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SUPPLY CHAIN SIMULATION: A SURVEY

By J.P.C. Kleijnen

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Supply chain simulation: a survey

Jack P.C. Kleijnen

Department of Information Systems and Management/

Center for Economic Research (CentER)

Tilburg University, Postbox 90153, 5000 LE Tilburg, The Netherlands

E-mail address: Kleijnen@UvT.NL

Web page: http://center.kub.nl/staff/kleijnen/

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Abstract

This paper provides a survey of simulation in supply chain management. It reviews four types of simulation, namely 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. Moreover, this paper summarizes novel sensitivity 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. Both analyses 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

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

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

Kleijnen and Smits (2003) distinguishes 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. 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. (2003a, b). DOE is important in simulation, because 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*.

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 responses are discussed—and placed in the context of the balanced scorecard (BSC)— by Kleijnen and Smits (2003).

Simulation may give insight into the *causes and effects* of the SC 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 SC) as a black box. 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.

The remainder of this paper is organized as follows. The four simulation types that Kleijnen and Smits (2003) distinguishes, are discussed in the four separate subsections of Section 2. Section 3 summarizes a case study that is detailed in Kleijnen et al. (2003a,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 29 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 Section 1).

In the following four subsections, I summarize the four simulation types that Kleijnen and Smits (2003) distinguishes.

2.1 Spreadsheet simulation

Corporate modelling has become popular with the introduction of spreadsheet software; see Plane (1997) and Powell (1997). 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. However, to evaluate the resulting MRP proposals, this type of simulation is 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 SC—without using the term 'SC'. His (theoretical, academic) SC has four links, namely retailer, wholesaler, distributor, and factory. He examines how these SC 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 SC. Much later, Lee et al. (1997) identified this amplification as one of the *bullwhip* effects.

A recent case study is provided by Ashayeri and Keij (1998), who use SD to study the distribution chain of Edisco, which is the European distribution arm of the US company Abbott Laboratories. Reviews of SD simulation of SCM are Angerhofer and Angelidis (2000), Beamon (1998), and Otto and Kotzab (2003).

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—this 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, pp. 1-982).

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:

$$\text{Waiting time of job}_{i} = \max(\text{Waiting time of job}_{i-1} + \text{Service time of job}_{i-1} - \text{Interarrival time of job}_{i}, 0). \qquad (3)$$

DEDS simulation has the following two characteristics:

(i) It represents *individual events* (for example, the arrival of an individual customer order; see equation 3).

(ii) It incorporates *uncertainties* (for example, customer orders arrive at random points in time; see again equation 3; machines may break down and require random repair times).

For more details I refer to the many textbooks, including the most popular (83,000 copies sold) textbook on this type of simulation—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 discuss a recent example of DEDS simulation that models three alternative designs for a SC 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 SC 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 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).

Kleijnen and Smits (2003) distinguishes two subtypes, namely 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. 2000, 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).

(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. These games are games against nature. Examples are games for training in production scheduling.

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.

3. Sensitivity, optimisation, and robustness analyses: a case study

In this section, I summarize a case study that is detailed in Kleijnen et al. (2003a,b). This study illustrates the importance of 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 SC. 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 SC. Details are given by Persson and Olhager (2002).

Kleijnen et al. (2003a) derive a shortlist with the most important factors; this process is also called *screening*. They apply a method called *sequential bifurcation* (SB). I summarize this study in Section 3.2.

Next, Kleijnen et al. (2003b) 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. (2003b) systematically investigate these controllable factors (using a reduced so-called central composite design). They randomly combine the important environmental factors into scenarios (using Latin Hypercube Sampling or 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 robust solution. I summarize this study in Section 3.3.

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).

3.2 Screening through sequential bifurcation

The total number of potentially important factors in the three simulation models is 92 in the Old, 78 in the Current, and 49 in the Next Generation simulation. 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. (2003a) 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.

(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 simulated in case the polynomial is 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 five.

In the case study, SB gives 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. (2003a) for details.

3.3 Robustness analysis

Taguchi is a 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). Kleijnen et al. (2003b), however, 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. (2003b) 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 3.2), there remain three controllable factors and six environmental factors. The challenge is to 'optimise' these *controllable* factors, denoted by (say) x_j (j = 1, … , k). A *second-order polynomial* approximation of the I/O behaviour of the simulation model is

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

with the overall mean β_0, the first-order effects β_j, the interactions (cross-products) $\beta_{j;j'}$, and the error term e_i—noise caused by the PRN plus the lack of fit—in scenario *i*.

To estimate the effects β in (4), Kleijnen et al. (2003b) augment the 2^k full factorial design with a one-factor-at-a-time design.

For the *environmental* factors, robustness analysis is not interested in a functional relationship like (4). Following Taguchi, Kleijnen et al. (2003b) treat these factors as noise. Unlike Taguchi, they sample environmental scenarios through LHS;

see McKay, Beckman, and Conover (1979).

As in a Taguchian design, Kleijnen et al. (2003b) *cross* (combine) the design (‘inner array’) for the controllable factors with the design (‘outer array’) for the environmental factors.

Unlike SB (Section 3.2), they do not replicate their crossed design: 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.

Next, 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? 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 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. (2003b).

4. Conclusions and further research

Simulation is an important tool for explaining how the SC's performance metrics react to environmental and controllable factors. The type of simulation (spreadsheet, SD, DEDS, game) depends on the type of questions to be answered by the model. For example, SD—possibly run as a game—suffices for demonstrating the bullwhip effect to SC 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 sensitivity and robustness analyses of that model. Sensitivity analysis serves several goals: it provides insight into the behaviour of the SC, and gives a shortlist of critical factors. Optimising the critical control factors may support BPR. In practice, it is more important to find robust solutions than the optimal solution

This paper summarized a novel methodology for finding 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 *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 robust solution.

This methodology has already been applied in a *case study*, namely simulation models of different supply chain configurations for Ericsson in Sweden.

Future research may examine this interpretation of Taguchi’s approach with that proposed by Al-Aomar (2002), Tsai (2002), and others.

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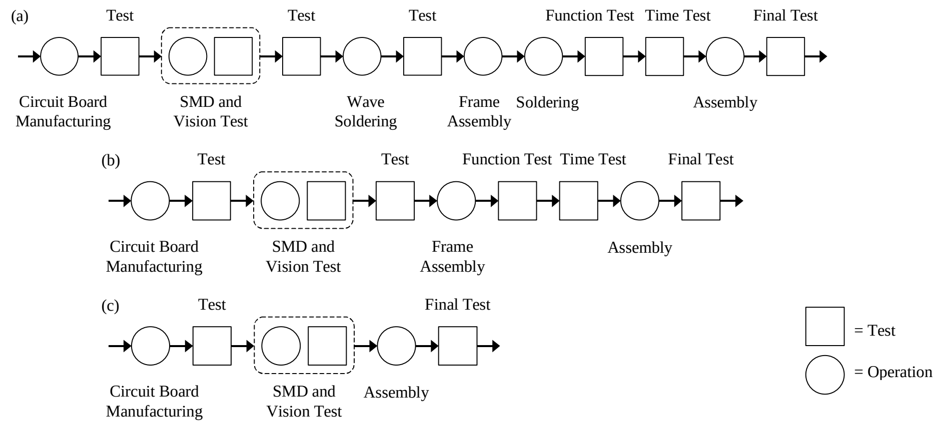

Figure 1: The three supply chain structures: (a) the old, (b) the current, and (c) the next generation

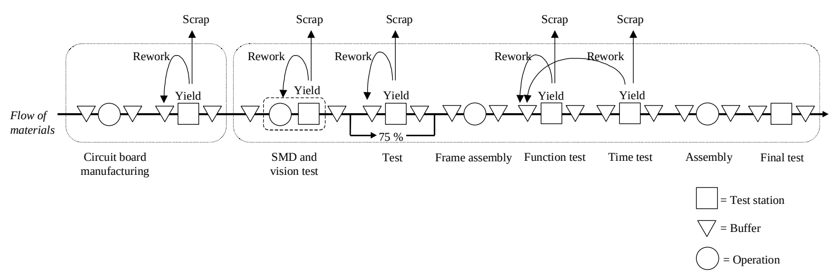

Figure 2: The simulation model of the current SC structure