In-line supervisory control in a photolithographic workcell

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ABSTRACT

In this paper we describe an in-line supervisory control system that uses statistical criteria in conjunction with feedback and feed-forward control in order to improve the capability of a photolithographic workcell. The three major components of the system, namely process monitoring, modeling and control, were developed together and thus are perfectly compatible. The issue of monitoring is addressed by the development of metrology suitable for the economical in-line measurement of photoresist thickness and reflectance. Statistically designed experiments are used to develop equipment models that relate the process settings to in-line measurable responses. Finally, the statistical process control concepts of the regression chart and acceptance chart are used as the basis of the criteria that initiate process control actions. A prototype of this system has been applied on the photolithographic sequence in the Berkeley microfabrication laboratory.

1. INTRODUCTION

Process engineers continuously strive to improve the overall quality of the integrated circuit (IC) products. One of the objectives is to reduce the variability of the critical dimensions (CDs) during pattern transfer operations. Since the photolithographic sequence consists of resist coating and baking, exposure, and development, there are two ways to reduce the overall variability. One is to strive to reduce the variability of each contributing step, and this can be achieved partly by the application of feedback control. The second way to reduce variability is to appropriately correlate the variation of consecutive steps so that their deviations cancel each other. This can be achieved by the application of feed-forward control across equipment within the workcell. These two types of control are collectively known as *supervisory control*. The application of supervisory control in a noisy, batch oriented environment such as semiconductor manufacturing must be based on robust statistical methods that can identify process drifts .[1] Once a drift is identified, it is possible to adjust the process settings of the remaining steps in order to control and even eliminate any deviations from the original specifications. A persistent deviation would signify a long-term change in one of the steps. This change can be compensated by finding new settings that bring the process back to its target value.

In this paper we present an in-line supervisory control system that makes systematic use of statistical process control (SPC) and feedback/feed-forward control in order to improve the performance of a photolithographic workcell. The workcell is shown in Fig. 1. Here, wafer flow is represented by thick lines and information flow by thin lines. Process control actions are based on conclusions drawn by the analysis of in-line measurements after each step. Empirical process step models are used to calculate optimum feedback or feed-forward corrections. The control scheme presented here is adaptive in nature, since the empirical models of the steps are reevaluated each time a significant discrepancy arises between the models and the equipment they represent. It should be noted that all the control actions described in this paper are effected on a run-by-run basis. Dynamic recipe changes, although desirable, are beyond the scope of this work. The three main parts of our strategy, namely monitoring, modeling and control are discussed in detail below.

2. PROCESS MONITORING

Traditionally, the only measurement used to monitor the photolithography process is the critical dimension (CD) of the developed photoresist. Occasionally, the thickness of the deposited photoresist has also been monitored. Resist thickness however carries no information about the exposure and develop process, and CDs can be measured only after the final step. This way, CD values carry the compounded effect of several previous steps. In order to perform supervisory control *within* the photolithographic workcell, it is necessary to monitor the process status at each step. It is therefore essential to develop suitable in-line measurements to be performed immediately after each of the steps of resist coating, baking, and exposure.

Two important parameters that are affected by these steps and that have been found to relate to the final CD value is the thickness of the photoresist layer and the concentration of the photoactive compound M within that layer. The value of M in the resist determines the resist dissolution rate, and combined with the influences of resist thickness, it directly determines both the exposure and the develop operation and ultimately the critical dimensions of the transferred pattern .[2,3] Unfortunately, M cannot be measured directly from the process. In this work, we are measuring the resist reflectance and we use it as a direct indicator of the photoactive compound M in the resist. The basic idea behind this approach is that the resist absorption constant α is related to M according to the equation :[4]

$$\alpha = A M + B \tag{1}$$

where A and B are constants whose value depends on the type of the photoresist. Furthermore, the resist reflectance is a function of α. This means that the changes of M induced by the process will result in different values of α, and these changes can be inferred by measuring the reflectance. Due to standing wave patterns within the resist however, the measured reflectance will also be a strong, periodic function of layer thickness. In order to use the reflectance as an indicator of M, we have to decouple the effects of thickness variation. This is accomplished by a novel approach which has been introduced for measuring reflectance using variable wavelengths of the probing light beam .[5] This new approach makes the measured reflectance sensitive to the variations of M while eliminating the effects of thickness variations.

Figure 1 shows how this process monitoring scheme interacts with the workcell by observing the process changes through in-line measurements of photoresist thickness and reflectance. After the resist coating and baking step, and after the exposure step, the resist thickness and reflectance are measured and used to identify process drifts. If a significant drift is detected, a control action is initiated. The control action is based on process step models, and the methodology for creating these models is described below.

3. PROCESS MODELING

Our process control scheme assumes the availability of accurate and efficient process models for each of the critical process steps. There have been many photoresist models reported in the literature, and most notably, the models that are used in the simulators such as SAMPLE[2] and PROLITH[3]. However, these models must be extensibly calibrated before applied to any specific process steps, and they cannot easily relate process settings to in-line measurable responses. Thus, these models cannot be easily adapted for use in a process control algorithm. Instead, we have developed empirical equipment models based on statistically designed experiments.[6]

The major advantage of statistical experimental design is that it can be used to relate measurable responses to process settings. The resulting models are usually quite simple and they represent the process steps quite accurately over the experimental space. If the equipment "age", it is easy to reconfigure these models in order to maintain their accuracy. The major disadvantage of empirical models is that they do not advance our physical understanding of the process, and that they cannot be used outside the original space of the experimentation.

The photolithographic workcell used for these experiments in the Berkeley microfabrication laboratory consists of three major pieces of equipment: a wafer track used for resist coating and baking, made by EATON, model LSI 45/60 Wafer Processing System; an align and expose stepper, made by GCA, model 6200 Wafer Stepper; and a developer made by MTI, called the MTI Omnichuck Photoresist Development Station. All these equipment are used for 4 inch wafers on a standard 2μm CMOS process. Empirical models have been developed for each of these equipment and are described in detail, along with the monitoring scheme in another paper.[7] As an example, the model that relates to the resist thickness after resist coat and bake is briefly described below.

The equipment settings for the EATON wafer track are spin speed, spin time, baking time, and baking temperature. The responses of the EATON track are resist thickness and reflectance. Therefore, there are four control factors and two responses. A full factorial experiment to determine all the effects and interactions for the four factors requires 2^4, or 16 experimental runs. The 2-level factorial "box" was enhanced by 4 center point replications. A linear model was originally fitted, but the analysis of variance indicated that a quadratic model was more suitable. The regression equation for the film thickness model has the form:

$$\mathrm{Log(T)} = A_0 + A_1\ \mathrm{SPS} + A_2\ \mathrm{BTE} + A_3\ \mathrm{BTI} + A_5\ \mathrm{SPS}^2 + A_6\ \mathrm{BTI}^2 \tag{2}$$

where A_0 to A_6 are model coefficients, SPS, BTE and BTI are the values of spin speed, baking temperature and baking time respectively. Analysis of variance for this model shows that all coefficients are statistically significant. Additional experiments were performed to verify this model and the results are shown in Fig. 2. In this figure, the x axis is the experimental thickness and the y axis is the model predicted thickness, both shown on a logarithmic scale. Each dot represents a comparison between a measured and a predicted value, and if the dot falls on the $y = x$ line, this would indicate perfect agreement. This particular plot shows good agreement between the model and the experimental data, and the model residuals can be attributed to random process variability.

Similarly, a model for the GCA stepper has been developed to link exposure time, reflectance before exposure, and thickness before exposure to resist thickness and reflectance after exposure. Finally, a model for the MTI Omnichuck developer links the development time, the reflectance before develop, and the thickness before develop, to the CD value of the developed resist. These models are being used in our process control algorithm as described below.

4. SUPERVISORY CONTROL

Our supervisory control system is an in-line decision maker that affects wafer flow and process operations. There are several possible actions after each in-line measurement, including no action, feedback/feed-forward adjustments, wafer rework, and equipment maintenance. These choices are based on several criteria as described below in some detail. Briefly, if the measured responses are close to the target value, the wafer is processed with standard settings, i.e. no action is taken. If the measured responses deviate significantly from their targets, the wafer might be salvaged through downstream recipe changes, i.e. through feed-forward control. Using the models for the downstream tests, we decide whether such a correction is possible. If not, the control system decides that the wafer should be reworked. Also, if a process step shows significant and consistent change, feedback control is implemented and the process model is updated. Beyond a certain amount of deviation, the control system might decide that equipment maintenance should be scheduled or even that the equipment should be shut down for immediate repairs. Obviously, the criteria used for each of these actions are very important and are described below in some detail.

4.1. Feedback control

In practice, it is very difficult and expensive to fully monitor all potential factors that can cause process output changes. For instance, in the equipment used for resist spin-coat and bake, factors like spin speed, spin time, baking temperature and baking time are measured and usually show small deviations around their set points. Other factors, such as ambient temperature, humidity and resist viscosity cannot be easily monitored, and they may also cause process variations. The process deviation caused by these factors can be compensated by adjusting the operation setting through feedback control.[8]

Fig. 3a shows a control chart of the in-line measurement of resist thickness after resist coating and baking over several months of operation. The operation settings for these samples are spin speed of 4600 rpm, spin time of 30 sec, baking temperature of 120° C, and baking time of 30 sec. However, the output (i.e., resist thickness) differs from sample to sample due to unknown causes. It is noticed that, before sample #19, the resist thickness randomly deviates around its target value. After sample #19 however, the resist thickness systematically drifts above the target value.

It is clear from this example that there are two kinds of unknown causes that will induce different types of process variation. One is the random, stationary noise observed before sample #19. During this period, the random deviations at each run seem to be independent from each other. Since each new deviation is independent from the previous ones, it is impossible to predict each new value, and therefore impossible to compensate for random, independent deviations with run-by-run feedback control. Another kind of change is the systematic drift seen after sample #19. Since the drift is consistent, long term feedback control can be used to compensate for it. It is therefore necessary to give a criterion that distinguishes between these two different types of process deviation.

The criterion that we have developed for this purpose is based on the cumulative student-t statistic. This statistic is used to identify a consistent departure of the process from its standard performance. The application of this criterion starts with the off-line development of an equipment model, when the equipment is operating according to specifications. If the process is in control, the residual between the actual and the model predicted value should be consistent with the prediction error of the model and the replication error of the equipment. The statistic[9] used for this test is given below:

$$t_n = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y}_i)}{\sqrt{\mathrm{var} \left(\sum_{i=1}^{n} (\hat{y}_i - \bar{y}_i) \right)}} \tag{3}$$

where $\hat{y}$ is the model predicted value and $\bar{y}_i$ is the measured value of the monitored process output, averaged over the ith wafer.

As an example, feedback control is employed on the EATON wafer track used for resist coating and baking. The equipment model of the EATON is described in section 3. For each new in-line measurement of resist thickness after spin-coat and bake, as shown in Fig. 3a, the student-t statistic is calculated and plotted in Fig. 3b. The control limits that ensure a 5% probability of false alarm are +/- 2.0. If the calculated student-t drifts outside these limits, we can conclude with 95% confidence that the process has indeed departed from its target. At this time, the systematic change is confirmed and feedback control action is taken.

The operation of the feedback control loop is shown in Fig 4. With the initial process settings, the actual output of the process is compared to the model predicted value via the cumulative student-t test. If the student-t statistic is within the control limits, no feedback control action is taken. If the student-t statistic exceeds the control limits, the equipment model should first be updated, and then new process settings are generated by solving the new model in reverse.

A simple method to update model coefficients is described next. First, the original model is developed off-line and has the form:

$$\hat{y} = f(\vec{\theta}, \vec{x}) \tag{4}$$

where y is the model process response, f is the regression equation of the model, $\vec{\theta}$ represents the model coefficients when the wafer has been processed – assuming that the model is still valid –, and $\vec{x}$ is the vector of process settings. The model is violated when the actual value of process response y_{new} drifts away from the model predicted value, $\hat{y}$. The model is updated by estimating a $\Delta\vec{\theta}$ for each coefficient.

$$y_{new} = f(\vec{\theta} + \Delta\vec{\theta}, \vec{x}) \tag{5}$$

Because in-line experimentation seldom offers enough degrees of freedom for estimating the entire vector $\Delta\vec{\theta}$, the model is updated by estimating the most significant $\Delta\vec{\theta}$ and by assuming that the rest are zero.

As an example, we use the EATON wafer track to demonstrate the performance of the feedback control strategy. As shown in Fig. 3b, the actual student-t exceeds its control limit at sample #34. At that moment, the system decides (with 95%

confidence) that the EATON track is out of statistical control due to some unknown cause. At this point, the deviation of resist thickness from its target value is $\Delta x \approx 0.026\ \mu m$. The first action that the system will take is to try to reconcile the original equipment model with the new pattern of process responses.

In this example, the process settings have been kept the same from run to run through sample #34. Therefore only the constant term in the model (i.e., Eq. 1) can be corrected by a $\Delta A_0 = 0.008856$. In order to force the resist thickness back to its target value, i.e., $\Delta x \approx 0$, the feedback controller uses the updated model and suggests that the spin speed should be increased by 186 rpm. An obvious extension to this strategy would be to employ a certain kind of evolutionary in-line experiment in order to update the model. This would potentially afford the re-estimation of all the model parameters, at the expense of introducing additional variations in the process.

4.2. Feed-forward control

As shown in Fig.1, the outputs of each process step are part of the inputs of the next step. It is therefore possible that an adjustment of process settings at the current step can cancel out the effects of deviations in the outputs of the previous step. The criterion used to decide whether this is possible is very important; since the critical dimension is the final product of the photolithographic process, the feasibility of feed-forward correction is determined by whether the predicted CD value falls within the process specifications.

In the process quality control, one can use a process target value (e.g., CD is 2.0 μm) with certain process tolerance defined by a lower specification limit LSL and an upper specification limit USL. If the spread σ of the equipment replication error is taken into account, whether or not the wafer should be processed with the standard recipe is decided by the following statistical test:

$$LSL + Z_\delta\, \sigma < \hat{Y} < USL - Z_\delta\, \sigma \tag{6}$$

where $\hat{y}$ is the predicted CD value (using the empirical model), δ is the acceptable yield loss, σ is the replication error of the equipment with normal distribution and Z_δ is the upper 100 (1 - δ) percentage point of the standard normal distribution. Here we assume that the model prediction error is much smaller than the equipment replication error. A similar, but more complicated statistical test can be used if the model prediction error is substantial.

In Fig. 5, the Gaussian profile that represents the equipment replication error is shown in relation to LSL and USL, the lower and upper specification limits of the process. The equipment replication profile is used to test for a certain, maximum acceptable yield loss (e.g, 5%). Suppose now that we have measured the resist thickness and the reflectance before the exposure step as shown in Fig. 6, and that they have varied from one run to another. We use the equipment model of the MTI developer to predict the final CD value for each of these runs. If the predicted CD value (assuming a standard development time) is between LCL and UCL (i.e., passed the test of Eq. 6), there should be no feed-forward action and the standard development time should be used. If, however, the predicted CD value is beyond LCL or UCL, the development time should be adjusted in order to set the CD distribution back to its target value. A real example demonstrates below the performance of this feed-forward control strategy.

Due to unknown disturbances in the EATON wafer track, the thickness and the reflectance in the resist layer after spin-coat and bake vary from one run to another as shown in Fig. 3a. In one such sample, the resist reflectance is found to be 39.5% which is close to its historic average of 39.7%, but the resist thickness was found to be 1.26 μm which is thicker than its historic average by 0.02 μm. If this wafer is processed at the standard exposure time (1.5 seconds), the resist reflectance after the exposure step is predicted to be about 72%. Using this prediction as an input to the development model, and using standard recipes, the CD value for this wafer is predicted to deviate from its target value by 5%. Based on this information, our feed-forward control algorithm suggests a non-standard exposure time of 1.6 seconds. The basic idea of this algorithm is that if we want to keep the CD value of this wafer close to its target value, the resist reflectance after exposure should be equal to 75.4%. In order to force the resist reflectance of this wafer to be 75.4%, the exposure time should be increased to 1.6

seconds from the standard 1.5 seconds setting.

5. CONCLUSION

As process specifications become tighter, the application of robust process compensation schemes is necessary in order to achieve acceptable process capability. Our results show that feedback and feed-forward control decisions can be made independently and that both can be based on solid statistical criteria. These criteria have adjustable error rates which can be set to minimize the cost of process fallout.

6. ACKNOWLEDGMENTS

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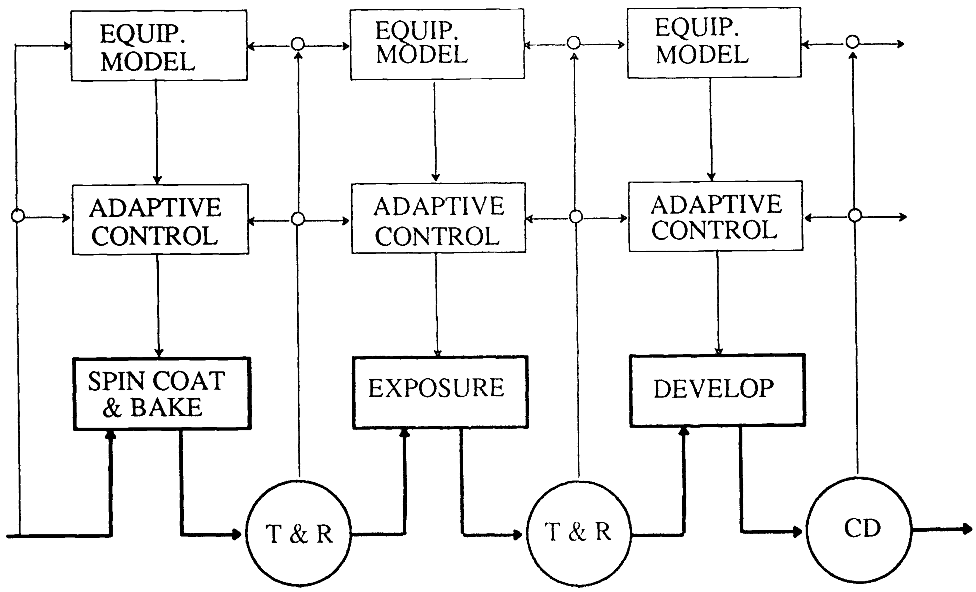

Fig. 1. Schematic representation of wafer (thick lines) and information flow (thin lines) in the photolithography workcell.

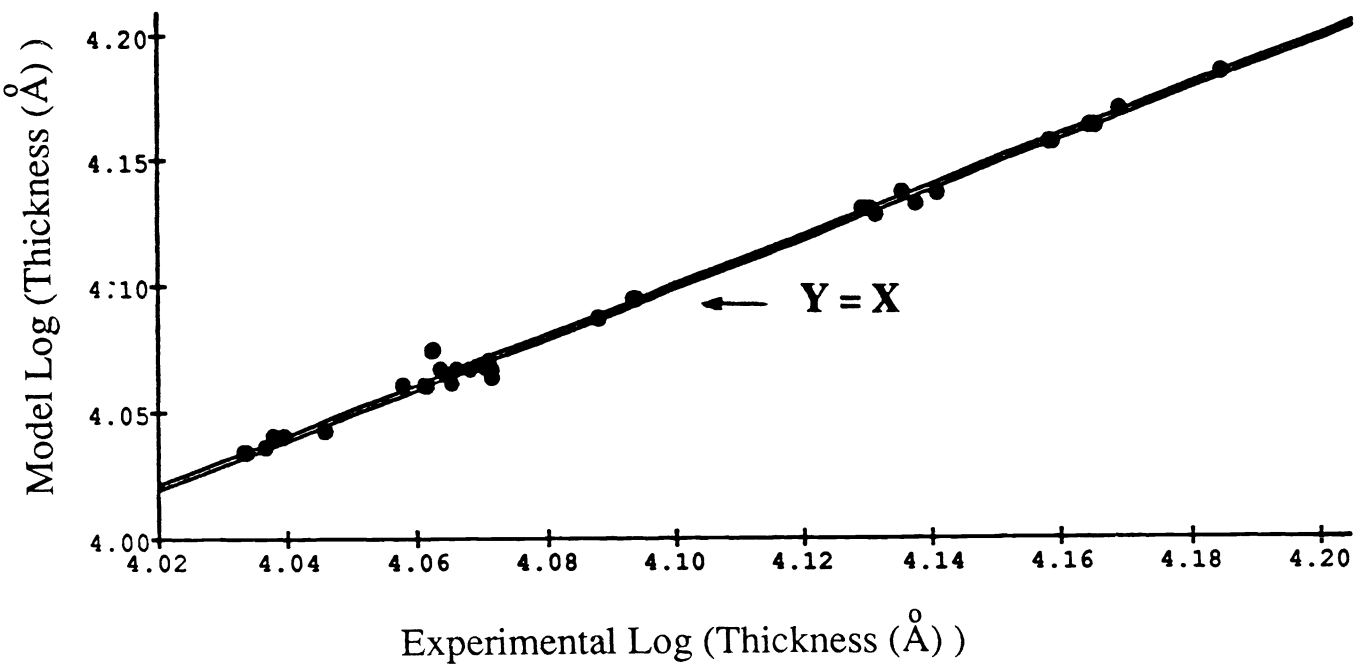

Fig. 2. Model verification of EATON wafer track for resist thickness after coating and baking.

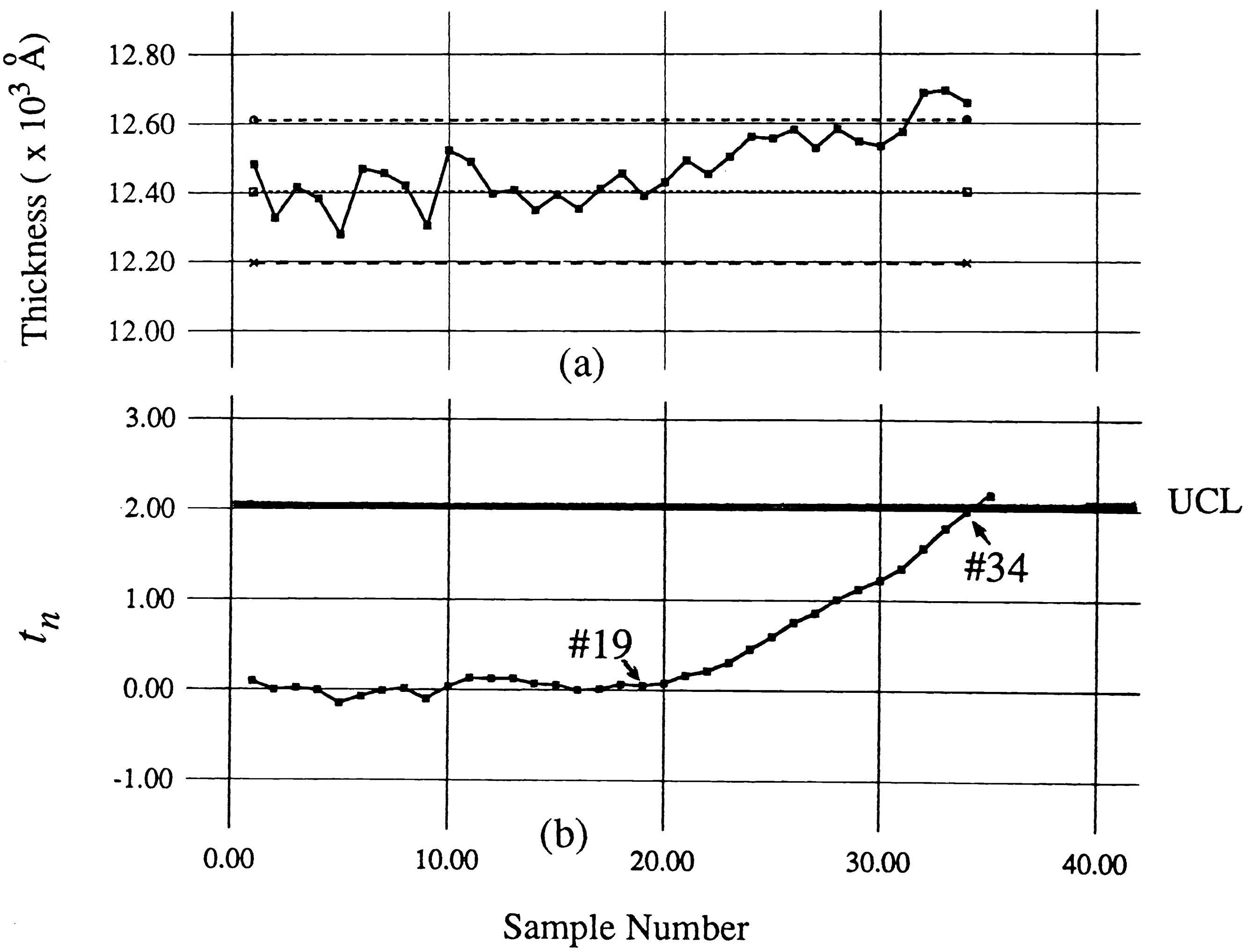

Fig. 3a. Schewhart chart of in-line measurement of resist thickness after coating and baking over several months of operation.

Fig. 3b. Calculated student-t statistic of each in-line measurement of resist thickness with control limits at the 5% level of significance.

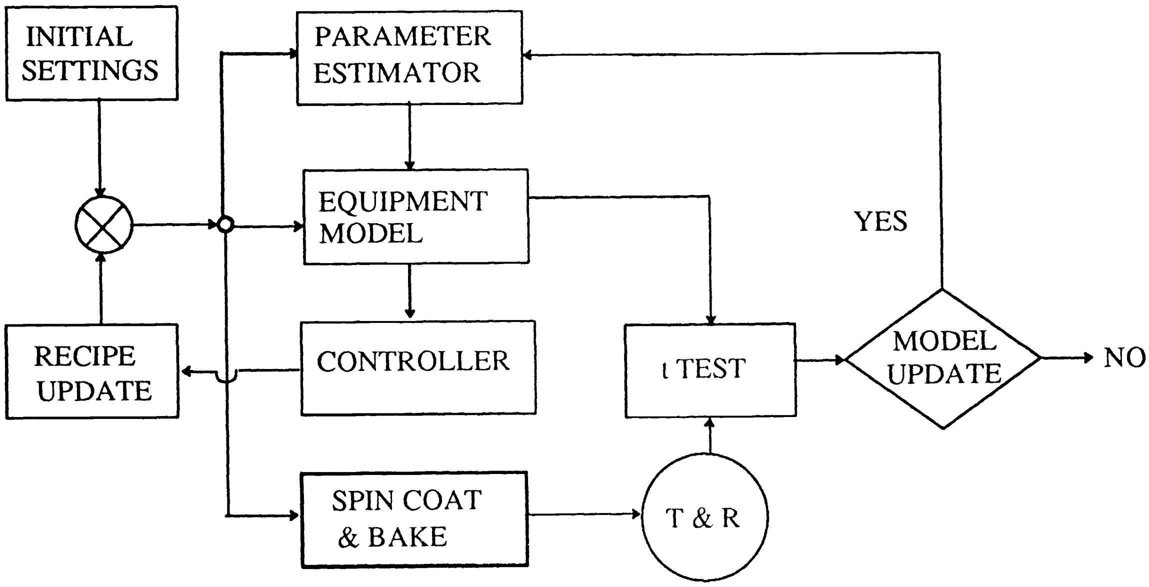

Fig. 4. Schematic representation of feedback control loop.

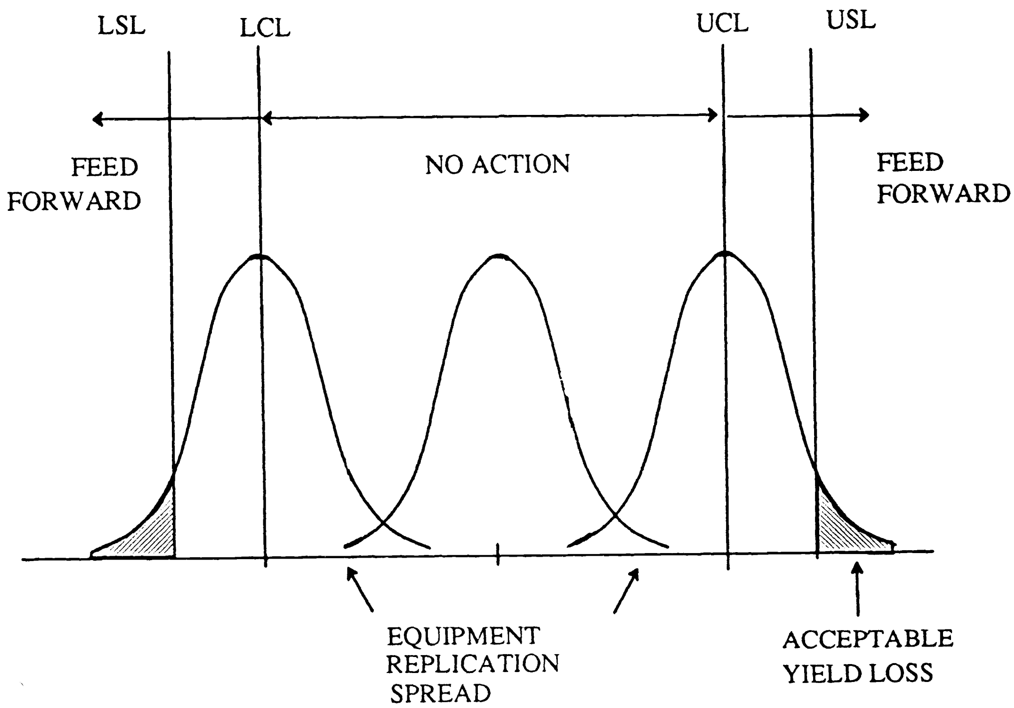

Fig. 5. In-line specifications and control limit for feed-forward control.

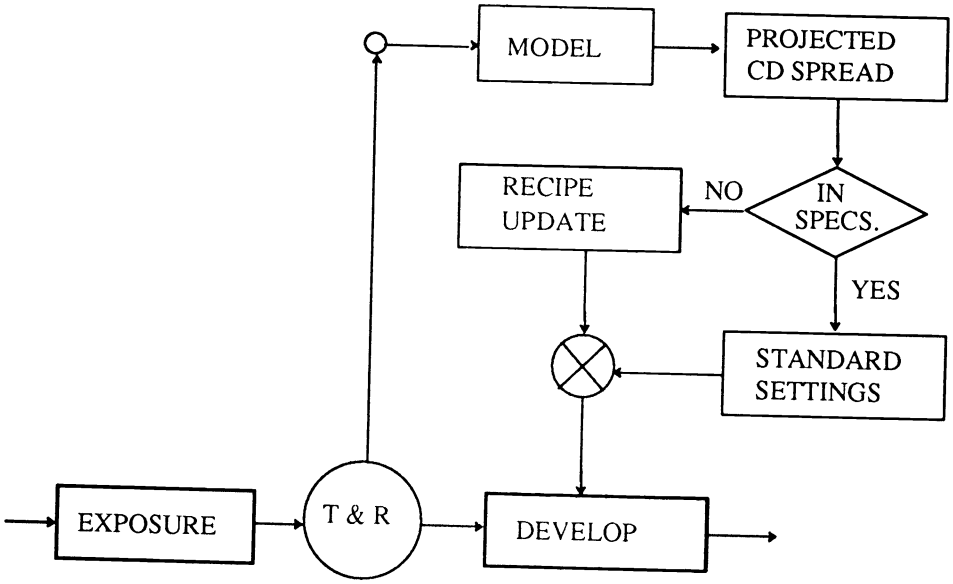

Fig. 6. Model-based CD prediction to determine the necessity of feed-forward control action.