THE COMPLEX RELATIONSHIPS BETWEEN FIBRES, PRODUCTION PARAMETERS AND SPINNING RESULTS

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ABSTRACT

Soft computing is a powerful tool that is suited to handle complex problems of modelling and optimisation. The relationships between fibres, production parameters and spinning results are such an example. The relationships can be modelled using neural networks, learning classifier systems and memory based learning. A comparison is made of these techniques with the traditional statistical regression models. For optimisation, price and spinnability are taking into account. It is shown that the price of the cotton blend can be reduced by several percents.

INTRODUCTION

One of the important production processes in the textile industry is the cotton spinning process (Sette et al, 1997). Using cotton fibres, yarns are created by means of a rotor or ring-spinning machine. In first instance, it is important for the industrial operator to predict if a certain machine setting and fibre quality results in a *spinnable yarn* (without actually starting the production process). If the yarn is spinnable, it is certainly as important to predict *the characteristics of the resulting yarn*. Preferable, not only a prediction of these yarn characteristics should take place, but also an *optimisation* towards *price versus yarn* characteristics. This optimisation should predict the corresponding machine settings and fibre blend (fibre quality) needed to realise the optimal yarn / price.

The fibre-to-yarn production process can be seen as a specific implementation of a more general production process *f*, schematically illustrated in figure 1.

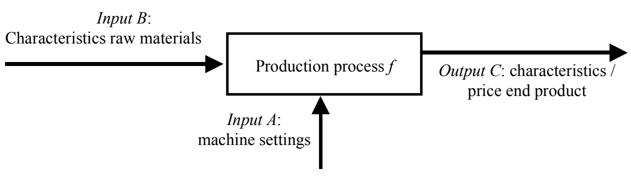

Figure 1: Structure of the Basic Process

The techniques represented in this paper are therefore also suited to other (textile) production processes as described in the above figure. The remainder of this paper will, however, only address the cotton fibre-to-yarn production process.
Input vectors A and B are seldom optimal because of the large number of different fibre characteristics and machine settings. Current industrial configurations are based upon the subjective experience of the human operator. A *global* optimal solution is highly unlikely.

EXPERIMENTAL SET-UP

The fibre-yarn data used in this research is based upon 20 different cotton fibre qualities with a wide variety of different fibre characteristics (BRITE/EURAM, 1990-1993). For each fibre, 73 fibre characteristics have been determined. During yarn production, 5 different machine settings were systematically changed (2 navel types, 3 yarn counts, 3 twists, 2 rotor speeds, 3 breaker speeds).

A total of (20 x 2 x 3 x 3 x 2 x 3 =) 2160 different production set-ups have been realised. A total of 1380 were spinnable. Of all (spinnable) yarns the corresponding strength and elongation were determined. Vector A will consist of the aforementioned 5 machine settings, while vector B will consist of a selection out of the 73 fibre characteristics. Vector C will hold two components: yarn strength and yarn elongation. Price and spinnability are additional parameters.

PREDICTION OF THE SPINNABILITY OF FIBRES

No mathematical model of a spinning machine that predicts spinnability (or part of vector C) exists. As a consequence of the large input (and possible output) dimensions and the multiple complex interdependence between parameters, it is highly unlikely that an exact mathematical model will ever be developed. A black box model can be constructed by means of a neural network using a Backpropagation learning rule. The construction and behaviour of this neural network has been extensively described in (Pynckels et al. 1995). The data has been divided in a learn file and a test file. The test file was used only to verify the resulting model (it was never used during learning). 90% of the spinnable and 95% of the not spinnable configurations are correctly classified. Less then 6% of the testing samples had a dubious classification.

PREDICTION OF YARN CHARACTERISTICS USING NEURAL NETWORKS

A first model for the predictions of yarn characteristics was constructed (Pynckels et al., 1997). For each yarn characteristic a separate neural network was constructed. Post and pre filtering allowed for the reduction of input parameters and the checking of intercorrelation between output parameters. An extensive discussion of these filters is given in the paper. The obtained (relative) procentual error on the predicted yarn characteristics is smaller then 5% in more then 90% of all (unknown) test fibres. The maximum relative error was about 10%.

The current configuration used by the authors for the prediction of yarn characteristics is a simplified version of the aforementioned combination of neural networks using only one neural network with a Backpropagation learning rule combined with a Bayesian regularisation.

GENERATING A RULE SET FOR THE FIBRE-TO-YARN PRODUCTION PROCESS BY MEANS OF LEARNING CLASSIFIER SYSTEMS

The modelling by neural networks (as described in the two previous paragraphs) does not give any physical interpretable information about *how* the model arrives at a certain prediction. However, Learning Classifier Systems (LCS) generate a rule set by means of an automated learning algorithm where each rule has a condition part (IF…) and an action part (THEN…). The condition part will consist of (a selection from) the fibre characteristics and machine settings, while the action part will consist of spinnability or yarn characteristics.

The authors (Sette et al, 2000) have constructed a more complex LCS, named Fuzzy Efficiency based Classifier System which allows the modelling (creation of a rule set) for a real production process (including continuous parameters, errors, fuzzy values, long time memory, etc.).
Using FECS the spinnability was predicted with an accuracy of 94%, resulting in a rule set of 123 physical interpretable rules. The 20 most important rules predicted 58% of all presented samples. A typical rule looks as follows (the rule with the largest number of selections for k=3):

00	0#	1	0#	0	0	#	0	#	#	0

can be interpreted as:

IF the yarn count and the rotor speed is low (00) (0)
AND twist and breaker speed are low (00) or medium (01)
AND a carved navel (1) is used
AND fibre length and strength is low (0)
THEN micronaire, uniformity and elongation don’t matter
AND the resulting yarn strength will be low (0)

The advantage of this technique is that it can generate rules for cases that do not follow the general rules of the majority of examples. Moreover the rules have a clear physical meaning.

MEMORY BASED REASONING (MBR)

(also known as Instance Based Reasoning)
MBR is similar to human reasoning based upon experience:

1. Identifying similar cases from experience (opposite to the other techniques, that learn from *all* examples)
2. Applying the obtained information from these cases to the new problem

It is one of the more thoroughly analysed algorithms in machine learning due to its simplicity and its age (Mitchell,1997) .
MBR only uses two operators:

1. *Distance function* between any two cases (records)
2. *Combination function* to arrive at an answer

First training samples are stored in a database as separate records. No immediate generalisation is done. When a new query is submitted, the relation (*distance function*) to the stored records is examined. A target function (or *combination function*) is assigned based on aforementioned distance. Most of the time this will include only a limited number of records ‘close’ to the query.

Advantages of MBR:

1. The ability to model complex target functions by a collection of less complex local approximations
2. Training examples are never lost (all training examples are explicitly stored).

Some disadvantages of MBR are:

1. High computing cost *during* classification (calculation of distances + construction of combination function is done at the moment of the query). Other learning methods construct their target function *before* the query (high computing cost during learning phase) but can afterwards immediately evaluate a query.
2. The distance function basically considers all attributes of a record as equal (including less important or useless attributes). If dependant on only a few attributes ‘similar’ instances could be a large distance apart, resulting in a wrong choice of records to build a local target function. A possible solution to overcoming this problem is to weight each attribute differently when calculating the distance between two instances.

The results of using this technique are equal for modelling yarn characteristics to neural networks, but for spinnability MBL is problematic (due to the discrete assessment of spinnability (0/1).

COMPARISON OF MODELLING TECHNIQUES

Multiple linear regression: correlation 91% for considered case
+ few data required
+ well known and widely available
+ fast (training and recall)
- not for complex cases

Neural networks: correlation 95% for considered case
+ excellent for complex cases
+ widely applicable
+ excellent generalising properties
- black box: no insight in model
- more art than science
- many data required
- learning phase time consuming

Learning classifier systems: correlation 94% for considered case
+ easy interpretation (rules)
+ capable of generating separate rules for deviating cases
- configuration of rules is critical factor
- learning phase time consuming

Memory based learning: correlation 95% for considered case
+ looks at relevant examples only
- time consuming
- not always applicable.

OPTIMISATION OF THE YARN CHARACTERISTICS

Due to the high dimensionality (vector A + vector B + vector C) of the production process and the fact that an exact mathematical approach (model) is not feasible, a genetic algorithm was used to obtain a multi dimensional optimisation of vector C. Genetic algorithms. For an extensive introduction to genetic algorithms and possible applications we refer to literature (Boullart L and S. Sette, 1997).

Using the model (obtained in paragraph 4) a specific blend can be determined (fibre qualities) and corresponding machine settings for a certain (optimal) yarn strength and elongation. As the optimisation is multi objective, the genetic algorithm has been expanded to include Pareto optimisation and a 'sharing' function. The sharing function allows the search for several optima (a set of optima), while the Pareto optimisation allows the optimisation of a multi dimensional output (Sette et al., 1996).

The aforementioned Genetic Algorithm (GA) allows calculating a group of optimal yarns (a so called Pareto front) for which the corresponding fibre qualities and machine settings are known (figure 2).

In the first GA implementation, the calculated fibre qualities were unlikely to correspond with any of the original 20 cotton fibre qualities (the neural network had no restraints on the diversity of fibre characteristics). An approximation to these predicted 'ideal' fibre characteristics was done by calculating an optimal blend of the 20 available fibre qualities. This blend, together with the predicted machine settings was used to produce a yarn (in a real production environment). A procentual accuracy of 96% for the elongation and 92% for the strength was obtained when compared to the predicted Pareto front of optimal yarns.

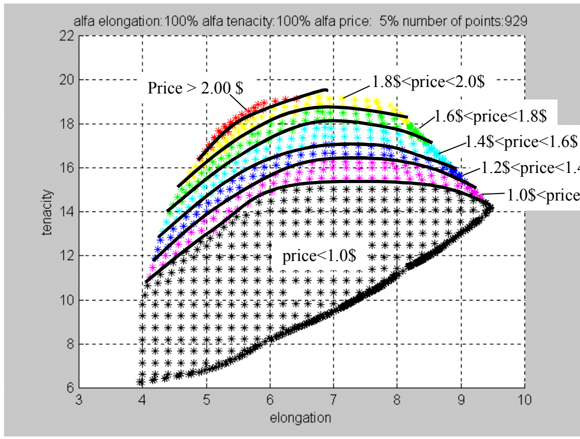

Figure 2: Optimization of Price and Quality of a Cotton Blend

GLOBAL OPTIMISATION TOWARDS YARN CHARACTERISTICS, SPINNABILITY AND PRICE

The aforementioned optimisation model still had several shortcomings:

1. Although a corresponding price could be calculated (based on the blend), the solution itself was not optimised versus price.
2. The predicted optimal blend was not verified versus spinnability (simulations have shown that for lower elongation and tenacity yarns, the calculated blend was not spinnable).
3. No realistic constraints (as can be expected in a real production environment due to limited availability, planning schedules, etc.) are taken into account.

To remedy these shortcomings several of the previous techniques and models (as seen in paragraph 3 to 5) have combined into one global structure as shown in figure 3.

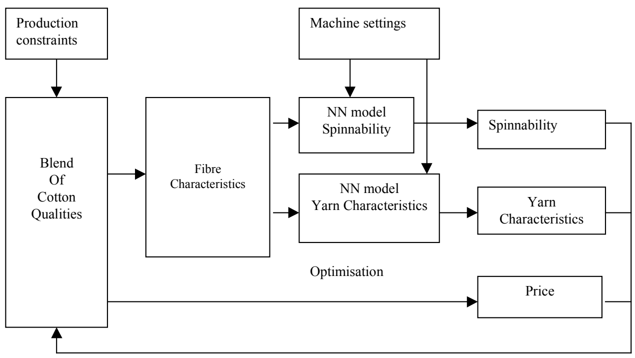

Figure 3: Global Optimisation Structure of the Fibre-to-Yarn Production Process

Two new added (or extended) components can be distinguished within the fibre-to-yarn model:

- The *optimisation* towards spinnability, yarn tenacity, elongation and price. To this end, a sequential quadratic programming algorithm was used. As the importance of each parameter may not be equal, weight factors can be attributed.
- Realistic constraints have been added to the optimisation. If c_i are the procentual blend coefficients corresponding with fibre quality *i*, then a basic general constraint is:

$$\sum_i c_i = 1.0 \quad \text{with} \quad 0.0 \le c_i \le 1.0 \qquad (1)$$

This corresponds with the fact that the sum of the procentual blend coefficients should correspond to a total of 100% and that each coefficient should be no lower then 0.0 % or higher then 100%. If a certain fibre quality *j* is not available an additional constraint $c_j = 0.0$ can be added. Constraints can easily be changed to implement practical production limitations. For example: if a certain fibre quality has to be included a minimum (higher then 0.0) or even a fixed procentual blend coefficient can be set.
Using the above constraint(s), each optimisation result corresponds with a totally realistic (and controllable) configuration, which has no need for any further approximations. The result of such an optimisation is presented in figure 4.

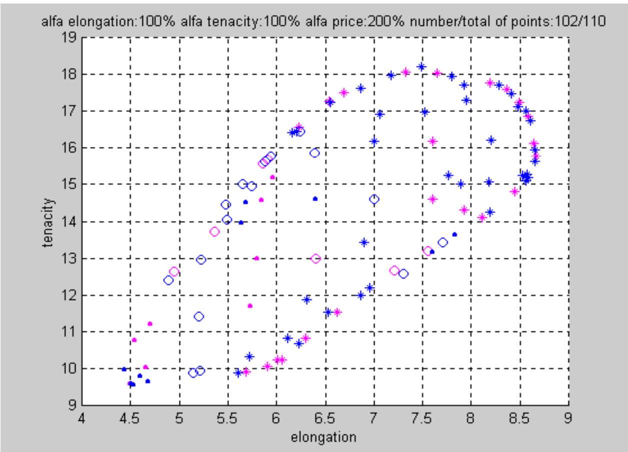

Figure 4: Result of the Global Optimization – real case
Spinnability: * good, 0 average, . weak

Finally, a real production test case (from an existing spinning mill) was implemented:

- 20 new (existing) cotton qualities with their corresponding prices (between 40 and 50) from a spinning mill were taken as input parameters
- Constraints were defined: no single quality could have more then 10% or less then 0% within a certain blend.
- A target elongation of 8% and tenacity of 15.7cN/tex was determined

The model suggested a blend of 12 qualities: 8 cotton qualities with a contribution of 10% and 4 cotton qualities with a contribution of 5%. The yarn was predicted as highly spinnable with a predicted strain of 7.5% and tenacity 15.4cN/tex. The final price of this blend was 41ct/lb. These results were compared with current production settings in the spinning mill. The resulting fibre characteristics of the blend and the predicted machine settings all corresponded very well with the settings at the spinning mill (as determined by a human expert). However, the final price of their blend was at a higher level: 42.5ct/lb.

CONCLUSIONS

Several techniques are available to model complex production processes, such as the fibre-to-yarn process. The best technique depends on the type of data, the available number of data, the expectations of the user, the use of the model, technical and mathematical knowledge of the user. For the case considered, neural networks (with backpropagation learning strategy) gives good results, both for quality and for processability as a function of fibre parameters and machine settings.

A global optimisation of the fibre-to-yarn production process has been presented in this paper. Price, yarn characteristics, spinnability and production constraints have all been taken into account to determine an optimal blend of fibre qualities. When the results were compared to the blends and settings of an existing spinning mill (optimised by a human expert) strikingly similar predictions were made. However, the blends suggested by the human expert, had a higher price (3.7%).

Future research will concentrate towards guaranteeing continuity of all the aforementioned fibre-to-yarn optimal settings in time, as the current optimisation present an immediate solution without taking into account stock limits or the arrival of new qualities within the near future.

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