Using neural networks to diagnose web breaks on a newsprint paper machine

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ABSTRACT

Artificial neural networks hold great promise for solving problems that are extremely difficult to solve using conventional methods. We used an artificial neural network to diagnose paper web breaks on a commercial newsprint paper machine. Process data for pulping and papermaking operations were collected from the paper machine's distributed control system. Additional data were obtained from on-line wet-end sensors (zeta potential, first-pass retention, conductivity, and pH) that were installed for this study. The essential variables contributing to paper web breaks were extracted using a three-stage multilayer neural network and back-propagation method. Great savings of production costs were achieved: the number of web breaks was reduced, fiber loss in the effluent was decreased, and workers spent less time cleaning, rethreading, and restarting the paper machine.

Application:

A case study showing how one mill used a neural network and conventional statistical analysis to identify an effective strategy for reducing web breaks.

WEB BREAKS ARE COMPLEX phenomena with multiple causes that can vary considerably from one process to another. A web break on the paper machine severely impairs production efficiency. Production loss during the outage is the principal consideration, but there is also the extra work required to clean, rethread, and restart the paper machine. Bringing the machine back on line consumes a great deal of time and raw materials.

Artificial neural networks have recently been advocated as a possible technique for fault detection and diagnosis in chemical plants. Neural networks have the ability to learn nonlinear relationships, so they hold great promise for solving problems that resist solution—or are extremely difficult to solve—using conventional methods. However, results for the few applications in the published literature *(1–3)* are mostly based on simulation. In the pulp and paper industries, Rudd *(4)* developed a network to estimate the pulp mat consistency in a bleach washer. Kohonen *(5)* created a self-organizing map to investigate web breaks on a paper machine. Dayal *(6)* applied feedforward neural networks and partial least-squares regression to model kappa number in a continuous Kamyr digester.

The present study applies artificial neural networks to diagnose web breaks on a commercial paper machine producing newsprint. Roisum *(7–8)* reviewed runnability studies of paper machines and found that shives accounted for most web breaks. In our mill, the importance of lowering shive content was well recognized, and various countermeasures had already been taken. Moreover, whenever the machine is shut down for any reason, the paper machine crew does a chemical boilout and carefully inspects the system to remove dirt and deposits. Given these circumstances, our Central Research Laboratory was asked to explore the causes of web breaks from a different point of view. After discussions with the mill and the Engineering Division at the head office, we decided to focus on wet-end chemistry. The mill had considered investigating wet-end chemistry as a possible means of reducing web breaks, but the well-known complexity of wet-end chemistry phenomena proved to be a daunting obstacle.

This report begins with a description of the paper machine and the measurement of process variables. The next section introduces the neural-network architecture suitable for diagnosing web breaks. Finally, the report presents the neural network's diagnosis and compares this with results obtained using conventional statistical methods (principal-component regression).

PAPER MACHINE MEASUREMENTS

Nippon Paper Industries has seven newsprint paper machines. The average record of the best paper machine was 10 web breaks per month. The Engineering Division at the head office wanted to reduce this by half, so they set a target of five breaks per month. The average number of breaks on the newsprint machine we were asked to diagnose was 20 per month. Our assigned objective was to decrease it to less than five breaks per month.

The newsprint machine is 280 in. wide with a twin-wire former (Bel Baie 2). The design capacity of the machine is 400 tons/day, and machine speed is 1000 m/min. Half of the pulp furnish is deinked old newsprint (DIP), with the balance made up of groundwood pulp (GP), thermomechanical pulp (TMP), and softwood bleached kraft pulp (SBKP). The paper machine is

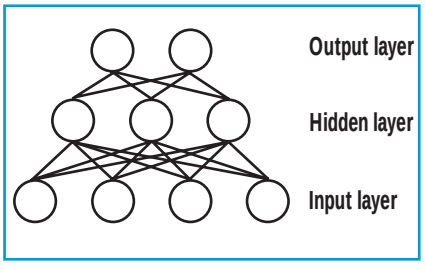
No.	Variable
On-line sensors[b]	
1	SBKP freeness
2	GP freeness
3	TMP freeness
4	1 DIP freeness
5	2 DIP freeness
6	Inlet pH
7	Inlet temperature
8	Inlet conductivity
9	Inlet zeta potential
10	Inlet consistency
11	White-water consistency
12	Inlet pressure
13	Wire suction-box vacuum
14	Pickup-felt vacuum
15	Couch vacuum
16	Dryer steam pressure
17	Wet-web moisture
18	Basis weight
19	Paper moisture
20	Caliper
21	Spot (large)
22	Spot (small)
23	Black spot (large)
24	Black spot (medium)
25	2P/3P draw
26	3P/1D draw
27	Machine speed
28	Broke ratio
29	Alum
30	Retention aid
31	SBKP ratio
32	GP ratio
33	TMP ratio
34	1 DIP ratio
35	2 DIP ratio
Laboratory measurements[c]	
36	Tear strength
37	Tensile strength
38	Stretch
39	Brightness
40	Opacity
41	Stuff-box freeness

[a] For a 280-in.-wide twin-wire (Bel Baie 2) machine producing newsprint at 1000 m/min with a production capacity of 400 tons/day.
[b] Monitored on-line at 3-min intervals
[c] Measured in laboratory at 4-h intervals

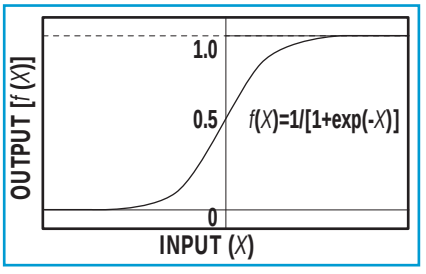
I. Variables used in web-break diagnosis[a]

	Output
Normal	[1 0]
Break	[0 1]

II. Output nodes for normal operating conditions and at web break



1. Typical neural-network architecture



2. General sigmoid function

equipped with a process-control system, but even with access to real-time data, the mill still could not collect enough data to understand the wet-end phenomena. To start our analysis, on-line wet-end sensors (zeta potential, first-pass retention, conductivity, and pH) were installed on the paper machine. Other on-line pulping and papermaking process data were collected from the distributed control system. Pulp and paper properties were also measured off-line in a mill laboratory on a regular basis. The total number of on-line and off-line measurements was 42, which included one web-break signal and 41 process variables and pulp and paper properties, which are listed in **Table I**. The neural network evolved its knowledge of web breaks from sets of data that were collected under normal operating conditions and when paper web breaks occurred.

Data were collected for about a month, and an 8-h average was calculated for each variable. Web breaks cause variation of process data, and this variation should not be interpreted as the process disturbance to create a web break. Hence the data obtained within an hour after each break were excluded from average calculations and were not used for break analysis.

With 8-h averaging, three data points were generated daily for each variable. By the end of the month, there were 79 averaged data points for each variable, which corresponds to 27 days. There were several short-term shutdowns during the course of the month, including nine web breaks. This was fewer than the average number of 20 breaks but still twice the target number of five breaks.

The original measurement data contained both small and large values. Without scaling, fluctuations in large measurement values would dominate the operation of a neural network. Consequently, all of the process variables were scaled to a continuous range from zero to one.

NEURAL NETWORKS

Architecture

The architecture of neural networks has been described in numerous articles *(1, 2)*. Neural networks are made up of highly interconnected layers that perform in a manner analogous to the basic biological neuron of the brain. These layers include an input layer and an output layer that contains the response to given inputs. There are also intermediate or hidden layers. Each input is multiplied by a weight factor, and the weighted inputs are then summed and propagated forward to the hidden layers and, finally, to the output layers.

Figure 1 illustrates the architecture for a typical neural network. The total input, net_j, to the jth processing element can be represented mathematically as

$$net_j = \sum [(X_n W_n) + \theta_j]$$

where

X_n = nth input
W_n = nth weight applied to nth input
θ_j = threshold

A sigmoid transfer function is applied to net_j to obtain the output of jth processing element, Y_j.

$$Y_j = f(net_j) = 1/[1 + \exp(-\beta \times net_j)]$$

where

β = constant gain term that determines the slope of the sigmoid function at $net_j = 0$.

Figure 2 shows a general sigmoid function.

The network is repeatedly presented with a set of input–output data for learning. Learning is accomplished by dynamically correcting the weights of all interconnections in an attempt to generate the desired output pattern for each presented set of input variables. The correction mechanism starts with the output layers and propagates back in the reverse direction. This process is continued until the network predictions are within some defined tolerance of acceptability.

Web-break diagnosis

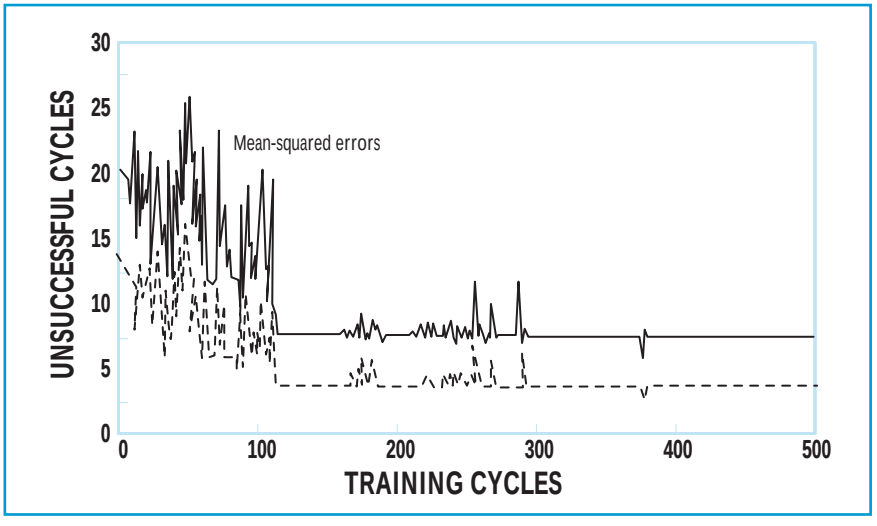
A three-stage multilayer neural network and back-propagation method were proposed to extract essential causes of paper web breaks. A computer software package (Neuro 7:Michizane, NEC) was used for neural-network diagnosis. The software manual introduced both a one-output-node model and a two-output-node model for fault diagnosis. The appropriate model for a given situation should be selected on a trial-and-error basis. In the one-output model, a "one" represents a break and zero is a normal condition. In the two-output model, two nodes are defined: one for normal operating conditions and another for when a web break occurs, as seen in **Table II**.

In web-break diagnosis, the model with two output nodes was found to generate more successful break predictions. The neural network contained 41 input nodes, 10 intermediate nodes, and two output nodes. The training data contained 79 measurement patterns. Of these, 70 patterns were of the normal operation, and nine patterns were of the web-break operation.

The network was trained 500 times. For each training, a mean-squared error, E, between the network output, y_k, and the desired output, d_k, was calculated as

$$E = \sum(d_k - y_k)^2$$

Figure 3 shows mean-squared errors and the number of unsuccessful training cycles. Unsuccessful training means erroneous web-break predictions. The number of unsuccessful trainings was decreased to 4 in 500 cycles. Because there was a total of 79 measurement patterns, the network attained 95% accuracy.



3. Back-propagation network training cycle

Variable	Effect on break	Interpretation
White-water consistency	+ +	Retention & drainage
Inlet temperature	– –	Retention & drainage
Stuff-box freeness	– –	Retention & drainage
TMP freeness	+ +	Shives
Machine speed	+	Machine speed

*Input nodes = 5; hidden-layer nodes = 8; output nodes = 2. After 500 training cycles, the mean-square error was 7.5, and successful training was 95%.

*III. Important process variables extracted from neural network diagnosis**

Principal component (PC) number	PRINCIPAL COMPONENT ANALYSIS Eigenvalue	Proportion	Cumulative proportion	Regression coefficient
PC 1	7.08	0.173	0.173	0.018
PC 2	5.75	0.140	0.313	0.038
PC 3	5.72	0.139	0.452	0.053
PC 4	4.17	0.102	0.554	–0.034
PC 5	2.26	0.055	0.609no correlation	

IV. Principal-component regression analysis

PC No.	Regression coefficient	Variables	PCA coefficient†	Effect on web break	Interpretation
PC 1	0.018	Retention aid	–0.349	–	Retention & drainage
		Paper stretch	0.283	+	Paper strength
		Tensile stretch	–0.267	–	Paper strength
		Tear strength	0.257	+*	Paper strength
PC 2	0.038	Machine speed	0.335	+	Machine speed
		2P/3P draw	0.323	+	Machine speed
		Wire suction box vacuum	–0.323	–	Machine speed
		Couch vacuum	–0.316	–	Machine speed
		DIP ratio	–0.282	–*	Paper strength
PC 3	0.053	Pickup-felt vacuum	0.347	+*	Retention & drainage
		Paper moisture	0.300	+	Paper strength
		GP freeness	–0.298	–	Retention & drainage
		Inlet temperature	–0.268	–	Retention & drainage
		DIP freeness	–0.266	–	Retention & drainage
		Zeta potential	–0.250	–	Retention & drainage
PC 4	-0.034	Inlet conductivity	0.343	–	Retention & drainage
		SBKP ratio	0.336	–	Paper strength
		SBKP freeness	0.335	–	Retention & drainage
		Basis weight	0.278	–	Paper strength

† Variables with a PCA coefficient with an absolute value >0.25 were selected. The value of 0.25 was arbitrarily chosen to select four to six variables in each PC.
* Variables whose sign of "effect of break" are difficult to interpret.

V. Coefficients in multiple regression and PCA and their interpretation

$$\text{accuracy} = (1 - 4/79) \times 100 = 95\%$$

Among the future projects our company was considering was the development of a web-break alarm system for the paper-machine operators. The most effective alarm system would be the one that provided the most accurate predictions with the fewest number of inputs. To this end, we were interested to see how the accuracy of the neural network was affected when the number of input variables was reduced.

Following the first calculation, 30 important variables that had large weight factors were selected from 41 input variables, and 11 variables with small weight factors were eliminated. A new neural network was created using these 30 input nodes. After 500 trainings, the number of unsuccessful trainings had decreased to three. Thus the accuracy was similar to that of the previous simulation with 41 input nodes.

$$\text{accuracy} = (1 - 3/79) \times 100 = 96\%$$

From the results of the 30-input simulation, 12 critical variables were selected, and a new neural network with these 12 input nodes was designed and run. After running the 12-input network simulation, a new neural network containing five important variables was created and trained. The number of unsuccessful trainings was four, and the mean squared error was 7.5. The accuracy of the five-input simulation was thus

$$\text{accuracy} = (1 - 4/79) \times 100 = 95\%$$

which was the same as that of the 41-input simulation. These results confirmed that the selected five inputs were the most influential variables, and the other 36 variables that were eliminated were of small importance.

Table III shows the five important process variables that were extracted by neural-network diagnosis. A plus sign (+) indicates a variable's positive influence on (i.e., an increase in) web breaks. Double plus signs (+ +) indicate a strong positive influence.

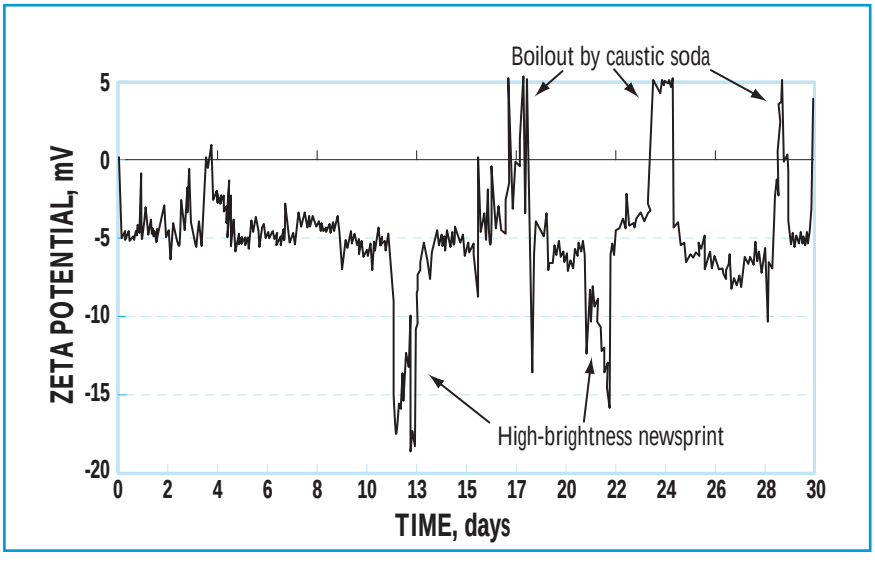
For example, white-water consistency was evaluated as "+ +." White water contains much fines and fillers, and it is recycled back through a fan pump to dilute the thick stock at the stock inlet. When the white-water consistency increases, the fines content at the stock inlet also increases, resulting in poor drainage and plugging of press felts. Moreover, there is a greater chance for slime and deposits to generate in the white water. Thus, higher white-water consistency would increase the possibility of web breaks. The effect of TMP freeness also was "+ +." TMP with higher freeness contains more shives and thus heightens the possibility of paper breaks. Machine speed was rated as a "+." Higher ma-

chine speeds apply a higher tension to the paper web, resulting in more paper breaks.

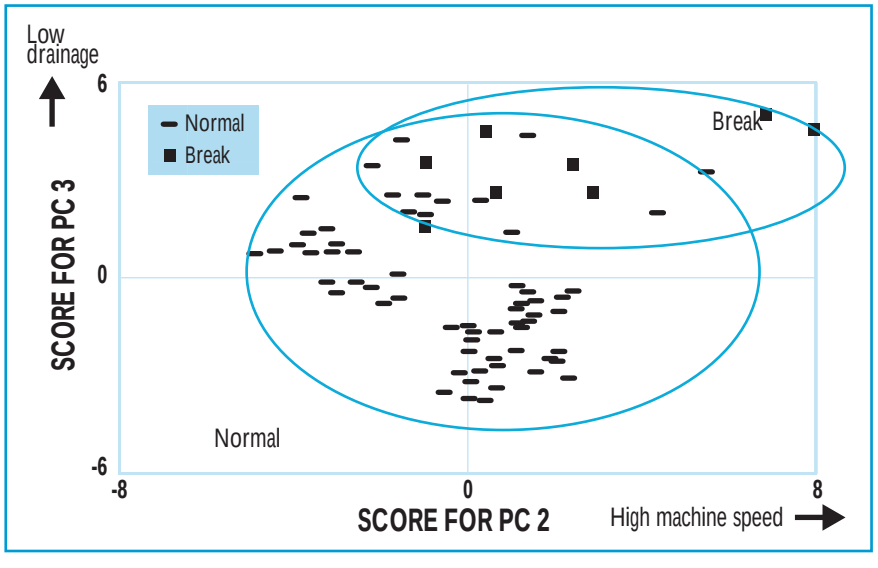
Variables that impose a negative influence on web breaks are assigned a minus sign (–), with a double minus sign (– –) indicating a strong negative influence (i.e., a decrease in web breaks). For instance, inlet temperature was "– –." Hot water has a lower viscosity and drains more readily in the wet end of the paper machine. Because a wet web with higher dryness is stronger, the higher inlet temperature would decrease paper web breaks. Stuff-box freeness also was rated as "– –." Pulp with higher freeness is rapidly dewatered on the wire and in the press section of a paper machine. Hence, when the stuff-box freeness increases, the frequency of web breaks decreases.

As shown in Table III, the extracted five variables were classified in one of three categories: retention and drainage, shives, or machine speed. The feasibility of manipulating these five variables in papermaking operations was investigated.

The ability to manipulate pulp freeness was limited by the product's specifications for physical and optical properties. Similarly, paper machine speed was determined by the basis weight and production schedules. There also was a limitation to the amount of available energy to increase the inlet temperature. Set points for four of the five identified process variables seemed difficult to change. On the other hand, the paper machine under investigation had never used any retention aids. The use of retention aids offered the possibility of increasing first-pass retention and decreasing the white-water consistency. Moreover, the capacity of the saveall system was not large enough to treat all of the excess white water, and it was believed that pulp was being spilled over to the sewer. Thus, in addition to the possibility of decreasing paper web breaks, retention aids offered the potential benefits of fiber recovery and a reduction in effluent loading.



4. Zeta potential at stock inlet over one month



5. Web-break situations presented in terms of the second and third principal components from Tables IV and V

A short-term retention-aid test was carried out during this analysis period. The addition rate was varied from 0 to 155 ppm, with an average of 80 ppm. We had to evaluate the effects of retention aid and decide whether to continue adding retention aid on a long-term basis. The neural-network diagnosis suggested that a wet-end-chemistry approach to improve the first-pass retention was effective in reducing web breaks.

PRINCIPAL-COMPONENT REGRESSION

Statistical analysis was performed to verify the neural-network results using the same set of data. The chosen technique was principal-component regression, which consists of principal-component analysis and multiple regression analysis. A description of principal-component

	Interpretation	Neural network	PC regression
Common	Retention & drainage	– –	– –
	Machine speed	+	+ +
Uncommon	Shives	+ +	…
	Paper strength	…	–

VI. Summary of results for neural network and principal-component regression

analysis theory is available in a textbook written by Jolliffe *(9)*.

The central idea of principal-component analysis (PCA) is to reduce the dimensionality of a data set in which there are a large number of interrelated variables while retaining as much of the variation present in the data set as possible. This reduction is achieved by transforming to a new set of variables—the principal components (PCs)—which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variables. In the web-break diagnosis, the number of measurements was so large that the visualization of the situation required a reduction of the measurement dimension. This was done by PCA.

Multiple regression quantifies the effects of the various PCs on paper web breaks. In multiple regression, one of the major difficulties with the usual least-squares estimators is the problem of multicollinearity, which occurs when there are near-constant linear functions for two or more of the predictor or regressor variables. Multicollinearities are often (but not always) indicated by large correlation coefficients between subsets of the variables. If multicollinearities exist, then the variances of some of the estimated regression coefficients can become very large, leading to unstable and often misleading estimates of the regression equation. To overcome this problem, principal-component regression simply starts by using PCs of the predictor variables in place of the predictor variables themselves. Since the PCs are uncorrelated, there are no multicollinearities between them. The use of PCs also simplifies the regression calculations.

A computer software package (SAS, Cary, NC) was used for statistical analysis. Principal-component analysis (PCA) was done using the PRINCOMP procedure. Using PCs as the predictor variables, multiple regression analysis was made with the STEPWISE procedure to predict paper web breaks. An approach using stepwise deletion is based solely on the size of the correlation coefficient between the dependent variable and each PC. Fewer PCs are retained using this approach, since small-variance components are rejected. **Table IV** shows the five PCs that were extracted using this statistical technique. As the cumulative proportion data show, the five PCs accounted for 60% of the total variance of the measurement data.

Partial regression coefficients of the first, second, and third PCs in multiple regression were positive, and the coefficient of the fourth PC was negative. The fifth PC had no correlation with web breaks. Each PC consists of many variables, and the variables of relative importance are listed in **Table V**. A coefficient of 0.25 in PCA was arbitrarily chosen as a cut-off level so that each PC would contain from four to six variables. Before attempting to interpret the five PCs and their associated variables, some explanation of Table V is necessary. Consider the addition of retention aid in PC 1 as an example.

Coefficient of retention aid in PC 1 = –0.349 = A

Regression coefficient of PC 1 = 0.018 = B

Effect on break = $A \times B$ = negative

The coefficient of retention aid in PCA was –0.349, which was negative, so the overall score for PC 1 decreases with increasing addition of retention aid. And since the regression coefficient for PC 1 in multiple regression was 0.018, a positive number, the frequency of paper web breaks would decrease when PC 1 decreases. The effect on break was calculated by multiplying these two coefficients. The result, of course, was negative, indicating that an increase of retention aid would decrease web breaks, thus confirming the effectiveness of retention aid on web break.

The same method was used to calculate the effects of other variables on web breaks. For example, the effect of inlet temperature was negative, indicating that web breaks would occur less frequently with higher temperature. As discussed previously, this makes sense, since high temperature would accelerate water drainage in the wire section. The effects of freeness for groundwood pulp (GP), deinked pulp (DIP), and softwood bleached kraft pulp (SBKP) also were negative, since pulp with higher freeness would drain more easily, resulting in a drier wet web at the press section and thus a decrease in web breaks.

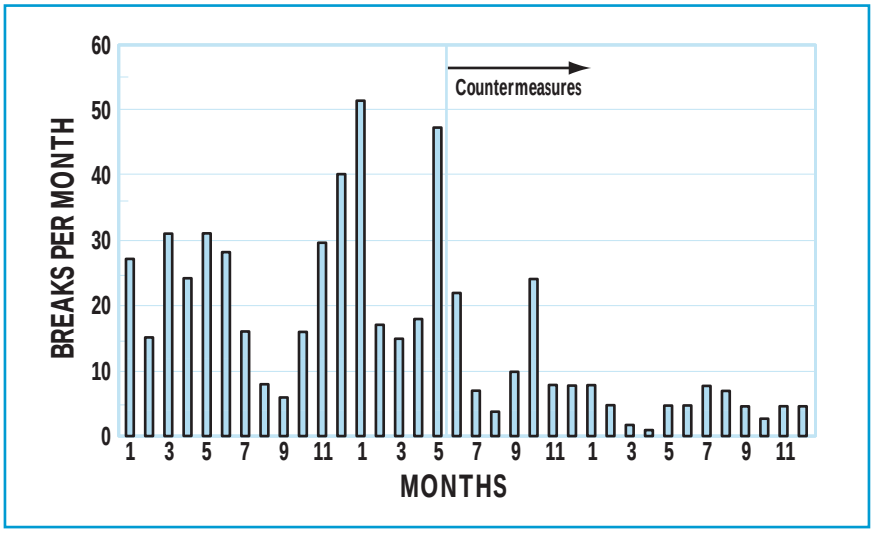
Figure 4 shows zeta potential at the stock inlet. Zeta potential was continuously monitored by measuring streaming potential. The zeta potential was fairly stable at around –5 mV, although it rose during chemical boilout when the machine was shut down. Production of high-brightness newsprint also disrupted zeta potential, dropping it to –15 mV. This disruption was likely caused by carry-

over of anionic trash (such as sodium silicate used in hydrogen peroxide bleaching of TMP), dissolved lignin fragments, and carbohydrates to the paper machine. If wet-end chemicals (retention aids, sizing agents, strength agents, etc.) were to be used effectively, more alum would be needed to scavenge the anionic-trash carryover and boost zeta potential to the proper range. (Addition of alum increases conductivity.) Since the effects of zeta potential and inlet conductivity were negative, paper web breaks would decrease by increasing them. Variables such as retention aid, pulp freeness, and alum addition were interpreted as "retention and drainage" components, and the frequency of web breaks decreases as these components are increased.

When the machine speed increases, paper draw increases, and the vacuum of the wire suction box and the couch becomes higher. Vacuum pressure is always negative, and when high vacuum is generated, the value of vacuum pressure decreases. Vacuum and machine speed were classified as "machine speed" components, and the frequency of web breaks increases with higher machine speed.

Basis weight, moisture, stretch, tensile strength, and SBKP ratio were grouped as "paper strength" components. Web breaks decrease with increasing paper strength.

In Table IV, the absolute value of PC regression coefficients in multiple regression shows that the order of effects of PCs on breaks decreased as follows: PC 3 > PC 2 > PC 4 > PC 1. The data can be plotted with respect to the two largest PCs (PC 3 and PC 2), thus giving a straightforward visual presentation of what the data look like instead of digesting a large mass of numbers. **Figure 5** visualizes the web-break diagnosis problem in terms of the scores for PC 3 (retention and drainage) and PC 2 (machine speed).



6. Web breaks per month over three years

Plots of the normal operation were uniformly distributed in all of the areas. However, plots of measurements for the web-break situations were distinctly different from the cluster for normal operation. As shown in Table V, PC 2 was interpreted as the paper machine speed, while PC 3 was related to retention and drainage. An increase in machine speed increased the score for PC 2 (horizontal axis), while a decrease for retention and drainage increased the score for PC 3 (vertical axis). When scores for both PCs increased, the probability of a web break increased. In other words, the most effective ways to reduce web breaks were to (a) decrease paper machine speed or (b) increase retention and drainage.

COMPARISON OF NEURAL NETWORK AND CONVENTIONAL STATISTICAL METHODS

There were three variables whose effects on web breaks were difficult to interpret: tear strength, pickup-felt vacuum, and DIP ratio (all marked with asterisks in Table V). High tear strength was expected to help prevent web breaks. Vacuum pressure is always negative, and the value of vacuum pressure increases at low vacuum. When the water content in the press felt decreases, the seal of the press felt against the pickup-felt vacuum box decreases, and the amount of water removal also decreases. Hence low pickup-felt vacuum indicated a high dryness of the wet web at the press section. A decrease of DIP ratio might lower the amount of adhesives and impurities in the papermaking furnish. This was expected to decrease web breaks, but the simulated results showed the opposite effect.

Considering that the number of original variables was 41—only three of which were not understandable—the validity of principal-component regression was not impaired. But our experience leads us to believe that one mathematical analysis is not enough to reach a conclusive diagnosis of a phenomenon as complex as a web break on a paper machine. A comparison of results obtained from at least two methods is advisable, and the final decision should be made by papermakers, not by a computer.

Table VI summarizes the results of our diagnosis. Both the neural network and principal-component regression evaluated retention and drainage and machine speed as important variables. Shives was also selected by the neural network, while paper strength was selected by PC regression. Because the machine speed was determined by the paper production schedule and could not

be changed with ease, retention and drainage was the only important process variable that could be manipulated.

CONCLUSION

A neural-network diagnosis of web breaks on a newsprint machine—in combination with results from principal-component regression analysis—suggested that web breaks could be reduced by manipulating wet-end chemistry variables. The mill responded by taking a variety of countermeasures:

- Addition of retention aid was continued.
- Alum was adjusted to bring the zeta potential within a suitable range during production of high-brightness newsprint.
- The pH was automatically controlled by adding sulfuric acid.
- A suitable slime-control agent was chosen.

As a consequence, the following objectives were achieved.

1. First-pass retention and first-pass ash retention were improved by 3% and 4%, respectively. Sheet formation was not affected by the retention aid.
2. As more fines were retained in the newsprint, opacity and print-through were improved.
3. Fiber loss in the effluent decreased, and sludge generation from the effluent clarifier was reduced by 1%, resulting in great cost savings.
4. Alum usage was decreased by automatic pH control using sulfuric acid.
5. As pH became stable and enough aluminum ion was maintained, the emulsion rosin size worked more effectively, reducing variation in paper sizing. Indeed, constant paper sizing was obtained, which is very important in offset newsprint. Paper deposits were also decreased.
6. Paper machine operation and paper quality became more stable than before, reducing downtime and thus mitigating the need to clean, rethread, and restart the machine.
7. The number of web breaks decreased to five per month after countermeasures were taken, as seen in **Fig. 6**, thus fulfilling the prime objective of the study.
8. The validity of wet-end chemistry in improving papermaking performance was well demonstrated. The total annual cost reduction amounted to US$ 1 million. TJ

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