A CORRELATION BETWEEN TENSILE YARN PARAMETERS AND PRODUCTION CHARACTERISTICS

I. Bauer-Kurz and W. Oxenham
College of Textiles
North Carolina State University
Raleigh, NC

Abstract

Tensile data of various rotor and ring spun knitting yarns with different finishing treatments are analyzed in order to produce a correlation with yarn performance and production parameters. Among the fitted theoretical distributions, the Weibull and the Normal distribution function are closest to the experimental data distribution. The fit of both distributions deteriorates as the data increases. The data are also analyzed statistically with the "Moving Average" test and a Spectral Analysis. From the wavelengths of obvious periodic errors in the yarns it can be seen that these were produced mainly in the last production passages before spinning. Furthermore, a clear trend corresponding to a periodicity with the huge wavelength of a whole cone can be revealed for the ring spun yarns. The process parameter "spinning system" can be predicted clearly with a Neural Back-propagation Network. Knitting performance does not show a good correlation. The correlation results achieved with the Neural Network confirm that the Weibull distribution gives even a slightly better description of the experimental data than the Normal distribution.

Introduction

The information obtained from traditional tensile testing has not enabled the spinner to accurately predict the performance of the yarn in subsequent processing stages, since parameters of tensile data produced by conventional slow speed testing do not show a good correlation with the yarn's further processing performance.

The high speed tensile tester Tensojet® is capable of very rapidly generating a large amount of data about the tensile properties of yarns, but there is yet no definitive way to utilize this data. At present the main application is the identification of "seldomly occurring weak places" in the yarn, which is of obvious practical importance in terms of weavability of the yarn. It is however believed that the data contains other information, which is not being utilized and could give better indications of the processability of the yarn and quality of products made from the yarn.

Reprinted from the *Proceedings of the Beltwide Cotton Conference*
Volume 1:809-816 (1998)
National Cotton Council, Memphis TN

Three specific aspects come to mind and these are:

- There is still uncertainty about which is the best statistical distribution to apply to the strength of yarns and whether different yarns follow the same distribution. This is of great importance since it forms the basis of models for predicting end breaks during yarn processing. The difficulty faced by earlier research workers (the generation of sufficient data to validate proposed models) has been overcome with the availability of high speed testing, data acquisition and analysis.
- The variation of yarn strength may not be random but could be influenced by systematic changes in spinning conditions (such as changes in tension associated with package "build" in spinning). By using appropriate analysis tools it should be possible to determine whether such variations are present in the yarn.
- The variation of yarn strength is likely to be a combination of "random" and "systematic" components. The latter could be related to defects in machinery and/or feed materials and by isolating the effects of each component of variation it could be possible to identify, and hopefully remove, processing deficiencies. The approach that would be followed is to utilize the time series of strength data and to analyze this for variations which are non random.

The goal of the investigations presented in this paper is to enhance the knowledge about the tensile characteristics of yarns, and ultimately develop a routine for providing useful and concise information from the yarn tester, which can give an indication of possible difficulties that may occur in subsequent processing as well as defects that may have been introduced during manufacture.

Tensile Testing

Tests were carried out on a range of 100% cotton knitting yarns using the Uster Tensojet® in order to:

- determine the distribution of tensile data and the occurrence of weak places;
- correlate tensile yarn characteristics with process parameters during spinning;
- winding and correlate tensile yarn characteristics with yarn performance during subsequent processing.

Three different commercial ring-spun yarns and three commercial rotor yarns were tested with the Tensojet®, each yarn had three different "finishing" treatments. The different finishes applied to the yarns were

- unwaxed – the yarn was supplied from the manufacturer without any surface finish (apart from any natural wax) but was rewound to be consistent with other samples;
- waxed – the unwaxed supply yarn was run over a wax disc on a winding machine – as is normal for knitting preparation;
- emulsion coated – the yarn was run over a "lick roll" on a winding machine to apply "liquid wax" to the yarn surface.

As the "finish" may have an essential influence on the knitting performance, it was necessary to determine also the influence of the finish on the tensile properties of the yarns.

With the Uster Tensojet®, the mechanism, which is used for applying a tensile force to extend and ultimately break a specimen, consists of two pairs of eccentric rollers arranged at a distance of 500 mm. The yarn end is inserted between the rollers and extended with a maximum testing speed of 400 m/min according to the principle of CRE (**C**onstant **R**ate of **E**longation). Because of the extremely high testing speed, a single full measurement cycle takes just 0.12 seconds. Figure 1 demonstrates the function principle.

Every yarn was tested without coating, waxed and with emulsion by the Tensojet in 8192 single tests. The printed outputs of the Tensojet include a summary "Uster Quality Report", see Figure 2, histograms of Breaking Force and Elongation and stroke diagrams. The most important characteristic values measured by the Tensojet are summarized for all tested yarns in Figure 3. As expected, the mean values of the tensile parameters for the ring spun yarns are substantially higher than those for the rotor yarns. Furthermore, the three rotor yarns showed a much better homogeneity of the tensile characteristics than the ring spun yarns.

The practical testing of the waxed yarns revealed substantial problems, since the yarns broke immediately in the feeding zone and created wraps on the rollers. The testing performance could be improved by manually setting a slightly lower pretension. As showed in Figure 3, in general the values of Breaking Force and Elongation and consequently the Work-to-break values are higher for the waxed yarns. This different behavior may be due to the lower testing pretensions for these yarns. Like the unwaxed rotor yarns, the waxed ones show a good uniformity and an equally elliptic scatter plot for the tensile characteristics. The irregularities and periodicities detected for the Ring spun yarns and are likewise detectable for the waxed yarns.

The testing of the emulsion yarns showed the same problems as during the testing of the waxed yarns, but even more extremely. The elongation values of the emulsion yarns are higher than those of the uncoated yarns, which may again be caused by the lower pretension. However, in comparison with the waxed yarns, the elongation values are lower, even when applying the same pretension. Waxing may give more elasticity to the yarns than emulsion coating. These different influences of wax and emulsion are even more pronounced when looking at the force values. In general the breaking force of the emulsion yarns is lower than that one of the uncoated ones, whereas the breaking force of the waxed yarns is even higher than the one of the uncoated ones in most cases. The results of the comparative testing of yarn C – Ring with emulsion under the three different pretensions of 15, 16 and 16.5 grams, see Figure 4, show that indeed the mean values of Breaking Force, Elongation and Work go down with a higher pretension. However, this difference ranges around 1% for the Force values and around 5% for Elongation and Work, which is even small in comparison to the difference between values of yarns with different coating treatment.

Data Distribution

Data basis for the analysis of the distribution were the data for Breaking Force, Elongation and Work-to-Break produced by the Tensojet®. The variously sized data sets of 8192, 4056, …, 64 single data points were analyzed by running the statistical software program SAS©. The four theoretical distribution functions defined in Figure 5 were fit to the experimental data. In general, the analysis of each data set consists of two steps:

- Determining the distribution parameters for the best fit
- Interpretation of the goodness-of-fit of these optimized distribution curves

The fitting characteristics of the various theoretical distributions can easily be evaluated from the graphical display of the distributions provided by SAS©, exemplary shown in Figure 6. The minimum CHI-Square values for every distribution and the corresponding probability values were summarized for each yarn. Since especially for the interpretation of weak spots, the data points at the lower end of the distribution curve might be of great importance, the 1% and 5% values were also reported. Furthermore, all these parameters were monitored in dependence of the different data set sizes, as shown in Figures 7 to 10. The summary of these investigations is shown in Figure 11. From the detailed analysis of the fitting characteristics, the following conclusions for the data distribution can be drawn:

- In general, the Weibull and the Normal distribution functions provide the best fit to the experimental data distribution.
- In comparison with each other, the Normal distribution fits better than the Weibull distribution for bigger data sets, and the Weibull distribution fits better for data sets with less single data points.

- Both distributions fit reasonably well for smaller data sets, based on the CHI-square criterium, with a probability of CHI-square greater than 0.05 for data sets with approximately N<1024.
- However, the error of the predicted percentiles (1% and 5% values) in comparison to the experimental values does not depend on the data set size.
- Generally, the Normal distribution calculates too high percentile values, whereas the Weibull distribution calculates too low percentiles. This means, that the Weibull distribution predicts too many weak places, which is on the safe side and thus better than assuming too few weak places for actual production performance.
- The work data cannot be fit to any theoretical distribution.
- No pronounced difference in fitting could be found for tensile data of different yarns, especially for rotor and ring spun yarns.
- Elongation and Force data fit equally well.

Test of Moving Average

In order to explain why the fit of statistical distributions gets worse with the growth of the number of data points within a data set, the Moving Average analysis tool of Excel© is used to analyze the data. This analysis tool and its formula can project values in the forecast period, based on the average value of the variable over a specific number of precedent periods. From Figure 12, representatively for the elongation data, can be seen, how the average calculated of the last 256 data points moves within the whole data set of 8192 data points for the ring spun yarns. Due to the non-stability of the mean, it is obvious that the data can't be considered as being randomly distributed. This supports the experience that a smaller sized data set, within which the mean is much more stable than in a larger one, can be traced much better with a statistical distribution function.

However, the rotor yarns, see Figure 13, produce a fairly constant mean, which still does not explain why bigger data sets fit worse to a Normal or Weibull distribution than smaller ones. Finally, the only reason that can explain this behavior is that obviously the data collection cannot be considered as random. This might be due to the fact that not every yarn spot is measured successively, but there are 30 cm of non-tested material between to subsequent 50 cm tested yarn pieces. Furthermore, the data value of the tested piece is not representative for the whole length of the piece, since it is only the value of the weakest spot.

Fourier Analysis

The Fourier Analysis of the tensile data is completed with the SAS© Procedure Spectra.

For the tensile data of yarn A-OE, all three parameters show a fairly flat spectrum with pronounced peaks.
The data of yarn C – OE produce a spectrum with a more or less White Noise few visible peaks.

- Yarn D – OE shows a smooth spectrum with some strong peaks for all three parameters. Especially the Force spectrum has a clear spike at the frequency of 0.55 and spikes at the corresponding harmonics, which can be seen from Figure 14. This means the Force data of yarn D – OE contain periodic components that are not exactly sinusoidal. Partially, this periodicity can be observed again in the Work data.
- The spectra for the Force and Elongation data of yarn B - Ring show various visible peaks at corresponding frequencies, whereas the Work data show a spectrum of pure White Noise.
- For both, yarn C – Ring and D – Ring, a few peaks can be observed for each of the tensile parameters Force, Elongation and Work.
- The spectra for the waxed Rotor yarns in general show a lot of White Noise, so that periodicity peaks can barely be detected. Only for yarn D – OE waxed a few peaks might strike in the eye. In addition, for yarn A - OE waxed, the spectrogram of the parameters Force and Work show a slight Positive Autocorrelation.
- The waxed Ring yarns in general have similar spectra to the uncoated corresponding yarns. The parameters Force and Elongation produce visible peaks.
- In general, the yarns with Emulsion coating show similar spectral characteristics as the uncoated and the waxed yarns.

Figure 15 shows the frequencies and the resulting wavelengths of substantial periodicities of the yarns. Several conclusions can be drawn:

- None of the yarns exhibited periodicities of big wavelengths, e.g. caused by mistakes during early drawing passages or carding. Periodic errors produced in the early yarn forming process may be drawn out again in later drawing passages. Therefore, originally periodic errors of big wavelengths will not produce a clear signal in the spectrogram of the produced yarn. Only errors that have been produced in the final drawing passage or during spinning or winding cause clear periodicities in the final yarn.
- The winding process when waxing or putting emulsion on the yarns did not cause any periodic errors. As all yarns were waxed while running on the same machine, an error caused by this machine would appear as a peak at a

steady frequency for all waxed yarns. Additionally, since the periodic errors with the shortest wavelength range still around 2.5 meters - which is far more than the circumference of any rotating part that could cause an error during winding - no errors in the winding process can be detected.

- The range of wavelengths at which substantial periodic errors could be detected for the ring spun yarns, 2.5 to 18.5 meters, points to problems with rollers before the final spinning draft. A periodic error with a wavelength of 5 meters also could have been caused by the cycle of the cone winding, since 5 meters is approximately the yarn length wound on an average cone from top to bottom to top during one spindle bank movement cycle.
- In general, two reasons for periodic effects in the sliver entering the ring spinning frame can be considered: Roller defects in the drafting system or a drafting wave typically built up by accumulations of shorter and longer fibers during the drafting process (for cotton approximately with a wavelength of 60 mm). The corresponding places and wavelengths of the produced periodicities can be seen from Figure 16.
- Likewise, substantial periodicities detected for the rotor yarns are either produced in the last drawing passage or in the feeding zone of the rotor spinning frame.

Correlation with Yarn Performance

The correlation of the tensile data with performance characteristics was done with a Neural Network using the *Backpropagation* algorithm. Fundamental structure and characteristics of the network used are summarized in Figure 17.

The yarns were knitted on a Monarch circular knitting machine model PXC-45B with 64 feeds. In order to produce a visible number of machine stops, the machine was operated at a fairly high speed of 58.7 revolutions per minute with a circular length of 165 inches. Two kinds of errors were monitored: top stops caused by end breaks in the yarn transport due to bad packages etc. and bottom stops because of slubs due to lint built-up. Since the amounts of knitted yarn differ, the counted numbers of end breaks were normalized by dividing the original numbers by the weight of the knitted yarn.

In general, the ring spun yarns produced more end breaks than the rotor yarns. Considering that these yarns are even stronger than rotor yarns of the same yarn count, this shows that knitting performance does not primarily depend on the tensile strength, but also on other factors such as the hairiness. Weaving performance would certainly give a better criterium for the tensile performance, but no weaving capacity was available during the course of this project. In spite of the lack of this obvious link between the tensile strength and the knitting breaks, it does make sense to correlate tensile parameters to knitting parameters. If a neural network is able to produce knitting performance parameters on the basis of yarn characteristics such as distribution parameters of tensile yarn characteristics, this means that it is in general possible to classify yarns on the basis of these tensile parameters. The hairiness, which may be the reason for the various knitting performance, is not explicitly considered as a parameter, but is implicitly included in the distribution parameters that characterize a yarn. Thus, it would even be a major step forward if general yarn characteristics such as the spinning system or the kind of coating treatment could be identified by distribution parameters of tensile characteristics. On this basis, it will be an easy task to correlate tensile characteristics and actual weaving performance.

Since the purpose of the data interpretation is the conclusion from tensile testing outputs to actual knitting performance or processability-dominating yarn characteristics, the inputs will be parameters of the Tensojet data and the outputs will be process parameters or general yarn characteristics. Appropriate input parameters are distribution parameters or consecutively calculated theoretical percentiles of the Weibull and the Normal distribution. For the Weibull distribution, two different input dat sets were considered: The first set contains just the three pure distribution parameters, whereas the second one consists of values theoretically calculated from the distribution function such as the theoretical mean, standard deviation and the percentiles. These values have the disadvantage of a more complicated calculation, but the advantage of being comparable to the corresponding parameters of the popular Normal distribution. A third input set consisting of parameters of the commonly used Normal distribution will also be used in order to compare the goodness of correlation. Finally, each of the three input sets is produced for the elongation and the force values and for all differently sized data sets.

The training and testing with the Neural Network delivered the following results:

- The Neural Network-based correlation shows that a distinction between the Ring and the Rotor spun yarns can be predicted fairly well, see Figure 18. However, the net can't recognize and finally learn the slightly more irregular output pattern of the bottom stops.
- The training of the variously sized data sets show that medium sized data sets of approximately 1024 single data points produce the best prediction quality. On the one hand, this behavior corresponds to the fact that the statistical goodness-of-fit criteria (CHI-square

statistics) is worse for bigger data sets. On the other hand, the slightly better fit for data sets of 1024 data points in comparison to data sets of 256 data points may be explained with the fact that 1024 data points represent better a typical sample of the yarn, so that a slightly worse fitted distribution curve to a better sample does still give a better description of the yarn.

- The training also showed that in general the force data produce a better fit than elongation data.
- Taking the Weibull distribution parameters as input, the results are not satisfying. However, when considering characteristically calculated values of the Weibull distribution like mean, standard deviation and the percentiles, the Weibull distribution even produces a slightly better fit and prediction than the Normal distribution. Only 3 input parameters in comparison to the given 4 of the Normal distribution might simply be too few. However, it seems to be reasonable that characteristic values, like the mean and the percentiles (no matter if calculated for a fitted Normal distribution or out of the Weibull distribution parameters) are of great importance for the prediction of spinning parameters such as the Spinning system.
- Figure 18 shows that in general a correlation between tensile yarn parameters and other system parameters is possible. The bad fit to the actual knitting performance has to be explained with too few and non-representative processing data. In fact, since the two bottom stop counts for yarn D-Ring waxed and B-Ring emulsion fairly deviate from the general pattern of knitting performance, for a small pattern of only 18 observations that is more than 10% deviation and might cause the net to not learn the pattern properly.

Results and Conclusions

The analysis of the data distribution with the program SAS© showed that for most of the data sets, the Weibull and the Normal distribution functions fit best to the experimental data distribution. According to statistical goodness-of-fit criteria like the CHI-square test, in general both of these distributions trace much worse the experimental data with a growing number of single data points. Since per definition an idealized random sample will approach a Normal distribution function with a growing number of observations, this contradictory behavior shows that the collected tensile data are not at all random. This may have the following reasons:

- The data points were not randomly collected (since there are 30 cm of non-tested material between two successive Tensojet tests, that deliver a minimum value, the collected data does not represent a random sample),
- the data within big data sets show a long term trend that is not revealed in smaller data sets - This moving average may cause the bad fit of theoretical distribution functions,
- the data show periodicities that are more pronounced when interpreting larger data sets.

The last two points were analyzed statistically with the "Moving average" test and a Spectral Analysis. From the wavelengths of obvious periodic errors in the yarns could be seen that various tensile periodicities were produced mainly in the last drawing passage, during roving (for ring spinning), or at the feeding devices of the spinning frames for yarns of both spinning systems. The test of the moving average revealed a clear trend corresponding to a periodicity with the huge wavelength of a whole cone for the ring spun yarns, which could not be detected by the Fourier analysis.

In order to correlate the tensile data to yarn performance in further processing, distribution parameters and characteristic values were calculated for the best-fitted theoretical distributions of the Weibull and the Normal functions. Since knitting performance is mainly determined by the hairiness of the yarn, a correlation between tensile yarn parameters and knitting performance corresponds to a correlation with the yarns' parameters "spinning system". However, this correlation makes sense, because any correlation between Tensojet testing results and typical general yarn parameters shows that these testing results give reproducible information about other yarn parameters, that may determine the yarn performance.

With a Neural *Backpropagation* Network the process parameter "spinning system" could be predicted clearly. This shows representatively, that Tensojet data do contain a lot more information than simply breaking force and elongation. The knitting performance could not be traced well, but this behavior could be explained by too few and not representative performance data, since only two collected data points that do not fit into the expected pattern value more than 10% of the data entity and may cause the net not to recognize the pattern.

The training with the Neural Network again demonstrated that distribution characteristics calculated with Weibull parameters fit even a little better than parameters of the Normal distribution. However, the three Weibull distribution parameters their self do not give a good picture of the data distribution, but Weibull mean, standard deviation and the percentiles calculated subsequently give a clear description of the experimental data distribution.

Acknowledgements

The authors wish to thank Prof. Dr.-Ing. Burkhard Wulfhorst, who laid the foundations for this work by supporting the teamwork between the RWTH Aachen and the North Carolina State University. Further more, deep appreciation goes to Dipl.-Ing. Dieter Veit who provided interesting and helpful ideas.

Sincere thanks are extended to the "Walter Reiners-Stiftung des Deutschen Textilmaschinenbaues" and Cotton Inc. for financially supporting this study.

References

Douglas, K. Zellweger Uster: Tensojet Yarn Tensile Tester. Textile World, April 1993, P111-112.

Zellweger Uster. Uster Statistics 1989. No. 36 October 1989.

Bona, Mario. Statistical methods for the textile industry. Textilia, Istituto per la Tradizione e la Texnologia Tessile S.p.A., Biella, Italy 1993.

O'Neil, Peter V. Advanced Engineering Mathematics. PWS Publishing Company, Boston, USA, 4th edition, 1995.

SAS Institute Inc. User's Guide. Basics, Version 5. 1985 Cary, NC.

SAS Procedure Capability. User's Guide. 1986 Cary, NC.

SAS System for Forecasting Time Series. 1986 Cary, NC.

Sette, S., Boullart, L. Fault detection and quality assessment in textiles by means of neural networks. International Journal of Clothing Science and Technology. Volume 8 Number 1 / 2. MCB University press limited. Bradford, England. 1996.

Zeidenberg, M. Neural Networks in Artificial Intelligence. Ellis Horwood limited. 1990.

Veit, D., Bauer-Kurz, I., Wulfhorst, B. Prediction of the yarn characteristics in the false-twist texturing process with neural networks. Chemical Fibers International 47 (1997), 82.

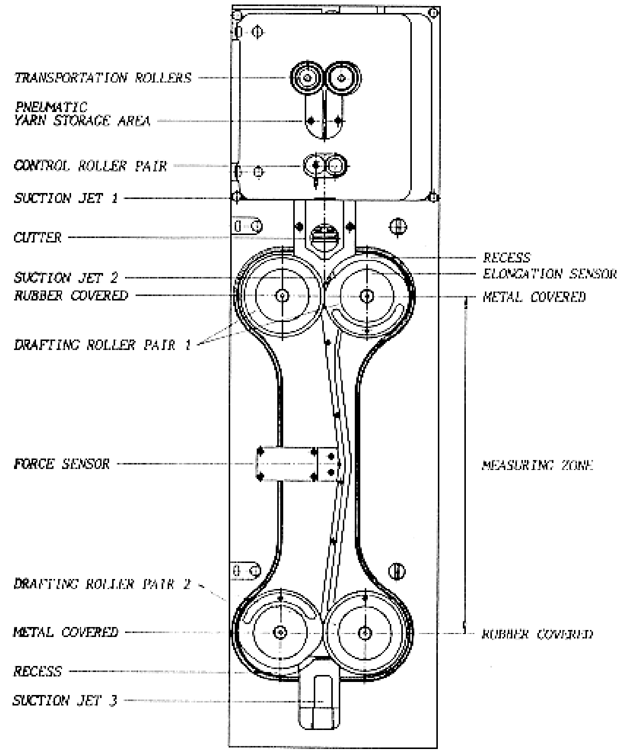
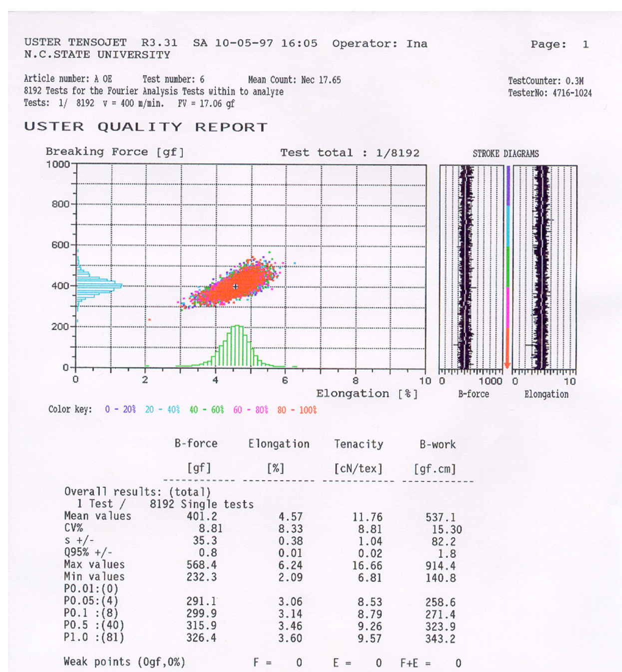


Figure 1: Uster® Tensojet function principle


USTER TENSOJET R3.31 SA 10-05-97 16:05 Operator: Ina Page: 1
N.C.STATE UNIVERSITY

Article number: A OE Test number: 6 Mean Count: Nec 17.65 TestCounter: 0.3M
8192 Tests for the Fourier Analysis Tests within to analyze TesterNo: 4716-1024
Tests: 1/ 8192 v = 400 m/min. FV = 17.06 gf

USTER QUALITY REPORT

	B-force [gf]	Elongation [%]	Tenacity [cN/tex]	B-work [gf.cm]
Overall results: (total)				
1 Test / 8192 Single tests				
Mean values	401.2	4.57	11.76	537.1
CV%	8.81	8.33	8.81	15.30
s +/-	35.3	0.38	1.04	82.2
Q95% +/-	0.8	0.01	0.02	1.8
Max values	568.4	6.24	16.66	914.4
Min values	232.3	2.09	6.81	140.8
P0.01:(0)				
P0.05:(4)	291.1	3.06	8.53	258.6
P0.1 :(8)	299.9	3.14	8.79	271.4
P0.5 :(40)	315.9	3.46	9.26	323.9
P1.0 :(81)	326.4	3.60	9.57	343.2

Weak points (0gf,0%) F = 0 E = 0 F+E = 0

Figure 2: Uster® Quality Report

	Pretension [g]			Breaking Force (Mean) [g]			Elongation (Mean) [%]			Work-to-break (Mean) [g•cm]		
Yarn	Un-coated	Waxed	With Emul-sion	Un-coated	Waxed	With Emul-sion	Un-coated	Waxed	With Emul-sion	Un-coated	Waxed	With Emul-sion
A-OE	17.06	15.00	15.00	401.2	423.6	387.8	4.57	5.54	5.09	537.1	650.6	562.4
C-OE	16.65	15.50	15.00	404.8	415.6	392.2	4.56	5.17	5.22	544.1	603.7	586.7
D-OE	17.12	16.00	15.00	394.5	374.0	384.5	4.55	4.94	4.88	481.4	515.1	531.2
B-Ring	18.22	15.00	15.00	546.1	574.7	544.7	5.5	6.47	6.13	839.0	986.9	903.1
C-Ring	16.3	16.00	15.00	497.1	519.7	478.2	5.48	6.05	5.64	752.8	851.0	736.7
D-Ring	16.65	15.00	15.00	527.8	553.3	498.3	5.24	6.13	5.65	765.8	896.1	764.5

Figure 3: Summary of Tensojet testing conditions and results

Pretension [g]	Breaking Force [g]	Elongation [%]	Work-to-Break [g*cm]
15	478.2	5.64	736.7
16	473.4	5.41	707.9
16.5	471.1	5.39	697.6

Figure 4: Mean values of tensile parameters of yarn B-Ring with emulsion in dependence of the applied pretension

Normal distribution

$$p(X) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{X-\mu}{\sigma}\right)^2}$$

Gamma distribution

$$p(X) = \frac{h}{\Gamma(\alpha)\sigma} \bullet \left(\frac{x-\theta}{\sigma}\right)^{\alpha-1} \bullet e^{-\left(\frac{x-\theta}{\sigma}\right)}$$

Logarithmic-normal distribution

$$p(X) = \frac{h}{\sigma\sqrt{2\pi}} \bullet e^{\left(-\frac{(\log(X-\theta)-\zeta)^2}{2\sigma^2}\right)} \bullet \frac{1}{X-\theta}$$

Weibull distribution

$$p(X) = \frac{c \cdot h}{\sigma} \bullet \left(\frac{X-\theta}{\sigma}\right)^{c-1} \bullet e^{-\left(\frac{X-\theta}{\sigma}\right)^c}$$

Figure 5. Fitted theoretical distribution functions (Probability density functions p)

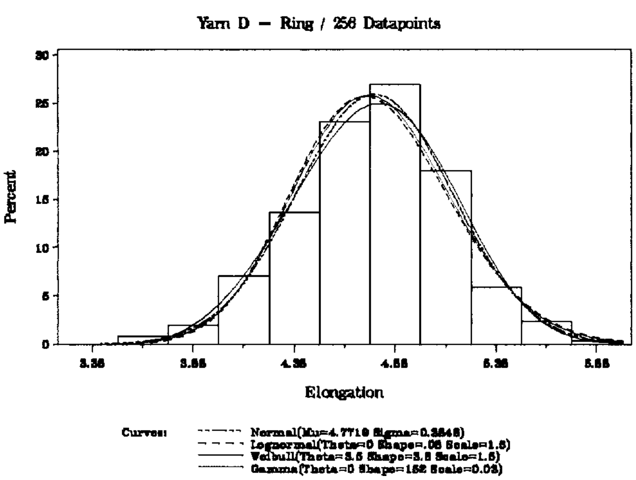


Figure 6. SAS© computed histogram and fitted distributions

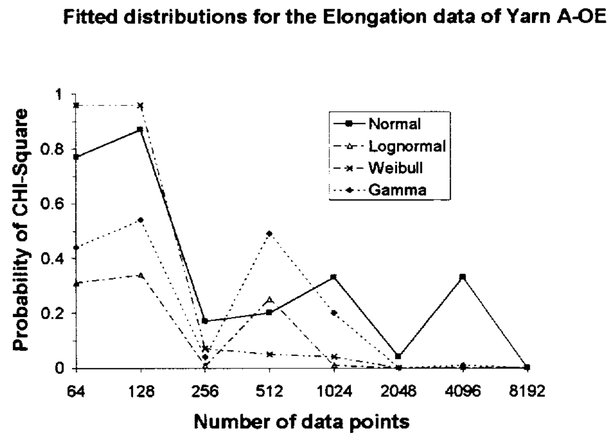


Figure 7. CHI-Square values in dependence of the data set size

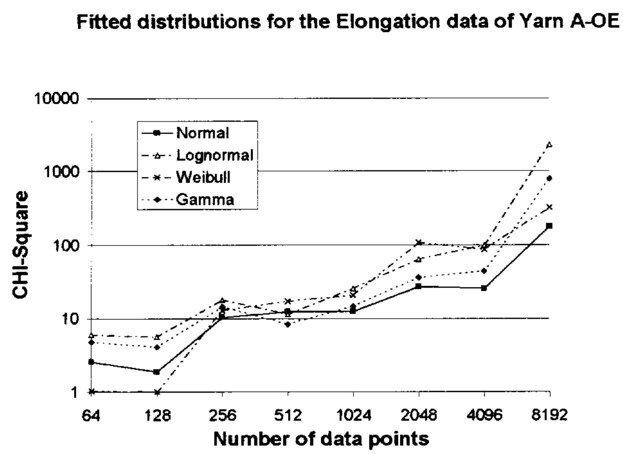


Figure 8. Probability of CHI-Square in dependence of the data set size

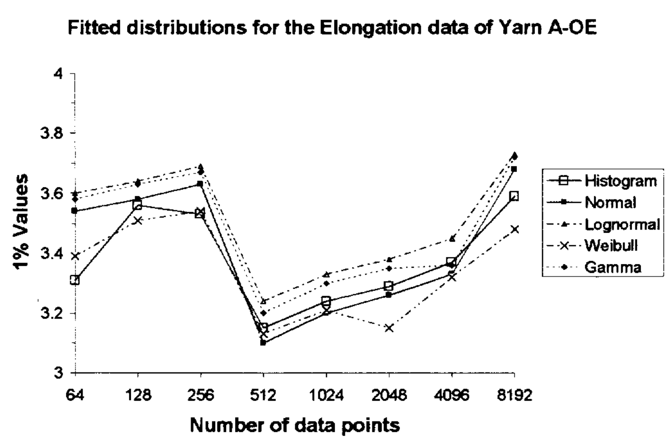


Figure 9. 1% values in dependence of the data set size

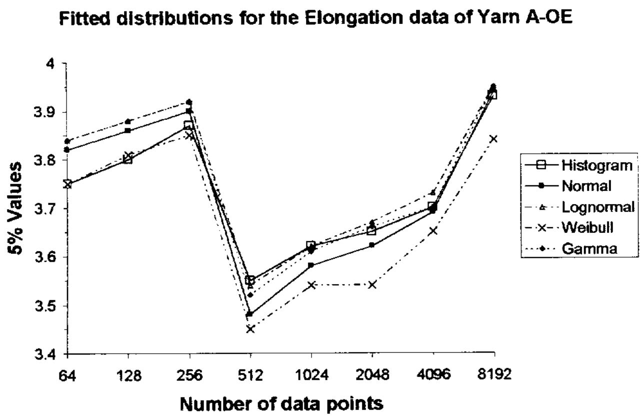


Figure 10. 5% values in dependence of the data set size

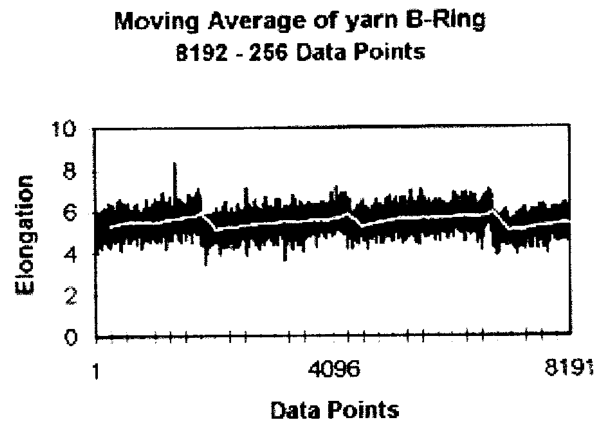


Figure 12. Moving Average Test for a ring spun yarn (Elongation)

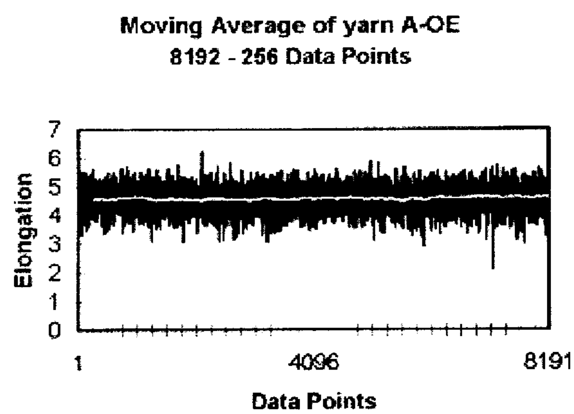


Figure 13. Moving Average Test for a rotor spun yarn (Elongation)

Parameter	Spinning System	Lowest value for CHI-Square	Probability of CHI-Square ≥ 0.05	Best fit for 1% & 5% values
Elongation	Rotor yarns	Weibull: N<512, Normal: N≥512	Normal & Weibull for N<1024	Weibull for N<1024, Normal for N≥1024 Weibull values too low, Normal values too high
	Ring yarns	Normal & Weibull	Normal & Weibull for N<2048	Normal & Weibull; Weibull values too low, Normal values too high
Breaking Force	Rotor yarns	Normal for N>256, Weibull for N≤256	Weibull for N≤256; Normal for N≤1024	Weibull; Normal sometimes for N≥512
	Ring yarns	Normal for N≥1024, Weibull for N<1024	Normal & Weibull for N<4096	Normal & Weibull Normal predicts rather too high values Weibull slightly better for small data sets
Work-to-break	Rotor yarns	Normal for bigger, Weibull for smaller data sets	Normal & Weibull for N<2048	Weibull slightly better Normal values too high
	Ring yarns	Too high values for all distributions	If at all, only for data sets with N≤128 for all distributions	Bad fit for all distributions

Figure 11: Summary - Best-fitted theoretical distribution functions for the tensile data

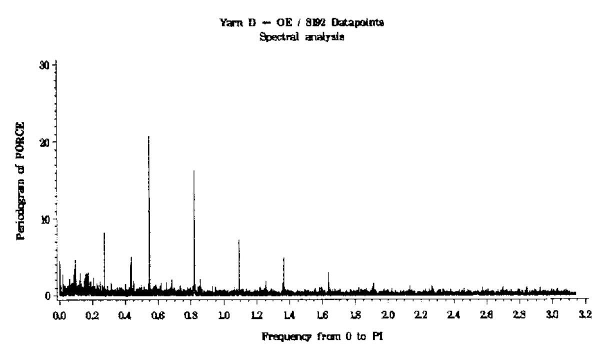


Figure 14. Fourier Analysis of yarn D-OE

yarns	uncoated			waxed			with Emulsion			sub-stantial perio-dicity
	fre-quency	perio-dicity	wave-length	fre-quency	perio-dicity	wave-length	fre-quency	perio-dicity	wave-length	
A-OE	0.60	10.42	8.34				0.60	10.44	8.35	8.34
	0.31	20.33	16.27							
C-OE							0.52	12.13	9.70	
	0.43	14.61	11.69							
	0.30	20.81	16.64							
	0.05	125.66	100.53							
D-OE	1.64	3.84	3.07							
	1.36	4.61	3.69	1.35	4.65	3.72	1.37	4.59	3.67	3.7
	1.09	5.76	4.61	1.10	5.72	4.57	1.10	5.73	4.58	4.6
	0.82	7.68	6.14	0.82	7.66	6.13	0.82	7.63	6.11	6.1
	0.55	11.47	9.17	0.55	11.49	9.19	0.55	11.47	9.17	9.2
	0.45	13.90	11.12							
	0.30	20.81	16.64							
	0.27	23.02	18.41	0.28	22.44	17.95	0.27	23.71	18.97	18.5
				0.10	65.45	52.36				
							0.07	92.40	73.92	
	0.05	139.63	111.70	0.05	125.66	100.53				
B-Ring	2.03	3.10	2.48				1.92	3.28	2.62	
	1.02	6.16	4.93	1.01	6.23	4.99	1.03	6.10	4.88	4.9
	0.62	10.13	8.11	0.70	9.03	7.22				
	0.30	20.94	16.76	0.33	19.27	15.42				
	0.15	41.61	33.29				0.13	46.89	37.51	
				0.09	72.22	57.78				
C-Ring							3.00	2.09	1.67	
	1.63	3.85	3.08	1.64	3.82	3.06	1.64	3.83	3.06	3.1
							1.53	4.11	3.29	
							0.20	31.57	25.26	
				0.12	52.36	41.89	0.13	49.87	39.89	
D-Ring	1.97	3.19	2.56	1.98	3.17	2.54	1.99	3.17	2.53	2.5
				1.45	4.33	3.47				
	1.15	5.46	4.37	1.17	5.39	4.31				
	0.99	6.35	5.08	0.99	6.33	5.07	1.00	6.29	5.03	5.1
	0.88	7.14	5.71	0.87	7.21	5.77	0.89	7.10	5.68	5.7
	0.86	7.31	5.84				0.86	7.29	5.83	
	0.59	10.70	8.56	0.58	10.80	8.64	0.59	10.69	8.55	8.6
	0.57	10.97	8.77							
				0.12	51.08	40.87				

1 parameter
2 parameters
all 3 parameters

Figure 15. "Major" peridoicities revealed by the Fourier Analysis

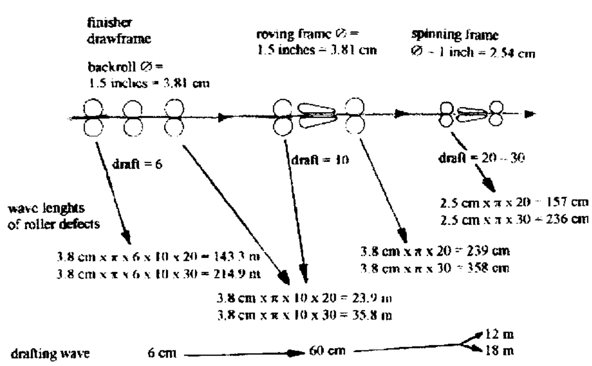


Figure 16. Possible places in production to cause the periodicities in the yarn

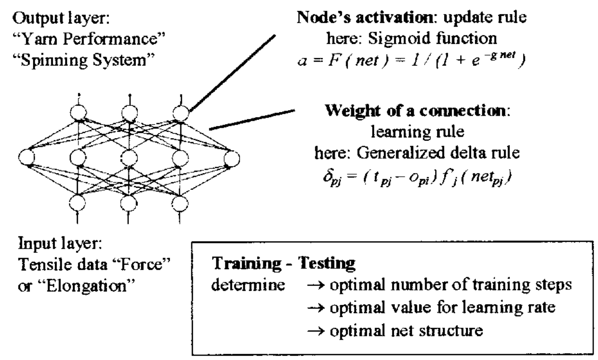


Figure 17. Function principle of a Neural network using the Backpropagation Algorithm

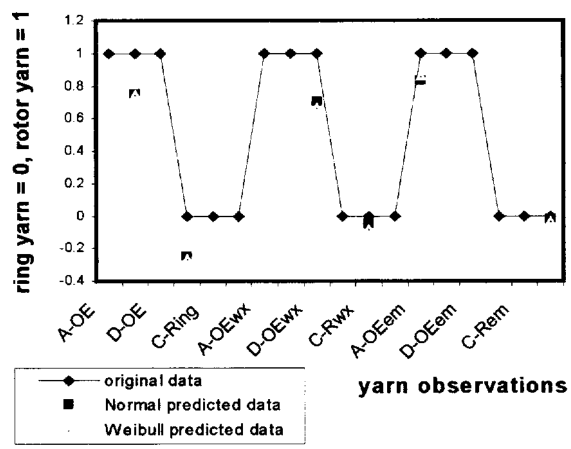


Figure 18. Prediction of the parameter "Spinning System"