Statistical Analysis and Design of Semiconductor Manufacturing Systems

Argon Chen*, R.-S. Guo† and Puffy Lin*
*Graduate Institute of Indutrial Engineering † Department of Industrial Management
National Taiwan University, Taipei, Taiwan, 106
achen@ccms.ntu.edu.tw

Abstract – *The enormous complexity of a semiconductor manufacturing system is the main obstacle for making quality manufacturing control decisions. Conventional methodologies, such as queueing network and simulation analysis, are often too complex to be used effectively. In this paper, we will demonstrate a methodology to build simple statistical models that faithfully characterize the manufacturing system. We then show how these models can help improve the quality of manufacturing control decisions.*

Index Terms – *Manufacturing control, Robust design, Statistical process control*

INTRODUCTION

Wafer fabrication, one of the key processes in semiconductor manufacturing, is perhaps the most complex manufacturing process. A major process flow in a wafer fabrication factory may contain over 200~300 separate steps or operations. Its complicated processes (reentrant characteristics, queue time limit, batching requirement, etc.) and uncertainties (machine down, rework, yield, etc.) make its production planning and control even harder [1]. In this research, we demonstrate how to make quality decisions for both long-term manufacturing strategy and short-term manufacturing control using simple, but effective, statistical modeling and analysis methods.

The first objective of this research is to develop a statistical procedure to select manufacturing strategies that optimize production performance. By conducting full factorial experiments with a validated simulation model, the simulation results are analyzed using off-line quality engineering techniques including Taguchi method [2] and response surface methodology (RSM) [3]. The affecting factors selected in the experiments include product mix, hot lot ratio and batching rule. And production performance measures include throughput, WIP, and cycle time. Experimental data are collected and analyzed to determine factor levels that optimize the production performance through S/N ratios and/or steepest ascent methodologies. Based on the experimental results, we'll be able to propose the best manufacturing strategies to manage the trade-off among different or conflicting production objectives and to reduce the production variability.

The second objective is to build statistical time series models for real-time control and monitoring [4]. To illustrate how to apply on-line quality monitoring and control techniques [5] to production systems, we collect actual production data from a local semiconductor fabrication factory and use time series models, including ARIMA, transfer function, and VARIMA models [6], to characterize the factory operations. Two control charts are then constructed: common-cause and special-cause control charts. The common-cause chart shows the trends of production conditions, which are accurately predicted by the time series models, and is used for real-time manufacturing control. The prediction residuals are used to construct the special-cause control chart for monitoring and detecting any production deficiencies caused by unusual operational problems.

ROBUST DESIGN OF MANUFACTURING SYSTEM

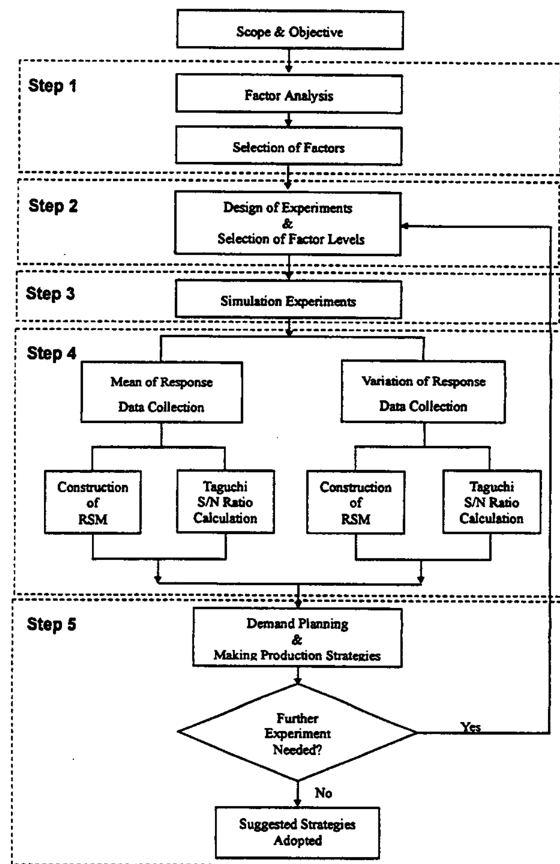

Fig. 1 Robust design of manufacturing system

Since the semiconductor manufacturing system is so complex that analytical approaches to designing a reliable manufacturing system are often impractical. Here, we utlize the methodolgies of "robust design" in off-line quality engineering, including Taguchi method and RSM, to design

the manufacturing system. We first examine critical factors that affect the system's performanc. Factors are selected and used to design and conduct experiments in a simulation system. Results are analyzed and corresponding mathematical models are constructed. Strategic decisions can be then made based on the analysis. Fig. 1 shows the steps.

In this study, we cooperate with a local fab producing four types of products: M-ROM, DRAM, logic and flash memory. Three factors are deemed critical to the manufacturing control: product mix (X_1), hot lot ratio (X_2) and batch tool policy (X_3). A simulation model is built and the following central-composite-design experiment is performed (3 replicates for each test):

Table 1 CCD experimental design

	Coded Test Conditions			Actual Test Conditions		
Test	X_1_ProductMix	X_2_HotLotRatio	X_3_BatchRule	X_1	X_2	X_3
1	-1	-1	-1	4.00	1/12	0.3
2	1	-1	-1	4.67	1/12	0.3
3	-1	1	-1	4.00	3/12	0.3
4	1	1	-1	4.67	3/12	0.3
5	-1	-1	1	4.00	1/12	0.7
6	1	-1	1	4.67	1/12	0.7
7	-1	1	1	4.00	3/12	0.7
8	1	1	1	4.67	3/12	0.7
9	0	0	0	4.33	2/12	0.5
10	-2	0	0	3.67	2/12	0.5
11	2	0	0	5.00	2/12	0.5
12	0	-2	0	4.33	0	0.5
13	0	2	0	4.33	4/12	0.5
14	0	0	-2	4.33	2/12	0.1
15	0	0	2	4.33	2/12	0.9

Three manufacturing performance indices are considered in the analysis of experimental results: cycle time, work-in-process (WIP) level and throughput. In this paper, we will present the analysis results for cycle time performance.

Average Cycle Time

Since the shorter the cycle time the better the system, we use smaller-the-better S/N ratio to evaluate the cycle time performance under different factor levels. Fig. 2 shows the results:

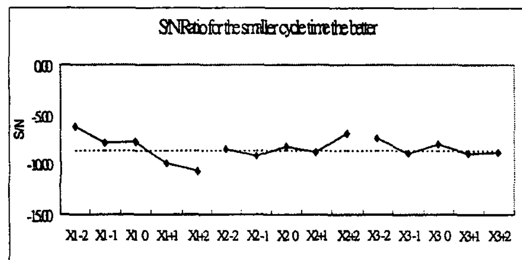

Fig. 2 Averge cycle time evaluation using S/N ratio

From Fig. 2, to achieve shorter manufacturing cycle time we can choose the first level (-2) of product mix, the fourth level (2) of hot-lot ratio and the first level (-2) of batch policy. To more precisely characterize the effects of three factors on the average cycle time, a response surface model can be constructed:

CycleTime_Mean = 8.99236 - 3.89715*ProductMix - 10.9257*HotLotRatio + 3.19421*BatchRule + 0.56732*ProductMix^2 +2.3469*ProductMix*HotLotRatio - 0.775758*ProductMix*BatchRule -3.5006*HotLotRatio^2 + 2.01151*HotLotRatio*BatchRule +0.103089*BatchRule^2

We can then determine how a shorter cycle time can be achieved through adjustment of factor levels. A steepest descent direction of factor level adjustement is shown in Fig. 3:

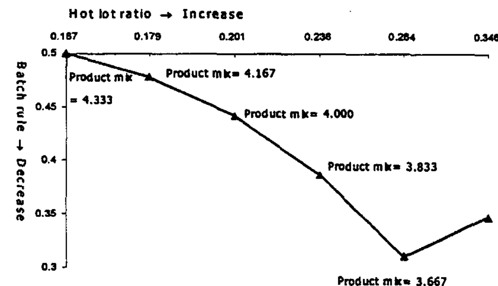

Fig. 3 Steepest descent direction to achieve shorter cycle time

We summarize the best factor level selection for cycle time performance in Table 2.

Table 2 Optimal level settings for cycle time

Factor	Low Level	High Level	Optimum Level
X_1:Product Mix	3.66667	5.00000	3.67728
X_2:Hot Lot Ratio	0.0	0.33333	0.33333
X_3: Batch Rule	0.1	0.9	0.1
Optimum Cycle Time_Mean Value=1.2811			

Cycle Time Variation

Similarly, we can determine appropriate factor levels to minimize the cycle time variation. Again, the smaller the cycle time variation the better the system. Thus, we use smaller-the-better S/N ratio to evaluate the cycle time variation under different factor levels. Fig. 4 shows the results:

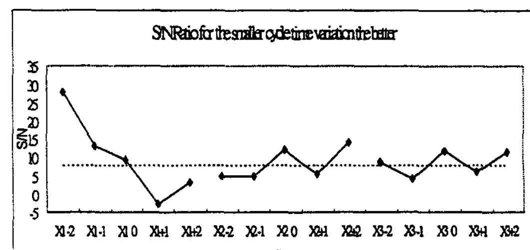

Fig. 4 Cycle time variation evaluation using S/N ratio

From Fig. 4, to achieve smaller cycle time variation, we

can choose the first level (-2) of product mix, the fifth level (2) of hot-lot ratio and the fifth level (2) of batch policy. Combining considerations in Figs. 2 and 4, the first level, fifth and third levels of product mix, hot-lot ratio and batch policy, respectively, can be chosen for the best overall cycle time performance.

To more precisely characterize the effects of three factors on the average cycle time, a response surface model can be constructed:

CycleTime_SD = -9.31178 + 4.2409*ProductMix - 13.126*HotLotRatio - 1.34675*BatchRule - 0.458533*ProductMix^2 +3.16988*ProductMix*HotLotRatio + 0.57683*ProductMix*BatchRule -6.88484*HotLotRatio^2 + 2.91721*HotLotRatio*BatchRule -1.69625*BatchRule^2

We can then determine how a smaller cycle time variation can be achieved through adjustment of factor levels. A steepest descent direction of factor level adjustement is shown in Fig. 5:

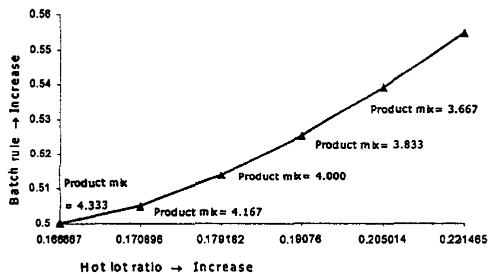

Fig. 5 Steepest descent direction for smaller cycle time variation

For the overall cycle time performance, a weighted average of the cycle time average and variation performance can be taken as an objective:

Minimize $Z = W_1 \cdot (\text{CycleTime_Mean})^2 + W_2 \cdot (\text{CycleTime_Std deviation})^2$

When we set the weights $W_1=W_2=1$, the steepest descent direction can be found as in Fig. 6:

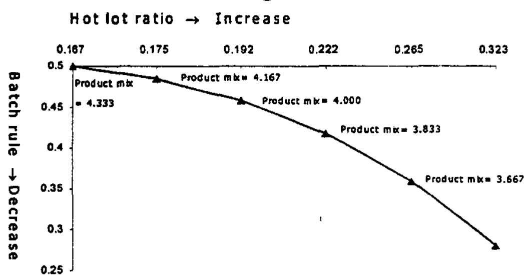

Fig. 6 Steepest descent for overall cycle time performance

We summarize the best factor level selection for overall cycle time performance in Table 3.

Table 3 Optimal level settings for overall cycle time performance

Factor	Low Level	High Level	Optimum Level
X_1: Product Mix	3.66667	5.00000	3.70128
X_2: Hot Lot Ratio	0.0	0.33333	0.31014
X_3: Batch Rule	0.1	0.9	0.26448
Optimum Cycle Time_Mean&SD Value=-6.93889E-18			

REAL-TIME MANUFACTURING MONITORING AND CONTROL

Since all the manufacturing performance indices are time dependent, we first build the time series models (ARMA, transfer function, or V-ARMA models) to characterize and predict the system performance over time. We can then construct two control charts: common-cause control chart and special-cause control chart. The former is used for real-time manufacturing control and the latter is used for real-time manufacturing monitoring. Fig. 7 shows the steps:

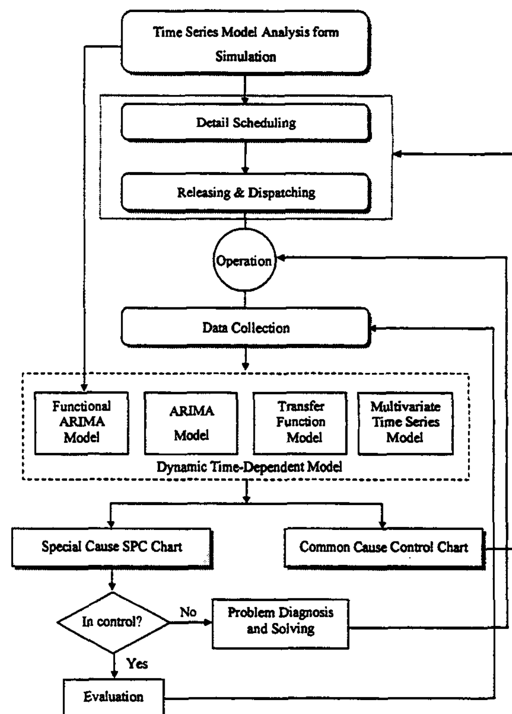

Fig. 7 Real-time manufacturing monitoring and control

In this paper, we will use the cycle time as an example to demonstrate the methodologies.

Construction of Time Series Models

Actual cycle time (shown in Fig. 8), WIP level, and wafer-out data are collected from a local fab and used to construct the time series model.

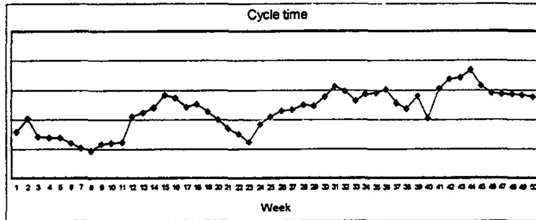

Fig. 8 Actual cycle time trend

Here, we demonstrate the multivariate time series model (Vector-ARMA, VARMA) constructed for cycle time:

$$CycleTime_t = CycleTime_{t-1} - 0.3795 + \frac{0.0007B^7}{(1-1.3761B+0.5101B^2)}$$

$$(1-B)WaferStart_t + \frac{1}{1+0.0674B}a_t$$

Cycle Time Common-cuase Chart and Real-time Control

Using the multivariate time series model, the manufacturing system's cycle time can be then predicted. Fig. 9 shows the trend of the predicted cycle time.

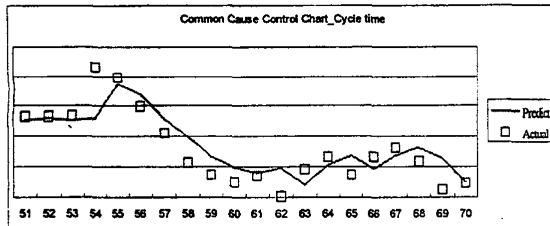

Fig. 9 Trend of predicted cycle time vs. actual cycle time

From Fig. 9, it can be seen that the trend of cycle time can be accurately predicted and thus some real-time manufacturing control decisions can be made accordingly to achieve a better manufacturing performance. For example, when a downward trend of cycle time is predicted, a real-time control decision can be made to increase the wafer-start level.

Cycle Time Special-cause Control Chart and Monitoring

The prediction residuals of the cycle time (differences between the preducted and actual cycle times) can be used to construct a statistical process control (SPC) chart for detecting special causes. Fig 10 shows the SPC chart for the cycle time residuals.

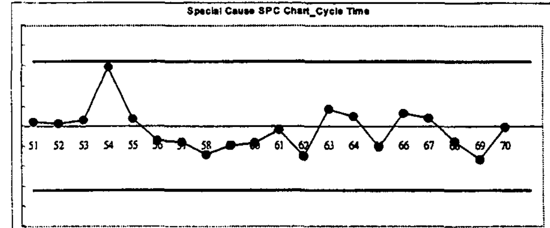

Fig. 10 SPC chart for cycle time

The SPC chart is used to detect special operation problems such as unexpected bottleneck machine breakdown, dispatching inefficiency, transportation problems, etc. In contrast to the common-cause chart, the SPC chart is used to find problems that need to be discovered and corrected. Fig. 10 shows an in-control process, though one of the cycle time residuals appears very large and close to the control limit. This large value of cycle time residual indicates an unexpectedly low actual cycle time that may be caused by a sudden drop of wafer-start level.

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