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Evaluation of Scheduling Strategies on the Performance of a Flexible Manufacturing Cell - A Simulation Study

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ABSTRACT:

The current trend in semiconductor manufacturing is characterized by expanding product variety, decreasing lead times from order to delivery, exacting standards of quality, and competitive prices. One possible means of achieving this is in the form of increased flexibility. Providing flexibility is typically an expensive proposition so, industrial engineers aim to provide more economic approaches to enable flexible manufacturing cells and related equipment to operate appropriately in an efficient manner. It is essential to characterize these tools in detail before the production plans are finalized. Using state-of-the-art computer simulation, a generic model of photolithography tools has been developed. The model examines the impact of changing product volumes, buffer size, product sequence and product-mix on performance criteria, e.g. throughput time. The high investment cost of flexible manufacturing cells justifies the use of computer simulation support to maintain high system performance and reduce risk by predicting the system behavior under any feasible production schedule. Simulation results presented in a Taguchi experimental design framework offer a robust methodology to gain quick insights into the behavior of selected parameters within flexible manufacturing system environments. The developed model has been evaluated and found to be relatively more effective than simplified deterministic approaches when measured against actual production.

KEY WORDS: Flexible Manufacturing, Simulation, Photolithography, Semiconductor Manufacturing, Taguchi Experimental Design.

1. INTRODUCTION

Semiconductor manufacturing is one of the most complex manufacturing systems in terms of technology and procedure. Along with increasing market pressures, manufacturing systems face new challenges to survive and grow in the marketplace. In an attempt to cope with such multifaceted problems, new technologies advocate increased automation and flexibility. Flexible manufacturing systems (FMS) are the key to success coping with the market changes in an efficient and effective manner. It is worth mentioning that 90% (if not more) of semiconductor manufacturing plants are FMSs. The high risk in terms of lost/delayed production means that many scheduling problems remain unsolved in FMS. Therefore, one should consider the implications of optimizing the major production parameters within the domain of scheduling.

The operating conditions within the semiconductor manufacturing environment are characterized by dynamic flow. Within such an environment, it is useful to ensure that the manufacturing system has an appropriate level of wafer starts, as well as product-mix, to develop an understanding of its impact on tools performance. Further, because system planners and controllers often are compelled to operate within stringent time constraints when reviewing alternate control or scheduling decisions, there is little justification, if any, for conducting an exhaustive search when attempting to find optimal parameter combinations. Not only would this be computationally prohibitive, it also would be a very time-consuming exercise. There hence is a need for identifying a methodology that, with reasonable levels of confidence, could achieve the planning staff objectives and expectations.

Photolithography is considered the constraint process within semiconductor manufacturing due to complex technology, critical dimensions, and re-entrant flow. During the photolithography process the

circuit pattern is transferred from a mask onto photosensitive polymer so that replicates the pattern in the underlying layer. The object of this process is the accurate and precise definition of a three-dimensional pattern on a semiconductor substrate. Although vast body of literature concerning semiconductor manufacturing (Uzsoy *et al.*, 1994), there is still lack of solutions to optimize photolithography process (Arisha, 2003).

The objectives of this research can be summarized as follows:

1. To determine the significance of the impact of the production parameters on the performance of a photolithography tool.
2. To find the relative impact of the parameters (in terms of their main factor effects) on the selected performance criteria.
3. To optimize the performance of the photolithography tool by getting the appropriate combinations of parameters.
4. To provide the production and control staff with a flexible methodology to evaluate the scheduling decisions before implementation.

2. FLEXIBLE MANUFACTURING CELL SCHEDULING PROBLEM

Flexible manufacturing systems (FMS) have been designed to serve complex industries by providing a mixture of high productivity and production flexibility. Flexible Manufacturing Cells (FMC) are the main elements in FMS and every FMC can be considered as an independent integrated system having its own automated workstations, material handling system, storage devices and capability for rapid reconfiguring to produce multiple products (Boer, 1994) and (Liu and MacCarthy, 1996).

The challenge of flexible manufacturing scheduling in photolithography area is to select the appropriate level of each process control parameter in order to enhance the performance. The Flexible manufacturing cell used in photolithography process is shown in a schematic layout in Figure 1. The pattern of production in the cell is similar to a flow shop, where every product has to go through the 13 operations for process completion. The cell can be adapted to produce up to 15 different products and about 13 different layers. Every product/layer has its own configuration (e.g. processing time, setup time). The buffer shown in the cell has a variable capacity. Scheduling the photolithography FMC is a challenging task due to many factors such as, many process parameters, complexity in production procedure, and complex production flow.

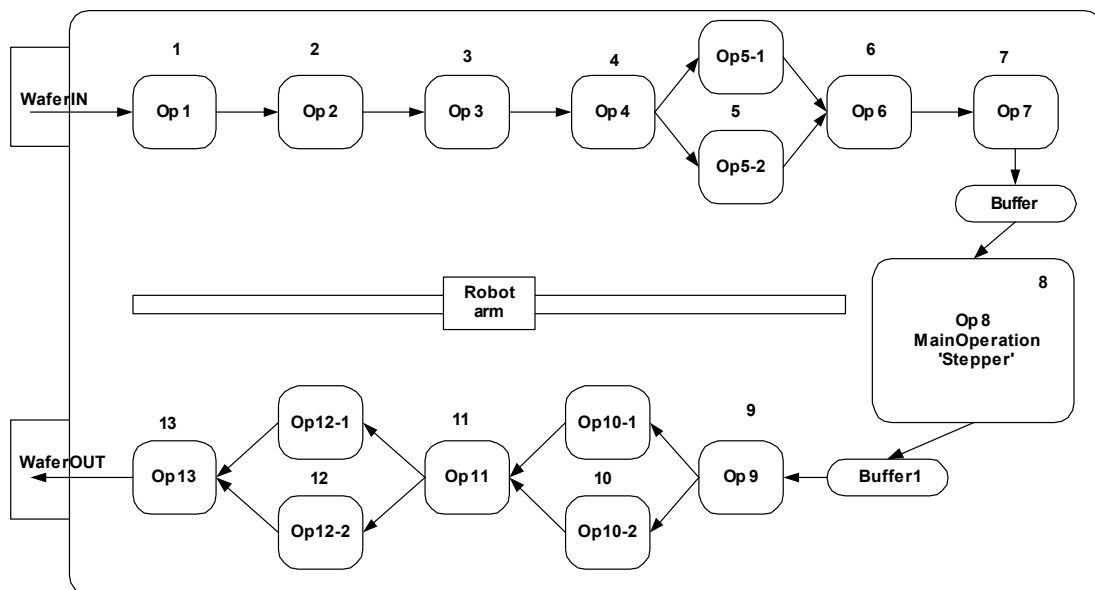


Figure 1. Schematic diagram of flexible manufacturing cell in photolithography

This research studies the FMC in semiconductor manufacturing in two phases; building a time-time simulation model and then optimizing the process control parameters.

3. MODEL PARAMETERS

In order for a system to be evaluated, some form of measures must be agreed with the production personnel. The most critical planning parameters were:

- a) Wafer starts;
- b) Number of products on production (product-mix);
- c) Product sequence (dispatching rule);
- d) Local buffer size (stepper's buffer).

The performance measure of most interest is the total throughput time (TPT) and the goal of this work is to outline a methodology that helps planning and control engineers gain quick insights into the relative importance of the parameters with respect to this.

4. SIMULATION MODEL

The simulation model assumed that all the wafers are available at the start of the simulation run (i.e. wafers arriving at the cell are not stochastically generated). Operation times and product-mix were assumed to be pre-specified at the beginning of each experiment. Rework/scrap wafers were considered as a percentage of the overall production. Other assumptions were set concerning the maintenance scheduling and repair delays. The time-based simulation model was verified using three approaches; comparisons with actual production data, validated with existing models, and check the reasonableness of the output.

Figure 2 shows the verification results. These show the effective performance of the simulation model to mimic the actual production cell. The model was then used to perform a series of experiments to optimize the performance of the system in response to several input parameters. The experimental design was based on Taguchi paradigm.

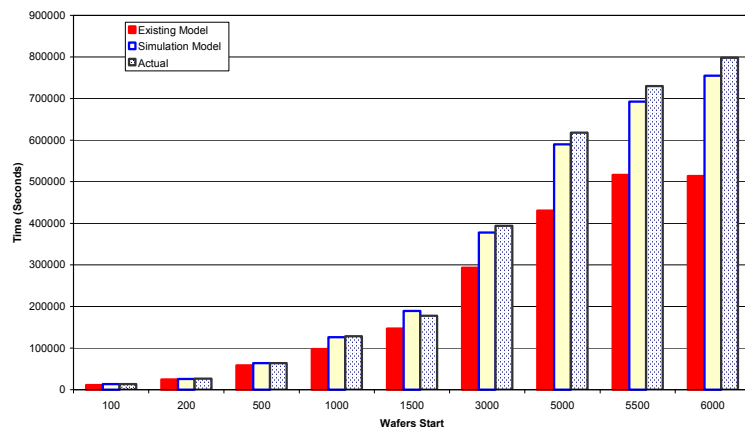


Figure 2. Comparison between simulation output, actual data, and deterministic models

5. TAGUCHI EXPERIMENTAL DESIGN

Taguchi experimental design is based on a matrix containing a set of experiments where the settings of the process parameters under study are determined. The experimental data generated is subsequently analyzed to determine the effects of various process parameters. The experimental matrices are special orthogonal arrays, which allow the simultaneous effect of several process parameters to be studied efficiently (Phadke, 1989). The real benefit in using matrix experiments is the economy they afford in terms of the number of experiments to be conducted. In the present study, because we need to experiment with four factors, each at five levels, a full factorial experiment would have required $5^4 = 625$ experiments. In contrast, it is found that Taguchi's L25 orthogonal array is suitable for our purposes, and only 25 experiments need to be conducted.

The purpose of conducting orthogonal experiments is twofold:

1. To determine the factor combinations that will optimize a defined objective function (i.e., to determine the optimal level for each factor)
2. To establish the relative significance of individual factors in terms of their effects on the objective function.

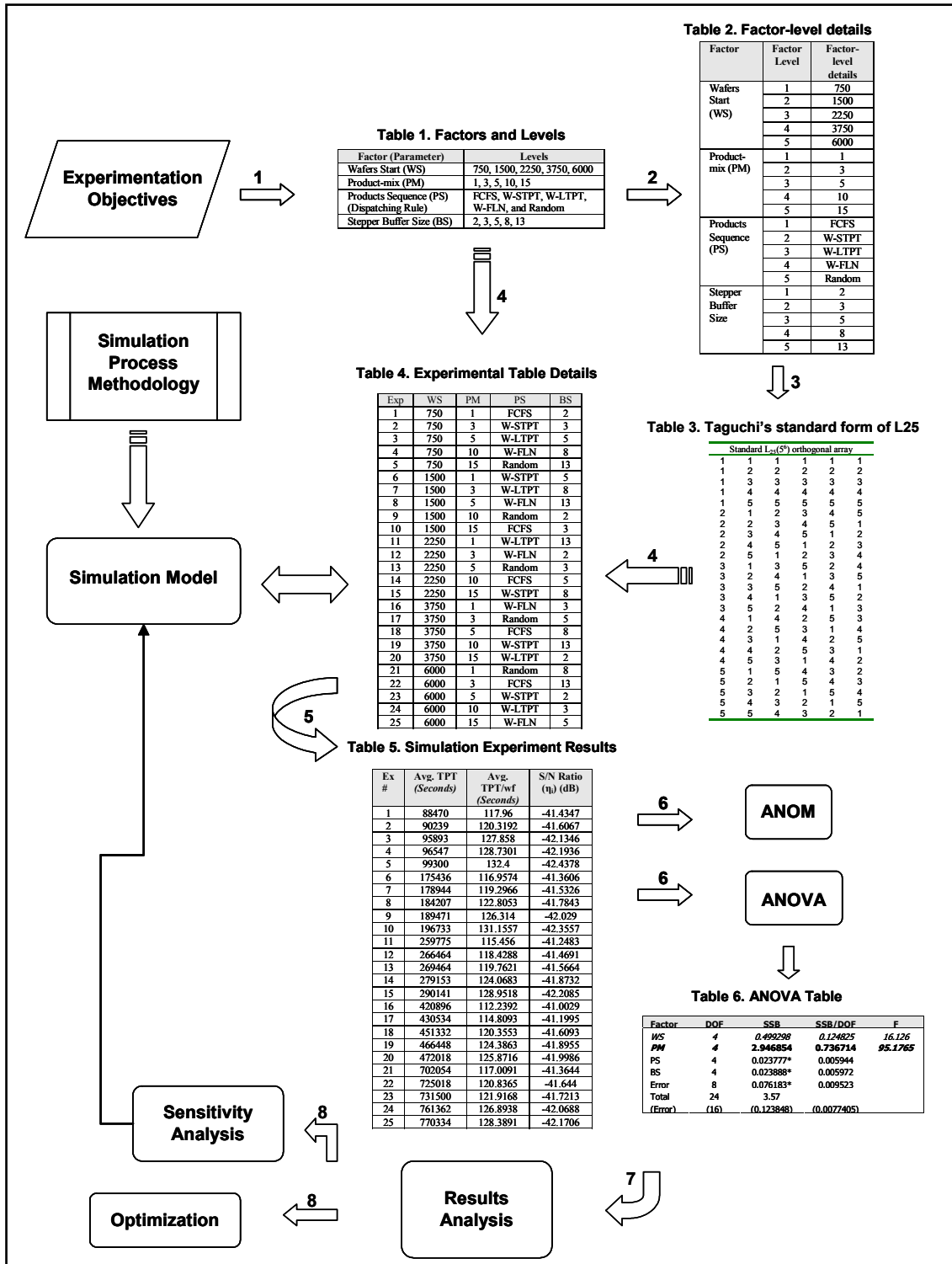


Figure 3. Taguchi's experimental framework

Taguchi suggests using a summary statistic, η , called the signal-to-noise (S/N) ratio, as the objective function for matrix experiments. Phadke discusses the rationale for using η as the objective function. Taguchi classifies objective functions into one of three categories: the smaller-the-better type, the larger-the-better type; and the nominal-the-best type (Roy, 2001). Figure 3 shows the particular application used in this instance, with Figure 4 outlining the main analysis functions used to examine the results of the experiments.

$\eta_i = -10 \text{Log}_{10} (MSD)$	Eq. 1	η_i = observed Signal/Noise (S/N) ratio. for the i^{th} orthogonal experiment.
$MSD = \frac{\sum_{i=1}^n Results^2}{n}$	Eq. 2	MSD = mean square deviation for smaller-the-better. $Results$ = the output or readings collected.
$m = \frac{\left[\sum_{i=1}^n \eta_i \right]}{n}$	Eq. 3	m = overall mean value of η n = number of experiments performed. i = experiment number.
ANOVA		
$SST = SSB + SSE$	Eq. 4	SST = Total sum of squares.
And,		SSB = Sum of the sums of squares due to various factors.
$SST = GTSS - SSM$	Eq. 5	SSE = Sum of squares due to error.
GTSS and SSM can be calculated as;		$GTSS$ = Grand total sum of squares.
$GTSS = \sum_{i=1}^n \eta_i^2$	Eq. 6	SSM = Sum of squares due to the mean.
$SSM = n \times m^2$	Eq. 7	
Then,		
$SSB = \sum_{j=1}^c \left[l_j \sum_{k=1}^{l_j} (m_{jk} - m)^2 \right]$	Eq. 8	c = number of factors, l_j = number of levels for factors j.
or;		
$SSB = SSB_1 + SSB_2 + SSB_3 + \dots + SSB_c$		
In the case under study,		
$SSB = SSB_{WS} + SSB_{PM} + SSB_{PS} + SSB_{BS}$		
for example,		
$SSB_{WS} = 5 \left[(m_{ws1} - m)^2 + \dots + (m_{ws5} - m)^2 \right]$		
The error variance (σ_e^2), defined as		
$\sigma_e^2 = \frac{SSE}{ErrorDOF}$	Eq. 9	σ_e^2 = Error variance.

Figure 4. Summary of equations used in statistical analysis

Throughput time is the selected criterion to measure the cell performance; it can be suitably modified into the corresponding Signal to Noise (S/N) ratio – as shown in eq. 1 (Figure 4) – for incorporation into the matrix experiment. It may be noted that, the real benefit in using S/N ratios is for situations where multiple replications are performed.

Simulation experiments are performed using the photolithography simulation model. Identical experimental testing conditions for each simulation scenario are ensured using the method of common random numbers. Each experiment constitutes five repetitions, which is statistically proved to justify

the model output. Mean Square Deviation (MSD) has been calculated using eq. 2 (Figure 4). The results obtained from simulation model based on the matrix experiment are detailed in (Table 5 in Figure).

The data analysis using Taguchi experimental framework involves the analysis of means (ANOM) and analysis of variance (ANOVA). ANOM helps to identify the optimal/near optimal factor combinations, whereas ANOVA establishes the relative significance of factors in terms of their contribution to the objective function. Figure 5 plots the main effects of each factor level. The optimal or near optimal for each factor can be easily identified as the smallest value is the better.

The main formulas that have been used in conducting the ANOVA, based on (Roy, 2001) are summarized in Figure 4. Phadke suggests using F ratio resulting from ANOVA only to establish the relative magnitude of the effect of each factor on the objective function and to estimate the error variance. However, probability statements regarding the significance of the individual factors are not made. From the ANOVA output, (Table 6 in Figure 3) the relative effects of the factors the product-mix and the number of wafers start are seen to be most important, followed by factors such as product sequence and stepper buffer size. This is in agreement with the ANOM results.

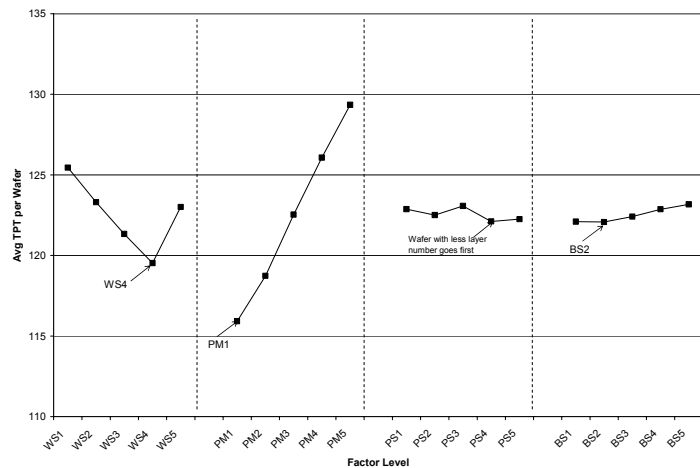


Figure 5. Analysis of means of factor main effects (ANOM)

6. VERIFICATION AND VALIDATION PHASE

In experiment results, an arithmetic means to estimate the factor effects has been used. The assumption of additivity essentially implies the absence of significant interaction effects between factors. Taguchi suggests that a verification experiment (with factors at their optimum levels) be run to validate the additivity assumption. After running a verification experiment, (Phadke, 1989) points out “If the predicted and observed η are close to each other, then we may conclude that the additive model is adequate for describing the dependence of η on the various parameters.... On the contrary, if the observation is drastically different from the prediction, then we say the additive model is inadequate.... This is evidence of a strong interaction among the parameters”. In fact, Taguchi considers the ability to detect the presence of interactions to be the primary reason for using orthogonal arrays to conduct matrix experiments.

To validate the assumption of additivity, comparing verification experiment results with a predicted optimal/near optimal value has been applied. If the prediction error happens to fall within a two-standard-deviation confidence limit of the variance of prediction error, the additivity assumption can be assumed justified. The corresponding two-standard-deviation confidence limits for the prediction error found to be $\pm 0.132dB$, while the prediction error = $0.064dB$ happens to be well within the calculated confidence limits, so the additivity assumption is justified.

7. RESULTS DISCUSSION

Taguchi experimental design paradigm has been used to gain better understanding of the behavior of the assumed parameters. Based on the ANOVA table 6 (Figure 3), the main control parameters (i.e., the number of wafers start and product-mix) have a statistically significant impact on the throughput

time. In contrast, the parameters such as product sequence and stepper buffer size are not seen to be statistically significant. The results suggest that experimentation should focus attention on the alternatives available for the product-mix and wafers start and only then the other parameters for improving the shop global performance. The result is noteworthy, because shop controllers and planning team could have typically been tempted to experiment with alternative control rules without regard to the possible benefits of trying other controllable factors. The ANOM plot (Figure 5) provides two useful insights with regard to wafers start: an increase in the WS from level 1 to level 4 reduces the TPT as the utilization of the machines gets higher, until it reaches the best TPT per wafer at WS4. For WS5 the performance reduces as a result of increasing waiting times. Moreover, the ANOM plot justifies the intuitive opinion with regard to the impact of increasing the product-mix on cell performance.

8. CONCLUSIONS

Simulation combined with Taguchi experimental design provides a comprehensive understanding of the photolithography flexible manufacturing cell performance. This allows investigation of many parameters such as product-mix, product volumes, wafers start, product sequence, stepper buffer size, number of layers, .etc. with regard to their effect on system performance. Based on ANOM and ANOVA, the significant impact of increasing product-mix and wafers start on throughput time are shown. Further, the statistical analysis provided useful insights with regard to near optimum figures of product-mix and wafer starts. The results have shown that the effect of changing stepper buffer size and product sequence is not significant on throughput time as well as the product sequence. The result is noteworthy, because shop controllers have typically been tempted to experiment with alternative product sequence to find benefits. The integration between simulation and Taguchi's methodology has provided an expedient platform for quickly checking the parameters that need to be given priority. The state-of-the-art time-based simulation model has characterized the performance of photolithography tools under various operating conditions efficiently. Moreover, the model is reusable for similar tools. The quality of the output has been verified with actual floor data of similar conditions. The computer time required to run the simulation model for one experiment was so economic as to encourage the production staff to experiment many scenarios.

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