UDK 677-487.5

BIMODALITY OF THE COTTON COMPACT YARN HAIRINESS INDEX*

JIŘÍ MILITKÝ, SAYED IBRAHIM, DEMET YILMAZ, FATMA GOKTEPE

**(Dept. of Textile Materials, Dept. of Textile Technology, Textile Faculty,
Technical University of Liberec (Czech Republic),
Textile Engineering Dept., Suleyman Demirel University (Turkey))**

The yarn hairiness depends on the fibers on the outer layer of the yarn that do not directly adhere to the core. Some of them have an end in the core of the yarn gripped by other fibers, whereas others, because of the mechanical properties of the fiber (rigidity, shape, etc.) emerge to the surface. During the twisting of the yarn, other fibers are further displaced from their central position to the yarn surface.

Yarn hairiness is therefore a complex concept, which generally cannot be completely defined by a single figure. Hairiness can be considered as the fiber ends and loops standing out from the main compact yarn body. Beside other instruments, there are two major testing equipments available on the market used for evaluating the yarn hairiness. The most popular instrument is the Uster hairiness system, which characterizes the hairiness by H value, and is defined as the total length of all hairs within one centimeter of yarn. The hairiness H is an average value giving no indication of the distribution of the length of hairs. The H value suppresses information as all averages do. The spectrogram of hairiness is also available. The second major instrument used is the Zweigle hairiness tester. The numbers of hairs of different lengths are counted separately. In addition the S3 value is given as the sum of the number of hairs 3 mm and longer. The information obtained from both systems is limited, and the available methods either compress the data into a single vale H or S3 or convert the entire data set into a spectrogram deleting the important spatial information.

Modern USTER devices have possibility to give raw data about whole yarn hairiness. These data can be used for more complex evaluation of hairiness characteristics in the time and frequency domain. The yarn hairiness can be described according to the:

– periodic components;
– random variation;
– chaotic behavior.

For these goals, it is possible to use system based on the characterization of long term and short-term dependence of variance. The so-called Hurst exponent or fractal dimension can describe especially long-term dependence.

The yarn hairiness complex characterization can be divided to the two phases. The core of pretreatment phase is creation of power spectral density (PSD) curve. Rough PSD estimator is based on the FFT i.e. the squared spectral amplitudes abs $(Pk)^2$.

The hairiness complexity can be classified according to the slope S of log(PSD) on the log(frequency):

1. Fractional Gaussian noise f_G for range $1<S<0.38$. In this case the fractal dimension from power spectrum can be used but variogram is not suitable.

2. Fractional Brownian motion f_B for range $1.04<S<3$. In this case the variogram can be used for estimation of fractal dimension as well.

3. Transition case for range of S between 0.38 and 1.04. For this case the cumulative sum of SHV should be created (transformation to the case 2).

* This work was supported by the research project 1M4674788501 - “Textile Center” of Czech Ministry of Education.

4. No fractal behavior for cases when the power law model is invalid (in two decade range). For this case the chaotic models (broad bands) or ARIMA models (narrow peaks) have to be used.

Special techniques for estimation of Hurst exponent and fractal dimension for the above-mentioned cases can be used. The proposed approach is the core of HYARN program written in Matlab code. Application of this program for deeper characterization of selected cotton type yarns was shown in [1].

In this contribution HYARN program is used for creation of H values empirical probability density function (PDF) and fitting this PDF by mixture of Gaussian distributions.

PROBABILITY DENSITY FUNCTION OF H. As an estimator of the empirical probability density function histogram with constant or variable bins (number of bins is M) is often constructed. Smooth kernel type density estimator is natural generalization of histogram.

Histogram is piecewise constant estimator of sample probability density. Histogram height in jth class bounded by values (t_j-1, t_j) is calculated from the relationship

$$f_H(x) = \frac{C_N(t_{j-1}, t_j)}{N\, h_j},$$

where the function C_N(a, b) denotes the number of sample elements within interval <a, b> and $h_j = t_j - t_{j-1}$ is the length of the j-th interval. Now, the problem encountered is the choice of boundary values {t_j} j=1,...M, the number of class intervals M and their lengths h_j with respect to the histogram quality. In our programs the simple data based two-stage technique is used. In the first stage the number of class intervals

$$M = \text{int}[2{,}46\ (N\text{-}1)^{0{,}4}]$$

is computed. Here int[x] is integer part of number x.

In the second stage the individual lengths h_j are determined. The estimation of h_j is based on the requirement of equal probability in all classes. For this purpose the empirical quantile function Q(P) based on the order statistics $x_{(i)}$ is used.

In practice the P-axis is divided into identical intervals having the size of 1/M. For these intervals the corresponding quantile estimates $t_j = x_{(j/M)}$ are constructed by using the relation

$$x_{(P)} = (N+1)\left(\frac{PN + P - i}{N+1}\right)(x_{(i+1)} - x_{(i)}) + x_{(i)},$$

where P = j/M. Practical experiences have hitherto proven that this construction is suitable even for strongly skewed sample distributions.

The kernel type nonparametric estimator of sample probability density f(x) can be constructed on the basis of Lejenne-Dodge-Kaelin procedure [1]. The final estimator has the form

$$f(x) = \frac{1}{N}\sum_{i=1}^{N} K\left[\frac{x - x_i}{h_i}\right].$$

Selection of kernel function K[x] and computation of bandwidths h_i is described in [1].

In the case of bimodal distribution the mixture of Gausians is often a good model. We used two Gaussian mixture model in the form

$$f_G(x_i) = A1\exp\left(-\frac{(x_i - B1)}{C1}\right)^2 + A2\exp\left(-\frac{(x_i - B2)}{C2}\right)^2,$$

where A1, A2 are proportions of smaller hairiness (first Gaussian having index 1) or higher hairiness (second Gaussian having index 2). Parameters B1 and B2 are mean H values for individual component and parameters C1, C2 correspond to standard deviations.

To obtain the coefficient estimates (A1, A2, B1, B2, C1 and C2), the least squares method minimizing the summed square of residuals is used. The residual for the ith data point r_i is defined as the difference between the observed response value and the fitted response value

$$r_i = f_H(x_i) - f_G(x_i).$$

The summed square of residuals is given by

$$S = \sum_{i=1}^{N} r_i^2 ,$$

where N is the number of data points included in the fit and S is the sum of squares error estimate. Assumption leading to the minimization of S is given in the book [1].

Model of two Gaussians mixture is nonlinear regression model.

Nonlinear models are more difficult to fit than linear models because the coefficients cannot be estimated using simple matrix techniques. Instead, an iterative approach is required.

The MATLAB toolbox used in HYARN provides these algorithms:

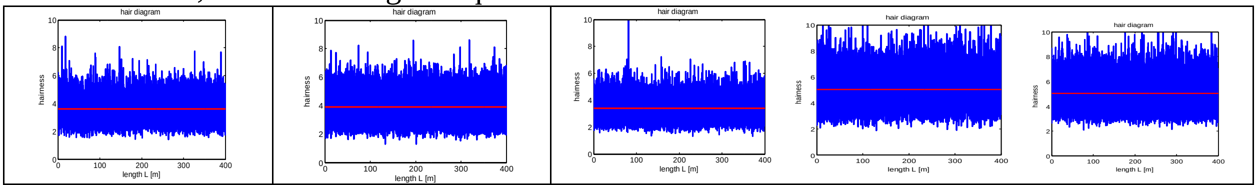
– Trust-region -- This is the default algorithm. It can solve difficult nonlinear problems more efficiently than the other algorithms and it represents an improvement over the well-known Levenberg-Marquardt algorithm.

– Levenberg-Marquardt -- This algorithm has been used for many years and has been proved to work most of the time in a wide range of nonlinear models and starting values. If the trust-region algorithm does not produce a reasonable fit, and there are no coefficient constraints, the Levenberg-Marquardt is good starting algorithm.

More information about these algorithms is given in the book [1]

EXPERIMENTAL PART AND METHOD OF EVALUATION. Experimental Part: Three cotton combed yarn of count 14.6 tex (Ne 41) were produced on Rieter com4, Sussen , and Zinser compact spinning machines. The in-feed roving and row material characteristics were constant for all yarn types. The main fiber properties are as follows: staple length 30.1 mm, fiber fineness 1.8 dtex (micronaire 4.6 μ/inch), fiber tenacity 30 cN/tex, and Short fiber index SFI 7.3. Furtheremore one open-end of tex 20, and a ring spun yarn of tex 15.2 were considered. All of these yarnes were tested on Uster tester 4 for yarn hairiness at 400 m/min for one minute. The results are as follows: Rieter yarn has mean hairiness H= 3.6, Suessen yarn has H=3.9, and Zinser yarn has H=3.41. The ring spun yarn has H= 5.05, and the OE –rotor yarn H=4.35.

METHOD OF EVALUATION. The individual readings of yarn hairiness were extracted from Uster 4 unevenness tester .The raw data of hair diagram were fed to a program (HYARN) written in MatLab for comlex evaluation of yarn hairiness.



a b c d e

Fig. 1. Hairiness diagram a) Rieter, b) Suesen c) Zinser, d) Ring spun and e) OE-rotor yarns

RESULTS AND DISCUSSION. In the first part of our discussion we shall consider the distribution of hair for all types of yarns to find out if the distribution of the hairiness is a typically bi-modal distribution or only typically for some types of yarns. It was proven that parameter H comprise bimodal distribution for all yarns and this distribution can be well approximated by mixture of two Gaussians distributions. In the Fig. 2 the histograms for four sub samples (division of data for 400 meter yarn into 100 meter pieces) are given. It is clear that in all cases the bimodality is markedly appeared. The histograms of full samples are given in the Fig. 3.

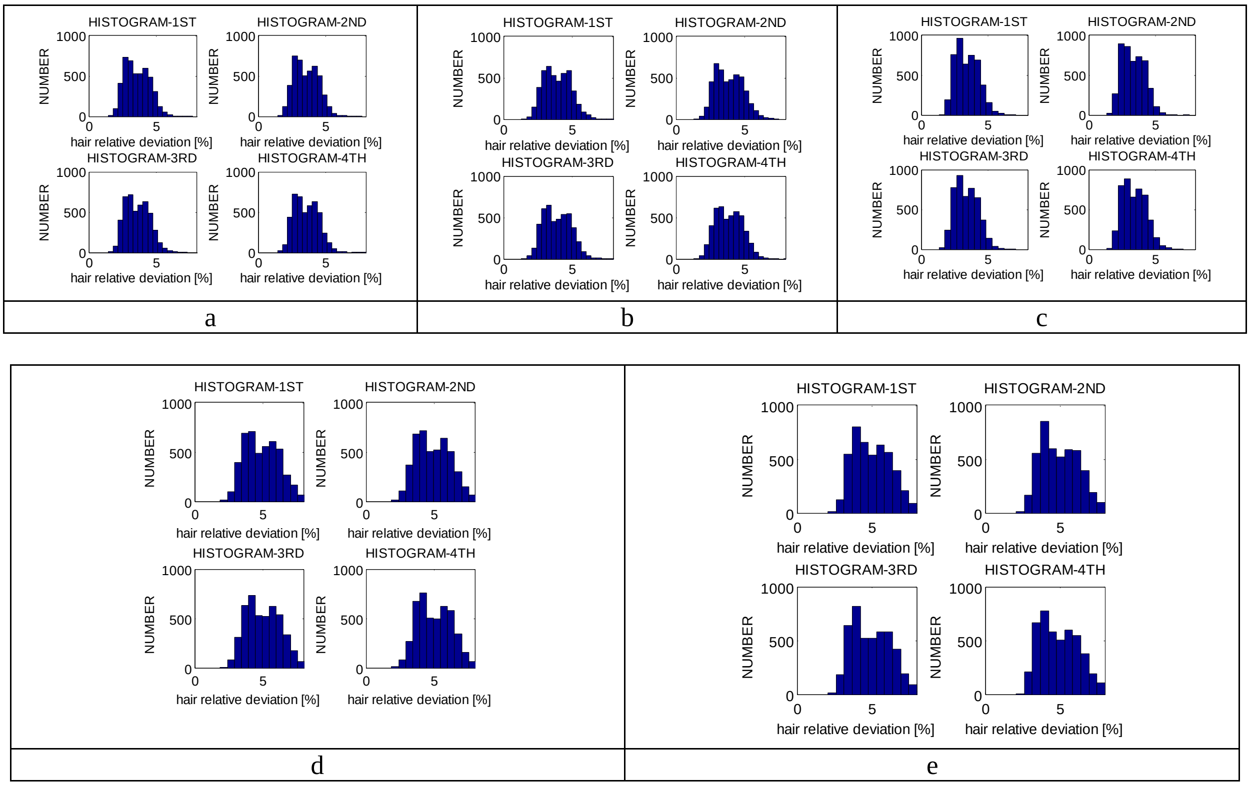


Fig. 2. Hairiness index H distribution for four subsamples
a) Rieter, b) Suesen c) Zinser, d)Ring Spun, and e) OE-Rotor yarn
b)

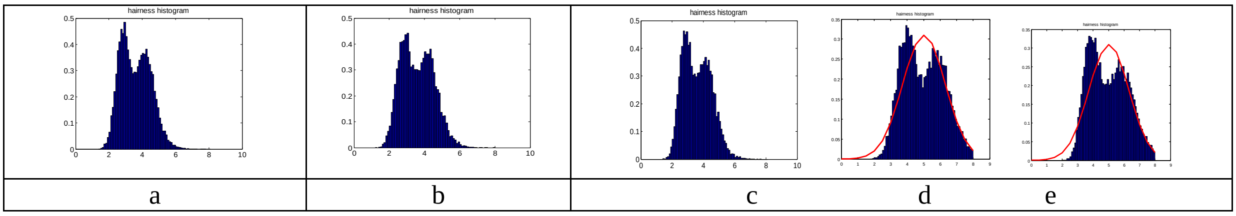


Fig. 3. Hairiness index H distribution for whole samples
a) Rieter, b) Suesen c) Zinser, d) Ring Spun and e) OE-Rotor yarn

At this point we shall limit our discussion to compare in details the fine differences between the compact yarns produced on different machines. The best fit by mixture of two Gaussians is in the Fig. 4.

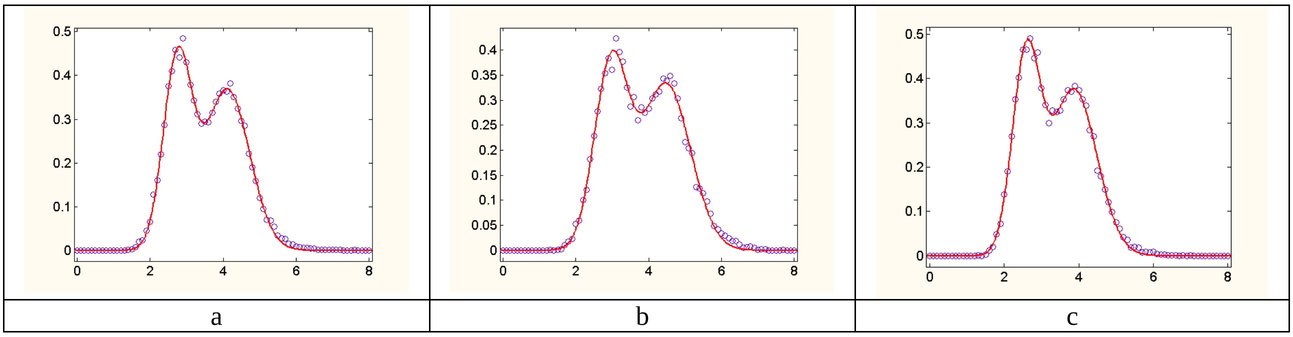


Fig. 4. Best fit of mixture of two Gaussians model a) Rieter, b) Suesen c) Zinser

The very good approximation for all cases is clearly visible. Parameter estimates of mixture of two Gaussians model obtained by nonlinear least squiares are given in the Table 1.

Table 1. Parameter estimates of mixture of two Gaussians model

Yarn	A1	B1	C1	A2	B2	C2
Rieter	0,4335	2,752	0,5521	0,369	4,113	0,8643
Sussen	0,3696	2,973	0,6578	0,3323	4,479	0,948
Zinser	0,4406	2,589	0,5282	0,3754	3,87	0,8734

It is interesting that differences between individual yarns are small but the yarn Zinser has biggest portion of smaller H and smaller mean values. Therefore the presence of long hairs will be probably low. Bimodality of H distribution has influence on majority of parameters computed for spatial characterization of hairiness as well because standard assumption is unimodality or strict normality. Illustrations are in the Fig. 5 autocorrelation functions in the Fig. 6.

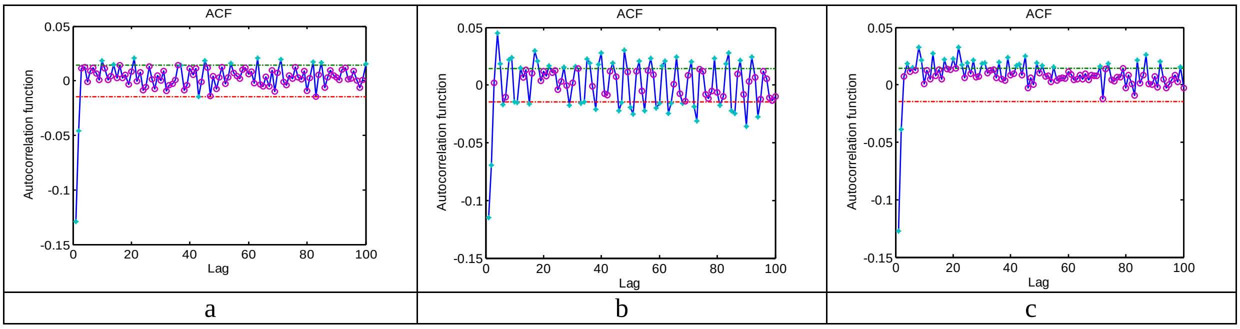


Fig. 5. Autocorrelation function a) Rieter, b) Suesen c) Zinser

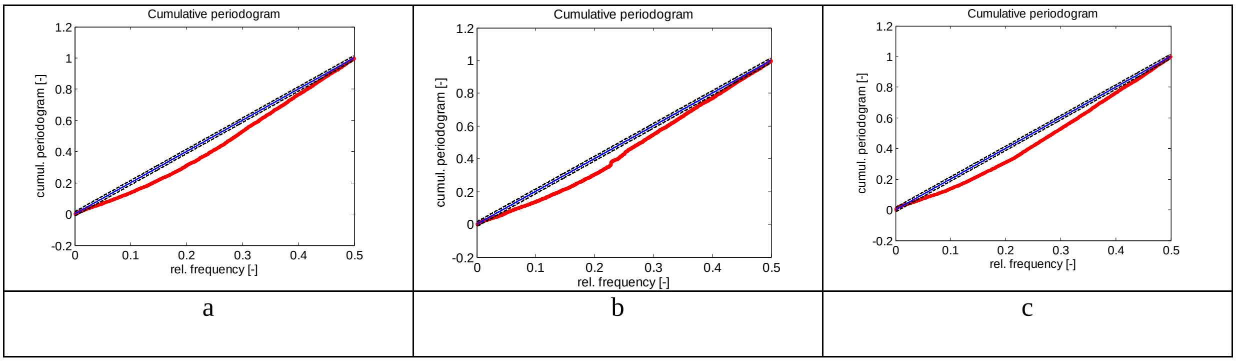


Fig. 6. Cumulative periodogram a) Rieter, b) Suesen c) Zinser

The assumption of white noise (blue lines on cumulative periodogram cannot be naturally accepted. Bimodality of H parameter distribution has many practical consequences. First of all the mean value used in Uster outputs is bad estimator because it lies between two peaks on H parameter distribution. Proper way in this case is to evaluate parameters of mixture of two Gaussians and use two mean values for hairiness characterization. On the other hand, the modus will be better for description of bimodality. Appearance of two various H distributions can be connected to two types of hairiness, but this hypothesis needs practical verification.

CONCLUSION

The distribution of H parameter characterizing the overall hairiness for cotton yarns is bimodal. This event has huge influence on the majority of parameters characterizing spatial behavior of hairiness process. It will be necessary to prove bimodality for yarns having various fineness, compositions and systems of spinning before deciding about replacement of Uster mean value by more characteristics. This method facilitates complex characterization of yarn hairiness more deeply, differentiating hairiness distribution in two parts, short and long hairs.

BIBLIOGRAPHY

1. *Militky J., Forina M.* "Chemometrics for Analytic Chemistry vol.I and II, Statistical models building", Ellis Horwood, Chichester, (1992 and 1994)

2. *Militky J., Ibrahim S.* “Yarn Hairiness Complex Characterization”, Proc. Annual Fibre Soc. Conf., St Galen, May 2005

Recommended by Scientific and Technical Counsil of Moscow State Textile University named aftert A.N. Kosygin. Received 05.06.09.