Proceedings of the 2002 Winter Simulation Conference
E. Yücesan, C.-H. Chen, J. L. Snowdon, and J. M. Charnes, eds.

NEW APPROACHES FOR SIMULATION OF WAFER FABRICATION: THE USE OF CONTROL VARIATES AND CALIBRATION METRICS

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ABSTRACT

Simulation-based wafer fabrication optimization models require extensive computational time to obtain accurate estimates of output parameters. This research seeks to develop goal-driven optimization methodologies for a variety of semiconductor manufacturing problems using appropriate combinations of "resource-driven" (R-D), "job-driven" (J-D), and Mixed (combination of R-D and J-D) models to reduce simulation run times. The initial phase of this research investigates two issues: a) the use of the R-D simulation control variates for the J-D simulation and b) development of metrics that calibrate the output from the R-D and J-D modeling paradigms. The use of the R-D model as a control variate is proposed to reduce the variance of J-D model output. Second, in order to use the R-D model output to predict the J-D model output, calibration metrics for the R-D and J-D modeling approaches were developed. Initial developments were tested using an M/M/1 queuing system and an M/D/1 queuing system.

1 INTRODUCTION

1.1 Motivation

Modeling semiconductor manufacturing systems is a nontrivial task. Issues related to appropriate model detail, sufficient run length for accurate output parameter estimation, and short project life cycles all influence the analysts' ability to produce results in a timely fashion. Currently, it takes too long to build and execute wafer fabrication simulation models. This is true for models that do not include automated material handling system (AMHS) and those that do. Obviously, this problem is even more profound when one attempts to use simulation as part of an optimization or goal-driven modeling effort.

Unlike mathematical methods, simulation cannot evaluate the performance of a system exactly but generates data in order to estimate it. In principle, one can eliminate this complication by making so many replications that the estimate has essentially no variance. This practice, however, requires a large amount of execution time, especially when one is trying to optimize a performance measurement of a complex system. With the combined use of R-D and J-D simulation in the approaches proposed in this paper, more replications can be obtained with the same amount of simulation time to reduce the variance of the estimate. These approaches can be applied to optimize a system design such that it helps us decide more effectively if one design is better than another when we try to move in an improving direction. More alternative designs could also be explored as less time is required to simulate each design.

In a joint effort to overcome these obstacles, the Semiconductor Research Corporation (SRC) and International SeMaTech (ISMT) have created the Factory Operations Research Center (FORCe). The center is charged with the mission of funding and directing university research in areas prioritized by the consortiums' member companies. The work presented here is a portion of the results to date for one of the projects funded through FORCe; Research #ID 878 - New Approaches for Simulation of Wafer Fabrication. The project has three interrelated tasks.

This research proposes methods to reduce run time and increase model usefulness through development of a new model building paradigm (Task 1) and the automatic generation of resource-driven models from job-driven models (Task 2). See Section 2.2 for further explanation. The development of a strategy for determining when and how to apply the appropriate modeling paradigms to optimally solve semiconductor-manufacturing problems that require discrete-event simulation is the focus of this research.

1.2 Research Outline

- **Phase 1:** Determine the metrics that permit comparison of the R-D and J-D modeling paradigms and investigate the feasibility of using control variates and calibration metrics in optimization schemes. Also, determine whether the R-D approach (fast execution) is effective as an estimator for the J-D approach (comprehensive detail) under certain sets of physical and/or logical model structures.
- **Phase 2:** Develop optimization strategies that incorporate the methods developed and test on various models with a variety of complexities inherent to the semiconductor-manufacturing environment.
- **Phase 3:** Optimization methods will be applied to various classes of semiconductor manufacturing problems, and an approach will be developed to compare other existing approaches in the literature.

2 BACKGROUND

2.1 Efficiency Improvement

In this paper, we refer to "efficiency improvement" by two goals: a) reducing the variance of a parameter estimate while having the same computational cost, and b) estimating a parameter with less computational cost.

2.2 R-D and J-D Concepts

Most conventional simulation software packages used for modeling and optimizing wafer fabrication dynamics are designed around a "job-driven" worldview. The jobs are modeled as active system entities while system resources are passive. Each entity is characterized by data values called attributes, which are recorded and maintained in a list. In a discrete-event simulation model, the collection of these attributes is used to describe system at a particular point in time, (Law and Kelton 2000). The J-D approach records and maintains every state of every job throughout the system. This practice leads to long execution times as the number of simultaneous entities increases. The speed and space complexity must be at least on the order of some polynomial of the entities in the system, see Schruben and Hyden (2000).

In the R-D paradigm proposed by Schruben and Hyden (2000), individual jobs are passive and system resources are active. Instead of attributes, integer counts for the numbers of jobs of particular types at different steps and the status of the resources are necessary to describe the system's state. Information of the system's state is not held locally in jobs but globally in vectors of integers. This practice can lead to a significant reduction of execution time since data processing requirements become related to the systems physical characteristics, not the density of entities.

The main disadvantage of the R-D paradigm is that since individual jobs cannot be easily tracked, there is a loss of detailed entity information. For example, it is easy to use Little's Law to estimate average cycle time but much more difficult to obtain the distribution of cycle time. More information of the R-D concept can be found in Schruben and Hyden (2000) and Hyden *et al.* (2001).

2.3 Control Variates

Control variates (CVs) is a variance reduction technique for improving the efficiency of simulation outputs without the need to increase the sample size. The main idea is to exploit certain variables correlated with variables of interest and to adjust their estimates in order to obtain variance reduction. Law and Kelton (2000) provide a detailed explanation on CV.

The sources of CVs are classified into two main categories: a) when the control variate mean is known, b) when it is unknown but can be estimated or approximated. For the known case, the CV can be obtained from the same model; examples of such CV's are input random variables whose expectations are generally known. Alternatively, CV can also be obtained from the external model, which generally is a simplification of the original model and it is possible to compute the simplified model's output.

The application of internal CVs can be found in Lavenberg and Welch (1981), Lavenberg *et al.* (1982), Avramidis and Wilson (1990), Schaeffer *et al.* (1995), Rubstein and Marcus (1985), and Moeller *et al.* (1979). Applications of external CV can be found in Sharon and Nelson (1988), Taaffe and Horn (1983), and Nelson *et al.* (1997). These authors study external CV where the control has a known mean.

For the unknown case, Schmeiser and Taaffe (1994) study the use of control variate estimation to the case where the control mean is only approximated from a simpler model. Taaffe *et al.* (2001) study biased control variate estimation where the tradeoff between correlations induced and the analysis error are considered. Taaffe *et al.* (2000) study the same problem but replace the control mean with an estimated value for the control mean, obtained from a prior simulation experiment. In all of these procedures, such a limited portion of the given simulation time is provided that asymptotic behavior cannot be achieved. Instead, fixed proportions of simulation time are allocated to estimate the mean.

However, Markus (2000) proposes a procedure, which allocates sufficient time to estimate an unknown CV mean and then proceeds with the classical control variate simulation by using the estimate in lieu of the unknown mean. The author also provides an asymptotic analysis of quasi CV in terms of asymptotic variance parameters. The method is effective when the mean of the control variable can be efficiently estimated in an auxiliary simulation that does not involve variables of interest.

2.4 Calibration Metrics

This section provides a brief background of the proposed method, "Calibration Metrics," that seeks to exploit a fast (R-D) simulation model to predict results of a slower (J-D) model. Specifically, random simulation outputs of R-D and J-D simulation model from an initial (small) number of replications are used to estimate a bias correction factor. This factor is then used to adjust the random simulation outputs of the R-D model to those of the J-D model.

Two forms of the bias correction factor (CF) were investigated:

1. Multiplicative CF = (JD_n /RD_n)
2. Additive CF = (JD_n – RD_n)

where n is the number of replications used to calculate CF, JD_n is an average of simulation output from n replications of the J-D model, and RD_n is an average of simulation output from n replications of the R-D model.

3 EXPERIMENTS AND ANALYSIS

3.1 A Comparison of J-D Vs. R-D Model Output to Validate the R-D Paradigm

In order to investigate the feasibility of using the control variate approach, we first needed to determine how well J-D and R-D simulation outputs compared. The example used is the simplified semiconductor manufacturing system, called Mini-Fab "Light" (*see Appendix A*), built in the R-D and J-D paradigms. The simulation models are constructed using the Sigma software package (Schruben and Schruben 2000). We used a paired-t test to validate that the R-D paradigm produced statistically indistinguishable results as compared to the same model coded in the J-D paradigm.

A paired-t test is performed in order to determine if the average cycle time from the two models is comparable. The null hypothesis (H_o) is that there is no difference in average cycle time between the J-D and R-D models. The alternative hypothesis (H_1) is that there is a difference in average cycle time between J-D and R-D models. The test statistic for this hypothesis is $t_o = \bar{d} / (S_d / \sqrt{n})$. The number of replications (n) is 10 runs and the confidence level (α) is 0.05. The results are shown in Table 1.

Results show that the confidence interval (CI) of the difference is (-1.010, -0.328). Since the CI does not contain zero, we reject the null hypothesis and conclude that there is a statistical difference in average cycle time between the J-D and R-D models at the 95% level of significance. However, even though we detect a statistical difference, it is actually very small (less than 0.1%) and we conclude that there is no *practical* difference (in this example).

Table 1: Paired-t Test Results for Average Cycle Times of the J-D and R-D Paradigms

Cycle Time	Simulation Paradigms		Cycle Time Difference
	Job-Driven	Resource-Driven	
Average	1166.656	1167.325	-0.669
Std Dev.	19.048	19.122	0.476
95% CI for Mean Difference			
n	10		
Lower	-1.010		
Upper	-0.328		

3.2 Using Control Variates (CV) to Reduce the Variance of Simulation Model Output

In this section, the R-D model is used as control variate to reduce the variance of simulation model output.

The steps that we undertook to use the method of control variates in J-D and R-D models were:

1. Let an R-D simulation of 1 million observations be taken as the expected value of cycle time, denoted as E[c].
2. Let an R-D simulation of 10000 observations be the observed value of cycle time for replication i, denoted as c_i.
3. Let a J-D simulation of 10000 observations be the actual estimate of cycle time for replication i, denoted as x_i.
4. We assume there exists a known positive correlation between the means of the R-D and J-D simulation output cycle time variables.
5. Compute the variance of the n observations of the R-D simulation.
6. Compute the covariance of the n observed value of cycle time in the R-D paradigm to the n observed values of cycle time from the J-D paradigm (from simulation).
7. Compute the scalar factor a^*

$$a^* = \frac{Cov(x,c)}{s^2(c)} \quad (1)$$

8. Compute the controlled estimate of the output variable.

$$x_{ci} = x_i - a^*(c_i - E[c]) \quad (2)$$

One run of one million observations from the control (R-D) model was executed to get the expected mean cycle time: E(c) = 1170.496. Table 2 shows the average and standard deviation of the average cycle time from 10 replications each from the J-D model, the R-D model, and from the J-D means adjusted by the control variates. The Cov(x, c) is 327.7036, a* is 0.8962, and correlation is 0.9997.

Table 2: Average Cycle Time Using Control Variates for Mini-Fab "Light" Model

Cycle Time	Simulation Paradigms		
	Job-Driven (Actual Estimate)	Resource-Driven (Observed Input)	Adjusted Job-Driven (Controlled Estimates)
Average	1166.656	1167.325	1169.498
Std Dev.	19.048	19.122	1.961

Note that, the use of control variate reduces the sample variance from 19.122 to 1.961, which is about a 90% reduction in standard deviation (and thus the half-width of the confidence interval) of the J-D model output. Confidence intervals (α=0.05) on the average cycle time for the J-D model and the J-D model adjusted by the control variates are shown in Table 3.

Table 3: Confidence Interval with and without the Use of Control Variates for the J-D Model

Models	N	Mean	Std. Dev.	SE Mean	95% CI
JD	10	1166.66	19.05	6.02	(1153.03, 1180.28)
Adjusted J-D	10	1169.50	1.96	0.62	(1168.10, 1170.90)

3.3 Calibration Metrics for J-D and R-D Models (M/M/1-M/D/1 systems)

The objective is to investigate the feasibility of using calibration metrics to determine whether the R-D approach (fast execution) is effective as an estimator for the J-D approach (comprehensive detail) under certain model structures. An M/D/1 queuing system built in the R-D paradigm is used to estimate the average cycle time of an M/M/1 priority-queuing system simulation model built in the J-D paradigm. A procedure using calibration metrics for R-D and J-D simulation was also developed.

To estimate the J-D output from the R-D model, a bias correction factor estimated from initial runs of the J-D and R-D models is used. The quality of the bias correction factor is one of the major concerns in this investigation. Two types of analysis were conducted. The first one uses queuing theory to calculate the theoretical (true) value of the bias correction factor. For the second analysis, different numbers of replications are run to estimate the value of the bias correction factor. Five to fifteen replications of the M/M1 and M/D/1 queuing systems are used to estimate the value of this factor.

The hypothesis of this experiment is that the quality of the factor depends on the number of replications used to estimate it and the correlation of the output of the two models. This research aims to find a methodology to determine an appropriate number of replications to adequately estimate the factor. In addition, we are investigating the relationship between the number of replications, correlation, and paired-t confidence intervals.

The experiment also uses the method of common random numbers (CRN) to facilitate the comparison between actual simulation output of the J-D model and estimated output of the J-D model. To implement this, we dedicated one random number stream to generating service times and a different random number stream to generating interarrival times. For each replication, the J-D and R-D simulations start off with the same seed value for each random-number stream.

In addition to the use of CRN's, we investigate the use of Antithetic Variates (AV) as a variance reduction technique for simulation models in this study. When using AV's, we make n pairs of runs of the simulation with the length of m, which results in a pair of sample means $(\overline{X}^{+}_{i,m}, \overline{X}^{-}_{i,m})$, where $\overline{X}^{+}_{i,m}$ is from the first run of ith pair and $\overline{X}^{-}_{i,m}$ is from the antithetic run. A sample mean of the AV average of each replication is defined as $\overline{X}_{i,m}$ = $(\overline{X}^{+}_{i,m}, \overline{X}^{-}_{i,m})/2$, (Law and Kelton 2000).

3.3.1 Calibration Metrics Using Theoretical Bias Correction Factors

To illustrate the use of calibration metrics, let Model 1 be the M/M/1 priority-queue system with the mean service rate, μ, of 0.25 parts per unit time, and the mean arrival rate, λ, of 0.245 parts per unit time. The long-run traffic intensity, ρ, for this system is 98%. The parts are processed according to highest-value-first rule and a uniform distribution with range of [0,1] is used to generate the value. Let Model 2 be the M/D/1 system with the same service and arrival rate as Model 1. Parts are processed in FIFO order. *Appendix B1* describes a generic procedure using calibration metrics for the case of theoretical bias correction factors (TBCF). The following shows the step-by-step procedure for our example:

- Step 1: Based on queuing theory, Gross and Harris (1998), the long-run average cycle time, w, of model 1 (M/M/1) priority queuing system) is 200.
- Step 2: The long-run average cycle time, w, of model 2 (M/D/1 queuing system) is 102.
- Step 3: Multiplicative CF = (200/102) = 1.961
  Additive CF = 200 - 102 = 98.

Step 4: Obtain average cycle time of 30 replications from R-D model, shown in Table 4.
Step 5: The estimated outputs of Model 1 from 30 replications of Model 2 for both multiplicative and additive correction factor are shown in Table 4.

A paired-t test is performed in order to test if the estimated average J-D cycle time from the R-D runs is statistically different from the average cycle time of the J-D runs. The null hypothesis (H_o) is that there is no difference in the average cycle times. The alternative hypothesis (H_1) is that there is a difference in the average cycle times. The test statistic for this hypothesis is $t_o = \bar{d} / (S_d / \sqrt{n})$. The number of replications is 30 and the confidence level is 0.05. Table 4 shows the results from the cases where CRN's and TBCF are used, while Table 5 shows cases where CRN's/AV's and TBCF are used.

Table 4: Results of Using Model 2 Output to Predict Model 1 (CRN's TBCF)

Paired-t Test	N	Mean	Std Dev	SE Mean
J-D	30	196.77	17.88	3.26
Estimated J-D (Multiplicative)	30	199.83	10.40	1.90
Difference	30	-3.06	16.78	3.06

95% CI for Mean Difference: (-9.32,3.21)

Paired-t Test	N	Mean	Std Dev	SE Mean
J-D	30	196.77	17.88	3.26
Estimated J-D (Additive)	30	199.91	5.30	0.97
Difference	30	-3.14	16.53	3.02

95% CI for Mean Difference: (-9.32,3.03)

Table 5: Results of Using Model 2 Output to Predict Model 1 (CRN's/AV TBCF)

Paired-t Test	N	Mean	Std Dev	SE Mean
J-D	30	196.16	9.55	1.74
Estimated J-D (Multiplicative)	30	198.86	6.01	1.10
Difference	30	-2.70	7.49	1.37

95% CI for Mean Difference: (-5.50,0.09)

Paired-t Test	N	Mean	Std Dev	SE Mean
J-D	30	196.16	9.55	1.74
Estimated J-D (Additive)	30	199.42	3.07	0.56
Difference	30	-3.26	8.01	1.46

95% CI for Mean Difference: (-6.25,-0.27)

For the cases without using AV's, we conclude that we cannot reject H_O: $\mu_d = 0$ for both tests at 0.05 level of significance. The estimated J-D average cycle time from the R-D runs is not statistically different than the average cycle time of the J-D model when theoretical bias correction factors are used.

When we use AV's, the estimated J-D average cycle time from the R-D runs is not statistically different from the average cycle time of the J-D model when the theoretical bias correction factor is used for the multiplicative case. However, in the additive case, we reject the null hypothesis and conclude that the results are statistically different.

3.3.2 Calibration Metrics Using Estimated Bias Correction Factors

This section illustrates a procedure using the R-D model to estimate the bias correction factor from a preliminary set of R-D and J-D runs and then making additional R-D runs to estimate J-D model output. We are interested in the performance of the estimated bias correction factor when different numbers of replications are used. The generic procedure is shown in *Appendix B2*.

Consider the previous models: M/M/1 priority queuing system for the J-D model, and the M/D/1 queuing system for the R-D model. A case using 10 replications to determine the bias correction factors is illustrated in detail as shown below.

Calibration Metrics for n_1 = 10 and n_2 = 20 replications

Step 1: Average $CT_{MM1,\ 10\ replications}$ = 195.96 minutes
Step 2: Average $CT_{MD1,\ 10\ replications}$ = 102.89 minutes
Step 3: Multiplicative CF = 1.9046
Additive CF = 93.070
Step 4: Obtain average cycle time of 20 additional replications from R-D model.
Step 5: Estimated outputs of Model 1 from 30 replications of R-D Model for both multiplicative and additive correction factors are shown in Table 6.
Step 6: Obtain average cycle time of 20 additional replications from J-D model.
Step 7: Build and compare CI of R-D and J-D model, shown in Table 6.

A paired-t test is performed in order to determine if the estimated average J-D cycle time from the R-D runs is statistically different from the average cycle times of the J-D model. The null hypothesis (H_o) is that there is no difference in average cycle time between them. The results are shown in Table 6.

It can be concluded that we cannot reject H_O: $\mu_d = 0$ for either test at a 0.05 level of significance. The estimated average J-D cycle time from the R-D runs is not statistically different than the average cycle times of the J-D model when 10 replications are used to estimate the bias correction factor.

Table 6: Results of Using R-D Model Output to Estimate J-D Model Output (n_1 = 10 and n_2 = 20 Replications)

Paired-t Test	N	Mean	Std Dev	SE Mean
JD	30	196.77	17.89	3.26
Estimated J-D (Multiplicative)	30	194.10	10.10	1.84
Difference	30	2.67	16.72	3.05

95% CI for Mean Difference: (-3.57,8.92)

Paired-t Test	N	Mean	Std Dev	SE Mean
JD	30	196.77	17.88	3.26
Estimated J-D (Additive)	30	194.98	5.30	0.97
Difference	30	1.79	16.53	3.02

95% CI for Mean Difference: (-4.39,7.96)

3.3.3 Execution Time Comparison

This section shows the benefit of using the R-D paradigm, which is more efficient than the J-D paradigm in terms of execution time. Specifically, execution time using solely the J-D model to generate a confidence interval of simulation output is compared to using the R-D model output to estimate J-D model output. Table 7 shows the execution time of using R-D model output to estimate J-D model output for the case with n_1 = 10 and n_2 = 20 replications as described above.

Table 7: Execution Time of Using R-D Model Output to Predict J-D Model Output for Case n_1 = 10 and n_2 = 20 Replications

Models	Execution Time (Seconds)
J-D 10 Rep.	159.10
J-D 30 Rep.	478.00
R-D 10 Rep.	88.90
R-D 10 Rep.	178.40

To get estimated J-D output in this case, we need to run the J-D and R-D models 10 replications each to obtain bias correction factors and another 20 replications of the R-D model. The total execution time to predict the J-D output is 426.4 seconds. The execution time to run 30 replications of the J-D model is 478 seconds. It can be seen that using the R-D model output to estimate the J-D model output is more efficient than using only the J-D model to do the same task. There was a 10.8% improvement in execution time in this experiment. The systems used in this experiment were very simple and we expect greater benefits of using the R-D approach will be realized in more complex models.

3.3.4 Percentage of Experiments with Confidence Intervals Containing Zero

This section illustrates the performance of the estimated bias correction factor when different numbers of replications are used. A case using 5 replications to determine the BCF was also performed. We found that the percentage of experiments with CI containing zero, which is at a range of 60%, was not acceptable. Experiments using 5, 6, 7, 8, 9, 10, and 15 replications to estimate the bias correction factor are conducted for further analysis. For each case, we perform 100 independent experiments of 30 replications each. Table 8 shows the percentage of the 100 independent experiments in which the estimated average J-D cycle time from the R-D runs is not statistically different than the J-D model at alpha = 0.05. Note that the paired-t test was used to perform the calculations.

Table 8: Percentage of 100 95% CI's in which the Estimated Average J-D Cycle Time from the R-D Model is not Statistically Different from the J-D Model

Factor Determined by x Replications	CRN		CRN + AV	
	Mul. Factor	Additive Factor	Mul. Factor	Additive Factor
True	83%	81%	81%	60%
5	60%	67%	57%	61%
6	63%	69%	61%	66%
7	77%	75%	72%	74%
8	72%	77%	75%	83%
9	79%	80%	80%	82%
10	83%	90%	84%	88%
15	97%	97%	97%	97%

The result shows that the chance of the confidence interval containing zero increases as more replications are used to estimate the bias correction factor, but at a corresponding higher cost of simulating execution time.

4 CONCLUSIONS AND FUTURE DIRECTIONS

During the first phase, the Mini-Fab "Light" model was built in the J-D and R-D paradigm using the Sigma software package. The two models have been exercised to investigate the possible use of the R-D simulation model control variates for the J-D simulation. The result shows that the standard deviation of the adjusted J-D average cycle time is reduced by 90% compared to the case where control variates are not used.

In addition, a procedure to determine metrics that permit comparison of R-D and J-D modeling was developed. This procedure was tested with M/M/1 (J-D) and M/D/1 (R-D) queuing systems. Determining the bias correction factor, which is used to estimate J-D output from R-D output, is an important issue in this experiment. We investigated the use of the theoretical value for the bias correction factor and considered different numbers of replications to estimate the bias correction factor. The results show that estimated J-D simulation outputs become similar to the J-D simulation outputs as the number of replications used to estimate the bias correction factor increases. In our specific example, there was a 10.8% reduction in the computer time needed to build the confidence intervals. This procedure is expected to be more efficient as the system becomes more complex.

It is obvious that the success of the Control Variates and Calibration Metrics Method depends on the relationship among replications, correlation, and confidence interval between the R-D and J-D simulation. In the simple systems as illustrated in this paper, it is easy to show the relationship between the two models and to exploit it by the Control Variates and Calibration Metrics approaches. However, in a more complex system with batch tools and downtimes of machines, a methodology to obtain an R-D model with a relationship (such as that obtained for the simple models) is needed. Specifically, the key question is how we are to build the R-D model, which is correlated to the more complex system built in J-D model.

Summarized below are the outstanding issues regarding the use of calibration metrics:

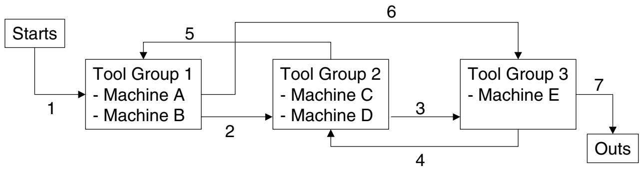
1. When is the additive correction factor preferable to the multiplicative correction factor, and vice versa? Should other factors be considered?
2. How many replications are needed to reasonably estimate the bias correction factors?
3. How can we characterize the relationships among replications, correlation and confidence intervals?

ACKNOWLEDGMENTS

All four authors are partially supported by the Factory Operations Research Center, which is jointly funded by the Semiconductor Research Corporation and International SEMATECH, under contract 2001-WS-878.

APPENDIX A: MINI-FAB "LIGHT" MODEL DESCRIPTION

The Mini-Fab "Light" model consists of three groups of machines with two identical machines (A and B) in tool group 1, two identical machines (C and D) in tool group 2, and one machine (E) in tool group 3. There are six processing steps and the processing times for each step are shown in Figure 1. Machines A and B are used for processing steps S1 and S5, machines C and D are used for processing steps S2 and S4, and machine E is used for processing steps S3 and S6. Steps S1 and S5 are batching process steps with a batching policy that allows lots from both steps to processed together in batches of 3 lots. There is only one part type in the model and it has a mean interarrival time of 120 minutes. First-In-First-Out (FIFO) dispatching is used at all tool groups.



Process Step	Tool Group (machines)	Process Time (mins)	Batch Size (lots)
1	1 (A, B)	225	3
2	2 (C, D)	30	1
3	3 (E)	55	1
4	2 (C, D)	50	1
5	1 (A, B)	255	3
6	3 (E)	10	1

Figure 1: Process Flow and Processing Time of Mini-Fab "Light" Model

APPENDIX B: CALIBRATION METRICS FOR SIMPLE MODELS – USING MODEL 2 OUTPUT TO PREDICT MODEL 1 OUTPUT

B-1 Theoretical Bias Correction Factors

Step 1: Use queuing theory to calculate the true value of the output parameter for Model 1

Step 2: Use queuing theory to calculate the true value of the output parameter for Model 2, a *more abstract model*

Step 3: Determine the bias correction factors (CF) for Model 1
- a) Multiplicative CF = (Model 1/Model 2)
- b) Additive CF = (Model 1 - Model 2)

Step 4: Run *N* replications of Model 2

Step 5: Calculate estimated outputs of Model 1 from N replications of Model 2
- a) Using Multiplicative CF: Estimated Model 1 = Simulated Output of Model 2 * Multiplicative CF
- b) Using Additive CF: Estimated Model 1 = Simulated Output of Model 2 + Additive CF

B-1 Estimation of Bias Correction Factors

Step 1: Run n_1 replications of a J-D Model.

Step 2: Run n_1 replications of a R-D Model.

Step 3: Determine bias correction factors (CF) for J-D Model.
- a) Multiplicative CF = (JD/RD)
- b) Additive CF = (JD - RD)

Step 4: Run n_2 replications of R-D Model

Step 5: Calculate the estimated outputs of the J-D model from $N\ (= n_1 + n_2)$ replications of R-D model

a) Using Multiplicative CF: Estimated JD = RD * (JD / RD)

b) Using Additive CF: Estimated JD = RD + (JD - RD)

Step 6: (For testing/validation only) Obtain another n_2 replications of J-D model

Step 7: Build and compare CI of estimated J-D (from step 5) with J-D model (from steps 1 & 6) on *N* replications.

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