OPTIMISING THE FIBRE-TO-YARN PRODUCTION PROCESS: FINDING A BLEND OF FIBRE QUALITIES TO CREATE AN OPTIMAL PRICE/QUALITY YARN

S. Sette, L. van Langenhove
Department of Textiles, Universiteit Gent
Technologiepark 9, 9052 Zwijnaarde, Belgium

E-mail: stefan.sette@rug.ac.be

Abstract

An important aspect of the fibre-to-yarn production process is the quality and price of the resulting yarn. The yarn should have optimal product characteristics, while maintaining as low a price as possible. Early optimisation models of the fibre-to-yarn process, based on neural networks and genetic algorithms, were severely limited in their potential applications as they generated unrealistic (ideal) conditions for the process. In this paper, a method is presented to model and optimise the fibre-to-yarn production process which avoids the aforementioned problems. A neural network is used to model the process, with the machine settings and fibre quality parameters as input and yarn tenacity and elongation as output. A constrained optimisation algorithm is used afterwards to optimise the blend of fibre qualities to obtain the best yarns. This results in an optimal price-yarn quality surface where each point corresponds with a set of blend coefficients and machine settings. Furthermore, constraints can easily be adjusted to correspond to real-life production environments.

1. Introduction

One of the important production processes in the textile industry is the spinning process. Starting with cotton fibres, yarns are (usually) created on a rotor or ring-spinning machine. The quality of the resulting yarn is very important in determining their possible applications . The three most important characteristics of a yarn are:

- tenacity,
- elongation
- corresponding price.

The first two characteristics are physical yarn characteristics, while the third is the price of producing the yarn. The price depends on the blend of fibre qualities used in the fibre-to-yarn production process.

Modelling and optimisation of the fibre-to-yarn production process has already been done using neural networks and genetic algorithms [1, 2]. The basic components of this model are shown in Figure 1.

A feed-forward neural network with the Backpropagation learning rule was used to model the spinning process: yarn strength and yarn elongation (output vector) were predicted using the machine settings and fibre qualities (input vector). The genetic algorithm was applied to the input parameters to generate an optimal yarn (maximum strength and elongation). Because of the multi-objective nature of this optimisation, the genetic algorithm was extended with a ‘sharing function’ and the concept of Pareto optimisation. This multi-objective optimisation algorithm generated a new input vector consisting of the optimal machine settings and the optimal ideal fibre characteristics needed to produce a yarn with maximum strength and elongation [2]. Based on the ideal fibre characteristics, an optimal blend of available fibre qualities was constructed. Finally, the blend coefficients were used to calculate the price of the new yarn.

Optimisation could also be carried out on any predetermined values for the yarn strength and elongation. Using the aforementioned methodology, a price-yarn quality surface was constructed [1], allowing the spinner to strike a balance between price and the quality of the yarn.
Although good results were achieved a serious problem remained: no constraints are taken into consideration allowing unrealistic (ideal) fibre coefficients to be generated. In other words, physical limitations (such as available fibre qualities) are *not* considered. This was a consequence of the

created model which used the fibre characteristics and machine settings as input vectors, and yarn tenacity and elongation as output. When blend coefficients were calculated, no exact fitting match to the ideal fibre characteristics could be found. This resulted in some large deviations in a number of fibre parameters. Furthermore, the calculation of a price-yarn quality surface was limited to a dozen combinations (which, as has been mentioned above, are only approximations). This resulted in only a very rough and unrealistic price-yarn characteristics model.

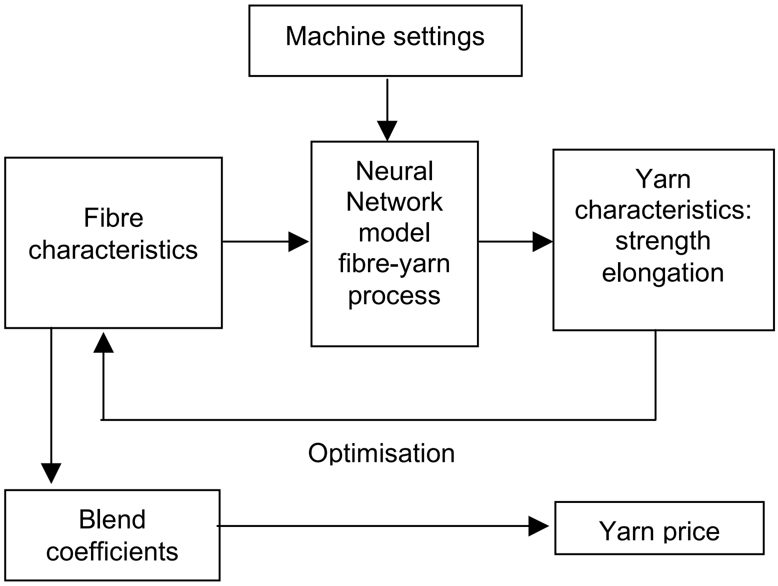

Figure 1: Fibre-yarn model based on fibre characteristics

2. Fibre-to-yarn model based on blend coefficients

To avoid the aforementioned problem, a global fibre-to-yarn model has to be developed which calculates the three important yarn characteristics (output vector: tenacity, elongation and price) based on blend coefficients and machine settings (input vector). Optimisation has to be carried out immediately on the blend coefficients. A schematic presentation of this model is given in figure 2.

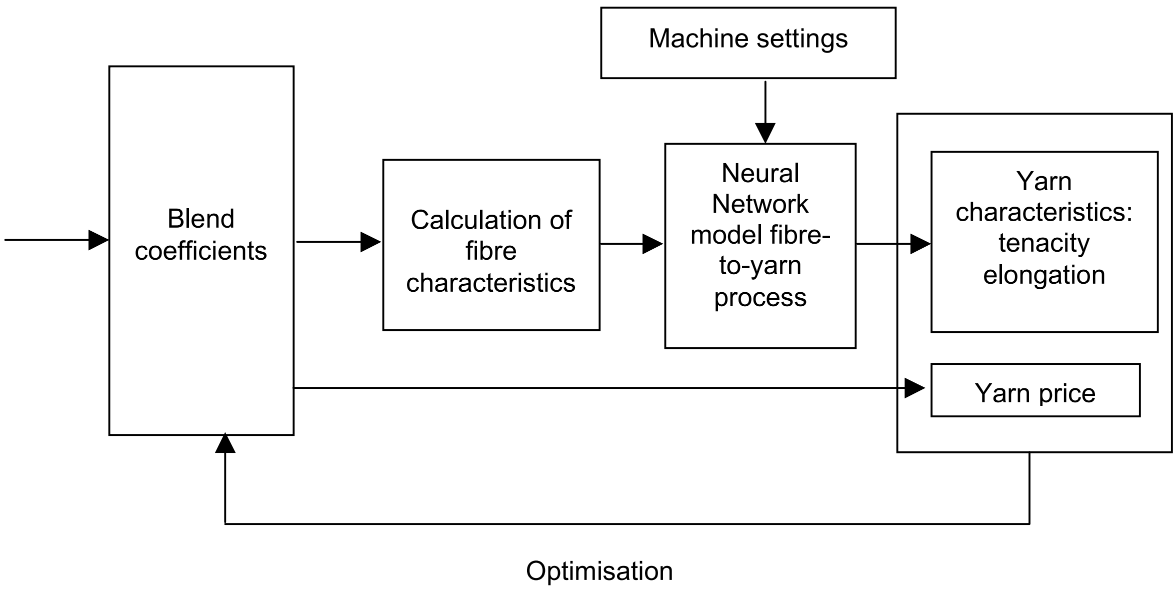

Figure 2: Fibre-to-yarn model based on blend coefficients.

The neural network of the previous fibre-to-yarn model has been retained: calculation of yarn characteristics (tenacity and elongation) is still made departing from fibre characteristics (and machine settings).

Optimisation is done towards the blend coefficients and is restricted by a number of constraints. If c_i are the blend coefficients in percent 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 blend coefficients in percent 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 blend coefficient in percent can be set.

Using the above constraint(s), each optimisation result corresponds with a fully realistic (and controllable) configuration which has no need for any further approximations.

3. Implementation

The experimental set-up and resulting fibre-to-yarn database used for this modelling/optimisation problem is extensively described in [2].

Three basic components can be distinguished within the fibre-to-yarn model:

1. *The Neural Network model*. As already mentioned, the neural network does not differ from the original construction as defined in [2]. Moreover no new learning phase is needed, as the fibre-to-yarn database is the same. It should be noted that any valid model relating fibre characteristics & machine settings to yarn characteristics could be inserted here without altering the proposed optimisation sequence. This modular approach allows the scope of this experiment to be easily enlarged: mathematical or neural network models could be developed and inserted to predict diverse yarn qualities of not only cotton, but also of flax or any other textile material where blending of raw materials is needed.

2. *The blending equations*, which are also identical to those used in [2] (i.e. a simple linear mixture model [3]). Price calculation is a direct result of blending coefficients and the cost of the selected fibre qualities.

3. *The constrained optimisation* of yarn tenacity *t*, elongation *e* and price *p*. To this end, a sequential quadratic programming algorithm was used [4]. The constraints are given by equation (1), while the optimising function *f* (to be minimised) is given by:

$$f(T,E,P,t,e,p) = w_t|T-t| + w_e|E-e| + w_p|P-p|$$

with

T: target value for tenacity
E: target value for elongation
P: target price (= minimum possible price)
w_t, w_e, w_p : weights corresponding with tenacity, elongation and price

In order to generate a price-yarn quality surface, the target values for tenacity and elongation were systematically incremented along a grid (31 tenacity values equally distributed between 6 and 21, 30 elongation values equally distributed between 4 to 10) resulting in 930 tenacity-elongation-price points.

4. Results

The weights for tenacity and elongation were chosen 1.0, while the weight for the price was chosen 0.0, 0.01 and 0.05. The results are shown in Figure 3, Figure 4 and Figure 5. The colour indicates the price level:

Red:	price ≥ 200
Yellow:	180 ≤ price < 200
Green:	160 ≤ price < 180
Light blue:	140 ≤ price < 160
Blue:	120 ≤ price < 140
Purple:	100 ≤ price < 120
Black:	80 ≤ price < 100

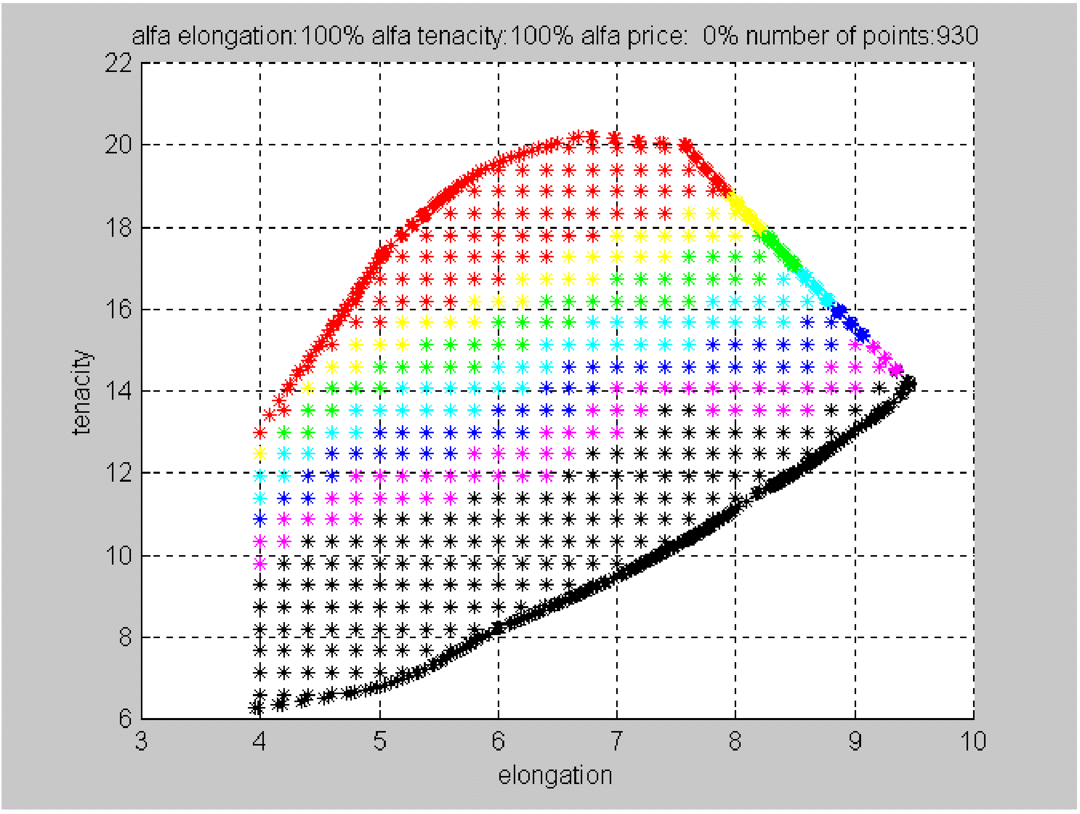

Figure 3: price-tenacity-elongation graph with $w_p = 0.0$

The following observations can be made

- The shape of the tenacity-elongation cloud is severely limited, and does not have the square shape which was used to initialise the target tenacity-elongation values. Most particularly, the target combinations of (high tenacity, high elongation), (high tenacity, low elongation) or (low tenacity, high elongation) could not be realised. The corresponding optimal tenacity-elongation values are found at the border of the cloud, defining a realistic limit of what can be produced. It is clear from these figures that a substantial amount of tenacity-elongation target values cannot be realised due to these constraints. The real surface will not therefore be the target tenacity-elongation square, but will be a deformed surface. The boundaries show the limit of what is possible given the current set of constraints.
- Figure 4 can be considered as the most 'complete' graph: tenacity, elongation and price are optimised while retaining the total tenacity-elongation area as obtained in Figure 3. As the weight factor for the price increases (Figure 5) the part of this area with tenacity near 20 is eliminated, as this corresponds to a very high price.

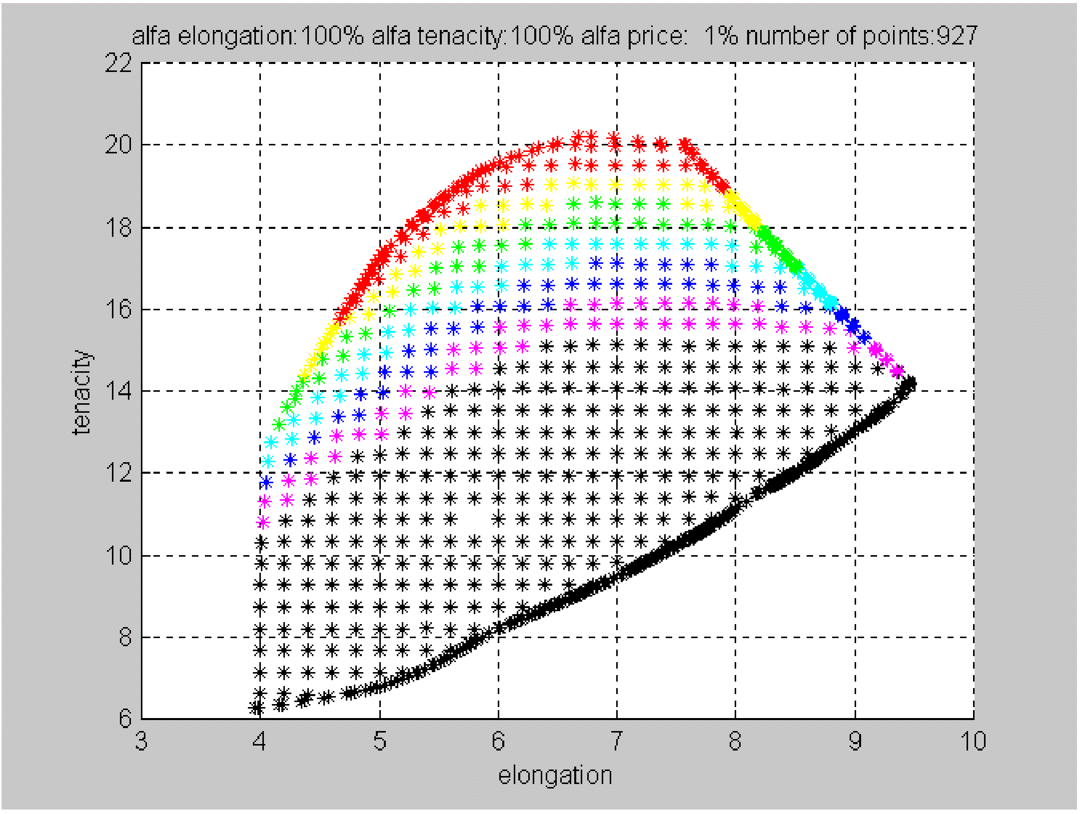

Figure 4: price-tenacity-elongation graph with $w_p = 0.01$

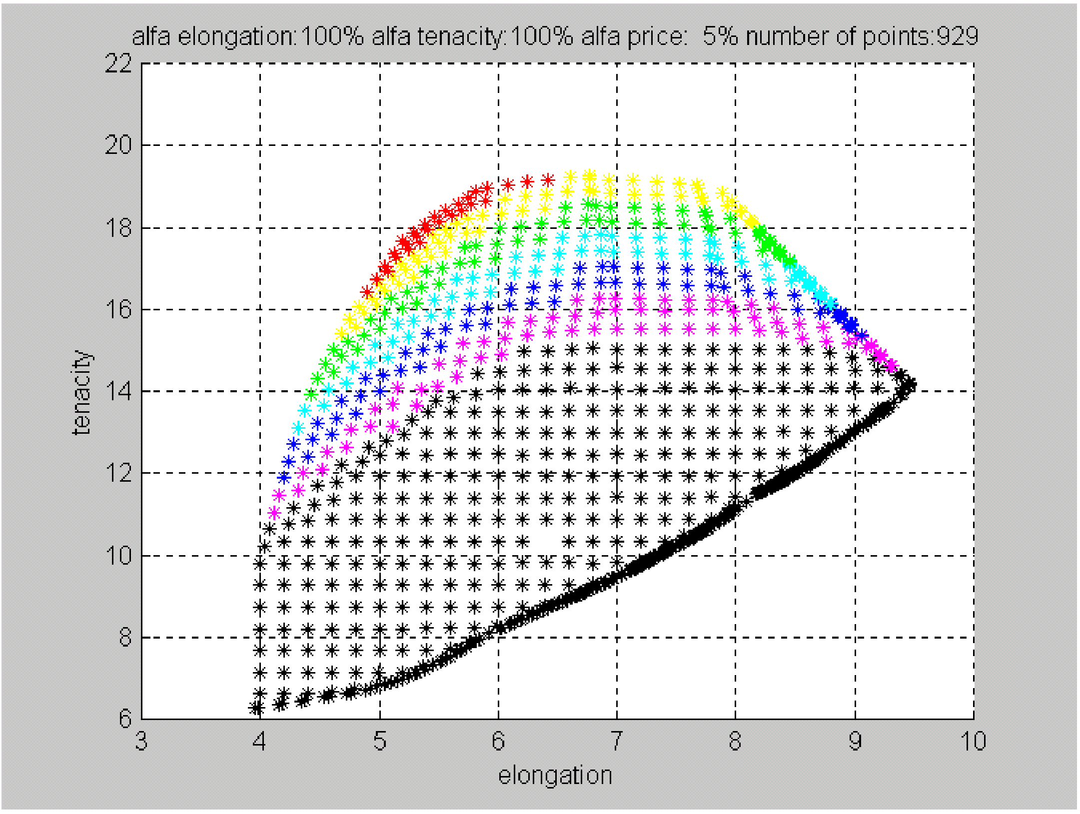

Figure 5: price-tenacity-elongation graph with w_p=0.05

- A Pareto front is seen in Figure 3 running from tenacity-elongation (14, 9.5) to (20, 7.6). This is repeated in Figures 4 and 5 (although the higher price part is removed in Figure 5). This

Pareto front shows all maximum tenacity-elongation values which can be constructed together with their corresponding price.

- In Figure 3 no optimisation took place with regard to the price. All price categories are represented but a certain tenacity-elongation value does not necessarily have the lowest price. This is in contrast to Figures 4 and 5 which both include price optimisations. Regions of the same price class have moved towards higher tenacity. For example: the tenacity-elongation value (16, 8) in Figure 3 was situated in a price class [140, 160], while in Figures 4 and 5 the price class changed to [100, 120]. It should be noted that Figures 4 and 5 show almost no differences regarding the location of price classes.

- For each tenacity-elongation value of the calculated surface, the corresponding blend coefficients and machine settings are available. No further approximations are needed. Figure 6 shows the blend coefficients for a target tenacity-elongation (16, 8) for a price weight 0.0 and a price weight 0.05.

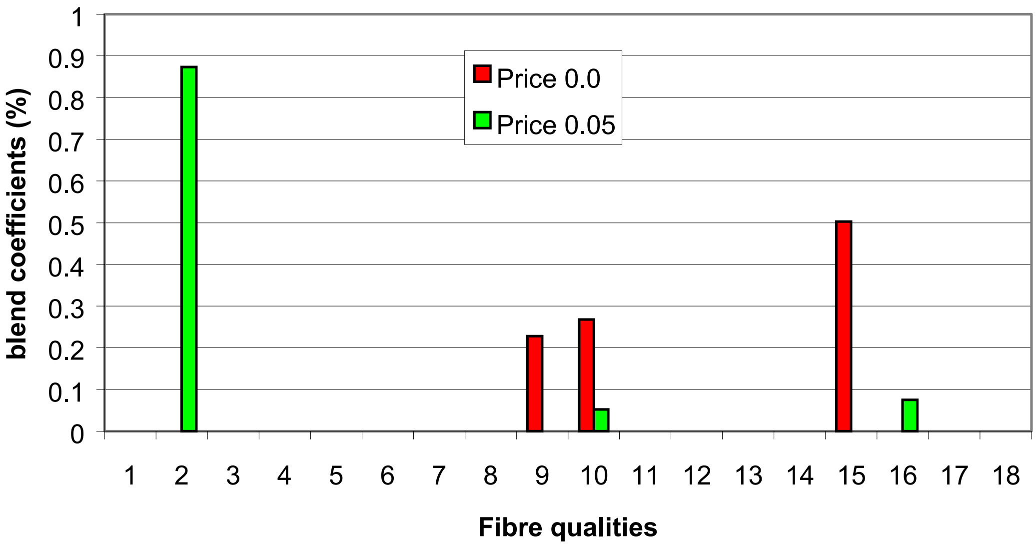

Figure 6: Tenacity-elongation (16,8)

The achieved tenacity-elongation-price value is (16.2, 8.0, 158.5) for w_p = 0.0 and (15.9, 8.0, 107.7) for w_p = 0.05. Although the tenacity and elongation are almost exactly the same, the resulting price (107.7 versus 158.5) is clearly in favour of w_p = 0.05. This corresponds with the predicted price zone as seen in figure 5. The corresponding optimal blend consists of 87% fibre quality 2, 5% fibre quality 10 and 8% fibre quality 16.

5. Conclusions

A new method to model and optimise a fibre-to-yarn production process based on blend coefficients has been proposed. Restrained optimisation is carried out directly on the blend coefficients, including real-life constraints. This algorithm corrects the basic problems which occurred in a previous optimisation model based on fibre characteristics, which only generated an ideal yarn which most of the time would be impossible to manufacture. The current model also greatly extends the accuracy and detail of the final price-yarn quality surface. This allows the spinner to strike a balance between price and quality of yarn while keeping in mind his current stock of fibre qualities.

Further research will have to concentrate on verifying this model in a real-life production environment, testing several blends and produced yarns with the results presented by the model.

References

[1] Sette S, van Langenhove L., Boullart L.; 'Optimisation of the Fibre-to-Yarn process using Genetic Algorithms'; 23rd International Cotton Conference Bremen: Optimisation Production Process; Germany, March 6-9, (1996), pp 233-246

[2] Sette S, Boullart L, van Langenhove L, Kiekens P; 'Optimising the fibre-to-yarn process with a combined Neural Networks/Genetic Algorithm approach'; Textile Research Journal, Vol. 67, No. 2, (1997), pp 84-93

[3] Garde A R, Subramanian T A; 'Process Control in Cotton Spinning'; ATIRA, Ahmedabad, India, (1974), pp 23-34

[4] Fletcher R; Practical Methods of Optimization; Vol 2, Constrained optimization, John Wiley and Sons, (1980)