Distributed and Hybrid Simulations for Manufacturing Systems and Integrated Enterprise

Jayendran Venkateswaran and Young-Jun Son
Department of Systems and Industrial Engineering
The University of Arizona
Tucson, AZ 85721-0020, USA

Abstract

Two categories of simulation that have gained prominence in the past decade are discrete event simulation (DES) and system dynamic simulation (SD). DES is used to model a system in detail to comprehend the actual behavior of the individual components. In contrast, SD simulation is used to build models using aggregated data for system wide dynamic flow analysis of managerial decisions. The need for an integrated hybrid simulation environment is highlighted and prototype architecture is presented. An application methodology in the area of hierarchical production planning in a manufacturing enterprise along with a preliminary feasibility analysis is then presented.

Keywords
Hierarchical modeling, hybrid simulation, system dynamics, discrete-event

1. Introduction
Modeling of complex systems such as manufacturing systems is an arduous task. The success of a model in predicting the future behavior of the system and deciding the best alternative course of actions depends on *how* the system is modeled. The same system can be represented using different types of models depending on (i) the purpose of the model, (ii) the elements of the system modeled, and (iii) the perceived interaction between the elements. Also, the validity of the model and applicability of the results are critical upon its operating assumptions. A detailed monolithic model can be used to analyze a manufacturing enterprise. The primary drawbacks of such a model are the high computation time, high memory requirements, and the requirement of accurate information on all aspects of manufacturing. Well defined information may be available for certain aspects of production such as processing times, set-up times and part routing data, while only rough estimates may be available for other aspects such as operator efficiency and machine failures. This results in different components of manufacturing to be modeled in different degrees of detail. This may not provide an accurate estimation of the performance measure. Hierarchical modeling of manufacturing system at multiple levels of abstraction can be used to overcome the above mentioned drawbacks. In a hierarchical model two or more models at *different* levels of detail interact with each other to arrive at the best possible solution.

Operations research, heuristics and simulation techniques can be used to model a system. Among these, simulation techniques have gained prominence over the past decade for modeling and evaluating complex systems, especially manufacturing systems. By far, discrete event simulation (DES) has been the most popular technique to analyze manufacturing systems [1]. DES models are typically used to study system behaviors in response to specific and detailed events at discrete points in time. The advantage of DES modeling is that the system can be represented in detail which increases the accuracy of analysis. In system dynamics (SD) simulation, the flow interactions within the system are modeled using causal relationships with a feedback structure [2, 3]. SD has also been found to achieve good results in appraising the performance of the system, provided all the exogenous and endogenous components and their interactions are captured [4]. Table 1 presents a comparison of DES and SD techniques.

In this work a hierarchical hybrid simulation environment, combining system dynamic and discrete-event simulation, is proposed. SD models use aggregated data for understanding the dynamics of the system and DES models consider detailed information to comprehend the actual behavior of the individual system components. A given manufacturing system is represented using both SD and DES models. These models complement each other to arrive at the best possible solution. This paper presents a sketch of the hybrid simulation along with an example in the manufacturing domain.

Table 1: Comparison of DES and SD techniques

Factor	Discrete Event Simulation	System Dynamics Simulation
What is modeled?	Tasks/ events using state variables & their attributes	Flow using stocks, rates, auxiliary variables
Relative level of analysis	Operational decision analysis (lower level) using detailed representation of the system	Managerial decision analysis (upper level) using aggregated data
Complexity	Increases exponentially with the system complexity	Increases linearly with system complexity; complex system can be modeled with limited information
What is known?	Behavior of the individual items	Interaction between the components via feedback loops
What is unknown?	Interaction between the various items; and the influence of an item on the system outcome	Behavior of the individual components; and the influence of a component on the system outcome
Model validity depends on …	Ability to capture all the items of the system and model their behavior to all possible scenarios	Ability to aggregate all the key system data and quantify their possible influence on each other
Statistical details	General system wide statistics as well as individual item statistics such as utilization, number in queue	General system wide statistics such as production rate, inventory level
Typical usage	To determine operational decision such as in scheduling, capacity planning; Understand the behavior of the system components	To design and determine strategic policies for supply chain; Understand the underlying dynamics of the system; Study the stability

2. Literature Review

Simulation package combining discrete-event and continuous-time simulations have gained importance in the past few years. χ language has been used by Van Beek et al. [5] to model and simulate discrete-continuous systems. The continuous time aspects of the system are modeled using differential algebraic equations. The interaction between the discrete and continuous parts is achieved by synchronous communication. Architecture for hybrid simulation using Simple^{++} and SAM simulator to model the discrete and continuous aspects of a flexible manufacturing system, respectively, has been presented by Petropoulakis and Giacomini [6]. Hurdles in the integration of the simulations in terms of time and information coordination were encountered. Lee et al. [7] proposed another framework of discrete-continuous combined modeling for a supply chain system. They presented equations to represent the continuous aspects of the supply chain (e.g., ordering rate, shipping rate and inventory) which is then integrated with the discrete aspects such as transportation activities. The results of the combined approach are found to be comparable with those of discrete-event simulation. Rabelo et al. [1] have described the potential merit of integrating SD and DES models to evaluate the impact of local production decisions on the global enterprise. It is observed that in the past works [1, 5-7] the hierarchical decomposition and vertical integration of the tasks and objectives at the various levels of the enterprise are missing. Zülch et al. [8] used the simulation modeling tool *OSim*, to allow for the integration of variously detailed sub-models into an overall global model of the system. A global simulation model was hierarchically combined with sub-models which were invoked to provide an accurate estimation of the parameters. Ball [9] has shown that hierarchical simulation technique that allows for the appropriate level of detail is required to simplify models and expedite analysis. The rules and procedures to carry out the hierarchical decomposition were also presented [9]. Scholl [10] presents a cross study between agent-based modeling and SD where the benefit of individual based modeling and aggregate feedback modeling is emphasized.

3. Hybrid Simulation Environment

The hybrid simulation consists of two layers. In the lower layer, the individual system components are modeled in detail using DES. In the upper layer, aggregated data is used to model the system dynamics. The demarcation of the layers are purely relative and based on the observation that DES models are more suitable for the analysis of operational decisions (low level) while SD models are more suitable for dynamic flow analysis of managerial decisions (high level). It is noted that the DES model and SD model represent the same system from two different perspectives. The models will not duplicate each other, but would instead complement each other. DES models the detailed operations of the system where the movement of individual items though the system is traced. The SD model abstracts the detailed operations along with the other exogenous and endogenous activities that influence the dynamics of the system. Figure 1 presents the prototype architecture of the hybrid environment. As shown in Figure 1, functional activities modeled in SD can be decomposed into multiple detailed DES models. The scope of the SD model is broader (e.g., entire enterprise) while the DES models are specific and detailed (e.g., individual member of enterprise). Each SD and DES model is associated with a separate optimization module. Further description of the hybrid simulation system is presented using an application specific example in Section 4.

The mapping (illustrated in Figure 1) between the low level DES model and the high level SD model is achieved via (i) the level of aggregation (disaggregation); (ii) boundary expansion (compression), and (iii) causation. The level of aggregation refers to the number of internal components represented, where an aggregate model indicates an abstract model and a disaggregate model indicates a detailed model. The manufacturing enterprise can be disaggregated into the most detailed model which will be represented using DES rather than SD. This is mainly due to the following reasons [1]: (i) DES has the ability to describe the complex system; (ii) DES allows one to track the status of individual components through the system and estimate numerous performance measures. Boundary refers to how extensive the flow of material and information is represented. The boundaries are illustrated by clouds at the start or the end of flow rate arrows representing infinite source or sink respectively (see Figures 1 and 2). This may result in erroneous analysis of a system, as components that may influence the system performance are unwittingly left out. Causal relationship represents the system's feedback structure. A causal loop diagram consists of variables connected by arrows denoting the causal influence among the variables. The important feedback loops are identified and help create a complete dynamic model of the system.

3.1 Interaction Specification

In the current research work, the simulation models that are to be coupled differ in the level of detail. Framework for the interoperability of multiple simulations has been provided through the development of High Level Architecture (HLA). Several works have been presented in which multiple simulation models, all at the same level of detail, have been integrated horizontally. Several factory level simulation models are integrated to analyze the supply chain system [11]; or several cell level simulations are constructed to simulate the factory [12]. The HLA-framework establishes the technical foundation for combination of sub-models, but does not solve the problem that arises if different paradigms, points of view and levels of detail occur when simulation models are coupled [8]. Typical interactions between multiple simulation models can be broadly classified into information synchronization and time synchronization. Time synchronization is conducted to ensure that the simulation events of each model are processed in the correct time-stepped order [13]. This is critical for simulations where the time dependent status of the common variables needs to be coordinated. Synchronization of information must specify as to what information needs to be exchanged between the low level DES and the high level SD models, when the exchange must take place, how information is transformed, and how the information is utilized by the models. Informal specification of the interaction for a specific case is illustrated in Sections 4 and 5. Formal specifications for generic interactions of a manufacturing enterprise are on going work.

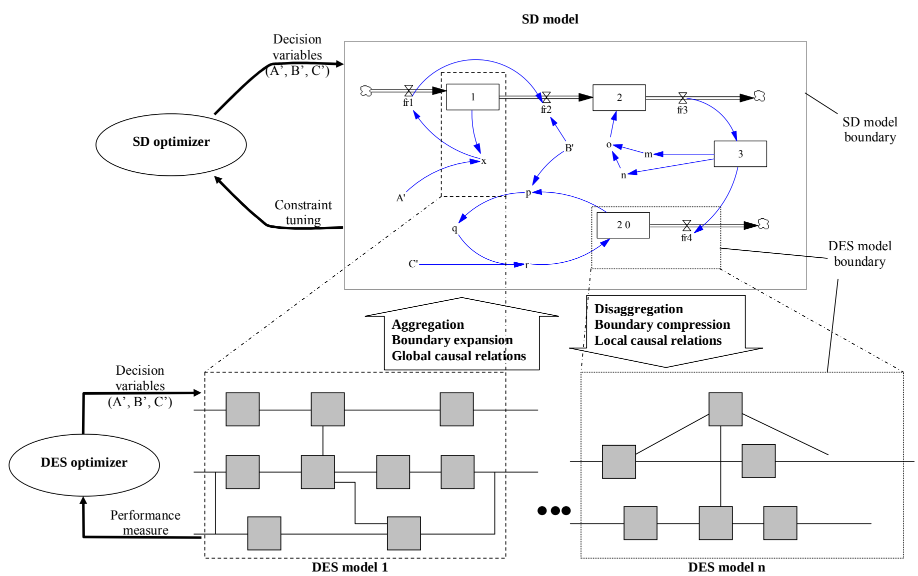

Figure 1: Architecture and mapping between DES and SD models

4. Application to Hierarchical Production Planning (HPP) Problem

Production planning is fundamental to the operation of a manufacturing system. The basic problem is to determine the type and quantity of the products to produce, meeting fluctuating demand in the future time periods. This problem can be formulated analytically which, more often than not result in very large scale monolithic mathematical programming models. The practical infeasibility (and difficulty to solve) of such a single central planning module in taking long term and short term decisions is well known. An alternative approach is to separate the planning problem into distinct sub-models based on the length, time and the associated cost of the planning horizon. This is referred to as HPP and is typically modeled using higher level aggregate models and lower level detailed models. Consider the scenario where the manufacturing enterprise produces multiple products, where each product is made of a number of component parts. The enterprise consists of two plants: a finished goods manufacturer and the work-in-progress component parts supplier. The players operate in a decentralized manner. The end customer places demand on the manufacturer, which in turn places demand on the supplier. Unknown stochastic demand and operational disturbances of the players are considered to be the norm rather than the exception. Information with regards to the operational disturbances can be easily incorporated within a DES model of the player. The global performance of the player's inventory management, forecasting and ordering policies can be captured better by the SD model than a DES model. Hence, for the problem of interest, a novel but efficient approach is taken to combine the SD and DES aspects to complement each other.

The aggregate level planning decisions are modeled using a SD model where the production activities are approximated as flow rates over longer time horizons. The detailed level scheduling decisions are modeled using DES to capture various uncertainties in production. Based on the generic architecture presented in Figure 1, the manufacturer and supplier are represented by a SD model and a DES model, respectively. Each SD and DES model is associated with individual optimization modules referred to as SD optimizer and DES optimizer, respectively. The functionalities of each of the modules are as follows.

- *SD Optimizer*: The decision variable of the SD optimizer is the production quantity of the final products on a period-by-period basis. A sample formulation for the manufacturer is shown below where the objective function (1) strives to achieve the minimum cost assignment of the production quantities over the time horizon.

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

  The planned production quantity is constrained by the available capacity (2)-(4), projected demand (5) and inventory balance equations (6)-(8). The projected demand over the time horizon will be the 'driving constraint' of the model. Similar formulation can be framed for the supplier.

$$X_{it} \le MAXCAP_{it} \quad (2)$$

$$MAXCAP_{it} = p_{it} \cdot TOTALCAP_{t} \quad (3)$$

$$\sum_{i=1}^{N} p_{it} = 1 \quad (4)$$

$$PD_{it} = FD_{it} + AD_{it} \quad (5)$$

$$I_{it} = I_{it-1} + X_{it} + PD_{it} \quad (6)$$

$$I_{it} = I_{it}^{+} + I_{it}^{-} \quad (7)$$

$$I_{it}^{+} \cdot I_{it}^{-} = 0 \quad (8)$$

c_{it}, h_{it}, s_{it}:	Production cost, holding cost & shortage cost of product *i* in period *t*.
X_{it}:	Production quantity of product *i* in period *t*.
$MAXCAP_{it}$:	Max capacity of product *i* in period *t*.
$TOTALCAP_{it}$:	Total production capacity at period *t*.
p_{it}:	Capacity allocated for product *i* in period *t*
I_{it}:	Inventory of product *i* at the end of period *t*.
I_{it}^{+}, I_{it}^{-} :	Indicates positive and negative inventory
PD_{it}, FD_{it}, AD_{it}:	Projected demand, forecasted demand and actual demand of product *i* in period *t*.

- *SD Model*: Based on the production plan (of products) input from the SD optimizer, the SD model simulates the production dynamics of the individual component parts. If the production plan is found to be infeasible, the information is fed back to the SD optimizer in terms of modified capacity constraints. Also, the SD models of the supplier and the manufacturer interact with each other to develop a globally efficient production plan. A negotiation based game theoretic approach is utilized for the coordination of the supplier and manufacturer production plan.
- *DES Model*: The DES model represents the detailed operations including material processing, transfer and storage activities. It receives as inputs the production plan of the component part from the SD model, forecasted demand and the actual customer orders. DES optimizer is used to determine the optimum schedule based on part dispatching rules. The interaction specification between the between the SD and DES model are also significant. Consider that the six month production plan is generated by the SD model. Upon execution of the plan by DES, the validity of the plan will be threatened by the unpredictable behavior of the enterprise such as change in demand pattern, failure of equipments etc. Hence, the plan needs to be updated to continue efficient operations. The DES can report back to the SD to generate a new plan when, (i) one or *n* consecutive weeks' production plan is not met, (ii) inventory levels cross pre-determined threshold limits, (iii) actual demand is significantly different from the projected demand, (iv) combination of above methods.

The development of formal specifications and implementation of the HPP problem is on going work.

5. Preliminary Study

As an initial step, the potential benefits of combining SD and DES are evaluated by modeling a sample manufacturing system in this section, where the effect of operational disturbances such as machine failures onto the inventory management policy of the manufacturing enterprise is studied. The manufacturing facility is said to produce the final product by assembling components A, B and C. One final product is assembled with one element each of components A and C and two elements of component B. Infinite supply of each component is available. The Manufacturer, operating 24 hours a day, consists of six machines of unit capacity each. The processing times are deterministic and inter-machine part routing times are ignored. The DES model has been built using the modeling package Arena^{TM}. The wholesome SD model of the facility illustrating the inventory management procedure is shown in Figure 2 A [3]. All customer orders are assumed to be fulfilled instantaneously. The production order rate is modeled as a function of the forecasted demand, desired inventory, actual inventory, desired WIP and current WIP. The production rate and manufacturing cycle time of the SD model are determined based on trial runs conducted using the DES model. The SD model has been built in Powersim^{TM} 2.5.

The interaction between the SD model and the DES model is shown in Figure 2 B. The dotted box in Figure 2 A is now replaced by the DES model within the dotted box in Figure 2 B. The SD model determines the desired production start rate based on the customer demand trend. Estimates of the production rate and manufacturing cycle time complete the feedback loop in the SD model. Instead of using the rough estimates, the desired production start rates can be given as an input to the DES model, which would yield the actual (more accurate) production rates. In the DES model, the production rate is converted into time between arrivals of the raw materials, which is updated for every integration time step of the SD model. The production rate obtained can be used instead in the SD model to analyze the system behavior more accurately.

Figure 3 illustrates the behavior of the manufacturing system as estimated by the SD model and the actual behavior as shown by the DES model. Figure 3, left and right graphs, shows the behavior in response to a step demand and a triangular blip in demand, respectively. The production rate as estimated by the SD model (shown by black dotted line) differs quite significantly from the production rate calculated by the DES model (shown by grey dashed line). To reflect a more realistic setting, the production rate in response to random machine failures (shown by grey mesh line) is also plotted using DES. The estimation of the rates by the SD model and the actual value as seen from the DES model are summarized in Table 2. The high peak and low peak values are obtained after the demand change has been applied. Triangular blip in demand (100 to 115 to 100 units/week) causes the desired production start rate to increase by 30% and decrease by 14%. The production rate as estimated by SD model increase by 16% and decreases by 5%. When the desired production start rate is translated to the DES model, it results in an actual 17% increase and 13% decrease in the production rate. This clearly indicates the need for an integrated model development and analysis based on both DES and SD techniques.

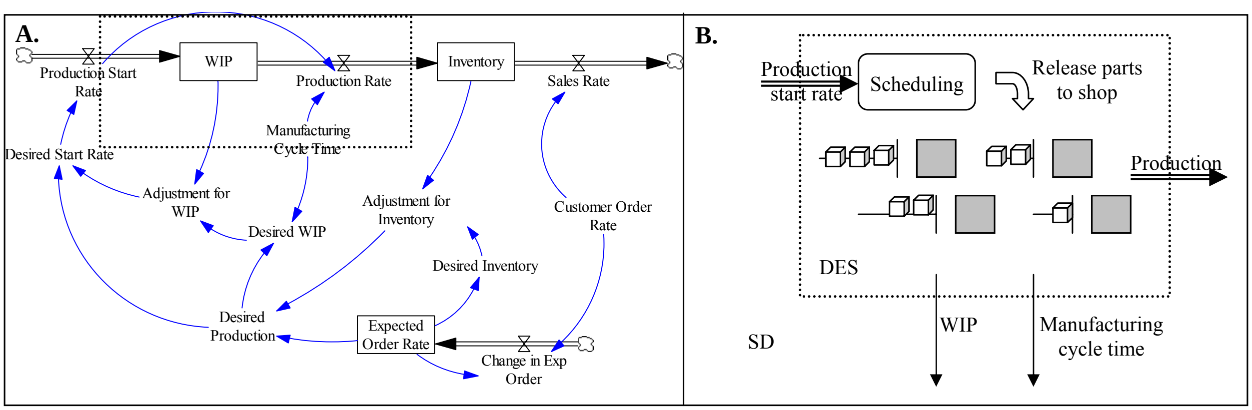

Figure 2: A. SD model of inventory management; B. Interaction between SD and DES

Table 2: {High peak, Low peak} values of production rate in SD and DES model (units/week)

Demand Pattern	Production Start Rate (SD)	Production Rate (SD)	Production Rate [DES, no machine failures]	Production Rate [DES, with machine failures]
Step increase:	{123, 107}	{115, 110}	{117, 109}	{117, 101}
Triangular blip:	{130, 86}	{116, 95}	{117, 87}	{117, 87}

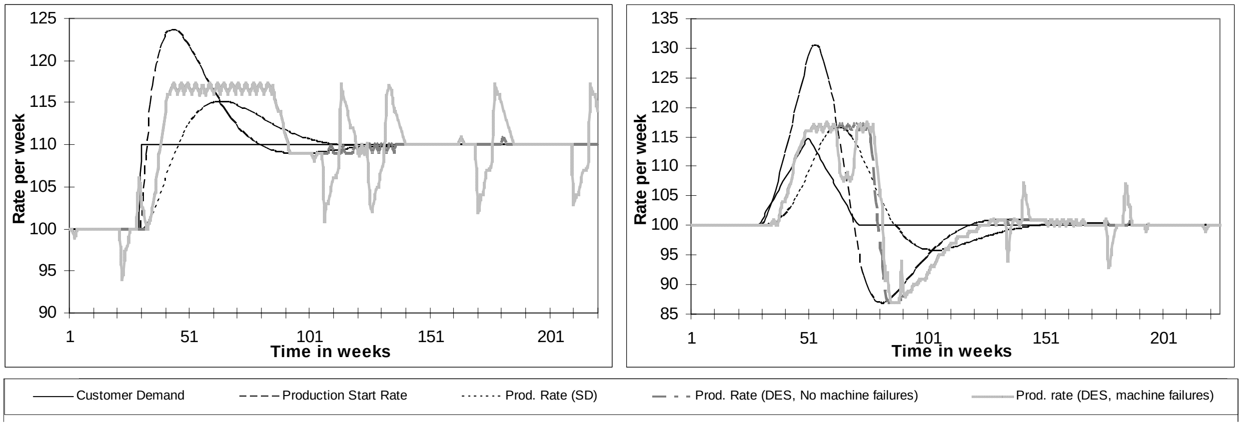

Figure 3: Behavior of manufacturing system (SD and DES model)

6. Conclusion

A hybrid simulation environment that takes advantage of both discrete event simulation and system dynamic simulation has been proposed. The hybrid simulation consists of two layers. In the lower layer, the individual system components are modeled in detail using DES. In the upper layer, aggregated data is used to model the system dynamics. A preliminary study has been carried out in which the inventory management aspects of a facility are modeled using SD and the shop floor operations are modeled using DES. It has been found that though the SD model can provide a good approximation of the system behavior; unknown operational-level disturbances are better captured using the DES model. The proposed hybrid simulation environment provides a viable alternative in which the stability of the system and the long term effects of system policies along with the short-term operational procedures can be analyzed together. Future work is to define formal methods for the interaction between the SD and DES models, and transforming the managerial goals to the operational decisions through the impact analysis.

References

1. Rabelo, L., Helal, M., Jones, A., Min, J., Son, Y.J., Deshmukh, A, 2003, "A Hybrid Approach to Manufacturing Enterprise Simulation," Proc. of the Winter Simulation Conf., 1125-1133, New Orleans.
2. Forrester, J., 1958, Industrial Dynamics, Productivity Press, Oregon.
3. Sterman, J.D., 2000, Business Dynamics: Systems Thinking and Modeling for a Complex World, McGraw-Hill, New York.
4. Kritchanchail, D., and MacCarthy, B.L., 2000, "Discrete or Continuous: Which is More Appropriate for Supply Chain Simulation Modeling?," Proceedings of the 2000 International Conference on Production Research, Bangkok, Thailand.
5. Van Beek, D.A., Gordijn, S.H.F., and Rooda, J.E., 1997, "Integrating continuous-time and discrete-event concepts in modeling and simulation of manufacturing machines," Simulation Practice and Theory, 5.
6. Petropoulakis, L., Giacomini, L., 1998, "Development of Hybrid Simulator for Manufacturing Process," Computers in Industry, 36, 117-124.
7. Lee, Y.H., Cho, M.K., and Kim, Y.B., 2002, "A Discrete-Continuous Combined Modeling Approach for Supply Chain Simulation," Simulation, 78(5).
8. Zülch, G., Jonsson, U., and Fischer, J., 2002, "Hierarchical Simulation of Complex Production Systems by Coupling of Models," International Journal of Production Economics, 77, 39-51.
9. Ball, P., 1998, "Abstracting Performance in Hierarchical Manufacturing Simulation," Journal of Material Processing Technology, 76, 246-251.
10. Scholl, H.J., 2001, "Agent-based and System Dynamics Modeling: A Call for Cross Study and Joint Research," Proc. of the 34th Hawaii International Conf. on System Science.
11. 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.
12. Fujii, S., Kaihara, T., and Morita, H, 2000, "A distributed virtual factory in agile manufacturing environment," International Journal of Production Research, 38(17), 4113–4128.
13. Misra, S., Venkateswaran, J., and Son, Y.J., 2003, "Framework for adaptive time synchronization mechanism for the integration of distributed, heterogeneous, supply chain simulations," Proc. of the 2003 ASEM Conf., Saint Louis.