Proceedings of the 1999 Winter Simulation Conference
P. A. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans, eds.

INCREASING FIRST PASS ACCURACY OF AMHS SIMULATION OUTPUT USING LEGACY DATA

Scott Wu
John Rayter
Igor Paprotny

Automation Planning and Design Group
PRI Automation, Inc.
Mesa, AZ 85208, USA

Gerald T. Mackulak
Joakim Yngve

Department of Industrial Engineering
Arizona State University
Tempe, AZ 85287-5906, USA

ABSTRACT

The operating characteristics of wafer production facilities are extremely dynamic, driven by short product life cycles, rapid equipment obsolescence and recurring layout expansion. These factors also have an impact on the design of the Automated Material Handling System (AMHS). The AMHS must be able to react and accept change as rapidly as the production process dictates. The AMHS design engineer faces a significant challenge in that modeling efforts must be proactive and anticipate the long-term requirements of a given facility.

There are, of course, several methods available for addressing this issue. This paper will point out the limitations to these methods when applied to AMHS modeling and propose an alternative. Specifically, behavioral trends from historical data can be exploited when appropriate. Simulation results from legacy designs may prove to be an efficient indicator of the validity of new designs.

1 INTRODUCTION

Based primarily on the performance increases available on PC's, computer simulation has evolved into an extremely powerful, widely used, flexible modeling tool. This is quite beneficial because the complexity and size of most real systems typically precludes analysis via analytical methods. Simulation is the only viable alternative for analysis of many of these complicated problems. However, simulation in itself does not offer a panacea for solving analytically intractable problems (Gross and Harris, 1985).

Models can only be regarded as abstractions of systems. It is impossible and typically not necessary to capture 100% of reality. In constructing the model, the analyst must first decide upon the desired goal or objective to be obtained. Based on this, decisions must then be made as to the depth and breadth of detail to be included in order to achieve this objective. Aside from the analyst's judgment in determining the significant system elements for model inclusion, there are many other factors that influence the level of detail available for incorporation. First, there may be time and cost constraints that constrain data collection strategies. Second, there will usually be some point at which increasing levels of detail will yield marginal increases in accuracy. Finally, and perhaps most importantly, actual system data may simply be unavailable. The best example of this is for systems that do not yet exist.

These issues must be dealt with on a regular basis in the design of semiconductor AMHS. Additionally, most design work involves facilities that are still in the planning stage and have yet to be constructed. The analyst must design a material handling system that is based only on preliminary customer requirements. These requirements revolve around little more than projected tool layouts and a general idea of product flow, yet the AMHS must not only accommodate these requirements it must anticipate deviations from them. The AMHS must be designed with enough robustness to manage the inevitable variability that the system will display, yet do so with little "real" data during design.

In order to design a practical solution under these conditions, the statistical and operational assumptions that the analyst must make with regards to anticipated fab behavior become of paramount concern. The purpose of this paper is to present a discussion of several traditional methods for resolving this issue, along with their inherent limitations and/or advantages. An alternative methodology is then proposed. The alternative approach uses legacy performance from implemented designs as a platform to enhance the level of confidence in new, "first pass" designs. Fortunately, although each semiconductor fab could be characterized as unique with regards to its size, capacity, and operational policies, there is enough commonality in the AMHS performance characteristics that conclusions are transferable. Behavioral trends for a given facility can be generalized to new designs having common operational elements.

2 BACKGROUND DISCUSSION

Semiconductor AMHS simulation models are based on customer-provided information about the expected steady state movement rates at both the bay and fab levels. This information is typically limited since it is early in the design process and the production steps have yet to be finalized. The movement rates may be provided either in the form of a generic process flow or a from-to movement table. The from-to table is generated from move rates between proposed functional areas on a per unit time basis. This data reflects only an average or expected steady state movement rate within customers' facilities, and usually does not incorporate variability issues.

Semiconductor fabs are today facing an extremely volatile market. Many semiconductor enterprises are operating in a build to order fashion, that alone dictates many of the manufacturing issues that currently challenge the semiconductor industry. To begin with, new product introductions are a fact of life, consequently shrinking not only product but also equipment life cycles. As a result, frequent changes are made to fab operational policies, the layout of equipment in new facilities, and the frequency and type of usage for equipment in existing facilities. The net effect of these concerns is that traditional statistical and modeling assumptions in the simulation of AMHS designs may not hold under a wide variety of conditions.

Figures 1 and 2 display the move rate behavior of an installed AMHS against a simulation of the same system.

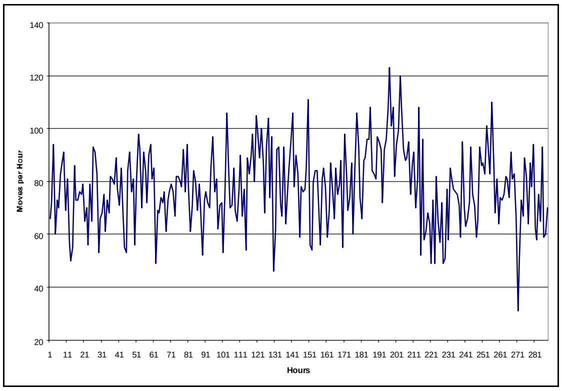

Figure 1: Hourly Move Rate Behavior Collected From Actual AMHS

The simulation uses does not explicitly model the production process since it is a model of the AMHS only, but instead uses exponentially distributed time between arrivals to generate move requests. The model does use very accurate actual movement logic for computing move path, move time, blockage, and interference delays.

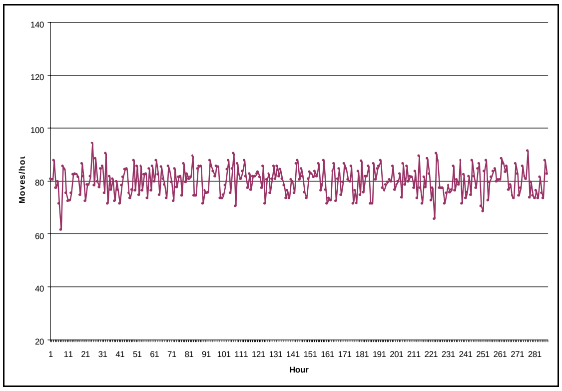

Figure 2: Hourly Move Rate from a Simulation of the Same System with No Prior Information and Employing Conventional Simulation Assumptions

The figures clearly indicate that conventional simulation modeling assumptions may grossly underestimate system variability, and hence, possible system requirements. Therefore, some method must be developed to account for the variability that the actual system will tend to exhibit. The method will be used to build in the robustness the system will need to handle actual variability. The following is a discussion of some common approaches to this modeling variability problem.

2.1 Full Fab Simulation

In the 300mm era, in which both intrabay and interbay AMHS must work together, one possible alternative for capturing total system variability would be to construct a full fab simulation model that reflects the full spectrum of system operation. However, this would require a large, complicated, time consuming modeling effort, and may not be consistent with an AMHS design firm's workload targets. By the time the model is complete the results may no longer be useful.

A full fab modeling effort may still create problems from a production perspective, even if the extraordinary amount of necessary data were available and construction simplification heuristics could be developed. The inordinate amount of CPU time that may be required to run such a detailed simulation to statistically accurate conclusions may again preclude the full fab approach. Despite the introduction of faster and faster central processors in a typical PC or workstation unit, the real-time execution speed for one replication of such a model may be days instead of hours. Obviously, the approach to build a detailed model of a fab to help design the AMHS is not preferable, although it might still be applicable for some special cases.

2.2 Static Estimation

In *static estimation*, the AMHS performance is estimated by the use of parametric and non-parametric analytical tools that are either user defined or bundled into some sort of commercial software application. Examples of user applications include multiple regression and neural net models. Commercial applications can include software packages such as FactoryFLOW™, a factory planner/flow analyzer that employs iterative algorithms to validate factory designs as well as their components, to include AMHS.

Static tools normally work best on problems of reasonable size and complexity. One of the most important motivations to employ simulation modeling is because the size and complexity issues can be handled given sufficient time and funding. Semiconductor AMHS problems are too large or complex to be solved through static methods. Static solutions may provide accurate information on components of the system (predicting the number of automated vehicles required through regression analysis, for example) but seem inappropriate for total system performance prediction. Static estimators can also be used to render an adequate "first pass" performance estimate of a preliminary design (through use of software packages such as FactoryFLOW™). This is beneficial to the overall design process by reducing the time that would be otherwise invested in pursuing sub-optimal alternatives. However, by themselves, these approaches will typically be incapable of achieving the depth of detail necessary for the final solution.

It is believed that static solutions cannot capture more than 70-80% of a given system's behavior (Pillai, 1999). There are various reasons that could account for this. First, there may be a lack of sufficient data to formulate an adequate static model. Also, it is a possibility that there will be no generalized, quantifiable relationships between the predictive variables and the responses. The analyst may not be capable of mathematically formulating the required relationships I sufficient detail. Finally, and perhaps most importantly, static methods often fail to capture the stochastic nature of most systems and this is critical in the performance of AMHS.

2.3 Simplified Simulation

Another approach is the *simplified simulation* method. The customer-provided information is implemented in a simplified simulation through use of commonly assumed distributions. Data and logic is tailored to the types of activities that the information usually represents. For example, arrival processes could be typically rendered as exponential, with service processes as perhaps lognormal or normal, if the service mechanism can be characterized as a mechanically repetitive process (Law and Kelton, 1991). The model is then executed in an attempt to predict performance detail that was not really available in the data or the logic implemented.

In order to mitigate unanticipated behavior in this type of approach, a safety factor is introduced. The safety factor artificially increases the workload of the system to a level above design specifications. The simulation then predicts performance at some percentage of throughput above and beyond that created by customer requirements. The underlying assumption is that variability overlooked by the implementation of standard assumptions can be handled if the mean performance requirement is shifted up. The intent is to anticipate and alleviate actual performance deviations by running the simulation at a higher stress level than what can be expected in the real system, thus providing blanket coverage for any unforeseeable peak in performance variability. Figure 3 displays an example of this approach.

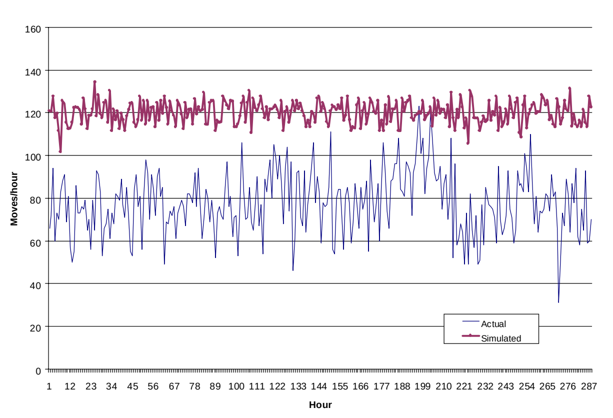

Figure 3: Safety Factor Approach to Mitigating System Variability

While this is little more than an implementation of conservative design principles, it has limitations when applied to the design of AMHS. Without definitive information, it can be quite difficult to quantify the required amount of safety factor to apply for a given design. A low estimate may lead to designs that cannot accommodate actual variability from expected behavior. A high safety factor may create an overestimation of the necessary equipment and may lead to the addition of excess capability in the system. Excess equipment will drive up capital costs and negatively impact cost of ownership. Since the safety factor is selected somewhat arbitrarily, it cannot be associated with a statistical statement on performance improvement. Figure 4 is a typical representation of how the total capital costs may increase due to overestimation of the safety factor.

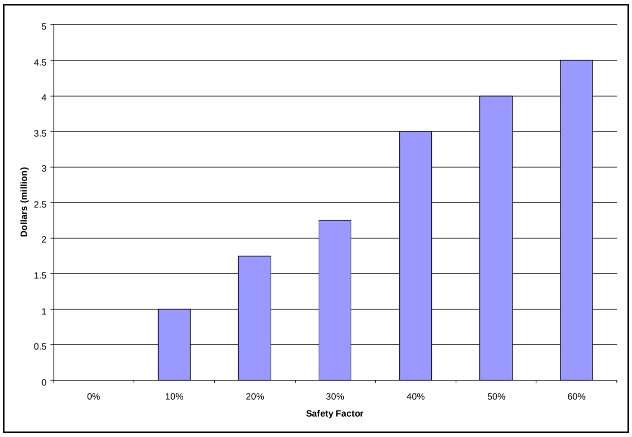

Figure 4: Typical Increases in AMHS Capital Costs Due to Overestimation of the Safety Factor in the Simulation Analysis.

3 THE PROPOSED METHOD

It is clear that while some of the previously discussed methods can be viable alternatives under a wide variety of circumstances, it is the nature of AMHS themselves that probably precludes their maximum effectiveness for this application. As an alternative, however, historical data from AMHS that have been built and operating for some period of time may be obtained and catalogued. From this, it may be possible to extract behavioral trends and implement them in new designs that share elements of commonality with some or all of them as a means to gauge their variability requirements. At any rate, the data provided by the legacy information will inherently contain an abstraction of information that had heretofore been typically unavailable to the analyst. These include operator behavior, surge patterns and operational policies.

Fortunately, a sound MCS (Material Control System) has the capability to extract and log practically every event of AMHS operation for as long a collection period as desired. This feature is usually designed for maintenance and failure documentation, but can easily serve to facilitate the collection of simulation legacy data as well. Although the volume of data can be somewhat large, data filtering tools are available to identify and separate the relevant information from the noise. The needed data can be formatted for database storage.

A sample list of relevant information for extraction is presented in Table 1. To the maximum extent possible, the variable set follows the elements of commonality orientation previously discussed.

Table 1: Candidate Elements to Extract From the Legacy Designs (This List is Not Exhaustive)

-Typical Product Type
-Wafer Size
-Batching Behavior
-Facility size (sq. ft)
-Labor Shifts
-Observed Move Rate Average
-Observe Move Rate Variance
-Observed Delivery Time Average
-Observed Delivery Time Variance
-Throughput rates per functional area

Note that not all of these elements are necessarily from the legacy data but rather are physical descriptors of the system. Additionally, the overall performance averages and variance values can be rendered as single values. The throughput rates of the functional areas are interpreted as the overall introduction of product into the AMHS per unit time for diffusion, photolithography, etc. Any fab will likely have these and other functional areas in common, and based on the data, each will have some measurable throughput. Once enough of these values are obtained, it may be possible to employ them as predictors in some form of metamodel (e.g. multiple regression) that will reasonably predict the degree of variability necessary for simulating a new design.

Another approach discussed in the computing literature is data mining. The concept is to see if relationships exist within large collected data sets. A database search technique may over time, find consistencies in certain areas of fab operation that could lead to more realistic assumptions for general application to new designs.

Rather than implementing the conventional criteria discussed earlier (exponential time between arrivals, etc.), the diffusion area, for example, may have some characteristic distribution function. Additionally, certain product types (DRAM, Logic) may have common behavior patterns that also suggest trends in their production characteristics. The following describes one example of how these methods may be employed in the future.

4 CASE STUDY EXAMPLE

The following example illustrates this concept applied to the diffusion area. It shows promise in being able to generalize a characteristic distribution function for throughput behavior. This data was gathered from a typical fab and its legacy database. It will demonstrate some alternatives to modeling the distributed time between arrival behavior as a customized distribution rather than employing more conventional assumptions.

Figure 5 displays a histogram of data taken from an operating fab. The data plots the observed time intervals between AMHS movement requests in the diffusion area. The depicted curve is an attempt to fit an exponential distribution to the data set. This is an example of the consequences of following conventional assumptions for arrival processes vs. what has actually occurred. Note that while the histogram generally follows the characteristics of an exponential function, there is a large "spike" to the left of the plot that indicates a high incidence of relatively short delays before the next product movement request. The fitted exponential function truncates this cell, and produces time between arrivals that are considerably longer, on average, than what has been reflected by the actual behavior. This is indicated by the "white space" between the fitted curve and the cells of the histogram as it trails away to the right. The net effect is that the exponential distribution will tend to place less stress on the system, and as a result, less variability.

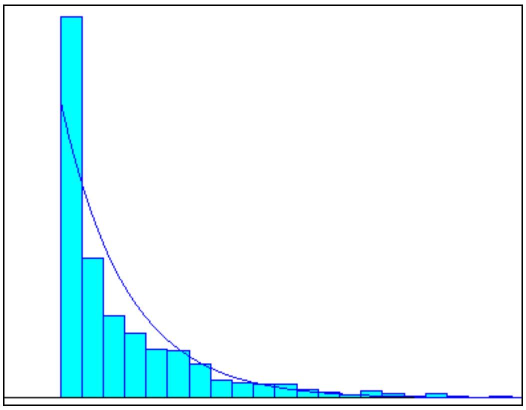

Figure 5: Exponential Distribution Curve vs. Histogram of Actual Data Set

A more viable approach would be to use a piece-wise thinning estimation method to develop a distribution to fit the data set. Figure 6 shows an example curve. It can be noted there is significant reduction of the "white space" between the fitted curve and the histogram cells, indicating the improvement in the goodness of the fit. The reason that this more sophisticated estimation procedure may be more appropriate than conventional distribution fitting method is that it compartmentalizes the observed variability into a form that is more manageable. That is, it separates the far-left cell that includes the relative majority of the observed distribution and treats it separate from the rest of the cells. This allows for each part of the observed histograms to be treated as separate distributions that are run concurrently. By doing this, it further allows the actual observed performance to be reflected in the model more succinctly than can be achieved by using a single, assumed continuous distribution.

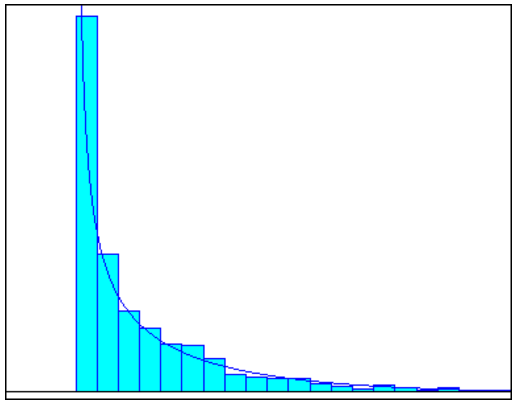

Figure 6: A Piece-wise Distribution Curve Estimator vs. Histogram of Actual Data Set

5 CONCLUSIONS

In this paper, three different methods were examined as techniques for modeling semiconductor AMHS. In the course of this paper, the following conclusions were drawn. Simulations of full system renditions are inappropriate when considering the lack of available data and CPU investment. In running such large and complex models, the answer is obtained after it is needed. Static models may be very accurate and may be the tools of choice in some cases. They are particularly attractive when you are only estimating components of the AMHS. Finally, simplified simulation using a large safety factor will account for more variability than the static approach, but it may also overestimate the capital cost of AMHS equipment. This is unacceptable in today's extremely competitive environment. Moreover, it still does not accurately model the true variability seen in semiconductor manufacturing.

As a result of these discussions, the best approach to AMHS design uses simulation models driven by historical data. These models are as accurate as simulation models for AMHS can be, they account for almost all of the variability of a real system, and they enable the analyst to design an AMHS that is accurate, flexible, and robust. The designer will have results he or she will have very high confidence in.

Future work in this area will focus on building databases that characterize the common elements in semiconductor facilities and AMHS performance. This data can then be pulled from the database and used as input for simulation models. As the legacy database improves, so too will the accuracy of the AMHS designed for the next generation of wafer fabs.

REFERENCES

Gross, D. and Harris, C.M. 1985. *Fundamentals of Queuing Theory, Second Edition,*. John Wiley and Sons, Inc. USA.

Law, A. and Kelton, W.D. 1991. *Simulation Modeling and Analysis, Second Edition,*. McGraw–Hill, Inc. USA.

Pillai, D. 1999. Integrated Factory Design Using Modeling and Simulation. In *Proceedings of Simulation Solution '99* (Mesa, AZ, March 22-24). Institute of Industrial Engineers., Norcross, GA. USA.

AUTHOR BIOGRAPHIES

SCOTT WU, Senior Simulation Engineer, joined PRI Automation in 1998. Over the past year he has developed simulation models for semiconductor AMHS. His present focus is on the evaluation of AMHS design and simulation analyses for 200 and 300mm interbay as well as intrabay systems. Mr. Wu holds a Masters Degree in Industrial Engineering from Arizona State University.

JOHN RAYTER, Senior Industrial Engineer, joined PRI Automation in 1997. Mr. Rayter received his Bachelor of Science degree from the United States Air Force Academy. He also holds a M.S.I.E. from Arizona State University.

GERALD T. MACKULAK is an Associate Professor in the Department of Industrial Engineering at Arizona State University. His research interests center on improvements to simulation methodology, material handling modeling, and production scheduling in high technology manufacturing. He holds B.S.I.E., M.S.I.E., and Ph.D. degrees from Purdue University.

IGOR PAPROTNY, Simulation Engineer II, joined PRI Automation in 1999. For the past year and a half he worked on an internship with PRI Automation, building AMHS simulation models and conducting research in the area of simulation cycle time reduction. He is currently working on projects that aim to streamline the design of AMHS for semiconductor industry. Mr. Paprotny holds a Bachelor Degree in Industrial Engineering from Arizona State University.

JOAKIM K. YNGVE is a graduate student in the Department of Industrial Engineering at Arizona State University. He is currently working as a research assistant for PRI Automation. His current research is focusing on simulation of material handling systems, simulation output analysis, and the effect of re-entrant processes on intrabay AMHS performance. Mr. Yngve holds a B.S.I.E. from Arizona State University.