Use of Neural Nets for Determining the Spinnability of Fibres

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Abstract

It is very important for a spinner to be able to predict the degree of spinnability of a given fibre quality. Certain process conditions must be considered here. This article describes how spinnability of a given fibre quality on a rotor and ring spinning machine can be predicted with a reliability of 95% by means of a neural network. The structure and the characteristics of the neural net used will be considered in greater depth, and a simple method of implementation of such a neural net will be dealt with.

1. Introduction

The aim of the present study (which falls within the framework of a BRITE/EURAM project BREU0052) consists in predicting the spinnability of fibres with certain properties under certain production conditions. These conditions are determined by the type of machines and their settings. Determining the spinning limits is no easy task at all because of the complex interactions between the parameters mentioned. In this context, neural networks offer an acceptable and cheap solution for predicting spinnability.

2. Test set-up

20 cotton types have been selected based on their very divergent properties. 73 important properties were determined from which a selection of 35 representative parameters was made using statistical methods. The fibre origin and the properties studied are to be found in Appendix A.

Yarns of 25, 30 and 50 tex were spun with twist factors atex of 3,500, 4,000 and 4,500. Ring spinning was done on an SKF lab ring spinning machine. Rotor spinning was carried out on a Platt rotor spinner. The machine parameters considered were the speed of the opening roller, the rotor speed and the navel type (smooth or with 16 grooves). Each time it was established empirically whether spinning was possible with the selected properties. A yarn was considered unspinnable if more than 5 breakages occurred during the first 3 minutes of the spinning process. In total, 2,150 tests (each of which had a different set of conditions) were executed, spinning only 500 g per test, which complicated the assessment of the spinnability. 763 tests out of the 2,150 were regarded as unspinnable and 1,371 as spinnable. 16 tests were totally uncertain. The fibre and machine parameters of these spinning tests were kept to assess whether the method used is capable of classifying tests with uncertain spinnability as spinnable or unspinnable.

3. Statistical methods

To express the influence of several factors on a variable, multiple regression is most frequently used. However, this technique does not always give satisfactory results. The main reasons for this are that the factors are supposed to be independent, which is often not true, and that the relationships are not always linear as is being put foreward. The interdependence of the factors is illustrated in table 1, which shows the single correlation coefficients between the independent parameters.

Stat. Basic stats	Correlations Marked correlations are significant at $p < 0.05$											
Variable	B	C	D	E	I	J	O	P	Q	R	AE	AF
B	1.00	☞ 0.59	☞ 1.00	☞ 0.90	☞ 0.72	☞ 1.00	☞ 0.97	☞ 1.00	☞ 1.00	0.30	☞ 1.00	☞ 1.00
C	☞ 0.59	1.00	☞ 0.57	☞ 0.50	-0.03	☞ 0.57	☞ 0.54	☞ 0.56	☞ 0.58	0.00	☞ 0.58	☞ 0.57
D	☞ 1.00	☞ 0.57	1.00	☞ 0.90	☞ 0.73	☞ 1.00	☞ 0.97	☞ 1.00	☞ 1.00	0.30	☞ 1.00	☞ 1.00
E	☞ 0.90	☞ 0.50	☞ 0.90	1.00	☞ 0.65	☞ 0.90	☞ 0.95	☞ 0.90	☞ 0.90	☞ 0.47	☞ 0.90	☞ 0.90
I	☞ 0.72	-0.03	☞ 0.73	☞ 0.65	1.00	☞ 0.71	☞ 0.68	☞ 0.74	☞ 0.73	0.32	☞ 0.73	☞ 0.73
J	☞ 1.00	☞ 0.57	☞ 1.00	☞ 0.90	☞ 0.71	1.00	☞ 0.97	☞ 1.00	☞ 1.00	0.29	☞ 1.00	☞ 1.00
O	☞ 0.97	☞ 0.54	☞ 0.97	☞ 0.95	☞ 0.68	☞ 0.97	1.00	☞ 0.97	☞ 0.97	0.38	☞ 0.97	☞ 0.97
P	☞ 1.00	☞ 0.56	☞ 1.00	☞ 0.90	☞ 0.74	☞ 1.00	☞ 0.97	1.00	☞ 1.00	0.30	☞ 1.00	☞ 1.00
Q	☞ 1.00	☞ 0.58	☞ 1.00	☞ 0.90	☞ 0.73	☞ 1.00	☞ 0.97	☞ 1.00	1.00	0.30	☞ 1.00	☞ 1.00
R	0.30	0.00	0.30	☞ 0.47	0.32	0.29	0.38	0.30	0.30	1.00	0.30	0.30
AE	☞ 1.00	☞ 0.58	☞ 1.00	☞ 0.90	☞ 0.73	☞ 1.00	☞ 0.97	☞ 1.00	☞ 1.00	0.30	1.00	☞ 1.00
AF	☞ 1.00	☞ 0.57	☞ 1.00	☞ 0.90	☞ 0.73	☞ 1.00	☞ 0.97	☞ 1.00	☞ 1.00	0.30	☞ 1.00	1.00

B HVIarea, C HVIcount, D HVI length, E HVIuniformity, I HVI rd, J HVI b, O Stelo strength, P Stelo elongation, Q FMT fineness, R FMT maturity, AE Wax, AF Sugar

Table 1 : Single correlation between independent (?) variables

This table shows that the correlation between the factors is not negligable. Consequently, multiple regression will not give reliable results. The results are illustrated in table 2. It is clear that the correlation coefficient is very low. So, this model cannot be used to predict spinnability.

Stat. Multiple Regress.	Regression summary for dependent variable : AN R = 0.26089059, R^2 = 0.06806390, Adjusted R^2 = 0.06632683 F(4,2146) - 39.163, Std. error of estimate = 8.5961			
N = 2151	B	St. Err. of B	t (2146)	p-level
Intercpt	3.46181	0.687504	5.03533	0.000001
Yarntwist	-1.16820	0.453310	-2.57703	0.010031
rotorspeed	-9.75023	2.331171	-1.18598	0.000030
HVI length	4.48063	1.576001	2.84304	0.004511
AFIS diameter	7.41152	1.924203	3.85174	0.000121

Table 2 : Multiple linear regression

4. Method

The aim of the designed method is to predict the spinnability of fibres. Since statistical methods have a tendency of oversimplifying problems (for example, because of linearization) self-training systems were opted for, more precisely neural networks.

4.1. Basic concepts on neural nets

Neural nets are an interconnection of a great number of simple computational elements. The functional operation of these elements can be compared to the building stones of the human nervous system and of the human brain: neurons (see fig. 1). By analogy with the biological neurons, these computational elements are also called *neurons*. The biological neurons receive their input signals via dendrites. These signals are combined in the nucleus. If the combined signal is strong enough, the neuron will fire an output signal, which is brought to the dendrites of other neurons via the axon. By analogy with its biological namesake the working of an artificial neuron is as follows (see fig. 2).

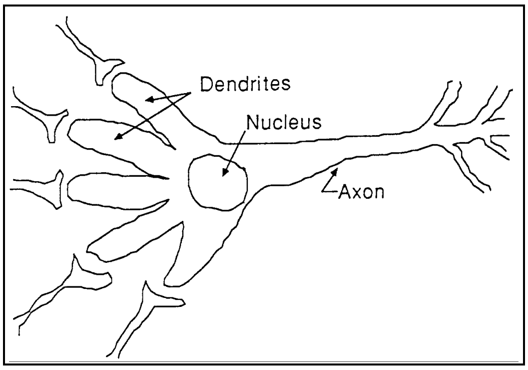

Figure 1: Schematic representation of a neuron

The weighted sum is made of the inputs Xi, after which a transfer function f is applied to generate an output Yj. This is expressed as follows

$$Y_j = f\left(\sum_{i=0}^{N} W_{ji}\ X_i\right)$$

Xi is called an input, j the layer, Wji a weight factor, f a transfer function and Yj the output.

A classical neural network consists of multiple layers of neurons with equal characteristics, where the output of one layer is the input of the next layer. The input layer, however, receives its input values from outside, and the output layer gives output values to the outside world (see fig. 3). A description into greater detail of neural networks is to be found in Lippmann [4].

4.2. Learning rules and collection of knowledge

For a certain input, an output can be calculated by repeatedly using the formula mentioned above. All Wji together determine the relationship between Xi and Yj. In other words, the knowledge of the system lies in the weight factors Wji. Hence, the neural network can collect knowledge by adapting Wji in a certain way. A method which is often used consists in the application of learn values, where both Xi and Yj are known. The output Zj generated by the neural network with input Xi is calculated. Hence, the generated error on the output j is |Zj-Yj|. This error can be back propagated through the network, where the importance of each weight Wji on the output (and on the error) will determine the extent to which this weight factor needs to be adapted for representing the knowledge as well as possible. Such a method to minimize the error by adapting the weights is called a *learning rule*. The method by which input-output values are applied for learning is called a *supervised learning rule*.

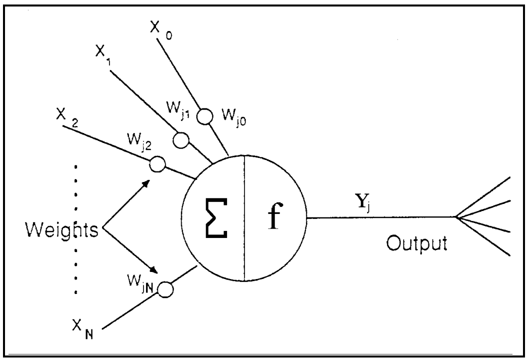

Figure 2: Implementation of a neuron

As an example of the implementation of a neural network, appendix B includes all formulas and an algorithm description of a *cumulative backpropagation network*. The output error of a number (N) of input-output sets will be summed (cumulated) and will be back propagated through the network (backpropagation).

4.3. Possibilities and limitations

The neural net model described above contains only one of the many possible topologies and methods. Hence, it is impossible to talk about the possibilities or limitations of a neural net. Each type of neural net has its own possibilities and limitations. Therefore, much study was needed before deciding to use a variant of the cumulative backpropagation network for the determination of the spinnability of fibres. This topology can easily be implemented, allows supervision and is capable of minimizing variations between the applied input-output learn values (due to erroneous empirical measurements). On the other hand, allowance must be made for the intensive computational nature of this network. Since each neuron in a layer is linked to each neuron of the previous layer and to each neuron of the following layer, calculating the output and back propagating the error may require many thousands of floating point operations.

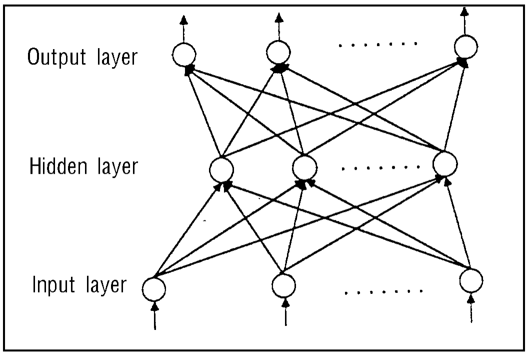

Figure 3 : Implementation of a neural network

5. Optimization and training of a neural network

Several factors are important when choosing and training the neural network. The most relevant factors will be discussed below. A cumulative backpropagation network was chosen and not a classifying network, although the problem is clearly a classification problem. The reasons behind this decision will not be dealt with here, since it would lead us to far. More information to base a choice upon can be found in [3] and [4].

5.1. Number of hidden layers

Although there is only one hidden layer on fig. 3, it is conceptually possible to implement two or more hidden layers in a neural network. However, great care should be taken here, since too large a number of layers will increase the computation time for a digital simulation exponentially. It can also be shown that for certain neural net types three layers guarantee maximum functionality, so that extra layers are useless.

5.2. Number of neurons per layer

The number of neurons of the in- and output layers are determined by the number of in- and output parameters. This is not the case with hidden layers, whose number of neurons cannot be derived from the problem. Experience and research have shown that networks where the number of neurons in every hidden layer (except for some specific cases) is taken larger than the number of input neurons behave best during training.

5.3. Number of connections between the layers

The connections between the neurons of each layer constitute a problem which offers a choice between a *fully connected network* and a *sparse connected network*. In the former case, each neuron of a layer is connected to each neuron of the previous and next layers (see fig. 3). In the latter case, not all neurons are connected to each other. Both methods can be used in certain cases and research has shown that the number of connections is not always directly proportional to the quality of the network. With a sparse connected network the choice of neurons to be connected can be made in many ways. One method consists in using certain parts of the network for a given task after analysing the problem. By means of this task division it can be determined how many and which connections are needed. Another method which gives good results in some cases is to make an arbitrary choice of the connections to be established.

5.4. Learning and testing values

The basis of the problem is the classification of several spinning sets, characterized by values of parameters determined beforehand, into two groups (spinnable or not). To this end, learning values (input-output series) of both groups must be available during training of the network. It was also found that an equal number of learning values of each output value is to be used. Otherwise, the neural net will be trained in a biased way. This means that during classification of doubtful cases these will preferably be classified in the class which presents the largest number of learning values during the training. In some cases, such a form of privilege may be useful and even desirable, but not in this case. Therefore, a random selection was made of 700 spinnable and 700 unspinnable yarns which were used for the training. The other input-output values were used to test the trained network for values which it did not know during the training. We call them test values.

5.5. Generalization versus specification

When training a neural network two specific behaviour patterns must be considered: generalizing and specifying behaviour.

The *generalization property* can be defined as the inherent behaviour of every neural network to risk a calculated bet on what the output values will be in case of unknown input values. A kind of generalized interpolation with error minimizing will be applied here, so that extreme errors are excluded (even outside the input area). The generalizing behaviour can be poorly or well developed depending on the type of network and the training. Experience has shown that as a network traverses more training cycles (during which the same input-output learning values are offered), it loses its generalizing property.

The *specification property*, also called *associative behaviour*, is the neural net property of being able to reproduce the values which it is presented during the learning stage faultlessly. This property turns the neural network into an associative memory. It goes without saying that the specifying behaviour of a network is directly proportional to the number of training cycles, but is also determined by the type of network and the convergence behaviour of the network.

Experience has shown that for the chosen network type the generalizing and specifying behaviour are each other's counterparts. Since they both depend on the number of cycles run through, it can be stated that the overall error of the network can be minimized by choosing this number of learning cycles (T) so that

$$\varphi(T) + \xi(T) \leq \varphi(t) + \xi(t) \qquad \forall\, t \in N_0$$

where $\varphi(t)$ is the overall error made by the network for the test values after t learning cycles (generalization error), and where $\xi(t)$ is the overall error made by the network for the learning values after t learning cycles (specification error). It was always found possible to determine an approximate value for T (see fig. 4).

The following should be considered. Most neural nets are implemented as digital simulations. As mentioned above, one learning cycle may entail many thousands of floating point operations. Since the duration of the learning phase directly depends on the number of learning cycles, this number must be kept limited to allow digital simulation. This can be done, for example, by using an alternative solution instead of looking for an absolute minimum of the error curve as discussed in the previous paragraph. This alternative solution consists in determining positive values $\varepsilon_0 \in R^+$, $\varepsilon_1 \in R^+$ and a sufficiently large value $\eta \in N_0$ so that the smallest possible T is chosen for which

$$\varphi(t_0) + \xi(t_0) - \varphi(t_1) - \xi(t_1) \leq \varepsilon_0 \quad \forall\, t_0, t_1 \in [T, T+\eta]$$

and

$$\varphi(T) + \xi(T) \leq \varepsilon_1$$

In other words, the smallest possible value T will be chosen for which $\varphi(t) + \xi(t)$ only make small fluctuations within a limited range $[T, T+\eta]$. Also, $\varphi(T) + \xi(T)$ must be acceptably small. It goes without saying that such a method does not find the absolute minimum of the error curve. However, it was always found possible to find a satisfactory value for T by carefully choosing ε_0, ε_1 and η.

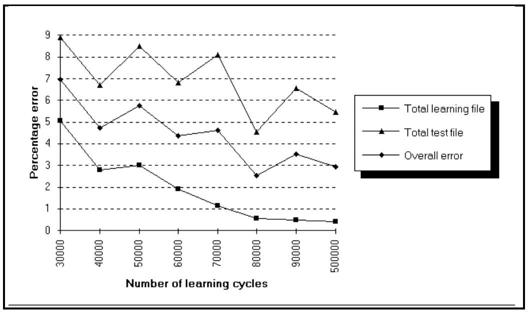

Figure 4: Curve of the error during the learning process

6. Results

6.1. Spinnability

The spinnability of each of the 2,150 yarns was determined. A yarn difficult to spin was given a 0 rating and a yarn which was well spinnable received a 1. The results of a rotor-spun yarn of 25 tex with a twist coefficient α_{tex} of 3,500 are represented in figures 7 and 8.

6.2. Prediction of the spinnability by means of neural networks

When learning the network, phases of ten thousand learning cycles were used. After each phase, the output generated by the network was determined both for the test and the learning series. It was then compared to the output values to be expected. In this way, a learning and a test error were determined. Figures 5 and 6 show the percentage error measured after several learning cycles.

Fig. 5 shows that the results of the learning series are on average improving till 80,000 learning cycles. After 80,000 learning cycles however, no significant improvements occur.

Fig. 6 shows that the fluctuation of the overall error for the test values decreases starting at 80,000 learning cycles. If we take this into account and choose ε_0 = 1%, ε_1 = 4% and η = 400,000 than

T = 80,000 is evident. It must be noted that in figures 4, 5 and 6 the values on the x-axis between 100,000 and 500,000 have been left out because they burden the graph without providing any relevant new information. The value of the error curves at 500,000 learning cycles is representative for the entire course of these curves for a number of learning cycles between 100,000 and 500,000.

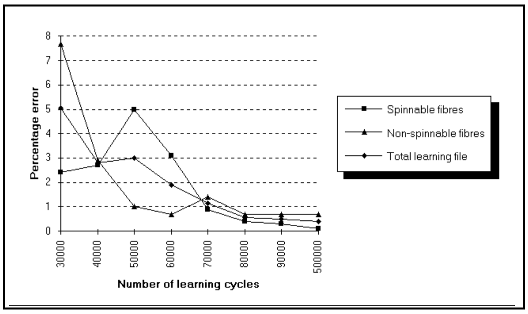

Figure 5: Error percentage on the learning series

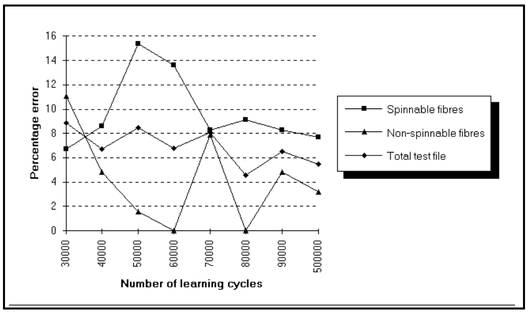

Figure 6: Error percentage on the test series

The classification carried out by the neural net after 80,000 learning cycles is shown in figures 7 and 8. The network output lies between 0.5 and 1 for the input parameter sets that are considered spinnable. The input parameter sets that are classified as unspinnable generate an output between 0 and 0.5.

Both curves in figure 7 represent the classification figures given by the network to the input parameter sets from the test file that are respectively spinnable (black squares) and unspinnable (black circles). The x-axis was rescaled to show the percentage of the entire number (100%) of spinnable fibres (i.e. that should generate an output between 0.5 and 1) that were classified as unspinnable (generated an output between 0 and 0.5) and vice versa. This graph shows that 90% of the spinnable fibres and 95% of the unspinnable fibres were correctly classified.

The classification carried out by the neural net generates a figure between 0 and 1. The values around 0.5 are doubtful cases. Obvious, a classification method should generate as few doubtful cases as possible. Figure 7 shows that less than 6% of the cases generate an output between 0.25 and 0.75.

Figure 8 shows the classification carried out by the neural net of the cases that are uncertain. Here as well the neural net carries out a clear classification, in which only 1 case generates an output between 0.25 and 0.75 (more precisely 0.37).

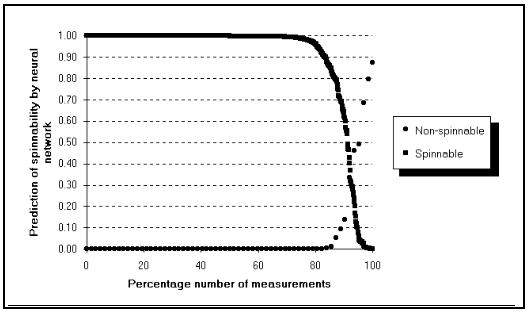

Figure 7: Classification of known test series values

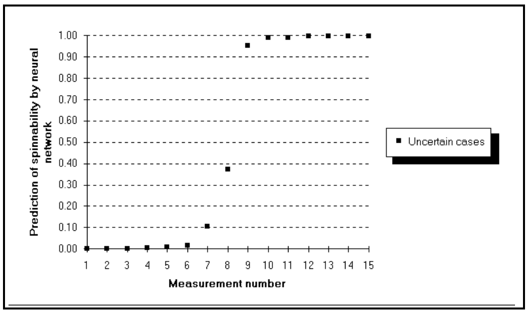

Figure 8: Classification of the uncertain test series values

7. Conclusion

It can be stated that a neural network is a very useful method to predict the spinnability of a yarn. The results have shown that a reliability of 95% can be reached.

Naturally, these figures must be interpreted with the necessary caution, since it concerns tests on a very small scale (despite the large number of tests). The basic structure of the neural network which was used can be applied for the prediction of the breakage rate on a rotor or ring spinning machine. Therefore, the network must be retrained with a series of data on fibre properties, machine settings and yarn specifications.

Further research is conducted in three fields. First, making the network output continuous, so that the network can generate a breakage rate instead of a classification. Subsequently, a network can be built which, in case of spinnability, determines the yarn properties by means of the fibre properties and machine settings. Finally, a neural network can be used to determine the way in which a certain type of spinning machine must be set in order to spin a fibre type into a yarn with properties determined beforehand.

8. Literature

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9. Acknowledgements

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Appendix A. List of the symbols used for the fibre properties

List of the symbols used for the fibre properties

Parameters measured at the Textile Department of the University of Ghent

Symbol	Instrument	Fibre Property
rugLEN	HVI	mean length
rugUN	HVI	length uniformity
rugSTR	HVI	strength
rugEL	HVI	elongation at break
rugMIC	HVI	micronaire

Parameters measured at the laboratory of the Institut Textile de France - Section Nord (Lille, France)

Symbol	Instrument	Fibre Property
itfFINdtex	FMT	fineness, expressed in dtex
itfPM	FMT	% mature fibres
itfB	HVI	yellowness
itfRD	HVI	brightness
itfAREA	HVI	amount of trash
itfMIC	HVI	micronaire
itfWAX	extraction	wax content
itfSUGAR	extraction	sugar content

Parameters measured at the laboratory of Trûtzschler (Mönchengladbach, Germany)

Symbol	Instrument	Fibre Property
trutDUST	Shirley Analyzer	percentage of dust
trutSEED	manual measurement	number of seed particles
trutTOTNEP	manual measurement	total number of neps
trutBIGNEP	manual measurement	number of large neps

Parameters measured at the laboratory of Harlander Coats (Ochsenburg, Austria) on the AL-meter instrument

Symbol	Fibre Property
NR-CV	coefficient of variation of length, weighted by number
NR-SF	percentage of short fibres, weighted by number

Parameters measured at the laboratory of Zellweger (Uster - Switzerland) on the AFIS instrument

Symbol	Fibre property
diam	mean diameter of the neps
diamCV	coefficient of variation of the nep diameter
cvNpg	coefficient of variation of the number of neps per gram
L-LWcv	coefficient of variation of the mean length, weighted by length
L-UNW	uniformity of the length, weighted by length
L-UNWcv	coefficient of variation of the length uniformity,weighted by length
L-UNN	length uniformity, weighted by number
L-SFCN	percentage of short fibres, weighted by number
L-D	mean diameter
L-Dcv	coefficient of variation of the mean diameter

Appendix B. List of the fibre properties considered

quality	ruglen	rugUN	rugSTR	rugEL	rugMIC	itfFINdtex	itfIPM	itfB	itfRD	itfAREA	itfMIC	itfwax	itfsugar	TrutDUST	TrutSEED
1	1.09	83.5	23.9	5.6	4.6	2.04	80.6	10.27	75.8	0.15	4.6	0.42	0.2	0.544	46.5
2	1.39	85.73	33.27	6.59	4.27	1.62	86.2	12.2	65.4	0.12	4.3	0.5	0	0.387	25.7
3	1.22	86.55	35.05	6.81	5.15	1.86	86.3	9.33	74.5	0.23	5.3	0.4	0	0.457	29.3
4	1.14	83.64	31.04	5.84	4.23	1.7	87.3	8.39	78.1	0.4	5.8	0.46	0.1	0.328	138
5	1.12	82.52	24.9	5.76	4.5	2.04	77.7	8.03	73.9	0.63	4.4	0.39	0	0.323	91
6	1.15	83.78	22.75	6.18	3.89	1.72	77.3	9.87	75.7	0.24	4.1	0.46	0	0.483	87
7	1.19	84.76	26.29	6.17	4.15	1.82	72.1	9.46	76	0.09	4.3	0.47	0.15	0.464	60
8	1.11	83.26	24.13	6.17	4.74	1.89	83.2	9.27	78.6	0.04	4.7	0.45	0.2	0.41	60
9	1.31	84.73	27.97	6.01	3.45	1.57	68.1	9.23	78.2	0.13	5.2	0.56	0.4	0.589	103
10	1.1	84.43	25.07	5.74	4.69	2.33	77.3	9.33	72.4	0.74	5	0.45	0.15	0.353	79
11	1.11	80.84	26.82	6.18	3.17	1.37	59.3	8.53	77.2	0.06	3.1	0.73	0.25	0.656	108
12	1.12	81.6	27.7	6.2	3.3	1.57	62.5	8.9	76.2	0.18	3.3	0.79	0.3	0.595	89
13	1.12	83.6	28.1	6.1	4.3	1.82	82.2	11.67	74.1	0.08	4.2	0.52	0.2	0.365	99
14	1.1	84.6	27.8	6.4	4	1.73	76.5	8.96	79.4	0.04	5.5	0.6	0	0.38	42
15	1.15	82.9	26.5	6	4.2	1.82	73.1	10.17	70.5	0.11	4.4	0.59	0.1	0.458	110
16	1.08	82.19	27.26	5.3	3.04	1.55	57.6	12.33	65.9	0.28	4.4	0.66	0	1.175	53
17	1.4	88.18	37.56	6.6	4.2	1.64	80.7	9.53	72.1	0.38	4.3	0.56	0	0.444	18
18	1.1	82.9	25.5	5.8	4.15	1.86	71.3	8.9	57.1	1.29	4.2	0.63	0	0.94	35
19	1.15	82.32	25.88	6.03	4.45	1.98	80.2	8.36	74.4	0.72	5.3	0.55	0	0.434	29
20	1.17	82.04	28.55	5.74	3.99	1.68	83.1	9.73	72.6	0.13	3.9	0.4	0	0.483	95

TrutTOTNEP	BIGNEP	NR_CV	NR_SF	Ndiam	NdiamCV	cvNpg	L_LWcv	L_UNW	L_UNWcv	L_UNN	L_SFCN	L_D	L_Dcv
242	4	37.6	17.1	0.76	3.09	12.89	0.3	31.9	0.5	43.7	23.7	15.6	0.7
132	3	35.4	7.9	0.74	5.59	38.95	1.1	33.7	4.7	45.8	18.4	13.7	3.5
143	2	33.2	8.4	0.7	12.56	29.21	4	29.3	2.3	39.3	15.2	13.8	2
359	10	34.1	11.6	0.77	3.21	7.61	0.9	31.2	0.7	41.9	20.3	14.3	0.1
316	8	38.5	17.4	0.75	0.51	7.21	1.9	33.6	0.3	45	25.9	15.5	1
189	2	33.5	11.8	0.74	3.07	14.97	1.1	33.5	4.9	44.4	24	14.5	4.1
145	2	32.2	8.9	0.72	6.71	38.34	2.8	33.1	1.6	47.1	25.6	14.4	1
213	5	36.4	14.2	0.74	1.2	9.99	0.3	32.9	0.8	45.1	24.9	15.2	0.6
269	3	42.1	17.4	0.71	4.57	37.67	2.6	34.4	4.4	47.1	22	13.7	1.7
173	0	35.1	14.4	0.72	6.12	46.76	3.9	31.8	2.8	43.6	24.7	15.3	2.6
429	23	35.5	14	0.8	1.15	8.74	1.6	34.2	1.6	44.6	27.3	14.4	1.2
358	13	36.2	14.3	0.81	1.9	8.94	0.8	31.2	2.3	43.5	22.7	15.4	1.9
229	5	32.9	10.8	0.73	2.58	10.33	3.6	32.1	2.5	42.1	22.1	14.6	0.7
143	7	30.4	8.3	0.71	0.76	7.29	0.8	29.7	4.4	40.2	19.3	14.5	0.4
235	4	32.3	8	0.73	1.78	7.35	1.8	34.4	2.7	46	25.3	14.9	1.1
329	10	38.1	19.5	0.83	2.04	13.25	2	33.7	0.9	45.2	26.6	14.3	0.9
113	2	39.5	11.9	0.73	7.09	23.94	2.6	32.7	6.1	46.7	18.7	13.4	3.5
476	3	35.4	14.3	0.77	4.24	10.2	1.8	33.7	1.1	49.1	29.2	14.7	1.4
299	4	38.7	18.1	0.74	2.24	10.12	1.6	32.8	1.8	45.8	24.4	14.9	1.1
246	3	41.1	20.8	0.77	2.94	16.42	1.4	32.6	0.8	43.9	21.9	14	1.3