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IMPENDING FAILURE DETECTION FOR A DISCRETE PROCESS

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Signals from a discrete process contain a strong modulation as a result of the discrete events in the process, such as paper passage in a recirculating document feeder (RDF). This paper presents a study of the methodology of process monitoring for a RDF system. A fault tree has been established that shows the cause-and-effect relationship regarding possible malfunctions of a RDF system. Critical components of the RDF system have been identified for condition monitoring. The signature from the measurements of position, vibration, vacuum pressure, and drive motor current have been analysed. A data separation scheme was used in signal processing to demodulate the strong signal component associated with paper passage. Unique index extraction algorithms based on time series analysis and modeling have been developed to detect failures of these components. A decision-making scheme based on multiple voting has been implemented.

1. INTRODUCTION

A discrete process refers to a situation where parts are processed separately in a discrete-timing manner. Dominant variables of this process are usually modulated by inherent discrete-event type interruptions. Numerous fault detection and diagnosis methods have been developed, mainly for a continuous process such as machining and rotating in power machineries. Difficulties, however, are often encountered when applying these methods directly to a discrete process. This is because for a discrete process, (a) the signals are not stationary due to event-modulation, (b) time duration between two discrete events is very short so that sampling and data processing time is very critical, and (c) a large margin of uncertainty exists between events at different instances, which makes the signal less correlated as compared to continuous processes for the same time duration.

This paper attempts to address these issues by presenting a case study on impending failure detection for an RDF system. The RDF is a complete unit where paper is fed, transported, registered, and restacked. Such a device is used in all copy machines at different speeds, ranging from a few seconds to a fraction of a second per page. As a typical discrete process, the paper circulating motion in an RDF is dominated by the paper passage through the circle. The possible signals, such as sound and vibration, are all modulated by the motion of corresponding single paper passing through the unit.

The most prominent failure mode in a RDF system is, practically, the paper jam. It results in down-time and damage to the original document. The ultimate goal of this study is to identify suitable signals and algorithms that can be used to monitor the performance of the RDF, so that a jam-free paper handling system can be achieved. For this purpose, failure mode analysis was carried out and a fault tree was established. The critical components were accordingly identified. Signals from vibration, vacuum pressure, and motor current were used. A data separation scheme was facilitated to reduce the modulation

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effects due to paper passage. Algorithms based on statistical analysis, and a inverse filtering were used to extract multiple indices, and a voting scheme was employed for decision-making. Results of the experimental tests are also given.

2. FAILURE MODE ANALYSIS

A simplified diagram of a typical RDF is shown in Fig. 1. There are five primary functional units involved in circulating a document. They are: 1, OVF tube, 2, nip rollers, 3, vacuum belts; 4, registration gate; 5, exit rollers.

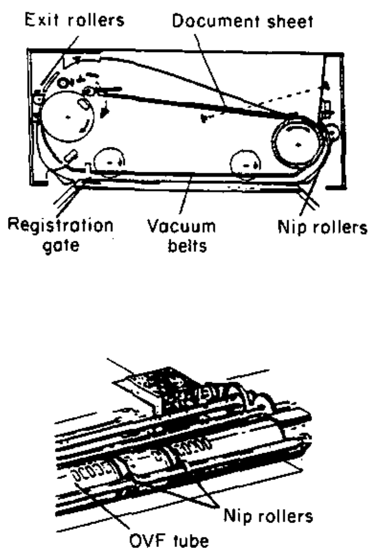

Figure 1. Schematic diagram of the RDF.

During the recirculating cycle, the paper is first moved to the nip rollers by the OVF tube with a force provided by the vacuum pressure. Ideally, the two nip rollers then provide an even force to move the paper smoothly through and send it to the vacuum belts, which further drive the paper to the registration gate. At this position, the paper will be copied, and then moved via the vacuum belt through the exit rollers back to the feeder platform.

The ultimate failures of the RDF are: misaligned image, paper jam and damage to the document. The direct causes of the paper jam can be: skewness of paper; paper delay; stoppage; paper condition variations.

The root causes of the above conditions can be identified. Skewness of paper is found to cause the following factors: uneven nip force due to spring deterioration and nip wear; uneven vacuum pressure due to leakage; registration gate open unevenly due to bending of the gate bar, paper quality variation (e.g., different weights, surface, thickness, etc.).

Paper delay may be created by: OVF tube vacuum unable to pull a sheet to the take away nip due to lower pressure or paper sticking; OVF motion slower or faster due to transmission error or belt looseness; belt vaccum not strong enough to pull a sheet due to low pressure; transmission error due to malfunctions in motor, gears or bearing defects.

The stoppage may be incited by: Double feed at OVF due to poor paper; registration gate not opening due to timing error; excessive nip roller force due to spring deterioration.

The paper condition variations can be attributed to the following factors: poor originals; fast wear out due to large nip roller forces or irregularities in path.

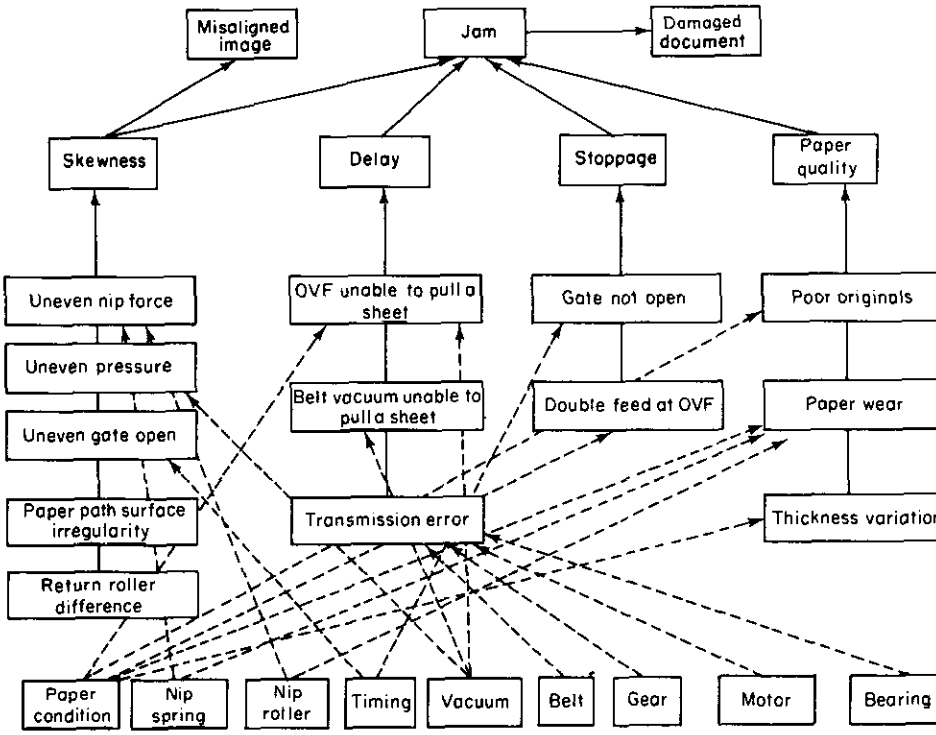

Figure 2. Fault tree for the RDF.

Based on the above analysis, a fault tree showing the relationship among the failure modes, their immediate causes, and root causes can be constructed and is shown in Fig. 2. Since our purpose is to identify critical components of the RDF which should be monitored closely to prevent failure, the inherent correlation between the root causes and the RDF components should also be established. In Fig. 2, the dotted lines represent such correlations. Therefore, paper condition, nip-spring structure, vacuum, and belt are identified to be critical components for jam prevention. On the other hand, though the motor, bearings and gears in the RDF also contribute to the paper and since they are relatively stable and durable, they will not be studied further. Therefore, the most important conditions which should be monitored are: paper variation; nip roller force variation; vacuum pressure changes; motion variations.

Sensing devices are subsequently selected, shown in Fig. 3. Two eddy-current probes are placed near the nip rollers to pick up displacements when paper is passing through. This information can be used to monitor the conditions of skewness, delay, nip roller spring and motion variation. Piezo film is used to gather the data on vacuum pressure. The motor current is also measured to monitor the motion and paper variations.

3. ALGORITHMS

The monitoring procedure based on the data acquired from sensors includes three steps: 1, data pre-processing; 2, index extraction; 3, decision-making.

3.1. DATA PRE-PROCESSING

Many monitoring techniques fail in application because of the excessive noise level embedded in data. To deal with this situation, a data pre-processing unit was designed to

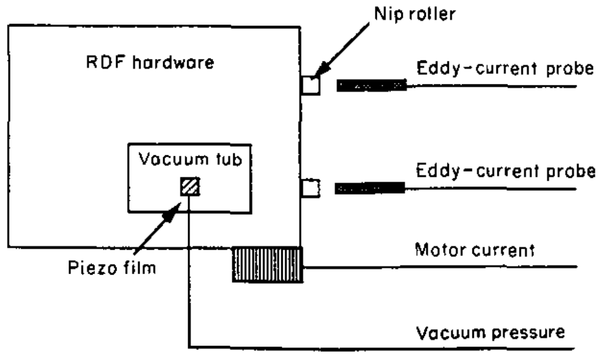

Figure 3. Sensing device arrangement.

suppress possible noise in signals. Some standard algorithms, such as digital filtering, linear and non-linear smoothing etc., were employed [8]. The non-linear smoothing algorithm is degined by

$$Y_t = M_t[x(i)] \quad \text{for } [t-(N-1)/2] \leqslant i \leqslant [t+(N-1)/2]. \tag{1}$$

where N is the window length, i.e. the number of data in each signal segment. The operator, M_t, on a segment of signals is simply their middle number. Therefore, such an algorithm is also called running median smoothing. The feature of the non-linear smoothing is that the running medians will follow the discontinuities in the signal. This is desirable for a discrete process such as the paper handling process where many discontinuities exist due to paper passage modulation. In addition, a special signal separation scheme for the data picked up from the nip roller was developed to remove the modulation effect in signal processing.

As mentioned earlier, the pair of nip rollers at the first gate of the paper recirculating process play a critical role for possible paper jam. Figure 4 shows the details of the nip roller–spring structure. When paper passes through the rollers, it will force the nip rollers to move away a little from the OVF tube, and the roller will place a force on the paper while driving it through. The nip roller force is provided by the preloaded nip spring connected through a linkage. The amount of the pre-load can be adjusted by turning a nut adjacent to each spring. Ideally, the two nip rollers would be synchronised and provide identical force to the paper passing through them. Thus the paper will pass through the gate smoothly without skewness. In practice, however, deterioration of the spring can

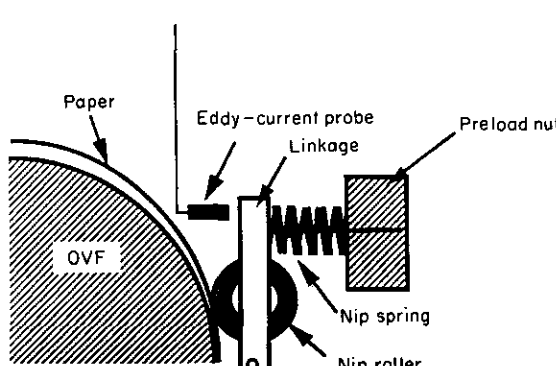

Figure 4. Schematic of the nip roller–spring structure.

occur and cause the nip roller force to be swept away from a pre-set value for normal operation. Uneven forces applied to paper is the main reason for skewness. If the paper is properly positioned without skewness, the two nip rollers will be synchronised. In order to detect any possible defect in this motion, the eddy current probe is placed in the position shown in Fig. 4 to measure the displacement of the linkage to which the nip roller and spring are attached. It is obvious that by evaluating the delay between the displacements of the two linkages, the skewness of the paper at this position can be monitored. The spring condition can also be monitored by assessing the dynamics of the spring–roller structure.

Information about the dynamics of the spring–roller and about the delay is, however, located in different frequency ranges of the measured displacement data from the probe. Figure 5 is a plot of raw data as measured from the two probes. As can be seen, the signals are modulated by the paper passage motion, so that high frequency components are embedded in a lower frequency, square-wave type carrier. This modulation makes further signal processing difficult. To alleviate this problem, the following moving average window was applied to the raw data x_t.

$$y_t = \frac{1}{N} \sum_{i=t-(N-1)/2}^{t+(N-1)/2} x_i \tag{2}$$

where N is the window length, and y_t represents the new data after smoothing. The residual between the raw data, x_t and the smoothed portion, y_t, is the rough part of the data which represents the high frequency components, and is donated by z_t. As shown in Fig. 5, the rough part, z_t, of the signal is no longer modulated by the paper passage motion. Actually the impulse response of the spring–roller structure subjected to the paper insertion dominated the rough part, z_t. Therefore, the motion of the paper when passing through the nip roller can be accessed by evaluating the smooth part of the measurement, y_t, while the spring condition can be monitored by information embedded in z_t.

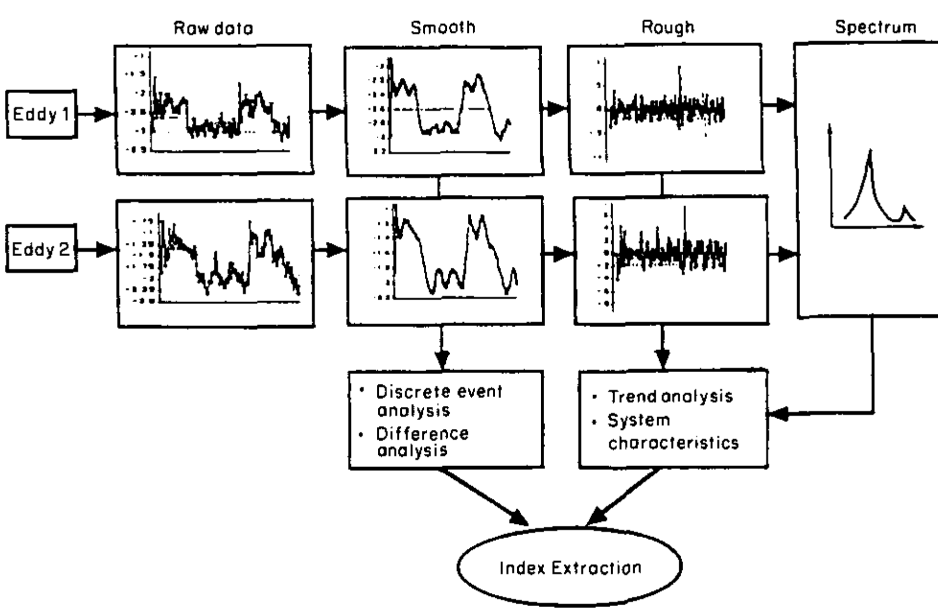

Figure 5. Pre-processing for eddy current measurements.

3.2. INDEX EXTRACTION

After signal pre-proceesing, an index extraction module was designed to estimate the quantities that reveal the condition of the process. For improved reliability of the algorithm, more than one index were used. Table 1 is a list of essential indices adopted for the detection of impending failures of the RDF.

TABLE 1

Potential indices

Symbol	Meaning
PR1, PR2	average of period from Ch.1† and Ch.2†
DPR	maximum difference of period between Ch.1 and Ch.2
DU1, DU2	average of duration of Ch.1 and Ch.2
DDU	maximum difference of duration between Ch.1 and Ch.2
R	correlation of Ch.1 and Ch.2
RMS1	root mean square value of Ch.1
RMS2	root mean square value of Ch.2
RMS3	root mean square value of Ch.3
RMS4	root mean square value of Ch.4
FREQ1	natural frequency of Ch.1 (rough part)
FREQ2	natural frequency of Ch.2 (rough part)
FAI1	AR parameter of Ch.1 (rough part)
FAI2	AR parameter of Ch.2 (rough part)
FAI3	AR parameter of CH.3†
FAI4	AR parameter of Ch.4†
MEAN3	mean value of Ch.3
MEAN4	mean value of Ch.4

† Ch.1, eddy current probe 1; Ch.2, eddy current probe 2; Ch.3, pressure of vacuum; Ch.4, motor current.

3.2.1. *Period and duration*

The period (PR) refers to the time interval between the arrival of two consecutive sheets of paper at the nip roller. In the same way the duration (DU) represents the time needed for a single sheet of paper passing through the nip roller as observed by the two eddy current probes. The differences in the period (denoted by DPR) and the duration (DDU) as measured from the left and right probes, clearly indicate any possible delay and skewness of paper. Therefore by establishing an acceptable safe range for DPR and DDU, a quantitive assessment of paper in terms of possible skewness is possible.

3.2.2. *Natural frequency and AR parameters*

The deterioration in the spring of the nip roller structure will result in a change in its characteristics. Such a change is usually hard to see merely by viewing the raw data, especially at an early stage of deterioration. However, if the response can be modeled, the model parameters, such as the natural frequency and damping ratio, are sensitive to any change in the system characteristics. To this end, an Autoregressive Moving-Average (ARMA) modeling method [7] was used to estimate the dynamic characteristics of the spring–roller structure. As mentioned earlier, the raw data from the probes cannot be used directly in modeling due to strong modulation in the motion of paper passage. The rough part z_t after data separation is, however, suitable for modeling. An nth order ARMA model is given by

$$x_t - \phi_1 x_{t-1} - \cdots - \phi_n x_{t-n} = a_t - \theta_1 a_{t-1} - \cdots - \theta_m a_{t-m} \tag{3}$$

where ϕ_i are the autoregressive parameters and θ_i are the moving average parameters. A detailed illustration of the modeling procedure is given in [7]. The adequate model, equation (3), contains pertinent information about the system. For instance, the natural frequency f_n and damping ratio ζ can be calculated using the following equations:

$$f_n=\frac{\pi}{\Delta}\sqrt{[\ln(\lambda\lambda^*)]^2+4\left[\cos^{-1}\left(\frac{\lambda+\lambda^*}{2\sqrt{\lambda\lambda^*}}\right)\right]^2}$$

$$\zeta=\frac{\ln(\lambda\lambda^*)}{\sqrt{[\ln(\lambda\lambda^*)]^2+4\left[\cos^{-1}\left(\frac{\lambda+\lambda^*}{2\sqrt{\lambda\lambda^*}}\right)\right]^2}} \tag{4}$$

where Δ is the sampling interval. The complex conjugate pair, λ and λ^*, is the characteristic root of the model which can be obtained by solving the following eigen-equation

$$\lambda^n-\sum_{j=1}^{n}\phi_j\lambda^{n-j}=0. \tag{5}$$

In this way, deterioration of the spring can be detected by identifying the variation of the estimated value of the natural frequency and, indirectly, the AR parameter ϕ.

3.2.3. *Inverse filtering*

The inverse filtering algorithm [1] is used to evaluate the overall performance of the paper handling process using signals from all available channels. This algorithm is based on the assumption that a machine or process can be represented by an ARMA model given in equation (3). Note that equation (3) is a recursive difference equation, which shows the relationship between values of x_t at different time instances. The future value of response can then be predicted based on the available measurements, such as

$$x_t|_{t-1}=\phi_1x_{t-1}+\cdots+\phi_nx_{t-n}-\theta_1a_{t-1}-\cdots-\theta_ma_{t-m} \tag{6}$$

which is based on the fact that at time $t-1$, the values of $x_{t-1},\ldots,x_{t-n}$ and $a_{t-1},\ldots,a_{t-m}$ are known constants. The prediction error e_t, which is the difference between the predicted value and the true measurement, is given by

$$e_t=x_t-x_t|_{t-1}. \tag{7}$$

According to optimal prediction theory, the prediction error should be a sequence of zero mean, white Gaussian process with minimum variance. However, if the system is away from normal operation for any reason, the model equation (3) will no longer be adequate for the current condition and the statistical properties of the prediction error process will vary.

It is therefore valid to check to see if the system is still operating under normal condition by simply evaluating the statistical properties of the prediction errors. Three indices are formed to evaluate the statistical properties of the prediction error series: normalised variance (NV), kurtosis (KT), and autocorrelation (AC).

3.3. MULTIPLE VOTING

Since a larger margin of uncertainty exists in the paper recirculating process, and there is no single index that is exclusively superior to others for all possible conditions, several indices were used in order to improve the reliability and consistency of the monitoring system. The decision, however, based on multiple indices was not made aribtrarily, but rather in a weighted voting manner [2]. That is, a voting grade, G_j, is defined by

$$G_j = \Sigma\, W_i \cdot P(\text{index}_i) \tag{8}$$

where W_i, $i=1,\ldots,M$ (M = number of indices) is a weighting factor associated with the index i, and P(index i) is the probability of index i falling into an abnormal region. The weighted factors W_i were estimated through a learning procedure based on information measures of each index to the process. Namely, the information gain of each index i can be quantitatively defined as

$$G(\mathbf{y}) = H(C_i) = H(C_i \mid \mathbf{y}_k). \tag{9}$$

The estimation of the information gain can be calculated by [2]

$$G_\Omega(\mathbf{y}) = -\sum_{i=1}^{Nc} \frac{N_i^c}{N} \log_2 \frac{N_i^c}{N} + \sum_{j=1}^{Nc} \sum_{i=1}^{Nc} \frac{n_{ij}}{N_j^R} \log_2 \frac{n_{ij}}{N_j^R} \tag{10}$$

where N is the total number of data in a learning process. The higher the information gain, the more paramount is the index to the process. The weighting function

$$W_k = G_\Omega(\mathbf{y}_k) \qquad k=1,\ldots,M \tag{11}$$

can be obtained

The details of the learning procedure are referred to reference [2]. Finally, the classification decision is based on the following voting:

if:	G_j {normal range}
then:	the current condition is normal
otherwise:	the current condition is abnormal

4. EXPERIMENT RESULTS AND DISCUSSION

The following conditions were created to test an RDF system: paper variation—by using different papers and bad paper; spring variation—adjusting the preload nut; speed variation—adjusting the motor speed from 320 to 470 rpm; vaccum pressure variation—adjusting the pressure level; belt variation— by adjusting the tension of the belt.

Typical data under different conditions are shown in Fig. 6. Figures 7 and 8 show changes of indices when different papers were used. The rms value generally is not very sensitive to the type of paper used, while the correlation is sensitive to this change. However, both indices show significant change when bad paper is added to the recirculating process. Therefore, these indices can be used to detect a bad paper. As shown in Fig. 9, there is a clear decline in the trend of the natural frequency estimated by ARMA modeling when the spring is softened. It should be emphasised that this trend in frequency is consistent since it represents the characteristics of the spring which are not coupled with noise from other sources. Other indices, however, such as rms value, did not show the same trend corresponding to spring softening. Figure 10 shows that the range value is a good indicator for speed variation. The frequency of ARMA modeling from the motor current measurement is sensitive to belt variation (Fig. 11). Figure 12 illustrates the mean value of the pressure measurement is, naturally, a good index to monitor the pressure variation of the vacuum tub.

A test for the inverse filtering algorithm was also conducted, and the results shown in Fig. 13. With 20 sets of data gathered under normal operating conditions, an ARMA (6,4) model was found to be adequate. In Fig. 13, the first three observations were made for normal operating conditions, and all three indices calculated after inverse filtering, NV, KT, AC, confirmed this. The rest of the observations were made under various abnormal

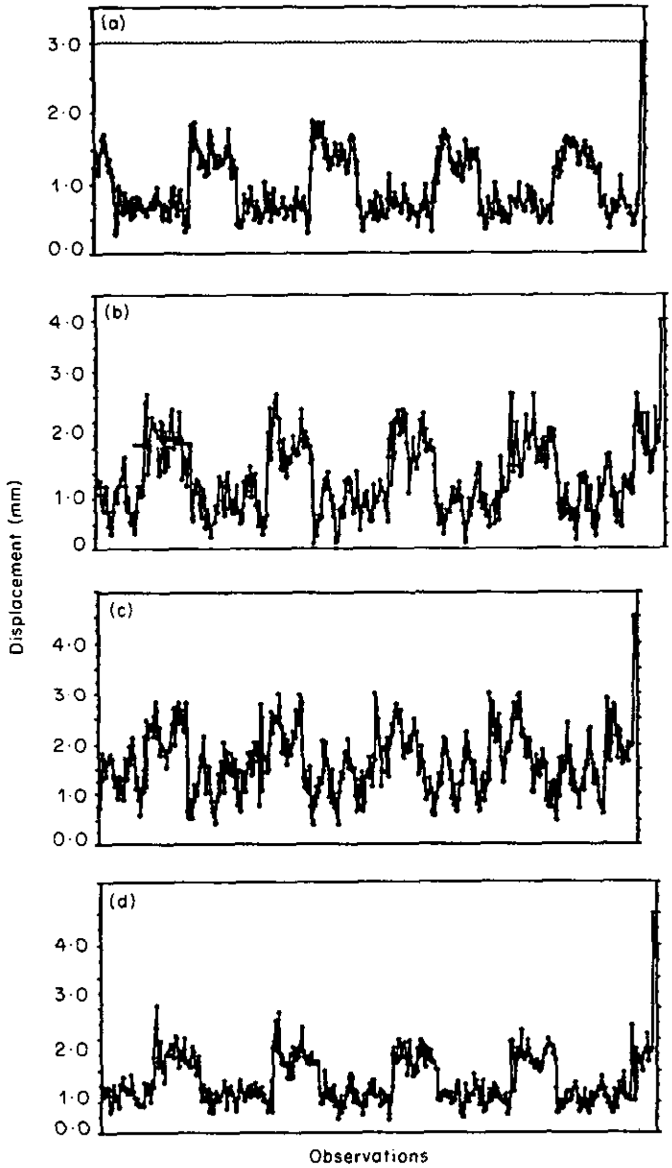

Figure 6. Plot of raw data under varying conditions. (a) Normal; (b) spring loosening; (c) structure loosening; (d) bad paper.

conditions, such as adding bad paper, spring loosening, structure loosening. It is shown that there is a clear distinction between normal and abnormal conditions from the plot. Though the estimation of the normal model takes some time, it can be done in the learning process before the monitoring process starts. In the monitoring process, no ARMA modeling is needed and the only calculation is the inverse filtering which can be done very quickly so that real-time application is possible.

Since timing is a critical factor to be considered in signal processing, most of the indices are extracted using only simple arithmetic calculation, such as the peak to peak value, average, rms, etc. These calculations can be done in a very short time, thus allowing

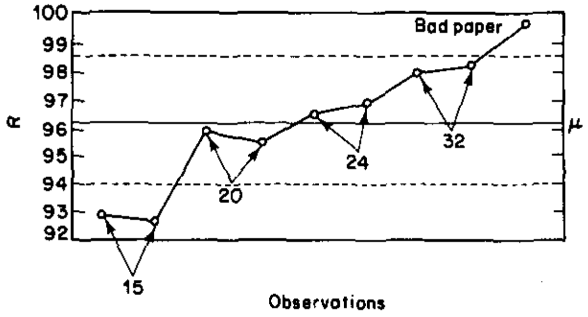

Figure 7. Plot of index R under paper variation.

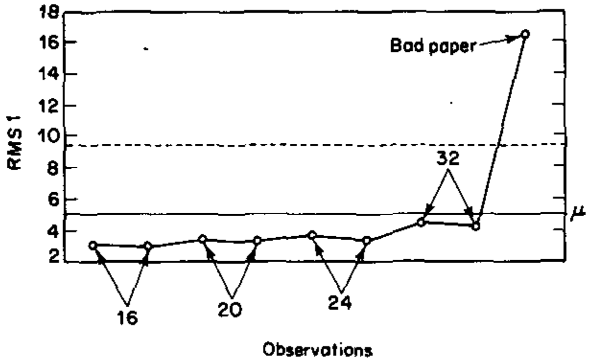

Figure 8. Plot of index RMS1 under paper variation.

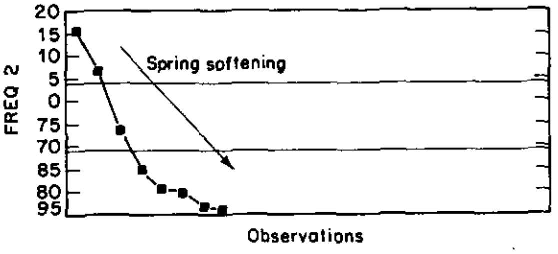

Figure 9. Plot of index FREQ2 under spring variation.

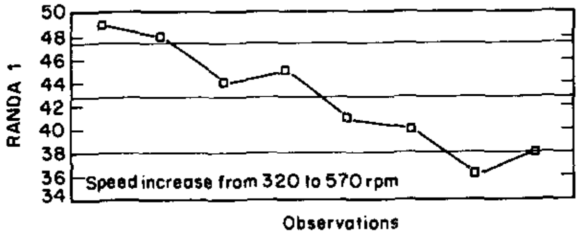

Figure 10. Plot of index RANDA1 under speed variation.

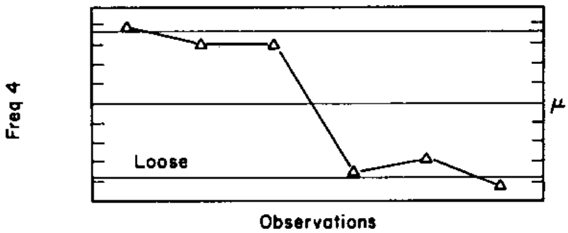

Figure 11. Plot of index: FREQ4 under belt variation.

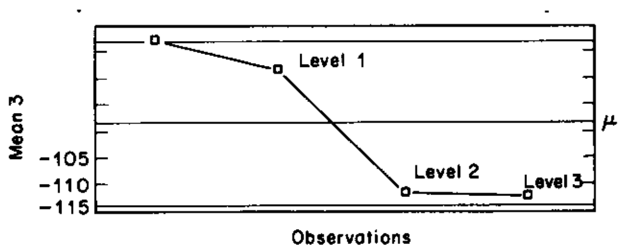

Figure 12. Plot of index MEAN3 under pressure variation.

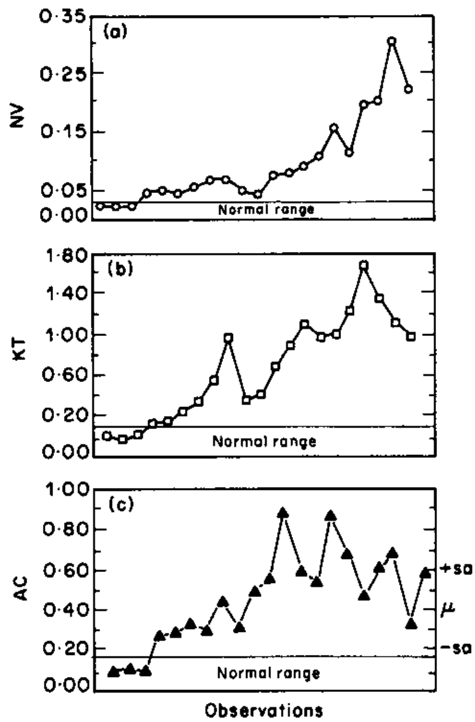

Figure 13. Plot of indices (a) NV, (b) KT, and (c) AC under normal and abnormal conditions.

continuous monitoring of the process without interruption. However, there are also some indices whose extraction involve more sophisticated calculation, such as the natural frequency and damping ratio. AR modeling was used to estimate dynamic characteristics of the system because it gives a parametric model of the system which can be compared with the normal model. The AR model also yields a better estimate of the natural frequency and damping ratio, although it takes longer to compare the estimation of simple indices. Fortunately, AR modeling is used for monitoring of the spring condition only and change is usually not of a catastrophic type. The deterioration of the spring happens over a sufficiently lengthy period to enable AR modeling to catch the variation.

5. CONCLUSIONS

Monitoring of a discrete-event dominated process, such as the paper handling process, can be extremely difficult due to short-timing and a large margin of uncertainty pertinent to the discrete process. The monitoring task, however, can be achieved by detecting the impending failure of critical components of the system. The prevention of failure in a paper handling device, such as a paper recirculating feeder, can be made by the detection of the abnormal condition in critical components at the earliest possible time. The measurements of position, vibration and pressure are good choices for monitoring of the RDF system. Multiple indices should be used to ensure reliability. Therefore, different algorithms should be applied to different components. It has been found that skewness of paper can be detected using indices that need only simple arithmetic calculation. Model-based algorithms can also be employed where timing is not so critical.

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