# Time-Series Analysis to Relate the Density Profiles of Sliver to those of Roving

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## INTRODUCTION

The process/quality control strategies through on-line measurements of sliver, roving and yarn unevenness are becoming the center of future R&D activities in the technology of spun yarn production. Developments of various types of sensors, along with the availability of affordable computing and analysis modes, provide an opportunity that was never before conceivable. The potentials for this type of research are in improvement of product qualities, productivity and profitability through global optimization strategies.

This paper has been focused on experimental work for relating the density profiles of sliver to those of roving by using time-series analysis methods. A statistical model is proposed for separating the input variance and the process variance. A spline method and a cross spectrum analysis have demonstrated that the density profiles of a sliver and the resulting roving are strongly correlated and the relationship can be traced effectively.

## EXPERIMENTAL

A cotton sliver, weighing 70 grains, was used for measuring the density profiles and then drafted to a roving with a mechanical draft ratio of 1:8 using a Saco Lowell roving frame.

The analog signals were captured while the sliver and roving were measured for their unevenness with a Uster Tester-3®. The material speed on the Uster Tester-3® was 25 m/min and the sampling rate of the data acquisition system was 0.0208 KHz. This sampling rate corresponds to measurement of the mass at every 20 mm segment of sliver and 12 mm for roving.

## RESULTS AND DISCUSSION

Figure 1 shows density profiles of a sliver captured by the data acquisition system. It constitutes a time series made up of the amplitude values of sliver weights, each 20 mm long. By examining the diagram, there existed no obvious trend or cyclical pattern although there were lots of peaks and valleys in the series. The expected random fluctuations were present in this series. It was also assumed that there existed an autocorrelation between the time-dependent data. Autocorrelation is a measure which distinguishes time series from other methods of statistical analysis.

Figure 2 is a correlogram of a tested sliver. This correlogram shows a high auto-correlation between the adjacent sliver segments. The correlation coefficient at lag 1 (length of 20 mm) was 0.498 but damped to 0 very rapidly. Lots of fibers lying between adjacent sliver segments are caused by high correlation coefficient. This result leads us to conclude that the mass profile of a sliver can be adequately modeled by a time series analysis.

In our time series analysis, we used the Box-Jenkins[1] approach, known as ARMA model. The general ARMA model can be described as follows:

$$Y_t = \theta_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t .$$

where

| | |
|---|---|
| $Y_t$ | is a time series variable, |
| $\theta_0$ | is a constant parameter, |
| $\varphi_1, \ldots, \varphi_p$ | are the autoregressive parameters |
| $Y_{t-1}, \ldots, Y_{t-p}$ | are values of the time series in the previous time period, |
| $\theta_1, \ldots, \theta_q$ | are moving average parameters, |
| $\varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ | are random errors for the previous time period, and |
| $\varepsilon_t$ | is a random error term uncorrelated over time, called white noise. |

Many attempts were made to identify the time series and estimate the model parameters employing SAS-ETS®. The results are shown in Table 1. These results lead us to conclude that the mass profile of a sliver can be adequately modeled by an ARMA(1,(2)). Particularly, this time series of the sliver is modeled as follows:

$$Y_t = -253.67 + 0.43775 Y_{t-1} + 0.1886 \varepsilon_{t-2} + \varepsilon_t .$$

This analysis method will be applied to the roving and yarn data to characterize them.

In order to study the density profiles of spun yarns, the mass per unit length of slivers, rovings and yarns in three separate time domains have to be characterized through statistical modeling of their variations. It must also be realized that the input variances of the previous processes need to be separated from the variations that are associated with the present process.

As a start, we have investigated the density profiles of a sliver and the resulting roving in this paper. Theoretically, the density variation of a roving can be quantified by the input variance of the sliver and the variance imparted by the roving process itself and perhaps that from other external causes.

Let the mass amplitudes of the sliver length units be $(X_1, X_2, X_3, \ldots, X_n)$. Then, the mean and variance of the unit mass, $X$, can be expressed as:

$$\hat{E}(X) = \frac{1}{n} \sum_{i=1}^{n} X_i \qquad \text{and}$$

$$\hat{V}(X) = \frac{1}{n} \sum_{i=1}^{n} (X_i - \hat{E}(X))^2 \qquad \text{, respectively.}$$

If the sliver is attenuated to $d$ times the original length, the mean and variance of the unit mass, $x$, of the roving become:

$$\hat{E}(x) = \frac{1}{d} \hat{E}(X)$$

$$\hat{V}(x) = \frac{1}{d^2}\,\hat{V}(X) + \sigma^2_{r|s}$$

where $x$ is the amplitude values of the unit length of roving. The term $\sigma^2_{r|s}$ is the portion of the within variance associated with the roving process whereas the $\frac{1}{d^2}\,\hat{V}(X)$ is the variance component inherited from the sliver, that is the input variance. The numerical results in Table 2 shows that about 30 percent to 60 percent of roving variance comes from the roving process itself.

Figure 3 shows the density profiles of a sliver(first 100 data) and the corresponding roving(first 800 data). Each contains the variance component coming from the process itself and the component inherited from the previous process and other external causes.

As might be seen from the figure, it is quite difficult to match the profiles of the sliver data to that of the roving data. To resolve this, a spline method was adopted. This method tries out varying draft ratios in such a way that the resemblance between the two profiles can be maximized at a given ratio by comparing the two oscillating time series. Results from an analysis using S-PLUS® package revealed that the most probable actual draft ratio from the sliver to the roving was 7.752. Based on this, every 7.752 roving segments were added together and matched against the corresponding sliver segments. Figure 4 shows this result. In the figure, the density profile of the compacted roving can be easily traceable to that of the sliver.

For a more detailed investigation as to how often the two series oscillate at frequencies around $f$, a series of *cross spectrum* analyses[2,3] was performed by computing the following value:

$$0 \le coh_{xy}(f)^2 = \frac{|S_{xy}(f)|^2}{S_{xx}(f)\cdot S_{yy}(f)} \le 1$$

A correlation-like quantity, $coh_{xy}(f)^2$, is called the coherence or squared coherency. Here, the value 0 represents no correlation and value 1 a perfect correlation.

Figure 6 shows the squared coherency of the two series (compacted roving data using 7.752 draft ratios and the corresponding sliver data) over a specified range of frequencies. This figure is shown to be much superior (high correlation) to a similar diagram obtained from 8.0 draft ratio (Figure 5). This analysis demonstrates that a frequency domain analysis, such as the cross spectrum squared coherency analysis used above, is quite effective in studying the density profiles of fibrous assemblies..

## CONCLUSION

Density profiles of slivers based on the captured analog signals fit well with an ARMA(1,(2)) model. Prospects are good for applying this model to rovings and yarns as well. The captured signals can be processed effectively to separate the density variation of a roving into the input variance of the sliver and the variance imparted by the roving process numerically. The spline method is shown to be highly effective in estimating the most probable actual draft ratio in roving process. A correlation-like quantity, called "squared coherency", over a specified range of frequencies shows that a cross spectrum analysis is also applicable in this type of signal processing research.

## REFERENCES

1. Box,G.E.P. and Jenkins, G.M., *Time Series Analysis: Forecasting and Control*, Holden-Day, San Francisco, 1970.
2. Bloomfield, P., *Fourier Analysis of Time Series: An Introduction*, John Wiley & Sons, New York, 1976.
3. Brocklebank, J.C. and Dickey, D.A., *SAS® System for Forecasting Time Series*, SAS Institute Inc., Cary, NC, 1986


Table 1. The time series analysis results of sliver density profiles

| Model | Autocorrelation check of residuals (Prob) | AIC value |
|---|---|---|
| AR(1) | 0.006 | 4430 |
| AR(2) | 0.257 | 4421 |
| MA(1) | 0.000 | 4479 |
| MA(2) | 0.006 | 4430 |
| ARMA(1,1) | 0.080 | 4424 |
| ARMA(1,2) | 0.685 | 4419 |
| ARMA(1,(2)) | 0.782 | 4417 |

Table 2. The mean and variance of slivers and the corresponding rovings

| Material | Data No. | Mean | Variance |
|---|---|---|---|
| Sliver-1 | 500 | 451.34 | 546.78 |
| Sliver-2 | 511 | 451.22 | 738.41 |
| Roving-1 | 4000 | 56.75 | 21.39 |
| Roving-2 | 3800 | 56.21 | 18.52 |

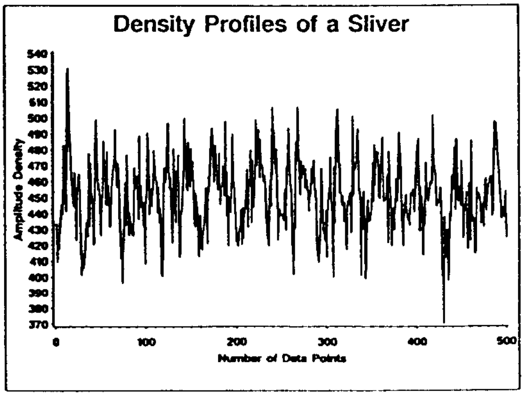


Figure 1. Density Profiles of a Sliver from the DAS

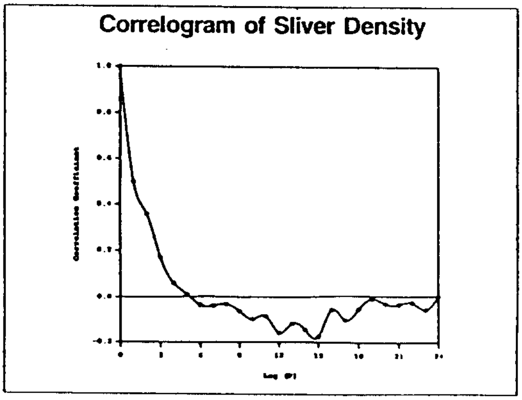


Figure 2. Correlogram of Sliver Density

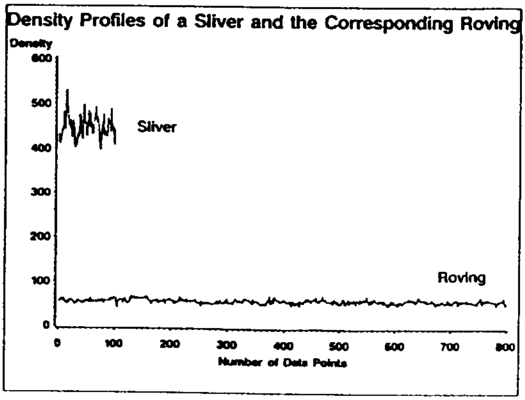


Figure 3. Density Profiles of a Sliver and the Corresponding Roving

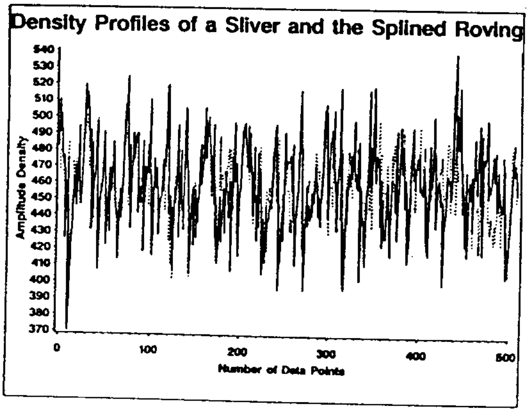


Figure 4. Density Profiles of a Sliver and Splined Roving

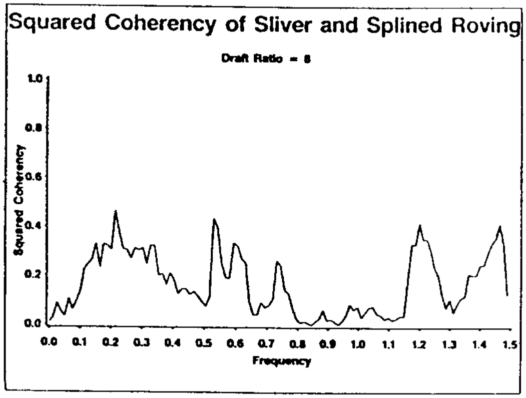


Figure 5. Squared Coherency of a Sliver and the Splined Roving (d.r.=8)

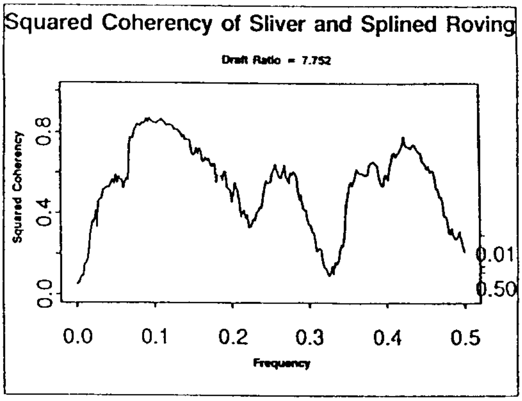


Figure 6. Squared Coherencey of a Sliver and the Splined Roving (d.r.=7.752)