Applications of Simulation in Semiconductor Manufacturing Facilities

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Funder: Intel - Ireland

APPLICATIONS OF SIMULATION IN SEMICONDUCTOR MANUFACTURING FACILITIES

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ABSTRACT

Semiconductor fabrication facilities face many challenges through the many phases of their life cycle including design, build, various production ramps, and many levels of production. Confronted with global competition and rapidly changing technology and customer requirements, there is an increasing demand for rapid solution techniques to improve efficiency in manufacturing. The complexities and forces of both market and the process combine to make the use of simulation crucial at many different planning and control levels. While not a panacea for sustainable performance, simulation provides an effective vehicle for defining the path from competitive concepts to real world solutions and gives an opportunity to experiment with, and assess the impact of, production plans, aiding the management and production teams' decisions. Integrating simulation with common approaches; Operations Research (OR) and Artificial Intelligence (AI) to solve manufacturing problems is a new trend towards higher quality solutions. This paper presents an overview of how simulation can be employed to improve manufacturing performance and reduce costs.

KEYWORDS: Simulation Applications, Semiconductor Manufacturing.

1. INTRODUCTION

Semiconductor manufacturing is one of the most complex industries in terms of technology and manufacturing procedure. A semiconductor facility (FAB) goes through many phases, including factory layout design, factory construction, process selection and design, start-up and full production, all of which require careful planning at many levels (Figure 1). In order to ensure that the increasing consumer demands, of greater product complexity and diversity at lower cost, can be met profitably it is important that the correct planning decisions are made from the outset and that the operating policies in existing and proposed factories maximize the product output without sacrificing product quality or factory reliability [1].

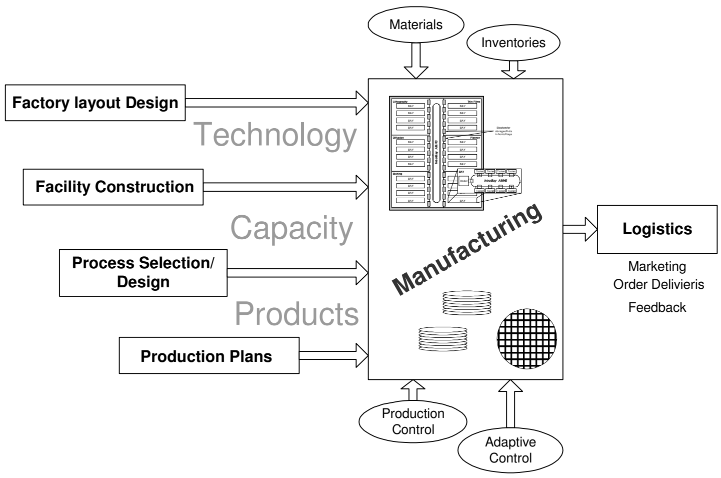

Figure 1. Supply lines and inputs in Semiconductor Manufacturing

While factory design is difficult in itself, the flexibility in semi-conductor manufacturing which results from a high product-mix, re-entrant flow, and parallel equipment using different technologies make scheduling a major challenge in this environment. Specifically, this challenge is to guarantee the ability of the facility to meet due date commitments. To further complicate this task, the flexible manufacturing cells are extremely expensive (both in capital and running costs) and hence there is no possibility to run scheduling experiments within the facility [2]. Despite this the current climate makes high demands from production management:

- Faster and better decisions are expected with the exponential growth of information and knowledge management capabilities.
- Shorter lead time for introduction of higher quality products with guaranteed delivery dates
- Accurate adaptive schedules to cope with the dynamic nature of production systems.

There is, therefore, an immense need for effective and powerful approaches which can capture and analyze manufacturing systems to support these decisions. Simulation allows experimentation with a model of a system instead of experimenting with the real system which might cause production loss and disruption [3]. The use of simulation within dynamic manufacturing systems provides the only method to study the impact of new layouts and production plans on factory performance for which analytic and static deterministic models provide at best a low fidelity model with corresponding low accuracy. Simulation modeling, if used wisely, allows system developers and analysts to predict the performance of existing or proposed systems under different configurations or operating policies [4]. This process, carried out before the existing system is actually changed or the new system is built, reduces the risk of unforeseen bottlenecks, under- or over-utilization of resources, and failure to meet specified system requirements.

2. SIMULATION

Manufacturing simulation has become one of the primary application areas of simulation technology. It has been widely used to improve and validate the designs of a broad range of manufacturing systems. Typically, manufacturing simulation models are usually used either to predict system performance or to compare two or more system designs or scenarios [5].

There are many forms for simulation models, such as static, dynamic, deterministic, stochastic, continuous, discrete and mixed simulation models [6]. Discrete-event simulation (DES) is one of the most widely used methods to study, analyze, design, and improve manufacturing systems. A discrete-event simulation is one in which the state of a model changes at only a discrete, but possibly random, set of simulated time points. During a simulation run an internally managed stored data value tracks the passage of simulated time, which advances in discrete steps (typically of unequal size) during the run. After all possible actions have been taken at a given simulated time; the time is advanced to the start of the next earliest event [7]. Time is advanced using a time advance mechanism, which is done by ordering all known events into a chronological order of occurrence, and letting the simulation time advance from one event to the next in the ordered sequence. The state of the model between events remains unchanged, thus skipping from one event to the next, without considering the time in between those two events, loses no information [8].

The execution of a run thus takes the form of a two-phase, "carry out all possible actions at the current simulated time" and "advance the simulated time", loop, repeated over and over again until a run-ending condition is reached. A number of modeling concepts have to be defined so that a discrete-event simulation model can be well understood [9].

The application of simulation to solve scheduling issues is not simple as each problem must be addressed on its own merits; however there are essential steps which are common to all such activities [6]. In addition, it must be clearly understood that, simulation alone cannot provide the solution as it is a tool for evaluating the behaviour of the system in response to external influences. The keys to successful application are a quality model which provides the right representation of the actual system and a structured approach to the optimisation of input parameters to find the best performance of the system.

2.1 Simulation Modeling

The goal of simulation modelling is the representation of a system, whether existing or planned, in software such that the response of the system and the response of the model to the same controlling inputs are identical. Models, as has already been indicated, range from simple deterministic models to complicated non-linear stochastic models. As with the technology they represent, the models are growing in both size and complexity as the capabilities of modelling software and data collection tools increase. However, it is not necessarily true that the more complex the model the better the result [10]. The validity of any model must be judged carefully in relation to the specific system under examination and there are at least three considerations which must be satisfied when designing a valid model:

- Good correlation with existing system performance: The response of the key outputs from the model must match similar measures on the existing system. Where the system under investigation does not yet exist, similar systems may be used to provide the validation data.
- Good integrity in the model: Not only should the final results match those of the system, but interim results and internal logic in the model should also provide a reasonable match.
- Timeliness: The time required to build the model and generate the results should be such that the outcome of the study can be applied to improve the manufacturing system.

These are not on/off criteria, rather the model will achieve a level on each scale and the success of the project depends on getting a balance between the conflicting elements of each. For instance, for a particular scenario it may be possible to achieve exact replication of the output measures while the internal variables show differing characteristics to the real system. Such a model, if applied in a different scenario would be expected to deliver incorrect results. Similarly, the level of detailed modelling required providing very precise correlation of internal variables may require too much construction time for the results to be applicable rendering the model useless. This delicate balance between output correlation, detailed accuracy, and speed indicates that without the appropriate modelling expertise there is a significant probability that the simulation study will result in a costly incorrect decision or that the results will never be used.

There is consensus amongst the simulation community that a simple model is generally preferable to a complex one. "*Model Simple – Think Complicated*" is one of the best principles [4] and as a result the best model is only as complex as necessary to provide accurate answers. A more complex model will require more resources without providing any more useful information in return. The danger is that the model will be too simple and not prove correct for all the scenarios under consideration. Table 1 gives a brief summary of some of the benefits and pitfalls of using simple or complex models in industrial applications.

Table 1: Comparison between simple and complex simulation models

	Complex Model	*Simpler Model*
Model Scope	Variable	Usually High
Level of detail	High	Low
Modeling Time	3 month – 1 year or more	Less than 6 months
Data Collection	Difficult – wide scope, specific information required	Easy – general data
Validation	Difficult	Easier
Accuracy	High	Low
Conceptual modeling	Difficult due to complex interactions between entities	Easy
Coding	Complex and time consuming	Easier
Customer Satisfaction	Very high or Very Low	Generally satisfied
Modeller	Experts needed to build good models	Can be done with less experienced modellers
Computer Performance	Long run times, even with high specification computers	Quick models
Results Analysis	Specialist analysis required	Easy to interpret
Knowledge	Comprehensive	Surface only
Simulation Software	Usually software capabilities is crucial and selection is an issue	Less complex packages
Visualization Tools	Animation and 3-D may be required	Standard graphs and static 2D images sufficient
Reusability	Can be built into design	Low possibility
Real System	Provides understanding of the real system	Causes of system issues may nopt be resolved

Data collection is one of the key activities, in addition to careful selection of the model scope and detail, which will have a major impact on the quality of the results [11]. The adage of "garbage in, garbage out" is particularly true where modelling is concerned. Models with wider scope and more detail require more information to define the system correctly. While the IT systems currently in use can track many parameters regarding factory performance, the sheer volume of information can make finding the correct data difficult. Often, in an attempt to reduce the amount of information in storage, summary statistics are the only records available and their content may reflect the minimum level of information which was relevant at the time the software was installed. As a result, even with the use of data mining algorithms, this stage often requires considerable interaction with production staff to ensure the validity of the information.
The major two things that limit the proliferation of the effective use of operational modelling and simulation in the semiconductor industry are:

1) The amount of time and effort that go into identifying, specifying, collecting, synthesizing, and maintaining the data used in modelling efforts.
2) The lack of perceived value of some of the simulation efforts by semiconductor management.

2.2 Design and Analysis of Experiments

There are two aspects to the design and analysis of simulation experiments. The first concerns the quality of the output in relation to a single experiment while the second must consider the problem under review and ensure that the results from a group of experiments map the solution field to provide relevant answers. Table 2 provides a summary of some of the key elements.

Table 2: Experiment features for simulation models

Simulation Feature	*Notes*	*Advantages*
Length of Simulation Run	Type: - Terminating - Non-Terminating	- Specify the run condition - Save time
Warm-up Period	Data is not stationary during the warm-up period must be removed from calculations	- High quality output - Avoid misinterpretation of outputs
Number of Replications	Runs must use different random seeds	- Precise outputs - Better statistical control
Design of Simulation Experiment	Using DOE techniques to run simulation experiments	- Economic - Better understanding to outputs

While there may be a certainty about the scenario used for a particular simulation run, much of the information used to define the system parameters has a stochastic nature. As a result, the simulation run produces a statistical estimate of the (true) performance measure not the measure itself [51] which can only be found by running the same scenario several times under differing random seeds. The number of runs required will vary depending on the accuracy required and the characteristics of the data (e.g. mean & standard deviation). In order for an estimate to be statistically precise (have a small variance) and free of bias the set of results must be representative of a stationary phenomenon. So the analyst must consider, for each scenario of interest, parameters such as:

- Length of Simulation Run
- Warm-up Period
- Number of replications

Since the simulation model is replacing the actual manufacturing system, the design of a set of experiments to map the solution space and find answers to the questions posed can follow any of the standard design of experiments (DOE) procedures. These methods, such as Taguchi, reduce the number of experiments required to provide a set of results which give a reliable indication of the effect of changing particular control parameters on the outputs [12]. This approach also allows the use of Artificial Intelligence (AI) techniques to drive the input parameters, within valid ranges, and search for optimal performance from the model. Here it is important that both the input ranges and the outputs used for optimisation accurately reflect behaviour on the factory floor. In this manner, capacity planning, routing, and production scheduling can all be investigated by driving the model appropriately. It should be noted, however, that it may not be possible to use a single model to undertake all these studies as the detail and scope required to answer these different problems may not be identical.

3. SIMULATION IN SEMICONDUCTOR MANUFACTURING

Semiconductor FAB's are, typically, automated flexible manufacturing installations containing parallel process paths with highly re-entrant flow and thousands of simultaneous production lots. As a result, a simulation model of a FAB will not only contains a great deal of information about each structural element (process, tool, material handling etc.) but must maintain dynamic records of the state of each lot as it moves through the FAB. Such a record may contain a number of key parameters relating to the performance of the system. The number of dynamic variables in a full FAB model will therefore be at least on the order of some polynomial of the number of lots in the factory. It has been clearly shown that the calculation time for such models increases exponentially with the size of the system being simulated [13].

In semiconductor manufacturing discrete event simulation (DES) and hybrid simulation models are most commonly used to address manufacturing problems. The wafer fab is by its nature a man-made, discrete system and cannot be modelled using continuous models as outlined in Table 3.

Table 3: Comparison of discrete and continuous models for semiconductor manufacturing [14]

	Discrete Model	*Continuous Model*
System	Wafer Fab	Circuit/Device Design/Test
Mathematics	If-Then Rules Logic statements Algebraic Functions	Differential Equations & PDEs
Method of Solution	Discrete Event	Finite Difference

Traditionally simulation in semiconductor manufacturing has been used for high level capacity planning; however its use is now rapidly growing in other fields such as strategic and operational planning levels (e.g. scheduling, detailed equipment modelling and manufacturing control). Figure 2 shows some of the areas in which this growth has occurred.

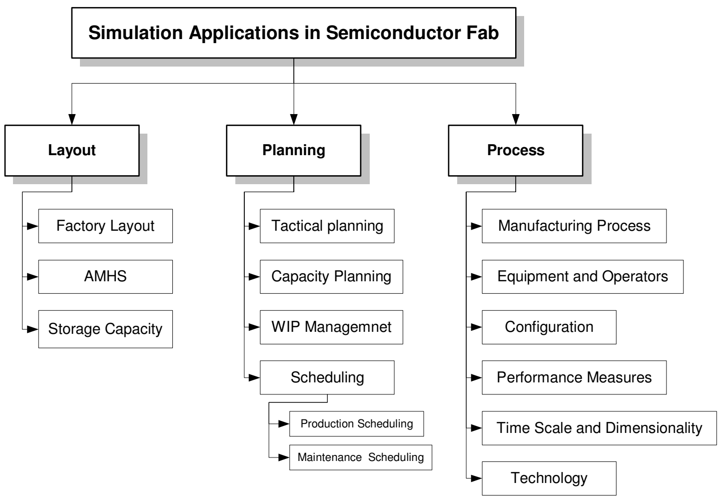

Figure 2: Simulation applications in semiconductor Fab [6]

For existing FAB's the greatest potential for simulation lies in sensitivity analysis of operating policies, with a focus on meeting production goals while avoiding new equipment purchases. There is particular benefit to come from a better understanding of the impact of product-mix changes and production volume on the capacity and performance of the system. On the other hand for new FAB's, simulation is expected to be used effectively to evaluate and analyze solutions for equipment layout, material flow, and automated material handling systems to minimize tool count, WIP, and cycle time.

Each level in Figure 3 represents a distinct area where simulation may be applied. At the base, detailed models can be built which reflect the performance of an individual tool or piece of equipment. As the tools used are flexible, these models are often complex and may contain queues and parallel processing, acting as a manufacturing system in their own right. At this level of detail good correlation of all aspects of the workflow is expected.

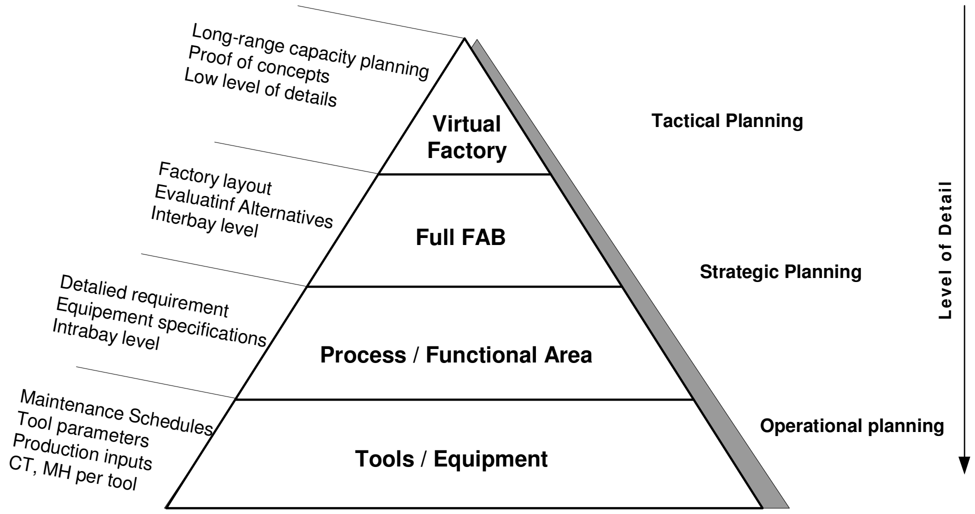

Figure 3: Variation in level of detail with application of a model

Process or Functional Area models will be made up of a group of tools which may be performing the same or complementary tasks. In general, these models are used to examine the performance of the group of tools and will not have great detail of the operation within each tool. Tools identified as bottlenecks or constraints in such a study may then be addressed with a specific model. Local scheduling, lot transport or capacity may be analysed using such models. Interaction with the rest of the FAB may be modelled by considering the time spent in external processes as a delay on the lot returning to the model. Intrabay material handling, WIP management, bay layout, maintenance and equipment performance are some of the key operational planning issues addressed by these models.

A Full FAB model will contain elements which represent each section of the facility, either at tool or group level. It is normal to reduce the size of such models by grouping tools or functions and representing their performance with summary statistics. Unless this reduction in model size and detail is undertaken the calculation time is uneconomic. Different approaches to such models have been used, such as break the model into sub-modules [15][16][17], simulate the whole model with increased level of detail on particular areas [18], or simulate a single area in details then integrate the modules together [19].

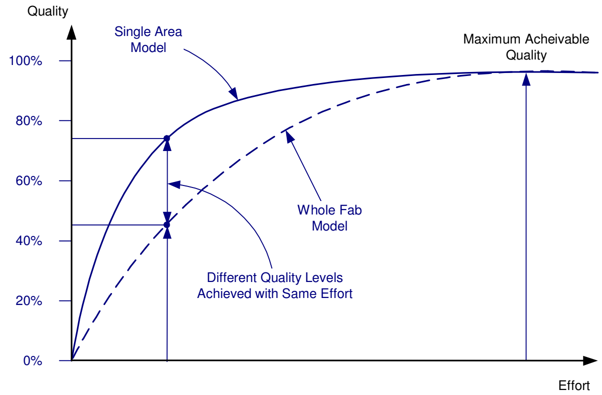

Figure 4: Relationship between effort and quality for Full FAB and Area models [19]

This last approach seeks to utilise the "quality factor" gained from modelling a single area in an adequate level of details over the same effort applied to a full fab model (Figure 4), suggesting that careful consideration should be given before embarking on a full FAB model. Full FAB models are used to examine the impact of different production strategies on productivity [20], however the effort needed to capture the interaction between the model elements is tremendous. In addition, validation of such a large system model is difficult as the data required is often difficult to obtain. In particular they may be used to analyze the alternative solutions for factory layout, material handling, equipment usage, and protective capacity [21].

At the global level, Virtual Factories are the term used for models of multiple factories that produce same products or use same processes. Long range capacity planning, loading and equipment use/reuse are the main questions to be answered by such simulations.

4. ADVANTAGES OF SIMULATION

Many publications have shown the advantages of using simulation as a tool in developing manufacturing systems (e.g.,[6],[11],[22],[23]&[24]). The main advantages can be summarized as follows:

- Most complex, real-world systems with stochastic elements cannot be accurately described by mathematical models that can be evaluated analytically. Thus, simulation is often the only type of investigation possible.
- Simulation allows the estimation of performance of existing and non-existing systems.
- New hardware designs, physical layouts, transportation systems…etc. can be tested.
- Time can be compressed or expanded allowing for speed up or slow down of the phenomena under investigation.
- Insight can be obtained into the interaction and the importance of variables to the performance of the system.
- Provide an understanding of how the system really operates rather than how individuals think the system operates.
- "What-if" questions can be answered, useful in the design of new systems.
- Proposed alternative system designs can be compared.

5. PITFALLS OF SIMULATION PROJECTS

While simulation projects have provided tremendous insight in many cases, there are some common pitfalls which reduce the effectiveness of the studies. From experience and a critical review of the literature (particularly [6],[9],[11],[21]&[25]) a summary list follows:

- Failure to have a well-defined set of objectives at the outset.
- Failure to communicate with the client on a regular basis.
- Poor knowledge of simulation methodology, probability and statistics.
- Inappropriate level of model detail.
- Failure to collect good system data.
- Belief that so-called "easy-to-use" simulation packages require a significantly lower level of technical competence.
- Selection of an inappropriate simulation approach [26].
- Misuse of animation.
- Failure to perform a proper output-data analysis.
- Simulation models are often expensive and time-consuming to develop.
- Sometimes an analytical solution is possible, or even preferable.

6. INTEGRATING SIMULATION WITH OTHER TOOLS

As mentioned previously simulation can only replicate the behaviour of the system under observation and cannot, in and of itself, provide improvements in the performance of the system. It does however offer a suitable method for assessing the effect of control parameters on the behaviour of the system. In response to a particular set of inputs the model provides an output which can be used to measure the performance of the system. The inputs are decision variables, and simulation outputs are used to model an objective function and constraints for an optimisation algorithm. The goal is to find the optimal setting of the input factors that can achieve the best output from the system.

Table 4: Examples of Hybrid techniques reported in literature

Author(s)	*Hybrid Techniques*	*Notes*
Sereco *et al*. [27]	KBS	Optimization techniques, hierarchical planning, and heuristic search
Dagli *et al*. [29]	Lawler's Algorithm & NN	Algorithm generates schedules to train NN
Rabelo *et al*. [30]	ES & NN	IFMSS: intelligent FMS scheduling, expert system and a back propagation NN
Rabelo *et al*. [31]	IFMSS	Enhancing the model with adding simulation and GA to his control architecture
Yih *et al*. [32]	AI& Simulation	Hybrid model of AI and simulation for a small set of candidate scheduling heuristics
Yih *et al*. [33]	Semi-Markov & ANN	Semi-Markov optimization and ANN for robot scheduling in a circuit board production
MacCarthy *et al*. [34]	LP & Simulation	Rule-based framework; mathematical optimization procedure and simulation.
Sim *et al*. [35]	ES & NN	Expert system to train NN to reduce the time required for training.
Szelke *et al*. [36]	CBR & Machine Learning	Reactive learning of machine for shop floor scheduling
Kim *et al*. [37]	Inductive Learning & NN	Multi-objective FMS schedulers
Lee *et al*. [38]	GA & Machine Learning	To generate empirical results using machine learning for releasing jobs to the shop floor and GA to dispatch jobs.

Optimisation routines can now be integrated into DES models, providing a single user-friendly interface to the casual user. The current trend in such hybrid intelligent models is towards a combination of the three common approaches; Operations Research-based, simulation-based and AI-based. Samples of efforts to use a mixture of several of the above paradigms are shown in the Table 4.

7. CONCLUSIONS

Semiconductor manufacturing is a very competitive environment where the demands of the market place a huge importance on achieving maximum performance from a cutting edge, highly flexible manufacturing system. In this environment, simulation is an essential tool as semiconductor factories are too large, too complex, too dynamic and too costly to optimize and refine by any other means. As this is a relatively new field and solution techniques are still under development, confidence in this approach to factory optimisation is still low and:

- It is critical that simulation models provide meaningful data in a timely manner. This depends primarily on accurate system analysis, input data accuracy, model building and validation. It is also essential that the model be kept up-to-date in order to reflect the current factory scenario. This can be accomplished by having a good, user friendly interface between simulation model and manufacturing users.
- "Credibility is not a gift – it has to be earned" and is built up one step at a time, supported by facts and consistency. Further, "credibility is never owned; it is rented, because it can be taken away at any time" [26]. Researchers must therefore focus on providing robust industrial models with quality outputs.
- Based upon authors' industrial experience, they provided a protocol to follow for simulation projects which includes a systematic methodology for optimizing simulations [6]. As part of this, the initial stages concentrate on delivering measurable concrete results to provide confidence in simulation.
- The dynamic nature of manufacturing requires that the models, once developed, should be easily re-used and reconfigured by those who know the system best, the manufacturing engineers.

Many operational decisions are made in semiconductor manufacturing based on prior knowledge, experience and intuition. The need of reliable decision support systems brings a new dimension of integrated tools of simulation and optimization to provide better and effective solutions.

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