FROM PREDICTIVE MODELS TO PROFITABILITY IN THE WEB-HANDLING INDUSTRY

by

Z. Hakiel

Eastman Kodak Company
Rochester, N.Y.

ABSTRACT

This paper attempts to put some of the work being done by researchers in the web-handling field, including some of the papers to be presented at this conference, into a broader business context. Various ways of utilizing predictive models are discussed, ranging from troubleshooting to robust product-process design. A future-state vision for a highly effective web-handling predictive model is defined. An example consisting of the application of an analytical wound-roll stress model in conjunction with statistical methods to the robust design of a roll-winding process is described to illustrate the potential value of such an approach.

NOMENCLATURE

A_c	cost associated with shutting down the line due to catastrophic roll cinching on unwinder
A_p	total cost of roll
E	Young's modulus of the web in tension
ECOR	radial compressive modulus of the core
ESF	scaling factor for the radial modulus of the web/roll
GBA	gage band amplitude
GBWR	gage band width ratio
l	length of roll
l_p	length of web within roll affected by pressure damage defect
L	quality loss function

$\overline{L}$	average value of quality loss function
$\underline{L}$	standard deviation of quality loss function due to noise factors
L_c	quality loss due to cinching problem
L_p	quality loss due to pressure damage defect
$\overline{P}$	interlayer pressure in wound-roll averaged over width direction
r	in-roll radius
ST	winding tension at the core
TEMP	temperature of the roll at time of unwinding
TTD	diameter at which winding tension transitions from a constant tension to a constant torque profile
y_c	minimum transmittable torque for the unwinding roll
y_o	maximum unwinding torque, including safety factors

THE VALUE OF WEB-HANDLING PROCESS MODELS

The overall objective for this paper is to suggest ways of bringing web-handling-model development and applications to a higher, more effective level. Specifically, the goals for the paper are the following:

- To put some of the work on model development, which will be presented at this conference, into a broader business context.
- To show how future work on web-handling-model development can be made even more useful and relevant to industry.
- To review various ways of using predictive models and suggest additional ways which are more powerful and result in greater benefit to industry.

As the title of this paper suggests, the ultimate reason for the development and application of predictive web-handling models is to improve the profitability of the industry. Models are applied at various levels in the web-handling industry. At the most basic level, models are used to obtain a qualitative understanding of how the process operates and to develop the so-called "rules-of-thumb" for the process. This qualitative understanding is then used by the people operating the web line to solve problems and analyze web-handling-related product defects. At a higher level, predictive models are used to simulate specific problems and to suggest solutions which can then be verified experimentally or on the production web line. While there are numerous examples of these types of applications of predictive models, the premise of this paper is that the full potential and power of such models has not yet been fully explored.

The challenge is not just to use predictive models for solving today's problems on the web line, although that clearly in itself is extremely valuable to industry, but to anticipate and solve these problems before they ever occur. To accomplish this, what is needed is a marriage of predictive process models with modern statistical techniques to design processes and products which are optimized and robust. To enable this, improved analytical models are needed for web-handling processes, which are not just easy to use and accessible to practitioners, but which include the effects of all the critical real-world factors, both control and noise, which ultimately determine the success of our operations.

The future-state vision of a very effective web-handling predictive model includes these key elements:

- must be based on scientific principles, fundamental in nature, and applicable to a variety of specific conditions
- must include all key process and product variables including those that are controlled and those which are noise factors
- must predict outcomes which are meaningful to industry, such as defects, so that those outcomes can be converted to an assessment of their value (cost) to industry
- can be used to examine the effect of variability in both the control and noise factors by employing statistical analysis tools
- must be accessible to the intended users, in terms of understanding and hardware requirements.

There is no better audience for this message than this international conference on web-handling. The people who can actualize this future vision of a higher, and ultimately more profitable, level of web-handling-model development and application come from university and industry and are well represented at this conference. There are people in attendance here who do research on the web-handling process, develop models, design equipment, run that equipment, execute experiments, produce product, design products, and most of all worry about the money they stand to lose or make from the entire enterprise. These are the people who can and are developing more powerful models of web-handling. These are also the people who can point the way to more effective applications of these models, which will further enhance the value of their own work.

Various types of web-handling models have been developed and are being utilized in the industry. Some of them are based on the underlying first principles and thus can be applied to a broad range of practical situations. Others are based on observations and tend to be more specific to a particular machine or application. Some of the processes are so complex that they require sophisticated numerical code and high-powered computers. Others can be reduced to simple equations or performance curves. Some examples of these models which will be discussed at this conference include the following: wound-roll stress models, models of lateral dynamics and control, models of longitudinal dynamics and tension control, models of air-supported web transport, models of air entrainment, models of web - roller interactions, and models of nip mechanics.

Web-handling processes can have a major impact on the profitability of web converting manufacturing operations. First, in order to perform any of the converting operations and "make product," it is required that the webs be unwound, transported, and wound. In the process of handling the webs, there may be numerous opportunities to impart defects to the webs, such as scratches, pressure damage, and wrinkles. The reliability of the web-handling processes will have a direct impact on the reliability of the entire operation. Tear-offs and shifted rolls, for example, can cause the entire web line to shut down, resulting in significant losses of material and production time. When new products need to be produced, it is imperative that they be compatible with the web-handling processes being employed on the web line, so that costly manufacturability problems can be avoided. In some cases, the web-handling processes may limit the speed at which a manufacturing operation can be operated at and will therefore have a direct impact on productivity and the cost to manufacture product.

There are numerous ways for predictive web-handling models to be used to improve the web-handling process and, as a result, to increase the profitability of the manufacturing operation. The applications of predictive web-handling process models range from troubleshooting web line problems to designing future processes or products. Examples of how web-handling process models can be used include the following:

- troubleshoot process - fix problems on the line
- fix product defects by examining effect of product and process parameters on defect
- develop understanding of process and develop "rules of thumb" through parametric studies done with the models
- use of models to teach or learn basic principles of process
- optimize process - set conditions to minimize a response function such as waste
- use statistical analysis with models to rank importance of sources of variability
- incorporate models into web-handling process control scheme
- use models in conjunction with process measurements to verify that process is operating correctly
- use models to help design products for manufacturability
- use models to help define robust process and product design (minimize sensitivity to variability in process and incoming materials)

In all of the above applications, predictive models offer the advantage of lower cost, lower risk, and shorter cycle time over empirical studies done in a lab or on the production line. Large quantities of web materials are not needed to run models. Machine time does not need to be scheduled or utilized. There is no risk of damaging the equipment by running "far out" conditions to explore the limits of the process. There is an opportunity to study the effect of process or product variability without running a very large number of experiments and at much lower cost. Most importantly, perhaps, there is an opportunity to look forward to future process conditions, future products and future web lines to anticipate web-handling problems before they ever occur and prevent them through optimum robust design of the process, product, and equipment.

AN EXAMPLE OF ROBUST WOUND-ROLL DESIGN

Introduction

In order to illustrate the high-level application of a predictive web-handling model, we will employ a wound-roll stress model in conjunction with statistical methods to develop a robust wound-roll design. In particular, we will show how the winding process and the product web can be optimized in a way which minimizes the overall cost of the manufacturing process and its sensitivity to noise factors. Thus, solving the problem of robust wound-roll design will allow us to answer the fundamental question of the roll-winding process: "How to Wind the Best Roll?"

Before proceeding with the specific case study, let us first define more precisely what we mean by the "Best Roll." The basic premise is that the "Best Roll" is the one which results in the greatest overall value to "society." The paper makers have a saying: "You don't make paper on the winder." This is equally true for all web-converting operations and all web-handling processes. We cannot improve the product web by winding or transporting it. However, we do need to wind and transport webs in order to make them, coat them, slit them, print them, and ultimately sell them. And while we are transporting and winding webs, there is ample opportunity to damage them by allowing various imperfections or defects to occur. The cost of these defects must be included in our consideration of overall value. Other manufacturing costs including the impact of reliability, productivity, and new product cycle time must be accounted for, as well. A useful way of doing that is by utilizing the concept of a Quality Loss Function. This is analogous to the Quality Loss Function utilized in formal Robust Design Methodology, as is described, for example, by Phadke (1), and will be illustrated in the example below.

Problem Statement

The objective is to design a winding process for a hypothetical web product, which will be optimum in the sense that the value of the corresponding Quality Loss Function will be minimized and its sensitivity to various noise factors will be minimized as well. The variables which will be considered in this example are listed below, in the order of increasing difficulty to change or control. The first three of the factors are considered to be "control factors," since they can be changed, although at considerable cost in some cases. The last three factors are considered "noise factors," in that their variability is a given and their values cannot be changed.

Control Factors

Winding Tension is assumed to follow the winding tension profile depicted in Figure 1. This profile can be completely characterized by the value of the tension at the core (**ST**) - and the diameter of the roll at which the profile changes from a constant tension to a constant torque formula (**TTD**). Winding Tension is a process variable which is readily changed and controlled.

Radial Modulus of Web is assumed to follow the previously determined function of interlayer pressure, which is depicted in Figure 2. It can be changed by a redesign of the web surface roughness and the degree of change is characterized by a scaling factor on the radial modulus function (**ESF**). Radial modulus can be changed from the nominal value, but some cost and time would be involved in redesigning the surface of the product.

Widthwise Thickness Uniformity for the purpose of the current example is represented by the idealized profile shown in Figure 3. This profile can be completely characterized by the value of the gage band thickness (**GBA**) and the gage band width ratio (**GBWR**), as defined in Figure 3. Changing the thickness uniformity of the film would require significant development and capital investment and both of these would require significant time to complete.

Noise Factors

Core Modulus - the radial modulus of the core (**ECOR**) is determined by the design of the existing cores being used by the factory. Measurements of core modulus indicate a range of 605,000 to 645,000 psi. Due to the large investment in the cores and associated infrastructure, changing the core or reducing their variability will not be considered.

Young's Modulus - the elastic modulus of the web in tension (**E**) is a characteristic of the basic web material. Variability in the existing base-making process and in the raw materials result in a range of 590,000 to 630,000 psi for the Young's modulus of the web and it is impractical to reduce this range.

Storage/Unwinding Temperature (**TEMP**) is controlled in all of the manufacturing areas. However, variability in shipping and storage conditions due to seasonal changes are known to affect the final temperature of the unwinding roll. Measurements of the unwinding roll temperature indicate a range of 57 to 83 degrees F. Major changes to the shipping and storage operations would be required to reduce this range and will not be considered.

Quality Loss Function

Based on prior manufacturing experience with the given film product, it is known that most of the variable costs associated with the manufacturing of this product are due to two problem areas. The first of these is a pressure-induced imperfection which damages a thin coating applied to the web. The second is the structural failure of the unwinding roll in a downstream operation on the unwinder, which is caused by cinching of the roll through torque transmission failure. Since all of the other costs associated with the manufacturing of this product are fixed, we will only include the effect of these two imperfections on the Quality Loss Function.

Thus, we define the Quality Loss Function as

$$L = L_p + L_c \tag{1}$$

where L_p is the quality loss associated with the pressure-induced imperfection and L_c is the quality loss associated with the roll-cinching problem. Following Phadke (1), we further define the quality loss due to the pressure-induced imperfection using his "smaller-the-better" formulation as

$$L_p = A_p \{\frac{l_p}{l}\}^2 \qquad (2)$$

where l_p is the length within the roll of web affected by the imperfection, l is the total length of the roll, and A_p is the total cost of the roll.

We use Phadke's (1) "larger-the-better" formulation to define the quality loss due to the cinching problem as

$$L_c = A_c \{\frac{y_o}{y_c}\}^2 \qquad (3)$$

where A_c is the cost associated with shutting down the line due to catastrophic roll-cinching on the unwinder, y_o is the maximum unwinding torque applied to the roll on the unwinder including safety factors, and y_c is the minimum transmittable torque for the unwinding roll without layer-to-layer slippage.

In order to evaluate the Quality Loss Function, L, as a function of the control and noise factors listed above, the nonlinear-orthotropic wound-roll stress model with width effects was utilized, which was previously described by Cole and Hakiel (2) and which is depicted schematically in Figure 4. In Figure 4, BVP refers to the boundary-value-problem of the one-dimensional nonlinear wound-roll stress model previously described by Hakiel (3). In addition, a simple thermal stress model was applied to the results of the wound-roll stress model in order to determine the effect of storage temperature. From the wound-roll stress model, we are able to compute the predicted interlayer pressure, P, as a function of roll radius and width, as described in reference (2). By comparing the predicted pressure to the critical pressure at which damage to the product can occur, we can compute the length of the product which is at risk for the pressure-induced imperfection, l_p. We also utilize the predicted pressure distribution to compute the minimum transmissible torque within the roll by using the following simple torque balance:

$$y_c = \min\{2\pi * f * \overline{P}(r) * r^2\} \qquad (4)$$

where f is the coefficient of friction of the web against itself (front-to-back) and $\overline{P}(r)$ is the radial interlayer pressure distribution predicted by the wound-roll stress model and averaged across the width of the roll.

Since the other terms in equations (1) - (3) are fixed, by using the control and noise factors defined above as inputs to the wound-roll stress model, we are able to compute the Quality Loss Function as a function of those factors.

Numerical Experiment and Results

In order to identify the combination of values for the control factors which will minimize the Quality Loss Function, while at the same time minimizing its sensitivity to the variability in the noise factors, we start out by performing a numerical experiment utilizing the methodology defined above for computing the Quality Loss Function. A central-composite experimental design will be used for the five control factors. This experimental design consists of 27 unique combinations of the control variables. In addition, to determine the effect of the noise factors at each of the control factor settings, four variations of the noise factors were considered at each of the 27 control factor combinations. This resulted in a total of 108 combinations for the numerical experiment, as is depicted in Table 1. The Quality Loss Function, L, was computed for each of the 108 runs and its value is also given in Table 1. From the computed L values, the average, $\overline{L}$, and standard deviation due to the noise factors, Ƚ, were computed for each of the 27 settings of the control factors and are displayed in Table 2. The following values were assumed for the purpose of this computation:

$$\boxed{\begin{array}{l} A_c = 2000 \\ A_p = 1000 \\ y_o = 3000 \end{array}}$$

The average value and range of L for each of the 27 control factor settings are depicted graphically in Figure 5. As can be seen there, some of the combinations of control factors yielded very high values of the Quality Loss Function, while others resulted in values close to zero. Similarly, the range of the L values for some of the settings is quite large indicating a high degree of sensitivity to the noise factors, while for some settings of the control factors the range is very low. Visual examination of Figure 5 suggests that control factor settings 6, 12, 18, 21, 23, and 27 appear to offer a combination of low $\overline{L}$ values and low sensitivity to the noise factors, as indicated by the range. A closer examination of these settings reveals that among them, setting number 27 looks especially attractive, as it results in the least sensitivity to the noise factors and does not require the control factors **GBA** and **GBWR**, which describe the thickness variability of the base and are the most difficult of the control factors to change, to be modified from their middle values. The values for setting number 27 are

GBWR	0.082
GBA	0.1
ST	90
TTD	8.83
ESF	0.9

In order to take the optimization of the control factors a step further, a second-order polynomial model was fitted to the average values, $\overline{L}$, as a function of the control factors. Similarly, a second-order polynomial model was fitted to the standard deviation values due to the noise factors, Ƚ, as a function of the control factors. The model of the average values resulted in a very good numerical fit with an R-Square value of 0.97. The model of the standard deviations resulted in an R-Square value of 0.87. The models were used to generate a mesh of 10,500 points at which $\overline{L}$ and Ł due to noise factors were predicted. A grid-search was performed on these points to identify the optimum setting at which the sum of the squares of $\overline{L}$ and Ł was minimized. The optimum setting resulting from the grid-search optimization is

GBWR	0.066
GBA	0.05
ST	110
TTD	10.5
ESF	0.95

The $\overline{L}$ and Ł values as predicted by the polynomial models for this setting were 0.18 and 1.54 respectively. A confirmation run done with the analytical models resulted in slightly higher values of 12.68 and 3.95 for $\overline{L}$ and Ł. Although these values are better than the values previously obtained for setting number 27, which were 21.33 and 4.36 for $\overline{L}$ and Ł respectively, the optimum selected by the grid-search optimization routine requires an improvement in the thickness variation of the web which may be difficult and costly to obtain. Consequently, the control factor setting number 27 may represent a better overall choice for the optimum conditions.

SUMMARY

- Various types of predictive web-handling models and ways of applying them to industry problems were briefly described.

- A future-state vision for a very effective predictive model was defined and included the capability to deal with control and noise factors and the ability to predict outcomes, such as defects, which can be related to cost in manufacturing.

- A case study was used to illustrate the use of a predictive wound-roll stress model in conjunction with statistical analysis to develop a robust design for a web-winding process. In this case study, a numerical experiment was used to minimize the Quality Loss Function and its sensitivity to noise factors.

ACKNOWLEDGMENTS

The author is indebted to his colleagues: Dr. K. A. Cole and Ms. S. A. Guzman, for their assistance with executing the wound-roll stress models and Dr. B. R. Knoebel, for performing the statistical analysis.

REFERENCES

1. Phadke, M. S., Quality Engineering using Robust Design, P T R Prentice-Hall, Englewood Cliffs, New Jersey, 1989

2. Cole, K. A. and Hakiel, Z., "A Nonlinear Wound-roll Stress Model Accounting for Widthwise Web Thickness Nonuniformities," Web-handling Proceedings of the Winter Annual Meeting of ASME, AMD-Vol 149, pp. 13-24.

3. Hakiel, Z., "Nonlinear Model for Wound-roll Stresses," TAPPI Journal, Vol. 70, No. 5, 1987, pp. 113-117.

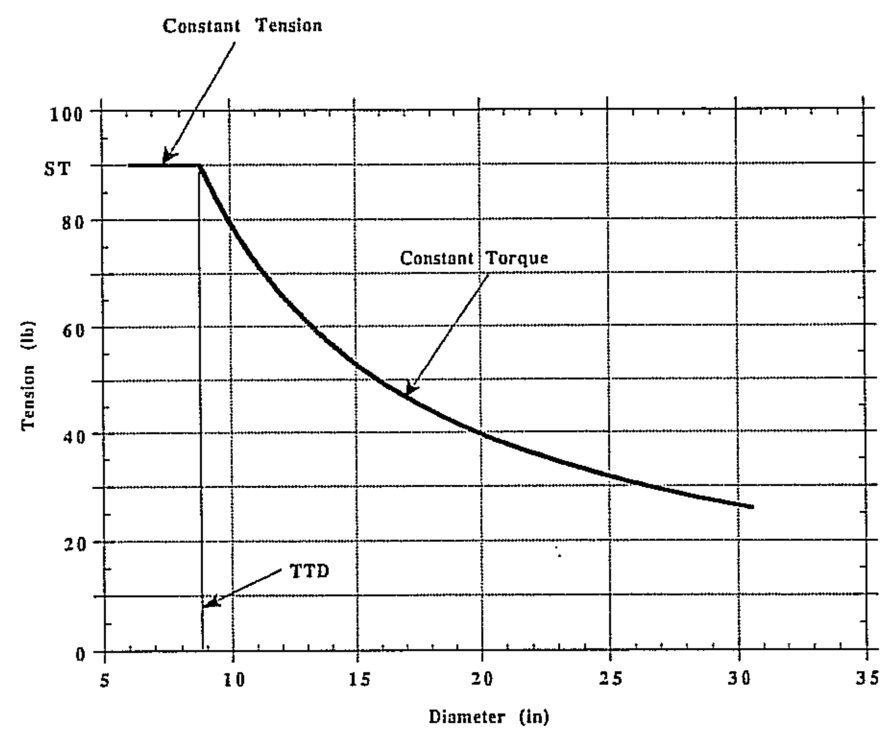

Figure 1 - Winding Tension Profile Used in Wound-Roll Stress Simulation

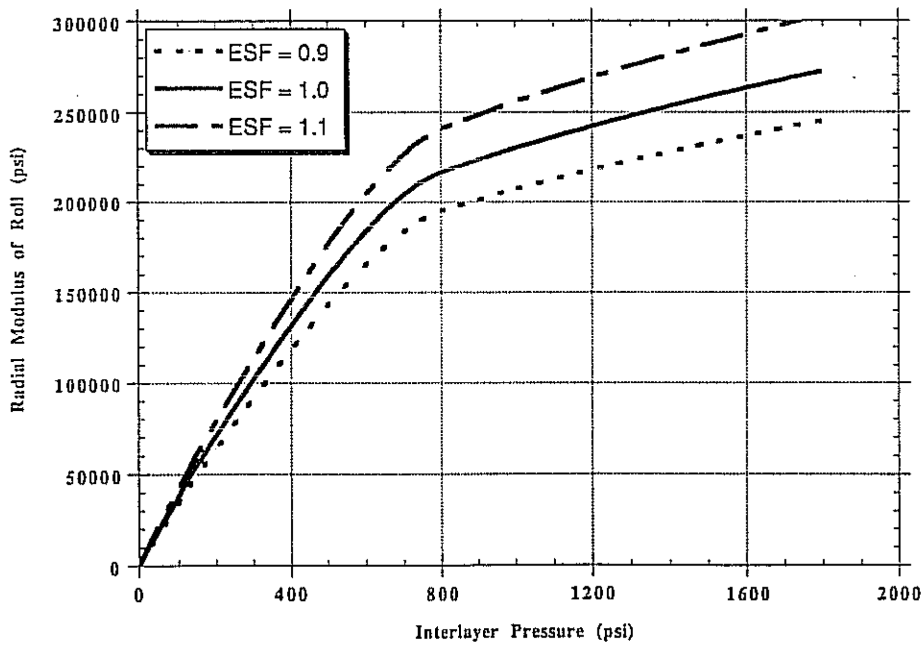

Figure 2 - Radial Modulus of the Roll Used in Wound-Roll Stress Simulation

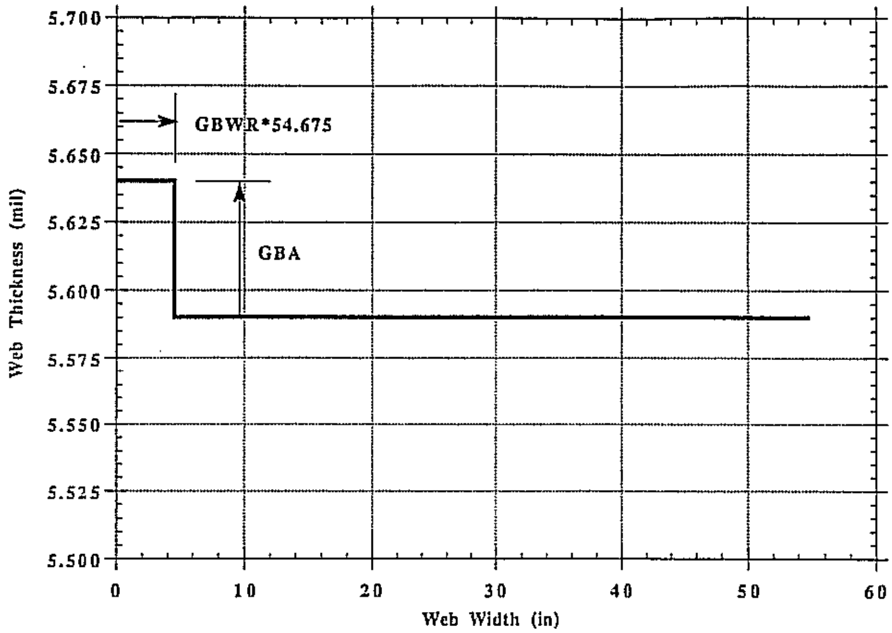

Figure 3 - Idealized Widthwise Thickness Profile Used in Wound-Roll Stress Simulation

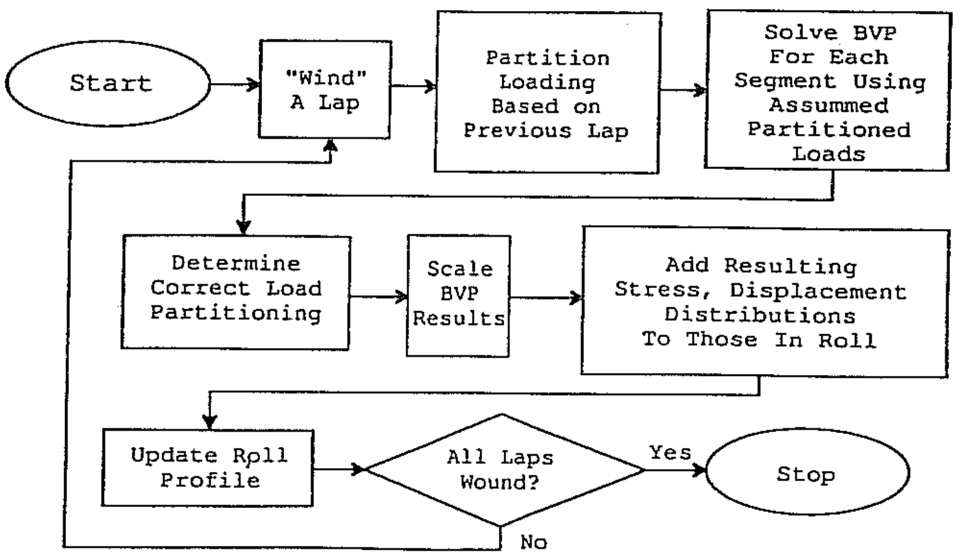

Figure 4 - Flow Chart of Wound-Roll Stress Model of Reference (2).

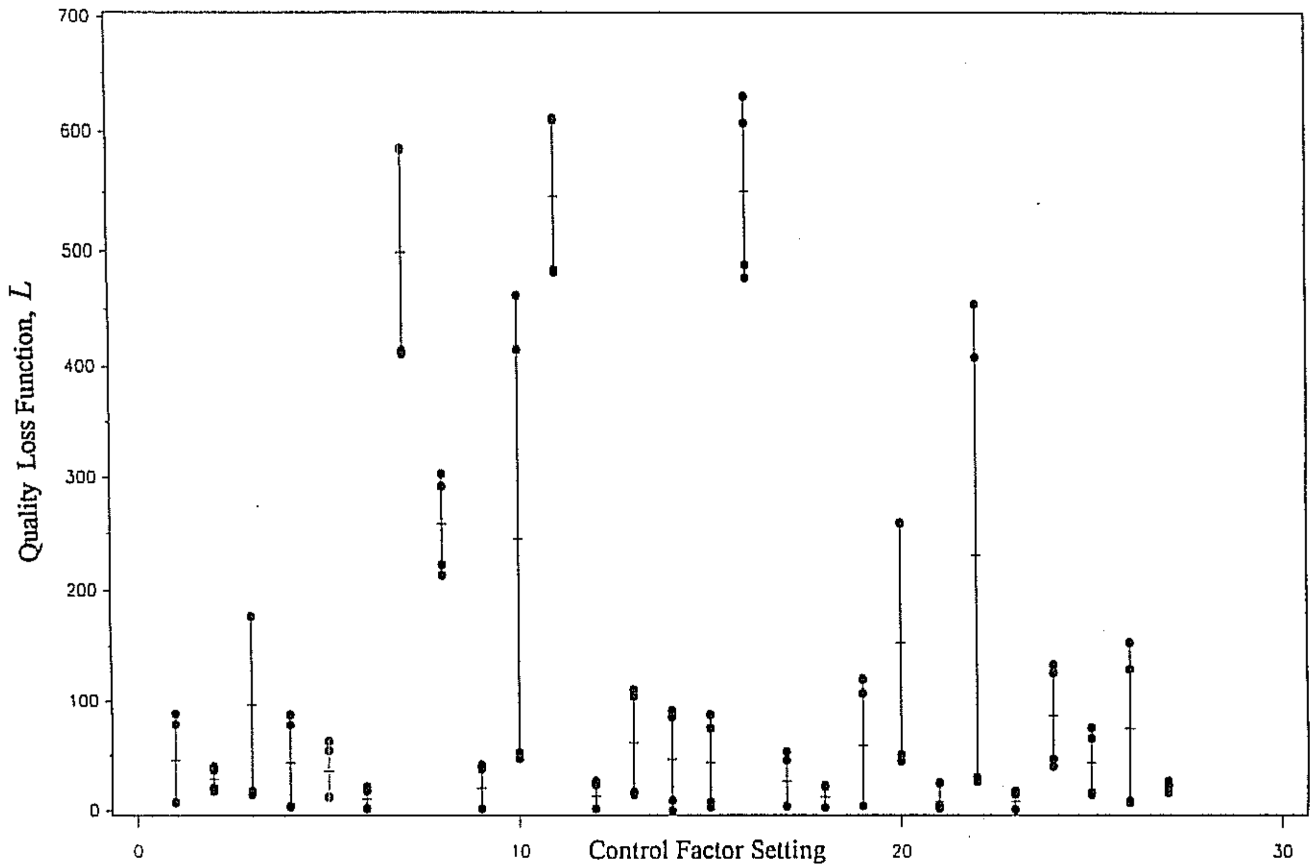

Figure 5 - Quality Loss Function, L, as a Function of the Control Factors. The Individual Values, Means and Ranges are Shown for Each Control Factor Setting.

						ECOR			
						605000		645000	
						E		E	
						590000	630000	590000	630000
						TEMP	TEMP	TEMP	TEMP
						83	57	57	83
						L	L	L	L
CFN	ESF	GBA	GBWR	TTD	ST				
1	0.9	0	0.00674	6.155	110	7.33	88.30	78.90	8.38
2	1	0.1	0.0821	8.828	90	39.70	20.90	18.20	36.90
3	0.9	0	0.00674	11.5	70	15.30	177.00	177.00	18.20
4	1.1	0	0.368	6.155	110	3.76	87.30	78.20	4.33
5	1	0.1	0.0821	8.828	70	12.90	63.30	54.60	12.70
6	0.9	0	0.368	11.5	110	1.83	21.70	18.30	2.14
7	1.1	0.2	0.00674	6.155	110	585.00	414.00	411.00	585.00
8	0.9	0.2	0.00674	6.155	70	303.00	222.00	213.00	292.00
9	1.1	0.2	0.368	11.5	110	41.00	1.95	1.67	37.80
10	0.9	0	0.368	6.155	70	47.10	462.00	415.00	52.80
11	1.1	0.2	0.00674	11.5	70	610.00	484.00	482.00	611.00
12	0.9	0.2	0.368	6.155	110	1.64	26.60	23.50	1.78
13	1	0.1	0.0821	11.5	90	110.00	17.10	14.60	104.00
14	1	0.1	0.0821	8.828	110	90.70	9.16	0.08	85.10
15	1	0.1	0.0821	6.155	90	3.13	87.00	74.90	8.07
16	0.9	0.2	0.00674	11.5	110	607.00	477.00	488.00	630.00
17	1	0	0.0821	8.828	90	3.71	53.20	45.50	4.28
18	0.9	0.2	0.368	11.5	70	3.04	22.00	22.40	3.22
19	1.1	0.2	0.368	6.155	70	4.37	120.00	107.00	4.78
20	1	0.2	0.0821	8.828	90	258.00	44.60	51.00	258.00
21	1	0.1	0.368	8.828	90	1.92	25.00	4.76	2.15
22	1.1	0	0.00674	6.155	70	26.60	454.00	408.00	30.10
23	1.1	0	0.00674	11.5	110	0.99	18.00	15.00	1.14
24	1	0.1	0.00674	8.828	90	133.00	46.60	40.00	126.00
25	1.1	0.1	0.0821	8.828	90	75.10	16.90	14.70	65.70
26	1.1	0	0.368	11.5	70	7.45	153.00	129.00	8.83
27	0.9	0.1	0.0821	8.828	90	19.30	26.50	23.00	16.50

Table 1 - Quality Loss Function, L, as a Function of the Control Factors, for Various Values of the Noise Factors.

	ESF	GBA	GBWR	TTD	ST	$\bar{L}$	$\not{L}$
1	0.9	0	0.00674	6.155	110	45.728	43.902
2	1	0.1	0.0821	8.828	90	28.925	10.941
3	0.9	0	0.00674	11.5	70	96.875	92.528
4	1.1	0	0.368	6.155	110	43.398	45.593
5	1	0.1	0.0821	8.828	70	35.875	26.881
6	0.9	0	0.368	11.5	110	10.993	10.494
7	1.1	0.2	0.00674	6.155	110	498.750	99.600
8	0.9	0.2	0.00674	6.155	70	257.500	46.551
9	1.1	0.2	0.368	11.5	110	20.605	21.742
10	0.9	0	0.368	6.155	70	244.225	225.161
11	1.1	0.2	0.00674	11.5	70	546.750	73.618
12	0.9	0.2	0.368	6.155	110	13.380	13.535
13	1	0.1	0.0821	11.5	90	61.425	52.692
14	1	0.1	0.0821	8.828	110	46.260	48.279
15	1	0.1	0.0821	6.155	90	43.275	43.829
16	0.9	0.2	0.00674	11.5	110	550.500	79.206
17	1	0	0.0821	8.828	90	26.673	26.375
18	0.9	0.2	0.368	11.5	70	12.665	11.012
19	1.1	0.2	0.368	6.155	70	59.038	63.112
20	1	0.2	0.0821	8.828	90	152.900	121.387
21	1	0.1	0.368	8.828	90	8.458	11.103
22	1.1	0	0.00674	6.155	70	229.675	233.232
23	1.1	0	0.00674	11.5	110	8.784	8.994
24	1	0.1	0.00674	8.828	90	86.400	49.922
25	1.1	0.1	0.0821	8.828	90	43.100	31.769
26	1.1	0	0.368	11.5	70	74.570	77.332
27	0.9	0.1	0.0821	8.828	90	21.325	4.358

Table 2

Average Values of the Quality Loss Function, $\bar{L}$, and the Deviation in the Quality Loss Function Due to the Noise Factors, $\not{L}$, as a Function of the Control Factors.

Hakiel, Z.
From Predictive Models to Profitability in Web Handling Industry
6/19/95 Keynote 9:00 - 9:50 a.m.

Question - OSU - Have you made any money this way?

Answer - Making money all the time.

Question - You said you made the objective function by using control factor contribution and by noise factor contribution, but there are infinite factors. What is the rule to select numbers, how do you know which way to go depending upon selection of one?

Answer - To paraphrase - How do you select the finite number of combinations of control and noise factors when there are infinite combinations in the real world. Its a very good question and I think its something you have to do using your practical experience. First of all, there aren't infinite numbers but there are range numbers of combinations. Practical speaking you have to think about what your control factors really are; things you know will influence how the process will operate-so if you should first select those variables. For each of these variables, you should select a typical range and two to three levels within that range. In terms of noise factors, what is typically done is, what is done by people working on robust design methodology which is to use the worst combination of them.

Thank you.