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Improving Textile Product and Process Qualities: Failure Mechanisms and New Directions for the Future

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1. INTRODUCTION

It is often startling to discover that textile-manufacturing operations throughout the world seldom make use of the vast amount of advanced technical information accumulated during the last 50 years for their quality-control and improvement efforts. A large number of scientific and engineering equations remain unused in practice, whether understood or not. Whereas some may blame the industry for this, it is imperative to examine the causes in the light of rapidly developing measurement, control, and computing technologies. The information explosion, through inexpensive measurement and data storage, challenges the industry with a profound question: how can we improve the processes and products under the expanding information database?

This paper examines the contributions of previous textile science and engineering research from a quality-control standpoint and proposes a set of new directions for the future.

2. MODERN NEED FOR QUALITY AND PROCESS IMPROVEMENT

In an earlier paper, the present author [1] has demonstrated the large potential that exists for improving the profitability of the US textile industry, which has been a 'random-walk' process during the last 20 years. In textile manufacturing, choices are often quite limited in the selection of raw materials, machinery, and processing conditions for many practical reasons. Unless the desired level of process or product quality is largely unmet, an opportunity to re-examine critically the choices of raw materials, machinery, and processing conditions does not exist. On the other hand, exceptions to the expected range of qualities always occur, whether the exceptions are highly desirable or undesirable. In a statistical sense, such an 'out-of-control' situation merely indicates that there existed a set of conditions which were significantly deviating from the norms. This, however, is insufficient for pinpointing the factors of time, location, and the mechanism through which the exception was realized. In spite of the vast amount of knowledge in textile technology, the diagnostics relating to the off-quality products and processes remain a pseudo-science, if not witch-hunting. First, the reasons for this are to be outlined below.

3. FAILURES OF PAST TEXTILE RESEARCH IN QUALITY CONTROL AND IMPROVEMENT

3.1 Failure Mechanism (I): Forward-prediction Equations

Much textile research falls under the category of forward prediction and characterization. Predicting yarn and fabric properties based on fiber and processing characteristics [2–4] is a typical example. This knowledge base, while critical for general optimization, has not been utilized primarily for three reasons: (*a*) the prediction equations are not applicable for the specific choices of raw materials, machinery, and processing conditions, thus accompanying large amounts of bias and errors, (*b*) the forward-prediction equations are useless in tracing back the responsible factors and processing conditions that produced the specific 'out-of-control' situations on a daily basis, and (c) the predictions usually link no more than two stages, with no capability to go back beyond the immediate past step.

In a three-stage process involving fibers, yarn, and fabrics, let us designate the properties as:

$$\text{fibers:}\quad \underline{X}' = \left[X_1, X_2, \ldots, X_{n_1}\right]$$

$$\text{yarns:}\quad \underline{Y}' = \left[Y_1, Y_2, \ldots, Y_{n_2}\right]$$

$$\text{fabrics:}\quad \underline{Z}' = \left[Z_1, Z_2, \ldots, Z_{n_3}\right]$$

The characteristics above could be breaking strength, breaking elongation, modulus, friction coefficient, drapability, etc. For simplicity, let us assume that every yarn factor Y_j ($j = 1, 2, \ldots, n_2$) is affected by all X_i's, and that every fabric factor Z_k ($k = 1, 2, \ldots, n_3$) is affected by all Y_j's.

If, for an example, Z_2 is to be probed for its exceptional value, we must face two mammoth tasks; one is to know all the structural or stochastic equations linking the factors to Z_2, and the other is to determine, backward, which of the factors are responsible. Mathematically, we must know:

$$Z_2 = g_2\left(Y_1, Y_2, \ldots, Y_{n_2}\right) = g_2(\underline{Y}) \tag{1}$$

$$= g_2\left[f_1(\underline{X}), f_2(\underline{X}), \ldots, f_{n_2}(\underline{X})\right] \tag{2}$$

where $g_2(\underline{Y})$ and $f_i(\underline{X})$, $i=1, 2, \ldots, n_2$, are the forward-prediction equations. In spite of our broad knowledge base, it is seldom possible to find all the necessary equations to probe the excessive variation in Z_2. More importantly, a set of forward-prediction equations is grossly inadequate for a backward projection owing to the fact that the mapping between Z_2 and Y_j's and X_i's is not unique in a backward-search process. This fact usually leads textile quality control to disappointing guesswork rather than an effective corrective action. In summary, the forward equations are both incomplete and disjoint for making a truly satisfactory forward prediction, while the ultimate equation, even if it is found, cannot move backward to a set of unique prior-process conditions which produced the specific outcome.

3.2 Failure Mechanism (II): Deterministic Modeling

Multi-factor, multi-variate models based on deterministic, non-stochastic models have long been used to illustrate the 'average' phenomena based on the input or predictor variables. Depending on the functional forms, the variances and/or the coefficients of variation (CV) of the output factors are often found to be much greater than those of the individual input factors. For example, in a simple product function $Z = X \cdot Y$, elementary statistical theory provides the following approximation:

$$\sigma_z^2 = \mu_x^2\sigma_y^2 + \mu_y^2\sigma_x^2 + \sigma_x^2\sigma_y^2 \tag{3}$$

Here, μ_x, μ_y, μ_z, σ_x^2, σ_y^2, and σ_z^2 are the means and variances of the random variables matching the subscripts. By assuming that X and Y are independent, the CV of Z can be expressed in terms of the CVs of X and Y as

$$\begin{aligned} CV^2(Z) &= \frac{\sigma_z^2}{\mu_z^2} = \frac{1}{\mu_x^2\mu_y^2}\left(\mu_x^2\sigma_y^2 + \mu_y^2\sigma_x^2 + \sigma_x^2\sigma_y^2\right) \\ &= CV^2(X) + CV^2(Y) + CV^2(X)\cdot CV^2(Y) \end{aligned} \tag{4}$$

From this, it is trivial to see that the function $Z = X \cdot Y$ accompanies a CV greater than that of X or Y. Numerically, it can be shown that, when $CV(X) = CV(Y)$ is 0.05, 0.1, and 0.2, the corresponding $CV(Z)$ become 0.07, 0.142, and 0.286, respectively, or roughly 1.4 times the values of $CV(X)$ or $CV(Y)$.

As the complexity of the functional form and the number of predictor variables increase, the precision of the factor to be predicted becomes extremely low. When this reality is added to the introduction of the 'process variance', it is not surprising at all that the multitudes of forward-prediction equations are seldom used in quality-control and quality-improvement practice in textile manufacturing.

Fig. 1 is added to this discussion merely to consider the effects the cotton-fiber tensile properties have on the resulting yarn and fabric tensile properties. The figure represents the breaking loads and breaking elongations of 8000 cotton fibers of type 'T' tested on MANTIS, a prototype single-fiber tester developed by Zellweger Uster. The tests were performed in the College of Textiles, North Carolina State University. The database actually contains over 1000 load–extension data points for each fiber up to its breaking point. One has to consider the consequence of having to pick one breaking-load and one breaking-elongation value as input factors in a forward-prediction equation for estimating the yarn and fabric properties. Undoubtedly, such an exercise would be futile without a proper analysis on the variances of the input and output variables.

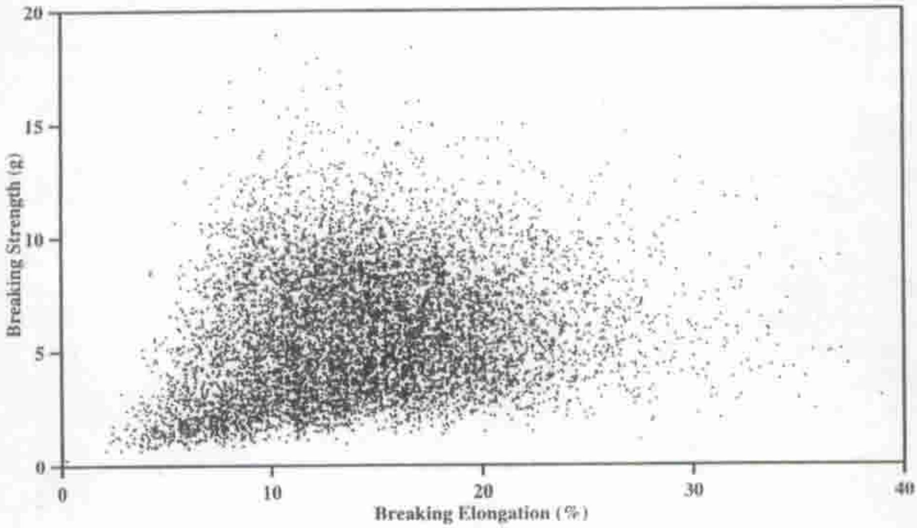

Fig. 1 Breaking elongation vs. strength of cotton fibers (based on 8000 tests of 'T' cotton)

3.3 Failure Mechanism (III): Sample Sizes and Sampling Practices

In a homogeneous population, the sample sizes are determined on the basis of the required precision of the estimates under prespecified levels of error. In manufacturing quality control, however, the purpose of the sampling is often to detect the out-of-control situations in the process averages that change with time. Sampling intervals and sampling frequencies are therefore as important as the sample sizes and the sampling fraction. Based on these, the random-sampling and testing practice which prevails now is grossly inadequate and superfluous. The first is that none of the sampling/testing methods for raw materials, intermediate fiber assemblies (say, slivers and rovings), yarns, and fabrics have been time-aligned or location-specific to provide a meaningful analysis. When random samples are taken at infinitely small fractions and analyzed for statistical correlations only, the likelihood of either confirming an existing correlation or pinning down the root causes of the observed deviations becomes extremely low. On the other hand, a significant correlation confirmed by a set of actual data is as likely to be from spurious data as from a true cause–effect relationship.

In addition, the sample sizes and sampling fractions for today's off-line textile quality-control practice are adequate perhaps only for establishing the long-term process averages, but totally inadequate for searching for the causes of specific out-of-control situations. An example may be drawn from the testing of cotton bales by using an HVI (High Volume Instrument). Although each and every bale is tested for uniform laydown and blending purposes in the USA today, 2000 cotton fibers may not adequately represent the entire bale of a single test beard consisting of roughly 500 lb, or 272 000 g, to say the least. If every fiber is assumed to be 1 in. (2.54 cm) long and to have a fineness of 4 micronaire units (i.e. a linear density of 0.157 tex), a bale of cotton contains 56.7 billion fibers, or enough to go around the earth 36 times when the circumference of the equator is estimated at 40 000 km. In terms of the sampling fraction, the HVI testing is equivalent to testing one out of every 28.35 million fibers. Whereas the testing of yarn and fabric properties is somewhat better than this, there exists little chance of isolating an out-of-control situation based on this type of current sampling and testing practice.

3.4 Failure Mechanism (IV): Regression and Correlation Analysis

A significant deterrent to the advancement of textile research has been the use of regression and correlation analysis instead of finding the true structural relationships. The estimated coefficients found from specific populations and operating conditions are often highly volatile and unstable. Furthermore, the existence of a statistically significant correlation coefficient does not guarantee the existence of a true cause–effect relationship. More importantly, any effort to apply regression models for optimization is bound to fail under a high degree of multi-collinearity among the predictor variables. Correlation analyses are also made by collapsing the time- and location-specific quality measurements, thus making it most difficult to trace the quality traits. In spite of these obvious deficiencies, the use and abuse of statistical methods for ill-designed experiments continue as stopgap measures.

4. NEW DIRECTIONS FOR THE FUTURE

4.1 On-line Signal Processing: Time-domain Analysis, Data Reduction, and Quality 'Fingerprinting'

Rapid developments in sensors, microprocessors, and computing/storage technologies, together with the ever-declining costs for these, provide the textile industry with both an enormous opportunity and a dilemma. In spite of the relatively inexpensive memory, it is too costly to capture all the on-line data, nor is it possible to make use of the captured data fully through the currently available analysis and decision strategies. In ring spinning, a typical on-line measurement system can generate a massive amount of data in a short time period, as shown in Table I.

Table I
On-line Data-acquisition Potential and Storage Requirements in Ring Spinning and Rotor Spinning

Process Product	Carding Sliver	Roving Roving	Ring Spinning Yarn	Rotor Spinning Yarn
Linear speed (yd/min)	30	25	30	300
Measuring field (mm)	20	12	8	8
Number of data points per hour	82 296	114 300	205 740	2 057 400
Memory space for storing data (MB/day)*	4	5.5	10	100
Time to fill 1-gigabyte disk drive (days)*	250	182	100	10
Time to fill 1-gigabyte disk drive (hours)	608	4.37	0.243	0.122
(Number of units)	(10)	(1000)	(10 000)	(2000)

*Approximate figures based on 2 bytes per datum.

As is obvious from the table, it is almost unthinkable to retain the entire data in time domain, perhaps with exceptions in carding and drawing. Any data-reduction strategy, on the other hand, would be meaningless unless the variation profiles were kept intact with respect to the time axis. One promising approach would be to 'fingerprint' only the extreme deviations in time domain as a future reference in a delayed on-line decision mode. In the normal regions, the profiles may be kept by collapsing the time addresses. The mechanism for data reduction should be the very subject of future research, since it would depend on the sensitivity of the analysis and the computing and storage capacities.

In Fig. 2, as an example, only the mean ($\mu_{1,2}$) and variance ($\sigma_{1,2}{}^2$) of the on-line signal may be kept between times t_1 and t_2, whereas the entire time-series data, $Z_t(2,3)$, may be kept between times t_2 and t_3 by observing the highly deviating patterns of the process mean ($\mu_{2,3}$) and process variance ($\sigma_{2,3}{}^2$). Between times t_3 and t_4, only the mean ($\mu_{3,4}$) may be retained for its significant deviation. The variances $\sigma_{1,2}{}^2$ and $\sigma_{3,4}{}^2$ may not have to be 'fingerprinted' unless they are significantly deviating from the process norm $\sigma_0{}^2$.

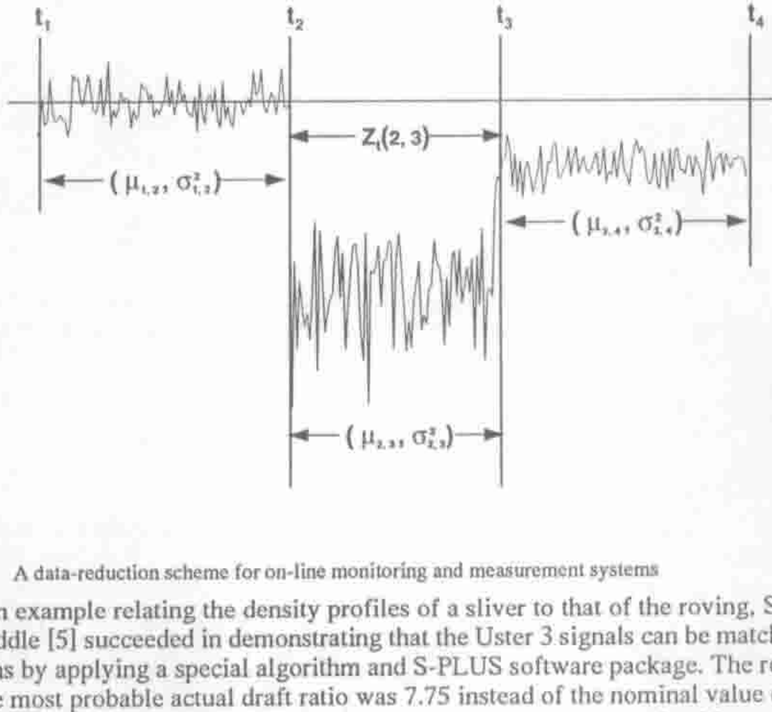

Fig. 2 A data-reduction scheme for on-line monitoring and measurement systems

In an example relating the density profiles of a sliver to that of the roving, Suh, Jeong, and Riddle [5] succeeded in demonstrating that the Uster 3 signals can be matched in time domains by applying a special algorithm and S-PLUS software package. The results were that the most probable actual draft ratio was 7.75 instead of the nominal value of 8.0 used for machine setting. The two oscillating time series could be examined by use of cross-spectrum analyses [6,7] and the 'squared coherence function', $0 \leq \mathrm{Coh}_{xy}(f)^2 \leq 1$, of series x and y around frequency f acting like a correlation coefficient. Where there is no need for a time-domain analysis, the mass amplitudes of a sliver

$$(X_1, X_2, X_3, \ldots, X_n)$$

with μ_x and $\sigma_x{}^2$ as its mean and variance, are channelled down to the mass amplitudes of the resulting roving

$$(Y_1, Y_2, \ldots, Y_{dn})$$

as

$$\mu_y = \frac{1}{d}\mu_x \tag{5}$$

$$\sigma_y{}^2 = \frac{1}{d^2}\sigma_x{}^2 + \sigma_{r|s}{}^2 \tag{6}$$

Here, d is the draft ratio, μ_y and σ_y^2 are the mean and variance of the resulting roving with dn elements, and $\sigma_{n_3}^2$ is the process variance associated with roving. The variance σ_x^2 is an input variance inherited from the sliver profile or the carding process. The paper by Suh, Jeong, and Riddle [5] has shown that the process variance introduced by roving was as much as 38–60% of the total variance of the roving.

Although the relevant research is in its infancy, the conceptual frame already exists for linking fibers, slivers, rovings, and yarns in a geometrically equivalent time axis. This application is not unique to spun-yarn-manufacturing processes.

Time-domain analysis can be considered within a frame of input and output systems as demonstrated by Godfrey [8]. When an input $u(t)$ is averaged by a weighting function $h(t)$ and added to a noise $n(t)$, the output signal $Z(t)$ can be written as:

$$Z(t) = \int_0^{T_s} h(\lambda)\, u(t-\lambda)\,\mathrm{d}\lambda + n(t) \tag{7}$$

where T_s is the 'setting time' of the system.

If the system is linear, the sum of the inputs $[\mu_1(t) + \mu_2(t) + \ldots]$ produces a response $[y_1(t) + y_2(t) + \ldots]$ through the convolution mechanisms. In a multi-stage textile-processing operation, the input responses of the previous stages are important when an output signal is to be analyzed as the input signal to the next stage in the process. Godfrey [8] shows several application examples of feedback and feedforward controls based on open-loop responses.

In recent years, time-frequency analyses (see Cohen [9] and Boashash [10] for examples) and *wavelet analyses* (see Chui [11] for examples) are rapidly gaining popularity with developments in both theory and computing. Whereas the standard Fourier analysis allows decomposition of a signal into individual frequency components, it fails to show the change in the spectral content of a signal in time. In many textile operations, the time-domain analyses are not sufficient to describe the signals that consist of many components and frequency distributions in a given time. As textile-process control moves into on-line control through signal processing, these new techniques are expected to play a major role.

4.2 Variance Decomposition and Channelling under Structural Relationships

The search for 'assignable causes' in quality control fails when a non-random signal (causes) cannot be separated from random noises that are compounded, large, and numerically inseparable in terms of their variance components. In textile-manufacturing operations, the processing data are often sufficient to estimate such important variance components due to raw materials, machines, units (spindles, feeds, etc.) within a machine, operators, environment (temperature, r.h., etc.), and time. In a given product, the variance of a quality characteristic can be decomposed into that of subcomponents. In controlling the weight per square meter of a tufted nylon carpet, for example, the variance of latex weight during the lamination process is critical to the resistance forces against pile pull-out and separation of secondary backing. In order to control the amount of the latex across the fabric width and along the machine direction, one must know the weight profiles of the tufts, primary backing, and secondary backing. That is, unless each of these variance components is known, a precise control of latex weight during lamination is not possible.

As already highlighted in Section 4.1, the concept of variance channelling is equally important if a given process stage is to be controlled precisely. The variance profiles that are inherited from the previous stages must be quantified within or outside the time axis. In a continuous process with k stages of processing, the present author [12] has shown that the process average μ_j and process variance σ_j^2 of the jth stage can be expressed as:

$$\mu_j = \mathrm{f}_j\left(\mu_{j-1}\right) + B_j, \quad j = 1,2,\ldots,k \tag{8}$$

$$\sigma_j^{\,2} = \sum_{j=0}^{j} \sigma_i^{\,2}, \quad j = 1,2,\ldots,k \tag{9}$$

Here, μ_0 and σ_0^2 are the input mean and variance, respectively, and B_j is the bias or systematic deviation from the target introduced at stage j. The structural equations, $f_j(\mu_{j-1})$, are the forward–prediction equations linking μ_{j-1} to μ_j, the process target means for stages $j-1$ and j.

The significance of Equations (8) and (9) is that the conventional control-chart procedures can be modified to isolate the control status of the present stage j from that of all previous stages. When this can be done in a continuous time domain, it may be called a *dynamic control-chart procedure* [13]. The importance of the structural equations, $f_j(\mu_{j-1})$, cannot be overstressed in making this on-line dynamic control-chart procedure a success. To date, even the most sophisticated control systems have failed to incorporate this simple model, primarily owing to lack of confidence in the structural relations and inability to separate the signals (μ_j's and B_j's) from the noises (σ_j^2's). Needless to say, μ_j's can be a vector representing more than one random variable.

4.3 Decision Strategies under New Analysis Methods

The control and improvement strategies of textile process and product qualities in the future must come from multitudes of disjoint information pools, which include on-line, time-aligned processing data, off-line test data, and other knowledge bases on the raw materials, machinery, and environment relating to the processes and products. The decision mechanisms cannot therefore be solely equation-based or logic-based. In addition, inferences drawn from more than one method may not be compatible with each other. For this reason, the control and improvement decisions must rely on numerical analysis as well as on heuristics. Such modern approaches as expert systems or fuzzy logic show much promise. Dastoor *et al.* [14] applied an expert-systems approach for developing industrial fabrics by mixing the heuristics with numerically based structural equations. The much-heralded CIM (computer-integrated manufacturing) has not so far been effective in textile quality control, primarily owing to the fact that sensors, monitoring, and measurements alone could not lead to meaningful automated decision-making for control and improvement. Two key areas, namely, variance analysis and structural relationships, are yet to be incorporated into the CIM decision structure. Without them, CIM would remain as a computerized fact-finding tool, far short of fulfilling the global objectives of controlling and improving textile process and product qualities.

5. CONCLUDING WORDS

The large textile-science and textile-engineering knowledge base has not been much utilized for textile production and quality control for reasons that can be amply justified. The recent measurement, control, and computing technologies, however, provide a great opportunity to convert the dormant knowledge base into practical gains. On-line measurement, time-aligned signal-processing techniques, and backward-quality prediction and fingerprinting techniques, together with novel analysis strategies, must be fully explored in order to capitalize on the available technology resources. The future for textile technology will have to rely as much on these new high-tech process-control systems as on the new process and machinery developments.

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