Constructing Multivariate Simulation Metamodels for Supporting Supply Chain Management

JANICE K. WINCH
Department of Management and Management Science
Lubin School of Business Pace University New York, NY, USA
Email: jwinch@pace.edu
Tel: +12126186564

CHU-HUA KUEI
Department of Management and Management Science
Lubin School of Business Pace University New York, NY, USA
Email: ckuei@pace.edu

CHRISTIAN N. MADU
Department of Management and Management Science
Lubin School of Business Pace University New York, NY, USA
Email: cmadu@pace.edu

Abstract

This paper describes a multivariate simulation metamodeling approach for supporting supply chain management. We use discrete event simulation to examine the links between controllable factors and the supply chain performance. Based on the results of the simulation, regression metamodels are developed. The resource allocation decision on the controllable factors is made by a linear programming model. The paper also presents three modeling frameworks in which the metamodeling approach can be used. They are the hierarchical model, the SCOR model and the integrated supply chain model. The simulation metamodeling approach and the strategic modeling frameworks demonstrated in this paper will assist supply chain managers in resource allocation decisions as they initiate and plan supply chain improvement projects.

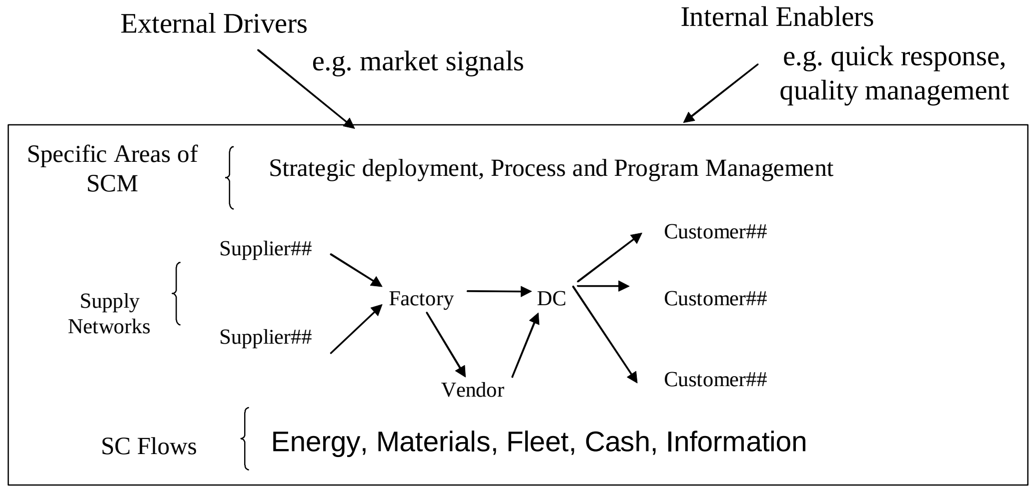
Key Words: *Multivariate Simulation Metamodel, Supply Chain Management, Supply Chain Design, Supply Chain Simulation Model, Taguchi Method.*

Introduction

Supply Chain Management (SCM) has a profound effect on business practices and performance. As noted by Chow et al. (2008), Madu and Kuei (2004), and Kuei, Madu, Lin, and Chow (2002), SCM is a holistic and a strategic approach to demand, operations, procurement, and logistics management. Two observations about SCM are depicted in Figure 1 and summarized here.

First, SCM seeks to respond to market demands correctly and profitably. Facing operations management paradigm shifts, demand and supply uncertainties, and constant conflicts among supply chain units, listening to market signals and synchronizing countermeasures is more important than ever. Market signals in this context can be considered as external drivers of supply chain *management* design and practices, while countermeasures such as quick response and quality management can be noted as internal enablers. Over the past decade, industry leaders such as Zara (the Spanish apparel manufacturer and retailer), Nokia, Toyota, Cisco, Microsoft, and Hewlett-Packard have adopted customer-centric supply chain initiatives and cross-enterprise processes. As noted by Chow et al. (2008, p.666), for example, Zara “learned to introduce more than 11,000 products per year.

Figure 1 Supply Chains and SCM



From the drawing board to store racks, new fashions can be brought into markets in two weeks. Zara's supply chain system can deliver new shipments to its six hundred or so stores around the globe every few days." SCM with a special focus on quick response is one of the key determinants of Zara's success. Lee (2004) also used Saturn and RR Donnelley (a printer company) as examples to illustrate the importance of supply chain alignment efforts among suppliers, assemblers, distributors, and retailers.

Second, there is increasing attention on understanding how to proactively manage supply networks to build competitive advantage. Madu and Kuei (2004) identified three distinctive areas of supply chain management: supply chain policy deployment, supply chain process management, and supply chain quality management. Madu and Kuei (2004), for example, suggest that a supply chain should establish a sense of purpose for being in the market and know where it intends to be in the long run. Strategic deployment should thus be used as a means to realizing the full potential of entire supply networks. Further, Madu and Kuei (2004) also suggest that supply chains should be studied from a business process point of view with special emphases on program management. Supply chain processes, in general, include returns, demand management, order fulfillment, customer relationship management, customer service management, manufacturing flow management, supplier relationship management, and product development and commercialization (Madu and Kuei 2004). Quality management can also help align a firm's customer-centric strategy with its supply chain partners' interests and business processes. Kelle and Akbulut (2005) and Lee (2004), for example, contend that it is difficult for any firm to launch initiatives and enable conditions for better performance without Lean and Six-sigma suppliers in the first place. Haier, one of the world's top five producers of household appliances, for example, has been using its customer-centric quality policy to guide its supply chain operations. In the early 1980s, this Chinese appliance maker had more than $10 million in debt. With a well-executed policy deployment procedure, Haier today has more than $12 billion in revenue. As noted by Haier's CEO, "the quality of the goods represented not only a company, but the whole country (Schafer, 2005)."

For supporting supply chain management, decision science models such as simulation are useful tools for effective decision making. Longo and Mirabelli (2008), Kuei, Madu, and Lin (2009), Kuei, Madu, and Winch (2008), and Madu and Kuei (2004), for example, show that a simulator can help make better decisions in numerous areas of SCM such as network configuration, resource allocation, supplier selection, inventory control, transportation, quality improvement, and environmental issues. Maloni and Benton (1997) also challenge operations researchers to utilize tools such as simulation, heuristics, game theory, and optimization to help firms understand the true benefits of effective supply chain integration. Areas of decision science applications in this regard include: throughput, initial strategic analysis phase, supplier selection and evaluation phase, partnership establishment phase, and maintenance phase. Kelle and Akbulut (2005) also provide a literature review on quantitative support for supply chain optimization. Through the use of quantitative models, supply chain relationships, either in the form of partnership or adversarial relationship, can be quantified and evaluated in terms of costs and benefits. Two main results from their quantitative analyses are:

- The joint optimal policy will always benefit the entire supply chain.
- Coordinating the safety stock policy will always result in cost savings.

In addition, Madu and Kuei (2004) employ linear programming (LP) models for the postponement decisions. Monte Carlo simulations for assessing inventory policy and behavior during early-sales period are also discussed.

In this paper, we show how a combination of simulation-based metamodeling and linear programming can be used to improve supply chain decisions. We first identify the specific relationships between controllable factors and performance outcomes in a supply chain simulation setting through using the metamodeling approach. Then we formulate a linear programming model with these relationships and solve it to find the optimal supply chain design. This paper is organized as follows. In the next section, we focus on earlier research on critical aspects of supply chain systems and regression metamodeling in computer simulation. In section 3 we illustrate our modeling approach and results. In section 4 we discuss frameworks for potential applications and follow with conclusions in section 5.

Research Background

Past Work on Modeling Supply Chain Systems

The subject of simulation modeling approaches for complex supply chain systems has received considerable interest in the literature. Bottani and Montanari (2009), for example, use discrete-event simulation models to understand the behavior of a fast moving consumer goods supply chain and optimize supply chain design. In their simulation study, thirty supply chain configurations were tested for logistical costs and the demand variance. Major parameters adopted by Bottani and Montanari (2009) include (a) numbers of echelons (from three to five), (b) inventory policies (EOQ or economic order interval (EOI)), (c) information sharing mechanisms (absence or presence of such a mechanism), (d) daily final customer's demand values and behavior, and (e) the responsiveness of supply chain players. Three supply chain flows such as product, order, and information are also noted in the supply chain simulation model.

In a similar fashion, Zhang and Zhang (2007) propose a supply chain simulation model with four different supply chain performance measures. They are service, inventory cost, backlog cost, and total cost. Major experimental settings center on demand variance and location of distributor in China. Rabelo, Eskandari, Shaalan, and Helal (2007) present a hybrid approach that integrates system dynamics, discrete-event simulation, and the Analytic Hierarchy Process (AHP) to model the service and manufacturing activities of a multinational construction equipment firm's global supply chain.

Longo and Mirabelli (2008) also contend that a parametric supply chain simulator is a decision making tool capable of analyzing different supply chain scenarios. Major parameters considered by Longo and Mirabelli (2008) include inventory policies, lead times, and customers' demand intensity and variability. Three supply chain nodes such as stores, distribution centers, and plants are presented. Their simulation models were tested for three supply chain performance measures: fill rate, on hand inventory, and inventory costs. Metamodels, or statistical models used to express Y (i.e., dependent variable such as fill rate) as function of x_i (i.e., independent variables or factors such as inventory policies, lead times, and customers' demand) are also constructed by Longo and Mirabelli (2008) for each performance measure.

Both Kuei, Madu, and Winch (2008) and Shang, Li, and Tadikamalla (2004) elaborate on the use of Taguchi design and metamodeling approaches to model a relatively complex supply chain network. L16 Taguchi design is used by Kuei et al. (2008).

Shang et al. (2004) choose L27 Taguchi design for controllable factors. Chwif, Barretto, and Saliby (2002) compare spreadsheet-based and simulation-based tools in the analysis of a supply chain system. They conclude that discrete event simulation is the right tool when conducting in-depth supply chain analyses. Jain, Lim, Gan, and Low (1999) used simulation to study the behavior of supply chain networks and were able to identify logistics and business processes as the two major issues surround such networks. Towill, Naim, and Wikner (1992) compared different quick-response-to-orders strategies based on a supply chain simulation model.

The aforementioned studies illustrate how simulation models have been used to assess the impact of controllable factors on supply chain performances under various supply chain configurations. In this paper, the data generated by the simulation models are used to build regression metamodels that explicitly describe such relationships.

Regression Metamodeling in Computer Simulation

Longo and Mirabelli (2008), Kuei et al. (2008), Friedman and Pressman (1988), and Madu and Kuei (1993, 1994) offer a comprehensive review on regression metamodeling in computer simulation. As reported by Kuei et al. (2008, p.135) and Friedman and Pressman (1988), "the benefits of constructing a metamodel in a simulation study include model simplification, enhanced exploration and interpretation of the model generation to other models of the same type, sensitivity analyses, optimization, answering inverse questions, and providing the researcher with a better understanding of the behavior of the system under study." When developing metamodels, researchers and decision makers need to consider the following three issues: establishing the mathematical form of metamodel, preparing full or fractional factorial design plans, and conducting single-stage or multiple-stage experiments. In the following, we shall briefly discuss these three issues.

(1) Establishing the mathematical form of metamodel

If we assume that the simulation model yields a system performance *Y* equal to the additive effects of the inputs $x_i (i = 1, \ldots, k)$, then

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + e \tag{1}$$

where β_0 is the grand mean; β_i is the coefficient of single factor *i*; and *e* is the experimental error. If we assume that the simulation input factors also interact, then we have a second-order regression model

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i \prec j}^{k} \sum_{j=2}^{k} \beta_{ij} x_i x_j + e \tag{2}$$

where β_{ij} denotes the coefficient of the interaction between group factors *i* and *j*. This is the form adopted by Kuei et al. (2008). More complicated forms and models can be found in Longo and Mirabelli (2008) and Shang et al. (2004). Other examples of using regression metamodels for decision making appear in Kumar, Satsangi, and Prajapati (2013) and Winch, Madu, and Kuei (2012). Kumar, et al. (2013) use second-order metamodels to minimize casting defect in a melt shop industry. Winch et al. (2012) illustrate how metamodeling combined with goal programming can be used to minimize operational cost and waste in a reverse logistics system.

(2) Preparing full or fractional factorial design plans

As noted by Shang et al. (2004, p.3835), an ideal experimental design plan "provides the maximum amount of information with the minimum number of trials. Taguchi developed orthogonal arrays, linear graphs, and triangular tables to reduce the experiment time and to increase accuracy." If decision makers need to consider five factors, for example, at two levels each, then the total number of factor combinations is 2^5, or 32. In other words, thirty two simulation runs are expected if this full factorial design is adopted. When the full factorial plan is executed, higher-order interactions such as three-factor interaction can be estimated. However, in many situations, this plan is too expensive and impracticable since high-order interactions are often insignificant (Kuei et al. 2008).

If decision makers can assume that the higher-order interactions are not significant, then they can adopt fractional factorial design plans. With the same five input factors, that means only 2^{5-1}, or 16 simulation runs are required. In a Taguchi design, decision makers can set up the fractional factorial design plan based on the L16 orthogonal arrays and the corresponding linear graphs (Kuei et al. 2008, Madu and Kuei 1993, Peace 1993, Taguchi and Wu 1980). Shang et al. (2004), referring to Taguchi's orthogonal array tables, choose the L27 design for controllable factors such as reliability, capacity, lead time, reorder quantity, information sharing, and delayed differentiation in their simulation study. To examine the effects of these six controllable factors, at three levels each, then the total number of factor combinations is 3^6, or 729. Using the Taguchi method, only 27 experiments are required.

(3) Conducting Single-stage or Multiple-stage Experiments

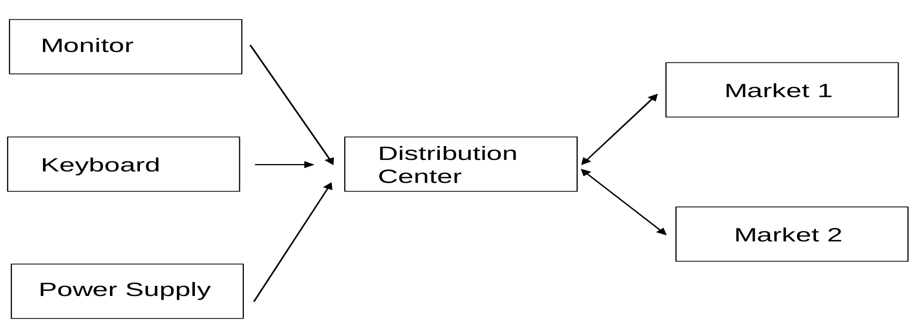
As noted by Kuei et al. (2008) and Madu and Kuei (1993, 1994), if the number of simulation input factors is small (say $k \leq 5$), a single-stage approach is sufficient when constructing metamodels. This approach is adopted by both Longo and Mirabelli (2008) and Shang et al. (2004). When many input factors are considered (e.g., $k > 5$), however, multiple-stage experiments are more appropriate. As noted by Kuei et al. (2008), it is unwise to investigate all the controllable factors in the initial stage of an experiment. In some situations, individual factors can also be aggregated into groups. With a large number of input factors and/or group factors, the attempt should center on screening experimentation and identifying the most important (individual and/or group) factors. In the follow-up experiment, single factors and any group factors of interest can be further tested and investigated. With the *exception* of a few recent studies, *little work* of any depth has been published on the multiple-stage experimentation in a supply chain setting. In this simulation study, we will follow the multiple-stage experimentation procedure outlined by Kuei et al. (2008) and Madu and Kuei (1994).

Metamodeling and Optimizing a Supply Chain Network

Problem Setting

With the aim of analyzing a supply chain system through using simulation modeling approaches, we need to first frame the issues and define our problem. For the purpose of this study, we consider a single laptop computer supply chain network operating with one distribution center and two customer zones (see Figure 2).

Figure 2 Supply Chain Network



The distribution center purchases monitors, keyboards, and power supply modules from three supply groups. The final assembly is done in the distribution center. End user orders from those two customer zones are consolidated in the order fulfillment office. They are fulfilled subsequently by the distribution center. The supply chain system described here is in line with that of Longo and Mirabelli (2008) and Towers and Burnes (2008). For example, lead time management is considered by Towers and Burnes (2008) as one of the primary strategic and operational requirements in a supply chain setting.

We want to see how the overall lead time for the customer is related to the intermediate lead times within the supply chain network and perhaps the time to repair defective items, if any. With all time units in hours, the definitions of both the dependent and input variables in our first stage of experimentation are given below. The assumed distributions with their parameters for the input variables are shown in Table 1.

Dependent variables:

LTime (Market 1): average lead time needed for the first customer zone
LTime (Market 2): average lead time needed for the second customer zone

Input variables:

Demand (Market 1): the variation of demand in the first customer zone
Demand (Market 2): the variation of demand in the second customer zone
DCTR LTime: lead time between the distribution center and customer zones
Supply Group LTime: lead time between supply groups and the distribution center
MTTR: Mean Time to Repair

Table 1 Original Data

	Demand	Lead Time	MTTR
Market 1 - Demand	N(60,12)		
Market 2 - Demand	EXP(60)		
Distribution Center		EXP(48)	EXP(48)
Power Supply		EXP(60)	
Monitor		EXP(48)	
Keyboard		EXP(48)	

N(mean, standard deviation): Normal Distribution
EXP(MTTR): Exponential Dist (Mean Time to Repair)
All time units are in hours.

The primary assumptions of the supply chain model here are summarized as follows:

- End user orders from the first customer zone are consolidated and follow the normal distribution.
- End user orders from the second customer zone are consolidated and follow the exponential distribution.
- The lead time between the distribution center and two customer zones follows the exponential distribution.
- The lead time between the distribution center and suppliers follows the exponential distribution.
- At the distribution center, the defective rate for the first customer zone's orders is ten percent.
- The defective items are repairable and are assumed to be completely rejuvenated after each repair.
- The repair time follows the exponential distribution.

Simulation Model

The simulation model for the described supply network setting is shown in Figure 3. This model was coded in GPSS/H for our experiments. As can be seen in Figure 3, there are four major segments and one module in the simulation model. The first two segments represent market demands and customer orders. The third segment represents the operation of the distribution center. The fourth segment depicts the operations of three supply groups and the assembly process in the distribution center. The quality module (see Figure 4) is included in the third segment to simulate the failure and repair processes.
In the remainder of section, we describe a sequential procedure for utilizing the simulation results to construct and apply regression metamodels (see Figure 5). This new cycle of modeling and optimizing supply chain systems involves four steps: experimental designs, regression analyses, validation tests, and decision models.

Experimental Designs

From the problem description, five input factors were identified that may affect supply chain network's operations. To see the effect of varying input values, each factor was examined at two levels as shown in Table 2. Notice the level 2 parameters are lower and thus correspond to shorter lead times and repair times.

Figure 3 SCM Model

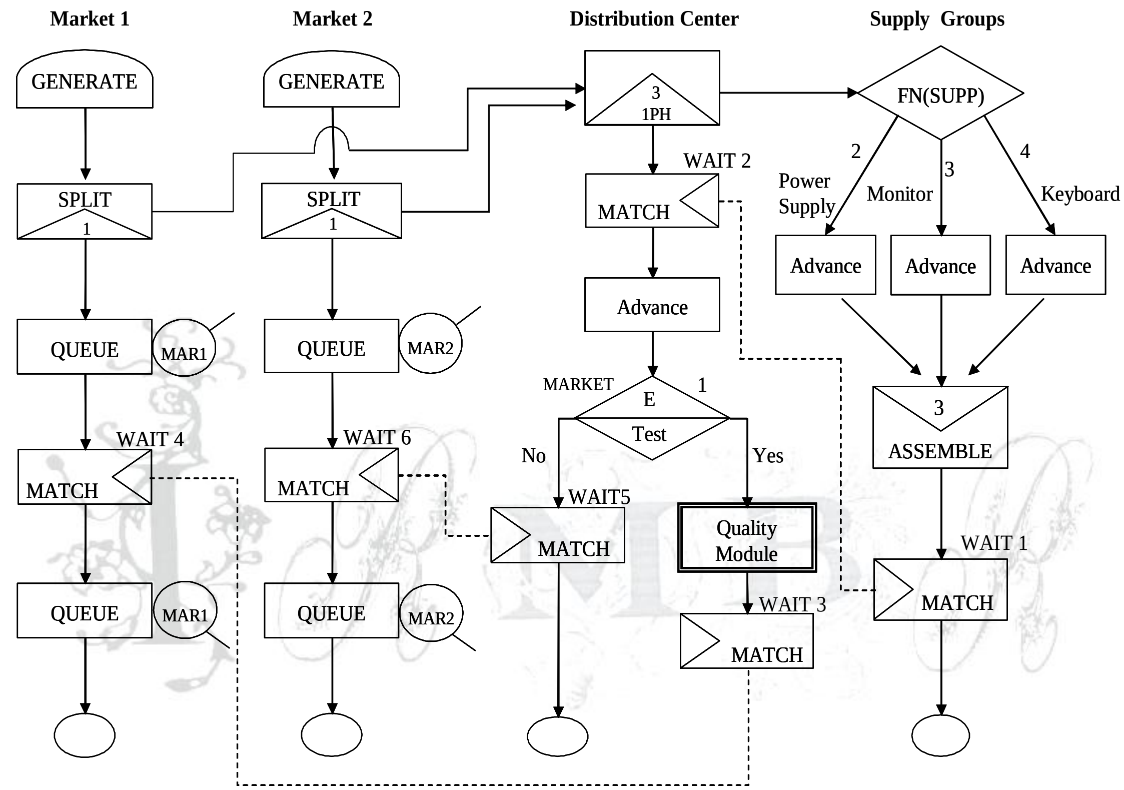


Figure 4 Quality Module

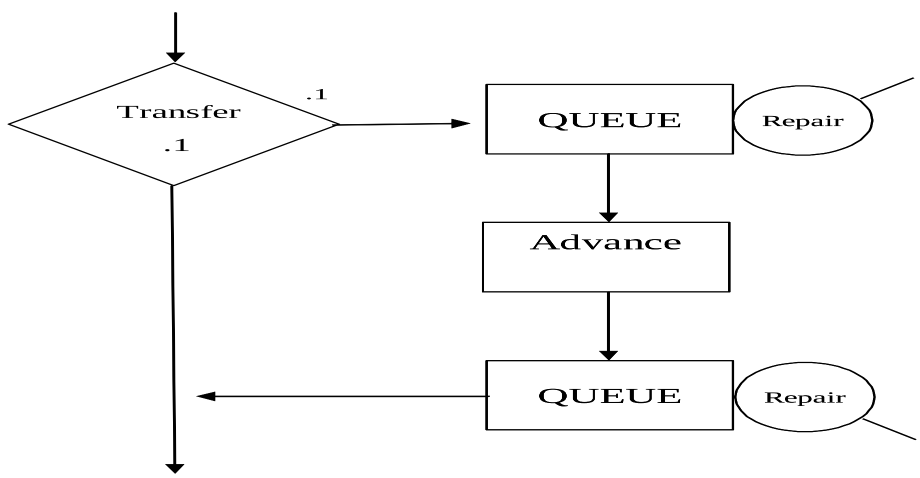
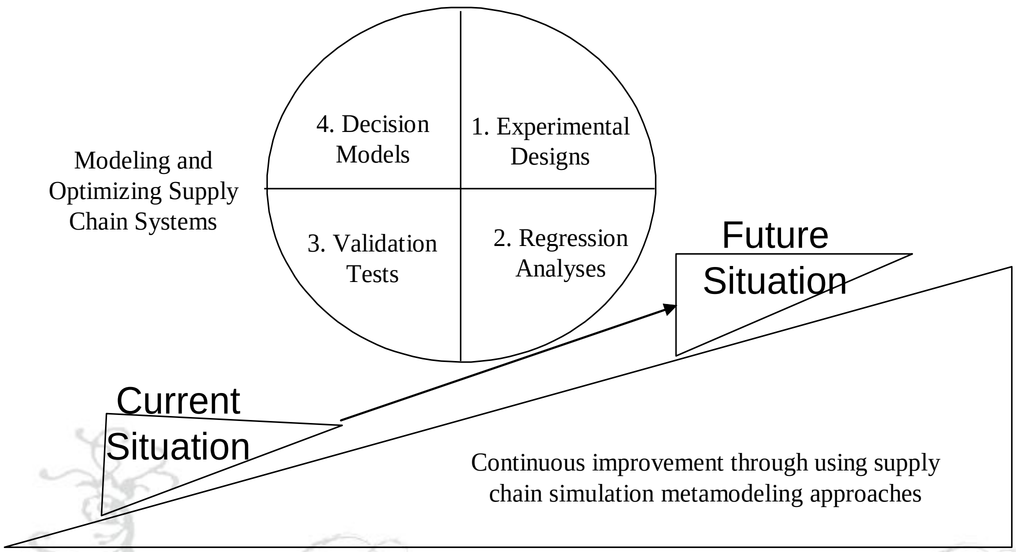


Figure 5 Modeling and Optimizing Supply Chain Systems



Since each factor is examined at two levels, only the linear effects of each factor on the dependent variables can be assessed. Equation (2) was adopted here for the purpose of this study. According to this proposed mathematical model, the L_{16} factional factorial design was used. As a result, the main effects of the input factors and their two-factor interaction effects can be estimated with only sixteen simulation runs. Table 3 presents the experimental design and the results of the discrete simulation. Each simulation run was conducted for 4,800 hours and a total of thirty replications were carried out for each experiment. The presented LTime (Market 1) and LTime (Market 2) are, thus, the average of the thirty replications.

Table 2 Screening Experimentation - Individual Factors and Levels

Factor	Name	Level 1	Level 2
A	Market 1 - Demand Uncertainty	N(60,12)	N(36,6)
B	Market 2 - Demand Uncertainty	EXP(60)	EXP(30)
C	Distribution Lead Time	EXP(48)	EXP(12)
D	Mean Time to Repair (MTTR)	EXP (48)*	EXP (6)*
E**	Supply Lead Time	EXP(60)# EXP(48)##	EXP(12)# EXP(12)##

*: Defective Rate between Market 1 and Distribution Center: 10%
#: Power Supply Module
##: Monitor and Keyboard
N( ): Normal Distribution
EXP ( ): Exponential Distribution
**factor E is a group factor

Table 3 Screening Experimentation - Systematic Assignment to Five Factors and Multivariate Simulation Results

	Factor A	Factor B	Factor C	Factor D	Factor E	Avg. LTime (M1)	Avg. LTime (M2)
1	Level 1	Level 1	Level 1	Level 1	Level 1	145.10	139.82
2	Level 1	Level 1	Level 1	Level 2	Level 2	69.27	70.95
3	Level 1	Level 1	Level 2	Level 1	Level 2	72.68	70.95
4	Level 1	Level 1	Level 2	Level 2	Level 1	108.92	103.86
5	Level 1	Level 2	Level 1	Level 1	Level 2	75.89	70.01
6	Level 1	Level 2	Level 1	Level 2	Level 1	143.36	139.04
7	Level 1	Level 2	Level 2	Level 1	Level 1	111.03	106.67
8	Level 1	Level 2	Level 2	Level 2	Level 2	35.33	33.11
9	Level 2	Level 1	Level 1	Level 1	Level 2	73.24	68.17
10	Level 2	Level 1	Level 1	Level 2	Level 1	141.91	141.39
11	Level 2	Level 1	Level 2	Level 1	Level 1	111.83	107.71
12	Level 2	Level 1	Level 2	Level 2	Level 2	35.06	33.36
13	Level 2	Level 2	Level 1	Level 1	Level 1	145.49	141.14
14	Level 2	Level 2	Level 1	Level 2	Level 2	69.18	68.92
15	Level 2	Level 2	Level 2	Level 1	Level 2	38.97	33.73
16	Level 2	Level 2	Level 2	Level 2	Level 1	106.49	106.17

LTime is in hours. M1 = Market 1, M2 = Market 2

The analysis of variance (ANOVA) procedure was applied to test the significance of both the main and two-factor interaction effects (Kuei et al. 2008, Longo and Mirabelli 2008). The ANOVA tests in Table 4 show that factors C (DCTR LTime) and E (Supply Group LTime) are statistically significant at $\alpha = 0.01$. Notice that factor E is a group factor. Notice also that the "pooling" technique is employed to estimate the experimental error. For example, for the case of LTime (M1), since the sum of squares (SS) values of factor A, factor B, factor D, and all the two-factor interactions are very small, they are aggregated and used to estimate the experimental error.

Table 4 ANOVA Results

	Avg. LTime (M1)			Avg. LTime (M2)		
Source	SS	MS	F	SS	MS	F
Factor A	97			71		
Factor B	65			88		
Factor C	3695	3695	43.06#	3717	3717	42.75#
Factor D	262			107		
Factor E	18531	18531	215.98#	17996	17996	206.97#
A * B	51			81		
A * C	63			70		
B * C	105			76		
D * E	96			63		
A * D	60			98		
B * D	59			67		
C * E	64			57		
C * D	67			119		
B * E	54			90		
A * E	72			143		
Pool Error:		86			87	

#: At least 99% confidence

Given the new information about our initial experimental factors, in the follow-up experiment, we consider the following five factors:

DCTR LTime: lead time between the distribution center and customer zones
PSM LTime: lead time between our Power Supply Module group and the distribution center
Monitor LTime: lead time between our Monitor group and the distribution center
Keyboard LTime: lead time between our Keyboard group and the distribution center
MTTR: Mean Time to Repair (the defective rates at the supply groups and the distribution center are identical in the follow-up experiment)

The levels used are shown in Table 5. The L_{16} factional factorial design plan and simulation results are shown in Table 6. Table 7 shows the results based on the ANOVA test. It turns out that all experimental factors in the follow-up experiment are significant at α = 0.01.

Table 5 Follow-up Experimentation - Individual Factors and Levels

Factor	Name	Level 1	Level 2
A	Distribution Lead Time	EXP(48)	EXP(12)
B	Power Supply Lead Time	EXP(60)	EXP(12)
C	Monitor Supply Lead Time	EXP(48)	EXP(12)
D	Keyboard Supply Lead Time	EXP(48)	EXP(12)
E	Distribution and Supply Group's MTTR	EXP (48)	EXP (6)

EXP ( ): Exponential Distribution

Table 6 Follow-up Experimentation - Systematic Assignment to Five Factors and Multivariate Simulation Results

	Factor A	Factor B	Factor C	Factor D	Factor E	Avg. LTime (M1)	Avg. LTime (M2)
1	Level 1	Level 1	Level 1	Level 1	Level 1	151.39	149.97
2	Level 1	Level 1	Level 1	Level 2	Level 2	128.70	131.03
3	Level 1	Level 1	Level 2	Level 1	Level 2	128.57	126.75
4	Level 1	Level 1	Level 2	Level 2	Level 1	123.08	118.92
5	Level 1	Level 2	Level 1	Level 1	Level 2	119.52	120.12
6	Level 1	Level 2	Level 1	Level 2	Level 1	114.98	107.58
7	Level 1	Level 2	Level 2	Level 1	Level 1	114.97	105.51
8	Level 1	Level 2	Level 2	Level 2	Level 2	71.63	68.53
9	Level 2	Level 1	Level 1	Level 1	Level 2	106.38	107.83
10	Level 2	Level 1	Level 1	Level 2	Level 1	104.02	103.26
11	Level 2	Level 1	Level 2	Level 1	Level 1	105.86	101.57
12	Level 2	Level 1	Level 2	Level 2	Level 2	74.56	76.04
13	Level 2	Level 2	Level 1	Level 1	Level 1	96.55	92.81
14	Level 2	Level 2	Level 1	Level 2	Level 2	63.42	65.81
15	Level 2	Level 2	Level 2	Level 1	Level 2	66.60	65.02
16	Level 2	Level 2	Level 2	Level 2	Level 1	50.57	45.87

M1: Market 1's Average Lead Time (Hours); M2: Market 2's Average Lead Time (Hours)

Table 7 Follow-up Experimentation – ANOVA Results

	Avg. LTime (M1)			Avg. LTime (M2)		
Source	SS	MS	F	SS	MS	F
Factor A	5072	5072	217.98#	4563	4563	210.61#
Factor B	3145	3145	135.16#	3725	3725	171.92#
Factor C	1390	1390	59.73#	1811	1811	83.57#
Factor D	1578	1578	67.80#	1454	1454	67.12#
Factor E	651	651	27.97#	259	259	11.95#
A * B	1			81		
A * C	1			70		
B * C	65			76		
D * E	3			63		
A * D	3			98		
B * D	77			67		
C * E	1			57		
C * D	70			119		
B * E	6			90		
A * E	6			143		
Pool Error:		23			22	

#:At least 99% confidence

Regression Analyses and Validation

Since all five input factors in Table 7 were statistically significant, all of them were included as independent variables in the regression metamodels predicting the average lead times needed for the two customer zones. The data in Table 6 were used to develop these least-square linear regression equations. Equation (3) shows the regression for LTime (Market 1) with the first customer zone (R^2=0.981, P < 0.0001).

LTime (Market 1) = 10.312** + 0.989 (DCTR LTime)*** + 0.584 (PSM LTime)***
+ 0.518 (Monitor LTime)*** + 0.552 (Keyboard LTime)*** + 0.304 (MTTR)***
(*: P < 0.10, ** P < 0.05, ***: P < 0.01) (3)

Equation (3) shows the regression for LTime (Market 2) with the second customer zone (R^2=0.982, P < 0.0001).

LTime (Market 2) = 9.341* + 0.938 (DCTR LTime)*** + 0.636 (PSM LTime)***
+ 0.591 (Monitor LTime)*** + 0.530 (Keyboard LTime)*** + 0.192 (MTTR)***
(*: P < 0.10, ** P < 0.05, ***: P < 0.01) (4)

As expected, equations (3) and (4) show that the average lead times for both markets are positively related to the input lead times and the mean time to repair.
For validation of metamodels, ten new design points were randomly selected and tested. The average LTime (M1) and LTime (M2) values were obtained from simulation runs and compared to the values from the metamodels in (3) and (4). The results are shown in Table 8. The mean absolute percentage error (MAPE) for each metamodel was estimated as:

$$\text{MAPE} = 100\% * \left(\frac{1}{10} \sum_{i=1}^{10} \left| \frac{Meta(i) - Simulation(i)}{Simulation(i)} \right| \right) \quad (5)$$

where Meta(i) = output value from the metamodel in experiment i, and Simulation(i) = output value from the simulation in experiment i. The MAPEs of 2.9% and 3.7% were observed for our two regression metamodels respectively. We therefore conclude that the metamodel is valid in estimating the response lead times in both customer zones.

Table 8 Validation Test for LTime (M1) and LTime (M2)

						LTime (M1)			LTime (M2)		
	A	B	C	D	E	Simulation	Metamodel	% Error	Simulation	Metamodel	% Error
1	38	55	19	22	40	113.54	114.16	0.5%	109.63	110.53	0.8%
2	42	26	39	35	38	113.70	118.11	3.9%	111.59	114.17	2.3%
3	20	34	42	37	17	93.78	97.30	3.7%	92.09	97.42	5.8%
4	18	15	35	42	29	83.94	87.00	3.7%	82.56	84.28	2.1%
5	33	28	41	16	19	93.80	95.15	1.4%	88.99	94.46	6.1%
6	45	45	15	19	38	110.44	110.91	0.4%	103.64	106.40	2.7%
7	25	51	24	31	42	103.66	107.13	3.4%	101.52	103.91	2.3%
8	16	16	36	42	36	85.63	88.26	3.1%	82.64	84.97	2.8%
9	29	38	28	26	22	91.18	96.73	6.1%	87.64	95.26	8.7%
10	34	42	14	15	25	89.49	91.60	2.4%	86.28	88.97	3.1%
							MAPE	2.9%		MAPE	3.7%

Decision Model

The essence of optimizing supply chain systems is to find the best solution for a given objective. At this point, we have a good sense about which areas in our supply networks should be targeted for improvement. Our next task is centered on resource allocation. Suppose the goal is to decrease the average response time in the first market to 100 hours (the current response time is 151.39 hours in the first market). Given that improving the supply chain speed requires additional investment, we wish to satisfy this requirement at the minimum additional cost. The specifics of the investment areas and possibilities are shown in Table 9. Here, we can use the linear programming solution approach to minimize the cost of improving supply chain speed for market 1. Notice that there are two set of decision variables: X_i represents the individual factor or area, while Y_i is defined as the number of units (levels) that each factor or area could be improved (i = *A, B, C, D, and E*). Notice that equation (3) is incorporated in our linear programming model for the supply chain speed computation. Note also that we move the constant 10 from the left-hand side to the right-hand side (For simplicity, we use 10, instead of 10.312). The marginal improvement cost (MIC) can also be found in Table 9.

Table 9 Original Data - Decision Model

Factor	Normal Scenario (NS)	Best Scenario (BS)	Maximum Reduction (MR=NS-BS)	Normal Cost (NC)	Cost for the BS (CBS)	Extra Cost (EC=CBS-NC)	Marginal Improvement Cost (MIC=EC/MR)
A	48	12	36	$100	$280	$180	$5.0
B	60	12	48	$50	$98	$48	$1.0
C	48	12	36	$40	$94	$54	$1.5
D	48	12	36	$40	$76	$36	$1.0
E	48	6	42	$10	$31	$21	$0.5

The factors are as defined in Table 5. Time units are in hours and cost units are in $thousands.

Linear Programming Model (LP)

$$\begin{array}{lll} \text{Minimize} \quad Z = & \$5Y_A + \$1Y_B + \$1.5Y_C + \$1Y_D + \$0.5Y_E & \text{(Improvement Cost)} \\ \text{Subject to} & 0.989X_A + 0.584X_B + 0.518X_C + 0.552X_D + 0.304X_E \le 90 & \text{(Response Time Limit)} \\ & X_A \ge 48 - Y_A & \\ & X_B \ge 60 - Y_B & \\ & X_C \ge 48 - Y_C & \\ & X_D \ge 48 - Y_D & \\ & X_E \ge 48 - Y_E & \\ & Y_A \le 36, Y_B \le 48, Y_C \le 36, Y_D \le 36, Y_E \le 42 & \\ & X_i, Y_i \ge 0 & i = A, B, C, D, E \end{array}$$

Solving the linear programming model gives the following solution indicating we should direct investment to three factors:
Factor or Area B (PSM LTime): \$48,000 should be invested here ($Y_B = 48$)
Factor or Area D (Keyboard LTime): \$32,000 should be invested here ($Y_D = 32$)
Factor or Area E (MTTR): \$21,000 should be invested here ($Y_E = 42$)
The total investment as a result is \$101,000 ($Z = 101$).

Further, the new level needed in each critical area for meeting the customer lead-time requirement are:
Factor or Area A (DCTR LTime): 48 ($X_A = 48$)
Factor or Area B (PSM LTime): 12 ($X_B = 12$)
Factor or Area C (Monitor LTime): 48 ($X_C = 48$)
Factor or Area D (Keyboard LTime): 16 ($X_D = 16$)
Factor or Area E (MTTR): 6 ($X_E = 6$)

With decision science models such as simulation and linear programming (LP), we are able to make effective and quality supply chain decisions.

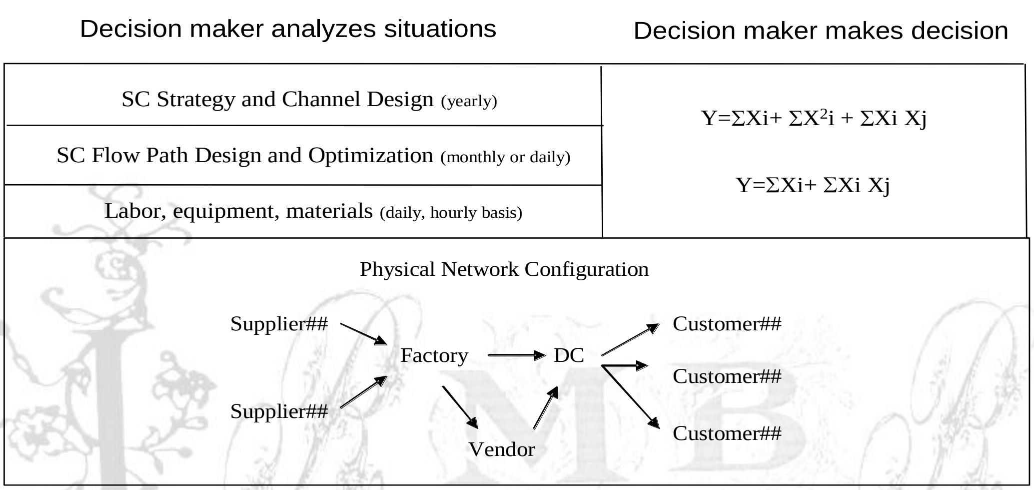
Discussion of Potential Applications

In the previous section, we illustrated a four-stage metamodeling process that will assist in decision making in the context of improving supply chains. The four-stage process involved experimental designs, regression analyses, validation tests, and decision models. In this section, we describe three frameworks of modeling supply chains in which this metamodeling approach will be useful. They are a hierarchical model, the SCOR model and an integrated supply chain model.

A Hierarchical Model

By drawing on the conceptual model of SCM presented by Simchi-Levi, Kaminsky, and Simchi-Levi (2000), we report on the possible use of our four-stage problem-solving strategies in dealing with supply chain issues. Figure 6.1 presents our proposed investigation strategies for a hierarchical model. At the strategic level, as can be seen in Figure 6.1, company management tends to make high level strategic choice. Supply chain simulation metamodel can be used in dealing with the selection of number, location, capacity of supply chain nodes, and the flow of material through the logistics network. The impact of supply chain quality management (Prado-Prado 2009, Kuei et al. 2008, Kannan & Tan 2007, Fynes, Burca, & Voss 2005, Robinson & Malhotra 2005), green supply chain management (Kuei, Madu, & Lin 2009, Preuss 2009, Zhu, Sarkis, Cordeiro, & Lai 2008, Zhu, Sarkis, & Lai 2008), supply chain design initiatives (Bottani, E. Montanari R. 2009), Collaborative Planning Forecasting and Replenishment programs (Madu & Kuei 2004), and quick response strategies (Madu & Kuei 2004) can also be evaluated at this strategic level. Typical examples include reverse logistics strategies (open-loop recycling vs. closed-loop recycling), distribution strategies (exclusive distribution vs. selective distribution), and transportation strategies (centralized system vs. decentralized system). At the tactical level, the aim is to optimize flow of goods across time horizon. T*actical level* linear and/or nonlinear metamodeling approach can help to bridge solutions determined at a higher strategic level. Specifically, metamodels can be constructed to deal with purchasing policies (ISO 9000:2000 certified or not, ISO 14000 certified or not), inventory policies (EOQ vs. EOI), production scheduling policies (FIFO or not), and fulfillment policies. At the operational level, decision makers need to deal with labor, equipment, and materials on a daily/hourly basis. They can use metamodels to analyze short-term operations issues such as daily production scheduling and truck routing and loading. A specific supply chain scenario and configuration can thus be constructed for a better understanding of design and operations options at hand.

Figure 6.1 A Hierarchical Model for Supply Chain Optimization



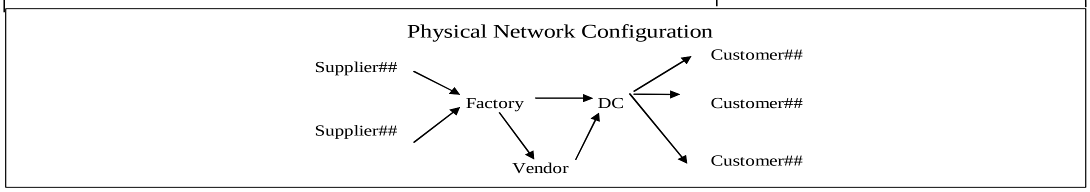
The SCOR Model

Alternatively, decision makers can adopt the Supply Chain Operations Reference (SCOR) model in understanding and analyzing the structure of supply chain systems as illustrated in Figure 6.2. The study by Persson and Araldi (2009) is perhaps among the first to craft the investigation strategies through using discrete event simulation models along the SCOR. The SCOR model, consisting of three levels, is developed by the Supply Chain Council (http://www.supply-chain.org). As can be seen in Figure 6.2, with the help of the SCOR model, decision makers and model builders can develop analytical skills and holistic thinking to understand and critically assess all sides of complex supply chain issues and concerns. At level 1, for example, five major processes are identified. They are: Plan (P), Source (S), Make (M), Deliver (D), and Return (R). At level 2, each process at a higher level can be further elaborated in terms of process types. Two examples, namely, sourcing and making, are shown in Figure 6.2. As for level 3, each process type identified at level 2 can be further broken into smaller activities. For the case of stocked product (S1), five activities are reported and shown in Figure 6.2.

With the SCOR model in place, the decision makers still need to use the appropriate tool to make decisions. Persson and Araldi (2009) use Arena, a commercial simulation software with the SCOR template, to model complex supply chains. Through the use of ten modules available in Arena, the system of interest can be adequately analyzed without unrealistic assumptions. On the other hand, compared to using simulation models alone, the supply chain decision making process can be greatly enhanced by utilizing the output of the simulation in an optimization model as illustrated in this paper. Systematic execution of simulations with Taguchi design and the resulting optimization model makes possible optimal resource allocation in the supply chains.

Figure 6.2 The Supply Chain Operations Reference (SCOR) Model

Decision maker analyzes situations	Decision maker makes decision
Level 1 Plan (P), Source (S), Make (M), Deliver (D), Return (R)*	$Y=\Sigma Xi+ \Sigma X^2i + \Sigma Xi\ Xj$
Level 2 Source (e.g. stocked product (S1)) Make (make-to-stock (M1), make-to-order (M2), engineer-to-order (M3))*	
Level 3 Stocked Product (schedule product deliveries (S1.1), receive product (S1.2), verify product (S1.3), transfer product (S1.4), authorize supplier payment (S1.5))*	$Y=\Sigma Xi+ \Sigma Xi\ Xj$



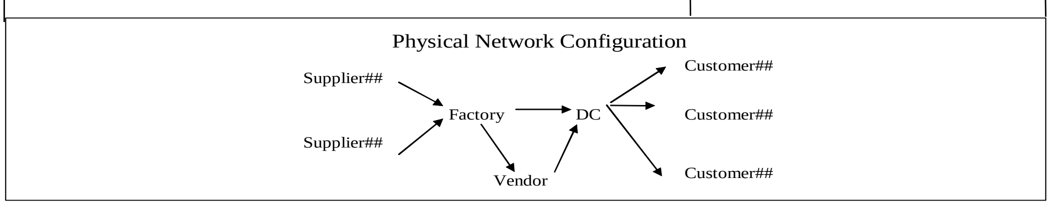
*: Source: Persson and Araldi (2009)

An Integrated *Supply Chain Model*

The third framework is based on the three levels of an integrated supply chain: supply chain integration, supply chain practices, and e-SCM capabilities (see Figure 6.3). This model *has its origins in* the theory of supply chain integration (Stevens 1989). Other similar works include Hafeez, Keoy, Zairi, Hanneman, and Koh (2010), Kim (2009), and Zhai, Shi, and Gregory (2007). Hafeez et al. (2010), for example, outline details for enabling focal firms along a supply chain to move from a traditional functional paradigm towards a fully integrated supply network. Kim (2009) further provides constructs for each dimension of integrated supply chain systems. Specifically, for the level of supply chain integration, firms need to pay attention to cross functional integration within the organization and the integration issues with both suppliers and customers. For the level of SCM practices, concerns of practicing managers center on three areas: technical, logistical, and structural. As for the case of e-SCM, decision makers and model builders also need to *make* well-considered decisions along the three dimensions of capability outlined in Figure 6.3.

Figure 6.3. An Integrated Supply Chain Model

Decision maker analyzes situations	Decision maker makes decision
Level of supply chain integration Focal firm's integration with suppliers and customers Cross functional integration within the focal firm	$Y=\Sigma Xi+ \Sigma X^2i + \Sigma Xi\ Xj$
Level of supply chain management practices Technical factor, Logistical factor, and Structural factor	
Level of e-supply chain management capability Technological capability, Organizational capability, Human Resource	$Y=\Sigma Xi+ \Sigma Xi\ Xj$



To begin with, they need to make the process of choice more effective. These issues, however, to the best of our knowledge, have not been linked with the supply chain simulation metamodels. To answer a "how to do things better along the three levels of an integrated supply chain" question, it is important to choose the right decision science tool. Since the simulation metamodeling process illustrated in this paper can involve several controllable factors and the possible interactions among input variables, adoption of this process will be helpful in making decisions along an integrated supply chain.

Conclusion

Much has been written about strategizing supply chain systems. Effective supply chain management that enables a firm to respond to market requirements quickly, reliably, and cost-effectively provides a competitive advantage. To help develop this advantage, in this paper, we illustrate a four-stage method, involving experimental designs, regression analyses, validation tests, and decision models, for optimizing supply chain systems. Three strategic frameworks (see Figures 6.1, 6.2, and 6.3) are also proposed with respect to the possible use of our metamodeling approaches in dealing with supply chain issues. Our methods and frameworks will assist in the development of better and effective supply chains at strategic, tactical and operations levels, and under different organizational conditions.

Potential extensions of the present paper include analyses on the relationships between the effectiveness of overall supply chain networks and factors such as supply group capacities, reliability of the supply chain stages, green purchasing policies and promotion tactics. Future research can also include consideration of stages of growth models and supply chain improvement initiatives such as green supply chain management and the triple bottom line strategies.

Acknowledgements

This study is partly funded by a grant from the National Science Council, Taiwan, Republic of China (**NSC95-2416-H-006-044-MY2**).

References

Bottani, E. & Montanari R. (2009). Supply chain design and cost analysis through simulation. *International Journal of Production Research, 48*(10), 1-28.

Chow, W.S., Madu, C.N., Kuei, C., Lu, M.H., Lin, C., & Tseng, H. (2008). Supply chain management in the US and Taiwan: an empirical study. *Omega, 36*(5), 665-679.

Chwif, L., Barretto, M.R.P., & Saliby, E. (2002). Supply chain analysis: spreadsheet or simulation? *Proceedings of the 2002 Winter Simulation Conference*, 59-66.

Friedman, L.W. & Pressman, I. (1988). The metamodel in simulation analysis: can it be trusted? *Journal of Operations Research Society*, *39*(10), 939-948.

Fynes. B., Burca. S., & Voss. C. (2005). Supply chain relationship quality, the competitive environment and performance. *International Journal of Production Research, 43*(16), 3303-3320.

Hafeez, K., Keoy, K.H.A., Zairi, M., Hanneman, R., & Koh, S.C.L. (2010). E-supply chain operational and operational and behavioral perspectives: an empirical study of Malaysian SMEs. *International Journal of Production Research, 48*(2), 525-546.

Jain, S., Lim, C., Gan, B, & Low, Y. (1999). Criticality of detailed modeling in semiconductor supply chain simulation. *Proceedings of the 1999 Winter Simulation Conference*, 888-896.

Kannan, V.R., & Tan, K.C. (2007). The impact of operational quality: a supply chain view. *Supply Chain Management: An International Journal, 12*(1), 14-19.

Kelle, P., & Akbulut, A. (2005). The role of ERP tools in supply chain information sharing, cooperation, and cost optimization. *International Journal of Production Economics, 93-94*, 41-52.

Kim, S.W. (2009). An investigation on the direct and indirect effect of supply chain integration on firm performance. *International Journal of Production Economics, 119*, 328-346.

Kuei, C., Madu, C.N., & Lin, C. (2009). Setting priorities for environmental policies and programs: an environmental decision making approach. *Journal of Design Principles and Practices, 3*(5), 315-332.

Kuei, C., Madu, C.N., Lin, C., & Chow, W.S. (2002). Developing supply chain strategies based on the survey of supply chain quality and technology management. *International Journal of Quality & Reliability Management, 19*(7), 889-901.

Kuei, C., Madu, C.N., & Winch, J.K. (2008). Supply chain quality management: a simulation study. *International Journal of Information and Management Sciences, 19*(1), 131-151.

Kumar, S., Satsangi, P.S., & Prajapati, D.R. (2013). Optimization of process factors for controlling defects due to melt shop using Taguchi method. *International Journal of Quality and Reliability Management, 30*(1), 4-22.

Lee, H.L. (2004). The triple-A supply chain. *Harvard Business Review, 82*(10), 102-113.

Longo, F. & Mirabelli, G. (2008). An advanced supply chain management tool based on modeling and simulation. *Computers and Industrial Engineering, 54*, 570-588.

Madu, C.N., & Kuei, C. (1993). *Experimental Statistical Designs and Analysis in Simulation Modeling*. Westport, CT: Quorum.

Madu, C.N., & Kuei, C. (1994). Regression metamodeling in computer simulation – the state of the art. *Simulation Practice and Theory, 2*, 27-41.

Madu, C.N., & Kuei, C. (2004). *ERP and Supply Chain Management*. Fairfield, Connecticut: Chi Publishers.

Maloni, M.J. & Benton, W.C. (1997). Supply chain partnerships: opportunities for operations research. *European Journal of Operational Research, 101*, 419-429.

Peace, G.S. (1993). *Taguchi Methods*. New York, NY: Addison-Wesley.

Persson, F. & Araldi, M. (2009). The development of a dynamic supply chain analysis tool – integration of SCOR and discrete event simulation. *International Journal of Production Economics, 121*, 574-583.

Prado-Prado, J. C. (2009). Continuous improvement in the supply chain. *Total Quality Management, 20*(3), 301-309.

Preuss, L. (2009). Addressing sustainable development through public procurement: the case of local government. *Supply Chain Management: An International Journal, 14*(3), 213-223.

Rabelo, L., Eskandari, H., Shaalan, T., and Helal, M. (2007). Value chain analysis using hybrid simulation and AHP. *International Journal of Production Economics, 105*, 536-547.

Robinson, C.J. & Malhotra, M.K. (2005). Defining the concept of supply chain quality management and its relevance to academic and industrial practice. *International Journal of Production Economics, 96*, 315-337.

Schafer, S. (2005). A Jack Welch of communists. *Business Week,* May 9, 30-31.

Shang, J.S., Li, S., & Tadikamalla, P. (2004). Operational design of a supply chain using the Taguchi method, response surface methodology, simulation, and optimization. *International Journal of Production Research, 42*(18), 3823-3849.

Shapiro, J.F. (2001). *Modeling the Supply Chain*. Pacific Grove, CA: Duxbury.

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2000). *Designing and Managing the Supply Chain*. New York, NY: McGraw-Hill,

Stevens, G.C. (1989). Integrating the supply chain. *International Journal of Physical Distribution and Materials Management*, *19*(8), 3–8.

Taguchi, C. & Wu, Y. (1980). *Introduction to Off-line Quality Control*. Nogoya, Japan: Central Japan Quality Control Association.

Towers, N. & Burnes, B. (2008). A composite framework of supply chain management and enterprise planning for small and medium-sized manufacturing enterprises. *Supply Chain Management: An International Journal*, *13*(5), 349-355.

Towill, D.R., Naim, M.M., & Wikner, J. (1992). Industrial dynamics simulation models in the design of supply chains. *International Journal of Physical Distribution and Logistics Management*, 22(5), 3-13.

Winch, J. K., Madu, C.N., & Kuei, C. (2012). Metamodeling and optimizing a reverse logistics system. *International Journal of Information and Management Science, 23*(1), 41-58.

Zhai, E., Shi, Y., & Gregory, M. (2007). The growth and capability development of electronics manufacturing service companies. *Internal Journal of Production Economics, 107*, 1-19.

Zhang, C. & Zhang C.H. (2007). Design and simulation of demand information sharing in a supply chain. *Simulation Modeling Practices and Theory, 15*, 32-46.

Zhu, Q., Sarkis, J., Cordeiro, J.J., & Lai, K. (2008). Firm-level correlates of emergent green supply chain management practices in the Chinese context. *Omega, 36*, 577-591.

Zhu, Q., Sarkis, J., & Lai, K. (2008). Green supply chain management implications for “closing the loop.” *Transportation Research Part E: Logistics and Transportation Review, 44*(1), 1-18.