at Battenfeld and sheet equipment at Cincinnati – and protect them against the anticipated downturn in the extrusion equipment market. The support functions of the two companies will be pooled with combined strategic purchasing, production, logistics and financial administration. Manufacture of components such as extruder screws and extrusion dies, which requires specific know-how, will remain where it is at the sites in Vienna, Bad Oeynhausen and McPherson, USA (American Maplan). However there will be a focus on reducing delivery times using tools such as Lean Six Sigma, which has been used in Bad Oeynhausen and Vienna since the beginning of this year.