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MEASUREMENT FOR PAPERMACHINE CONTROL

D. L. COOPER, The Research Association for the Paper and Board, Printing and Packaging Industries, Kenley, Surrey

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Synopsis This paper reviews some of the problems in the interpretation of measurements of papermachine process variables. It is directed to papermakers or scientists who are not specialists in this field. The viewpoint is that of a statistician.

The main problem discussed is the analysis of continuous signals from process instruments, in so far as they are affected by the papermaking system. Specific hardware problems are not considered. Sampling problems for control are also discussed.

Introduction

THE distinguishing feature of the basis of automatic process control over manual methods is its total dependence on measurement. Whereas subjective assessment of the operation of the papermachine may influence the decisions made by papermakers in manual control, computer or automatic control depends—except when overridden in periods of crisis—on measurements taken from sensing devices that monitor the operation of the machine. This paper reviews some of the problems of the analysis and interpretation of such measurement; it is directed specifically to papermakers and scientists unfamiliar with control theory. It is hoped that the paper may also give the opportunity for those active in the field to reconsider the basic problems with which they have to deal.

The viewpoint from which this paper is presented is that of a statistician interested in but neither expert nor active in process control. What follows is a description of part of a basic papermaking system in its simplest terms. Ideally, thick stock and backwater, each at known consistency and rate of flow, are mixed in appropriate proportions. This thin stock is delivered to a breast box, whence it emerges at constant velocity on to a moving wire. The water and some fibre drains through the wire and is subsequently used for dilution. The web is then transferred from the wire to the drying section, where excess water is removed to yield a paper of specified weight per unit area and moisture content. Elements of this simple system that have to be

Under the chairmanship of Prof. J. A. Van den Akker monitored are therefore—flow, pressure, consistency, speed, basis weight and moisture. In the context of control, the output variables are basis weight and moisture content; the input variables are flow, pressure and consistency. The instruments used to measure these properties usually produce a continuous signal of either voltage or pressure. The problems of the adequacy of such instruments and of installation and maintenance are not the concern of this paper. It will be assumed that each instrument satisfactorily measures the property concerned.

The problems of measurement to be considered are those imposed by the papermaking system itself. For convenience, these are separated into two areas—

1. The analysis of process measurement.
2. Sampling for control.

The analysis of process measurement

THE derivation in mathematical terms of the model of the papermachine, on which control algorithms are to be based involves the measurement of input and output variables. The relationship between such variables forms the basis for control.

Regression analysis

During the early investigations, it was hoped that, if sufficient information were collected by data logging, then it could be analysed by conventional statistical techniques such as regression. The problems encountered, when such techniques are tried, are not peculiar to papermachine investigations or, indeed, to any process analysis. Problems of interpretation are almost as complex in situations in which the time factor is absent. The general form for such an analysis is—

$$y = b_0+b_1x_1+b_2x_2+ \ldots b_ix_i+b_jx_j \ldots$$

where x_j may be a function of x_i. In simple terms, having collected sets of data for a 'dependent' variable y and a number of so-called 'independent variables' x_i, the values of b_i are calculated so that the righthand side predicts the dependent variable y with least error. The simplest case is, of course, fitting a 'best' line through sets of points in a scatter diagram. In the complex situation and, in particular, when a time element has also to be considered, problems arise because the variables on the righthand side are often highly correlated. Even if two variables such as consistency and breast box pressure are not directly related, they may both move in step with a third variable such as flow. When the complex recirculation systems of the wet end are considered in detail, it is not surprising that some of the process variables that influence the dependent variables are correlated in the statistical sense. The interpretation of such multi-variate regression analysis is complex in the extreme. It was originally hoped that the application of such techniques to data collected from papermachine operation under different operating circumstances would automatically identify a model on which a satisfactory control algorithm could be based. Such hopes have proved to be not entirely justified.

Dynamic analysis

Control algorithms are developed by applying known impulses to a system and by analysing the consequent changes in output variables. Such methods include applying sinusoidal frequencies, step functions or unit impulses to the input variables. The response of the output variable is measured and the appropriate transfer functions can be deduced. Whether such methods are ideally suited to systems that often exhibit cyclic variation under so-called normal operation is not entirely clear. The response of the system may well depend on the point in time at which the impulse is applied.

Time series analysis

Alternative methods involve the analysis of the process variable, taking into account that the measurements are related in time. Even non-specialists will intuitively recognise the fact that consecutive values (in time) of a measured variable are more than likely to be high correlated. Indeed, the fact that trends occur over time implies a degree of correlation between consecutive values of a variable. But, as has been suggested, other than trend situations are present in papermachine operation.

Pira has for some years been active in the field of analysis of process variables in time. The methods of analysis are appropriate not only for establishing basic sources of variation in papermachine performance, but may also be used in the first stages of model building. It is appropriate, therefore, that the problems encountered in such should be discussed in some detail. The basic problem is to consider the analysis of signals taken from instruments on the machine. The output of such an instrument is a function of time and is called a time series. The most familiar form of such a signal is as it appears when recorded as a graph. Just as quality control results are analysed to yield the information content of the data, in a way both meaningful and susceptible to an objective assessment, so time series analysis aims to establish the basic structure of a continuous measurement.

Invariably, in the context of control, consideration has to be given to the relationships between the time series analysis of more than one signal. For simplicity, however, the problems that arise in the analysis of a single time-dependent variable will be considered. An example of part of a typical trace of basis weight variation is shown in Fig. 1.

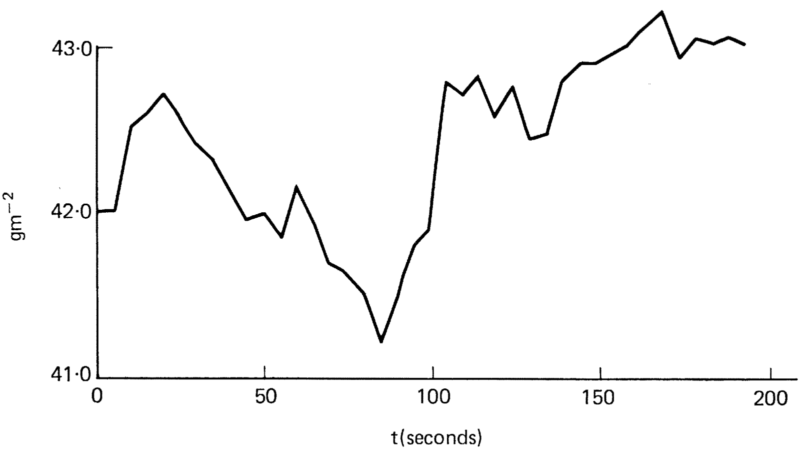

Fig. 1—Trace of basis weight variation

The electronic or pneumatic transducer that produces the signal will, either by design or default, restrict the amount of information to be conveyed because of limitations in its response. Having accepted this, it is reasonable to take as a starting point that the time series comprises a mixture of regular (but perhaps varying) components of a cyclic variation at different frequencies and also of a random component. Spectrum analysis will assess the proportion of the total variability that can be ascribed to particular frequencies. The plot of mean square power as a function of frequency is called the spectral density.

Analog techniques—One method of analysing the signal is to apply the appropriate electronic filters directly to the analog signal. The appropriate circuits will allow only a particular frequency or band of frequencies to pass and will measure the power than can be attributed to this frequency. By changing the filter, the whole range of frequencies can be analysed and the graph of power against frequency plotted.

Digital techniques—As an alternative to analog methods, digital techniques can be applied. The first problem encountered is in sampling the analog signal to obtain values on which to operate. Suppose that the sampling interval chosen is 1 s and that the signal takes the form of a simple sine wave (Fig. 2), then there can be no information available to us concerning any frequency higher than 0·5 Hz (in c/s), since at least two points are needed to describe such a frequency. Any calculations of spectral density carried out on the sampled data points for frequency (the so-called Nyquist frequency) carries in its wake contributions for all frequencies that cannot be distinguished by the analysis from the Nyquist frequency. This problem is called aliasing. It follows that the task of choosing the appropriate sampling interval must take account of the aliasing problem.

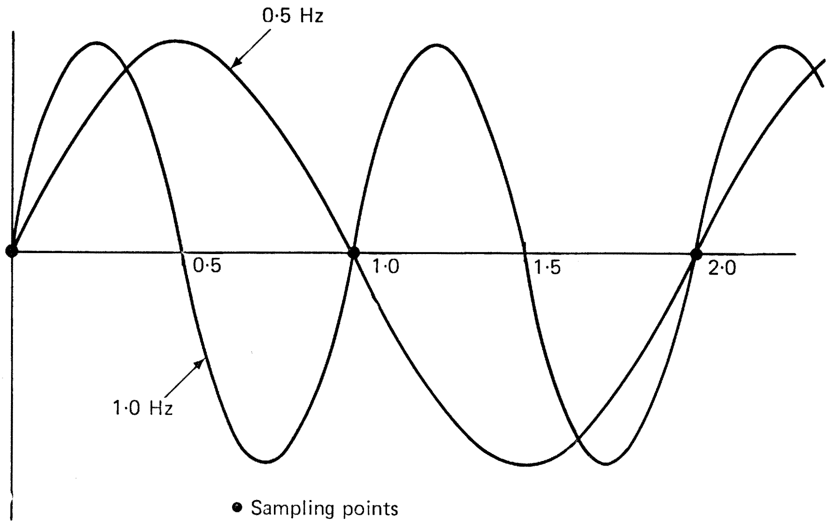

Fig. 2—Problem of aliasing

It might seem appropriate, from consideration of classical harmonic analysis, to produce a Schuster periodogram. As engineers will know, however, applying such techniques to analyse noise signals yields a highly spiked periodogram that defies interpretation. The reason for this is that, whereas signals containing fixed frequencies and additive error terms can be analysed satisfactorily by this method, sets of data that exhibit variation of a statistical nature are not so amenable. Just as the set of results of basis weight obtained from sampling the web yields an *estimate* of the basis weight, so the analysis of a set of values in time yields an *estimate* of the frequency. That is to say, such measures have error terms appropriate to their sampling distributions.

The two situations are identical from a statistical point of view. Indeed, the reason for the spiked periodogram has been shown by Bartlett[(1)] to be caused by the sampling properties of spectral estimates. The consequence of taking a larger sample of data points does not yield an estimate with lower variance, as is the case with satisfactory estimators such as the mean.

To improve the spectral estimates, Bartlett[1] suggested that the samples should be split into sets of equal length and the analysis carried out independently on each set. Then the variance of the averaged spectral estimates can be reduced by increasing the number of sets into which the series is broken up.

Autocorrelation analysis—This leads to an alternative approach to the analysis of such series—autocorrelation. The natural starting point for autocorrelation techniques depends on the intuitive consideration that consecutive points in a series are likely to be correlated. Consider the sine wave—

$$x = a \sin \theta$$

sampled at points $\theta = 2\pi t/16$,
where $t = 1, 2, 3 \ldots\ldots\ldots\ldots n$ (Fig. 3).

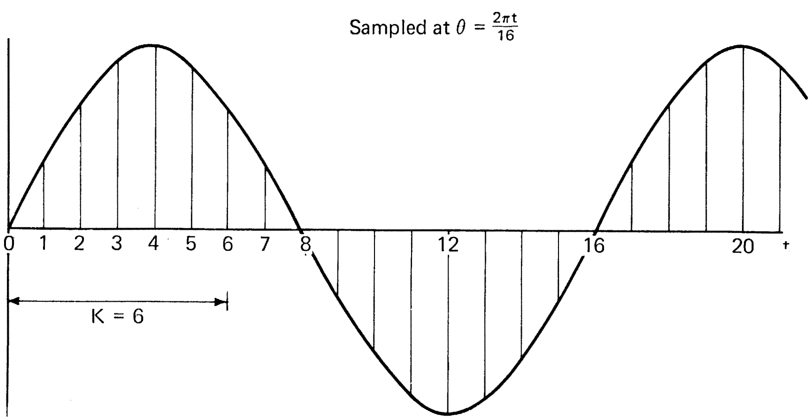

Fig. 3—Sampled sine wave $x = a \sin \theta$

Then, if we consider the two sets of consecutive points at k sampling intervals 'lags' apart—

$$\begin{array}{l} x_1 \ldots\ldots x_{k+1} \\ x_2 \ldots\ldots x_{k+2} \\ x_3 \ldots\ldots x_{k+3} \\ x_n \ldots\ldots x_{k+n} \end{array}$$

then the correlation between these points can be calculated. Suppose this is r(k). Remembering that the value of the correlation coefficient ranges between +1·0 (perfect positive relationship: high values with high, low with low) and −1·0 (perfect negative relationship: high values with low, low with high), then the plot of r(k) against k will yield, in this case, a perfect wave of amplitude 1·0 with the same frequency as the original wave, but moved 90° out of phase (Fig. 4).

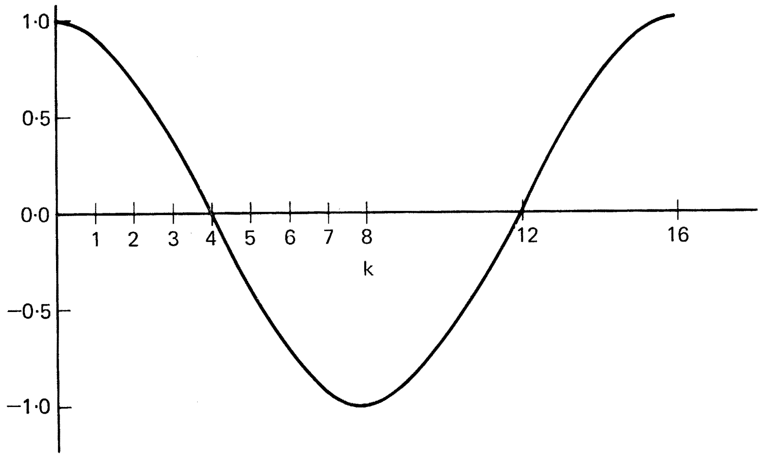

Fig. 4—Autocorrelation function for $x = a \sin \theta$

Autocorrelation analysis carried out on traces such as that shown in Fig. 1, where there is a substantial random element, will reproduce the structure of cyclic variation. If the waveform is damped, the values of r(k) will reduce with increasing k.

The autocorrelation function for a signal with many (and perhaps varying) frequencies can, by itself, yield information on the nature of the process. This is particularly so when random impulses act on systems that apply damping, but it can also be shown that the periodogram is the transform (from time to frequency) of the autocovariance or correlation function. The periodogram ordinates measure the proportion of the variance in the signal that can be assigned to the particular frequency. Furthermore, solving the problem of spiking of the periodogram by averaging is equivalent to calculating the spectral estimates with appropriate weighting of the autocorrelation coefficients.

The smoothed periodogram, however, is achieved only at the expense of making it hard to distinguish between frequencies that are close together. This is sometimes referred to as smudging. An example of a typical smoothed periodogram is shown in Fig. 5.

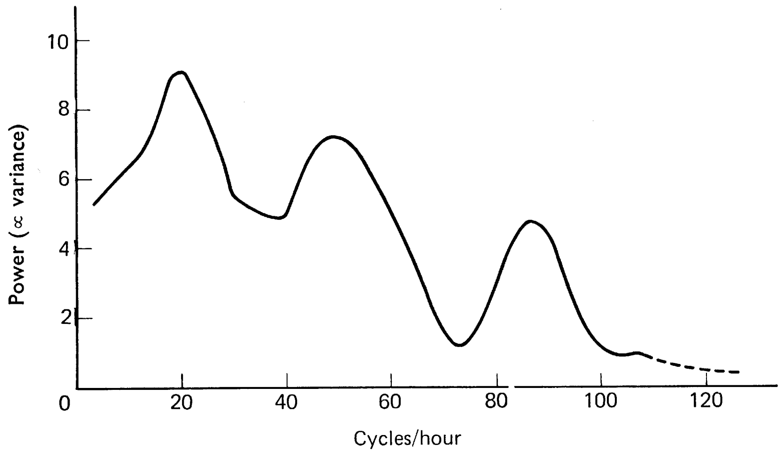

Fig. 5—Smoothed periodogram

The decision to calculate spectral estimates by direct methods or, alternatively, by forming the autocorrelation coefficients, then transforming them from the basis of time to the basis of frequency, is largely a matter of choice. Using recently developed methods of calculation, the direct approach is faster than the indirect, but the possibility of choosing alternative weighting functions is lost. The weights applied to the autocorrelation coefficients during the transformation correspond to selecting the shape of the 'window' through which the series is viewed in the direct method. The 'window' or 'kernel' is the equivalent, in the digital method of analysis, to the electronic filter used when spectral analysis is carried out by analog methods. The shape of the window will affect the interpretation of the spectrum.

Time lags—The problems involved in the interpretation of cross-spectral analysis include all those associated with the analysis of single variate time series. One aspect of cross-correlation analysis worth commenting on concerns estimating time lags in the system.

Once the sheet has been formed, the fact that the paper web is continuous determines the time lags in the system between couch and reel. Changes arising from variation in draw, even between different makings, are small compared with the time lag concerned. The situation at the wet end is more complex. The interaction between different recirculation times, difference drainage characteristics and different consistencies gives rise to problems not only in establishing time lags for each making, but also in building such estimates into control algorithms for a single making.

Cross-correlation analysis where x_{t+k} in the previous section is replaced by y_{t+k}, where y is the output and x the input variable, will yield values of $r_{xy}(k)$, the cross-correlation coefficient. The time lag between x and y can be regarded as the value of k for which $r(k)$ is maximum or minimum, but the fact that such analyses involve the signals produced by each instrument separately and that the parameters of each signal have been shown to have statistical properties implies that k itself is an estimate and has a sampling distribution.

This treatment of the technical aspects of time series analysis as applied to industrial processes leans heavily on papers published in *Technometrics.*[3]

Sampling for control

The two-dimensional problem

CONTROL of basis weight depends on the measurement of the weight per unit area of fibre at the dry end. Because of practical limitation in the instruments that measure basis weight, the control of the machine depends on sample measurement taken from the paper web.

The papermachine produces a three-dimensional product. From a theoretical viewpoint, the random variation that can be expected in the weight of a unit area of anything over microscopic proportions is very small indeed. Table 1 shows the average number of fibres to be expected in different areas (Rance[2]) and the approximate limits that would apply to the distribution of fibres in these areas, if individual fibres were distributed randomly in the statistical sense. From this, it can be assumed that departures from this random structure are caused by the mechanism by which the fibres are assembled together. Indeed, it may be thought that the papermachine should, ideally, try to form a structure that is more uniform than a random deposition of fibres in the sheet.

TABLE 1
NUMBERS OF FIBRES IN SAMPLES OF DIFFERENT AREA

Area	*Approx. number of fibres*	*Standard deviation*	*Coefficient of variation, per cent*
1 m^2	10^8	10^4	0·01
100 cm^2	10^6	10^3	0·1
1 cm^2	10^4	10^2	1·0

Note: This table assumes a 40 g/m^2 sheet and a random (Poisson) distribution of fibres

Because there are departures from the theoretical values and because of the possibility of variation in weight per unit area both in the machine-direction (MD) and the cross-direction (CD), a sampling problem exists. The control engineer requires a measurement with two important characteristics—(*a*) the measurement used for estimating the average basis weight should be chosen to be representative of the whole sheet and (*b*) the sampling should be carried out in such a way as to minimise the variability of the sampled measurement when the average weight per unit area remains constant. For example, a measurement taken at random (again in the statistical sense) from a two-dimensional sheet will satisfy the first criterion in the sense that it is unbiased, this having been ensured by selecting it at random; but it will have a high variability, since all components of the variation will be compounded in the value so obtained. Samples taken from a fixed CD position will have a smaller variability, but may be biased if the CD profile is such that there are significant differences in weight per unit area at different CD positions across the sheet. In the machine-direction, it is precisely such differences that a control system, manual or automatic, seeks to reduce. From a theoretical point of view, the control of a dynamically changing CD profile is inherently the same problem as that of control of MD trends in basis weight. Comparatively little is known about the departure from the random basis of formation of the web, even after account has been taken of the persistent MD and CD effects.

One method of achieving a representative measurement is by using a scanning beta-gauge. Defining the sample area as a two-dimensional sheet as wide as the machine and of length determined by the traverse time of the beta-gauge, then the average of readings at a number of positions across the web is representative of the sheet as a whole. Moreover, the sample is unbiased, since each MD and each CD position is represented with equal weight (Fig. 6).

In this way, the composite or average measurement used is representative and, assuming a simple additive model, estimates the mean value of the sample with a minimum variance for the number of sample points chosen.

The alternative method is to use measurements taken from a stationary beta-gauge. If the CD profile is constant, then due allowance can be made for the fact that it is situated at a specific position in the cross-direction. If such an assumption is made and the correction applied, the measurement taken will estimate the mean value of the sample with minimum variance. An advantage of the single position measuring instrument, apart from the practical and economic considerations, is that the interval over which the web is sampled is not a function of the time of traverse of the beta-gauge.

Systems checks on measurement

The fact that automatic control relies so heavily on accurate measurement leads to the advisability of systems checks on important variables. To achieve these, it may sometimes be possible to use measurements of a variable that is not required for control and that can also be calculated from those that are so required. It is good practice to include such redundant measurements whenever possible.

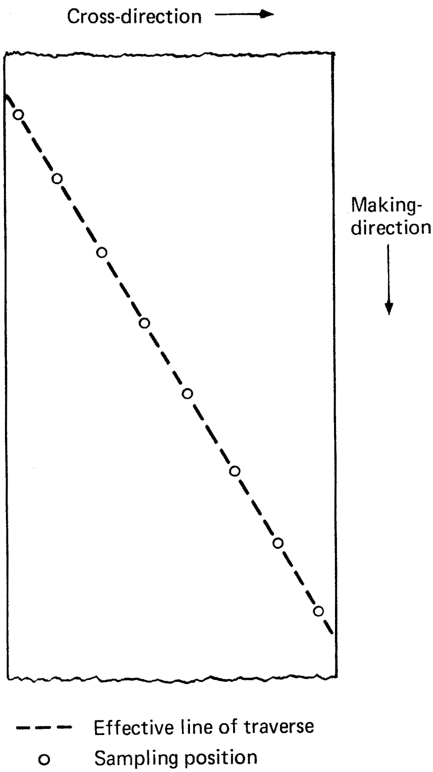

Fig. 6—Sampling a two-dimensional sheet

If continuous measurement is not feasible, then intermittent checks can be carried out. For example, the combination of yardage count and reel weight will permit reel end checks of average basis weight. The mass balance at the wet end could perhaps be checked if backwater consistency is measured.

Such systems checks are most important when viewed against the background of the sampling procedures that have to be employed. Apart from basis weight, which has already been discussed, many other measurements depend on the response of the instrument to only a small sample of the variable concerned, for example, consistency. Furthermore, many such instruments respond to changes in properties other than those for which they are intended—for example, instruments measuring consistency will respond to changes in clay content and in stock freeness.

Conclusions

ALTHOUGH the paper presents only a statistician's viewpoint of measurement for papermachine control, there is sufficient evidence, from the analysis of continuous records of many machines, that the papermaking system is one that operates in a statistical manner. Sample measurements form the basis for describing the system and the sampling problems are of two kinds. In many cases, only a small proportion of the total flow can be measured at one time and even that may not directly measure the desired property. Secondly and more important, the sample measurements taken represent only a small fraction of the possible population of measurement over a period of time. Control algorithms must take this into account no matter how they are derived.

Evidence exists to indicate that many papermachines exhibit short-term and long-term cyclic variations. In many cases, the sources of such variation are hard to trace. Why this should be so and why the papermachine should be prone to such variations—compared, for example, with other large continuous processes—has not been fully explained. One distinguishing feature of the process that may play an important part is the large mass flow required at the wet end to produce a comparatively low mass flow at the reel.

It is reasonable to ask therefore whether enough is known about papermachine systems to produce control algorithms of optimum performance. This is not to say that automatic control cannot achieve worthwhile savings in terms of increased production and better quality.

Yet the question has to be answered whether part of the considerable investment involved might not be as profitable if applied to establishing in more detail basic sources of variation in papermaking systems.

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Discussion

Mr R. E. Johnston I would like to confirm the results presented by Mr Bjerring on the equivalence between the two design methods. The proof can be made more rigorous than this presentation and, in fact, leads to the time constant that you should choose for the closed loop response being uniquely described by the disturbance characteristics that may be determined during the process of identification.

My question is that, since 'statistic' control systems are usually designed to cope with a disturbance that has a zero mean, how do you finish up with a controller that does not give you any offset after drifts or stop changes?

Mr A. K. Bjerring I have no personal experience with that, but I am sure that there are people here who have. Perhaps, they would like to comment.

Mr R. E. Jones The terms in the numerator of the dead time control algorithm can be shown to be equivalent to proportional plus integral control. Hence, there is reset action against long-term offset.

Mr Bjerring Yes, but, in Astrom's case, I believe that the reset terms are not there. This might have been what has been referred to by Mr Johnston. If you remove the dead time, you do not take into account the controller output a sampling interval ago. That does not enter into it.

Mr Johnston May I just add to that. The problem appears to be that in the first part of Astrom's paper he has assumed a model that in effect has a zero mean and a variance that is finite; but, in the last part, he assumes a model of the disturbance that has an infinite variance, yet eventually leads to a system that gives no offset. How you identify the constant parameters I do not know.

Dr A. P. Wardle When statistical methods are used for system identification, sampling is carried out over a finite time and the infinite limits of the summation terms involved become finite. What error does this introduce and how will the length of sample affect the accuracy of the results?

Dr D. B. Brewster Unfortunately, I did not have time to discuss this point. The estimation of the autocorrelation and power spectrum and the theory of stochastic control depend on the assumption of stationarity. This states that the statistics such as the mean, standard deviation, autocorrelation, etc. do not change with time. With a sample of finite length, very low frequency variations (which have a period greater than some submultiple of the sample length) will in effect show up as drifts in the mean. These drifts should be removed from the data before starting the calculations, otherwise a spurious result will occur. Jenkins & Watts' paper(5) goes into more detail on this, in particular on the relationship between length of sample and the lowest frequency that can be estimated. At the other end of the frequency range is the problem of aliasing, which is dealt with in the paper. When the sampling interval is restricted to reel changes, for example, the power spectrum almost inevitably will contain aliasing. The autocorrelation (or autocovariance), although normally more difficult to interpret, is more useful in this case.

Mr D. L. Cooper The procedure that we normally follow is this. If we have a very long series of results, we will see whether there is any long-term drift. In interpreting the spectrum, long-term drifts show up as frequencies; because you have only one or two peaks perhaps in the whole series. The errors associated with the estimate of those frequencies are very large. We normally do some very simple smoothing of the curve, taking out as far as we can what appears as long-term trends before we apply the autocorrelation function and obtain spectral estimates.

Dr J. N. Chubb The impression I receive from these two papers is that it would be wise to put more effort into improving the hardware side of data sampling techniques instead of concentrating so much on mathematical analysis. I suggest that, for example, instead of sampling at a fixed repetition rate, it would be better to sample only when there has been a significant deviation of a signal from the previous sampled value. This requires some signal storage and comparison on each input signal line and the ability to call the attention of the main processor when information transfer is required. This system would minimise the amount of computer attention required to ensure fully detailed tracing of a number of input signal variations.

Mr Bjerring To your first point, one comment is that this would be all right so long as we maintain the same control interval, which is the interval at which the controller output is sampled. A technique called modified z-transform analysis may be used here and must be used when using a sampling interval somewhere in your system that is not an integral multiple of the sampling measurement interval.

A Speaker There has been some work done with so-called sensitivity models. This sensitivity approach has been used for more generally adaptive schemes where you adjust your parameters on-line as in your Dahlin control, on a model reference approach. You can also extend that to the case of adjustable sampling parameters, for example, the sampling period. The basic work in these areas was done by Prof. George Beckie of the University of Southern California.

Dr Brewster I would like to ask a question that may sound a little heretical for a fundamental research symposium. Has this actually been used in industry?

A Speaker It is my understanding that the basis of the sensitivity model approach has been applied to the steel industry by Beckie and his associates.

Dr I. B. Sanborn One should remember, with the idea of sampling on the basis of a change of signals, that there will probably be a change of signal from the beta-gauge, owing to basis weight profile variations. One of the large problems in getting basis weight samples at high frequencies on papermachines is that one should be taking control actions on the average basis weight. In addition, the papermaker likes to see his profile so that appropriate corrective action can be taken at the slice.

There is a possibility that one could mount a second beta-gauge in a fixed position, but that costs 60 000 dollars or more. There are other approaches as well. For example, one could sample consecutively while traversing the web and estimate the deviation from the average profile (obtained via a 10 scan average) as a best estimate for basis weight change. How well this would work, however, is a difficult question.

One final comment about some practical information on Dahlin's approach. We have been using this approach at CPE for approximately two years and we have found that the basis weight stability of our papermachine has improved significantly. I think that the most important factor in the improvement, however, is that mass flow rate of stock to the machine is controlled by a tight loop with a 4–8 s sampling intervals. As a result, it would be foolish to use an algorithm such as Dahlin's to adjust the stock valve directly. Instead one should adjust the set point of a tight DDC loop on the stock valve.

Mr Johnston We have all been referring to Dahlin's approach and we should realise that this all stems from Smith's original work on designing controllers for systems with dead time. In that respect, the controllers designed by Dahlin, Smedhurst and Ramaz *et al.* and by others will all be identical, no matter how they are dressed up and in what terms they are expressed.