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# Supply chain simulation tools and techniques: a survey

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**Abstract**

The main contribution of this paper is twofold: (i) it surveys different types of simulation for supply chain management; (ii) it discusses several methodological issues. These different types of simulation are spreadsheet simulation, system dynamics, discrete-event simulation, and business games. Which simulation type should be applied, depends on the type of managerial question to be answered by the model. The methodological issues concern validation and verification, sensitivity, optimisation, and robustness analyses. This sensitivity analysis yields a shortlist of the truly important factors in large simulation models with (say) a hundred factors. The robustness analysis optimises the important factors controllable by management, while accounting for the noise created by the important non-controllable, environmental factors. The various methodological issues are illustrated by a case study involving the simulation of a supply chain in the mobile communications industry in Sweden. In general, simulation is important because it may support the quantification of the benefits resulting from supply chain management.

**Keywords**: logistics; performance measurement; Taguchi, risk analysis; uncertainty analysis; screening, sequential bifurcation

**1. Introduction**

Simulation analysts may want to quantify the benefits resulting from supply chain management (SCM), in order to support decision making at two levels:

(i)      the strategic level, including (re)designing a supply chain

(ii)     the operational level, including setting the values of control policies.

Kleijnen and Smits (2003) distinguish four simulation types for SCM:

(i)      spreadsheet simulation

(ii)     system dynamics (SD)

(iii)    discrete-event dynamic systems (DEDS) simulation

(iv)    business games.

Spreadsheets may be part of production control software. SD simulation may explain the bullwhip effect. DEDS simulation may predict fill rate values. Business games may educate and train users ('games' must be distinguished from 'gaming'; the latter derives analytical solutions including Nash equilibria; see Lau and Lau 2004 for a SCM application). In Section 2, I summarize these four simulation types and their role in SCM.

From the viewpoint of methodology, I distinguish four types of issues in simulation (in SCM and in other application domains):

(i)      validation and verification (V & V)

(ii)     sensitivity or 'what-if' analysis

(iii)    optimisation

(iv)    robustness, risk, or uncertainty analysis.

To address these four methodological issues, a variety of techniques may be used. I, however, focus on the use of statistical methods for the *design of experiments* (DOE). In Section 3, I describe these methods and illustrate their application through a case study—detailed in Kleijnen et al. (2004a, b). DOE is important in simulation, because —by definition—simulation is an experimental method; i.e., the analysts experiment with different input values and different model structures (representing different policies, etc.) of the simulation model—treated as a *black box* (by definition, a black

box means that only the inputs and outputs of that box are observed, not its internal operation).

Note: Some methods do not treat the simulation model as a black box; examples are Perturbation Analysis and Score Function methods; see Spall (2003). Unfortunately, these methods require that more mathematical conditions are satisfied, and that analysts are mathematically sophisticated.

In practice, simulation is a method that is relatively often used—when compared with other quantitative models. Several reasons may explain this popularity: no mathematical sophistication is needed (see the preceding Note), *multiple* responses are natural in simulation (in SCM, these responses may be the fill rate or service percentage, stocks including work in progress or WIP, sales, etc.). These various responses are discussed by Gunasekaran et al. (2003) and Kleijnen and Smits (2003).

Simulation may give insight into the *causes and effects* of the supply chain performance: which inputs (or factors) significantly affect which outputs? Indeed, simulation can help to understand causality, as simulation is a methodology that does not treat a system (for example, a supply chain) as a black box (DOE treats the simulation as a black box, as we saw above). For example, modern simulation software may model individual events such as order arrivals and machine breakdowns in great detail; see Kelton et al. (2004)'s manual for simulation in the Arena software. (Vamanan et al. 2004 compare Arena and other 'commercial off the shelf' (COTS) software; Biswas and Narahari 2004 present object-oriented software for simulation models and other model types of supply chains.)

The main contribution of this paper is twofold:

(i)     it surveys major tools and techniques for the simulation of supply chains

(ii)    it discusses several methodological issues, including a novel methodology for the robust design of supply chains.

The remainder of this paper is organized as follows. The four simulation types that Kleijnen and Smits (2003) distinguish, are discussed in the four separate subsections of Section 2. Section 3 summarizes a case study that is detailed in Kleijnen et al. (2004a,b); this study illustrates sensitivity analysis—used to derive a shortlist with the most important factors—and robustness analysis—inspired by Taguchi, and bootstrapping to derive a confidence region for the best input values. Section 4 gives conclusions. A list with 46 references for further study is included.

## 2. Four simulation types for supply chain management

By definition, a *simulation* model has the following three characteristics:

i.     It is a quantitative, mathematical, computer model.

ii.    It is a dynamic model; i.e., it has at least one equation with at least one variable that refers to at least two different points in time (examples are difference equations; more examples will follow below).

iii.   This model is not solved by mathematical analysis; instead, the time paths of the dependent variables (outputs) are computed—given the initial state of the simulated system, and given the values of the exogenous (input) variables.

Aspect (iii) implies that simulation does not give a 'closed form' solution. Instead, the simulation analysts experiment with different input values and model structures, to see what happens to the output—so-called *sensitivity analysis*. Next the analysts may perform V & V, optimisation, and robustness analyses (see Sections 1 and 3).

In the following four subsections, I summarize the four simulation types.

## 2.1 *Spreadsheet simulation*

Corporate modelling has become popular with the introduction of spreadsheet software; see Plane (1997) and Powell (1997). Indeed, this type of simulation has made simulation credible for managers.

A simple example of an equation that is easy to program through a spreadsheet is:

$$\text{new inventory} = \text{old inventory} + \text{production} - \text{sales}. \tag{1}$$

Equation (1) may be called a bookkeeping equation, a balance equation, a difference equation, etc. Such equations are also part of the more sophisticated simulation types discussed below.

Spreadsheets have been used to implement manufacturing resource planning (MRP), which is an important subsystem of SCM; see Sounderpandian (1989). A recent spreadsheet model of Vendor Managed Inventory (VMI) in supply chains is presented in Disney and Towill (2003). However, this type of simulation is often too simple and unrealistic; DEDS simulation provides a more realistic model (see Section 2.3 below).

## 2.2 *System dynamics (SD)*

Forrester (1961) developed *industrial dynamics*, which he later extended and called system dynamics. In fact, Forrester has already developed a model for the following supply chain—without using the term 'supply chain'. His supply chain (which is theoretical, academic) has four links, namely retailer, wholesaler, distributor, and factory. He examines how these links react to deviations between actual and target inventories. He finds that 'common sense' strategies may amplify fluctuations in the demand by final customers—up the supply chain. Much later, Lee et al. (1997) identified this amplification as one of the *bullwhip* effects; also see Disney and Towill (2003).

A recent case study is provided by Higuchi and Troutt (2004), who use SD to model the supply chain for the Japanese pet-toy called Tamagotchi. Spengler and Schröter (2003) also use SD; they study spare parts in closed-loop supply chains at Agfa-Gevaerts. Ashayeri and Keij (1998) model the distribution chain of Edisco (the European distribution arm of the US company Abbott Laboratories). Reviews of SD simulation of SCM are Angerhofer and Angelidis (2000), Beamon (1998), Otto and Kotzab (2003), and Van der Pol and Akkermans (2000).

From a methodological viewpoint, SD views companies as systems with six types of flows, namely materials, goods, personnel, money, orders, and information (examples of these input flows are production and sales; example output flows are fill rate and average WIP). Besides flows, SD distinguishes stocks (for example, WIP at a given point in time). SD assumes that managerial control is realized through the changing of rate variables (for example, production and sales rates), which change flows—and hence stocks. A crucial role in the SD worldview is played by the *feedback* principle; i.e., a manager compares a target value for a specific performance

metric with its realization, and—in case of undesirable deviation—the manager takes

corrective action. An example equation is

$$\text{Inventory.K} = \text{Inventory.J} + \text{DT} \times (\text{Production\_rate.JK} - \text{Sales\_rate.JK}) \qquad (2)$$

where Sales_rate.JK denotes the sales rate during the interval between the points of

time J and K; DT denotes the length of that interval; etc. For more details on SD, I

refer to a recent SD textbook such as Sterman (2000), which has 982 pages!

*2.3 Discrete-event dynamic system (DEDS) simulation*

A DEDS simulation is more detailed than the preceding two simulation types, as is

illustrated by comparing equations (1) and (2) with the following example DEDS

equation:

Waiting time of job $_i =$ max(0, Waiting time of job$_{i-1}$ + Service time of job$_{i-1}$

$\qquad$ - Interarrival time of job$_i$). $\hspace{4cm}$ (3)

DEDS simulation has the following two characteristics:

**(i)** It represents *individual events* (for example, the arrival of an individual

customer order; see equation 3), whereas SD has a much more aggregated view

including flows.

**(ii)** It incorporates *uncertainties* (for example, customer orders arrive at random

points in time; see again equation 3; machines break down at random points of time,

and require random repair times). The other three types of simulation models remain

relevant—even when eliminating randomness! For example, most SD models have no randomness, and yet their behaviour remains counter-intuitive because of the non-linear feedback loops. (Most econometric models are also sets of non-stochastic, non-linear difference equations.) Also see Gaonkar (1977).

For more details on DEDS simulation I refer to the many textbooks on this type of simulation, including the most popular (83,000 copies sold) one—Law and Kelton (2000).

DEDS simulation is an important method in SCM. For example, Banks et al. (2002) survey many SCM simulation studies—at IBM and Virtual Logistics—and they discuss strategic and operational SCM, distributed SCM simulation, commercial packages for SCM simulation, etc. Indeed, DEDS simulation is already part of the MRP/ERP toolbox for quantifying the costs and benefits of strategic and operational policies (ERP: Enterprise Resource Planning); see Vollmann et al. (1997). In Section 3, I shall discuss a recent example of DEDS simulation that models three alternative designs for a supply chain in the mobile communications industry in Sweden—centred on the Ericsson company.

*2.4. Business games*

It is relatively easy to simulate technological and economic processes, but it is much more difficult to model human behaviour. A solution is to let managers themselves operate within the simulated 'world', which may consist of a supply chain and its environment. Such an interactive simulation is called a business or management game.

Games may be used for both educational and research goals. For their education usage, I refer to Riis et al. (2000) and Ten Wolde (2000). For research usage, I refer to Kleijnen (1980). For example, Kleijnen (1980, pp. 157-186) uses an IBM management game to quantify the effects of information accuracy on return on investment (ROI). Another example is the use of games to study the confidence that managers have in their decisions. More recent references are given by Kleijnen and Smits (2003) and Riis et al. (2000).

There are strategic and operational games:

(i) *Strategic games* include several teams of players who represent companies that compete with each other in the simulated world. These players interact with the simulation model during (say) five to ten rounds. The simulation model may be a SD model; a famous example is the beer game, which illustrates the bullwhip effect (see Simchi-Levi et al. 2003, Sodhi 2001, and again Sterman 2000). The game may also be a corporate, economic, business model that illustrates the effects of prices, sales promotion, and research & development decisions on profits; see Kleijnen (1980, pp. 157-186). Also see Riis et al. (2000).

(ii) *Operational games* include a single team—which may consist of one or more players—interacting with the simulation model either during several rounds or in real time. This are games against nature. Examples are games for training in production scheduling; see again Riis et al. (2000).

*2.5 The roles of different simulation types in SCM*

Which of the four simulation types is applied in SCM depends on the problem to be solved. For example, SD aims at qualitative insight (not exact forecasts); for example,

SD can demonstrate the bullwhip effect. DEDS simulation can quantify fill rates, which are random variables. Games can educate and train users, since the players are active participants in the simulated world. Moreover, games can be used in research to study the effects of qualitative factors (such as type of decision support system, DSS) on profits, etc. For brevity's sake, I refer back to the publications that were discussed in the four preceding subsections.

## 3. V & V, sensitivity, optimisation, and robustness analyses: a case study

In this section, I summarize a case study that is detailed in Kleijnen et al. (2004a,b). This study illustrates the importance of V & V, sensitivity analysis, optimisation, and robustness analysis (which were mentioned in Section 1). The study concerns the strategic level of SCM; it uses DEDS simulation.

### 3.1 Overview

The case study consists of three simulation models that represent three alternative designs for a supply chain. Figure 1 illustrates that a newer configuration has fewer operations and tests. Figure 2 shows one of the simulation models—buffers (inventories) are located before and after every test station and operation; products are transported between all operations and test stations. The output is the steady-state mean costs of the total supply chain. Details are given by Persson and Olhager (2002).

Kleijnen et al. (2004a) derive a shortlist with the most important factors; this process is also called *screening*. They apply a method called *sequential bifurcation* (SB). I shall summarize this study in Section 3.3.

Next, Kleijnen et al. (2004b) derive a robust solution; i.e., they find appropriate values for the factors that management can control, while accounting for the randomness of the environmental factors. Their solution is inspired by Taguchi's approach for designing robust physical products; i.e., the important factors are divided into controllable and environmental factors. Kleijnen et al. (2004b) systematically investigate these controllable factors (using a reduced so-called central composite design). They randomly combine the environmental factors into scenarios (using Latin Hypercube Sampling, LHS). Then they estimate the controllable factor values that minimize the output's expected value and variance respectively. A confidence region for these optima is derived through bootstrapping. This confidence region can be used to select a (compromise) robust solution. I shall summarize that study in Section 3.4.

Note: The SCM literature distinguishes between robustness and flexibility. A *flexible* supply chain can react to a changing environment by adapting its operations. A *robust* supply chain keeps its design fixed, and can still accommodate many changes in its environment. So the two concepts focus on operational and strategic decisions respectively. Also see Van Landeghem and Vanmaele (2002) and Zhang et al. (2003). The effects of flexibility on supply chain performance are evaluated through simulation by Garavelli (2003).

Note: Robustness is also important outside DEDS simulation. For example, deterministic simulation—via non-linear difference equations—for Computer Aided Engineering (CAE) often aims at the optimal design of products such as automobiles, airplanes, etc.; see Simpson et al. (2001) for a survey. The coefficients of these equations are not exactly known, and the resulting solution cannot be exactly implemented, so the optimal solution should be 'robust'. In Mathematical

Programming, the search for robust solutions has made most progress and reached maturity, I think; see Ben-Tal and Nemirovski (2000).

*3.2 Validation and verification (V & V)*

The simulation model for the 'old' supply chain depicted in Figures 1 and 2 was validated and verified through discussions with Ericsson engineers; see again Persson and Olhager (2002). This establishes *face validity*; see Law and Kelton (2000).

*Quantitative* V & V may use DOE to check whether the estimated effects of changing inputs of the simulation model agree with the experts' qualitative knowledge about the system. A simple example is a queuing simulation: does an increase in simulated traffic give an increased average waiting time? A case study is reported by Kleijnen (1995): does the DEDS simulation give correct signs for the estimated effects of inputs (such as sonar tilt angle) on the output (detection of mines at the sea bottom)?

If data on the real-world output are available, then real and simulated outputs may be compared statistically. An overview of the role of different statistical techniques—dependent of the availability of data—in V & V is Kleijnen (1999).

*3.3 Screening through sequential bifurcation*

The total number of potentially important factors in the three simulation models is 92 in the Old model, 78 in the Current model , and 49 in the Next Generation model. The most important factor is defined as the one with the highest 'main effect'—also called the 'first-order effect'; see the SB assumptions below.

The SB method simulates relatively few scenarios (factor combinations); for example, Kleijnen et al. (2004a) simulate only 42 scenarios to find the 11 most important factors among the 92 potentially important factors. To realize this efficiency, SB uses two basic *assumptions*:

(i)      A first-order polynomial—possibly augmented with two-factor interactions—can adequately approximate the input/output (I/O) behaviour of the underlying simulation model. (Such approximations are also called metamodels, because they model the underlying simulation model's I/O behaviour.)

(ii)      The signs (or directions) of all main effects are known, so factors can be defined such that all main effects are non-negative (otherwise, main effects might compensate each other).

Because of assumption (i), SB simulates only two values per factor, namely a high and a low value. (In the case study, most factors change by 5 % of the base value; a few other factors by 25 %.) Estimation of main effects unbiased by two-factor interactions is enabled by a so-called *foldover* design, which doubles the number of scenarios that would be simulated in case the polynomial were known to have first-order effects only.

To estimate the statistical significance of the estimated effects, each scenario needs replication—using different, non-overlapping pseudo-random numbers (PRN). In the case study, this number of replicates is selected to be five.

In the case study, SB turns out to give only eleven important factors for the Old model, nine for the Current model, and seven for the Next Generation model. In all three simulation models, factor # 92 is the most important factor; this is the *demand* for product 1, which accounts for 90% of total demand. The other important factors represent yield and transportation. See Kleijnen et al. (2004a) for details.

*3.4 Robustness analysis*

*Taguchi* is the Japanese engineer who designed cars (for Toyota) that operate satisfactorily in many environments; see Taguchi (1987). His method is applied to simulation by Al-Aomar (2002) and Tsai (2002). Next, Kleijnen et al. (2004b) use Taguchi's view but not his statistical methods, because simulation experiments enable the exploration of many more factors and scenarios than are possible in real-life experiments.

Kleijnen et al. (2004b) try to minimize expected cost (as in classic optimisation), but also consider cost variance due to environmental disturbances (as Taguchi proposes).

For illustration purposes, I focus on the Current model. After the SB screening (Section 3.3), there remain only three important controllable factors (and six important environmental factors). The challenge is to 'optimise' these *controllable* factors, denoted by (say) $x_j$ ($j = 1, \dots, k$). A *second-order polynomial* approximation of the I/O behaviour of the simulation model is

$$
\begin{aligned}
y_i = \beta_0 &+ \sum_{j=1}^{k} \beta_j x_{i;j} + \sum_{j=1}^{k} \beta_{j;j} x_{i;j}^2 + \\
&+ \sum_{j=1}^{k-1} \sum_{j'=j+1}^{k} \beta_{j;j'} x_{i;j} x_{i;j'} + e_i \quad (i = 1, 2, \dots.)
\end{aligned}
\tag{4}
$$

with the overall mean $\beta_0$, the first-order effects $\beta_j$, the interactions (cross-products) $\beta_{j;j'}$, and the error term $e_i$—which represents noise caused by both the PRN and the lack of fit of the approximation in (4)—in scenario *i*.

To estimate the coefficients $\beta$ of the second-order polynomial in (4), Kleijnen et al. (2004b) augment the $2^k$ full factorial design with a one-factor-at-a-time design—so each factor is observed at more than two values.

For the *environmental* factors, robustness analysis is not interested in a functional relationship like (4). Following Taguchi, Kleijnen et al. (2004b) treat these factors as noise. Unlike Taguchi, they sample environmental scenarios through LHS; see McKay, Beckman, and Conover (1979).

Next—as in a Taguchian design—the design ('inner array') for the controllable factors is *crossed* (combined) with the design ('outer array') for the environmental factors.

Unlike SB (Section 3.3), this crossed design is not replicated: the standard error in each design point due to pure replication (using different PRN) turns out to be much smaller than the standard error across the environmental scenarios.

The optimisation of (4) for different environmental scenarios should account for the *box constraints* on the inputs: only changes of 5% and 25% are allowed. Mathematically, these constraints are incorporated through Lagrangian multipliers, which quantify the shadow prices of the constraints. All controllable factors turn out to minimize the mean costs when they are set at their lower boundary values. (Because these bounds are specified rather arbitrarily, I raise the question whether these boundary values should not be revised—and followed-up by a new analysis?)

Next, the response variable *y* in (4) is replaced by the *output variance*. One factor again has its optimal value at its lower boundary. The other factors, however, have conflicting optimal values when considering both outputs. Yet, these optimal input values are only estimates, so maybe the truly optimal inputs are the same for both outputs (mean and variance)? To answer this question, a confidence region is

needed for the optimal values.

Standard confidence regions do not hold, because the estimated optimal simulation inputs are *non-linear* functions of the simulation outputs and the corresponding regression estimates. Yet, a confidence region can be computed through *bootstrapping*.

Assuming that the estimated regression parameters $\hat{\beta}$ corresponding with (4) are *normally* distributed, the bootstrap resamples from a multi-variate normal distribution with a vector of means equal to the original estimates $\hat{\beta}$, and with a covariance matrix equal to the estimated matrix that is a standard output of regression software. The resulting bootstrapped estimated regression parameters (say) $\hat{\beta}^*$ give estimated optimal inputs $\hat{x}^*$. Bootstrapping repeats this sampling (say) 1,000 times, to get a confidence region for the values that minimize the mean and the variance of the output respectively. Using this region, *management* may select a robust solution that satisfies their preferences.

Note: Bootstrapping is computationally inexpensive, compared with the computer effort required to generate the simulation output.

Finally, comparing the optimum solution for the controllable factors accounting for many environmental scenarios—generated through LHS—and the solution accounting for a *single scenario*—namely the base scenario—*suggest that risk considerations do make a difference*; see Kleijnen et al. (2004b).

## 4. Conclusions

In this paper, I surveyed four types of simulation, and discussed four methodological issues. These four simulation types are spreadsheets, SD, DEDS, and gaming. I

explained how different types can answer different questions in SCM. For example, SD—possibly run as a game—suffices for demonstrating the bullwhip effect to supply chain stakeholders. DEDS is needed to estimate the probability of realizing a required fill rate—especially in a turbulent environment.

Once a simulation model has been built, it is necessary to perform V &V, sensitivity analysis, optimisation and robustness analysis of that model. V & V may use statistical techniques, including DOE. Sensitivity analysis serves several goals: it provides insight into the behaviour of the supply chain (including interactions between factors), and gives a shortlist of critical factors. Optimising the critical control factors may support Business Process Redesign (BPR). In practice, it is more important to find robust solutions than the optimal solution.

This paper summarized a novel methodology for searching for such a *robust* solution. This solution gives values for those factors that management can control, while accounting for the randomness of the environmental factors.

This robustness *methodology* was inspired by Taguchi's approach. Technically, however, other designs were proposed; for example, LHS. Moreover, a confidence region for the estimated optima was proposed, based on bootstrapping; management may use that region to select a compromise, robust solution.

The methodological issues were illustrated through a *case study*, namely simulation models of different supply chain configurations for Ericsson in Sweden.

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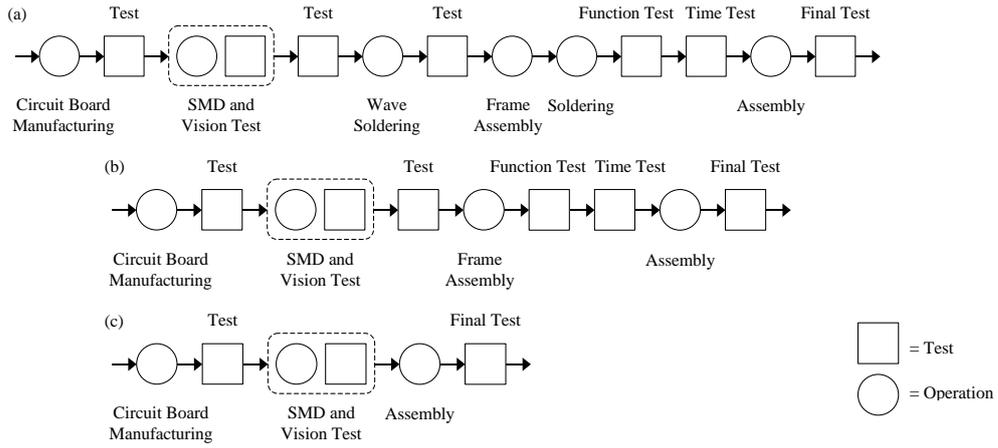
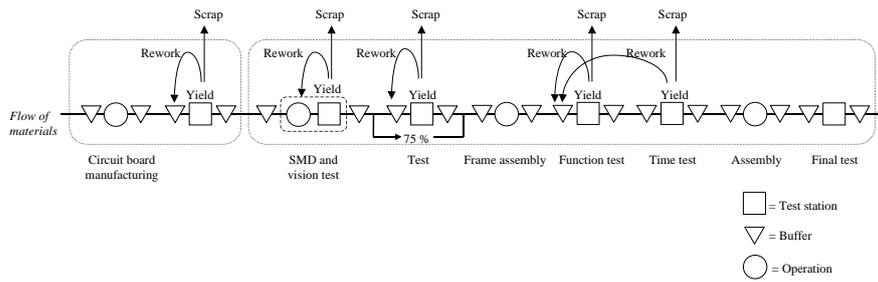Figure 1: The three supply chain structures: (a) the old, (b) the current, and (c) the
next generation



Figure 2: The simulation model of the current supply chain structure