Enterprise Simulation: A Hybrid System Approach

Luis Rabelo

Industrial Engineering & Mgmt Systems Dept, University of Central Florida – Orlando, FL 32816 – USA

Phone: 407 882 0091 Fax: 407 823 3413 – E-mail: lrabelo@mail.ucf.edu

Magdy Helal

Industrial Engineering & Mgmt Systems Dept, University of Central Florida – Orlando, FL 32816 – USA

Phone: 407 882 0285 Fax: 407 823 3413 – E-mail: mhelal@mail.ucf.edu

Albert Jones

National Institute of Standards and Technology; NIST,

Manufacturing Systems Integration Division, Gaithersburg, MD 20899, USA

Phone: 301-975-3554 Fax: 301-975-4694 – E-mail: albert.jones@nist.gov

Hyeung-Sik Min

National Institute of Standards and Technology; NIST,

Manufacturing Systems Integration Division, Gaithersburg, MD 20899, USA

Phone: 301-975-4626 Fax: 301-975-4694 – E-mail: jason.min@nist.gov

Abstract

Manufacturing enterprise decisions can be classified into four groups: business decisions, design decisions, engineering decisions, and production decisions. Numerous physical and software simulation techniques have been used to evaluate specific decisions by predicting their impact on either system performance or product performance. In this paper, we focus on the impact of production decisions, evaluated using discrete-event-simulation models, on enterprise-level performance measures. We argue that these discrete-event models alone are not enough to capture this impact. To address this problem, we propose integrating discrete-event simulation models with system dynamics models in a hybrid approach to the simulation of the entire enterprise. This hybrid approach is conceptually consistent with current business trend toward integrated systems. We show the potential for using this approach through an example of a semiconductor enterprise.

1. Introduction

In manufacturing enterprises, numerous strategic, tactical, and operational decisions are made everyday. These decisions, which have a huge impact on profitability and survivability, address four major branches of the enterprise: business, design, engineering, and production. Much research has been devoted to optimizing the performance of each of these branches. A large number of optimization techniques from the fields of operations research, artificial intelligence, and simulation, have been proposed in the literature. These techniques evaluate specific alternatives by predicting their impact as quantified in one or more performance measures.

Operations research (OR) techniques are highly mathematical in nature and usually attempt to find the optimal decision based on the given performance measures and some set of constraints. Some examples include mathematical programming, forecasting, inventory control, graph theory, and queuing theory. These techniques are based on sound mathematical theories, but they often require simplifying assumptions that limit their applicability to real-world problems.

Artificial intelligence (AI) techniques such as knowledge-based heuristics, neural networks, and genetic algorithms, have been widely used in conjunction with or instead of OR techniques. They are attractive for three main reasons. First, they allow qualitative as well as quantitative evaluation. Second, they can model complex relationships among factors that influence that evaluation. Third, they can generate complex heuristics that incorporate those relationships. They have, however, two serious disadvantages: they can be difficult to build, verify, and maintain; and, they generate only feasible, and sometimes poor solutions.

Over the last two decades, simulation has been used widely – sometimes alone and sometimes with OR and AI techniques - to evaluate alternatives and to optimize performance in all branches of the enterprise. Many types of simulation techniques are used including physical, process, discrete-event, and system-dynamics. Consider the following examples. Physical simulations are used in the design branch to evaluate alternative product designs. Process simulations are used in the engineering branch to evaluate the likelihood that a particular machine can fabricate a part to the desired tolerances. Discrete-event simulation (DES) is used in the production branch to evaluate planning, routing, and scheduling alternatives. And, system-dynamics simulations (SDS) are used in the business branch to evaluate the impact of business alternatives on the long-term profitability of the enterprise.

As just described, there has been considerable research related to the performance of individual branches of the enterprise; little research, however, has been reported on their interactions. In this paper, we focus on the interactions between the production branch and the business branch. Specifically, we consider how scheduling decisions, made using a discrete-event simulation (DES), in the production branch impact reinvestment decisions, made using a system-dynamics simulation (SDS), in the business branch. To do this, we will integrate the DES and the SDS into a distributed, enterprise simulation.

2. Background

In this section, we provide some background on the use of discrete-event simulation, system dynamics simulations, and distributed simulations in manufacturing.

2.1 Discrete event simulation in production decisions

In most manufacturing simulations, time is a major independent variable. Other variables are state variables that describe what is happening in the process or system as a function of time. In the DES approaches, state variables change only at discrete points in time, called event times. Examples of state variables include the number of jobs waiting in the queue in front of a machine, the status of each machine on the shop floor, and the location of each job in the factory. DES models are mainly flow models that track the flow of entities through the factory. The task of the modeler is to determine the state variables that capture the desired behaviour, events that change the values of those variables, and the logic associated with each event. Executing the logic associated with each event in a time-ordered sequence produces a simulation of the system. As each event occurs, it is removed from the sequence and the next event is activated. This continues until all the events have been processed. Statistics are gathered throughout the simulation and reported with performance measures (average delays, down time, and throughputs to name a few). Different probability distributions can be associated with each process to simulate natural variations.

In the production branch, DES has been applied to scheduling, and planning (Law 1991, O'Reilly 1999). The simulation models generally represent the flow of materials to and from processing machines and the operations, usually modeled as a time delay, at those machines. Planning decisions include capacity planning, production planning, and process planning. Capacity planning simulations evaluate the impact of changing product mix or demand. Production planning simulations evaluate the impact of various aggregation schemes and their associated material-order policies. The planner can use a DES model to test material reorder points and delivery procedures to manage inventory buffer. Process planning simulations evaluate assignments of jobs to machines and routings for those jobs through the shop. Scheduling simulations seeks solutions to daily issues including on-time order completion, priority changes, and unexpected changes in resource availability. DES helps a system engineer detect potential scheduling problems through the review of the resource and schedule performance during the scheduling interval (shift, day, or week). The new alternative policies are then executed and performances of the system for the different policies are compared. This process is repeated until a feasible and desired schedule is achieved (Jeong 1998, Kim 1998, Lin 2001, Min 2002, Vaidyanthan 1998).

From the preceding, brief discussion, we can see that DES is a widely used and increasingly popular method for studying the design and operations of manufacturing systems. In fact, DES is often the only type of investigation possible. There are three main reasons. First, DES has the ability to describe the most complex manufacturing systems and to include stochastic elements, which cannot be described easily by mathematical or analytical models. Second, DES allows one to track the status of individual entities and resources in the facility and estimate numerous performance measures associated with those entities under a wide range of projected operating conditions. Third, alternative facility designs or operation policies can be compared via DES to see which best meets a specified performance goal.

However, DES does have two major drawbacks. First, one can only establish estimations of and correlations among variables and performance measures using statistical models. The underlying reasons for or causes of these estimations and correlations cannot be deduced from the models themselves; they must be inferred. Although critical to effective decision-making, understanding the difference between correlation and causality is not always easy. Consequently, erroneous causal inferences can be drawn based on the estimated correlations. Second, DES models allow us to evaluate the system performance for specific values of decision variables or control policies. They do not allow us to determine the stability of the system in any region or neighborhood of those values or policies. This is of critical importance in complex systems where system performance may be driven by hidden, causal relationships that may be highly non-linear. In such systems, small deviations from the optimal decision point can cause disproportionately large changes in the system performance. To better understand these causal relationships and their possible non-linear effects, we turn to system dynamics simulations.

2.2 System dynamics simulation

System dynamics is a method for studying the evolution of many real-world systems. It has its origins in the control-engineering work of Jay Forrester (Forrester 1971, 2001). Peter Senge (Senge 1994) views system dynamics as a conceptual approach to facilitate the understanding of complex problems. Its central concept is that all the objects in a system interact through causal relationships. These relationships come about through feedback loops, where a change in one variable affects other variables over time; these variables, in turn, affect the original variable, and so on. System dynamics asserts that these relationships form a complex underlying structure for any system. This structure may be empirically or theoretically discovered. It is through this discovery that the causal relationships become clear and predictions of the future behaviour of the system becomes possible.

The creation of a complete dynamic model of a system requires the identification of the causal relationships that form the system’s feedback loops (Forrester 1971 and 2001, Sterman 2000). Feedback loops can be either negative or positive. A negative feedback loop is a series of causal relationships that tend to move behaviour towards a goal. In contrast, a positive feedback loop is self-reinforcing. It amplifies disturbances in the system to create high variations in behaviour. Causal loop diagrams are important tools for representing the feedback structure of the systems. A causal loop diagram consists of variables connected by arrows denoting the causal influence among the variables. The important feedback loops are also identified and displayed in the diagram (figure 1).

[Insert figure 1 here]

From these causal loops, we can develop a stock and flow graphical structure (figure 2). Stocks are accumulations of information or materials that characterize the state of the system. They generate the information upon which decisions and actions are based. They also create delays by accumulating the differences between the inflow and outflow of a process. Flows are rates that are added to or subtracted from a stock. This graphical description of the system can be mapped into a mathematical description of the system.

System Dynamics has been used extensively in the business branch. Its uses range from the analysis of various strategic and operational policies to the actual design of supply chains and their logistics. Jay Forrester (1958), who pioneered the modeling of supply chains using system dynamics, described them using flows of information, orders, materials, money, human resources, and capital equipment. In a recent paper, (Angerhofer and Angelides 2000), the authors argue the use of system dynamics modeling in supply chain management has only recently re-emerged after a lengthy slack period. They further argue that there are three main uses: theory building, problem solving, and improved modeling.

[Insert figure 2 here]

According to (Ackerman et al., 1999), research in theory building includes the uses of system dynamics to study the interrelationships among the different elements of a supply chain system. Towill uses systems dynamics as a methodology to solve difficult problems such inventory oscillations, supply chain re-engineering, and supply chain design (Towill, 1996). In (Naim and Towill, 1994), the authors use system dynamics as a simulation tool to model the dynamics of the supply chain.

2.3 Distributed simulation in manufacturing

The idea of using a distributed simulation to model manufacturing enterprises has recently gained favor. Typically, there is a single conceptual manufacturing simulation comprised of multiple individual simulations of enterprise systems. These individual simulations execute independently but interact with each other. There are two ways to ensure that this interaction goes smoothly and events are synchronized properly. The first uses the High Level Architecture (HLA), which was developed to provide a consistent approach and rules for integrating distributed, heterogeneous, defense simulations (Kuhl 1999). The first demonstration of the HLA-based manufacturing simulation was conducted as part of the MISSION project (Mission 1998). This international project demonstrated a distributed, heterogeneous, supply-chain simulation that integrated existing factory-level simulations (Riddick 2000). In (Venkateswaran 2002), the authors constructed another supply-chain simulation based on the HLA, the Distributed Manufacturing Simulation (DMS) Adaptor, and the scenario presented in (Umeda 1998).

The second is to use the time-stamping approach developed to synchronize events executed concurrently on different computing processes (Chandy 1979, Jefferson 1982). Fujii (Fujii 2000) adapted this approach for his factory simulation, which integrated distributed and precise cell-level simulations. Ramakrishnan (Ramakrishnan 2002) developed a master-event calendar mechanism for his supply-chain simulation. And, Misra (Misra 2003) presented a neural-network-based, adaptive-time-synchronization mechanism for the integration of supply chain simulations, where the best mechanism is identified dynamically based on federation conditions.

3. Hybrid SD-DES simulation approach

We believe that our proposed SD-DES approach to manufacturing enterprise simulation offers a simulation approach that is consistent with the increasing levels of integration in manufacturing enterprises. As manufacturing systems become more integrated and the entire enterprise becomes the subject of the simulation and the analysis process, DES capabilities will face serious challenges. First to mention is that the complexity of the DES models increases exponentially with the size of the simulated systems. Moreover DES limits the scope of simulation to a detailed analysis technique that is not recommended for the decisions in the aggregate and strategic levels (See Cranfield University Web site: http://www.cranfield.ac.uk/sims/mem/mdms/aitoroyarbide/researchaitoroyarbide.htm].

On the other hand SD focuses on the system structure and the feedback interrelationships among its components rather than detailed data requirements. A major advantage of the SD methodology is the ability to trace causal relationships among system components so as to follow any problematic behaviour to its real roots on any part of the system. Besides SD models are relatively easy to develop and the complexity of the models seems to be increasing linearly as compared to the DES models (Sterman 2000).

DES, however, seems to give more credible models and this is due to the level of details that can be included in the models. But when it comes to the strategic and aggregate levels then SD has some distinct advantages over DES (Baines 1999, Also see Cranfeild University web site)

A review of related literature has shown that integrated systems are more demanding and DES seems not to satisfy the analysts' needs. Some researchers have recommended the use of the continuous simulation methods rather than DES. Others have recommended the use of hybrid continuous-discrete simulation approaches. In both cases the use of DES alone has been subject to criticism (Barton 2001, Lee 2002, Gregoriades 2003).

Many variables in product and information flows in supply chains (SC) and enterprise systems can have continuous factors that might not be modeled properly using DES. Several problems would arise because of that. Inability to reflect the continuous nature of the process or the interaction among the continuous components, in addition to the growing complexity for the more detailed models and the too-much simplification needed for small-scaled models, are some of these problems [Lee et. al 2002]. To exemplify that Lee (2002) built a simple model of a SC using DES and then using DES with some continuous enhancements. The DES only model overestimated some of the state variables (inventory levels). That is unnecessary inventory would become necessary according the DES analysis results.

Some researchers preferred limiting the use of DES to certain problems areas in the SC, that could be in the tactical and operational levels in specific, or where few alternatives are available and detailed analysis is required (Chang 2001, Lee 2002). Huang et al (2003) investigated if a single model could be used to model all of the three levels of decision-making, and they did not believe it could. Barton (2001) in the other hand said that overall models with sufficient details are rare. But it is indicated that complete SC models based on SD, which is a continuous simulation approach, is not unusual. What can be concluded is that using DES for modelling the entire enterprise or SC is not recommended. Also the level of decision-making in an enterprise (strategic, tactical and operational) is a factor in determining which simulation approach to use. There is, in addition, a tendency toward recommending the use of SD. SD offers the following, among others (Mandal 1998, Bainess 1999, Gregoriades 2003,):

- SD integrates the many subsystems to give a holistic view of the entire manufacturing systems.
- It moves from focusing on individual decisions to focus on policy structure. Policies and strategic issues are the central focus in SD models.
- Feed back loops are the basic building blocks and policy decisions are embodied in the feed back loops.
- SD models allow the construction of the causal relationships among variables. A model is a dynamic picture of perceived cause-effect relationships among the real system elements.

Furthermore, SD models can address the qualitative issues in manufacturing systems, and, as a continuous simulation methodology, models are more intuitive than the discrete models (Gregoriades 2003, GroBler 2003, Levin 2003).

However, it is noticed that SD is not widely used in manufacturing although recommended as an alternative to DES or in hybrid systems. The use of SD for manufacturing systems applications has gone into a lengthy slack period since the pioneering work of Jay Forrester in the 60s and 70s, until about a decade ago. In fact manufacturing systems modeling was considered a missed opportunity for SD modeling, especially in the higher levels of decision-making (Baines 1999, Angerhofer 2000, Mandal 2003).

In a survey of the applications of SD, Baines (Baines 1999) and his coworker have found that whenever SD is used in manufacturing it is mainly used in the operational level, while there is a lack of the exploitation of SD at the higher levels. This could be unexpected since SD is supposed to be an overall system thinking approach. One could argue that analysts of manufacturing systems tried to use SD in the same way they used DES, or in the same areas of applications they used to work in. This can be called the *DES mentality* in conducting simulation. With SD this mentality is not expected to result in the desirable outcomes and this could be the reason why SD potentials are not sufficiently exploited in manufacturing systems as they are in ecological systems for example.

Gary et al. (Gary 2003) found that current SD environments do not provide the granularity needed to model the complex stochastic material flows for a semiconductor supply network in the operational level. And they preferred DES. The researchers at Cranfield University were working to develop manufacturing simulation tools based on SD, in order to replace DES but they are not getting promising results yet. All the above would provoke the use of SD and DES in a hybrid approach to model the manufacturing systems.

Hybrid systems are those where discrete and continuous factors coexist (Lee 2002, GroBler 2003, Huang 2003, Levin 2003). Levin et al. (2003) believe that hybrid models are reasonable approximation to continuous models and are easier to comprehend. They suggest using SD with DES in hybrid systems. They, however, believe that the stocks and flows (the basic tools of SD) are not intuitive enough and also the use of the causal loops to simplify the process was found problematic. In the Cranfield University research work, SD is not considered appropriate as it is for modeling manufacturing systems; and hence SD-based tools need to be developed for manufacturing systems modeling and in order to replace DES.

Based on that it can be concluded that DES models do not seem to be the best choice for modeling the entire manufacturing enterprises and SC, especially when considering the integrated systems nowadays. Hybrid discrete-continuous modeling systems are more reasonable and practical approaches. Hybrid models are also better in handle the differences in the requirements in modeling the three levels of the decision making process. In addition, SD is a recommended continuous modeling approach that is already being used more often than DES in modeling SC.

Consequently we believe that hybrid SD-DES models would provide a good, effective and satisfactory approach to model the entire manufacturing enterprise. Such hybrid models could be simple, yet effective and comprehensive, and able to model the stochastic, continuous and the qualitative aspects at all the levels of decision-making process. Some researchers believe (See for example Baines 1999 and Cranfeild University site) that SD can replace DES in simulating manufacturing systems. But the success of DES is not deniable and a replacement would need years to prove itself. It should be better to make use of the two approaches combined.

Aggregate and strategic decisions, which are made at the higher management level and aimed at maximizing firm's performance in a certain business areas of the firm, may result in unanticipated undesirable side effects on other areas of the firm. The scope of the simulation models should not be limited to certain areas within manufacturing systems but should include other internal key business functions, strategically, operationally, and tactically, as well as include necessary external elements like suppliers and customers. Hybrid SD-DES is expected to be able to provide for that.

4. Conceptual description of the SD-DES model

The proposed approach aims at building simulation models of the manufacturing enterprises. Basically a model is a SD model for the entire enterprise. Then for selected parts of the enterprise, especially the operational and some tactical level parts; DES models will be built to interact with the overall SD model. Where should DES models be needed is subjective, depending on the projected use of the model and the required levels of details. The most effective, feasible combination of models is desirable such that the advantages of both simulation methodologies are maintained, not compromised.

The next section presents a preliminary example to explain the essence of this approach. For the purpose of this paper the enterprise model is developed as a distributed simulation model. SD model and DES models will be built and run separately. Data from each model will be the input to the other models, in a feedback cycle. In the future the models will be communicating automatically with each other in a single running complete enterprise model. Communication issues are the subjects of a current research work.

5. An illustrative example

Our preliminary study investigated the potential of combining the DES and SD in modeling a manufacturing enterprise. This enterprise has two plants: a semiconductor fabrication plant (fab) and the sealer plant. The company is profitable, but the fab plant is contributing more to the company's total earnings. Strategic decisions of resource allocation are made at the top management levels. We are interested in the allocation of the financial resources to the plants. Capital can be allocated to plants according to one of three rules: proportional to net income, proportional to revenues, or proportional to profit margins. These decisions and all relevant information at the strategic level of the firm are modeled by the SD approach.

The operations at the plants are modeled using DES. Reinvestment decisions at the plant level, such as increasing capacity by acquiring new machine, hiring new people or improving existing facilities, will be validated and evaluated in the DES models. Feedback in terms of productivity and cost information and other measures will be given to the SD model. SD will react as appropriate to adjust the investment decision considering the feedback information and the allocation rules. The cycle continues until the best allocation of resources is obtained. Studying the interaction between the strategic planning and the shop floor activity is the core of this work.

5.1 The SD model

The principal objective is to study the dynamics of creating corporate growth with a positive economic value-added (EVA) in perpetuity. So far, no company has overcome the forces limiting corporate growth and making it vulnerable to ultimate merger, acquisition or failure. The model incorporates the corporate strategic level that decides the percentage of re-investment from the total profits and what portion of that re-investment will be allocated to each plant. In addition, the model captures the impacts of the decisions of the plant managers on how to invest the financial resources provided by corporate. The plant managers can buy more machines, increment/decrease the workforce, start R&D Projects (to increase sales and sustain the current product), and implement enhancement productivity projects (e.g., six-sigma). The model also models the supply chain of each plant, the decisions about the price of the different products and compiles the costs and revenues from each plant in order to generate the earnings before interest and taxes.

Causal loops were developed and transformed in differential equations. Figure 3 shows one of the causal loops developed. The two inner loops are both positive, while the outer loop is negative. Currently, the model has 10 differential equations and more than 50 auxiliary variables. Figure 4 shows a part of the stock-and-flow model related to the fab plant, and the decisions from the plant managers, and the results of the DES analysis of those decisions.

[Insert figure 3 here]

The corporate strategy in this firm is to re-invest 55% of the its earnings before interest and taxes (EBIT). The other 45% corresponds to taxes, interests, and dividends. The allocation of this re-investment can follow one of three different policies:

1. Proportional to Average Return. The reinvestment amount allocated to a plant will be based on the proportional size of its average return.
2. Proportional to Revenues. The re-investment amount allocated to a plant will be based on the proportional size of its revenues (with respect to the total revenues of the corporation).
3. Proportional to Earnings. The re-investment amount allocated to a plant will be based on the proportional size of its EBIT (with respect to the total EBIT of the corporation).

[Insert figure 4 here]

5.2 The DES model of the fab

The considered fab, which contains 24 workstations, is based on the work of (Wein 1988). With the exception of workstations 13 and 14, which have two and three identical machines respectively, each workstation has a single machine. The fab uses a single processing technology that requires 172 total operations at the 24 workstations. In this study we assumed only one type of wafer, so the processing sequence is the same for all orders.

[Insert figure 5 here]

Wafers are released into the fab in lots of 24 wafers, according to an exponential distribution with 42 hrs mean interarrival time. Lots are processed at each workstation according to First In First Served (FIFS) discipline. Processing times are based on Gamma distribution (shape parameter of two). Processing times are assumed to include setup times and transfer times between stations, and rework if needed. No limits on WIP capacity are assumed between workstations. However, machines are subject to failure and this is modeled by a Gamma distribution (shape parameter of 0.5). Values for mean processing times per lot at each machine, mean time between failure, and mean time to repair are taken from (Wein 1988).

The fab DES model is used to evaluate the impact of changes in demand and various decisions regarding the expenditures of additional financial resources. The DES outputs production rates, capacity projections, WIP information, and configuration data such as number of machines and workers. At the current capacity configuration and demand levels, the fab can complete 89.5% of released orders during the year, which corresponds to a production rate of 0.00056 lots/hr. However, machine utilization varies from 70% to 30%.

Market analysis has shown that the firm should expect and be ready for a considerable increase in demand, somewhere between 10% and 25%. The DES model shows that a 10% increase in demand would lead to a 7.8% reduction in completed orders, a 17.86% reduction in the production rate, and an increase in WIP of 33.33%. So, the plant cannot meet even the smallest projected increase in demand. Its only action is to expand capacity by getting more machines and more people.

Once the SD simulation decides how much of additional financial resources to provide the fab, the fab manager will decide how to allocate those resources to new machine and new people. The DES then computes the throughput and cost data, which are fed back to the SD where long-term earnings are estimated.

5.3 Results and implications

The integration of system dynamics and discrete-event simulation allowed us to simulate different hierarchical levels of the modern enterprise. The system developed was simulated with three different investment policies at the corporate level. The plant managers were able to balance between increased capacity, sustaining product improvement, and productivity projects. Figures 6, 7, and 8 have the results for three different investment policies. As can be seen on the charts, the allocation policy that is best for the corporate level is not so for both plants; only for one of them. Real time feedback information from the tactical and operational levels are needed and this is what our proposed hybrid model of the entire enterprise offers.

[Insert figure 6 here]

[Insert figure 7 here]

[Insert figure 8 here]

6. Conclusions and future work

This paper has been a preliminary analysis of the potentials of integrating system dynamics (SD) simulation models with discrete-event (DES) simulation models in an integrated hybrid approach to simulate manufacturing systems. We have shown the potential merit of such an approach in evaluating the impact of local production decisions on the entire enterprise. The SD simulations capture long-term effects of these decisions. They, SD and DES, also provide a more detailed analysis of the future stability of the enterprise.

The integration of SD and DES can provide a good framework for Enterprise Simulation. This framework can enable simulations at multiple resolutions in space and time. This will enhance the current modeling of the modern enterprise which is dominated by managerial hierarchies in which high corporate managers set objectives to their plant managers who, in turn, try to satisfy them by setting objectives and tasks to their personnel. Unfortunately, so far, the current enterprise simulation frameworks cannot mirror the hierarchical aspects of the enterprise and provide good answers to the decomposition of tasks and alignment of objectives at different levels.

Projected future work includes comprehensive studies to propose a set of criteria to define the attributes of manufacturing enterprise systems by which the modeler can decide on where DES model should fit in an overall SD model of the enterprise. The illustrative example in this paper has been in a distributed simulation-like model. The next step (which is currently under study) is to develop a methodology to communicate the DES models with the SD so that models run and interchange feedback information automatically in a single integrated simulation model.

References

Angerhofer, B., and Angelides, M., 2000, System dynamics modelling in supply chain management: research review. *Proceedings of the 2000 Winter Simulation Conference*, Joines, Barton, Kang, and Fishwick (editors).

Baines, T. S & Harrison, D. K., 1999, An opportunity for system dynamics in manufacturing system modeling. *Production Planning and Control*, 10 (6), 542-552

Barton, J. A., Love, D. M., Taylor, G. D., 2001, Evaluating design implementation strategies using simulation., *I. J of Production Economics*, 72, 285-299

Cardarelli, G. and Pelagage, P. J., 1995, Simulation tool for design and management optimization of automated material handling and storage systems for large wafer fab, *IEEE Transactions On Semiconductor Manufacturing*, 8(1), 44 - 49.

Chandy, K. M., and J., Misra, 1979, Distributed simulation: a case study in design and verification of distributed programs, *IEEE Transactions on Software Engineering*, 5(5), pp. 440-452.

Chang, Yoon & Makatsoris, Harris, 2001, Supply chain modelling using simulation, *I. J. of Simulation*, 2 (1), 24-30.

Cuburt, R. and Fishwick, P. (1997), Moose: An object-oriented multimodeling and simulation application framework, *Simulation*.

Delen, D., Benjamin, P., and Erraguntla, M. (1998), Integrated modeling and analysis generator environment (IMAGE): a decision support tool, *Proceedings of the 1998 Winter Simulation Conference*, pp.1401-1408.

Deshmukh, A. V., Talavage, J. J., and Barash, M. M., 1998, Complexity in manufacturing systems: part 1: analysis of static complexity, *IIE Transactions*, vol 30, number 7, pp. 645-655.

Ditto, W. L., Rauseo, S. N. and Spano, M. L. 1990. Experimental control of chaos, *Physical Review Letters* 65 (26): 3211-3214.

Ferscha, A., and Richter, M., 1997, Java based conservative distributed simulation. *Proceedings of the 1997 Winter Simulation Conference*, pp.381-388.

Fishwick, P. (1996), Web-based simulation: some personal observations, *Proceedings of the 1996 Winter Simulation Conference*, pp.772-779.

Forrester, J., 1958 *Industrial dynamics*, Productivity Press, Portland, OR, USA.

Forrester, J., 1971, *Principles of systems*. Pegasus Communications, Inc., Williston, VT, USA

Fox, Mark S. & Gurninger, Michael, 1998, Enterprise modeling., *AI Magazine*, 19 (3), 109-121

Fujii, S., Kaihara, T., and Morita, H., 2000, A distributed virtual factory in agile manufacturing environment, *International Journal of Production Research*, 38(17), pp. 4113-4128.

Gary W. Godding, Hessam S. Sarjoughian, & Karl G. Kempf, “Semiconductor supply network simulation”, *2003 Winter Simulation Conf, 7-10 Dec 03, New Orleans, USA*

Gregoriades, Andreas & Karakostas, Bill, 2003, Unifying business objects and systems dynamics as a paradigm for developing decision support systems. *Decision Support Systems*, 1049, 1-5.

Größler, Andreas, Stotz, Myrjam & Schieritz, Nadine, 2003, A software interface between system dynamics and agent-based simulations – linking Vensim® and RePast®”. 21st International conference, System Dynamics Society, July 20-24, New York, USA

Huang, George Q., Lau, Jason S. & Mak, K. L., 2003, The impact of sharing production information on supply chain dynamics: a review of literature., *I. J of Production Research*, 41 (7), 1483-1517.

Jefferson, D. and H. Sowizral, 1982, Fast concurrent simulation using the time warp mechanism; part I: local control, Technical Report N1906AF, Rand Corp.

Kim, Y. D., Lee, D. H., Kim, J. U. and Roh, H. K., 1998, A simulation study on lot release control, mask scheduling, batch scheduling in semiconductor wafer fabrication facilities, *Journal of Manufacturing Systems*, 17(2), 107 – 117.

Kuhl, F., R. Weatherly, and J. Dahmann. 1999. Creating computer simulations: an introduction to the high level architecture, Prentice Hall: Upper Saddle River, NJ.

Law, A. M. and Kelton, W. D., 1991, Simulation modeling & analysis, 2nd edition, McGraw-Hill.

Lee, Young Hae, Cho, Min Kwan, Kim, Seo Jin, Kim, Yun Bae, 2002, Supply chain simulation with discrete-continuous combined modeling. *Computer and Industrial Engineering*, 43, 375-392.

Levin, Tzur & Levin, Ilya, 2003, Integrating hybrid modeling with system dynamics. 21st International conference, System Dynamics Society, July 20-24, New York, USA

Lin, J. T., Wang, F. and Yen, P., 2001, Simulation analysis of dispatching rules for an automated interbay material handling system in wafer fab, *International Journal of Production Research*, 39(6), 1221-1238.

Mandal, Purnendu & Sohal, Amrik S. 1998, Modeling helps in understanding policy alternatives: a case. *Journal of Management in Engineering*, Jan/Feb, 41-48.

Min, H. S., 2002, Development of a real time multi-objective scheduler for semiconductor fabrication systems, Ph. D. Thesis, Purdue University, August, 2002.

Misra, S., Venkateswaran, J., and Son, Y., 2003, Framework for adaptive time synchronization mechanism for the integration of distributed, heterogeneous, supply chain simulations, *Proceedings of the 2003 ASME Conference*.

MISSION Consortium. 1998. *Intelligent manufacturing system (IMS) project proposal: modelling and simulation environments for design, planning and operation of globally distributed enterprises (MISSION), version 3.3*, Shimuzu Corporation, Tokyo, Japan.

Naim, M. and D. Towill, 1994, Establishing a framework for effective materials logistics management, *International Journal of Logistics Management*, Vol. 5, No. 1, 81-88.

O'Reilly, J. J. and Lilegdon, W. R., 1999, Introduction to FACTOR/AIM, *Proceedings of the 1999 Winter Simulation Conference*, 201 - 207.

Peters, B. A. and Yang T., 1997, Integrated facility layout and material handling system design in semiconductor fabrication facilities, *IEEE Transactions On Semiconductor Manufacturing*, 10(3), 360 - 369.

Ramakrishnan, S., S., Lee, and R., Wysk, 2002, Implementation of a simulation-based control architecture for supply chain integrations, *The 2002 Winter Simulation Conference, San Diego, CA*, *December 8-11*.

Cranfield University, 2000, Modeling and design of manufacturing systems, See: http://www.cranfield.ac.uk/sims/mem/mdms/aitoroyarbide/researchaitoroyarbide.htm.

Riddick, F and McLean, C., 2000, The IMS MISSION architecture for distributed manufacturing simulation, *Proceedings of the 2000 Winter Simulation Conference, Orlando, FL, December 10-13*.

Senge, P., 1994, *The Fifth Discipline.* Currency Doubleday, New York, NY, USA

Son, Y., Jones, A., and Wysk, R., 2003, Component based simulation modeling from neutral component libraries, *Computers and Industrial Engineering*, in press.

Sterman., J., 2000, *Business dynamics – systems thinking and modeling for a complex world*, McGraw Hill, New York, New York, USA.

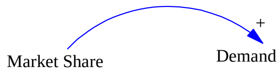
Towill, D., 1996, Industrial dynamics modeling of supply chain. *Logistics Information Management,* Vol. 9, No. 4.

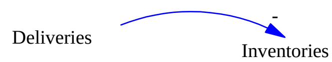
Umeda, S., and Jones, A., 1998, An integrated test-bed system for supply chain management, *Proceedings of the 1998 Winter Simulation Conference*, 1377-1385.

Venkateswaran, J. and Son, Y. 2003, Design and development of a prototype distributed simulation for evaluation of supply chains, *International Journal of Industrial Engineering*, in press.

Vernadat, F. B., 2002, Enterprise modeling and integration (EMI): current status and research perspectives., *Annual Reviews in Control*, 26, 15-25.

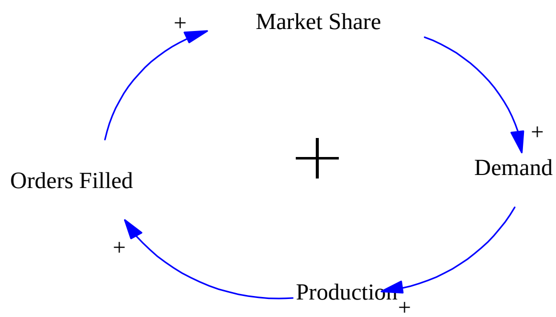
Wein, L M, 1988, Scheduling semiconductor wafer fabrication, *IEEE Transactions on Semiconductor Manufacturing*, Vol. 1, No. 3.

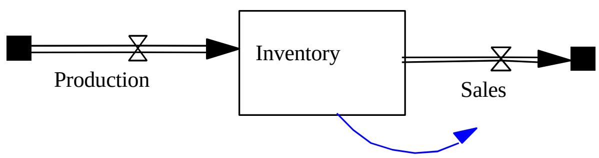




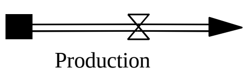
Link polarity positive:
If Market Share increases (decreases),
then Demand increases (decreases)

Link polarity negative:
If Deliveries increase (decrease),
then Inventories decrease (increase)





$$\frac{\partial(\underline{\text{Inventory}})}{\partial t} = \text{Sales - Production}$$

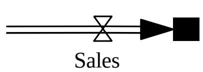


Inflow

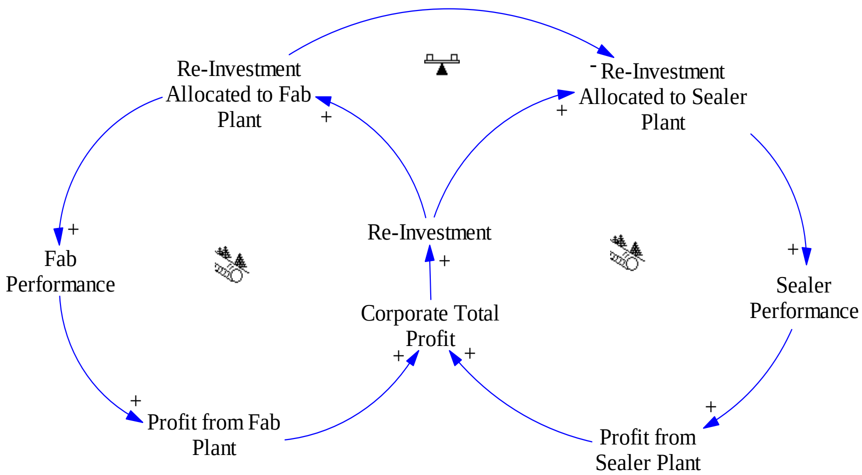
Stock


Sink or source

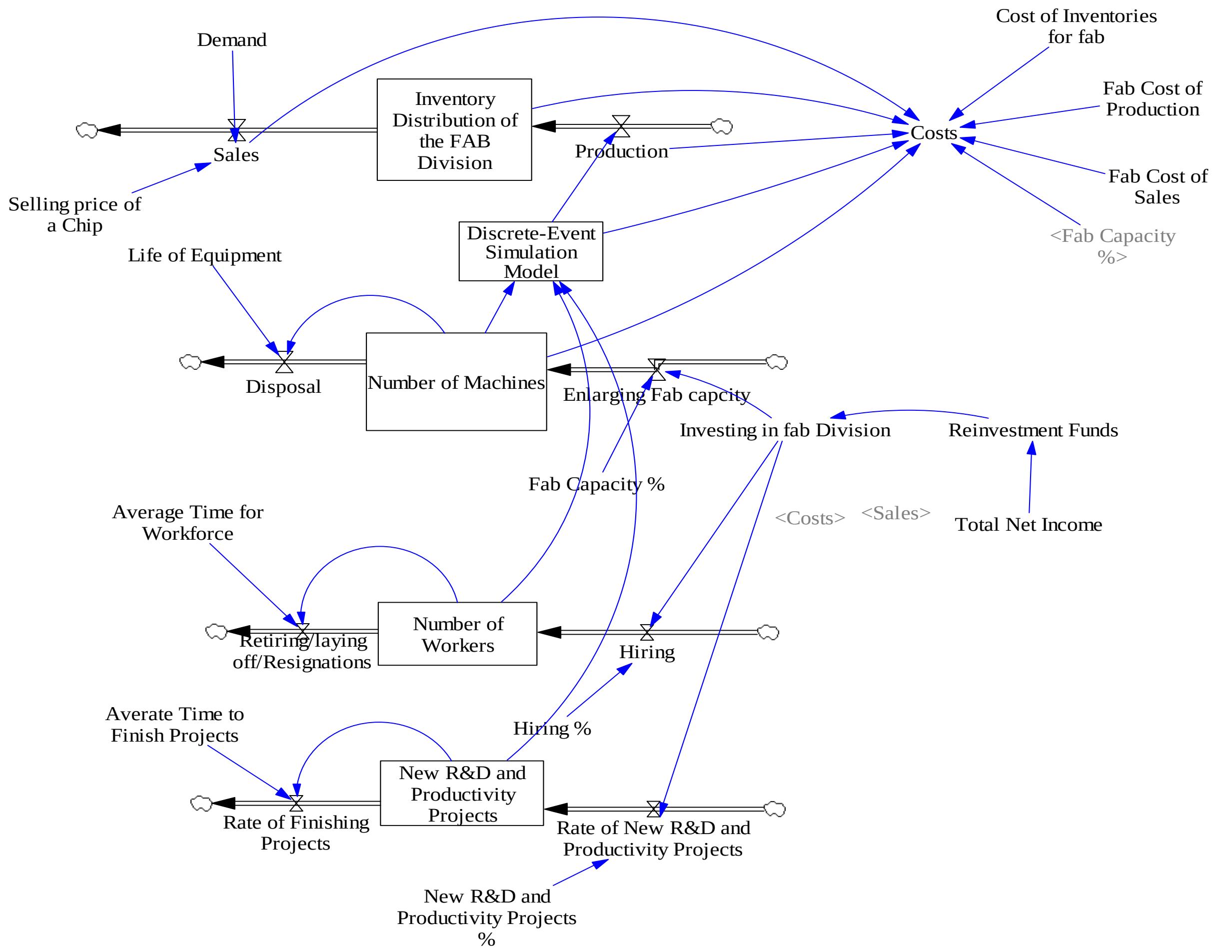

Valve



Outflow

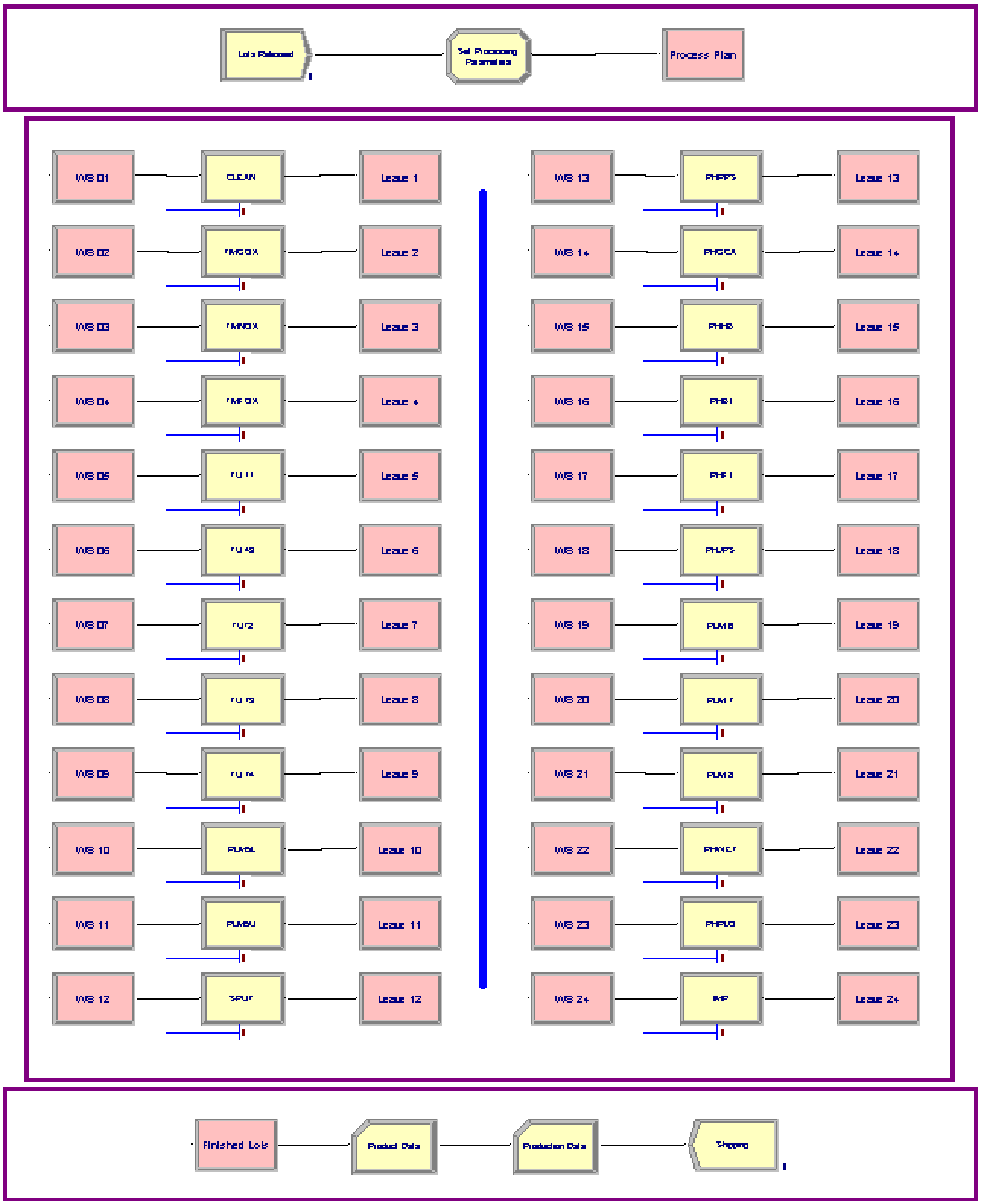


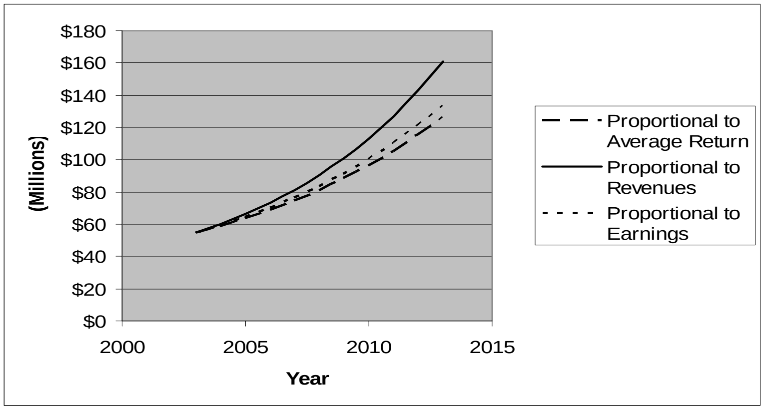
Re-Investment Allocated to Fab Plant
Re-Investment Allocated to Sealer Plant
Fab Performance
Re-Investment
Corporate Total Profit
Sealer Performance
Profit from Fab Plant
Profit from Sealer Plant

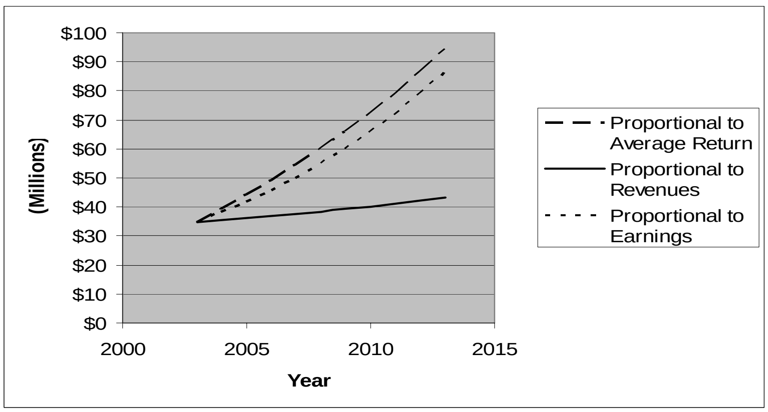


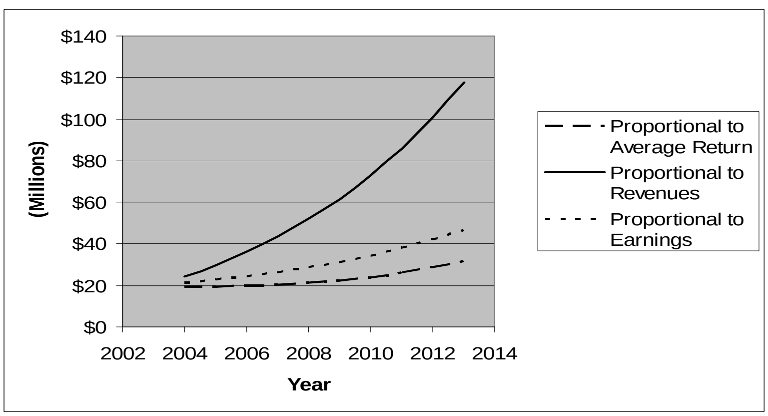
Demand
Cost of Inventories for fab
Inventory Distribution of the FAB Division
Fab Cost of Production
Costs
Sales
Production
Fab Cost of Sales
Selling price of a Chip
Discrete-Event Simulation Model
<Fab Capacity %>
Life of Equipment
Disposal
Number of Machines
Enlarging Fab capcity
Investing in fab Division
Reinvestment Funds
Fab Capacity %
<Costs>
<Sales>
Total Net Income
Average Time for Workforce
Number of Workers
Retiring/laying off/Resignations
Hiring
Averate Time to Finish Projects
Hiring %
New R&D and Productivity Projects
Rate of Finishing Projects
Rate of New R&D and Productivity Projects
New R&D and Productivity Projects %

The FAB Plant




$180
$160
$140
$120
$100
$80
$60
$40
$20
$0
(Millions)
2000
2005
2010
2015
Year
Proportional to Average Return
Proportional to Revenues
Proportional to Earnings


$100
$90
$80
$70
$60
$50
$40
$30
$20
$10
$0
(Millions)
2000
2005
2010
2015
Year
Proportional to Average Return
Proportional to Revenues
Proportional to Earnings


$140
$120
$100
$80
$60
$40
$20
$0
(Millions)
2002
2004
2006
2008
2010
2012
2014
Year
Proportional to Average Return
Proportional to Revenues
Proportional to Earnings

List of captions for figures