Proceedings of the 2004 Winter Simulation Conference
R .G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, eds.

HIERARCHICAL PRODUCTION PLANNING USING A HYBRID SYSTEM DYNAMIC-DISCRETE EVENT SIMULATION ARCHITECTURE

Jayendran Venkateswaran
Young-Jun Son

Department of Systems and Industrial Engineering
The University of Arizona
Tucson, AZ 85721-0020, U.S.A.

Albert Jones

National Institute of Standards and Technology
Manufacturing Systems Integration Division
Gaithersburg, MD 20899, U.S.A.

ABSTRACT

Hierarchical production planning provides a formal bridge between long-term plans and short-term schedules. A hybrid simulation-based production planning architecture consisting of system dynamics (SD) components at the higher decision level and discrete event simulation (DES) components at the lower decision level is presented. The need for the two types of simulation has been justified. The architecture consists of four modules: Enterprise-level decision maker, SD model of enterprise, Shop-level decision maker and DES model of shop. The decision makers select the optimal set of control parameters based on the estimated behavior of the system. These control parameters are used by the SD and DES models to determine the best plan based on the actual behavior of the system. High Level Architecture has been employed to interface SD and DES simulation models. Experimental results from a single-product manufacturing enterprise demonstrate the validity and scope of the proposed approach.

1 INTRODUCTION

All decisions in a manufacturing enterprise involve interactions between multiple departments or units, which are sometimes spread across geographic locations. There are no isolated decisions taken by any single department. For effective management of the enterprise, the global consequence of local decisions needs to be estimated. Global consequence refers to the impact of the policy decision of a department on both the policy selection of other departments and the future behavior of the entire enterprise. For example, the optimal order-quantity level, which is determined by the assembly department, influences (and is influenced by) the cycle time, the mode of transportation, shipment size and capacity requirements, all of which are determined by other departments.

Production planning is fundamental to the operation of a manufacturing enterprise. The basic problem is to determine the type and quantity of the products to produce, to meet uncertain demand in the future time periods. This problem can be formulated analytically, but it often results in very large-scale mathematical programming models. The computational requirements to solve such a centralized planning problem, which makes both long-term and short-term optimal decisions, are excessive. Hence it becomes necessary to develop alternate techniques which are computationally tractable and able to develop near optimal solutions. Decomposition techniques are one way to solve such large-scale models. A Hierarchical Production Planning (HPP) approach proposed by Hax and Meal (1975) is one such technique that separates the planning problem into distinct sub-problems based on the length of planning horizon, time and cost. The sub-problems correspond to different hierarchical levels of the manufacturing enterprise. They are solved such that the solution of the lower-level problem is constrained by the solution of the preceding higher-level problem.

Fundamental advantages of the hierarchical approach to production planning (Vicens, Alemany, Andrés, and Guarch 2001) include reduction of complexity, gradual absorption of random events, increased insight due to the use of aggregated figures, reduced need for detailed information, and better forecasting.

Numerous HPP models have been presented in the literature. Typically HPP is modeled as a two-level hierarchy – aggregate-planning level and detailed-scheduling level. The aggregate-planning level includes Master Production Scheduling (MPS) and Material Requirements Planning (MRP). At this level, three types of information aggregation are performed: parts to part families, time period to aggregate time periods, machine production rates (or capacity) to shop production rates (or capacity). The solution techniques depend on the scope and the specific manufacturing scenario. They include heuristics based on linear programming (LP) (Mehra, Minis, and Proth 1996; Qiu and Burch 1997), stochastic programming (Sethi, Zhang, and Zhang 2000), Enterprise Resource Planning

(ERP) tools (Das, Rickard, Shah, and Macchietto 2000; McKay and Wiers 2003), and optimization coupled with simulation-based evaluation (Byrne and Bakir 1999). Some of the drawbacks associated with such methods are given below:

- The use of deterministic data at the aggregate level does not account for the stochastic evolution of the actual system. Usually worst-case performance data are used at the aggregate level, leading to feasible but not optimal solutions. In addition, the dynamics of the underlying system are absent.
- Models assume infinite capacity and hence performance is assumed to remain constant irrespective of workload. This implies that Little's Law (which states that *Work-in-Progress = Throughput * Cycle time*) may be violated.
- Major drawback of the techniques is that they require reruns in case of unexpected external or internal events (Vicens, Alemany, Andrés, and Guarch 2001). Any exception (such as machine failures, new order arrivals) that endangers the validity of the current production plan leads to the regeneration of the entire plan.
- The solution of the models are optimal and valid only when the assumptions are true. Since the dynamics of the actual system is not accounted for, optimality is certainly questionable.
- The models are suitable only for simple planning scenarios. For more realistic scenarios, the sequential- solution approach may lead to sub-optimality, inconsistency, or infeasibility (Vicens, Alemany, Andrés, and Guarch 2001).

Similar kinds of uncertainties or disturbances occur at both the planning and scheduling levels. However, they are handled independently at each level. The interaction between the two levels are rarely considered. This is supported by past literature, which can be classified into two distinct areas: handling uncertainty in aggregate-planning models (Sethi, Zhang, and Zhang 2000; Byrne and Bakir 1999) and handling uncertainty in detailed-scheduling models (Piramuthu, Shaw, and Fulkerson 2000; Maione and Nayo 2001). These researchers deal with disturbances such as machine breakdowns, change in job priority, new order arrivals, and process time variation – but at one level or the other. This motivated our research to look at the impacts of planning level decisions on the scheduling function and scheduling level decisions on the planning function.

In this paper, we consider a manufacturing enterprise producing multiple products over multiple time periods, where each product is made up of a number of component parts. The focus here is to develop an integrated production plan and schedule for the enterprise. The manufacturing enterprise, which has a single fabrication facility, is modeled at two levels: an aggregate level and a detailed level. The aggregate model is used to generate the optimal assignment of production capacities to products over multiple time periods. These capacities are fed forward to the detailed model, which generates a daily production schedule. A feedback mechanism is employed so that the models are linked in time and space. The aggregate-level planning decisions are evaluated using a system dynamics (SD) model, in which the production activities are aggregated as flow rates over time. The detailed-level scheduling decisions are evaluated using a discrete event simulation (DES) model that captures the uncertainties in production.

A brief overview of the architecture of the integrated simulation environment for HPP along with a feasibility study was presented in Venkateswaran and Son (2004a). In this paper we provide more details about the architecture, specify the integration strategies, and discuss some of our experimental results.

2 PROPOSED ARCHITECTURE

We propose a two level HPP architecture, which is shown in Figure 1. The following four modules are identified in the architecture:

- Enterprise-level production planner
    - Enterprise-level decision maker,
    - System dynamics model of the enterprise.
- Shop-level production scheduler
    - Shop-level decision maker,
    - Discrete event simulation model of the shop.

The justification for using both a SD model and a DES model is presented below. We also give a detailed description of the different modules and their interactions.

The enterprise-level planner uses aggregated information that is generated by the shop-level scheduler. Four types of aggregation are performed: component parts into products; time period (minutes, hours) into aggregate time periods (weeks); machine production rates into shop production rate; part inventory into product inventory. We found it necessary to add the last one to the traditional approaches described above. The long-term forecasting and customer order arrivals are external to the scope of the current system.

The enterprise-level planner develops the production plan for products, and the shop-level scheduler develops the component-parts schedule. The enterprise-level decision maker selects the optimal set of control parameters based on: (1) the forecasted demand over the entire time horizon, and (2) the estimated product cycle time. The SD model captures the production and inventory dynamics of the enterprise, which are dictated by the decisions made by the shop scheduler. These control parameters are used by the SD model to determine the planned production order

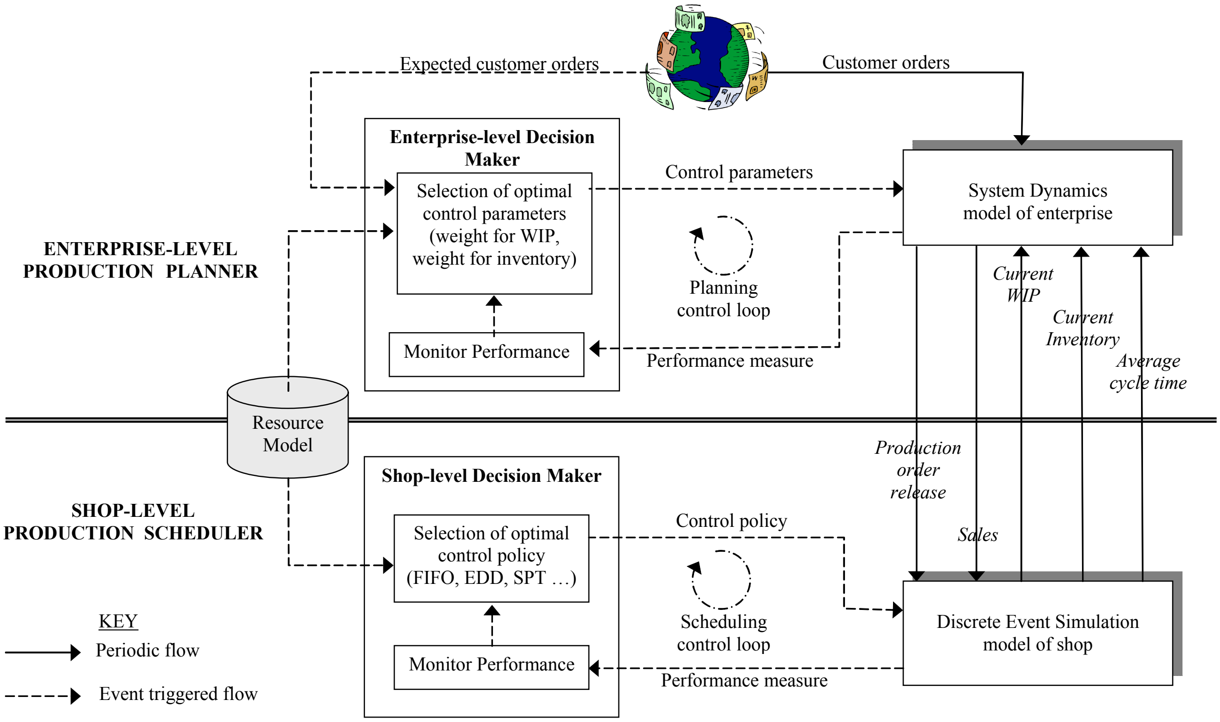

Figure 1: Architecture of Hybrid Simulation-Based Production Planning System

quantity to be released to the shop each period (a week). Further, the weekly production order release quantity of product is converted into daily order quantities and sent to the DES model of the shop.

The DES model captures the detailed operational procedures of the shop. The production order release quantity from the SD model is translated into release quantity of component parts whose flow through the shop is governed by queue rules or control policies. A shop-level decision maker determines the optimal control policies based on the estimated production order release quantities (obtained from enterprise-level decision maker). The daily update of work-in-process (WIP), inventory and average cycle time of products is fed back to the SD model from the DES model.

Feedback control loops are employed by the enterprise-level planner and shop-level scheduler to monitor the performance of the simulation models. The enterprise-level decision maker performs sensitivity analysis to determine the limits of variables (production completion rate of products and demand) for which the control parameters are still optimal. The performance of the SD model is monitored continuously; when the limits are crossed, the enterprise-level decision maker is invoked again to determine the new optimal control parameters. In a similar fashion, the shop-level decision maker monitors shop (DES model) performance and selects new control policies, as required. The shop performance is affected by disturbances such as machine failures and process time variations, which can be easily incorporated in to the DES model.

2.1 Why SD for Enterprise-level Simulation Model?

SD simulation consists of three core factors (Reid and Koljonen 1999): (1) the structure of the system, expressed in the form of feedback-based causal loop diagrams, (2) the frequency and duration of time delay in the feedback loops, and (3) the amplification of the information flows through the feedback structure. The behavior of the system is modeled as an interrelationship between the core factors. Thus, SD provides a framework to understand the operations of complex dynamic systems and view the impact of decisions on the entire enterprise.

In this case, the decision whose enterprise-wide impact must be assessed is the aggregate production plan. Traditional mathematical programming approaches to generate this plan use production capacity and demand forecasts as constraints, with both assumed to be known and fixed for each time period. However, making a prediction of the manufacturing system capacity at the beginning of each period is very difficult, often resulting in either overly optimistic or overly pessimistic constraints. This can result in sub-optimal or infeasible plans.

SD presents a natural way to model the dynamics associated with the production rates in the system. The interrelationships between the production rates with inventory, labor, and capacity utilizations can be explicitly modeled. The identification of the key factors, their relationships, and the time delays among those relationships can be captured in the causal feedback loops. Simulating such loops can provide insight into important causes and effects, which can lead to a better understanding of the dynamic and evolutionary behavior of the system as a whole. Hence, SD helps develop a time-based plan suitable to the actual dynamic system and not a predetermined plan based on a 'virtual' deterministic system analyzed by LP models.

2.2 Why DES for Shop-Level Simulation Model?

DES is typically used for performance data collection where important entities such as parts and resources are modeled using state variables that change only at discrete points in time, called event times. The simulation model advances by executing specific procedures at these event times and terminates when all events have passed. DES is a widely used method for studying the design and operations of manufacturing systems. There are two main reasons. First, DES can describe the most complex manufacturing systems and 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. These properties are especially important for the detailed scheduling level.

Traditional mathematical programming approaches to solving the detailed-level scheduling problem assume constant processing times, while in reality they are a function of the tool conditions, depth of cut, feed rate, etc. The stochastic events such as breakdowns, process time variations, deadlock, and new order arrivals cannot be considered. Hence, any violation of the aggregate plan by the detailed model or the violation of plan upon execution means that the entire HPP needs to be rerun.

As noted above, DES can model the uncertainty and unforeseen disturbances typical of manufacturing systems. Additionally, with some modifications, DES can even use real-time data collected from the shop floor. Hence, we believe that DES is the best choice to model accurately the required level of detail to ensure that the developed schedule is valid and the predetermined production plan can be met. Furthermore, the models can be changed easily and run quickly to reflect changes that occur in the real shop. When problems occur, the SD model can be informed immediately, as described below.

3 FUNCTIONALITY OF THE MODULES

Four types of modules are identified in the architecture (see Figure 1). The functionalities of the modules are presented in the following subsections.

3.1 Enterprise-Level Decision Maker

This module determines the optimal control parameters for use in the SD model. The control parameters or decision variables are the weights for the WIP factor and for the inventory factor; these weights are explained below. We give a sample formulation where the objective function (1) strives to achieve the minimum cost assignment of the production quantities of multiple products over the time horizon.

$$\min \sum_{t=1}^{T}\sum_{i=1}^{N} c_{it} X_{it} + \sum_{t=1}^{T}\sum_{i=1}^{N} s_{it} I_{it}^{-} + \sum_{t=1}^{T}\sum_{i=1}^{N} h_{it} I_{it}^{+} \qquad (1)$$

The planned production quantity (PO_{it}) is represented as a function of the work-in-process adjustment ($AWIP_{it}$), inventory adjustment (AI_{it}) and demand (D_{it}) (Equation 2). Equation (3) represents the WIP adjustment, with α as the weight for WIP factor. Equation (6) represents the inventory adjustment, with β as the weight for inventory factor. Equations (4)-(5) are the WIP balance equations and (7)-(9) are inventory balance equations. Production quantity (X_{it}) is further constrained by the expected performance (10) and the available capacity (11)-(12). The projected demand (D_{it}) over the time horizon will be the 'driving constraint' of the model.

$$PO_{it} = AWIP_{it} + AI_{it} + D_{it} \qquad (2)$$
$$AWIP_{it} = \alpha_i \left(DWIP_{it} - WIP_{it}\right) \qquad (3)$$
$$DWIP_{it} = D_{it} \times K_i \qquad (4)$$
$$WIP_{it} = WIP_{it-1} + PO_{it-1} - X_{it} \qquad (5)$$
$$AI_{it} = \beta_i \left(DI_{it} - I_{it}\right) \qquad (6)$$
$$DI_{it} = D_{it} \qquad (7)$$
$$I_{it} = I_{it-1} + X_{it} - D_{it} \qquad (8)$$
$$I_{it} = I_{it}^{+} - I_{it}^{-} \qquad (9)$$
$$X_{it} = WIP_{it-1} \div K_i \qquad (10)$$
$$X_{it} \le p_{it} \cdot TC_t \qquad (11)$$
$$\sum_{i=1}^{N} p_{it} = 1 \qquad (12)$$

In the above formulation, i is the index of products $\{1\ldots N\}$; t is the index of time periods $\{1\ldots T\}$ in weeks; c_{it}, h_{it}, s_{it} are the production, holding & shortage costs of product i in period t; X_{it} is the production quantity of product i in period t; PO_{it} is the production order release of product i in period t; $AWIP_{it}$ is the WIP adjustment of product i in period t; $DWIP_{it}$ is the desired WIP of product i in period t; WIP_{it} is the actual WIP of product i in period t; AI_{it} is the inventory adjustment of product i in period t; DI_{it} is the desired inventory of product i in period t; I_{it} is the inventory of product i at the end of period t with I_{it}^{+} and I_{it}^{-} indicating positive and negative inventory; K_i is the estimated cycle time of product i; TC_t the total available capacity at period t; p_{it} the percent capacity allocated for product i in period t; and D_{it} is the projected demand of product i in period t.

The output of the decision maker are two weights: the weight for the WIP factor (α), and the weight for the inventory factory (β). They are supplied to the SD model for use in calculating the weekly production order quantities. Sensitivity analysis on the values of α and β can be performed with respect to changes in the demand and the manufacturing cycle time. Limiting values of the demand and the cycle time, for which α and β values are optimal is determined. The performance of the SD model is continuously monitored and when the performance crosses the predefined limits, the enterprise-level decision maker is invoked to determine the new optimal values of α and β.

3.2 SD Model

The SD model simulates the production dynamics involved in the execution of the production plan. The dynamics are the result of the interrelationships between the different variables illustrated by the causal loop diagram in Figure 2. The enterprise decision maker supplies the inputs α and β, which are used in the calculations of normalized WIP (*NWIP*) and normalized inventory (*NINV*), respectively (Figure 2). Under conditions when the demand and production rates of the SD model are same as those estimated in the enterprise decision maker, then the production order release rate will match the values calculated in Equation (2). To accommodate variations in the demand and production rates, the production order release quantity is determined by the SD model based on the current dynamics of the system. The production rate (*PD*) can be more accurately represented as follows:

$$PR = f(\text{scheduling rules, resource status, WIP, CT}).$$

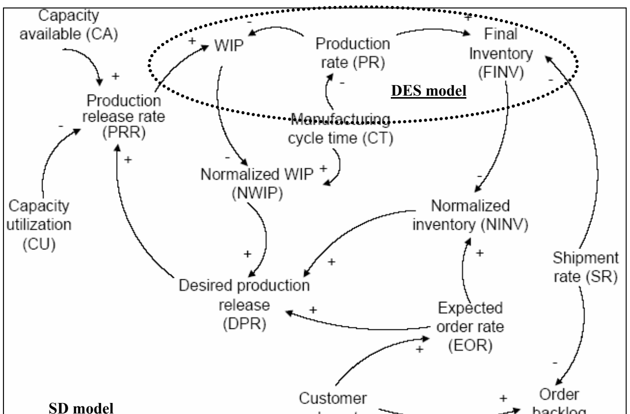

Figure 2: Causal Loop Diagram of the SD Model

Hence, at each integral time step of one day, the production order release to shop is sent to the shop-level DES model, and the current WIP, current inventory and average cycle time is received as input from the DES model.

3.3 Shop-Level Decision Maker

The shop-level decision maker determines the optimal scheduling rules to be used within the shop based on estimated production release quantities of products. In general, the schedule generated using optimization techniques, though provides optimal solution, cannot be directly executed in the shop floor. This prompted the use of dispatching rules and dispatching rule-based heuristic to decide as to which job is to be loaded next on a machine. The use of such rules has been shown, using simulation studies, to provide near optimal solutions. Adaptive scheduling technique is used in which the scheduling rules are tailored to the current state of the system. Techniques that incorporate a learning methodology for relating the various system parameters in determining the appropriate schedule are used for construction of the state-dependent schedule. The functions of the shop-level decision maker includes:

- Selection of a complete set of scheduling rules,
- Appropriate mapping of states to the scheduling rules,
- Ability to learn from the past decisions.

The queue rules thus selected are supplied to the DES model for use in determining the flow of the component parts.

Disturbances within the shop, such as machine breakdown or process time variations, cause deviations from the planned schedule. The performance of the DES model is monitored by the shop-level decision maker and when it crosses the predetermined threshold, new control policies are determined by the shop-level decision maker.

3.4 DES Model

The DES model represents the detailed operations including material processing, transfer and storage activities. It receives as inputs the production order release quantity of the product and the actual sales quantity of the product from the SD model. The production order release quantity of product is translated into release quantity of component parts. The flow of parts through the shop is governed by the control policies obtained from the shop-level decision maker. The current levels of inventory, WIP and cycle times are given as feedback to the SD model.

4 EXPERIMENT AND RESULTS

A manufacturing enterprise producing a single product consisting of three part components, A, B and C is considered. The product is assembled from one unit each of components A and C and two units of component B. Infinite supply of components is assumed available. The manufacturing shop, operating 24 hours a day, consists of 6 machines of unit capacity each. To account for real time variations in production, the processing time on each machine is represented as arbitrarily selected random distributions. Inter-machine part routing times are ignored.

4.1 Implementation Infrastructure

The enterprise-level SD model, as shown in Figure 3 is modeled using PowerSim®. The time units of simulation are in weeks. The time step of integration is chosen to be one day, which is small enough to capture the time frame of interest in the enterprise-level planner. The shop level DES model is built using Arena®. At each time step of the SD model, the production order release quantity and sales quantity are to be sent to the DES model and the current values of WIP, inventory and cycle time are to be obtained from the DES model.

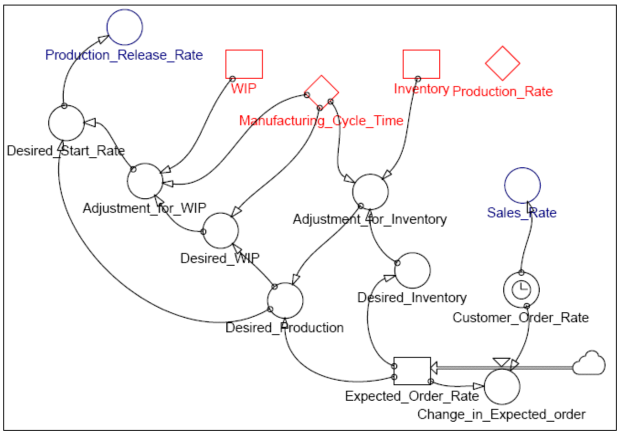

Figure 3: System Dynamics Model of the Enterprise

The interfacing between the SD (PowerSim®) and DES (Arena®) models has been enabled using the High Level Architecture's (HLA) RunTime Infrastructure (RTI) (Kuhl, Weatherly, and Dahmann 1999). The distributed Manufacturing Simulation (DMS) adapter (McLean and Riddick 2000) developed by NIST has been employed to interface the simulation models with the HLA/RTI. Previous work in using HLA/RTI to integrate multiple DES models has been successfully carried out by Venkateswaran and Son (2004b). To the best of our knowledge, this is the first time to successfully interface SD and DES models.

The sequence of interaction between the SD and DES models is illustrated in Figure 4. The DES model computes and sends the *WIP*, *Inventory* and average *Manufacturing_Cycle_Time* to the SD model (Figure 3). Upon receiving the data, the SD model integrates a time step and the rate of change of the variables *Production_Release_Rate* and *Sales_Rate* (Figure 3) is sent to the DES model. The product production release quantity received by the DES model is converted into component parts production quantities and released to the shop. The DES model is then simulated for a time period of 1 day, after which the feedback is sent to the SD model. The exchange of data between the models is achieved by transmitting eXtensible Markup Language (XML) based messages via the HLA/RTI.

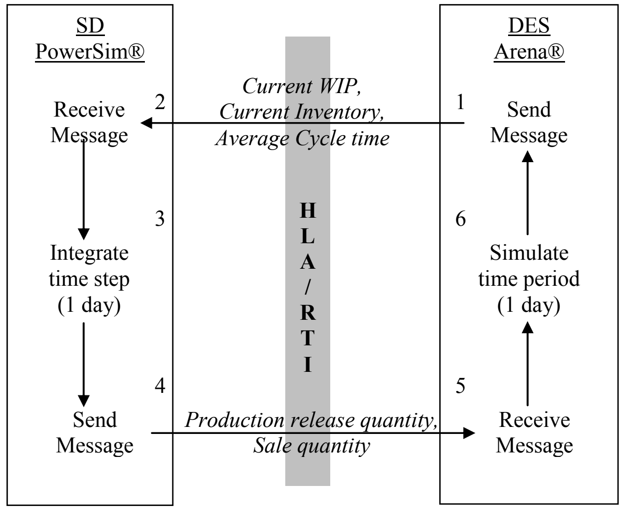

Figure 4: Sequence of Interaction between the SD and DES Models via HLA/RTI Platform

4.2 Selection of Decision Variables

The enterprise-level decision maker formulates and solves the non-linear program for a single product as specified by Equations (1)-(12) using LINGO®. The demand for product is estimated to be 100 units/ week. The cycle time is estimated to be 1.8 hours based on preliminary runs of the DES model of the shop. Upon solving the optimization program, the optimal values of control parameters α and β were found to be 1. These values of α and β are used in the SD model.

Since only a single product is handled by the shop, the queue rule First-In-First-Out was found to be the optimal control policy for all the machines.

4.3 Results

An integrated hybrid simulation model of the enterprise consisting of SD and DES models has been analyzed. Monitoring of the performance and the selection of new optimal control parameters at the enterprise and shop levels by the corresponding decision makers is ongoing work. In this paper, the interaction between the SD and DES models and the hybrid simulation infrastructure is validated.

The behavior of the hybrid simulation system in response to different demand trends has been analyzed. Under constant demand of 100 units/week, it is found that the simulation models reach steady state at week 8, as shown in Figure 5. It is noted that the *Customer_Order_Rate*, *Production_Release_Rate, Desired_WIP* and *Desired_Inventory* are obtained from the SD model while the *Production_Rate*, *Inventory* and *WIP* are obtained from the DES model. Under steady state, minor deviations of less than 5% from the *Cus-*

tomer_Order_Rate are observed in the *Production_Release_Rate* and *Production_Rate*. This is attributed to the process time variations within the shop, modeled by DES.

The stability of the system is studied under different demand patterns. A step increase of 10% in demand applied at week 18, resulted in the *Production_Release_Rate* to reach a maximum of 24% and the *Production_Rate* to reach a maximum of 18% (Figure 6). A rectangular blip in demand applied between weeks 18 to 23 resulted in the *Production_Release_Rate* to reach a maximum of 24% and minimum of -1% and the *Production_Rate* to reach a maximum of 18% and minimum of -8% (Figure 7).

The above observations (Figures 5-7) indicate that:

- The DES model behaves appropriately in response to the decisions taken by the higher level SD model,
- The SD model accurately accounts for the behavior of the lower level model. This is evident from the slight perturbations in the *production_release_rate* which is influenced indirectly by the *production_rate* from the DES model,
- The hybrid simulation framework provides a seamless integration between SD and DES models. Hence, this framework can be used to analyze the impact of higher level decision on the lower level and vice versa. Also, a simultaneous study of local and global behavior of system is enabled.

5 CONCLUSION AND FUTURE RESEARCH

A novel approach in solving the hierarchical production planning problem has been presented. The manufacturing enterprise is represented by an enterprise-level production

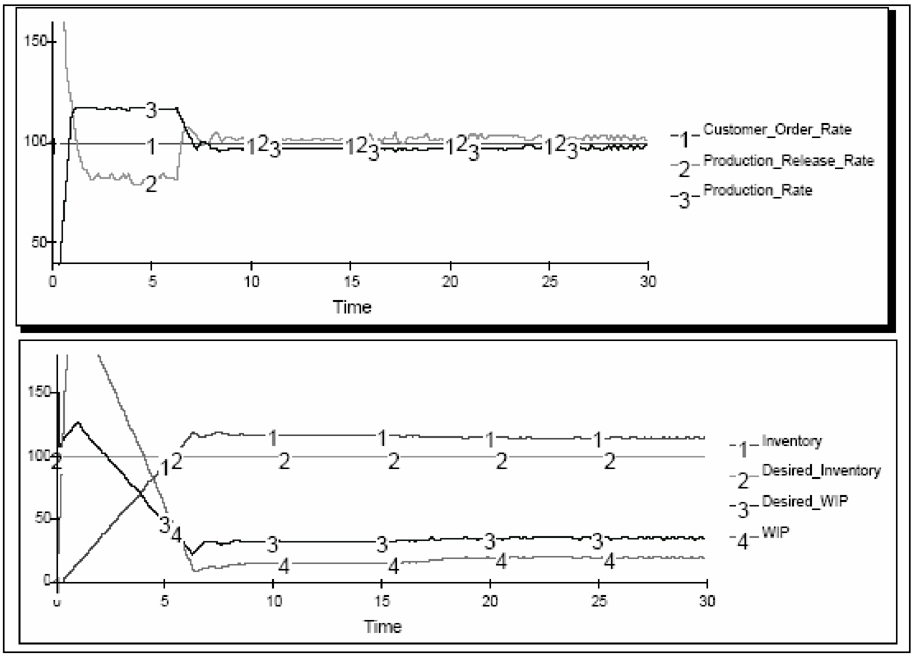

Figure 5: Behavior of System in Response to Constant Demand

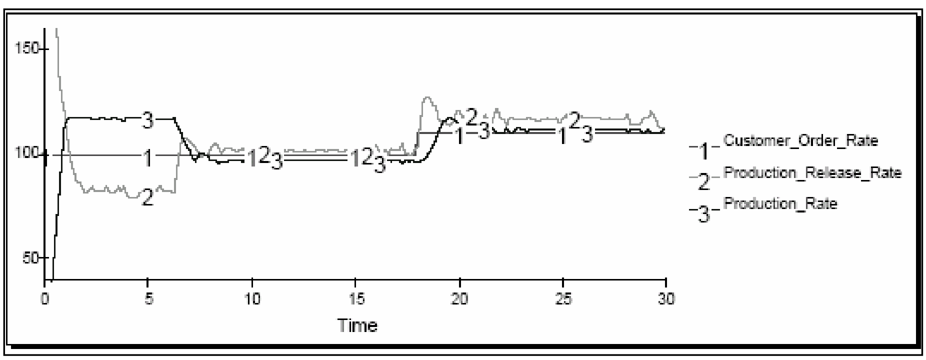

Figure 6: Behavior of System in Response to Step Increase in Demand

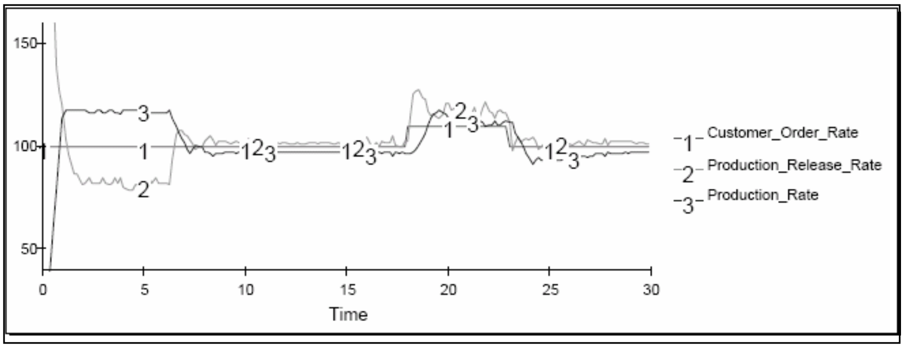

Figure 7: Behavior of System in Response to Rectangular Blip in Demand

planner (decision maker + SD model) and a shop-level production scheduler (decision maker + DES model). The enterprise-level decision maker selects the optimal set of control parameters, that is, weight for WIP and weight for inventory. These control parameters are used by the SD model. The production order release quantity of product and the sales per period, calculated by the SD model are sent to the shop-level DES model. The current WIP, current inventory and average cycle time are received as feedback from the DES model. A shop-level decision maker is employed to determine the queue rules or control policies to govern the flow of parts within the shop. Feedback control loops are employed at the enterprise-level and the shop-level to monitor system performance and update the control parameters.

The first stage of experiments has been conducted using a single-facility single-product manufacturing enterprise. The interactions between the different modules of the hybrid simulation-based architecture have been described. The SD and DES models have been integrated using HLA/RTI and DMS adapter. To the best of our knowledge, this work is the first to successfully interface SD and DES models. The validity of the hybrid simulation approach has been analyzed (Figures 5-7).

Work is currently being carried out to enhance and refine the interactions between the modules. Specifically, the selection of appropriate measure of performance for use in the feedback control loops; interface of the decision makers with the corresponding simulation models; and extensions to include multiple products. The performance of the proposed hybrid simulation model is to be benchmarked against existing HPP systems.

PRODUCT DISCLAIMER

Certain commercial software products are identified in this paper. This use does not imply approval or endorsement by NIST, nor does it imply that these products are necessarily the best available for the purpose.

REFERENCES

Byrne, M. D. and M. A. Bakir. 1999. Production planning using a hybrid simulation – analytical approach. *International Journal of Production Economics* 59: 305-311.

Das, B. P., J. G. Rickard, N. Shah and S. Macchietto. 2000. An investigation on integration of aggregate production planning, master production scheduling and short-term production scheduling of batch process operations through a common data model. *Computers and Chemical Engineering* 44: 63-72.

Hax, A. C. and H. C. Meal. 1975. Hierarchical integration of production planning and scheduling in *Studies in the Management Sciences*, ed. M. A., Geisler. Vol. I, *Logistics*, North-Holland, Amsterdam.

Kuhl, F., R. Weatherly and J. Dahmann. 1999. *Creating Computer Simulations: An Introduction to the High Level Architecture*. Upper Saddle River, NJ: Prentice-Hall.

Maione, B. and D. Naso. 2001. Evolutionary adaptation of dispatching agents in heterarchical manufacturing systems. *International Journal of Production Research* 39(7): 1481-1503.

McKay, K. N. and V. C. S. Wiers. 2003. Integrated decision support for planning, scheduling and dispatching tasks in a focused factory. *Computers in Industry* 50: 5-14.

McLean, C. and F. Riddick. 2000. The IMS Mission architecture for distributed manufacturing simulation. In *Proceedings of the 2000 Winter Simulation Conference*, ed. J. A. Joines, R. R. Barton, K. Kang, and P. A. Fishwick, 1540-1548. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Mehra, A., I. Minis and J. M. Proth. 1996. Hierarchical production planning for complex manufacturing systems. *Advances in Engineering Software* 26: 209-218.

Piramuthu, S., M. Shaw and B. Fulkerson. 2000. Information based dynamic manufacturing system scheduling. *International Journal of Flexible Manufacturing Systems* 12: 219-234.

Qui, M. M. and E. E. Burch. 1997. Hierarchical production planning and scheduling in a multi-product, multimachine environment. *International Journal of Production Research* 35(11): 3023-3042.

Reid, R. A. and E. L. Koljonen. 1999. Validating a manufacturing paradigm: a system dynamics modeling approach. In *Proceedings of the 1999 Winter Simulation Conference*, ed. P. M. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans, 759–765. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Sethi, S. P., H. Zhang and Q. Zhang. 2000. Hierarchical production control in a stochastic N-machine flow shop with limited buffers. *Journal of Mathematical Analysis and Applications* 246: 28-57.

Venkateswaran, J. and Y. Son. 2004a. Distributed and hybrid simulations for manufacturing systems and integrated enterprise. In *Proceedings of the 2004 Industrial Engineering Research Conference*.

Venkateswaran, J. and Y. Son. 2004b. Design and Development of a Prototype Distributed Simulation for Evaluation of Supply Chains. *International Journal of Industrial Engineering* 11(2): 151 - 160

Vicens, E., M. E. Alemany, C. Andrés and J. J. Guarch. 2001. A design and application methodology for hierarchical production planning decision support systems in an enterprise integration context. *International Journal of Production Economics* 74: 5-20.

AUTHOR BIOGRAPHIES

JAYENDRAN VENKATESWARAN is a Ph.D. candidate at the Department of Systems and Industrial Engineering at The University of Arizona, Tucson, Arizona. He received his M.S. in Industrial Engineering from The University of Arizona and his M.Sc. (Tech) in Engineering Technology from Birla Institute of Technology and Science, Pilani, India. His research interest lies in simulation and distributed decision making within integrated enterprise. He can be reached by email at <`jayendran_v@sie.arizona.edu`>.

YOUNG JUN SON is an assistant professor in the Department of Systems and Industrial Engineering at The University of Arizona. Dr. Son received his BS degree in Industrial Engineering with honors from POSTECH in Korea in 1996 and his M.S. and Ph.D. degrees in Industrial and Manufacturing Engineering from Penn State University in 1998 and 2000, respectively. His research focuses primarily on the application of distributed and hybrid simulation to the analysis and control of automated manufacturing system and integrated enterprise. He has been selected by the SME to receive their 2004 M. Eugene Merchant Outstanding Young Manufacturing Engineer Award. Dr. Son was the Rotary International Multi-Year Ambassadorial Scholar in 1996 and the Council of Logistics Management Scholar in 1997. He is an associate editor of the International Journal of Modeling and Simulation and the International Journal of Simulation and Process Modeling, and a professional member of ASME, IEEE, IIE, INFORMS, and SME. He can be reached by email at <`son@sie.arizona.edu`>.

ALBERT JONES is manager of the Enterprise Integration program at the National Institute of Standards and Technology (NIST). He also served as Deputy Director of the Automated Manufacturing Research Facility at NIST. His research includes the development of system architectures for shop floor control, cell control, distributed scheduling, and supply-chain simulation. For several years, Dr. Jones served on the Executive Board for the Winter Simulation Conference and is currently on the Advisory Boards for the Engineering School at Loyola College and Morgan State University. He has chaired or co-chaired several international conferences, and has served on several proposal evaluation panels for NSF, NIST, and DARPA. He can be reached by email at <`jonesa@cme.nist.gov`>.