Performance Analysis of Conjoined Supply Chains

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Abstract

This research is concerned with the performance behavior of conjoined supply chains, which typically arise in web-based retail. In particular, five performance measures, belonging to three performance measure classes, are used to study the performance effects of various operational factors on conjoined supply chains. The study is accomplished via experimental design and simulation analysis, and the results suggest the effects of the various factors on supply chain performance and identify the nature of the relationships among these factors and overall supply chain performance.

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1 Introduction

Virtually every manufacturing or service enterprise in the world may be classified as a supply chain (SC)--an organization that supplies products (or services) to customers via a chain of facilities comprising functional stages. The chain structure arises from the connected, chain-like facilities that work together to supply these products (or services). In a supply chain, each link represents the flow of materials and information that make possible the functions of procurement, processing (or manufacturing), storage, and distribution. For any given supply chain, each functional level comprises an echelon, and there may be numerous facilities within each echelon. The number of facilities, the number of echelons, and the structure of the material and information flows contribute to the complexity of the chain. This complexity has given rise to a structural classification scheme that is based on the material relationships among the facilities. For the purposes of this work, supply chain structures will be classified as: convergent (assembly), divergent (arborescent), conjoined, or general. Each of these classifications is defined below and an example of each is given in Table 1.

Convergent (Assembly)
Convergent structures are assembly-type structures, in which each node (or facility) in the chain has at most one successor, but may have any number of predecessors. Examples of supply chains in which convergent structures are commonplace are in certain types of shipbuilding, airplane manufacturing and building construction.

Divergent (Arborescent)
A supply chain may be classified as divergent (arborescent) if each node has at most one predecessor, but any number of successors. Such a chain may be thought of as the structural opposite of a convergent (assembly) supply chain. Most types of mineral processing organizations are divergent.

Conjoined
A conjoined structure is one that is a combination convergent and divergent structure, where each comprising sub-structure (convergent and divergent) is combined in sequence to form a single, connected structure. Conjoined supply chain structures are common in farming, merchandise catalog and web-based companies.

General (Network)
The final structural classification is a general (or network) structure, one that does not fall into any of the preceding three structural classes. Supply chains exhibiting a general structure are neither strictly convergent, divergent, nor conjoined. Examples of supply chains commonly exhibiting a general structure include automobile manufacturing and electronics manufacturing. Automobile and electronics manufacturing supply chains are typically classified as general, since although they follow an assembly-type (convergent) structure in the procurement and assembly functions and often follow a distribution-type (divergent) structure in distribution (which would imply a conjoined classification), a single facility typically procures materials from numerous suppliers (divergent) within the otherwise convergent portion of the chain, thus resulting in a general structural classification.

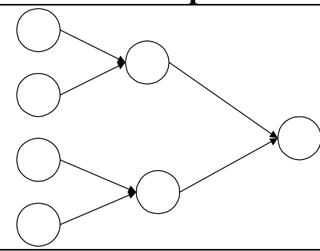
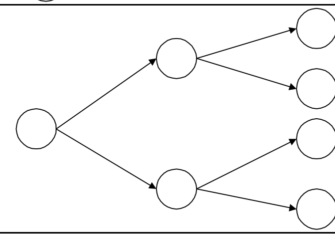
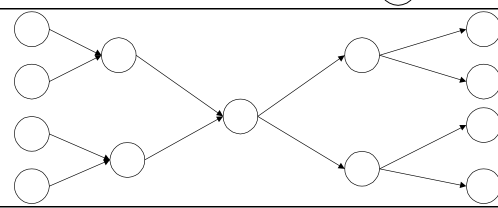
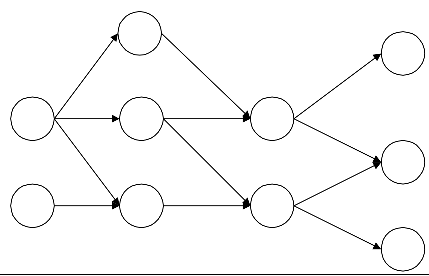
Classification Type	Example
Convergent (Assembly)	
Divergent (Arborescent)	
Conjoined	
General (Network)	

Table 1. Supply Chain Structural Classification

This work focuses on performance measurement of structurally conjoined supply chain systems. It is hoped that by limiting the study to conjoined structures, performance commonalities may be observed and more fully understood. More specifically, the objective of this research is to identify which operational and strategic factors have the most significant effects on supply chain performance and to then investigate the nature of the relationships among these critical factors and overall supply chain performance.

2 Literature Review

There are a number of supply chain simulation studies available in the literature. Although numerous supply chain studies use simulation as a tool for verification or illustration, this review focuses on research in which simulation is used as the primary analytical tool to study the behavior of multi-echelon or supply chain systems under various operational and/or strategic conditions.

2.1 Strategic Decision-Making

Early work in simulation analysis of supply chains may be found in del Vecchio and Towill (1990), which verified and validated the use of simulation modeling in production/distribution systems. Other early work includes Towill (1991) and Towill, et. al. (1992), which uses simulation techniques to evaluate the effects of various supply chain strategies (echelon elimination, information integration, just-in-time (JIT), and order quantity modification) on demand distortion and variance amplification. Demand distortion is the phenomenon in which "orders to the supplier have larger variance than sales to the buyer" and variance amplification occurs when the distortion of the demand "propagates upstream in amplified form" (Lee, et. al. 1997). Towill (1991) and Towill, et. al. (1992) use the basic Forrester SC model (Forrester 1961) as a baseline (reference) model, comprised of four basic echelons: (1) factory, (2) warehouse, (3) distributor, and (4) retailer. The authors then apply the supply chain strategies to this reference model. On the basis of the simulation analysis, the authors conclude that the JIT strategy and the echelon elimination strategy are the most effective in smoothing demand variations.

Related early work may be found in Wikner, et. al. (1991), who also use simulation to evaluate the effects of supply chain improvement strategies. As in Towill (1991) and Towill, et. al. (1992), Wikner et. al. (1991) use the Forrester model as a reference model (which includes a single factory (with an on-site warehouse), distribution facilities, and retailers), and then apply five supply chain strategies (decision rule tuning, time delay reduction, distribution stage elimination, decision rule improvement, and information flow integration). The implementation of each of these strategies is carried out using simulation, the results of which are then used to determine the effects of the various strategies on minimizing demand fluctuations. The authors conclude that the most effective improvement strategy is improving the flow of information throughout all levels in the chain.

2.2 Operational Decision-Making

Lot-Sizing Analysis

Gupta, et. al. (1992) apply simulation to a SC in order to evaluate the performance (in terms of schedule stability and cost) of various lot-sizing techniques. In particular, the authors study the following lot-sizing techniques: Wagner-Whitin (WW), Least Unit Cost (LUC), Silver-Meal (SM), Modified Silver-Meal (MSM), Simplified Part-Period Algorithm (SPPA), Modified Economic Order Quantity (EOQ), Marginal Cost Approach (MCA), Incremental Approach (ICA), and Gaither's Rule (GA). Their analysis considers five factors: (1) lot-sizing rules, (2) length of forecasting horizon, (3) demand variability, (4) product complexity (measured as the maximum number of levels of dependent relationships within the structure), and (5) cost structure (holding and set-up). Their multi-stage SC was assumed to be assembly-type, with each component having one parent node, and demand coming only from the preceding levels at each stage. The authors found that WW was best-suited for single-stage problems with short planning horizons and small forecast errors, and that SM and ICA outperformed MCA, MSM, GA, and SPPA, with EOQ and LUC exhibiting the worst performance.

Related subsequent work in the field of lot-sizing in multi-level SCs may be found in Gupta and Brennan (1994). In this work, the authors apply various back-order lot-sizing algorithms (on a rolling horizon basis) to a multi-level SC with random lead times. This work considers ten different lot-sizing algorithms: Lot for Lot (LFL), Economic Order Quantity (EOQ), Period Order Quantity (POQ), Least Unit Cost (LUC), Least Total Cost (LTC), Part Period Algorithm (PPA), Silver-Meal Algorithm (S-M), Wagner-Whitin Algorithm (W-W), Economic Order Quantity with Shortages (EQS), and Gupta-Brennan Algorithm (G-B). The authors then define an experiment that includes three cases (deterministic, uncertainty at all levels, and uncertainty at one level at a time) and six factors (lead time uncertainty, basic product structure, level of product structure at which uncertainty is applied, lot-sizing rules, costs, and product structure variant). The authors conclude that basic product structure, the lot-sizing rule, the set-up to holding cost ratio, and the shortage cost were significant in determining cost performance for cases one and two (deterministic and uncertainty at all levels), but that the level of the product structure at which uncertainty is applied is a cost determinant in the third case (uncertainty one level at a time). Moreover, the authors also found that across all lot-sizing rules considered, LUC was the most consistently low-cost performer.

Inventory Analysis

More recent work in SC simulation analysis may be found in Amin and Altiok (1997), who use simulation to study the effects of various manufacturing control policies ("look ahead" and "look ahead plus look back") and priority structures (static, dynamic global, and dynamic local) on SC performance in an effort to identify a set of control policies that may be appropriate for use in a SC environment. In this work, the authors first develop the structure for the test case, which consists of three product types (indexed by i) and three echelons (indexed by j), operating under a continuous review (R_i,r_i) inventory control policy. In order to test the effects of the various control policies, the authors use the following measures of performance: (1) average warehouse inventory levels, (2) average buffer work-in-process (WIP), (3) average backorder levels, (4) average backorder size per customer whose demand is not fully satisfied, (5) probability of backorder per customer arrival, and (6) average number of set-ups per unit time, where a set-up is incurred whenever production changes over from one product type to another. The authors then identify qualitative relationships observed between the various control policies/priority structures tested and the performance measures used.

Alfieri and Brandimarte (1998) utilize a modular approach to supply chain simulation modeling using OMT (object modeling technique) methodology. The authors' select a modular approach in order to reduce the inherent complexity of supply chain modeling, but realize that some higher level techniques will also be required in order to design the modules. The authors apply this approach to a small case study consisting of factories, stock points, and demand points (three echelons). They assume that each node in the second and third echelons has one supplier, with one product type, deterministic transportation and manufacturing lead times, and allow demand to be backordered. They use two inventory control policies: (1) a continuous review (S,s) policy, and (2) a periodic order-up-to review policy (R,r) with fixed cycle time (review interval) T. The objective of this work is to demonstrate the applicability of the modular approach to supply chain simulation modeling, and to concurrently emphasize the importance of higher level techniques for module design.

Petrovic, et. al. (1998) develop a hybrid fuzzy modeling/simulation approach to supply chain analysis. The authors identify two major sources of uncertainty in a supply chain: external supply of raw material and customer demands. Thus, they represent these two phenomena as fuzzy sets. The decisions obtained from the fuzzy modeling are input into a simulation modeler, which evaluates the effects of those decisions on supply chain performance. In their work, the authors apply their approach to a simple serial supply chain, in which all facilities are connected in series, from external supply through customer demand. For their system, they also assume that the chain produces one product, the inventory of which is controlled using an order-up-to periodic review system, and backorders are allowed. The capacities of the production facilities are assumed to be unlimited, and replenishment quantities (excluding those for raw material) are assumed to arrive according to a fixed lead time. The authors apply two different control strategies: decentralized control and partially coordinated control, and the performance measures studied are divided into two groups: individual inventory performance (which is calculated individually for each inventory stockpile in the system) and overall supply chain performance. The individual inventory performance measures used are: (1) total inventory cost per item demanded, (2) holding cost per item demanded, (3) inventory fill rate, and (4) total replenishment quantity requested by the inventory system. The overall supply chain performance measures used are: (1) total SC cost per end-product demanded, (2) SC holding cost, and (3) SC (i.e., end-product inventory) fill rate. The authors utilize their iterative approach in a decision support framework, with a view towards improving SC performance by modifying the order-up-to levels in the inventory control system.

Finally, van der Vorst, et. al. (2000) develop a simulation/petri-net modeling approach to supply chain analysis. The authors demonstrate their model using a case study from the food industry--in particular, a supply chain supplying chilled salads in the Netherlands. Their model is unique, in that it uses eight different performance indicators (three cost-based indicators and five service-based indicators). The objective of their study was to understand the effects of introducing EDI (Electronic Data Interchange) and a real-time inventory system on their performance indicators. The authors conclude that increasing ordering and delivery frequencies, reducing producer's lead time, and introducing new information systems improved overall supply chain performance.

Previous work in supply chain simulation has focused on decision-making on two basic levels: 1) strategic decision-making and 2) operational decision-making (including inventory and lot-sizing). This work has typically used a limited number of performance measures (in most cases, a single performance measure) in an effort to study specific problems related to specific supply chains. However, experimental simulation results can be used to extract general principles, as documented in Towill and McCullen (1999). This work proposes to design and analyze experiments for a conjoined supply chain using a performance vector consisting of multiple, critical, SC characteristics and then to use the experimental design to capture general tendencies and relationships between supply chain performance characteristics and design elements.

3 Performance Measures

The performance measure framework utilized in this analysis is based on the work of Beamon (1999). In particular, Beamon (1999) established the importance of resource, output, and flexibility measures as vital components to a supply chain measurement system. In this work, performance measures from each of these three categories will be used to form a supply chain measurement system. The performance measurement system used in this analysis is summarized below in Table 2, and detailed in this section.

Performance Measure Category (Type)	Measures
Resource	Average Periodic Inventory Level Average Transportation Cost
Output	Stockout Fraction Backorder Fraction
Flexibility	Volume Flexibility

Table 2. Supply Chain Performance Measurement System

3.1 Resource Measurement

The resource performance measures the level of resources in the system that are used to meet the system's objectives. In this study, inventory and transportation measures are used to analyze resource use.

3.1.1 Average Periodic Inventory Level ($\bar{I}$)

Average periodic inventory level, $\bar{I}$, is defined as the inventory level (i.e., total number of individual units) of held inventory per period per SKU (stock-keeping unit). This value will be calculated as:

$$\bar{I} = \frac{\text{total \# units of inventory held per period}}{\text{\# SKUs}}$$

This performance measure is distinguished by computing the value of on-hand inventory as an average over the number of SKUs held, which allows for more direct comparison of total on-hand inventory valuation across SCs of varying sizes and, relatedly, number of products offered. As inventory costs comprise a large portion of SC cost, and holding costs are typically charged on the amount of held inventory, the average periodic inventory level, $\bar{I}$, is significant.

3.1.2 Average Transportation Cost ($\overline{A}(t)$)

The average transportation cost, $\overline{A}(t)$, is calculated as the average cost of material transportation per SKU transported over the time horizon of interest, or

$$\overline{A}(t) = \frac{\text{inter - facility transportation cost during time } t}{\#\ \text{SKUs transported during time } t}$$

The distinguishing feature of this performance measure is that it is normalized by the number of SKUs, so as not to over-penalize large chains that would have inherently more substantial transportation requirements. This performance measure is chosen due to the commonly large contribution of transportation charges to SC cost. In fact, transportation cost is typically the single largest component of logistics cost, comprising nearly 60% of all Fortune 500 companies' logistics costs (Thomas and Griffin 1996, Spalding 1998).

3.2 Output Measurement

The primary objective of a supply chain is to supply products or services to customers. Output performance measures the effectiveness with which supply chains are able to supply. Generally, output performance measures correspond to an organization's strategic goals and to its customers' goals and values. The output performance measures used here are stockout fraction and throughput efficiency.

3.2.1 Stockout Fraction ($\overline{S}(t)$)

The stockout fraction, $\overline{S}(t)$, is a customer service measure that calculates the percentage of orders that result in a stockout at the retailer echelon during a particular time period *t*. This quantity is given by:

$$\overline{S}(t) = \frac{\#\,\text{SKU stockouts during time } t}{\#\ \text{SKUs ordered during time } t}$$

The stockout fraction is a measure of how well the SC is achieving customer service level objectives for end products.

3.2.2 Backorder Fraction ($\overline{B}(t)$)

The backorder fraction, $\overline{B}(t)$, is also a customer service measure, calculating the proportion of backorders at the manufacturing facility and distribution center echelons (the interior echelons) during a particular time period *t*. This quantity is given by:

$$\overline{B}(t) = \frac{\#\,\text{SKUs backordered during time } t}{\#\ \text{SKUs ordered during time } t}$$

The backorder fraction is a measure of how well the SC is achieving service level objectives for intermediate materials and sub-assemblies.

3.3 Flexibility Measurement: Volume Flexibility ($V(t|M)$)

Flexibility measures, as applied to supply chain analysis, describe the range of possible operating conditions that are profitably achievable by the chain. The calculation of volume flexibility, $V(t|M)$, which will be defined across all supply chain products, is an extension of the single-item volume flexibility measure developed by Beamon (1999). For this study, $V(t|M)$ measures the proportion of demand that can be met by the supply chain system in *t* time units given product mix *M*. The procedure used to calculate the volume flexibility (assuming an uncapacitated transportation system, the rate of supply is determined solely by manufacturing production rates) is given below.

1. Define $P_{\beta}^{\max}(t|M)$ as the maximum observed production rate (units/time) in any fixed duration of time *t* for product mix *M* at manufacturing facility β.

2. Calculate the total maximum production rate (units/time), $O_{\max}(t|M)$, across all manufacturing facilities β as:

$$O_{\max}(t|M) = \sum_{\beta} P_{\beta}^{\max}(t|M)$$

3. Similarly, $O_{\min}(t|M)$ will be defined as the minimum allowable production flow through the system in time *t*, given product mix *M*. Theoretically, the value of $O_{\min}(t|M)$ is zero, but due to economic or physical constraints dictating the minimum feasible production rate through the system in real-world systems, $O_{\min}(t|M)$ may reasonably be set at a positive, non-zero value.

4. Thus, the aggregate SC flexibility, $V(t|M)$, is defined as:

$$V(t|M) = F\left[O_{\max}(t|M)\right] - F\left[O_{\min}(t|M)\right]$$

   where $V(t|M) \in [0,1)$, and represents the long-run proportion of total demand that can be met by the supply chain system in *t* time units, given product mix *M*, and $F(\cdot)$ is the cumulative distribution function for the external customer demand.

   The objective of this measure is to describe the ability (in terms of the *range* and *speed* of response) with which the SC can respond to fluctuations in demand.

4 Operational Characteristics of Systems Studied

This section describes the operational characteristics that will govern the supply chain systems used in this analysis.

4.1 Inventory System

This sub-section describes the types of inventory control systems that are used by each of the facilities, and the assumptions that will govern these systems.

4.1.1 Assumptions

The following assumptions will hold for the inventory control system:

- All unfulfilled demand is backordered, with the exception of the retailers, at which all unfulfilled demand is lost.
- No expediting of orders is allowed.
- Demand is stochastic and independent across all item types.
- The length of the review period is fixed at the retailer echelon.
- The amount of raw material supply is uncapacitated.
- The composite production rate capabilities at the manufacturing facilities exceed the composite downstream demand rate of adjacent facilities.
- In the event of shortages in echelons 2 - 4, partial shipments may be supplied, where echelon 1 = suppliers, echelon 2 = manufacturing facilities, echelon 3 = distribution centers, and echelon 4 = retailers.

4.1.2 Control

For the purposes of the inventory control system, the inventory position at any given facility will be calculated based on *installation stock*. Installation stock is defined as equal to the stock on hand at that facility plus all outstanding orders to upstream facilities (less backorders). Thus, the installation stock is simply the amount of stock that an installation may expect to have within a lead time. This sub-section describes the inventory control that will govern the inventory at the retailers, manufacturing facilities, and distribution centers. The additional notation used in this sub-section is as follows:

θ = retailer index (echelon 4)
γ = distribution center index (echelon 3)
β = manufacturing facility index (echelon 2)
α = supplier index (echelon 1)

Retailers
All retailers will operate on a periodic review installation stock order-up-to $R_{i\theta}$ policy, such that the inventory is reviewed according to a fixed cycle (period), and if, upon review, the inventory

level has dropped below $R_{i\theta}$, an order is placed to return the inventory level to $R_{i\theta}$, the base stock level. In this case, the size of the replenishment order, $Q^*_{i\theta}$, will be determined as the difference between $R_{i\theta}$ and the current level of installation stock available, i.e.,

$$Q^*_{i\theta} = R_{i\theta} \text{ - available (on-hand) inventory at retailer } \theta$$

This type of inventory control system is common for retailers (e.g., "we receive shipments every Wednesday").

The retail level safety stock for each item *i* will be determined by a target stock-out risk *(SOR)*. More specifically, $(SOR)_i$ is the long-term proportion of inventory cycles in which item *i* will be stocked out, and will be used to calculate the base stock level for each item *i*, $R_{i\theta}$, as follows:

Given the target $(SOR)_i$, the target base stock, R_i^*, is calculated in two components: The first component is based on the expected demand during a lead time plus transportation time; the second component is the safety stock required in order to achieve the target stock-out risk. These calculations, which account for variable transportation lead times, may be found in many standard inventory texts, such as Waters (1996) and Narasimhan, et. al. (1995), and Johnson and Montgomery (1974).

Distribution Centers

All distribution centers will control their inventory independently using a continuous review installation stock $(Q_{i\gamma}, R_{i\gamma})$ policy, such that once the inventory level reaches R_i at distribution center γ, an amount Q_i^* is ordered. In these cases, the values of $Q_{i\gamma}^*$ will be determined by the economic order quantity, independently of the reorder point, $R_{i\gamma}^*$, which will be set equal to the average size of a downstream order, *RAVGQ* (Banerjee, et. al. 1996). It is important to note here that the although the stockout risk is partially dependent on the replenishment quantity $Q_{i\gamma}^*$, near-optimal solutions can generally be obtained by considering the replenishment quantity and the reorder point independently, which simplifies the computation (Waters 1996).

Manufacturing Facilities

All manufacturing facilities will have two governing inventory systems: one that controls the (incoming) raw material (RM) stockpile and one that controls the (outgoing) finished goods (FG) stockpile.

The incoming raw material (RM) stockpile at the manufacturing facilities will be replenished according to a $\left(Q_{i\beta}, (RMR)_{i\beta}\right)$ inventory policy, where $(RMR)_{i\beta}$ is the reorder point for the raw material stockpile for item *i* at manufacturing facility β, and $Q_{i\beta}$ is the reorder quantity for item *i* at manufacturing facility β. As before, $(RFG)^*_{i\beta}$, the reorder point for the FG inventory for item *i* at manufacturing facility is calculated as RAVGQ, the average downstream order quantity.

5 Scenarios Studied

The parameters for the SC sizes and the factor level values chosen for this study are derived from case studies and survey work by Camm, et. al. (1997), Geoffrion and Powers (1995), McMullan (1996), Newhart, et. al. (1993), Scott and Westbrook (1991), Shapiro, et. al. (1993), Stenger (1996), Towill (1997), and Vandemark (1997). This section describes the physical characteristics of the supply chain studied as well as the various associated scenarios (factors and levels).

5.1 Supply Chain Characteristics

The conjoined supply chain system used in this analysis has the following characteristics: four (4) suppliers, one (1) manufacturing facility, five (5) distribution centers, 50 retailers, and 50 final products. Notice that the following relation holds for the number of facilities of each type:

(# suppliers) > (# manufacturing facilities) < (# distribution centers) < (# retailers)

The SC structure studied is pictured below in Figure 1.

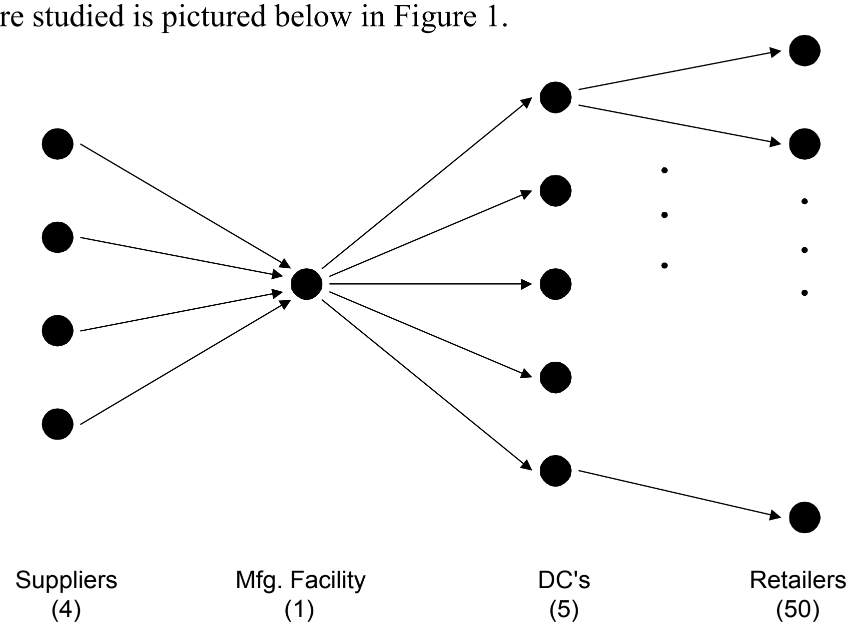


Figure 1. SC Structure

5.2 Experimental Variables (Factors and Levels)

Various scenarios will be studied, corresponding to the following five factors: supplier lead time, inventory system service levels, demand distributions, inter-facility logistics system transportation time, and manufacturing processing time. The factors and levels, summarized below in Table 3 will be applied to the SC system under study (as described in Section 5.1), and are described in this sub-section. The ranges on SLT, DD, TT, and PT within the table refer to the sizes of the ranges used for the triangular distribution that governs each factor. The triangular distribution is used here, due to the fact that its parameters are generally available in practice (e.g., "the transportation (or demand, etc.) is usually "c", but it is never higher than "b" or lower than "a" (Petrovic, et. al. 1998) while exhibiting similar properties to the widely-used normal distribution.

Level/Factor	**Inventory System Stock-Out Risk (SOR)** (%)	**Supplier Lead Time (SLT) Total Deviation** (hours)	**Demand Distribution (DD) Total Deviation** (units)	**Transportation Time (TT) Total Deviation** (hours)	**Processing Time (PT) Total Deviation** (hours)
High	20%	W	X	Y	Z
Medium	10%	0.5W	0.5X	0.5Y	0.5Z
Low	1%	0.2W	0.2X	0.2Y	0.2Z

Table 3. Supply Chain Factors and Levels

5.2.1 Inventory System Stock-Out Risk (SOR)

The target inventory system stock-out risk (*SOR*), which describes the overall service level (i.e., across all SKUs) determines the amount of inventory (safety stock) in the system. The *SOR* is defined for each item *i* as

$$(SOR)_i = \frac{\#\text{ cycles in which item } i \text{ is stocked out}}{\text{total } \#\text{ cycles}}$$

The target *SOR* will be studied at high (20%), medium (10%), and low (1%) levels in order to study the effects of the *SOR* on SC performance. The *SOR* values are set for each item across all inventory SKUs.

5.2.2 Supplier Lead Time (SLT)

The *range* (total deviation) of the supplier lead time (SLT) (triangular) distribution will be studied at high, medium, and low levels (corresponding to W, 0.5W, and 0.2W, respectively) in order to study the effects of the SLT variation on SC performance, where W is the mode of the triangular distribution for supplier lead time.

5.2.3 Demand Distribution (DD)

The external demand at each of the retailers is assumed to follow a triangular distribution. In order to study the effects of varying demand on SC performance, the *range* of the demand distribution (DD) will be studied at high (X), medium (0.5X), and low (0.2X) levels, where X represents the mode of the triangular distribution for demand.

5.2.4 Transportation Time (TT)

The inter-facility logistics system transportation time is also assumed to follow a triangular distribution. This distribution range of the transportation time corresponds to transportation between the second and third echelons and the third and fourth echelons only (since the SLT range covers the transportation time between the first and second echelons). The *range* of the TT distribution will be studied at high (Y), medium (0.5Y), and low (0.2Y) levels in order to study their effects on SC performance, where Y is the mode of the triangular distribution for transportation time.

5.2.5 Processing Time (PT)

The manufacturing processing time (PT) is modeled as a triangular random variable. The PT *range* will be studied at high (Z), medium (0.5Z), and low (0.2Z) levels in order to study the effects of the range of the PT distribution on SC performance, where Z is the mode of the triangular distribution for processing time.

6 Simulation Modeling

A simulation model was developed to execute the various experiments to be performed in this study. The model was developed using AweSim! v. 2.0 (using Visual SLAM), with user-defined inserts written in Microsoft Visual Basic v. 4.0, and is capable of simulating conjoined, four-echelon (supplier, manufacturer, warehouse, retailer) supply chain systems. The inputs to and outputs from the simulation model are shown below in Figure **2**.

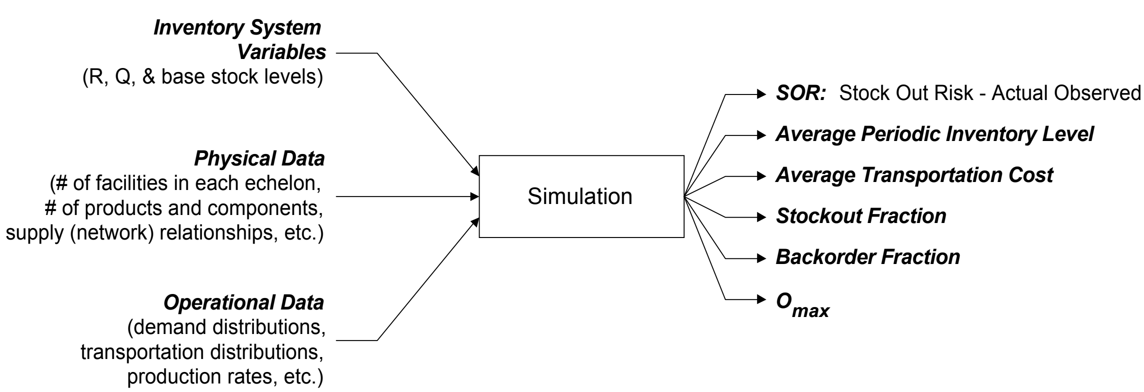


Figure 2. Simulation Model

The use of Visual Basic user-defined inserts improves the flexibility of the simulation model by enabling simulation of a variety of supply chain systems with the same general structure. The modeler has the ability to change the number of facilities in each echelon (suppliers, manufacturers, warehouses, retailers), the number of products and components, the inter-facility transportation time distributions, supplier lead time distributions, demand distributions, production rates, inventory system variables (R, Q, and base stock levels), and supply (network) relationships. These variables may be changed by changing the appropriate data stored in arrays available to the Visual Basic user-defined inserts. In this way, the simulation does not have to be redeveloped when, for example, the number of warehouses changes; only the data supplied to the model would change. It is anticipated that future versions of the model will include additional enhancements that would serve to broaden the number of structural types of supply chains that can be simulated. The simulation structure is given below in Figure 3.

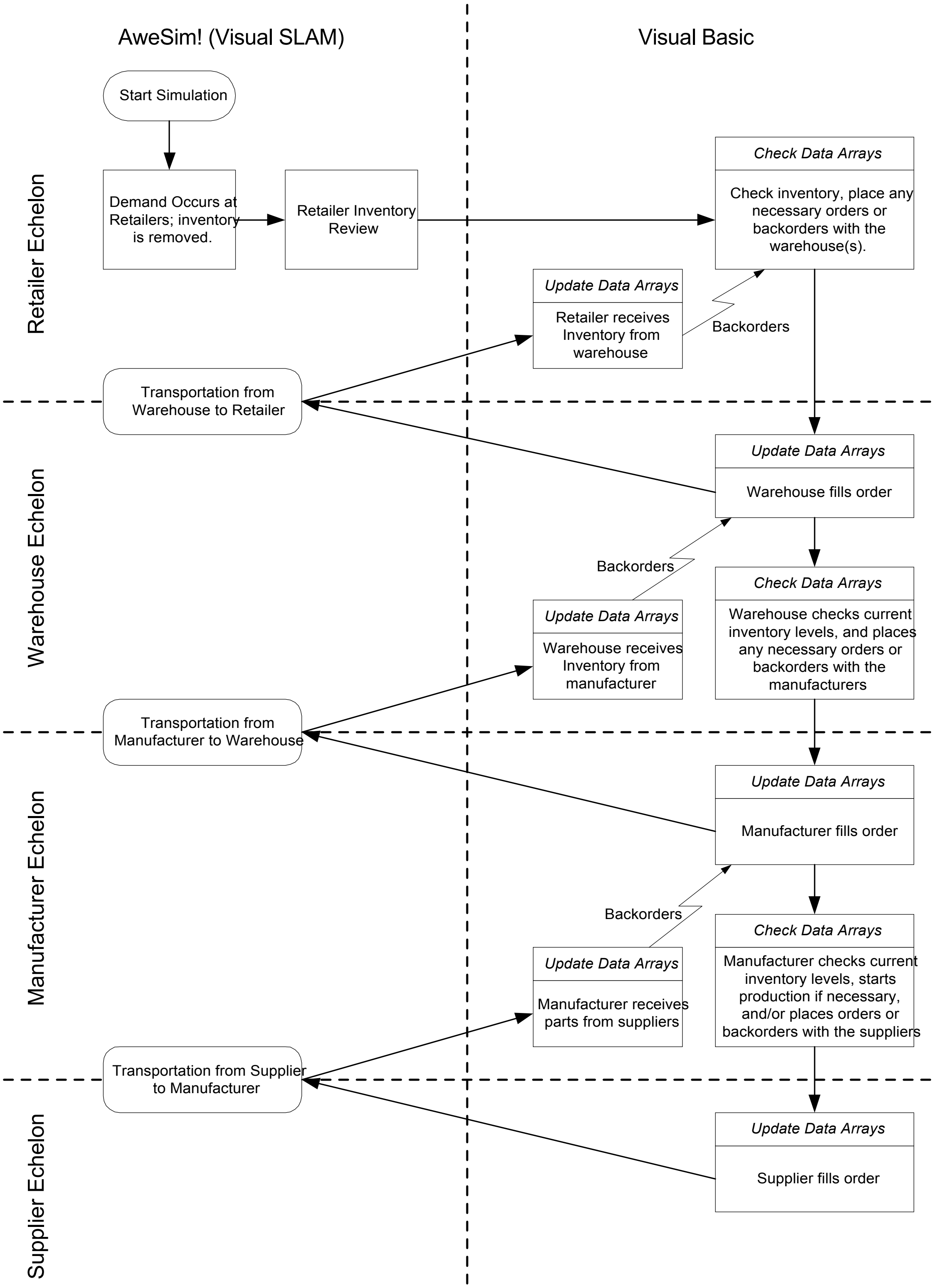


Figure 3. Simulation Model Structure

First, the modeler defines a supply chain (number of facilities, products/components, demand, etc.). Next the modeler needs to determine the appropriate values of R, Q , and base stock levels for the facilities in the supply chain. Microsoft Excel spreadsheets are used to perform the calculations for the inventory system variables for each echelon; the resulting variable values are then used by the simulation model. Figure 4 below illustrates the steps involved in running a new supply chain scenario.

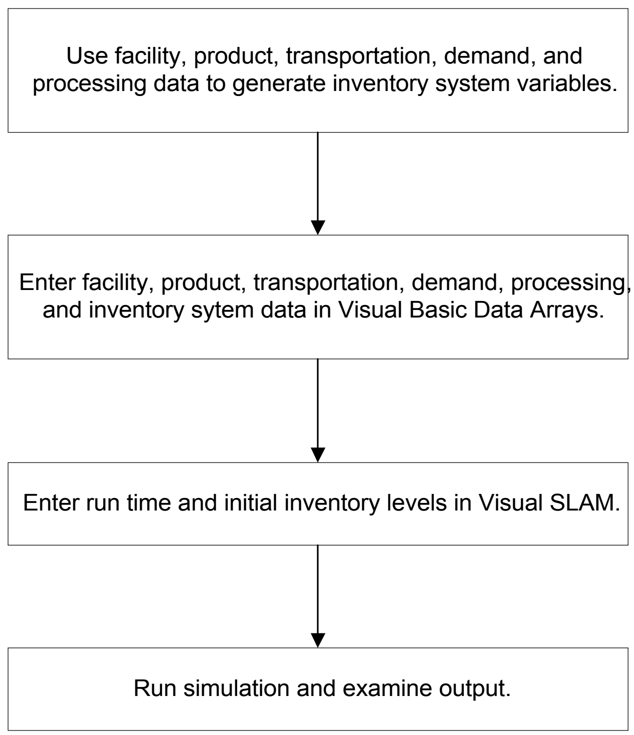


Figure 4. Steps to Running a New Scenario

7 Experimentation and Analysis

A statistical experimental design was constructed for the factors listed in Table 3 using a three-level (High, Medium, Low) Box-Behnken design for five factors (Box and Behnken 1960) consisting of 46 trials. These designs are appropriate for quadratic polynomial regression and are common in response surface methodology (Box and Draper, 1987). For each trial of the experimental design, the simulation in Section 6 was executed to obtain an “observed response” for the measures described in Sections 3.1 - 3.3, specifically, $\overline{I}$ (average periodic inventory level), $\overline{A}(t)$ (average transportation cost), $\overline{S}(t)$ (stockout fraction), $\overline{B}(t)$ (backorder fraction), and $V(t \mid M)$ (volume flexibility).

The separate quadratic regression models were constructed to for each of the five response measures as a function of the five factors. The general form of the model is:

$$Y = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \sum_{i=1}^{p} \beta_{ii} x_i^2 + \sum_{i=1}^{p} \beta_{ij} x_i x_j + \varepsilon$$

where Y is the response measure, $x_1, \ldots, x_p$ represent the factors, the β's are the unknown regression coefficients (β_0 is the constant), and ε represents error variability, which is assumed to be normally distributed with mean zero and standard deviation σ. The quadratic regression model permits estimation of curvature in the response and interactions between the factors. The assumptions of the regression model (normality, constant variance, outliers) were carefully verified via residual analysis.

7.1 Regression Models

The final regression models are shown and discussed in this section. These models include only the statistically significant regression terms (using a significance level of 0.10). Recall that SOR = inventory system stock-out risk, SLT = supplier lead time, DD = demand distribution, TT = transportation time, and PT = processing time. Figures 5-15, in the Appendix, are the estimated regression surfaces for the response variables as functions of the factor parameters.

Average periodic inventory level ($\overline{I}$): [R^2 = 98.3 %]

$$\overline{I} = 7489 - 4470\,\mathrm{SOR} + 819\,DD + 1225TT + 87.3\,(SOR)^2 + 27.5\,(TT)^2 - 34.3\,SOR \cdot DD - 62.1\,SOR \cdot TT - 29.7\,DD \cdot TT$$

The regression model for $\overline{I}$ includes only SOR, DD, and TT. Both SLT and PT are unimportant for $\overline{I}$, while SOR and TT are included as squared terms, indicating a curved relationship with $\overline{I}$. Curvature is evident for SOR in Figures 5 and 6, but only very slight for TT in Figures 6 and 7. Pairwise interaction terms among all three of the factors indicate that the effect of one factor on $\overline{I}$ depends on the levels of the other factors.

Average transportation cost ($\overline{A}(t)$): [R^2 = 87.4 %]

$$\overline{A}(t) = .0598 + .00333\,SOR + .00290\,SLT - .00163\,DD + .00148\,PT + .000088\,(SLT)^2 - .000202\,SLT \cdot PT$$

The regression model for $\overline{A}(t)$ includes SOR, SLT, DD, and PT. TT is unimportant for $\overline{A}(t)$, which is initially counter-intuitive, however, $\overline{A}(t)$ is a function of the per-mile price of transportation, and is therefore insensitive to time requirements. SLT is included as a squared term, indicating a curved relationship with $\overline{A}(t)$. Curvature is evident for SLT in Figure 9, while the relationships are linear in Figure 8.

Stockout fraction ($\bar{S}(t)$): [R^2 = 98.1 %]

$$\bar{S}(t) = .00303 + .00996\, SOR - .00406\, TT - .000114(DD)^2 + .000244\,(TT)^2$$

The regression model for $\bar{S}(t)$ includes SOR and TT. DD, SLT, and PT are unimportant for $\bar{S}(t)$, while DD and TT are included as squared terms, indicating a curved relationship with $\bar{S}(t)$. Curvature is evident for DD and TT in Figures 10 and 11. Figure 11 is most interesting because it shows a "saddle".

Backorder fraction ($\bar{B}(t)$): [R^2 = 99.1 %]

$$\bar{B}(t) = .207 + .0491\text{ SOR} + .0297\text{ SLT} - .0537\, DD - .0121\, TT + .0219\text{ PT} - .00156\,(SOR)^2 + .00870\,(\text{SLT})^2$$
$$+ .00117(DD)^2 - .000608\,(TT)^2 + .0017(PT)^2 + .000702\, SOR \cdot DD - .000723\, SLT \cdot PT$$

The regression model for $\bar{B}(t)$ includes all five factors singly, and as squared terms. These relationships are illustrated in Figures 12 - 14.

Volume flexibility ($V(t\,|\,M)$): [R^2 = 28.4 %]

$$V(t\,|\,M) = .506 - .013\, DD + .00896\, TT + .00171(DD)^2$$

The regression model for $V(t\,|\,M)$ includes DD and TT, and DD is also included as a squared term. SOR, SLT, and PT are unimportant for $V(t\,|\,M)$. Curvature is evident for DD in Figure 15. The R^2 value for this model indicates that only 28.4% of the variability in the response is explained in the model, which implies that more investigation may be needed to more adequately describe the regression surface for $V(t\,|\,M)$.

7.2 Implications

Interestingly, the results indicate that in all cases, each of the five factors (SOR, DD, TT, SLT, and PT) were significant in the regression estimate of at least two of the five performance measures (response variables): ($\bar{I}$ (average periodic inventory level), $\bar{A}(t)$ (average transportation cost), $\bar{S}(t)$ (stockout fraction), $\bar{B}(t)$ (backorder fraction), and $V(t\,|\,M)$ (volume flexibility)). In general, the factors SOR (which is pre-selected as a target), DD, and TT were most consistently significant (each appearing in the regression estimate of four of the five response variables), while SLT and PT were less significant overall (each appearing in the estimate for just two of the five response variables).

This indicates that, in terms of the performance measures used, the most important issues to target in the supply chain are:

- External Demand Variability. This is consistent with the commonly-held belief that high variability in the external demand distribution has a significant effect on SC performance. Therefore, steps should be considered to minimize controllable causes of variation in external demand, such as price promotions.

- Transportation Time Variability. This implies that it is of critical importance to reduce the variability in the transport process, indicating a need to consider routes, congestion, and scheduling to improve the consistency of transport times among facilities. This result also indicates that when choosing third-party transport, consistency of delivery (i.e., accuracy with respect to quoted transport times) may be of greater importance than speed of delivery.

Examining the results from the standpoint of the performance measures used (response variables), it is also interesting to note that some of the performance measures were "affected" by more factors than others (i.e., some performance measures included a higher number of factors in their regression estimates than others). That is, the backorder fraction, $\overline{B}(t)$, included all five factors in its regression estimate, followed by average transportation cost , $\overline{A}(t)$, (four factors included), average periodic inventory level, $\overline{I}$, (three factors included), and finally a tie between volume flexibility, $V(t \mid M)$, and stockout fraction, $\overline{S}(t)$, (each with two factors included).

This may provide some indication that the backorder fraction is, at least from a standpoint of performance measure inclusiveness, the most effective measure used, since it is affected by many different supply chain characteristics. As a result, backorder fraction should be considered as a performance measure, as it will likely be an effective indicator of SC performance. Backorder fraction may have been observed to be more inclusive since, although it is measured at only two echelons (manufacturers and DCs), these echelons are directly dependent on the other two (suppliers and retailers at each end). Average transport cost and inventory level are also effective indicators, whereas volume flexibility and stockout fraction are relatively ineffective performance indicators. The stockout fraction is likely ineffective in this case, since it only measures a small part of the chain (the retailer echelon). This also highlights a caution to using isolated, particularly end-of-pipe performance measures (which is a seductive temptation) as an indicator of overall SC performance.

8 Summary and Conclusions

This research was concerned with the performance behavior of conjoined supply chains, which typically arise in web-based retail. In particular, five performance measures, belonging to three performance measure classes, were used to study the performance effects of various operational factors on conjoined supply chains. Statistical results indicate that inventory system stock-out risk, the probability distribution of the demand, and the transportation time were most important in determining the effectiveness of the chain.

The unique impacts of this work were threefold: 1) there are potentially numerous factors important to supply chain performance; the general approach presented here can be used to illustrate, in practice, what factors should be examined first, 2) this work illustrated one method by which one can use multiple performance measures to gain a deeper understanding of the critical relationships in the supply chain, and 3) a simulation model was developed that will allow for further analysis of many different supply chain configurations and operational characteristics.

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Appendix

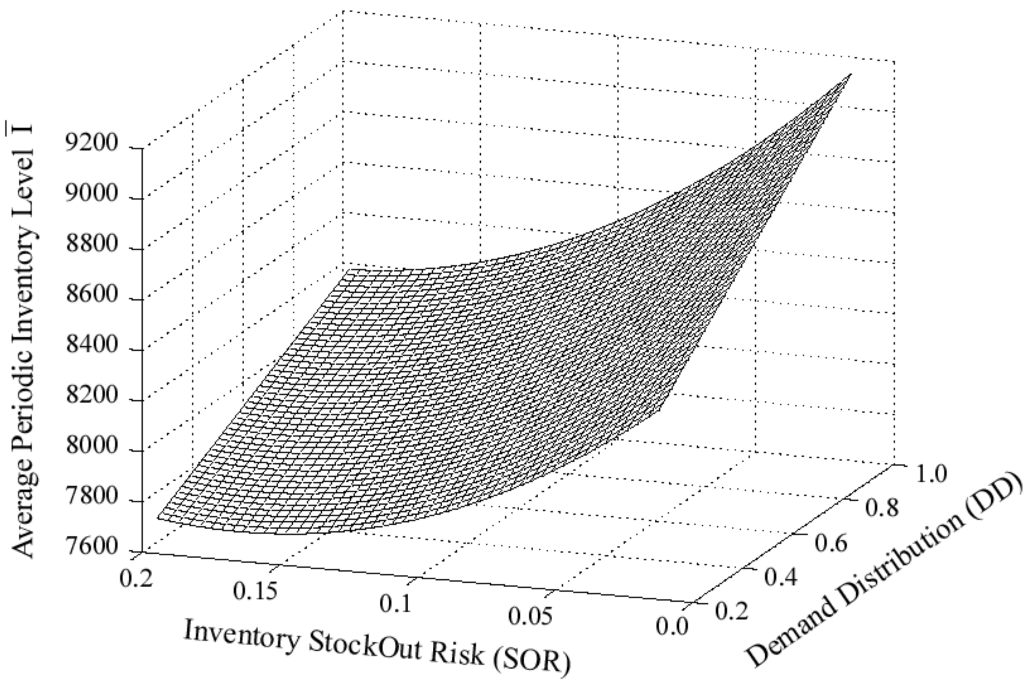

Figure 5: Estimated quadratic regression surface for the response $\bar{I}$ as a function of the parameters for SOR and DD with Transportation Time TT = 0.5Y. The model contains linear and quadratic terms for SOR, a linear term for DD, and an interaction between SOR and DD.

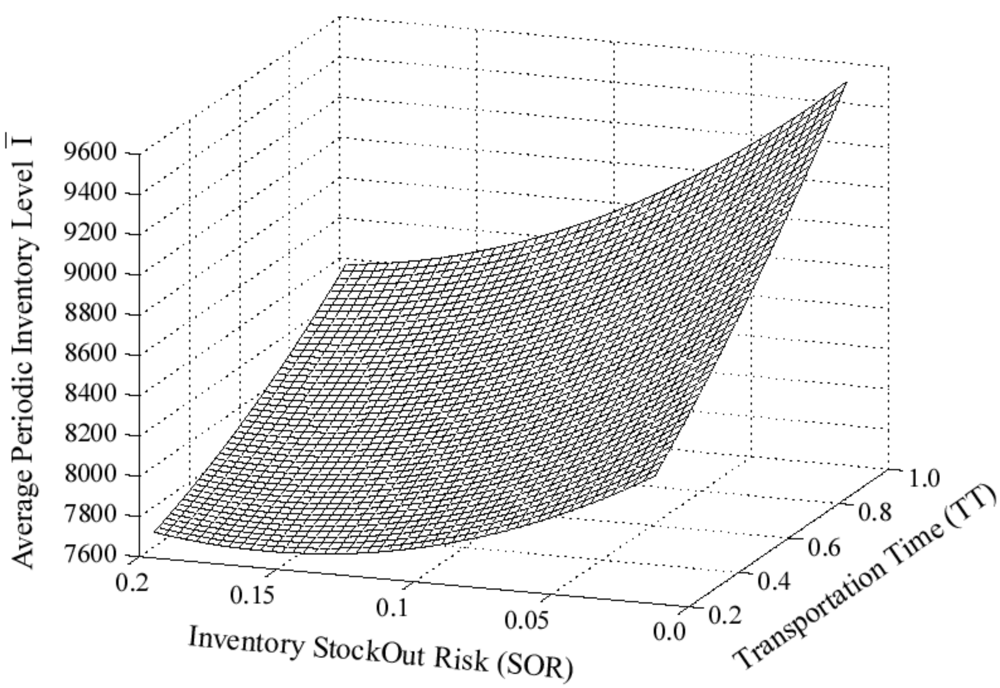

Figure 6: Estimated quadratic regression surface for the response $\bar{I}$ as a function of the parameters for SOR and TT with Demand Distribution DD = 0.5X. The model contains linear and quadratic terms for both SOR and TT, and an interaction between SOR and TT.

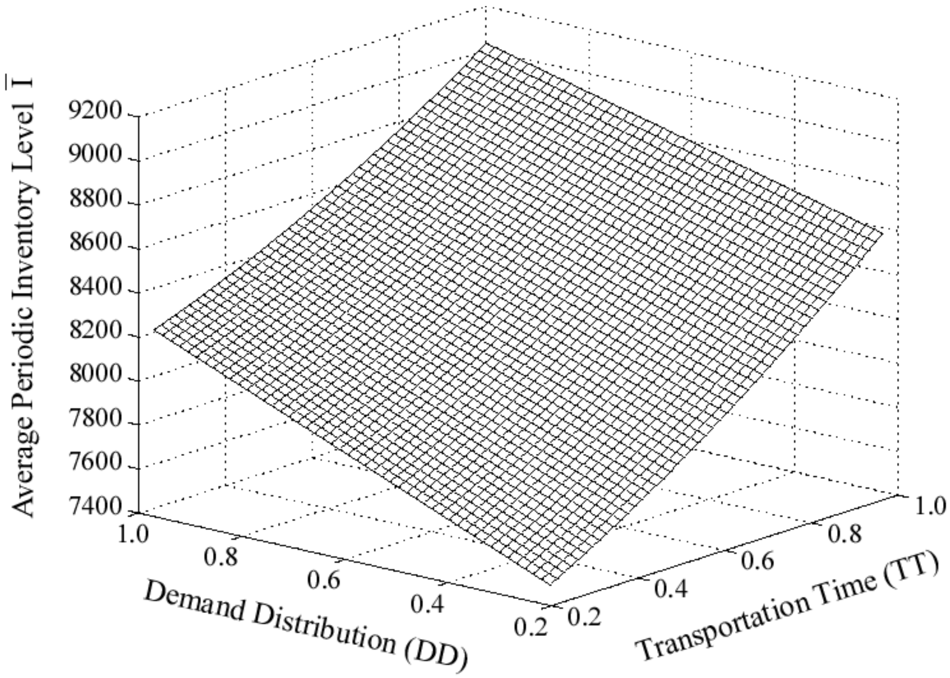

Figure 7: Estimated quadratic regression surface for the response $\bar{I}$ as a function of the parameters for DD and TT with Inventory System Stock-Out Risk SOR = 10%. The model contains a linear term for DD, linear and quadratic terms for TT, and an interaction between DD and TT.

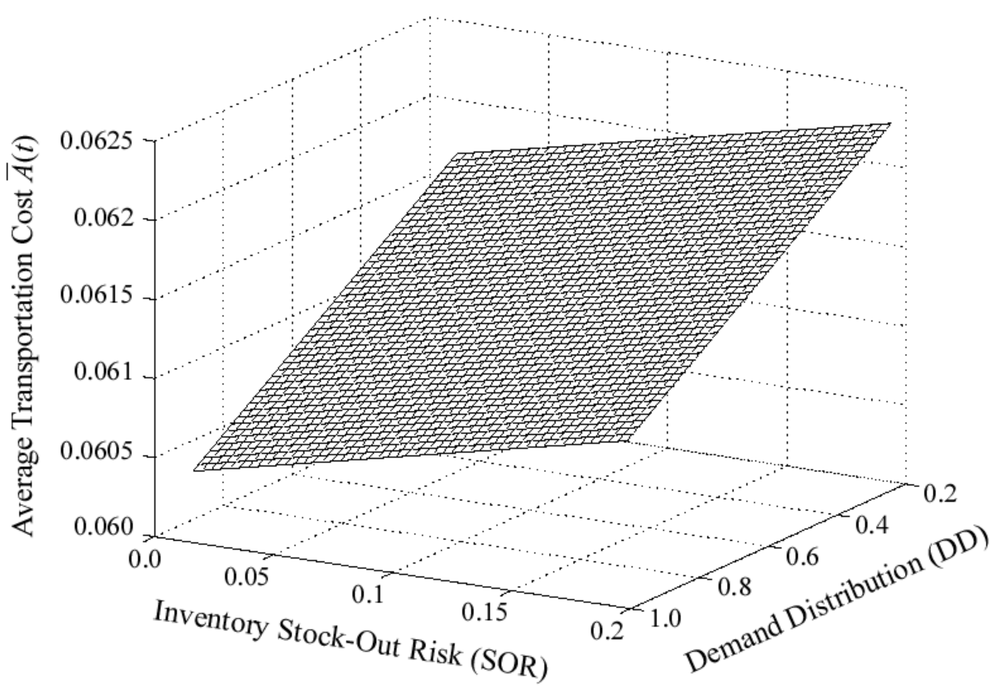

Figure 8: Estimated quadratic regression surface for the response $\overline{A}(t)$ as a function of the parameters for SOR and DD with Supplier Lead Time SLT = 0.5W and Processing Time PT = 0.5Z. The model contains only linear terms for both SOR and DD.

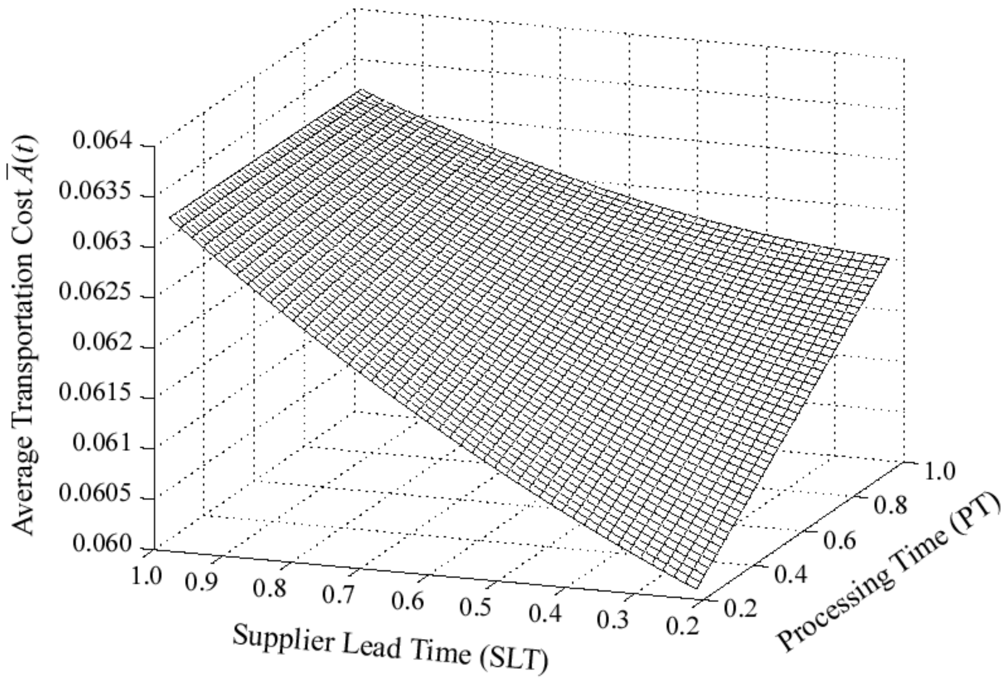

Figure 9: Estimated quadratic regression surface for the response $\overline{A}(t)$ as a function of the parameters for SLT and PT with Inventory System Stock-Out Risk SOR = 10% and Demand Distribution DD = 0.5X. The model contains linear and quadratic terms for SLT, a linear term for PT, and an interaction between SLT and PT.

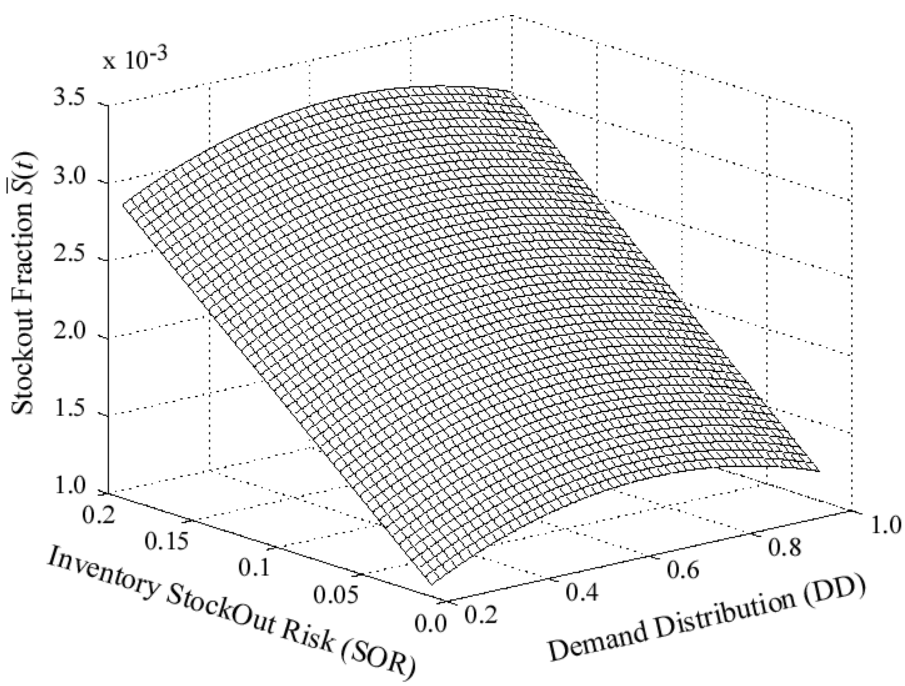

Figure 10: Estimated quadratic regression surface for the response $\overline{S}(t)$ as a function of the parameters for SOR and DD with Transportation Time TT = 0.5Y. The model contains a linear term for SOR, and linear and quadratic terms for DD.

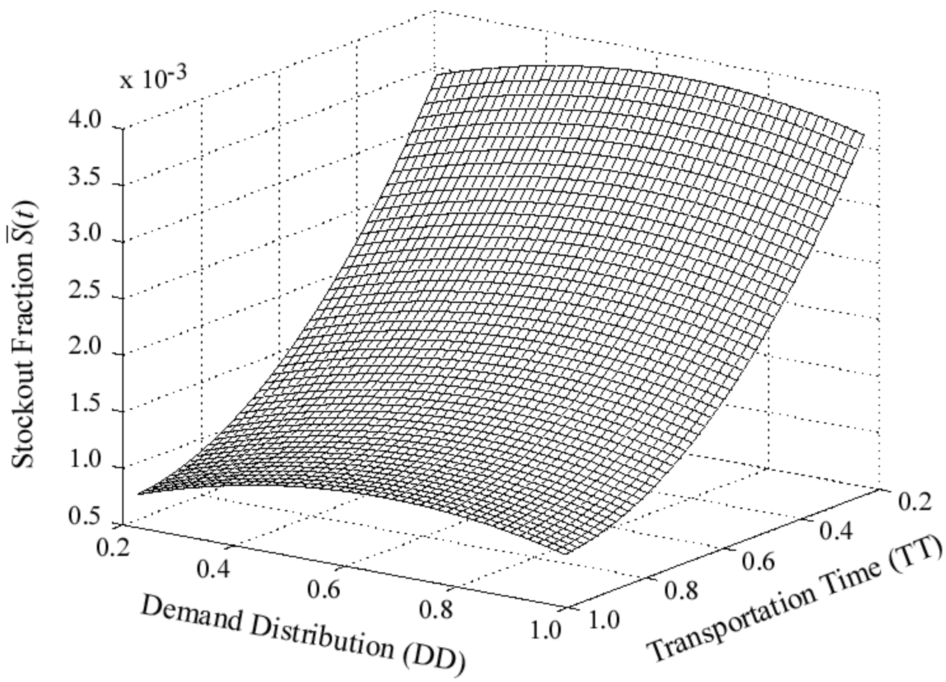

Figure 11: Estimated quadratic regression surface for the response $\overline{S}(t)$ as a function of the parameters for DD and TT with Inventory System Stock-Out Risk SOR = 10%. The model contains linear and quadratic terms for both DD and TT.

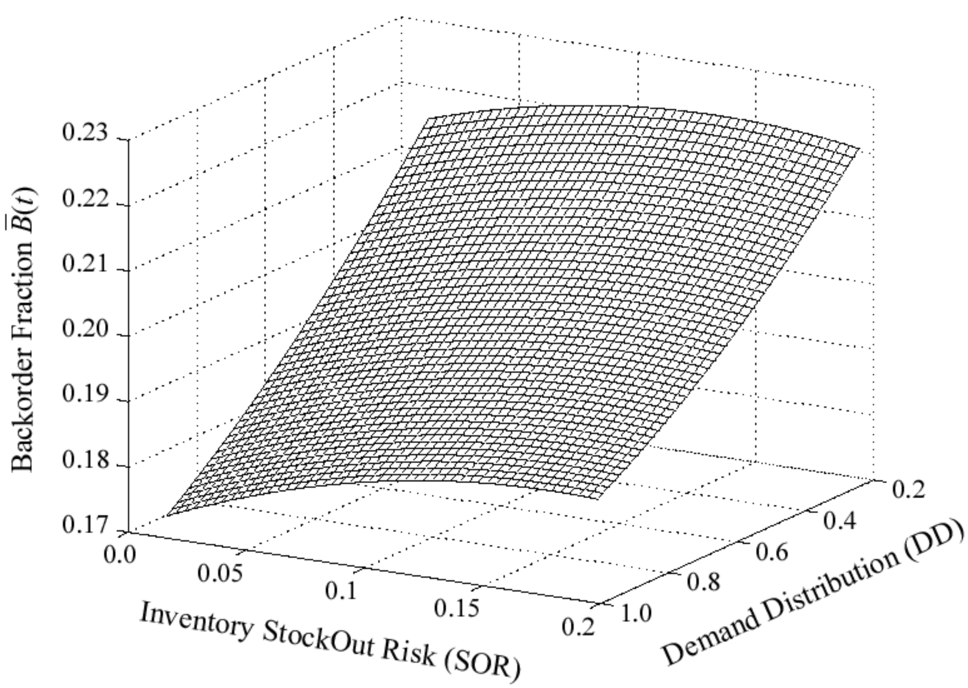

Figure 12: Estimated quadratic regression surface for the response $\overline{B}(t)$ as a function of the parameters for SOR and DD with Supplier Lead Time SLT = 0.5W, Transportation Time TT = 0.5Y, and Processing Time PT = 0.5Z. The model contains linear and quadratic terms for both SOR and DD, and an interaction between SOR and DD.

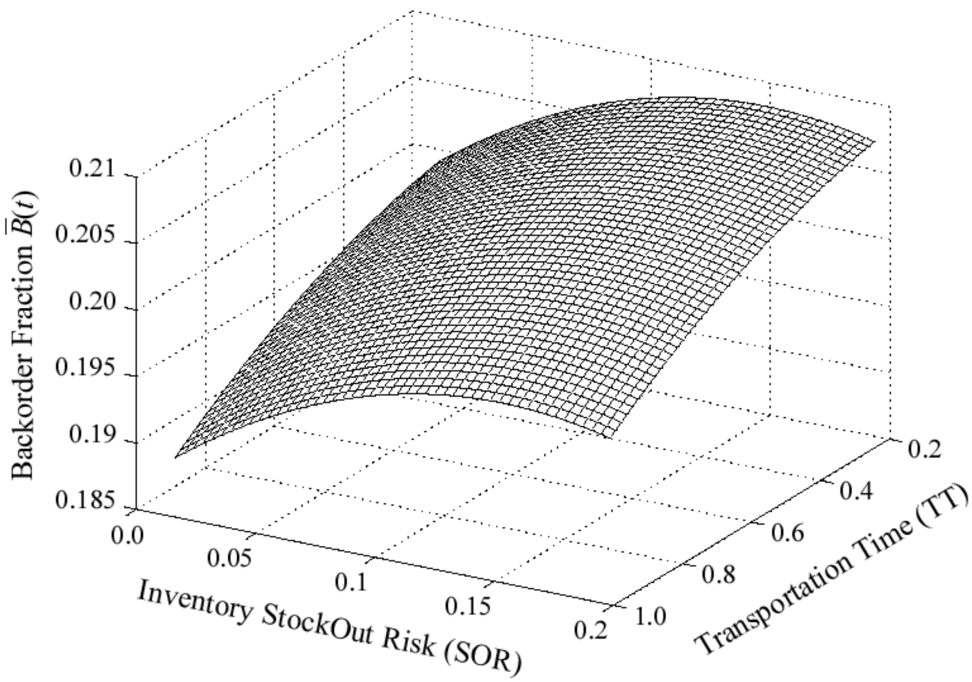

Figure 13: Estimated quadratic regression surface for the response $\overline{B}(t)$ as a function of the parameters for SOR and TT with Supplier Lead Time SLT = 0.5W, Demand Distribution DD = 0.5X, Processing Time PT = 0.5Z. The model contains linear and quadratic terms for both SOR and TT.

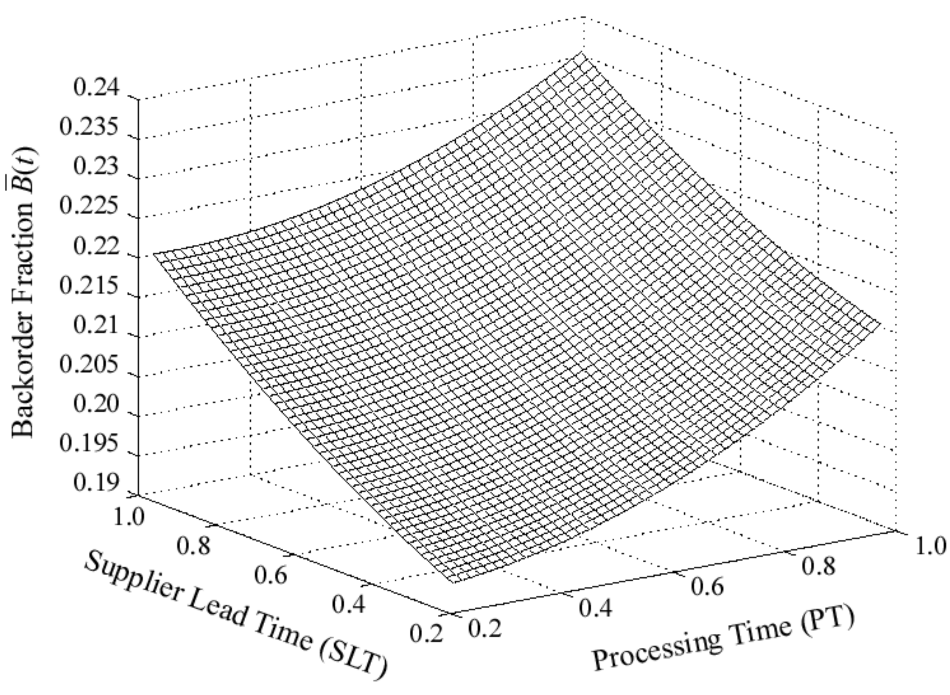

Figure 14: Estimated quadratic regression surface for the response $\overline{B}(t)$ as a function of the parameters for SLT and PT with Inventory System Stock-Out Risk SOR = 10%, Demand Distribution DD = 0.5X, and Transportation Time TT = 0.5Y. The model contains linear and quadratic terms for both SLT and PT, and an interaction between SLT and PT.

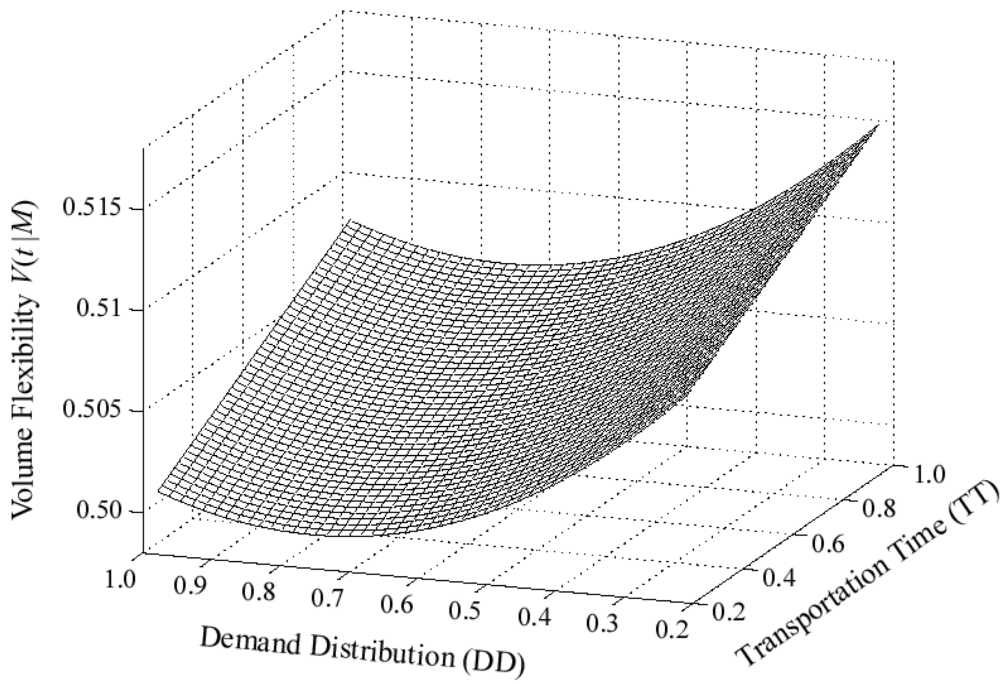

Figure 15: Estimated quadratic regression surface for the response $V(t \mid M)$ as a function of the parameters for DD and TT. The model contains linear and quadratic terms for DD and a linear term for TT.