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EVALUATION OF THE EFFECTIVENESS OF GROUP SCREENING METHODS AS COMPARED TO NO GROUP SCREENING

Dima Nazzal

Cirent Semiconductor
9333 S. John Young Parkway
Orlando, FL 32819, U.S.A.

Mansooreh Mollaghasemi
Linda Malone

Department of Industrial Engineering and Management Systems
University of Central Florida
Orlando, FL 32816, U.S.A.

ABSTRACT

The focus of the paper is on the comparison of results obtained using group screening versus not using group screening in an experimental design methodology applied to a semiconductor manufacturing simulation model. The experiments were performed on the cycle time for the main product in the fab, which takes about 250 steps before completion. High utilization and large queue sizes were the basis for determining the five most critical workstations in the fab. Three parameters for each workstation were set as factors for investigation plus another more general important factor making a total of 16 input factors. A 2-stage group-screening experiment and a 2^{k-p} factional factorial were performed to identify the significant factors affecting the cycle time for the product. The results showed that the two methods could be very similar or very different depending on the choice of significance level for group screening, particularly at the early stages of eliminating group-factors.

1 INTRODUCTION

Lucent Technologies Microelectronics is one of the leading companies in the highly competitive semiconductor manufacturing. Products' cycle time is one of the major indicators of how well the fab is performing and semiconductor manufacturers are investing huge amount of money in trying to minimize cycle time, seeking customer satisfaction and higher profit. Simulation modeling and operations research techniques assist analysts in having a better understanding of the complicated processes that products go through, making it easier to make critical decisions. Cycle time is only one of the important performance measures; others include Work-In-Process levels (WIP), product throughputs, and equipment utilization. While these measures contradict each other, simulation and experimental design can help coordinate different goals by optimizing overall performance. Simulation by itself lacks optimization capability since explicit relationships between inputs and outputs are not available, thus combining simulation modeling with experimental design and regression analysis can give effective and efficient results.

Simulation facilitates performing sensitivity analysis and answering what-if questions at no cost, and helps in detecting potential problems and bottlenecks in the fab. Additionally, capital planning can be done using simulation models in order to forecast capacity requirements. Experimental design helps in identifying the important input factors affecting some important system outputs such as cycle time, queue sizes, etc. The semiconductor industry is relatively complex and many parameters and variables can be considered as contributing to a single important response. Biles (1984) recommends the application of fractional factorial designs for simulation experiments in cases where the effects of less than 11 input factors are studied. Research presented by Hood and Welch (1990, 1993) shows the application of fractional factorial Resolution III and IV designs in modeling the logistics of semiconductor manufacturing lines. In cases where more than 11 input factors are studied, the recommended type of design is a group-screening design. A 2-stage group-screening procedure is introduced by Watson (1961) and further developed for multiple-stage designs by Patel (1962) and Li (1962). Mauro and Smith have made significant contributions to the group-screening design method in numerous papers on the robustness and effectiveness of the method (Mauro and Smith 1982, Mauro 1984, Mauro and Smith 1984). Li (1962) shows a methodology for choosing group sizes for multiple stage group screening in cases where the number of important factors in a model is known within some error margin. Morris (1994) talked about "effects sparsity" phenomenon, which means that in most cases few factors are found to be significant among a large number and group screening was applied to a computer model. Dean and Lewis (1999) suggested using the concept of group screening when noise factors exist without aliasing the main factors with noise interactions. Based on the experimental design results, regression analysis equations are built to define the relationships between the input factors and the measures of performance. Kleijnen (1979) introduces regression metamodel concepts to simulation. Friedman (Friedman, 1984, Friedman, 1987, Friedman, 1989) talks about the implementation of multiple response regression metamodels as part of simulation output analysis.

As mentioned earlier, group screening is recommended for large-scale situations such as semiconductor manufacturing environment. To date, little has been written concerning this type of application in the semiconductor manufacturing facilities. A 2-stage group-screening experiment and a factional factorial presented by Ivanova, Mollaghasemi and Malone (1999) results were compared, the results illustrated that the final models are different; the same total number (64) of experimental runs were used for each of the procedures. Additionally, the level of significance used can highly alter the results; the authors recommend the use of a 0.15 significance level in the first stage of group screening and switch to 0.05 in latter stages.

In this paper, cycle time for the main semiconductor product in one of Lucent Technologies manufacturing facilities is identified as the important response to be studied. The most important input factors are identified through a two stage group-screening experimental design. Furthermore, a 2^{k-p} fractional factorial design is applied to the same response again to identify the most important factors. The results of the two methodologies are compared, and finally conclusions are presented.

2 THEORETICAL BACKGROUNDS

2.1 Two-Stage Group Screening Design

In most cases, performing simulation runs for complex systems such as the semiconductor facility is very time-consuming, particularly considering the amount of factors involved in the experiments. The objective of factor screening is to detect as many important factors as possible in as few runs as possible. One of the most efficient experimental design techniques satisfying these objectives is the group-screening experimental design. Watson (1961) suggests that the k input factors in the model can be separated into (g) groups of (f) factors each, by any method. Each group is then considered as a single factor called group-factor. All factors in the group are to be set at their upper level for the group to be at its high level and vice versa, such that no cancellation of effects could occur. All factors within the group should be independent from each other. Watson (1961) also suggests several guidelines for forming the groups. Each group is treated as if it's a single factor and the first stage of experiments is performed. If a group-factor is found to be significant, a second stage of the design is set, where the original factors from the significant groups are tested individually. If after the first stage there is still a considerable number of important factors left in the experiment, further regrouping might be applied and the group-screening process will then have more than two stages (Li, 1962 and Patel, 1962). Several rules of thumb should be considered when using a group-screening experimental design technique in order to avoid cancellation of factors and to detect as many of the effective factors as possible (Ivanova, 1996):

- A factor with an unknown direction of effect should be placed alone in a group.
- Factors with assumed important positive effects should be placed in one group.
- Factors with assumed small effects and the same direction should be placed in a group.
- Factors with possible effects and the same direction should be placed in a group.
- Resolution IV design should be used to calculate main effects unbiased by possible second-order interactions.

2.2 Regression Metamodels

Following each stage during group screening, regression analysis is used to determine the most important groups/factors and a regression metamodel is built relating the most important factors to the response. The simplest regression metamodel is the additive linear first-order model. Hypothesis testing is necessary for determining the significant factors in the model. The significant factors/groups for a stage during group screening are kept for the next stage while insignificant factors/groups are dropped from the analysis. In the last stage in the group screening there would be no groups left and only individual factors are tested.

3 THE SIMULATION MODEL

3.1 Model Definition

The wafer fab simulation model allows the user to specify equipment, availability, products, routings, human operators and numerous other constraints. One basic process flow and one product is included in the simulation model for this research purpose. The ManSim/X simulator, developed by Tyecin Systems Inc., is used to build the simulation model. ManSim/X has been specifically designed for capacity analysis and production planning of semiconductor manufacturing facilities. The whole-line simulation presents a model of a 6"semiconductor wafer fab with more than 250 machines and operators, grouped into multiple work areas. One basic recipe for the main product is included in the simulation.

3.2 Output Analysis Results

The whole-line simulation model was initially used for the purpose of queue size analysis and eventually recognizing the potential factors that might affect the cycle time for the product under study. A warm-up period of 100 days was used. The queue size analysis revealed that five workstations have relatively large queue sizes for their tools formed for a stable model, these workstations were the Argon fillet, Etchers, Metal Deposition tools, Oxide Etcher and Implanters. These five workstations affect the overall performance of the fab and thus have a potential room for improvement. Later in the analysis section of the paper, different factors related to these five workstations will be tested for their level of influence on cycle time.

4 FACTOR IDENTIFICATION AND DEFINITIONS

The important response being studied here is the cycle time for the main product in the fab, and the objective is to determine the factors that are significantly affecting this response. After studying the queue sizes and utilization on all the workstations, five were identified as critical: Argon Fillet, Etcher, Implanters, Metal Deposition, and Oxide Etch facility groups. The percentage of hot lots released in the fab is also a potentially high influential factor. For each workstation, three parameters were considered to be dynamic and influential: Mean Time Between Failure (MTBF), The Operator to Machine Ratio (O/M) and the number of tools available for the workstation (n). Each factor has two levels (low and high) set according to historical observations in the fab. Table 1 shows a list of the 16 factors and the coded variables accompanied with each one.

5 GROUP-SCREENING EXPERIMENTAL DESIGN

5.1 Group-Screening - Stage I

According to the grouping rules suggested by Watson (1961), the first set of groups for stage I is formed coming to a total of 4 groups. Figure 1 shows how the groups were organized.

A two-level fractional factorial (2^{4-1}) resolution IV design with 8 runs was done, where the defining relation was D=ABC. The low level for each factor was chosen to be more constraining to the fab as compared to the high input factor levels. Trial simulation runs were performed to make sure that the model was stable under the low factor level setting. The high factor levels were set as an improvement over the base level for each factor. This method for setting the low and high factor levels ensures that there is sufficient resource capacity and that the model is stable for all the experimental design runs (Hood and Welch 1992). Table 2 shows the low and high levels for each group of factors.

The next step involves building a regression metamodel based on the Stage I experimental results and determining the significant group-factors. Minitab and JMP softwares were used for this purpose. It is assumed that no interactions exist between the factor-groups.

Table 1: Description of the 16 Factors in the Experiments

Coded Variable	Factor
x_1	MTBF for Argon Fillet ($MTBF_a$)
x_2	MTBF for Etchers ($MTBF_e$)
x_3	MTBF for Implanters ($MTBF_i$)
x_4	MTBF for Metal Deposition ($MTBF_m$)
x_5	MTBF for Oxide Etch ($MTBF_o$)
x_6	Number of Argon fillet tools (n_a)
x_7	Number of Etchers (n_e)
x_8	Number of Implanter tools (n_i)
x_9	Number of Metal Deposition tools (n_m)
x_{10}	Number of Oxide Etch tools (n_o)
x_{11}	Operator to machine ratio for Argon fillet (O/M_a)
x_{12}	Operator to machine ratio for Etchers (O/M_e)
x_{13}	Operator to machine ratio for Implanter (O/M_i)
x_{14}	Operator to machine ratio for Metal Deposition (O/M_m)
x_{15}	Operator to machine ratio for Oxide Etch (O/M_o)
x_{16}	Percentage of hot lots

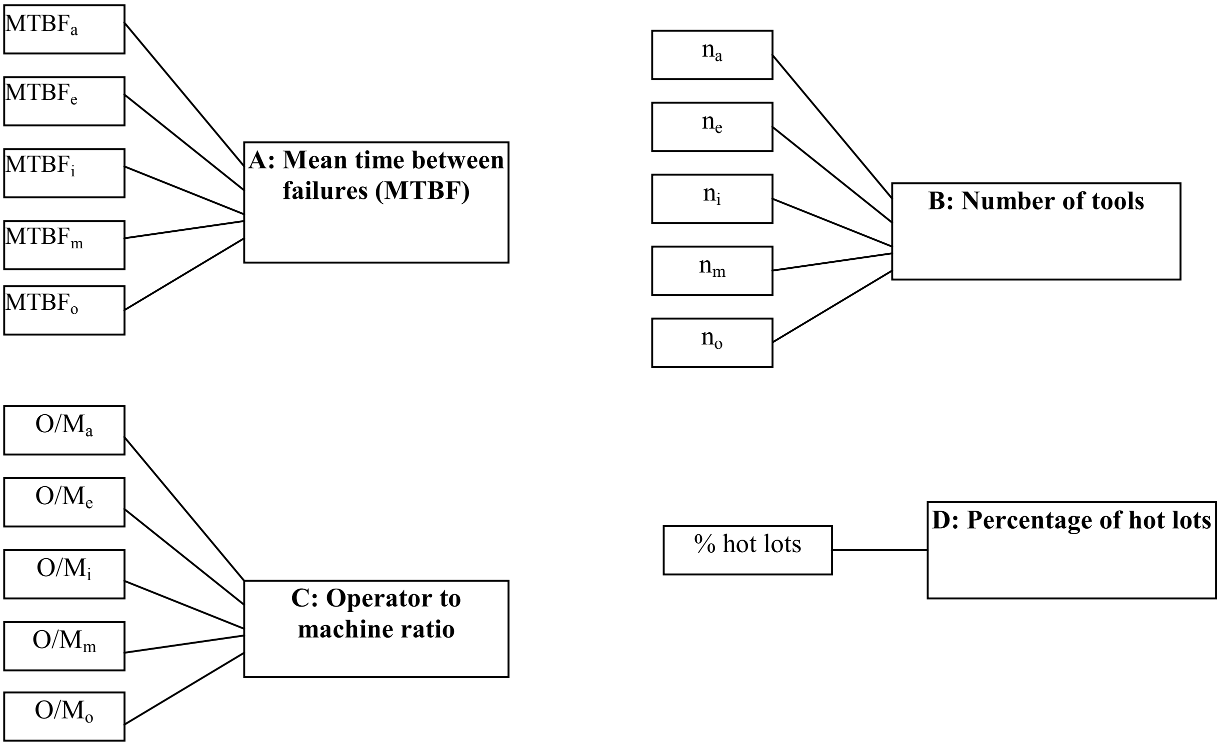

Figure 1: Group-Screening Design - Stage I

Table 2: Factors' Low Levels and High Levels

Group	Description	Low level	High level
A	Mean time between failures (MTBF)	Base	2*Base
B	Number of tools	Base	Base+1
C	Operator to machine ratio	Base	1.5*Base
D	Percentage of hot lots	Base	0.5*Base

The residuals values for the 8 design runs are tested for normality by using normal probability plots and for randomness using scatter diagrams. At a level of significance of .05, only group A of the group screening variables is significant. However, because this is an early stage of screening, we might decide to be more flexible in choosing the level of significance and decide to use .10 or even .15. This choice is critical for its influence on the final model. Using .10 as the significance level, the groups that are significant are A: mean time between failures (MTBF) and B: number of tools with R^2=87.9%.

At the end of Stage I of group screening, the choice of the significance level affects the number of groups found to be significant. In stage II, the insignificant groups were dropped from the experiment and individual factors of groups A and B were tested for significance.

5.2 Group-Screening Design - Stage II

In Stage II, the significant group-factors found from stage I were separated into individual factors and a second 2^{16-10} fracional factorial design was run. Using a level of significance of 0.10 in Stage I, the variables considered were:

x_1= MTBF for Argon Fillet ($MTBF_a$)
x_2= MTBF for Etchers ($MTBF_e$)
x_3= MTBF for Implanters ($MTBF_i$)
x_4= MTBF for Metal Deposition ($MTBF_m$)
x_5= MTBF for Oxide Etch ($MTBF_o$)
x_6= Number of Argon fillet tools (n_a)
x_7= Number of Etchers (n_e)
x_8= Number of Implanter tools (n_i)
x_9 = Number of Metal Deposition tools (n_m)
x_{10}=Number of Oxide Etch tools (n_o)

The 64 model fit allowed for some of the two-factor interactions to be tested and the results were that at α=0.05 all main factors were found to be significant except for x_4 (MTBF for metal deposition) and x_9 (number of metal deposition tools). At α=0.10 all factors were found significant except for x_9 (number of metal deposition tools). At both significance levels the interaction term between x_1 and x_6 was found to be significant (MTBF for Argon Fillet X number of Argon fillet tools).

6 ANALYSIS WITH A 2^{K-P} FRACTIONAL FACTORIAL DESIGN

A 64 run, 2^{16-10} resolution IV design was performed using all 16 of all the factors identified in Section 3 as well as some of the two factor interactions between the variables. Because of the size of the design, not all of the interactions could be fit. The significant factors of this design were found at a 0.05 significance level to be:

x_1: MTBF for Argon Fillet ($MTBF_a$)
x_2: MTBF for Etchers ($MTBF_e$)
x_3: MTBF for Implanters ($MTBF_i$)
x_5: MTBF for Oxide Etch $MTBF_o$
x_6: Number of Argon fillet tools (n_a)
x_7: Number of Etcher (n_e)
x_8: Number of Implanter tools (n_i)
x_{10}: Number of Oxide Etch tools (n_o)
x_{16}: Percentage of hot lots.

And the interaction term,

x_1x_6: MTBF for Argon Fillet X number of Argon fillet tools.

The model consisted of 10 variables plus the intercept at a significance level of 0.05. Choosing an α=0.10 didn't add any more terms to the model.

7 CONCLUSIONS

A 2-stage group-screening experiment and 2^{k-p} experiments were designed to study the efficiency of using group screening as compared to not using group screening. Almost the same number of runs was made for both cases. Table 3 summarizes the results with a look at the coefficient of determination (R_2) and Mean Square Error (MSE).

The results show that both group screening and fractional factorial design gave similar results if one was careful in choosing the significance level for stage I of group screening. It's interesting to note the low coefficient of determination (R^2) if one chose to use α to be 0.05 in the case of group screening and the considerable improvement if α was chosen to be 0.10. The appropriate level of significance is a critical factor during group screening stages; apparently it's safer to go with higher significance level in early the stages. Another interesting observation from the results is that the percentage of hot lots was found to be very significant using fractional factorial design as opposed to group screening stage I where this factor's significance was not detected. The low number of runs that were taken in stage I of group screening could have caused this to happen.

Table 3: Comparison Between Group Screening and 2^{k-p}

	Group screening		2^{k-p}	
	α=0.05	α=0.10	α=0.05	α=0.10
MTBF for Argon Fillet ($MTBF_a$)	S*	S	S	S
MTBF for FE Etch ($MTBF_f$)	S	S	S	S
MTBF for implanter ($MTBF_i$)	S	S	S	S
MTBF for metal deposition ($MTBF_m$)	I	S	I	I
MTBF for Oxide Etch ($MTBF_o$)	S	S	S	S
Number of Argon fillet tools (n_a)	I	S	S	S
Number of FE Etch tools (n_f)	I	S	S	S
Number of implanter tools (n_i)	I	S	S	S
Number of metal deposition tools (n_m)	I	I	I	I
Number of Oxide Etch tools (n_o)	I	S	S	S
Operator to machine ratio for Argon fillet (O/M_a)	I	I	I	I
Operator to machine ratio for FE Etch (O/M_f)	I	I	I	I
Operator to machine ratio for implanter (O/M_i)	I	I	I	I
Operator to machine ratio for metal deposition (O/M_m)	I	I	I	I
Operator to machine ratio for Oxide Etch (O/M_o)	I	I	I	I
Percentage of hot lots	I	I	S	S
MTBF for Argon Fillet $MTBF_a$ X Number of Argon fillet tools (n_a)	I	S	S	S
MSE	32.26	12.21	10.086	10.086
R^2	54.92%	84.69%	85.99%	85.99%
Model p-value	0.0001	0.0001	0.0001	0.0001

*** S: Significant Factor, I: Insignificant Factor**

8 FUTURE WORK

In future work, we might look at the throughput as a different performance measure that contradicts with cycle time. It might be interesting to try to optimize the settings of the different significant factors affecting these two performance measures so as to maximize the throughput and minimize cycle time then compare the benefits with the current settings. Considering the large number of runs that would be needed and the wasted computer time required for these runs, group-screening would be used instead of full or fractional factorial designs for running the experiments.

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AUTHOR BIOGRAPHIES

DIMA NAZZAL is a member of the Technical Staff in the Factory Integration Department at Lucent Technologies in Orlando. She received a B.S. in Industrial Engineering from University of Jordan, Amman, Jordan and is currently pursuing an M.S. degree in Industrial Engineering at the University of Central Florida in Orlando, Florida. Her present research interests include simulation modeling and analysis, design of experiments and capacity analysis and planning. She is a member of ASQ. Her email address is <dnazzal@mail.ucf.edu>.

MANSOOREH MOLLAGHASEMI is an associate professor of Industrial Engineering and Management Systems at the University of Central Florida. She received her Ph.D. in Industrial Engineering from the University of Louisville in 1991. She also holds a B.S. and an M.S. in Chemical Engineering from the same University. Her research interests involve simulation modeling and analysis, multiple response simulation optimization, and neural networks. She is a member of IIE and INFORMS. Her email and web addresses are <mollagha@ mail.ucf.edu> and <ie.engr.ucf.edu/ faculty/mollag>.

LINDA C. MALONE is an associate professor in the Industrial Engineering Department of the University of Central Florida. She earned a B.S. in mathematics from Emory and Henry College, a M.S. in mathematics from the University of Tennessee in Knoxville, and a Ph.D. in statistics from Virginia Polytechnic Institute and State University in 1979. Her major interests are in Design of Experiments, Response Surface Analysis, and Regression. She has a number of publications and has co-authored an introductory statistics textbook. Her email and web addresses are <malone@iems.engr.ucf.edu> and <ie.engr.ucf.edu/faculty/malone>.