



Improving the rigor of discrete-event simulation in logistics and supply chain research

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Abstract

Purpose – The purpose of this paper is to present an eight-step simulation model development process (SMDP) for the design, implementation, and evaluation of logistics and supply chain simulation models, and to identify rigor criteria for each step.

Design/methodology/approach – An extensive review of literature is undertaken to identify logistics and supply chain studies that employ discrete-event simulation modeling. From this pool, studies that report in detail on the steps taken during the simulation model development and model more than one echelon in logistics, supply chain, or distribution systems are included to illustrate rigor in developing such simulation models.

Findings – Literature review reveals that there are no preset rigor criteria for publication of logistics and supply chain simulation research, which is reflected in the fact that studies published in leading journals do not satisfactorily address and/or report the efforts taken to maintain the rigor of simulation studies. Although there has been a gradual improvement in rigor, more emphasis on the methodology required to ensure quality simulation research is warranted.

Research limitations/implications – The SMDP may be used by researchers to design and execute rigorous simulation research, and by reviewers for academic journals to establish the level of rigor when reviewing simulation research. It is expected that such prescriptive guidance will stimulate high quality simulation modeling research and ensure that only the highest quality studies are published.

Practical implications – The SMDP provides a checklist for assessment of the validity of simulation models prior to their use in practical decision making. It assists in making practitioners better informed about rigorous simulation design so that, when answering logistics and supply chain system questions, the practitioner can decide to what extent they should trust the results of published research.

Originality/value – This paper develops a framework based on some of the most rigorous studies published in leading journals, provides rigor evaluation criteria for each step, provides examples for each step from published studies, and illustrates the SMDP using a supply-chain risk management study.

Keywords Supply chain management, Simulation, Risk management

Paper type General review



1. Introduction

Simulation modeling is described as a mathematical depiction of a problem, with problems solved for various alternatives and solutions compared for decision making, drawing insights, testing hypotheses, and making inferences (Keebler, 2006).

Computer-based discrete-event simulation has long been a tool for analysis of logistics and supply chain systems. The uncertainties and resulting variances in these systems are significant considerations, and therefore, the capability of simulation to include stochastic situations makes simulation both a powerful research and decision-making tool (Lee *et al.*, 2002; Longo and Mirabelli, 2008). Computer-based discrete-event simulation enhances our understanding of logistics and supply chain systems by offering the flexibility to understand system behavior when cost parameters and policies are changed (Rosenfield *et al.*, 1985) and by permitting time compression (Chang and Makatsoris, 2001). Logistics and supply chain systems lend themselves to simulation because of the networks of facilities and connecting linkages, complex and stochastic linkages between components of the system, and the ability to generate data that are relatively quantifiable. In addition, the size and complexity of logistics and supply chain systems, their stochastic nature, level of detail necessary for investigation, and the inter-relationships between system components make simulation modeling an appropriate modeling approach to investigate and understand such systems.

Scholars have frequently made explicit calls for increased use of simulation modeling to study logistics and supply chain systems to identify and improve system performance and obtain better understanding of cost-service trade-offs (Bowersox and Closs, 1989), validate conventional managerial judgment (Allen and Emmelhainz, 1984), and evaluate dynamic decision rules for managing supply chains (Min and Zhou, 2002). Advance applications such as simulation using discrete-continuous combined modeling approaches (Lee *et al.*, 2002) and supply chain management tools (Longo and Mirabelli, 2008) demonstrate the strong potential of the approach. In a recent survey of eminent scholars of logistics and supply chain management, Davis-Sramek and Fugate (2007) found that many scholars called for more simulation research.

As a research method, mathematical modeling (including simulation) is the second most used method in the *Journal of Business Logistics* and the *International Journal of Physical Distribution and Logistics Management* and the third most used method in *Supply Chain Management: An International Journal* (Sachan and Datta, 2005). Unfortunately, a review of the literature reveals that research in logistics and supply chain journals does not satisfactorily address and/or report the efforts taken to maintain the rigor of simulation studies. There is the possibility that studies are executed rigorously but detailed descriptions of rigor criteria and processes followed in designing simulation models is missing. This limits the understanding of the applicability of a research study, raises questions about the credibility, and makes difficult the replication and further extension of the findings. In addition, more needs to be done to improve the overall quality and presentation of published logistics and supply chain simulation research.

One of the major reasons is the lack of ready guidance on developing logistics and supply chain simulation models to conduct rigorous simulation research (Keebler, 2006). Unlike other methods used in logistics and supply chain research, such as structural equation modeling, there are no preset rigor criteria for publication of simulation studies in logistics and supply chain journals. For example, Arlbjörn and Halldorsson (2002) present ideas on knowledge creation in the field of logistics by describing qualitative and quantitative empirical methods, but specify that experiment-oriented research such as modeling was outside the scope of their discussion.

Although researchers have provided several suggestions for improving the quality of simulation models (Keebler, 2006), a detailed and comprehensive discussion on rigor in discrete-event simulation studies in logistics and supply chain journals is missing. There is no widely accepted standard, or even a minimum standard, for assessing the rigor of simulation studies in the areas of logistics and supply chain management. This leads to publication of articles that do not adequately address and/or report on the process for developing the simulation model.

To address this gap, the purpose of this paper is to present an eight-step process, called the simulation model development process (SMDP), for the design, implementation, and evaluation of logistics and supply chain simulation models, and to identify rigor criteria for each step. The objective is to distil and compile knowledge from multiple sources on building simulation models, serve as a reference guide for further information, provide examples of good logistics and supply chain simulation research, present a model development process, and illustrate the process with an example. It is expected that such prescriptive guidance may stimulate high quality simulation modeling research by providing researchers a much-needed framework for designing, as well as presenting, their studies. The paper is also intended to create a heightened interest in the application of the methodology, particularly for those who are aware of the methodology, but have limited knowledge on the design and execution of simulation studies. This paper may also be useful for reviewers as it provides a framework and checklist to evaluate and identify rigorous studies, and thereby, increases the likelihood that only high quality simulation studies that provide adequate details on the methodology are published in logistics and supply chain management journals. For business practitioners, as consumers of research, this paper provides a checklist for assessment of the validity of simulation models prior to their use in practical decision making. This paper also presents an application of the SMDP that may be used by researchers as a template for presenting their studies.

This paper is organized as follows. First, a brief description of simulation as a research strategy is presented along with its strengths and weaknesses. Next, the SMDP is presented, followed by a detailed application of the SMDP model. The paper concludes with a discussion on theoretical and practical implications of the SMDP.

2. Simulation as a research strategy

According to McGrath (1982), methodological research strategies fall into the following four generic classes: settings in natural systems, contrived and created settings, behavior not setting dependent, and no observation of behavior needed. These classes differ according to which one of the following three research goals is maximized: maximum generalizability, maximum precision, or maximum realism of context. A study that uses simulation addresses the realism of context goal. When a simulation model is used as a basis for experimental analysis, it offers high precision in manipulation of variables, and therefore, also addresses the precision goal, but does not address generalizability (Biestock, 1994).

Computer-based simulation experimentation has several major strengths. For some processes, it is either too costly or impossible to obtain real world observations. In terms of experimental design, the fact that “real life” controlled experimentation of logistics and supply chain systems is extremely difficult makes experimental designs using computer simulation models an attractive alternative for understanding system

behavior (Chang and Makatsoris, 2001). Even when “real life” experiments are possible, cost and organizational disruptions may not permit extensive revisions of the systems (Rosenfield *et al.*, 1985). Through simulation, certain changes in a process or system, which would otherwise be impossible to accomplish, can be executed, and the effects of these changes on the system can be observed.

Simulation models are most useful when a limited number of alternatives are considered, and the objective is to understand the effects of change due to a single or a limited number of variables (Rosenfield *et al.*, 1985). Simulation also facilitates the examination of dynamic processes or systems over time by allowing the compression of real time. Simulation runs representing years can be accomplished in a matter of hours. This helps in drawing inferences about system behavior over a period of time and making timely decisions (Chang and Makatsoris, 2001).

No methodology is without limitations. First, simulation should not be used when the goal is to generalize a population of interest. Survey research is more appropriate in such cases. Second, simulation is usually not appropriate when an analytical solution is possible, or even preferable (Banks, 1998). Simulation models do not provide optimal results, but rather are best for comparing a fixed number of alternatives (Law, 2006). Third, simulation results may be difficult to interpret as most simulation outputs are essentially random variables and are based on random inputs. It may, at times, be difficult to interpret whether an observation results from system interrelationships or randomness (Banks, 1998).

3. A rigorous simulation model development process

This section outlines a process for general use in the design and execution of rigorous discrete-event simulation research. Examples of good research are provided to demonstrate the process. We build upon the works of Law (2006) and Banks (1998) to suggest an eight-step discrete-event simulation process for application specifically in logistics and supply chain research. The process is summarized in Figure 1 and referred to as the SMDP. The eight steps in SMDP lay out a process that can be implemented practically and represent a standard to which researchers may adhere in order to ensure academic rigor.

To a large extent, existing studies in logistics and supply chain journals report only a few of the eight steps in SMDP. Although there are instances of inadequate coverage for each of the steps, the most neglected (i.e. not reported or not sufficiently addressed) are Steps 3 and 5-7. The steps relatively well addressed in the literature are Steps 2, 4, and 8. This paper explores all eight steps, with greater focus on those not sufficiently addressed in the existing literature.

To illustrate the SMDP and establish the level of rigor generally present in the literature, ten studies were chosen from those published in a wide variety of logistics, supply chain, and related journals. The search started with articles using simulation methodology in the *Journal of Business Logistics*, *International Journal of Physical Distribution and Logistics Management*, *International Journal of Logistics: Research and Applications*, *International Journal of Production Research*, and *Transportation Journal*. A keyword search of simulation, and logistics or supply chain led us to articles in other journals such as *International Transactions in Operations Research*, *European Journal of Operational Research*, *Journal of Operational Risk Society*, and *Computers and Industrial Engineering*.

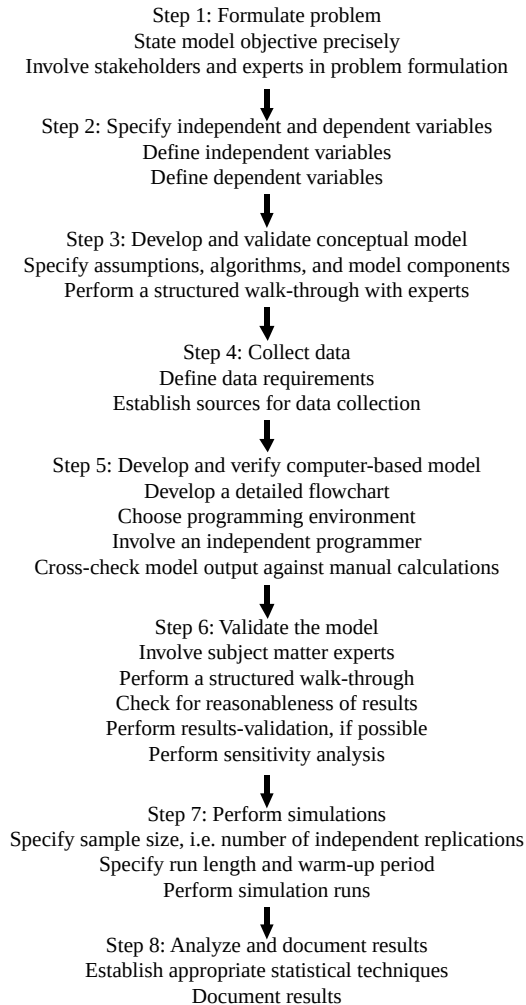


Figure 1.

Source: SMDP developed based on Law (2006), Banks (1998) and Bienstock (1994)

The first step in the selection process limited the pool of simulation studies to only those that dealt with simulating more than one echelon in logistics, supply chain, or distribution systems. Next, from this pool of studies, those that reported in detail on the steps taken during the model development process were chosen as they provide insights into the measures taken to maintain the rigor of the research at each step. This in no way implies that the studies that were not included in the sample were not rigorous. It only suggests that the authors were unable to draw inferences about the rigor of the research based on the details provided in the paper. We understand that, at times, details about methodology may be removed or shortened based on the request of the reviewers. We purposefully refrain from pointing to studies not included in our sample. Similarly for studies included in the sample, the objective is not to highlight

the deficiencies but to provide good references for each step. Table I specifies the manner in which each paper addressed each of the eight steps outlined in our proposed SMDP with the exception of Step 3. Step 3 is omitted from Table I, because only one study in our sample set (Appelqvist and Gubi, 2005) provided documentation of this important step.

3.1 Formulate problem

The purpose of problem formulation is to define overall objectives and specific questions to be answered with the simulation model. Lack of attention to this step is a leading cause of failure of models to perform satisfactorily (Keebler, 2006). Ambiguous purpose can result in incorrect analysis, lost time, bad or ineffective decisions, and incorrect inferences (Dhebar, 1993). The problem may not initially be stated precisely or in quantitative terms. Often an iterative process is necessary to facilitate problem formulation. It is a good practice to involve individuals who deal with the problem to ensure the correct and relevant problem is addressed. When the problem is clearly defined, performance measures of interest, scope of model, time frame, and resources required may be specified accurately and more efficiently.

3.2 Specify independent and dependent variables

Dependent variables reflect the performance criteria and independent variables include the system parameters. In a simulation model, independent variables are manipulated and their effect on dependent variables are recorded and analyzed. Analyses of dependent variable values provide answers to the problem formulated in Step 1. The outcome of a model depends on what is included in the model. Therefore, the objective of the research and the specific questions to be answered using the simulation model guide the selection of independent and dependent variables. Depending on the problem, all factors that influence the answers sought should be included, technical, legal, managerial, economic, psychological, organizational, monetary, and historical factors (Towill and Disney, 2008; Potter and Disney, 2006; Forrester, 1961). Model variables should correspond with those represented in the system, and should be measured in the same units as real variables.

Several sources may be consulted to identify the variables of interest. Past research may be referenced to identify models similar to those being developed and the variables included in those studies. People who deal with the problem under consideration and/or SMEs may be consulted to ensure that all relevant and important variables are included and that chosen variables are expressed in correct units. For example, in a study to estimate off-shoring risk for an automobile company, Canbolat *et al.* (2005) identified six key stakeholders in sourcing decisions: purchasing, supplier technical assistance, product development, material planning and logistics, manufacturing, and finance. They interviewed four executives and at least one subject matter expert (SME) in each of the stakeholder groups. They discovered almost forty risk factors (independent variables) and relationships among risk factors. This ensured that all variables and relationships relevant to stakeholders and experts were included in the model.

3.3 Develop and validate conceptual model

A conceptual model is an abstraction of the real-world system under investigation using mathematical and logical relationships concerning the components and structure

Table I.
Summary of past
simulation studies

<i>Author and year</i>	<i>Objective/problem formulation (Step 1)</i>	<i>Dependent variable(s) (Step 2)</i>	<i>Independent variable(s) (Step 2)</i>
Zhang and Zhang (2007)	Evaluating multiple business models and demand information sharing strategies	Demand fluctuation Demand correlation Demand covariance Lead time	Service level Inventory cost Backlog cost Total cost
Canbolat <i>et al.</i> (2005)	Estimating off-shoring risk for automotive components for an auto manufacturer (Ford)	Information sharing Dollar value of risks, i.e. expected total costs after adjusting for risks	Around 40 risk factors can be specified in the model Delay, and duration of delay are key ones
Appelqvist and Gubi (2005)	Quantifying the benefits of postponement for a consumer electronics company as well as supply chain of Bang and Olefsun	Fill rate Total inventory	Demand Order-up-to levels for retail-outlet inventory Number of basic units Number of colored fronts
Shang <i>et al.</i> (2004)	Identifying the best operating conditions for a supply chain to optimize performance	Total supply chain cost Service levels	Extent of differentiation Extent of information sharing Capacity limit Reorder quantity Lead time Reliability of the suppliers Inventory holding costs Demand variability
Holland and Sodhi (2004)	Quantifying the effect of causes of bullwhip effect in a supply chain	Observed variance of manufacturer's order size Observed variance of retailer's order size	Demand autocorrelation Variance of forecast error Retailer's lead time Manufacturer's lead time Retailer's order batch size Manufacturer's order batch size Standard deviation of the deviation from the retailer's optimal order size Standard deviation of the deviation from the manufacturer's optimal order size

(continued)

	Investigating outsourcing decision for motor carrier transportation (applied to company H)	Mean total shipment cost	Structure (private/leased or for-hire carrier)
Bienstock and Mentzer (1999)			Asset specificity Variation in loading, line-haul, and transportation times Volume and frequency of shipments Five improvement principles identified but the only ones discussed are: Delivery frequency Lead times Depends on the system being simulated
van der Vorst <i>et al.</i> (1998)	Improving performance in a real food supply chain	Inventory level at DC Inventory level at test outlet Product freshness at DC Product freshness at test outlet Total supply chain costs Depends on the system being simulated.	
Mentzer and Gomes (1991)	Developing a strategic decision-support system called SPM which can be configured to simulate different logistics systems. Illustrated using one academic and one managerial application	(As an example, see Gomes and Mentzer (1991) below who used SPM for their study)	
Gomes and Mentzer (1991)	Understanding influence of JIT systems on distribution channel performance	Profit Order cycle time Standard deviation of order cycle time Percent customer orders filled	Materials management JIT (with or without) Physical distribution JIT (with or without) Materials management uncertainty Demand uncertainty Response increase (% increase in sales during the incentive period) Demand uncertainty Payback (reduction in sales level from normal at the conclusion of the incentive) Incentive level <i>Model verification (Step 5)</i>
Powers and Closs (1987)	Understanding impact of trade incentives on a simulated grocery products distribution channel	Average distribution center inventory level Shipment size pattern Total number of shipments Customer service level Total financial performance	
Study (author and year) Zhang and Zhang (2007)	<i>Sources of data (Step 4)</i> Existing Literature Made-up/assumed data	<i>Programming environment (Step 5)</i> GPSS/world	Statistical analysis comparing simulation results with theoretic (calculated) values at 5% level of significance Three case studies (one with Ford die cast component illustrated in this paper)
Canbolat <i>et al.</i> (2005)	Personal interviews or surveys (questionnaire) of company executives, and SMEs	MS Excel with @RISK add-in	

(continued)

Table I.

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Appelqvist and Gubi (2005)	Historical data and made-up data Qualitative data from interviewing managers at the headquarters and retailers downstream	Not specified	Not specified
Shang <i>et al.</i> (2004)	Bass (1969) Model for generating demand Existing research for inventory holding costs Made-up data	ARENA	Verifying model architecture with literature and other researchers
Holland and Sodhi (2004)	Real companies	Gauss 5.0	Not specified
Bienstock and Mentzer (1999)	Published sources such as books, and statistics from American Trucking Association	SLAMSYSTEM, a FORTRAN based simulation software	Mentions that model was verified but the process is not specified
van der Vorst <i>et al.</i> (1998)	Actual data from a producer, a distributor, and retailer outlets of chilled salads	Not specified	Not specified
Mentzer and Gomes (1991)	Depends on the system being simulated	Not specified	Testing random number generators using χ^2 -test Compare short pilot model runs to hand calculation Verify model segments separately Replace stochastic elements with deterministic Use simplified probability distributions Use simple test data input Verified as per Fishman and Kiviat (1968) Verification of uniformity and independence of model's random number generators Testing programming logic through statistical output <i>Analysis techniques (Step 8)</i>
Gomes and Mentzer (1991)	Real companies, and published sources such as books	Not specified	<i>Other important details</i> ANOVA Multiple comparisons using Tukey's and Gomes-Howell's tests Used Replication/deletion approach to determine warm-up period
Powers and Closs (1987)	Made-up data built on Simulated Product Sales Forecasting model	Not specified	
<i>Study (author and year)</i> Zhang and Zhang (2007)	<i>Validation (Step 6)</i> Not specified	<i>Sample size and sample size determination (Step 7)</i> Analysis using ANOVA at 95 % confidence level to set up each scenario as 2000-period and 15 runs	

(continued)

<i>Canbolat et al.</i> (2005)	Validation using case studies	Not specified	Ranking of failure modes Mean, lower and upper limits, standard deviation, and 5th and 95th percentile of dollar value of risks Inspection of graphical outputs Percentage changes in performance measures	Same demand data sets used for all replications. This technique is known as correlated sampling and provides a high statistical confidence level
Appelqvist and Gubi (2005)	Using input-output transformation, i.e. comparing simulation data to real world data, on performance measures such as delivery times, delivery accuracy, and inventory levels Structured walk-through with company management Comparing simulation results with analytical models for simple known cases	Five replications for each unique scenario Each replication consisted of a 100 day warm-up period and a 1,000 day steady-state run		
Shang <i>et al.</i> (2004)		1,000 replications of the system for 20 months	Visual inspection of graphical output Taguchi (1986) method for parameter design Response surface methodology, i.e. fitting regression models to simulation output Regression analysis	
Holland and Sodhi (2004) Bienstock and Menitzer (1999)	Not specified Testing face validity using literature, and review of distribution system simulation models Interviews with employees of company H Comparison of model output with actual company data	186 time intervals (weeks), of which, middle 152 weeks were used 10 runs per cell determined as per Law and Kelton (1982) relative precision method	ANOVA	Tested for bias created by initial starting conditions
van der Vorst (1998)	Implementation of one scenario to two retail outlets, and measurement against a control outlet as well as simulated results	Not specified	Percentage changes in performance measures (such as inventory levels and remaining product freshness) at distributor and two retail outlets	

(continued)

Table I.

Table I.

Mentzer and Gomes (1991)	Extensively validated different SPM models in following ways: Compared simulation output with historical data from real system for by using χ^2 -tests, Kolmogorov-Smirnov tests, factor analysis, spectral analysis, simple regression, and Theil's inequality coefficient warm-up and transient period: no effect beyond first month stochastic convergence: none for up to 5 years SPM model had external validity (Mentzer and Gomes, 1991)	An example illustration uses sample variance from pilot runs and a desired confidence interval width and precision	Example illustrations use: ANOVA Percentage increases in response variables	Two applications – one on JIT systems and one on manufacturer and distributor of automotive aftermarket – are discussed in the paper
Gomes and Mentzer (1991)	SPM model had external validity (Mentzer and Gomes, 1991)	10 runs per cell determined as per 95% confidence interval start-up transient period effected only first few weeks	ANCOVA for response variable profit; ANOVA for main effects of all other response variables Scheffe's method for multiple comparisons of cell means Fisher's least significant difference method for pair-wise comparisons Graphically statistically using ANOVA	ANCOVA is used because profit is significantly correlated to demand
Powers and Closs (1987)	Testing face validity by review groups model stability and model sensitivity using ANOVA and sensitivity analysis	Not specified		

Notes: Strategic planning model, SPM; analysis of variance, ANOVA; analysis of covariance, ANCOVA; just-in-time, JIT

of the system (Banks, 1998). Explicit statements of assumptions and detailed descriptions of the relationships included in the conceptual model ensure that the model develops in accordance with the problem statement. The validity of the outcome of a system depends on what is included in the system description. Therefore, it is important to construct a conceptual model so that the model may be verified prior to investing resources in the development of a computer model.

A structured walk-through of the conceptual model before an audience that may include analysts, computer-programmers, and SMEs ensures the validity of the conceptual model (Law, 2005). This step makes sure the objectives, performance measures, model components and relationships between components, concepts, assumptions, algorithms, data summaries, and other model aspects of interest are correct and sufficiently detailed. In addition, this step ensures that the representation of the problem entity is “reasonable” for the intended purpose of the model (Sargent, 2007). Performing and documenting conceptual validation early in the model development process and describing the problem structure and the accompanying model in clear, simple language increases the credibility of the model researchers and practitioners (Law, 2005).

There is little evidence in the logistics and supply chain literature – both in the studies included as well as excluded in this research – of this critical step of conceptual model validation. Only one study in our sample provided documentation of this step. Appelqvist and Gubi (2005) specified that their model was compared to actual supply chain performance and reviewed in a structured walk-through with company management. However, it appears that conceptual validation and walk-through was done during simulation model validation (i.e. Step 6). In general, if researchers omit conceptual validation early in the model development process and attempt to validate the computer or computational model directly, it may be too late, too costly, or too time-consuming to fix errors and omissions in the computational model.

3.4 Collect data

Collecting data can be challenging as data may not be readily available in required formats or in an appropriate level of detail. Data collection may follow or proceed concurrently with conceptual model development. Data requirements must first be established to specify model parameters, system layout, operating procedures, and probability distributions of variables of interest. Data include company databases, interviews, surveys, books, and/or other published sources. Data may also be generated using computers if the actual data may be reasonably approximated by such commonly used distributions as normal, Poisson, exponential, or several others. Before incorporation into the model, data may need to be scanned, cleaned, and updated to account for discrepancies and/or missing data.

Each independent variable can be manifested using one of three approaches (Banks, 1998). First, the variable may be deterministic in nature. Second, an independent variable may be operationalized by fitting a probability distribution to the observed data. Third, a variable may be operationalized with an empirical distribution from observed data. Techniques such as Delphi and failure mode and effects analysis (FMEA) may also be employed to convert qualitative data into quantitative data and prioritize the elements that should go into the model. The Delphi method allows people to arrive at a consensus on an issue of interest through a series of repeated interrogations of knowledgeable individuals. After the initial interrogation of each

individual, usually by means of questionnaires, each subsequent interrogation is accompanied by information from the preceding one. Each participant is encouraged to reconsider and, if appropriate, change his/her previous reply (Makukha and Gray, 2004). FMEA is often used in engineering design analysis to identify and rank the potential failure modes of a design or manufacturing process, and to determine its effect on other components of the product or processes in order to document and prioritize improvement actions (Sankar and Prabhu, 2001).

Appelqvist and Gubi (2005) used a mix of qualitative and quantitative data to operationalize variables. They first collected qualitative data by interviewing managers in a supply chain. Based on the interviews, previous work at the case company, and insights from the literature, they developed alternative delivery concepts and evaluated them using discrete-event simulation and data from enterprise resource planning systems.

3.5 Develop and verify computer-based model

Banks (1998) suggests that modeling begin simply and complexity be added in steps until a model of acceptable detail and complexity has been developed. Verification is the determination of whether the computer implementation of the conceptual model, is correct. It is a continuous process better accomplished when carried out concurrently with model development than waiting until the entire model is coded (Banks, 1998; Sargent, 2007). Verification includes examining the outputs of sub-models and complete simulation model to ensure that the models are executing and behaving acceptably by debugging any errors in programming logic and code. Fishman and Kiviat (1968) identify two important benefits of verification: identification of unwanted system behavior, and determination whether an analytical or simple simulation substructure can be substituted for a complex one.

Several programming languages and software packages exist to simulate logistics and supply chain systems. Surprisingly, in our list of ten studies, only five state the simulation environment or programming platform used, namely MS Excel with add-ins, ARENA, SLAMSYSTEM, GPSS/World and Gauss 5.0. In the literature reviewed, there is no evidence of preference for a particular software package that clearly outperforms others.

Based on methods used in the studies in Table I, and Fishman and Kiviat (1968), model verification may be addressed in four ways. First, the code should be checked by at least one person other than the person who coded the model. Second, the output of parts of the model may be compared with manually calculated solutions to determine acceptable behavior. By running the model using a variety of input values, results may be checked to verify reasonable, expected, or known output values. Third, simulation results for short pilot runs of simple cases for the complete model may be compared with manual calculations to verify the entire model (structure) behaves acceptably. Fourth, events may be verified manually through each model segment, first with simple deterministic runs, next using simple probability distributions followed by stochastic checks with increasing integration of activities (Mentzer and Gomes, 1991). In addition, developing detailed flowcharts and making the model as self-documenting as possible helps in the verification process. Animation is also a useful tool in the verification process.

Only a few studies in our sample provided a good discussion of model verification. Bienstock and Mentzer (1999) mention that the model was verified and Powers and

Closs (1987) mention that programming logic was tested through statistical output but both studies fall short in explaining the process. Mentzer and Gomes (1991) provide a detailed discussion on model verification and validation. They identify additional statistical tests and analysis that can be used for further model verification. In summary, to demonstrate rigor, it is critical that details of the development and verification of the simulation model be documented and presented.

3.6 Validate model

Model validation is the process of determining whether a simulation is an accurate representation of the system under investigation (Law, 2006). A “valid” model can be used to make decisions similar to those that would be made if it were feasible and cost-effective to experiment with the system itself (Law, 2005). An invalid model may lead to erroneous conclusions and decisions.

Based on the methods used in the Table I studies, and Law (2006), the issue of validating the simulation model may be addressed in several ways, many of which are similar to those used to validate the conceptual model (Step 3). First, SMEs, including academic scholars and practitioners, may be consulted in the conceptual development of model components and relationships between components to ensure the correct problem is solved and reality is adequately modeled (Law, 2006). Second, a structured walk-through of the simulation model and a review of simulation results for reasonableness with a separate set of SMEs may be conducted. If the results are consistent with how the SMEs perceive the system should operate, the model is said to have face validity (Sargent, 2007). Face validity may be further confirmed by reviewing the literature and comparable simulation models in past research and comparing the results against existing knowledge and findings.

If feasible, computer-based simulation output is compared with output data from the actual system for input-output validation. A statistical technique used for analyzing actual or simulated time series is spectral analysis. Spectral analysis yields magnitudes of deviations from the average levels of a given activity and the period or length of these deviations (Naylor *et al.*, 1969). When results validation is not possible, Fishman and Kiviat (1968) suggest:

While validation is desirable, it is not always possible. Each investigator has the soul-searching responsibility of deciding how much importance to attach to his results. When no experience is available for comparison, an investigator is well advised to proceed in steps, first implementing results based on simple well-understood models and then using the results of this implementation to design more sophisticated models that yield stronger results. It is only thorough gradual development that a simulation can make any claim to approximate reality.

Finally, sensitivity analyses may be performed on the programmed model to identify model factors that have the greatest impact on the performance measures, to test the stability of the model, and to test the sensitivity of the analysis to changes in assumptions (Powers and Closs, 1987). Systematic sensitivity analysis facilitates explicit recognition of the important assumptions, improves the decision maker’s understanding of the problem, and is a useful way to identify and eliminate logical and methodological errors (Dhebar, 1993).

The issue of model validity was incorporated into almost all the studies reviewed, though the degree of importance of the issue varied significantly. In one good example, van der Vorst *et al.* (1998) measure their simulated output against actual

implementation of a simulated scenario to two retail outlets and a control retail outlet. Several others, including Bienstock and Mentzer (1999), Mentzer and Gomes (1991), and Appelqvist and Gubi (2005), validated their models by comparing simulated output to available company data.

3.7 Perform simulations

For each system configuration of interest, decisions have to be made on the number of independent model replications (sample size), run length, and warm-up period. Of the sample set, three out of ten studies fail to specify the sample size and only two elaborate on the procedure used to determine the sample size. In simulation, the benefits of increased sample size, may be gained by:

- increasing the number of replications (simulation runs) for each experimental condition;
- decreasing the length of subintervals, i.e. reducing the time unit to provide more subintervals for the same length of run; and
- increasing the length of the run to increase the number of subintervals (Mentzer and Gomes, 1991; Bienstock, 1994).

Each of these practices must be weighed against the cost in time and money to make additional runs.

The power of a statistical test to detect an effect increases with the number of replications (Mentzer and Gomes, 1991). Increasing the number of runs reduces the standard deviation of the sampling distribution, and therefore, for a given level of confidence, the half-width of the confidence interval decreases. This results in an increase in the absolute precision of the estimate of population of interest (where absolute precision is defined as the actual half-width of a confidence interval (Law, 2006)), but increasing the number of replications until statistically significant results are obtained makes the external validity of the results questionable.

An alternative to increasing absolute precision is “to let the number of replications be guided by a ‘practical’ degree of precision, i.e. a reasonable degree of precision, given the magnitude of population mean(s) that is (are) being estimated” (Bienstock, 1996, p. 45). A detailed discussion of this method called “relative precision method” can be found in Bienstock (1996), who contends that conclusions drawn from results in this manner are more meaningful both in terms of research goals and practical problem solutions. However, this technique is appropriate for successive independent replications of simulation runs; it is not appropriate for determination of achieved relative precision on subintervals of a single simulation run or in experimental designs that utilize variance reduction techniques (Bienstock, 1996). Bienstock and Mentzer (1999) adopt the relative precision method. Zhang and Zhang (2007) follow an iterative procedure by comparing output from scenarios under different combinations of run-length and number of replications. They use analysis of variance (ANOVA) and replication/deletion to ascertain the warm-up period, run length, and number of replications.

3.8 Analyze results

The studies in our sample employ several analysis techniques such as visual inspection of graphical outputs, mean, lower and upper limits, standard deviation, and percentiles of dependent variables, response surface methodology, ANCOVA, ANOVA and

different methods of multiple comparisons. Please refer to “analysis techniques” column of Table I for a list of techniques employed in the sample set. These are a subset of the techniques available to analyze simulation output. Modelers, reviewers, and practitioners should be aware of assumptions (e.g. normality or autocorrelation) that might affect the appropriateness of a given statistical technique for a given situation. The choice of analysis techniques varies considerably depending on the distribution of input and output variables. Therefore, the researcher must explain the choice.

4. An example of methodologically rigorous simulation study

The purpose of this section is to illustrate the SMDP by using a simulation study designed to understand the impact of risks on global supply chains, and presenting in detail how each step in the SMDP was executed to maintain a high degree of research rigor. The research question driving the simulation process was: how does performance of global supply chains vary under different combinations of environmental conditions (risks) and the strategy selected?

4.1 Formulate problem

This study consisted of three successive phases: an extensive literature review, a qualitative study, and a simulation study. The objective of the first two phases was to build a theory and the objective of third phase was to test a theory of environment-strategy fit for global supply chain risk management. The literature review was an integrative investigation of the logistics, supply chain management, operations management, economics, international business, and strategy literatures. Qualitative research was based on data from 14 in-depth qualitative interviews and a focus group meeting involving seven senior executives of a global manufacturing firm. Additional interviews were conducted during simulation model development to collect data and validate the model. Based on the qualitative study, the external supply chain environment comprised of supply and demand risks were incorporated in this simulation model. Four types of environments were operationalized as combinations of high and low levels of supply and demand risks. Eleven strategies were identified during the first two phases, of which the following four were included in this research: assuming (single-sourcing), hedging (dual sourcing), speculation (build to stock), and postponement (build to order). These were selected because interview participants identified them as more important and more likely than other strategies.

Eight hypotheses were developed about the impact of fit between environment and strategy on the performance of global supply chains. It is beyond the scope of this paper to elaborate on the development of the hypotheses, but they are presented in Table II. To test these hypotheses, a global supply chain with two suppliers, a manufacturer/distributor, and two customers was conceptualized (Figure 2). There is one supplier each in the USA (S1) and China (S2). The manufacturer/distributor (M/D) is based in Memphis, Tennessee, one customer (C1) in New York, New York, and one customer (C2) in Miami, Florida. The M/D sells two products – Product A to C1 and Product B to C2. Product A is composed of two components – A-Component (AC) unique to Product A and Common-Component (CC) shared between Product A and Product B. Product B is composed of two components – B-Component (BC) unique to Product B and Common-Component (CC). Both S1 and S2 can supply Product A and Product B, or components AC, BC, and CC.

Table II.
List of hypotheses

H1	Supply chains facing high supply risks that adopt a hedging strategy will show a higher profit than supply chains that adopt an assuming strategy
H2	Supply chains facing low supply risks that adopt an assuming strategy will show a higher profit than supply chains that adopt a hedging strategy
H3	Supply chains facing high demand risks that adopt a postponement strategy will show higher a profit than supply chains adopting a speculation strategy
H4	Supply chains facing low demand risks environments that adopt a speculation strategy will show a higher profit than supply chains that adopt a postponement strategy
H5	Supply chains facing low supply risks and low demand risks that adopt an assuming strategy on the supply side and a speculation strategy on the demand side will show a higher profit than other supply chains facing the same environment that adopt any other combination of strategies
H6	Supply chains facing low supply risks and high demand risks that adopt an assuming strategy on the supply side and a postponement strategy on the demand side will show a higher profit than other supply chains facing the same environment that adopt any other combination of strategies
H7	Supply chains facing high supply risks and low demand risks that adopt a hedging strategy on the supply side and a speculation strategy on the demand side will show a higher profit than other supply chains facing the same environment that adopt any other combination of strategies
H8	Supply chains facing high supply risks and high demand risks that adopt a hedging strategy on the supply side and a postponement strategy on the demand side will show a higher profit than other supply chains facing the same environment that adopt any other combination of strategies

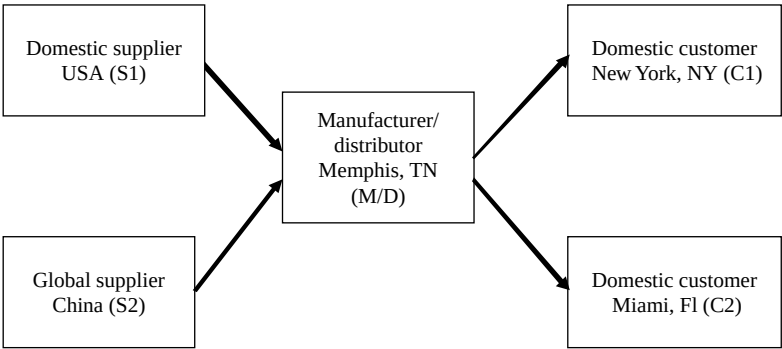


Figure 2.
Simulated supply chain

The product chosen for this study was a printer. A printer has a medium value-weight and weight-bulk ratio, which is important because extreme product characteristics can limit the usefulness of findings. In addition, printers are important because the import share of domestic demand in the printer market has grown steadily from 58.5 percent in 2001 to 77.2 percent in 2005.

4.2 Specify performance criteria and system parameters

Risk events serve as the independent variables for this event-driven model. For supply and demand risks, over 30 risk events were identified in the literature and the

qualitative study. Some examples of risk events are oil price changes, currency fluctuations, supplier bankruptcy, and demand uncertainty. However, due to time and resource constraints and to make sure the results can be interpreted, a short-list of events was created based on specific questions to be answered and events most salient to global supply chains. This also helped in maintaining the simplicity of the model without compromising the objectives of the research. Risk events were grouped into two categories (supply and demand) based on how risk events are manifest, relevance of risk events to this research, and the qualitative study.

Table III provides a list of all independent variables, their definitions, and values. Supply risk events are divided into lead time variability, cost variability, and quality variability. Lead time variability is further divided into order processing time variability, and transportation lead time variability. Although there is variability in transportation times, they do not change between the low risk and high risk Chinese suppliers. Therefore, transportation time is not an independent variable. Demand side risk is manifested by demand variability. Please note that data sources for all independent variables are discussed in detail under Step 3.

The values provided in Table III were used to operationalize supply chain environments and strategies. The low supply risk environment is operationalized as low supplier order processing time variability, low cost variability, and low levels of quality defects and the high supply risk environment as high supplier order processing time variability, high cost variability, and high levels of quality defects. The low demand risk environment is operationalized as low demand variability and the high demand risk environment as high demand variability.

The assuming strategy is operationalized by using the Chinese supplier and hedging by using both domestic and Chinese suppliers. In the speculation strategy, M/D sources finished products, PA and PB, from supplier(s). The goods are held in finished form at the M/D, i.e. made-to-stock, and are shipped to customers per demand. In the postponement strategy, M/D sources components AC, BC, and CC from the supplier(s). Goods are assembled at the M/D site, i.e. assemble-to-order policy, and are shipped to customers per demand.

Similar to independent variables, dependent variables were selected based on literature review, qualitative study, and the research objective. The testing of hypotheses is based on total supply chain profit as it takes into account several other performance measures including total supply chain costs (inventory, transportation, and production costs), total supply chain revenues, and penalty costs from late deliveries. In addition to total supply chain profit, several other measures were recorded (Table IV), including stock-outs, total inbound lead time, fill rates, delays to customers, and average inventory, to help in interpretation of results.

4.3 Develop and validate model conceptually

To conceptually validate the model, SMEs were consulted and interviewed at every step. The primary review and consultation team consisted of four academics. Two were content experts and have experience with simulation modeling, one was a content expert, and one was a management scientist with experience using stochastic data for modeling. Following Banks (1998), modeling began simply and complexity was added in steps. The academic team reviewed all add-ons and changes made to the model because of additional literature explored or data collected. After an acceptable level of detail and

Table III.
Independent variables

Risk factors	Definition distribution	Global (low)	Global (high)	US ^a
<i>Supply risk events</i>				
1. Supplier order processing time variability	Time from order placement to replenishment at the supplier facility Normal (Mean, SD)	N(15, 1.5) days	N(15, 4.5) days	N(10, 1) days
2. Cost variability	Sourcing cost variability due to changes in exchange rates, wage rates, shortage of goods, natural disasters, oil price increases, and any other unforeseen reasons T= Triangular (Min, Mean, Max) <i>Product A or Product B (\$)</i> <i>Component AC or Component BC (\$)</i> <i>Component CC (\$)</i>	T(60, 64.5, 69) T(15, 16.125, 17.25) T(35, 37.625, 40.25)	T(60, 73.5, 87) T(15, 18.375, 21.75) T(35, 42.875, 50.75)	80 20 50
3. Quality variability/yield	Receipt of lower usable quantity due to losses, damages, and pilferage in-transit, communication errors, market capacity, war and terrorism, and natural disasters. 1 % defects for domestic supplier, 2% for low risk China supplier, 3 % for high risk China supplier	0.98	0.97	0.99
<i>Demand risk event</i>				
1. Variability of demand	Average variation in daily demand Normal (Mean, SD)	N(1000, 100)	N(1000, 300)	
Note: ^a US values remain constant throughout all scenarios				

Performance criteria	Definition/operationalization	Measured as
Total supply chain cost	Sum total of costs incurred by the supply chain including transportation, inventory carrying, production, warehousing, and penalty costs	Dollar value distribution of dollar value
Total supply chain profit	Difference between total revenues earned and total costs	Dollar value distribution of dollar value
Stock-outs	The inability to meet customer demand for a given quantity by due date because of non-availability of inbound components, products, or raw materials	Units total penalty cost for late delivery
Total inbound lead time	The sum of supplier lead time, transportation time, and port clearance time	Number of days distribution of number of days
Fill rates	Order fill rate: for a given time period, the number of orders filled complete and on time divided by total number of orders. Unit fill rate: for a given order, the number of units shipped divided by the total number of units ordered. Line fill rate: for a given order, the number of lines filled complete divided by the total number of lines in an order	Percentages
Delays to customers	Orders delivered late and the length of delays	Length of delay distribution of length of delay
Average inventory	The average number of units at hand over a given period of time across the entire supply chain	Average number of units Dollar value of average inventory

Table IV.
Dependent variables

complexity was achieved as per this primary review team, two business practitioners separately reviewed the conceptual model.

The model flow for this study can be divided into the following six stages:

- (1) demand generated at the customer location;
- (2) order received and processed at the manufacturer/distributor;
- (3) order placed on the supplier(s);
- (4) order received at the supplier facility (order processing at suppliers);
- (5) order shipped from supplier to the assembler/distributor; and
- (6) order shipped from assembler/distributor to the customers.

The following discussion elaborates on each of the six stages. Detailed information on each step is provided and important mathematical calculations are explained.

4.3.1 Demand generated at the customer location. A model run is triggered by the generation of demand at the customer location. Demand is generated daily at both

customer sites, C1 and C2. The demand is distributed normally with a mean of 1,000 units per day per customer. The average demand for each customer is derived from secondary data of a major printer manufacturer company. The standard deviation is set to 100 units for the low demand risk scenario and 300 units for the high demand risk scenario. This sets the coefficients of variation to 0.1 and 0.3 for low and high demand risk scenarios, respectively. These coefficients of variation have been used in past research (Mentzer and Gomes, 1991) to operationalize low and high demand risk scenarios, and were supported during conceptual validation with practitioners. Demand generated at customers is transmitted instantaneously to the manufacturer/distributor at no cost. The order is due in 15 days.

4.3.2 Order received and processed at the manufacturer/distributor. Orders placed by customers are received instantaneously at the M/D, and order processing begins immediately. Processing at the M/D takes place eight hours a day, seven days a week, 365 days a year. In speculation scenarios, order processing includes picking products, packing, and shipping goods. In postponement scenarios, order processing includes picking components, assembling, packing, and shipping goods. Order processing capacity is set to 130 percent of average daily demand or 1,300 units per day. Goods are shipped to customers every day. For both products, picking and packing cost is \$10/unit, assembly cost is \$20/unit per unit, and shipping cost is \$10/unit.

Quality variability, one of the independent variables, is operationalized using variable yields from different suppliers. For the domestic supplier, every unit has a 1 percent chance of being defective, i.e. the yield is 0.99. For the low risk Chinese supplier, yield is 0.98. For the high risk Chinese supplier, yield is 0.97. Therefore, for assuming scenarios, yield is set to 0.98 in low risk scenarios and 0.97 in high risk scenarios. Orders are split equally between the two suppliers in the hedging scenario. Therefore, yield is set to 0.985 (average of 0.99 and 0.98) for the low risk scenarios, and yield is set to 0.98 (average of 0.99 and 0.97) for the high risk scenarios.

Inventory value of products and components is set at average purchase cost and accounts for the changing cost variability under different scenarios. Inventory cost is presented in Table VI along with purchase cost. Inventory carrying cost is set at 17 percent (Wilson, 2006).

4.3.3 Order placed on the supplier(s). As orders are processed, inventory levels for finished products A and B in the speculation scenario and for component parts AC, BC, and CC in the postponement scenario are checked every half hour. Whenever the inventory level for a given product or component goes below the reorder point (ROP), a replenishment order for a fixed quantity (Q) is placed with the supplier. For the speculation scenario, all orders are assigned to the single Chinese supplier. For the hedging scenario, each replenishment order has an equal probability, i.e. 0.5, of being assigned to either the Chinese or the domestic supplier. The value for ROP is calculated using the following formula (Mentzer and Krishnan, 1985) which is also a standard business practice:

$$ROP = \mu_{DDL T} + Z\sigma_{DDL T}$$

where, $\mu_{DDL T}$, average demand during lead time (DDL T); z , 1.00 for an 84 percent in-stock probability; $\sigma_{DDL T}$, standard deviation of DDL T.

The calculated value of ROP was rounded to the nearest integer that is a multiple of 500.

To calculate the value of Q , first the average and standard deviation of DDL T is calculated. Next, the probability of DDL T being greater than ROP level is calculated in

increments of 500 units. The incremental probability between two levels of DDLT is multiplied by the difference of DDLT and ROP to calculate the number of stock-outs for each level. The total stock-outs for each level are then added to find the expected number of stock-outs for a given ROP. The expected value of stock-outs is used to calculate the value of Q using the following formula (Coyle *et al.*, 2003):

$$Q = \sqrt{(2R(A + G)/IC)}$$

where, R , annual demand; A , order cost per order; G , stock-out cost per cycle; I , inventory carrying cost as a percent of product value; C , cost of product or component.

Finally, the calculated value of Q is rounded to the nearest integer that is a multiple of a container-load quantity for a given product or component. For the assuming scenario, ROP and Q values are based on lead times for the Chinese supplier. For the hedging scenario, ROP is based on the Chinese supplier. This is because of the large variation between the lead times for the domestic and Chinese suppliers, basing the ROP calculation on either the US supplier or averages of the Chinese and US supplier leads to frequent stock-outs and unduly reduces the performance of a hedging strategy. Q is calculated based on the ROP and average of purchase costs from the US and Chinese suppliers. Table V presents ROP and Q values for all scenarios. It is important to note that the inventory policy used for this research is just for illustration purposes. More advanced methods of determining inventory policies may be found in Fricker and Goodhart (2000) and Silver *et al.* (1998).

The product purchase price from the Chinese supplier was set to \$60/unit. Typically, the purchase cost of electronic products and components is 20-30 percent cheaper in China (Engardio *et al.*, 2004). Following discussions with practitioners, the purchase price from the US supplier is set to \$80 for a resultant cost differential of 25 percent. The cost of components sourced from the Chinese supplier was set to \$15 for components AC

Risks		Low supply low demand	High supply low demand	Low supply high demand	High supply high demand
<i>Assuming strategy</i>					
A or B product	ROP	4,6500	49,000	47,000	49,000
	Q	21,600	39,600	27,600	40,800
A or B component	ROP	46,500	49,000	47,000	49,000
	Q	43,920	78,080	53,680	82,960
C component	ROP	92,500	97,500	93,500	98,000
	Q	59,850	107,730	61,180	82,960
<i>Hedging strategy</i>					
A or B product	ROP	46,500	49,000	47,000	49,000
	Q	19,200	31,200	21,600	32,400
A or B component	ROP	46,500	49,000	47,000	49,000
	Q	39,040	63,440	43,920	63,440
C component	ROP	92,500	97,500	93,500	98,000
	Q	50,540	85,120	54,530	85,120

Notes: Q , based on carrying cost (17 percent), order cost (\$5/order), and stock-out cost (\$35/unit), rounded to nearest full container load; ROP, based on in-stock probability of 84 percent, rounded to nearest 500

Table V.
Reorder point-reorder
quantity (ROP- Q) values

and BC, and \$35 for the component CC. Using a similar 25 percent cost differential, the component prices were set to \$20 and \$50 for the US supplier. Unique components AC and BC are approximately 20 percent and common component CC approximately 80 percent of the value, weight, and volume of products A and B, respectively.

To operationalize the second aspect of supply risks, i.e. cost variability, the purchase cost of products and components from the Chinese supplier was set to a high of 15 percent for low risk scenarios and a high of 45 percent for high risk scenarios. The value of 15 percent was arrived at by extrapolating the current wage rate increase over the past six years and the gradual but continuous strengthening of the Chinese currency (Yuan) over 2007-2008. The high value was based on trends in price increases of raw materials and components (such as iron ore, silicon wafers, and polysilicon) that go into electronic products, labor shortages that can potentially lead to further increases in labor costs, and oil price increases. Table VI lists the minimum, mean, and maximum for the triangular distributions used to generate the purchase prices as well as inventory values for the products and components.

4.3.4 Order received at the supplier facility (order processing at suppliers). Orders at the supplier facility are processed using first-in-first-out priority. The supplier has no capacity constraints, there are no backorders and every order is filled complete. Order processing time at the domestic supplier is a normal distribution with a mean of 10 days and standard deviation of 1 day. Order processing time at the Chinese supplier is a normal distribution with a mean of 15 days and standard deviation of 1.5 days and 4.5 days, respectively, for low and high supply risk scenarios. This sets the coefficient of variation (CV) to 0.1 and 0.3 for low and high-risk scenarios, respectively. These CV values were used in past literature to operationalize low and high inbound supply variability (Gomes and Mentzer, 1991).

4.3.5 Order shipped from supplier to the assembler/distributor. After the Chinese supplier processes the order, the goods are sent to the Hong Kong port using domestic transportation where the goods are loaded onto a ship. The ship travels from the Hong Kong port to the US Los Angeles port. At the port, the goods are cleared through customs and loaded onto a truck. Trucks transport the goods from the US port to the M/D. After the domestic supplier processes an order, goods are shipped to the M/D using trucks. The goods are shipped from the domestic supplier to M/D in full truck loads. The transportation times from the US and Chinese suppliers are presented in Table VII.

4.3.6 Order shipped from assembler/distributor to the customers. After the M/D processes the orders, goods are shipped daily to customers. The transit time to

Product/component	Purchase price (\$)		Inventory value	
	Chinese supplier ^a	US Assuming (\$)	Hedging (\$)	
Product A and Product B	Low: T(60, 64.5, 69) High: T(60, 73.5, 87)	Low: 64.5 High: 73.5	Low: (64.5 + 80)/2 = 72.25 High: (73.5 + 80)/2 = 76.75	
Component AC and Component BC	Low: T(15, 16.125, 17.25) High: T(15, 18.375, 21.75)	Low: 16.125 High: 18.375	Low: (16.125 + 20)/2 = 18.0625 High: (18.375 + 20)/2 = 19.1875	
Component CC	Low: T(35, 37.625, 40.25) High: T(35, 42.875, 50.75)	Low: 37.635 High: 42.875	Low: (37.625 + 50)/2 = 43.8125 High: (42.875 + 50)/2 = 46.4375	

Note: ^aTriangular (min, mean, max)

Table VI.
Purchase costs and
inventory values

	Cost	Policy/remarks	Values (days)	Data source
<i>Chinese supplier</i>				
Ship complete order to HK Port	0	Transportation cost included in per container charge from China port to US port		
At Hong Kong Port	0	Port costs included in per container charge from China port to US port	T(4, 5, 6) ^a days	Data from interviews
HK Port to Los Angeles Port	\$3,000 per container	\$3,000/container includes the cost from China supplier through the Los Angeles port including all taxes, charges, and other duties	T(13, 15, 20) days	Report by Drewery Shipping Consultants Limited (Damas, Rahman, and Bahadur 2006)
At Los Angeles Port	0	Port costs cost included in per container charge from China port to US port	T(3, 4, 5) days	Data from interviews
From Los Angeles Port to manufacturer/distributor	\$3000 per truck-load		T(4, 5, 6) days	Cost quote from trucking agency; times validated in interviews
<i>US supplier</i>				
From supplier to manufacturer/distributor	\$3000 per TL		T(4, 5, 6) days	Cost quote from trucking agency; times validated in interviews

Note: ^aT = Triangular (mix, mean, max)

Table VII.
Transportation times

customers is fixed at three days. The goods are shipped with a charge of \$10/unit. The transit times and cost figures are based on qualitative interviews and quotes from freight companies. Orders delivered late to customers are assessed a penalty cost of \$35/unit. This is approximately 25 percent of the selling price (\$150) and was validated in qualitative interviews. The selling price of the products is \$150/unit based on secondary data of a major printer manufacturer that suggests the gross margins are around 32-35 percent. Average weighted gross margins with a selling price of \$150/unit for all scenarios under average price (i.e. considering cost risk) work out to around 31 percent. A slightly lower, 31 percent, gross margin was chosen as consumables like cartridges and toners have higher margins than printers.

4.4 Collect data

The data for this study came from the existing literature, secondary data sources, the qualitative study, and additional interviews with managers.

4.5 Develop and verify computer-based model

This research used a simulation package designed specifically to model supply chains called supply chain Guru (SC Guru) by Llamasoft Corporation, that combines full mixed-integer/linear programming optimization and discrete-event simulation.

This study addressed the issue of model verification in several ways. First, services of two programmers who are expert in modeling supply chains using SC Guru were employed. The first expert trained the researcher in building the model using SC Guru and helped set up and verify the basic model structure of the supply chain and four risk management strategies. The second expert, a programmer involved in the development of the software verified multiple aspects of the program. For example, at one point, the second expert verified the yield (quality variability) function was working correctly. At another point, verification of the initial structure of the model revealed an issue with the transfer of products at the Los Angeles port. Continuous involvement of the experts also minimized the possibility of programming errors (bugs).

Second, the output of parts of the model (sub-structures) was compared with manually calculated solutions to determine if they behaved acceptably. Typical validation during this process included verification of transportation times, queuing of shipments throughout the supply chain, and inventory policies. The uniformity and independence of the model's random number generators was inspected including purchase costs of components and products, demand for products A and B, order processing times at the suppliers, transportation times and variability, and quality variability.

Third, the simulation results for short pilot runs of simple cases for the complete model were compared with manual calculations to test whether the entire model (structure) behaved acceptably. Typical validation for all scenarios included inbound container load/truckload costs of transportation, average purchase costs for low and high risk scenarios, order processing and assembly costs at the M/D, picking and packing costs, and outbound cost/unit of transportation.

Fourth, all events were hand verified through each model segment. The model was built in stages where each sub-model was verified by replacing stochastic elements with deterministic elements and gradually integrating these sub-models into the main model.

4.6 Validate model

This study addressed the issue of model validation in several ways. First, SMEs, including academic scholars and practitioners, were consulted in the conceptual development of model components and relationships between components.

Second, a structured walk-through of the model and a review of the simulation results for reasonableness with a separate set of SMEs, including academic scholars and practitioners, were conducted. The results were consistent with how the SMEs perceived the system should operate. This step along with literature and review of supply chain simulation models in past research confirmed face validity.

For this study, input-output transformation, i.e. comparing simulation data to real world data, was not possible for two reasons. First, complexity of real world supply chains is greater than the one simulated. Therefore, it is difficult to isolate the effect of the variables in the real data. Second, it is difficult to find a company willing to share data on all variables included in this research. Through several attempts to acquire real data from multiple companies, data that corresponds to different parts of the supply chain was gathered. However, data that spanned more than two levels of a supply chain for a given product could not be gathered. These partial datasets were used to validate corresponding parts of the simulation model.

Finally, sensitivity analyses was performed on the programmed model and revealed that model parameters such as ROP and Q values have significant impact on the performance measures and, thus, were modeled carefully.

4.7 Perform simulations

Combinations of high and low levels of risks were used to generate four possible combinations of demand and supply risk levels. Four strategy combinations, i.e. assumption-speculation, assumption-postponement, hedging-speculation, and hedging-postponement, were simulated for each combination of supply and demand risk levels, for a total of 16 scenarios. The relative precision procedure discussed earlier was used for sample size determination in this study. For this study, the sample size for 5 percent relative precision is 28 runs per scenario. The run length was set to two years, which was validated in interviews as a typical contract period of an off-shoring decision. Multiple runs were made for each scenario and total cost and total revenues were recorded for runs where data were collected at the following three points: beginning of first month to end of 24 months, beginning of second month to end of 25 months, and beginning of third month to end of end of 26 months. All scenarios stabilized by the end of second month as reflected in the following: similar direction (negative or positive) of profit, stability in penalty costs of late deliveries, and stable order fill rates. Therefore, the warm-up period was set to 60 days. Other efforts to minimize the effect of initial conditions on the model included setting initial inventory at the M/D to the ROP.

4.8 Analyze results

Elaboration of the results is beyond the scope of this paper, but it is important to mention that main analyses are based on Tukey's multiple comparison of cell means. Tukey's method was used over other comparable methods because it uses the Studentized range distribution that is more conservative, i.e. declares fewer significant differences. In addition, methods used to analyze the results included visual inspection of graphical outputs; mean, lower and upper limits, standard deviation, and percentage changes in performance measures.

5. Implications

This paper presented an eight-step methodology, called SMDP, for logistics and supply chain models. A detailed discussion of each step, along with examples drawn from simulation studies reported in leading logistics journals, were presented. The SMDP process was elaborated using a simulation modeling study as an illustration of the level of detail that should be provided in any such study. This has several implications for future discrete-event simulation research for researchers, reviewers, and practitioners.

First, a review of logistics and supply simulation research reveals there are very few studies that report all eight steps in-depth. Thus, there is no set standard for evaluation of simulation studies in logistics and supply chain journals. To this end, Figure 1 provides a framework to design a rigorous simulation study. To summarize the SMDP discussion, Table VIII is presented for easy reference for both reviewers and researchers. Table VIII provides a practical framework and checklist to establish the rigor of simulation research. It provides insights into the basic standards to follow for

Steps	Questions to answer (at a minimum)
Problem formulation	What is the objective of the study? Is the problem stated and formulated clearly? Who was involved in problem formulation, particularly for real-life case studies?
Choice of dependent and independent variables	Are all relevant variables included? Are variables clearly defined? Who was involved in choice of variables? Is there evidence from prior literature on importance of variables? If no evidence from prior research, what is the rationale for the choice of variables?
Validation of conceptual model	Are important assumptions, algorithms, and model components described? Was anyone else other than the authors consulted for conceptual validation? Was a structured walk-through performed? Who served as the audience for walk-through?
Data collection	What data are required to specify model parameters, system layout, operating procedures, and distribution of variables of interest? Where are the sources of data?
Verification of computer model	Rationale for computer-generated data, if any? What programming environment was used? Were the model sub-components and the complete model checked with manually calculated data? Was the computer model checked by at least one person other than the person who coded the model? Was the output of parts of the model (sub-structures) compared with manually calculated solutions?
Model validation	Were experts other than authors consulted? Is there evidence of input-output transformation? Was a structured walk-through of the computer-based model performed? Was a review of the simulation results for reasonableness conducted?
Performing simulations	Is there evidence from literature of model design? What sample size, run length, and warm-up period were used? Is the rationale for sample size, run length, and warm-up period stated?
Analysis techniques	Which statistical techniques were used? Are the analysis techniques statistically appropriate?

Table VIII.
Evaluating the rigor of a
simulation research

rigorous simulation research. If modelers demonstrate they followed SMDP in Figure 1 and provide sufficient answers to the questions in Table VIII, they are more likely to convince the reader that the resultant models and conclusions are rigorous (i.e. trustworthy).

Although the framework provided is reasonably comprehensive, it is likely that some steps do not apply to a particular study. In such cases rationale for non-inclusion may be provided to preempt any doubts. Reviewers (in deciding whether specific

modeling research should be published) and practitioners (in deciding whether to trust the results of such research and apply it to real logistics and supply chain situations) must make judgment calls on whether each criterion has been satisfactorily addressed.

In the future, apart from addressing the eight steps in SMDP, researchers may also focus on some important aspects of the presentation of the study. First, the literature review reveals that often the assumptions are not explicitly stated and it is left to the reader to infer them. Such assumptions as probability distributions of variables or safety stock policies may have significant implications on the applicability and limitations of simulation results. Thus, it is critical that all assumptions be clearly stated. Second, the discussion of model limitations is usually missing or incomplete. A thorough discussion of limitations not only minimizes misguidance but also opens doors for future research that may attempt to relax assumptions or extend the model to reduce limitations. Third, as mentioned earlier, there is a variety of simulation tools available to modelers. A brief discussion on the choice of a tool or a package, and its advantages and disadvantages should also be included to assist other researchers in making an informed choice. The result of such increased rigor in simulation modeling should lead to increased confidence and application of modeling research in logistics and supply chain management.

Finally, a rigorous simulation study based upon the SMDP framework provides data sources and rationale for inclusion or exclusion of variables and parameters. This raises the level of confidence in the findings as well as the extent of applicability of the results.

In addition, the SMDP may be used by researchers to design and execute rigorous simulation research, by reviewers for academic journals to establish the level of rigor of simulation research, and by practitioners to answer logistics and supply chain system questions. The illustration may be used as a template for what should be specified in a paper to enhance the contribution of a study for both readers interested in results and readers who gain from methodological insights.

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