MULTI-ECHelon SUPPLY CHAIN NETWORK DESIGN FOR INNOVATIVE PRODUCTS IN AGILE MANUFACTURING

A Thesis in
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by

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ABSTRACT

Multi-echelon supply chain network design is widely discussed in the literature. Most studies in this area focus on mathematical model building and heuristic method to solve these models. Few of them have discussed a hybrid model method to solve this complex problem, especially with large customer demand with uncertainties. For innovative products, the biggest characteristics are the unpredicted customer demand and a focus on customer service level (CSL). In this thesis, a hybrid model is proposed combining a mixed integer linear program (MILP) and Monte Carlo simulation to solve a four-echelon supply chain network design problem for innovative products in a stochastic environment with three potential partners in each echelon. The objective is to get the maximum CSL at the lowest supply chain total cost. Compared to the deterministic model, the hybrid model results showed a 0.8% improvement in CSL when the demand variability is low and a 4.6% improvement when the demand variability is high. Then a trade-off analysis between CSL and total supply chain cost is carried out to provide useful suggestions to decision makers. A $2^4$ factorial experimental design is also conducted taking demand variability, capacity variability for selected partners, transportation capacity variability, and whether or not using the hybrid method as factors of interests. Among these factors, demand variability, whether or not using the hybrid model and their interaction proved to be significant. Finally, an efficiency test proved that the hybrid model can improve the CSL significantly compared with the MILP model.
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Chapter 1

Introduction

A supply chain is a system of information, people, resources, and organizations that are involved in the product or service flow from supplier to the end customer (Chopra and Meindl, 2004). If the sequence of operations in a supply chain is defined as echelons, then the nodes in each echelon will stand for cooperating partners (Chauhan, 2006) and arcs between nodes in two adjacent echelons will stand for transportation routes. The node-arc model with different number of echelons forms a multi-echelon supply chain network design problem. A good supply chain network design can not only reduce total costs, but also can improve customer responsiveness and be flexible enough to meet changes and new market challenges.

Before designing the supply chain, the first step is to consider the nature of the demand for the products one’s company supplies (Fisher, 1997). There are typically two kinds of product categories: functional products and innovative products. Functional products have low margins but the product variety is low and the demands are always predictable. For innovative product, the profit margins are always high while the product variety is also high, and the demands are unpredictable (Fisher, 1997). Thus working in a competitive environment with continuously emerging market opportunities and changing with uncertainty are the key issues for supply chain network design for innovative products (Pan and Nagi, 2013).

For innovative industries, most companies are faced with challenges of improving efficiency and reducing total cost at the same time in a competitive environment where all products need to be designed, manufactured, and distributed as fast as possible (Pan and Nagi,
2013). In order to meet various customer demands and lower the supply chain risk, supply chain management (SCM) has always been the key to solve these problems. SCM integrates suppliers, manufacturers, distributors, and customers through the use of information technology to meet customer demands efficiently and effectively. As a result, groups of companies can respond quickly and effectively in a unified manner with high-quality, differentiated products demanded by final consumers while achieving system-wide advantages in cost, time, and quality by applying SCM (Vonderembsea et al., 2006).

In response to these challenges, alliance between echelons is crucial, because they need a fast reaction from each other when a new market chance emerges. Many companies have increased the emphasis on developing closer relationships with suppliers, distributors or customers and there have been consequent movements towards longer-term relational policies and a growth in cooperating to reduce the supply chain risk (Smart, 2008). The premise of this approach is a co-operative philosophy leading to more integration of processes and systems with firms in the supply chain creating greater network-wide efficiencies (Lambert and Cooper, 2000). In an integrated supply chain, cooperators can share information, resources and core competencies at the same time. Therefore, the integrated supply chain between companies would enhance their ability to work efficiently when a new opportunity for innovative products emerges. (Chauhan et al., 2006).

1.1 Objective

The objective of this research is to develop a methodology to select companies in each echelon to form the supply chain network with unpredictable demand for innovative products in a stochastic environment in order to satisfy customer demands while minimizing the sum of
strategic, tactical, and operational costs. The performance measures taken into consideration are total fixed and variable costs, customer fill rate, and inventory levels.

1.2 Organization

The remainder of this thesis is organized as follows: Chapter 2 presents critical reviews of past work on multi-echelon supply chain modeling, network design, and typical methodologies used to solve these design problems. Chapter 3 presents the problem description, the hybrid model formulation and steps of implementation. The numerical results of a computational study and experiment results analysis are presented in Chapter 4. Finally, conclusions and future study suggestions are discussed in Chapter 5.
Chapter 2

Literature Review

A typical supply chain is a network of suppliers, manufacturing plants, warehouses, and distribution channels organized to acquire raw materials, convert these raw materials to finished products, and distribute these products to customers (Figure 2.1). It always involves two basic processes tightly integrated with each other: (1) the production planning and inventory control process, which deals with manufacturing, storage and their interfaces, and (2) the distribution and logistics process, which determines how products are retrieved and transported from the warehouse to distribution centers, from distribution centers to retailers, and from retailers to customers (Tsiakis et al., 2001).
In a supply chain, the flow of goods between a supplier and customer passes through several stages, and each stage may consist of many facilities. We define each stage as an “echelon” in the supply chain network. Usually the more echelons incorporated in a supply chain, the more complex it will be. The planning of a supply chain network involves making decisions to deal with long-term (strategic planning), medium term (tactical planning) as well as short-term (operational planning) issues. According to the importance and the length of the planning horizon taken into consideration, these decisions can be classified into three categories as the following: (1) the number, location and capacity of manufacturing plants, warehouses, distribution centers, and retailers (2) the supplier selection, product range assignment as well as distribution channel and transportation mode selection, (3) the flows of materials and information in the whole network.

Figure 2. 1 Typical supply chain network
Important benefits like reducing supply chain risks, satisfying customer demands and minimizing total strategic, and tactical/operational costs can be reached by treating the network as a whole and considering its various components simultaneously (Bidhandi et al., 2011). The supply chain network design decisions are usually costly and difficult to reverse, and their impact spans a long time horizon. Product and supply chain decisions should be tightly integrated, thus an efficient supply chain network design according to the product property is very crucial for companies to survive in the competitive environment.

For functional products, due to their properties of low product variety, predictable demand and low forecasting errors, and low margins and high customer demands, an efficient supply chain is a better fit to guarantee the sustained and relatively stable customer demands. For innovative products, they typically have the following characteristics: (1) demand is highly uncertain and supply may be unpredictable, (2) margins are often high, and time is crucial to gaining sales, (3) product availability is crucial to capturing the market, and (4) cost is often a secondary consideration (Chopra and Meindl, 2004). Since a responsive supply chain is more flexible to meet the rapidly changing needs of the marketplace, it is a better match for innovative products (Fisher, 1997). Responsiveness is defined as “the ability of a supply chain to respond rapidly to the changes in demand, both in terms of volume and mix of products” (Christopher, 2000; Holweg, 2005). Quick response will enable supply chains to synchronize the supply to meet the peaks and troughs of demand with ever-shorter lead time and minimize stock outs and obsolete inventory (You and Grossmann, 2008).

Supply chain management (SCM) facilitates organizational coordination required for innovative products including: (1) the development of an interconnected information network
involving a selected group of trained suppliers, (2) a successful balance between a low level of stocks with high-quality delivery service, (3) the designing of innovative products with the active collaboration of suppliers, and (4) cost effective delivery of the right products to the right customer at the right time (Gunasekaran et al., 2008). These aspects are usually considered when designing the supply chain network together with objectives of cost, flexibility, efficiency, or fill rate.

Most of the supply chain modeling research are extensions or integrations of the traditional problems of production planning and inventory control and distribution and logistics (Cheny and Paularaji, 2004). Due to the combinatorial nature, optimally solving an integrated production, inventory, and distribution routing problem is generally difficult (Lei et al. 2006). Supply chain network design models always include uncertainties associated with the demand or the production processes. These kinds of problems are usually NP hard and not easy to solve especially when they are in stochastic environment. Thus, how to build and solve supply chain network design models are widely discussed all along the time.

In this chapter, four kinds of supply chain network design models found in literatures are discussed: deterministic models, stochastic models, simulation models, and hybrid models.

2.1 Deterministic Models

Deterministic models are extensively discussed in multi-echelon supply chain network design. Most of the formulations in SCM are in the form of mixed integer programming (MIP) or mixed integer linear programming (MILP) models with several assumptions such as parameters given and transportation mode (Yan et al., 2003).
Shen et al. (2003) and Daskin et al. (2002) proposed a set-covering model to build the optimal supply chain with single echelon inventory cost, and they showed that this problem can be solved efficiently when the demand faced by each distribution center is Poisson distributed or deterministic. Shu et al. (2005) extended this model to arbitrary demand distributions. Romeijn et al. (2007) proposed a generic modeling framework aimed at integrating insights from modern inventory theory into multi-echelon supply chain network design. Correia et al. (2013) proposed two MILP models to design a two-echelon supply chain network over a multi-period horizon with objectives of cost minimization and profit optimization. In this case, it may not always completely satisfy demand requirements. Cohen and Lee (1989) built a model for a serial multi-stage, batch production process that a product was allowed to be processed on more than one line.

Chauhan et al. (2006) considered a problem of designing a partner-chain by an integrated production-logistics approach. A limitation of their work is the assumption that any member in the formed supply chain can only have one supplier partner and only one customer partner. Their objective is to select one partner from each echelon of the supply chain to meet the forecasted demand without backorders and minimize holistic supply chain production and logistic costs. They developed a large-scale mixed integer linear programming (MILP) model and a decomposition-based solution approach in a deterministic environment. The computational experiments showed that this approach was capable of generating fast heuristic solutions (Chauhan et al. 2006).

Pan and Nagi (2013) generalized the limiting assumption of Chauhan et al (2006), and allowed multiple partners to be selected at any stage of the supply chain, which made this problem closer to reality since companies usually have more than one cooperator. Although only a single assumption was relaxed, the problem structure was totally different. To solve this
problem, they developed a MILP model aiming at reducing total operation costs and a proposed lagrangian heuristic with adjustment techniques to improve the computational results for small-size, medium-size, and large-size problems. The new approach provided 15%–25% better solutions with less than 5% optimality gap (Pan and Nagi., 2013).

Bidhandi et al. (2009) proposed a MILP model for four-echelon supply chain network design in deterministic, multi-commodity, multi-product, and single-period contexts taking backorder penalties into consideration. The model integrated location and capacity choices for suppliers, plants and warehouses selection, product range assignment and production flows. A modified version of Benders’ decomposition was proposed to solve the MILP model. They also used surrogate constraints to replace main constraints of the master problem as a relaxation of the main problem. The number of iterations of the new approach was less and execution time was smaller than the Benders’ decomposition algorithm (Bidhandi et al., 2009).

2.2 Stochastic Models

Most research on addressing uncertainty can be distinguished into two primary approaches, referred to as the probabilistic approach and the scenario planning approach (Tsiakis et al., 2001). In probabilistic model approaches, the uncertainty aspects of the supply chain treating one or more parameters as random variables are considered with known probability distributions (Sridharan, 1995). Hidayat et al. (2011) adopted this approach and developed an analytical model to prove the benefits (such as reducing the supply chain total cost and the leadtime, increase the frequency of replenishment, and improve the service level) of Vender Managed Inventory (VMI) programs by implementation of VMI in a probabilistic inventory model with leadtime as a decision variable. They focused on a two-level supply chain problem
consists of single supplier and single buyer in a probabilistic demand environment (Hidayat et al., 2011).

On the other hand, the scenario planning approach is implemented in terms of a moderate number of discrete realizations of the stochastic quantities, constituting distinct scenarios in order to capture the uncertainty property of stochastic environments (Mulvey et al., 1997). The objective is to find robust solutions that will perform well under all kinds of scenarios. McLean and Li (2013) applied this approach to solve a strategic supply chain optimization problem under uncertainty customer demand. They concluded that their proposed scenario formulations could generate solutions with guaranteed feasibility or indicate infeasibility of the problem (McLean and Li, 2013).

On the basis of Chauhan et al. (2006), Pan and Nagi (2010) developed a model further added uncertain customer demands. The objective was to determine companies selected to form the supply chain and production, inventory and transportation planning. A scenario planning approach was used to handle the uncertainty of demands. To formulate a robust optimization model, an expected penalty for unfulfilled demand was added. They proposed a heuristic based on the k-shortest path algorithm by suing a surrogate distance to denote the effectiveness of each member in the supply chain. The results showed that the optimality gap was 0 for small and medium problems, and an average gap of 1.15% for large size problems (Chauhan et al., 2006; Pan and Nagi, 2010).

Bidhandi et al. (2011) developed a multi-commodity single-period integrated supply chain network design model with two levels of strategic and tactical variables corresponding to the strategic and tactical decisions in the decision-making process in a stochastic environment. The uncertainties are mostly found in the tactical stage because most tactical parameters are not
fully known when the strategic decisions have to be made. The main uncertain parameters are the operational costs, the customer demand and capacity of the facilities. They proposed an accelerated Benders’ decomposition approach and surrogate constraints method to solve the MILP problem with a probabilistic approach. The results showed that the proposed method significantly expedited the computational procedure compared with the original approach and the optimality gap was also improved (Bidhandi et al., 2011).

You and Grossmann (2010) developed an optimization model for simultaneously optimizing the transportation, inventory and network structure of a multi-echelon supply chain in the presence of uncertain customer demands. The model also captured risk-pooling effects by consolidating the safety stock inventory of downstream nodes to the upstream nodes in the multi-echelon supply chain. They formulated the problem as a mixed-integer nonlinear programming (MINLP) with a nonconvex objective function. A spatial decomposition algorithm based on lagrangean relaxation and piecewise linear approximation is proposed. As the results showed, usually near global optimal solutions typically within 1% of the global optimum could be achieved (You and Grossmann, 2010).

Fransoo et al. (2001) introduced a separate “resource planner” function to pool demand without breaking rules on service levels and without making use of local information. They did a quantitative analysis of a two-echelon divergent supply chain, with both cooperative and non-cooperative retail groups and showed how multi-echelon inventory theory can accommodate a setting with decentralized decision makers without complete information using the proposed method. The authors concluded that the inventory at the manufacturer could be reduced by the pooling effect when demand was roughly evenly distributed between cooperative and non-cooperative retailers (Fransoo et al., 2001).
Since stochastic models are NP hard problems, methodologies to solve stochastic models are mostly heuristic methods.

Sadjady and Davoudpour (2012) developed an efficient Lagrangian based heuristic solution algorithm for a two-echelon supply chain network design problem in deterministic, single-period, multi-commodity contexts. Bhatnagar (1995) formulated a Lagrangian relaxation and Lagrangian decomposition based heuristic procedure to find near-optimal solutions for the mathematical model of a simple case of two production facilities, which combined the objectives of the improving cost performance and profit while maintaining the relevant constraints.

Zhou et al. (2013) proposed an algorithm designed by Genetic Algorithm (GA) to solve a multi-product multi-echelon inventory control model with application of the joint replenishment strategy. Guinet (2001) proposed a primal-dual approach for a multi-site production planning problem. The author also applied a genetic algorithm to optimize production planning for global manufacturing. Yeh (2005) proposed an efficient hybrid heuristic algorithm (HHA) by combining a greedy method (GM), the linear programming technique (LP) and three local search methods (LSMs) and developed a revised mathematical model to correct the fatal error appearing in the existing models, which was incorrect mathematical model that violated the flow conservative law. Wang (2009) proposed a two-phase ant colony algorithm to solve the germane mathematical programming model they developed for a multi-echelon defective supply chain network design considering the reliability of the structure and the unbalance of this system caused by the losses of production, besides the cost of production and transportation.
2.3 Simulation Models

Simulation models have been widely discussed by researchers since they are able to give early insights and estimates of behaviors for complex systems (Nikolopoulou, 2012). Most of research papers discussing multi-echelon supply chain simulations are using discrete event simulations (DES). Monte Carlo simulations are more often used as a tool of verifications or illustrations.

Fu (2001) reviewed the simulation optimization techniques both for continuous and discrete decision variables. Fu defined simulation optimization as “optimization of performance measures based on outputs from stochastic (primarily discrete-event) simulations” (Fu, 2001).

Behdani et al. (2009) developed an agent-based model of a lube additive manufacturing supply chain and evaluated the dynamic behavior of supply networks, considering both the system-level performance as well as the components’ behavior particularly during abnormal situations. The simulation results showed that the preferred policy could reduce the total tardiness to zero and have only one nonfinished order (Behdani et al., 2009).

Enns and Suwanruji (2003) developed a simulation test bed for production and supply chain modeling in Arena. They used simulations to compare the performances of MRP/DRP, reorder point, and Kanban systems. The results showed that MRP/DRP systems performed the best and Kanban or reorder point systems had to depend on desired trade offs between inventory and delivery performance. Also, the simulation test bed could obtain insights into the behavior of both production and supply chain environments (Enns and Suwanruji, 2003).

Vila et al. (2009) proposed a sample average approximation (SAA) method based on Monte Carlo sampling techniques to solve production-distribution network design problem for the lumber industry in a stochastic environment. The results of the experiments showed that the
proposed approach gave much better supply chain designs which raised the expected return of the company significantly with lower fixed and variable costs than a comparable deterministic model based on averages (Vila et al., 2009).

Gunasekaran et al. (2006) used Monte Carlo simulation into quality function deployment (QFD) environment together with a fuzzy multi-criteria decision-making procedure to make the decisions of finding a set of optimal solution with respect to the performance of each supplier. The results showed that this new approach was more precise than that of conventional QFD through a case study problem (Gunasekaran et al., 2006).

Huq et al. (2009) used Monte Carlo simulation as a validation tool of testing a mathematical programming model which integrated production factors, purchasing, inventory, and trucking decisions to reach the objective of reducing potential inefficiencies in the supply chain network design. Monte Carlo simulation was applied to differentially test the fully developed model including standard production variables varying transportation costs, paired with similar instances of the model. Transportation costs played a significant role in this particular simulation since transportation costs significantly impact the performance of the model during the test procedure (Huq et al., 2009).

### 2.4 Hybrid Models

Most of the work studying multi-echelon supply chain network design are formulating MILP models then solving with heuristic or mathematical approaches. Though not widely discussed, hybrid modeling approaches have demonstrated the usefulness of simulation tools when combined with mathematical models (Lee & Kim, 2000; Lim et al., 2006). The hybrid mathematical-simulation approaches can give a more realistic representation of the supply chain
system. Agent-based simulation is largely employed to study supply chain systems. Simulation-based optimization is also an active area of research in the field of stochastic optimization, because these approaches can mimic real systems including stochastic and nonlinear elements.

Lee and Kim (2000) developed a hybrid method that combines analytic (Linear Programming, LP) and simulation models to solve multiproduct and multi-period production-distribution problems. The LP model minimizes the overall cost of production, distribution, inventory holding, and shortage costs. Production and distribution rates obtained from the LP model were input into the simulation model which subjected to realistic operational policies. The hybrid model keep changing the capacity of the LP model until production and distribution rates in the simulation model could be produced and distributed within the capacity. The authors concluded that the hybrid method could provide more realistic optimal solutions than the initial analytic solutions (Lee and Kim, 2000).

Lim et al. (2006) proposed a hybrid approach involving a genetic algorithm (GA) and simulation to solve a distribution plan problem with low cost and high customer satisfaction for a stochastic supply chain. GA was first employed to generate distribution schedules, and then a simulation model based on the generated distribution schedules was run. One feasible completion time was generated. If the result couldn’t yield the required level of value, change constraints in the GA using current simulation completion time and regenerate distribution schedules. If the termination condition was met, the distribution plan could be generated. GA was employed in order to quickly generate feasible distribution sequences. The simulation was used to minimize completion time for the distribution plan, considering uncertain factors such as queuing, breakdowns and repairing time in the supply chain. With the proposed hybrid approach, they
authors obtained more realistic distribution plans with optimal completion times that reflect stochasticity (Lim et al., 2006).

Nikolopoulou and Ierapetritou (2012) proposed a hybrid simulation optimization approach that addresses the problem of supply chain management and provided a good representation of supply chain reality. They formulated a large scale MILP model which minimizes the summation of production cost, transportation cost, inventory holding and shortage costs, subject to capacity and inventory balance constraints. A hybrid approach was developed by applying a MILP formulation in the context of an agent based simulation to solve the problem. The authors first initialized the simulation model and used its output as an input to the MILP model. Then, the output of the MILP model was fed to the simulation model and this procedure kept going iteratively until the desired results were obtained. They concluded that the proposed hybrid model could give more realistic results with less computational time (Nikolopoulou and Ierapetritou, 2012).

Safaei et al. (2010) proposed a hybrid MILP simulation model to solve an integrated multi-product, multi-period, multi-site production-distribution planning problem. To apply the hybrid method, first they need to solve the MILP model and obtain the production-distribution plan, then based on this plan, run simulation model to obtain a current simulation runtime (CRT). Use the CRT as capacity and resolve the MILP model until difference rate between preceding simulation runtime (PRT) and CRT is within the rate of 0.02. Finally optimal production-distribution plan was generated when the hybrid model stopped. Through the computational experiments, the authors demonstrated that the number of iterations to converge hybrid procedure would lessen when considering the production distribution problem in an integrated manner.
Also, supply chain overall costs would be reduced through the integration of production and distribution problems (Safaei et al., 2010).

2.5 Summary

Supply chain management is a crucial issue both in research and business. Designing a right supply chain according to the product profile is very important for cost reduction and profit gain. The multi-echelon supply chain network design may cover long term strategic design and medium term tactical design, thus this kind of supply chain design is closely related to the future development of an industry, especially for innovative products for its characteristics of unpredictable demands and high profit margins.

Previous work on multi-echelon network design mainly involves four kinds of models: deterministic models, stochastic models, simulation models and hybrid models according to the problem environment preemptive assumptions. Supply chain network design problems in stochastic environments usually include decisions about production planning, inventory control, distribution planning and logistics with considerations of cost, profit, flexibility, customer service level or robustness of the model, and demand and/or capacity uncertainties, the problems are mainly NP hard. To solve this kind of problem, most methodologies focus on heuristic approaches to solve the mathematical model. Hybrid methods that are a combination of mathematical model and simulation, can give a more realistic representation of the supply chain system. Current work involving hybrid methods to solve supply chain network design problems commonly use discrete event simulation and not Monte Carlo simulation as part of the hybrid solution method.
This thesis proposes a hybrid model for a four-echelon supply chain network design problem allowing multiple choices of cooperators in each echelon and the customer demand is stochastic. The hybrid model includes a MILP mathematical model and a Monte Carlo simulation as a problem solving tool to simulate the stochastic environment. The network design problem involves decisions of cooperators selection, production planning and inventory control at selected cooperators, and distribution planning between two adjacent echelons with the objective of minimized total fixed cost, operational costs, and number of backorders.
Chapter 3
Methodology

In this chapter, a hybrid model for solving a multi-echelon supply chain network design problem in a stochastic environment for innovative products is proposed. The problem environment and assumptions are presented in Section 3.1. The problem formulation and verification in a deterministic environment are discussed in Section 3.2. A Monte Carlo simulation for stochastic demand and a linear programming (LP) model to solve inventory level and backorder quantity are discussed in Section 3.3. In Section 3.4, the steps of applying the hybrid model combining the MILP and simulation models are proposed. At last, a conclusion for this chapter is drawn in Section 3.5.

3.1 Problem Environment

The problem environment discussed in this chapter is based on the work of Pan and Nagi (2013). The echelons of the network are representatives of components in a supply chain structure. Each echelon performs one operation in a supply chain, for example procurement, manufacturing or distribution. There are four echelons (E) in this problem: (E1) suppliers, (E2) plants, (E3) warehouses, and (E4) retailers (Colosi, 2006) (Shown as Figure 3.1). In each of the echelon more than one partner can be chosen from the candidate set of three, and one partner can be supplied by multiple partners in the previous echelon or can supply multiple partners in the next echelon. There are seven time periods taken into consideration in the deterministic model and each iteration stands for one time period in the stochastic model.
The main objective of this model is to select cooperating partners in each echelon to form the supply chain network in order to minimize the total fixed alliance and set-up costs and operational costs including unit processing cost, inventory holding cost per unit, and unit transportation cost. There is a fixed cost when choosing a partner, including the facility and workforce costs. The fixed cost of building up an alliance between two selected partners includes technology cost for information sharing, unified training cost, and resource sharing cost and so forth. Once a partner is selected, additional decision variables are the alliance between two selected partners, production quantities and inventory level at selected partners, and shipping quantities between two selected partners in adjacent echelons. This problem includes both long term strategic planning and medium term tactical planning in the decision making process.

The complexities of the problem are (a) fixed cost problem for alliances and node selection; (b) the multi-period production planning at selected companies; (c) the transportation problem constrained by (a) and (b) (Pan and Nagi, 2013). Thus, some assumptions are made to simplify the problem.
The following assumptions are adopted in this problem (Pan and Nagi, 2013; Chauhan et al., 2006; Colosi, 2006):

1. The supply chain produces a single end product corresponding to a new market opportunity, which means there is only one customer demand in each time period.
2. Operation time, including production and transportation, is one time period.
3. There is only one transportation mode, which is capacitated.
4. The flow is only allowed to be transferred between two consecutive echelons.
5. One unit from a supply source produces one unit of finished product.
6. Multiple partners can be chosen in each echelon to fulfill the customer demand.
7. Demand is stochastic and fulfilled by selected partners in the last echelon.
8. Shortages are permitted in the last echelon in the stochastic environment.
9. Transportation cost from the last echelon (retailers) to the customer is zero.

3.2 Mathematical Formulation

This section presents the MILP model to determine the partner selection and production planning problem in a deterministic environment. In this model, the binary decision variables help decide cooperating partners in the long run and continuous decision variables are representatives of production, manufacturing and distribution planning on a tactical level. The MILP model is based on the work of Pan and Nagi (2013). Different from the original model, no backorder is allowed at the last echelon, only one kind of inventory is considered, namely finished good inventory, and only three demand periods are considered in this proposed model. The results of this MILP model are the input values of the hybrid model in a stochastic environment, which will be discussed in detail in later sections.
3.2.1 Notations

S = Set of potential supplier locations, indexed by s, s=1,2,3

P = Set of potential plant locations, indexed by p, p=1,2,3

W = Set of potential warehouse locations, indexed by w, w=1,2,3

R = Set of potential retailers locations, indexed by r, r=1,2,3

C = Set of customers, indexed by c, c=1

T = Set of time periods, indexed by t, t=1,2,3,4,5,6,7

3.2.2 Parameters Given

\( FX_s \) = Fixed cost of selecting potential Supplier s

\( FX_p \) = Fixed cost of selecting potential Plant p

\( FX_w \) = Fixed cost of selecting potential Warehouse w

\( FX_r \) = Fixed cost of selecting potential Retailer r

\( U_{st} \) = Unit processing cost at Supplier s for period t

\( U_{pt} \) = Unit processing cost at Plant p for period t

\( U_{wt} \) = Unit processing cost at Warehouse w for period t
\[ U_{rt} = \text{Unit processing cost at Retailer } r \text{ for period } t \]

\[ I_{st} = \text{Inventory holding cost at Supplier } s \text{ for period } t \]

\[ I_{pt} = \text{Inventory holding cost at Plant } p \text{ for period } t \]

\[ I_{wt} = \text{Inventory holding cost at Warehouse } w \text{ for period } t \]

\[ I_{rt} = \text{Inventory holding cost at Retailer } r \text{ for period } t \]

\[ C_{st} = \text{Capacity of Supplier } s \text{ for period } t \]

\[ C_{pt} = \text{Capacity of Plant } p \text{ for period } t \]

\[ C_{wt} = \text{Capacity of Warehouse } w \text{ for period } t \]

\[ C_{rt} = \text{Capacity of Retailer } r \text{ for period } t \]

\[ F_{sp} = \text{Fixed set up cost for an alliance between Supplier } s \text{ and Plant } p \]

\[ F_{pw} = \text{Fixed set up cost for an alliance between Plant } p \text{ and Warehouse } w \]

\[ F_{wr} = \text{Fixed set up cost for an alliance between Warehouse } w \text{ and Retailer } r \]

\[ T_{spt} = \text{Unit transportation cost from Supplier } s \text{ to Plant } p \text{ for period } t \]

\[ T_{pwt} = \text{Unit transportation cost from Plant } p \text{ to Warehouse } w \text{ for period } t \]
$T_{wrt} = \text{Unit transportation cost from Warehouse w to Retailer r for period t}$

$TC_{spt} = \text{Transportation capacity from Supplier s to Plant p}$

$TC_{pwt} = \text{Transportation capacity from Plant p to Warehouse w}$

$TC_{wrt} = \text{Transportation capacity from Warehouse w to Retailer r}$

$D_t = \text{Demand for period t}$

### 3.2.3 Decision Variables

**Binary variables:**

$$X_s = \begin{cases} 1 & \text{if Supplier s is selected} \\ 0 & \text{otherwise} \end{cases}$$

$$X_p = \begin{cases} 1 & \text{if Plant p is selected} \\ 0 & \text{otherwise} \end{cases}$$

$$X_w = \begin{cases} 1 & \text{if Warehouse w is selected} \\ 0 & \text{otherwise} \end{cases}$$

$$X_r = \begin{cases} 1 & \text{if Retailer r is selected} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{sp} = \begin{cases} 1 & \text{if Supplier s is to supply Plant p} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{pw} = \begin{cases} 1 & \text{if Plant p is to supply Warehouse w} \\ 0 & \text{otherwise} \end{cases}$$
\( Y_{wr} = \begin{cases} 1 & \text{if Warehouse } w \text{ is to supply Retailer } r \\ 0 & \text{otherwise} \end{cases} \)

**Continuous variables:**

\( q_{st} = \text{Quantity of product processed at Supplier } s \text{ in period } t \)

\( q_{pt} = \text{Quantity of product processed at Plant } p \text{ in period } t \)

\( q_{wt} = \text{Quantity of product processed at Warehouse } w \text{ in period } t \)

\( q_{rt} = \text{Quantity of product processed at Retailer } r \text{ in period } t \)

\( \text{inven}_{st} = \text{Inventory of product at Supplier } s \text{ at the end of period } t \)

\( \text{inven}_{pt} = \text{Inventory of product at Plant } p \text{ at the end of period } t \)

\( \text{inven}_{wt} = \text{Inventory of product at Warehouse } w \text{ at the end of period } t \)

\( \text{inven}_{rt} = \text{Inventory of product at Retailer } r \text{ at the end of period } t \)

\( s_{spt} = \text{Quantity of product shipped form Supplier } s \text{ to Plant } p \text{ in period } t \)

\( s_{pwt} = \text{Quantity of product shipped form Plant } p \text{ to Warehouse } w \text{ in period } t \)

\( s_{wrt} = \text{Quantity of product shipped form Warehouse } w \text{ to Retailer } r \text{ in period } t \)
3.2.4 Model Formulation

Objective function:

The objective function of the MILP model minimizes the sum of the total fixed cost of selecting a potential partner in each echelon, total fixed cost of alliance built between two selected partners in adjacent echelons, total unit processing cost at selected partners, total inventory holding cost at selected partners, and total shipping cost between two selected partners in adjacent echelons.

\[
\begin{align*}
\text{Min.} & \quad \sum_{s} FX_{s} \cdot X_{s} + \sum_{p} FX_{p} \cdot X_{p} + \sum_{w} FX_{w} \cdot X_{w} + \sum_{r} FX_{r} \cdot X_{r} + \sum_{s} \sum_{p} F_{sp} \cdot Y_{sp} \\
& \quad + \sum_{p} \sum_{w} F_{pw} \cdot Y_{pw} + \sum_{w} \sum_{r} F_{wr} \cdot Y_{wr} + \sum_{s} \sum_{p} \sum_{t=1}^{T-4} T_{spt} \cdot S_{spt} \\
& \quad + \sum_{p} \sum_{w} \sum_{t=2}^{T-4+1} T_{pw} \cdot S_{pw} + \sum_{w} \sum_{r} \sum_{t=3}^{T-4+2} T_{wr} \cdot S_{wr} + \sum_{s} \sum_{t=1}^{T-4} U_{st} \cdot q_{st} \\
& \quad + \sum_{p} \sum_{t=2}^{T-4+1} U_{pt} \cdot q_{pt} + \sum_{w} \sum_{t=3}^{T-4+2} U_{wt} \cdot q_{wt} + \sum_{r} \sum_{t=4}^{T-4+3} U_{rt} \cdot q_{rt} \\
& \quad + \sum_{s} \sum_{t=1}^{T-4} I_{st} \cdot \text{inven}_{st} + \sum_{p} \sum_{t=2}^{T-4+1} I_{pt} \cdot \text{inven}_{pt} + \sum_{w} \sum_{t=3}^{T-4+2} I_{wt} \cdot \text{inven}_{wt} \\
& \quad + \sum_{r} \sum_{t=4}^{T-4+3} I_{rt} \cdot \text{inven}_{rt}
\end{align*}
\]

Constraints:

I. Network Structure Constraints:
A link between Supplier $s$ and Plant $p$ can exist only if Supplier $s$ is selected:

$$ Y_{sp} \leq X_s; \quad \forall s, p $$

(3.2.4.1)

A link between Supplier $s$ and Plant $p$ can exist only if Plant $p$ is selected:

$$ Y_{sp} \leq X_p; \quad \forall s, p $$

(3.2.4.2)

A link between Plant $p$ and Warehouse $w$ can exist only if Plant $p$ is selected:

$$ Y_{pw} \leq X_p; \quad \forall p, w $$

(3.2.4.3)

A link between Plant $p$ and Warehouse $w$ can exist only if Warehouse $w$ is selected:

$$ Y_{pw} \leq X_w; \quad \forall p, w $$

(3.2.4.4)

A link between Warehouse $w$ and Retailer $r$ can exist only if Warehouse $w$ is selected:

$$ Y_{wr} \leq X_w; \quad \forall w, r $$

(3.2.4.5)

A link between Warehouse $w$ and Retailer $r$ can exist only if Retailer $r$ is selected:

$$ Y_{wr} \leq X_r; \quad \forall w, r $$

(3.2.4.6)

A supplier can supply more than one plant:

$$ \sum_p Y_{sp} \geq X_s; \quad \forall s $$

(3.2.4.7)
A plant can be supplied by more than one supplier:

\[ \sum_s Y_{sp} \geq X_p; \; \forall p \]  \hspace{1cm} (3.2.4.8)

A plant can supply more than one warehouse:

\[ \sum_w Y_{pw} \geq X_p; \; \forall p \]  \hspace{1cm} (3.2.4.9)

A warehouse can be supplied by more than one plant:

\[ \sum_p Y_{pw} \geq X_w; \; \forall w \]  \hspace{1cm} (3.2.4.10)

A warehouse can supply more than one retailer:

\[ \sum_r Y_{wr} \geq X_w; \; \forall w \]  \hspace{1cm} (3.2.4.11)

A retailer can be supplied by more than one warehouse:

\[ \sum_w Y_{wr} \geq X_r; \; \forall r \]  \hspace{1cm} (3.2.4.12)

**II. Capacity Constraints:**

Quantity produced at Supplier s, Plant p, Warehouse w, and Retailer r cannot exceed the capacity limit.

\[ q_{st} \leq C_{st} \cdot X_s; \; \forall s; \; t = 1, ..., T - 4 \]  \hspace{1cm} (3.2.4.13)

\[ q_{pt} \leq C_{pt} \cdot X_p; \; \forall p; \; t = 2, ..., T - 4 + 1 \]  \hspace{1cm} (3.2.4.14)
Quantity shipped from Supplier s, Plant p, and Warehouse w to Plant p, Warehouse w, and Retailer r cannot exceed the transportation capacity limit.

\[ q_{wt} \leq C_{wt} \times X_w; \quad \forall w; t = 3, ..., T - 4 + 2 \quad (3.2.4.15) \]

\[ q_{rt} \leq C_{rt} \times X_r; \quad \forall r; t = 4, ..., T - 4 + 3 \quad (3.2.4.16) \]

III. Demand Constraints:

Finished products shipped from Retailer r to Customer is equal to customer demand

\[ \sum_r s_{rct} = D_{t+1}; \quad \forall c; t = 4, ..., T - 4 + 3 \quad (3.2.4.20) \]

IV. Inventory Constraints:

For each partner, the inventory level for current period equals inventory level of last period plus the production for current period less the total shipping amount to next echelon in current period.

\[ \text{inven}_{st} = \text{inven}_{s(t-1)} + q_{st} - \sum_p s_{spt}; \quad \forall s; t = 1, ..., T - 4 \quad (3.2.4.21) \]

\[ \text{inven}_{pt} = \text{inven}_{p(t-1)} + q_{pt} - \sum_w s_{pwt}; \quad \forall p; t = 2, ..., T - 4 + 1 \quad (3.2.4.22) \]
\[ \text{inven}_{wt} = \text{inven}_{w(t-1)} + q_{wt} - \sum_r s_{wrt}; \quad \forall w; t = 3, ..., T - 4 + 2 \quad (3.2.4.23) \]

\[ \text{inven}_{rt} = \text{inven}_{r(t-1)} + q_{rt} - s_{rci}; \quad \forall r; t = 4, ..., T - 4 + 3 \quad (3.2.4.24) \]

Initial inventory levels for Supplier s, Plant p, Warehouse w and Retailer r are zero:

\[ \text{inven}_{s0} = 0; \quad \forall s \quad (3.2.4.25) \]

\[ \text{inven}_{p0} = 0; \quad \forall p \quad (3.2.4.26) \]

\[ \text{inven}_{w0} = 0; \quad \forall w \quad (3.2.4.27) \]

\[ \text{inven}_{r0} = 0; \quad \forall r \quad (3.2.4.28) \]

V. Demand for each echelon:

From the aspect of relations of two adjacent echelons, the previous echelon should be able to produce more products than what are needed in the current echelon. For example, if producing in period t, the supplying echelon must have delivered necessary materials by the end of previous period (t-1).

In each period for each plant, the total shipping amount from supplier s to plant p during period t-1 equals production quantity at plant p during period t plus the inventory level at plant p at the end of period t less the inventory level at plant p at the end of period t-1;

\[ \sum_s s_{sp(t-1)} \geq q_{pt} + \text{inven}_{pt} - \text{inven}_{p(t-1)}; \quad \forall p; t = 2, ..., T - 4 + 1 \quad (3.2.4.29) \]
In each period for each warehouse, total shipping amount from plant $p$ to warehouse $w$ during period $t-1$ equals production quantity at warehouse $w$ during period $t$ plus the inventory level at warehouse $w$ at the end of period $t$ less the inventory level at warehouse $w$ at the end of period $t-1$;

$$\sum_p s_{pw(t-1)} \geq q_{wt} + \text{inven}_{wt} - \text{inven}_{w(t-1)}; \quad \forall w; \quad t = 3, \ldots, T - 4 + 2 \quad (3.2.4.30)$$

In each period for each retailer, total shipping amount from warehouse $w$ to retailer $r$ during period $t-1$ equals production quantity at retailer $r$ during period $t$ plus the inventory level at retailer $r$ at the end of period $t$ less the inventory level at retailer $r$ at the end of period $t-1$;

$$\sum_w s_{wr(t-1)} \geq q_{rt} + \text{inven}_{rt} - \text{inven}_{r(t-1)}; \quad \forall r; \quad t = 4, \ldots, T - 4 + 3 \quad (3.2.4.31)$$

VI. Non-negative and binary Constraints:

All continuous decision variables are greater than or equal to zero:

$$\text{inven}_{st}, \text{inven}_{pt}, \text{inven}_{wt}, \text{inven}_{rt}, s_{st}, s_{pt}, s_{tw}, s_{wr} \geq 0; \quad \forall s, p, w, d, t \quad (3.2.4.32)$$

Binary variables represent selection of partners and alliances built between two selected partners:

$$X_s, X_p, X_w, X_r, Y_{sp}, Y_{pw}, Y_{wr} \in \{0,1\}; \quad \forall s, p, w, d, t \quad (3.2.4.33)$$
3.2.5 Model Verification

Data used to verify the model are shown in Appendix A (Pan et al., 2013). Their result of a four-echelon supply chain network design problem with three partners in each echelon and three customer demand periods with one end customer is expected to be comparable with the MILP model result in this thesis. It is possible to some differences since Pan et al. (2013) took both raw material holding cost and finished good holding cost into consideration while in this thesis only finished good holding cost is under concern in order to reduce the problem’s complexity and save computation time. Moreover, in the original model built by Pan et al. (2013), there is no fixed cost when selecting one partner, but in this thesis this part of cost is taken into consideration. Since the customer demand is large, it is possible to choose more than one partner; but without taking fixed cost into consideration, only one of them might be chosen to produce products in one time period, which will reduce the supply chain efficiency. The MILP model is coded and solved in MATLAB version R2011a with CPLEX Studio IDE solver built in. The original code and result are presented in Appendix D. The optimal solution of the MILP model is $238,960. The optimal solution presented by Pan et al. (2013) for a four-echelon, 3 partners in each echelon, one end customer and three demand periods problem is $243,583. Compared to the result of this thesis, the difference is less than 1.9%. Thus the MILP model is validated.

3.3 Monte Carlo Simulation

In this section, Monte Carlo simulation is adopted to simulate the real world customer demand in a stochastic environment. Monte Carlo simulation is a numerical technique that allows us to experience the future with the aid of a computer (Kritzman, 1993). By running simulations many times, we can track the distribution of customer demands. We can also simulate the customer demand as a given distribution in a stochastic environment to mimic real world case.
The goal of Monte Carlo simulation used in this part is to test how good the deterministic solution performs in a “real world” stochastic environment and determine whether or not it is necessary to go back and resolve the MILP model.

As is shown in Figure 3.2, input parameters for the Monte Carlo simulation are partners selected to form the supply chain network and production levels at each of the selected partners. Since the simulation model is built to mimic the “real world” customer demand and test the effectiveness of a supply chain, Step 1 is to create an initial supply chain network design by solving the MILP model. Then the Step 2 is to simulate the customer as normal distribution with the mean of deterministic demands of the MILP model formed in Section 3.2. In each iteration of the simulation, a LP model is solved with the objective of minimizing total shipping cost, transportation cost and backorder numbers. After solving the LP model, we can get outputs of inventory level, back order quantities and customer service level for the current iteration, namely for the current time period. By running the simulation a thousand times, normal distributions of outputs like inventory levels, backorder quantities and customer service levels are formed. At last Step 3 is to get averages of on thousand iterations of these outputs and use them as performance measures in the stochastic environment.
3.3.1 Stochastic Environment Formulation

To introduce the stochastic environment to the hybrid system, Monte Carlo simulation is needed for “real world” customer demand generation. For each iteration of the Monte Carlo simulation, a customer demand is generated given the demand distribution, and then a LP model is solved with the demand generated.

Formulation of the LP model is similar to the MILP model. Since the LP model is used to generate performance measures using the initial supply chain network design created by the MILP model, there are less decision variables than the MILP model. The goal of this LP model is to generate performance measures like inventory levels, shipping quantities, and customer service.
level (CSL) at the minimum cost given the partner selection and production levels at the selected partners as known parameters. In the LP model, backorders are allowed in the last echelon. Notations and parameters are the same with Section 3.2.1 and Section 3.2.2. The CSL is evaluated with equation 3.1:

\[
CSL = \left(1 - \frac{\text{Backorder}}{\text{Demand}}\right) \times 100\%
\]  

(3.1)

3.3.1.1 Parameters Given:

In addition to the parameters given in Section 3.2.2, the following parameters are added:

\[q_s = \text{Quantity of raw material processed at Supplier } s\]

\[q_p = \text{Quantity of product processed at Plant } p\]

\[q_w = \text{Quantity of product processed at Warehouse } w\]

\[q_r = \text{Quantity of product processed at Retailer } r\]

\[\text{inven}_{0_s} = \text{Inventory of last iteration for suppliers}\]

\[\text{inven}_{0_p} = \text{Inventory of last iteration for plants}\]

\[\text{inven}_{0_w} = \text{Inventory of last iteration for warehouses}\]

\[\text{inven}_{0_r} = \text{Inventory of last iteration for retailers}\]
M = Backorder penalty cost, a very large number

3.3.1.2 Decision Variables:

\( inven_s \) = Inventory of raw materials at Supplier \( s \) at the end of iteration

\( inven_p \) = Inventory of finished goods at Plant \( p \) at the end of iteration

\( inven_w \) = Inventory of finished goods at Warehouse \( w \) at the end of iteration

\( inven_r \) = Inventory of finished goods at Retailer \( r \) at the end of iteration

\( s_{sp} \) = Quantity of raw material shipped from Supplier \( s \) to Plant \( p \)

\( s_{pw} \) = Quantity of finished good shipped from Plant \( p \) to Warehouse \( w \)

\( s_{wr} \) = Quantity of finished good shipped from Warehouse \( w \) to Retailer \( r \)

\( backorder \) = Quantity of backorders

3.3.1.3 Model Formulation:

The objective of the LP model is to minimized total operational costs, including inventory holding cost and transportation cost, and backorder quantities. Since production cost, fixed set-up cost, and fixed alliance cost are known after solving the MILP model, they are not in the objective function of the LP model.
Objective function:

\[
\text{Min. } \sum_{s} \sum_{p} T_{sp} * s_{sp} + \sum_{p} \sum_{w} T_{pw} * s_{pw} + \sum_{w} \sum_{r} T_{wr} * s_{wr} + \sum_{s} I_{s} * \text{inven}_{s} + \sum_{p} I_{p} * \text{inven}_{p} + \sum_{w} I_{w} * \text{inven}_{w} + \sum_{r} I_{r} * \text{inven}_{r} + M * \text{backorder}
\]

Constraints:

I. Capacity constraints:

Inventory level plus the production quantity cannot exceed the capacity limit at Supplier s, Plant p, Warehouse w, and Retailer r:

\[
inven_{s} + q_{s} \leq C_{s}; \quad \forall s \tag{3.2.3.1}
\]

\[
inven_{p} + q_{p} \leq C_{p}; \quad \forall p \tag{3.2.3.2}
\]

\[
inven_{w} + q_{w} \leq C_{w}; \quad \forall r \tag{3.2.3.3}
\]

\[
inven_{r} + q_{r} \leq C_{r}; \quad \forall r \tag{3.2.3.4}
\]

Quantity shipped form Supplier s, Plant p and Warehouse w to Plant p, Warehouse w, and Retailer r cannot exceed the transportation capacity limit:

\[
s_{sp} \leq TC_{sp}; \quad \forall s, p \tag{3.2.3.5}
\]

\[
s_{pw} \leq TC_{pw}; \quad \forall p, w \tag{3.2.3.6}
\]
II. Inventory Constraints

For each selected partner, inventory of current iteration = inventory for last iteration + production quantity of current iteration – total shipping amount to next echelon:

\[ \text{inven}_s = \text{inven}_0 + q_s - s_{sp}; \quad \forall s, p \]  
(3.2.3.8)

\[ \text{inven}_p = \text{inven}_0 + q_p - s_{pw}; \quad \forall p, w \]  
(3.2.3.9)

\[ \text{inven}_w = \text{inven}_0 + q_w - s_{wr}; \quad \forall w, r \]  
(3.2.3.10)

\[ \text{inven}_r = \text{inven}_0 + q_r - s_{rc}; \quad \forall s, p \]  
(3.2.3.11)

III. Demand constraints:

Finished products shipped from Retailer r to Customer c equal to customer demand minus backorder quantity:

\[ \sum r s_{rc} = D - \text{backorder}; \quad \forall c \]  
(3.2.3.12)

IV. Demand for each echelon:

For each Plant p, total shipping amount from Supplier s to Plant p = production quantity in Plant p – inventory level in Plant p:

\[ \sum s s_{sp} \geq q_p + \text{inven}_p - \text{inven}_0; \quad \forall p \]  
(3.2.3.13)
For each Warehouse \( w \), total shipping amount from Plant \( p \) to Warehouse \( w \) = production quantity in Warehouse \( w \) – inventory level in Warehouse \( w \):

\[
\sum_p s_{pw} \geq q_w + \text{inven}_w - \text{inven}_0; \quad \forall w (3.2.3.14)
\]

For each Retailer \( r \), total shipping amount from Warehouse \( w \) to Retailer \( r \) = production quantity in Retailer \( r \) – inventory level in Retailer \( r \):

\[
\sum_w s_{wr} \geq q_r + \text{inven}_r - \text{inven}_0; \quad \forall r (3.2.3.15)
\]

V. Non-negative constraints:

All decision variables are greater than or equal to zero:

\[
\text{inven}_s, \text{inven}_p, \text{inven}_w, \text{inven}_r, s_p, s_{pw}, s_{wr}, \text{backorder} \geq 0; \quad \forall s, p, w, r (3.2.3.16)
\]

3.4 Hybrid Model

The hybrid mathematical-simulation approach in this work is used to give a more realistic representation of the supply chain system in a stochastic environment. The hybrid model is the combination of the MILP model discussed in section 3.2 and simulation model discussed in section 3.3.

The hybrid model is based on Colossi’s work (2006). The author was also using the hybrid model to solve a multi-echelon supply chain network design problem but allowing only one partner to be selected in each echelon. Colossi used a discrete event simulation while in this thesis Monte Carlo simulation is adopted. Since there are differences in problem settings and
methodology using, an LP model is built during the simulation procedure. In this thesis, CSL is used to determine whether or not to go back and resolve MILP model while Colossi used backorder number as the performance measure.

Figure 3.3 is the flow chart of the hybrid method. The first step is to solve the MILP model and get partner selections and production levels at selected partners. Step 2 is to input these values to the simulation model. Step 3 is to generate customer demand as a normal distribution with the mean of deterministic demands using Monte Carlo simulation. The variance of the customer demand in a stochastic environment will be discussed in details later in experiment design sections in Chapter 4. The simulation model introduces the stochastic nature and generates customer demands as a normal distribution with the mean of deterministic demands in the MILP model. Step 4 is to solve the LP model and run 1000 replications of the simulation. Step 5 is to get average inventory level, backorder quantity and customer service level. Step 6 is to judge whether the CSL is 100% nor not. If the CSL is the 100%, go to Step 7a, if not, go to step 7b. Step 7a is to judge whether the current iteration is the 1st iteration or not. If the current iteration is the 1st iteration, it means the optimal solution of the deterministic model is also the best solution in the stochastic environment; go to Step 9 and stop. If not, it means the current iteration is best possible solution in stochastic environment; go to Step 9 and stop. Step 7b is to judge whether the CSL is greater than previous iteration or not. If it is greater than previous iteration, go to Step 8a and increase the customer demand in the MILP model by 5% and turn back Step 1 to resolve the MILP model, until CSL no longer increases and go to Step 8b. If the CSL is less than previous iteration, go to Step 8b and Select current iteration as solution in stochastic environment. Then go to Step 9 and stop.
Since the MILP model is built in a deterministic environment, it is highly possible that the CSL is not 100% with the initial inputs of production quantity and selected partners due to variability in customer demand. The variability in this system includes customer demand variability, capacity variability for the selected partners, and transportation capacity variability. Changing capacity variability for selected partners and/or transportation capacity variability would not have a big influence on CSL. However, changing the customer demand will have a quick effect on CSL. So the customer demand is changed to improve the hybrid system performance. When backorder occurs, if the CSL is still increasing, which means CSL can be increased by changing the supply chain design structures like partner selections or production levels in the MILP model, increase the customer demand in the MILP model and resolve it until CSL no longer increases. Since increasing the customer demand in the deterministic model will generate a different supply chain network design structure for the bigger demand, keep increasing the customer demand of the MILP model until the hybrid model terminates. Then the current iteration is the best possible solution in the stochastic environment.

The hybrid model stops when the CSL no longer increases or there’s no backorder at the 1st iteration. This happens in the following scenarios: (1) the formulated supply chain network met all customer demands both in deterministic and stochastic environments; (2) the supply chain is producing maximum number of product and cannot meet further demand; (3) required customer demand is fulfilled at minimum costs.
Step 1: Solve deterministic MILP

Step 2: Put MILP outputs as inputs:
1. Selected partners;
2. Production levels at selected partners.

Step 3: Generate 1000 customer demand using Monte Carlo simulation

Step 4: Solve LP model for each customer demand.

Step 5: Simulation outputs:
1. Average shortages;
2. Average total cost;
3. Average invent. level;
4. Average shipping quantity;
5. Average CSL.

Step 6: 100% CSL?

Step 7a: 1st iteration?

Step 7b: CSL >= previous iteration?

Current iteration is best possible solution in stochastic environment

Step 8a: Increase demand in MILP model by 5%

Step 8b: Select current iteration as solution in stochastic environment

Step 9: Stop

Figure 3. 3 Hybrid Method Flow Chart
This chapter proposes a hybrid model to solve multi-supply chain network design problem considering the unpredicted demands of innovative products. A MILP model is formulated and verified in a deterministic environment. Then a Monte Carlo simulation was applied to simulate customer demands in the real world. Another LP model is proposed to solve the inventory level and backorder quantities in stochastic environment. The MILP model and Monte Carlo simulations together formulate the hybrid model. The steps of applying the hybrid model are discussed in details.
Chapter 4

Result Analysis and Experimental Design

This chapter discusses the implementation, result analysis, and test of the hybrid model proposed in Chapter 3. First, a numerical example is presented to illustrate the hybrid model. A trade off analysis between cost and customer service level (CSL) is presented at different levels of demand uncertainty. Then a $2^4$ factorial design is carried out to determine which factor would affect the performance of the hybrid model significantly using CSL as the performance measure. Finally, efficiency test on one design point of the factorial design is implemented to test the effectiveness of the hybrid model.

4.1 Numerical Example of the Hybrid model

In this section, an illustrative example of the hybrid model is presented to show how the hybrid model works and how a trade off analysis of cost and CSL will help decision makers decide which combination is the best for them. For innovative products, the greatest challenge for innovative products is the demand variability (Fisher, 1997). Thus, the numerical example will focus on the influences of demand variability with capacity and transportation capacity staying unchanged. In this example, the supply chain network considered includes four echelons, namely suppliers, plants, warehouses, and retailers, with three potential partners in each echelon to be selected. The initial problem is using data generated by Pan and Nagi (2013) (Appendix A) as input data. There is only one end customer and it has one type of demand for all three periods, which is 830 units.
The first step is to formulate and solve the MILP model, which assumes a deterministic environment. The following results are generated: supply chain network structure, production and inventory level, and total supply chain cost. Solution to the MILP model is presented in Table 4.1 and Table 4.2. The supply chain consists of supplier 1 and 3, plant 1 and 2, warehouse 2 and 3, and retailer 2 and 3. There is no shortage and it can reach 100% CSL. The average inventory level across all the nodes at all echelons for the network is 6 units. A lowest cost for this supply chain network is $219,518.

Table 4. 1 MILP solution – Supply chain network structure

<table>
<thead>
<tr>
<th>Supply chain network structure</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Supplier (S)</strong></td>
</tr>
<tr>
<td>Supplier 1+3</td>
</tr>
<tr>
<td><strong>Plant (P)</strong></td>
</tr>
<tr>
<td>Plant 1+2</td>
</tr>
<tr>
<td><strong>Warehouse (W)</strong></td>
</tr>
<tr>
<td>Warehouse 2+3</td>
</tr>
<tr>
<td><strong>Retailer (R)</strong></td>
</tr>
<tr>
<td>Retailer 2+3</td>
</tr>
</tbody>
</table>

Table 4. 2 MILP solution – Supply chain performances

<table>
<thead>
<tr>
<th>Supply Chain Performances</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average Inventory</strong></td>
</tr>
<tr>
<td>6 units</td>
</tr>
<tr>
<td><strong>CSL</strong></td>
</tr>
<tr>
<td>100%</td>
</tr>
<tr>
<td><strong>Total Supply Chain Cost</strong></td>
</tr>
<tr>
<td>$219,518</td>
</tr>
</tbody>
</table>

Since the MILP model is built in a deterministic environment, it is highly possible that the initial optimal solution may not be optimal in a “real world” environment. Therefore, it is very necessary to test the robustness of the MILP solution in a stochastic environment and check the influences of variability. Then, the next step is to test the MILP result using Monte Carlo simulation to simulate the real world demands.
In the Monte Carlo simulation, stochastic features will be introduced into the system by taking demand uncertainty into consideration. Demand uncertainty is the customer demand variability in each time period. This is the lower bound of transportation level from last echelon to the end customer. A normal distribution is used to estimate the demand and introduce stochastic features to the system. The mean for demand is 830 units, which is the demand in the deterministic model. The coefficient of variation (CV) is used to specify different variability levels. When considering the coefficient of variance, the value of factors should not be negative when they are in high level of variability. Starting from 0.05, when it comes to 0.40, there are negative values in all of the three factors, capacity, transportation capacity, and demand, so 0.35 is taken as the high level of variability. In order to test the effects of the uncertainty, the smallest CV, which is 0.05, is taken as the low level of variability. The effects of demand variability on the hybrid model will be discussed with both capacity variability for selected partners and transportation capacity variability stay the same. The main effects and interactions of all these factors will be discussed in detail in Section 4.2.

The purpose of the Monte Carlo simulation is to test the performance of the MILP solution in a stochastic environment. If the results from the deterministic model still works, which means the results gained from the MILP model could still reach a satisfactory CSL no matter the demand variability is low or high, the MILP model result would also be the best solution in the “real-world” environment. However, if the MILP results could not reach a satisfactory CSL when the customer demand changes, it suggests that the deterministic model is not the best solution in a “real-world” environment and the hybrid model should be applied to improve the supply chain system efficiency. To create an environment to test the MILP model for both low and high demand variability, Monte Carlo simulation is adapted with customer demand distributed as
normal distribution with the mean of 830 and CV of 0.05 for low demand variability and 0.35 for high demand variability.

After defining the stochastic variables, the next step is to set input values for the Monte Carlo simulation according to the solution of MILP model. The production levels are set to the outputs of MILP model (Table 4.3). Then, run 1000 independent replicates of different demand representing a real-world stochastic demand scenario. To compare the MILP and simulation model, CSL, average inventory level, and total supply chain cost are taken as performance measures. The results of the simulation model are the average values of 1000 replicates. The total supply chain cost will increase in the simulation model since there will be more inventories when the demand uncertainty is introduced into the system. The inventory holding cost will increase and so will the total supply chain cost. The summary of initial result comparison between MILP and simulation models is shown in Table 4.4.

Table 4. 3 Production levels for simulation model

<table>
<thead>
<tr>
<th>Partner</th>
<th>Production (units)</th>
<th>Partner</th>
<th>Production (units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplier 1</td>
<td>442</td>
<td>Warehouse 1</td>
<td>0</td>
</tr>
<tr>
<td>Supplier 2</td>
<td>0</td>
<td>Warehouse 2</td>
<td>388</td>
</tr>
<tr>
<td>Supplier 3</td>
<td>388</td>
<td>Warehouse 3</td>
<td>442</td>
</tr>
<tr>
<td>Plant 1</td>
<td>388</td>
<td>Retailer 1</td>
<td>0</td>
</tr>
<tr>
<td>Plant 2</td>
<td>442</td>
<td>Retailer 2</td>
<td>388</td>
</tr>
<tr>
<td>Plant 3</td>
<td>0</td>
<td>Retailer 3</td>
<td>442</td>
</tr>
</tbody>
</table>

Table 4. 4 Initial results comparison for low demand variability

<table>
<thead>
<tr>
<th>Performance Measure</th>
<th>MILP</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average inventory level</td>
<td>6 units</td>
<td>40 units</td>
</tr>
<tr>
<td>CSL</td>
<td>100%</td>
<td>99.2%</td>
</tr>
<tr>
<td>Total supply chain cost</td>
<td>$219,518</td>
<td>$236,814</td>
</tr>
</tbody>
</table>
When the demand variability is low, the normal distribution of the demand is using mean of 830 and standard deviation of 42. As is shown in Table 4.4, the solution of MILP model will also have a 99% CSL with 8% increase in the total supply chain cost. It means that low level of demand variance does not influence the final result a lot and this supply chain network may also work well in a stochastic environment.

However, since the initial solution did not achieve 100% CSL, the hybrid model may be applied to improve the performance measures. Next, the iteration of the hybrid model will increase the customer demand by 5% and resolve the MILP model. A summary of the hybrid solution for four iterations is presented in Table 4.5.

The hybrid model terminates after four iterations and reached 100% CSL in the stochastic environment. The supply chain network structure stayed the same within these four iterations, which is supplier 1 and 3, plant 1 and 2, warehouse 2 and 3, and retailer 2 and 3 are chosen in this design. The CSL increase shown in Table 4.6 is the difference between the current iteration and the first iteration over the value of the first iteration. The total cost increase is also using the same calculation method. For CSL, total increase is 0.80% at the cost of $297,959, which has a 25.82% increase from the initial results (Table 4.6, Table 4.7). With the CSL increasing to 100%, total supply chain cost increases dramatically especially at the higher CSL. The ratio of increment, which is CSL increase over total cost increase, is shown in Table 4.6, and the trade-off curve between CSL and total supply chain cost is shown in Figure 4.1. We can see that for low demand variability, the MILP solution works well and can achieve a 99% CSL. The second iteration of the hybrid model can increase the CSL to 99.35% at only an increase of 5.73% of the total cost, which is a good balance between the CSL and total supply chain cost. In this case, it is not necessary to improve the supply chain CSL to 100% at a 25.82% higher cost.
Table 4. 5 Hybrid solutions for low demand variability

<table>
<thead>
<tr>
<th>Iteration</th>
<th>CSL</th>
<th>Total cost</th>
<th>Supplier</th>
<th>Plant</th>
<th>Warehouse</th>
<th>Retailer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>99.20%</td>
<td>$236,814</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
<tr>
<td>2</td>
<td>99.35%</td>
<td>$250,373</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
<tr>
<td>3</td>
<td>99.83%</td>
<td>$270,865</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
<tr>
<td>4</td>
<td>100.00%</td>
<td>$297,959</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
</tbody>
</table>

Table 4. 6 CSL and total cost increase for low demand variability

<table>
<thead>
<tr>
<th>CSL increase</th>
<th>Total cost increase</th>
<th>Ratio ($\frac{CSL\ increase}{Total\ cost\ increase}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00%</td>
<td>0.00%</td>
<td>NA</td>
</tr>
<tr>
<td>0.25%</td>
<td>5.73%</td>
<td>23.06</td>
</tr>
<tr>
<td>0.63%</td>
<td>15.38%</td>
<td>24.24</td>
</tr>
<tr>
<td>0.80%</td>
<td>25.82%</td>
<td>32.2</td>
</tr>
</tbody>
</table>

Figure 4. 1 Trade-off curve – low demand variability, CV=0.05

For high demand variability, production levels and supply chain structures are the same with those of low demand variability, since they are using the same initial solution of the MILP model. The normal distribution for high demand variability has the mean of 830 and standard
deviation of 290. The CSL is 94.8% and average inventory level is 53 units. Comparing with the MILP result, the total supply chain cost increased by 9% to $239,825. The result summary is shown in Table 4.7.

<table>
<thead>
<tr>
<th>Performance Measure</th>
<th>MILP</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average inventory level</td>
<td>6 units</td>
<td>53 units</td>
</tr>
<tr>
<td>CSL</td>
<td>100%</td>
<td>94.8%</td>
</tr>
<tr>
<td>Total supply chain cost</td>
<td>$219,518</td>
<td>$239,825</td>
</tr>
</tbody>
</table>

A 94.8% CSL may not be satisfactory for some companies since they want to have a solid customer base or customer is the first priority. Since this result did not meet all the customer demands, the initial MILP solution cannot be considered as the best solution in a stochastic environment. The hybrid model should be implemented to improve overall performance measures.

The hybrid model terminates after five iterations and reached 99.1% CSL in the stochastic environment. The supply chain network structure stayed the same within the first four iterations, and changed during the fifth iteration. The new supply chain network structure is supplier 1, 2 and 3, plant 1 and 2, warehouse 1, 2 and 3, and retailer 1, 2 and 3. The calculation for CSL and total cost increase is the same with low demand variability. For CSL, total increase is 4.58% at the cost of $320,018, which has a 33.44% increase from the initial results (Table 4.8, Table 4.9). With the CSL increasing to 99.1%, total supply chain cost increases dramatically after the third iteration. The ratio of increment is shown in Table 4.9, and the trade-off curve between CSL and total supply chain cost is shown in Figure 4.2. We can see that for high demand variability, the MILP solution is not optimal in stochastic environment and can be improved by the hybrid model. The third iteration of the hybrid model can increase the CSL to 97% at only an
increase of 3.57% of the total cost, which is a good balance between the CSL and total supply chain cost. Thus for high demand variability, the hybrid model is strongly recommended to improve the total supply chain efficiency. But for individual companies, they are the decision makers to decide which production level and supply chain network structure is best for them with their specific CSL and total budget.

Table 4. 8 Hybrid solutions for high demand variability

<table>
<thead>
<tr>
<th>Iteration</th>
<th>CSL</th>
<th>Total cost</th>
<th>Supplier</th>
<th>Plant</th>
<th>Warehouse</th>
<th>Retailer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>94.8%</td>
<td>$239,825</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
<tr>
<td>2</td>
<td>96.8%</td>
<td>$245,571</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
<tr>
<td>3</td>
<td>97.0%</td>
<td>$248,391</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
<tr>
<td>4</td>
<td>98.7%</td>
<td>$276,321</td>
<td>1+3</td>
<td>1+2</td>
<td>2+3</td>
<td>2+3</td>
</tr>
<tr>
<td>5</td>
<td>99.1%</td>
<td>$320,018</td>
<td>1+2+3</td>
<td>1+2</td>
<td>1+2+3</td>
<td>1+2+3</td>
</tr>
</tbody>
</table>

Table 4. 9 CSL and total cost increase for high demand variability

<table>
<thead>
<tr>
<th>CSL increase</th>
<th>Total cost increase</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00%</td>
<td>0.00%</td>
<td>NA</td>
</tr>
<tr>
<td>2.18%</td>
<td>2.40%</td>
<td>1.10</td>
</tr>
<tr>
<td>2.99%</td>
<td>3.57%</td>
<td>1.19</td>
</tr>
<tr>
<td>4.16%</td>
<td>15.22%</td>
<td>3.66</td>
</tr>
<tr>
<td>4.58%</td>
<td>33.44%</td>
<td>7.30</td>
</tr>
</tbody>
</table>

Figure 4. 2 Trade-off curve – high demand variability, CV=0.35
4.2 Factorial Design and ANOVA

To study the effects of some parameters that would affect the performance of the hybrid model significantly, a factorial design is carried out. The factorial design will help to investigate the effect of each factor on the response variable as well as the effects of interactions between factors on the response variable. The factors of interests are (1) demand variability, (2) capacity variability for selected partners, (3) transportation capacity variability, and (4) initial MILP solution vs. hybrid solution. The response variable is the CSL. The reason for choosing CSL as response variable is that the main concern for companies that produce innovative products is CSL. There are two variability levels for first three factors of interests, which are customer demand variability, capacity variability for selected partners, and transportation capacity variability, in the experimental design. The low and high levels are coefficient of variation (CV) of 0.05 and 0.35, respectively. Means for capacity and transportation capacity are 519 and 618, which are the mean values of the capacity and transportation capacity in the deterministic model. Table 4.10 is a summary of factors of interest and their levels. The demand variability is the same with the numerical example.

Table 4. 10 Factors and levels for the experimental design

<table>
<thead>
<tr>
<th>Factor</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low (-)</td>
</tr>
<tr>
<td>Demand</td>
<td>Norm(830,42)</td>
</tr>
<tr>
<td>Capacity</td>
<td>Norm(519,26)</td>
</tr>
<tr>
<td>Transportation Capacity</td>
<td>Norm(618,31)</td>
</tr>
<tr>
<td>Hybrid (?)</td>
<td>No</td>
</tr>
</tbody>
</table>

A $2^4$ factorial design with five replicates was conducted with 16 design points. 5 replicates for each design point. The sample size is 80 runs. Replicates on each design point can decrease errors in experiments, but too many replicates will make the sample size increase greatly.
and bring difficulties to the experiment. The experimental design and responses are recorded in Table 4.11. Experiment data were analyzed using “Minitab® 16” package.

Table 4.11 Factorial design and responses

<table>
<thead>
<tr>
<th>Factor</th>
<th>demand</th>
<th>capacity</th>
<th>trans cap</th>
<th>hybrid</th>
<th>y1</th>
<th>y2</th>
<th>y3</th>
<th>y4</th>
<th>y5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.9697</td>
<td>1</td>
<td>0.9462</td>
<td>1</td>
<td>0.9227</td>
</tr>
<tr>
<td>2</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.6448</td>
<td>1</td>
<td>0.7608</td>
<td>0.7356</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>0.9878</td>
<td>0.9967</td>
<td>0.7932</td>
<td>0.9358</td>
<td>0.8693</td>
</tr>
<tr>
<td>4</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>0.7794</td>
<td>0.9316</td>
<td>0.7998</td>
<td>0.5649</td>
<td>0.7925</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>0.9625</td>
<td>0.9568</td>
<td>1</td>
<td>0.9345</td>
<td>0.9862</td>
</tr>
<tr>
<td>6</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>1</td>
<td>0.8677</td>
<td>0.7967</td>
<td>0.8803</td>
<td>0.6908</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>0.9246</td>
<td>0.9598</td>
<td>0.9527</td>
<td>0.8737</td>
<td>0.9489</td>
</tr>
<tr>
<td>8</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>0.8562</td>
<td>0.5828</td>
<td>0.6043</td>
<td>0.9504</td>
<td>0.9992</td>
</tr>
<tr>
<td>9</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>1</td>
<td>0.9612</td>
<td>0.9695</td>
<td>0.9771</td>
<td>0.9745</td>
</tr>
<tr>
<td>10</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>0.936</td>
<td>0.9557</td>
<td>0.9034</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>0.9878</td>
<td>0.9928</td>
<td>0.9367</td>
<td>1</td>
<td>0.9932</td>
</tr>
<tr>
<td>12</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>0.8517</td>
<td>0.8746</td>
<td>1</td>
<td>0.9125</td>
<td>0.9825</td>
</tr>
<tr>
<td>13</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>0.9816</td>
<td>1</td>
<td>1</td>
<td>0.9874</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>0.912</td>
<td>0.9552</td>
<td>1</td>
<td>0.9627</td>
<td>0.9359</td>
</tr>
<tr>
<td>15</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>0.9238</td>
<td>0.8895</td>
<td>0.9954</td>
<td>1</td>
<td>0.9401</td>
</tr>
<tr>
<td>16</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>1</td>
<td>0.9008</td>
<td>0.9121</td>
<td>0.7902</td>
<td>1</td>
</tr>
</tbody>
</table>

It is very important to analyze the residuals and validate the adequacy of the model, since the assumptions for ANOVA test are normality, independence, and homogeneity of variance.

After checking the raw data, we find that the homogeneity of variance is violated because the plot of residuals vs. fitted values is funnel shaped. Though the F test is only slightly affected in the balanced (equal sample sizes in all treatments) fixed effects model, data transformation is often used to deal with non-constant variance (Montgomery, 2008). The logarithm transformation is adopted to reduce the non-constant variance (Figure 4.3). The alpha value used in this experimental design is 0.05.
Analysis of variance (ANOVA) is conducted using Minitab and normal plot of the standardized effect of lnCSL is drawn to address the significant factors. From the normal plot (Figure 4.4) and ANOVA table (Table 4.12), we can conclude that main effect demand and main effect hybrid can significantly affect the response lnCSL with p-values of 0. Two-way interactions between demand and hybrid can also influence the CSL significantly with p-value of 0.008.
Table 4. 12 ANOVA table for significant factors and interaction on lnCSL

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Seq SS</th>
<th>Adj SS</th>
<th>Adj MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main Effects</td>
<td>4</td>
<td>0.43615</td>
<td>0.43615</td>
<td>0.109036</td>
<td>9.90</td>
<td>0.000</td>
</tr>
<tr>
<td>Demand</td>
<td>1</td>
<td>0.21317</td>
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Significant main effects are demand and hybrid and their interaction. The main effect plot and two-way interaction plots are shown in Figure 4.5 and Figure 4.6. Figure 4.5 shows that the lnCSL value changes from -0.028 to -0.148 when changing the customer demand variability from low level to high level, and the corresponding CSL value changes from 97.3% to 86.2% with a 12.9% decrease. It means that when the demand variability changes from low to high, the system has a 12.9% decrease in CSL. So the conclusion can be made that CSL decrease dramatically when the customer demand variability is high (CV=0.35), while stays a relative high CSL when the demand variability is low (CV=0.05). The CSL increases significantly when using the hybrid
method compared to not using the hybrid model. As is shown in Figure 4.5, the lnCSL value changes from -0.142 to -0.037 when it changes from not using the hybrid model to using the hybrid model, and the corresponding CSL value changes from 86.7% to 96.7% with an 11.5% increase. It means that the using the hybrid method will increase the system CSL by 11.5% compared to not using the hybrid method. Thus, the conclusion can be made that the whether or not using the hybrid model can affect the CSL dramatically. Figure 4.6 shows that differences among the levels of the factor of demand depend on the levels on the factor of hybrid. At low level of demand variability, the value of lnCSL changes from -0.068 to -0.023 when the system changes from not using the hybrid model to using the hybrid model, and the corresponding CSL values changes from 93.4% to 97.8% with a 0.05% increase. At high level of demand variability, the value of lnCSL changes from -0.233 to -0.053 when the system changes from not using the hybrid model to using the hybrid model, and the corresponding CSL values changes from 79.2% to 94.9% with a 19.8% increase. The results show that when demand variability is low, the improvement from no hybrid to using the hybrid method is smaller than the larger improvement when demand variability is high. It means that the difference between two levels of demand variability is much stronger at high level of hybrid than at low level of hybrid, even though it is in the same direction. So the conclusion can be made that the interaction between demand variability and whether or not using the hybrid method is significant.
To test the efficiency and robustness of the hybrid model, an efficiency test is executed. Take design point 10 from the experimental design in Section 4.2 (demand-high, capacity-low, transportation capacity-low, and hybrid-high) and compare it with the MILP model. The goal of this efficiency test is to prove the hybrid method can improve the supply chain CSL greatly.
compared to the MILP method in a stochastic environment when the customer demand is high. In this efficiency test, all parameters are the same for the test point and control point. The only difference is whether or not using the hybrid method.

In the efficiency test, 20 demands are generated using a normal distribution with mean 830 and standard deviation of 290, then the problem was solved with the MILP model and hybrid model separately. For each run, MILP model and Hybrid model are using the same customer demand. Performance measures taking into consideration are CSL, total supply chain cost, and average inventory level. The result summary is shown in Table 4.13 and Table 4.14. Detailed results for each run are shown in Appendix C.

<table>
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<th>Retailer</th>
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<td>2, 3</td>
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<td>Hybrid</td>
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<td>1, 2, 3</td>
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<table>
<thead>
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<th>Demand</th>
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<th>Hybrid</th>
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<tbody>
<tr>
<td>CSL</td>
<td>Total cost</td>
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<tr>
<td>Average</td>
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</table>

From the result summary in Table 4.13 and Table 4.14, we find that by applying the hybrid model, average CSL increased by 9.5% from 87% to 96%. Total supply chain cost increased by 23.8%, from $227,347 to $ 281,528. Since the supply chain network structure changed from two partners selected in each echelon to three partners selected in echelon 1, 3, and 4, two echelons selected in echelon 2 (Table 4.13), there will be fixed cost increase due to the
structure expansion. Moreover, inventory level increased 50%, from 35 units to 56 units, which will also cause supply chain cost increase.

To test whether the two sets of data got from MILP method and hybrid method are statistically different or not, a t-test is needed. From the two-sample t-test results obtained with Minitab, the mean values of MILP method and the hybrid method are 87.3% and 95.6%, respectively. The t-value for mean of two CSL samples is -2.29 with a degree of freedom of 38 and 95% confidence interval for difference. Since the value -2.29 is smaller than -1.697, value from the t-test table at 38 degree of freedom and 95% confidence interval, we can conclude that the two sets of data are statistically different. It also means that the hybrid model can improve the CSL of the supply chain network significantly.

4.4 Summary

This chapter showed a numerical example to illustrate the hybrid model, an experimental design to check which factor would affect the response significantly, and an efficiency test to compare the hybrid model with the MILP model.

From the numerical example we can conclude that the MILP model may work well when the demand variability is low and the trade off analysis between CSL and supply chain total cost shows that it is not necessary to increase the CSL to 100%, while keeping it to 99.35% is the best strategy. For the high demand variability, the MILP model no longer has good performances in a stochastic environment and the hybrid model can increase the CSL up to 99.1%. However, the cost is also increasing dramatically. After the trade off analysis, a CSL of 97% is recommended with relative small increase in cost, which is 3.57% increase.
The experimental design took CSL as response variable and did five replicates at each of the 16 design point. From the ANOVA we can conclude that the factors that are significant are demand, hybrid and interaction between these two factors. The change of variability of these factors will have a great influence on CSL.

Finally, an efficiency test is conducted with design point 10 in the previous experimental design. Compared with MILP model, given equal customer demand in each run, the Hybrid model showed a 9.5% improvement. After the t-test of the two experiment data sets, we can conclude that the hybrid model can increase the supply chain efficiency significantly.
Chapter 5

Conclusion and Future Work

In this research, a hybrid model was developed for a multi-echelon supply chain network design for innovative products in a stochastic environment. The problem included both strategic planning such as partner selecting and transportation route planning, and tactical/operational planning such as production level and inventory level planning at selected partners. The objective of the problem was to select cooperating partners in each of the four echelons to build a supply chain network that would satisfy customer demands while minimizing the sum of strategic, tactical, and operational costs. The four echelons considered in thesis network design are Suppliers, Plants, Warehouses and Retailers.

A lot of researches have considered the multi-echelon supply chain network design problem, but most of them were using mathematical models like MILP or LP models with heuristic methods, like benders decomposition and lagrangian algorithm, to solve the models, or using discrete event simulations to compare different performance measures like MRP/DRP and reorder point. Few of them focused on using a hybrid model for innovative product supply chain network design.

Features for innovative products were uncertain demands, high profit margin, and CSL was always the priority while cost was the second consideration (Fisher, 1997). A responsive supply chain would be able to synchronize the supply to meet the peaks and troughs and reduce the risk of generating a large number of back orders.
Despite the complexity of the supply chain network design, the stochastic environment was a big difficulty in this problem. In order to simulate the real world demand and introduce the stochastic property to the system, Monte Carlo simulation was adopted. The uncertainties in this problem include customer demand, capacity at selected partners, and transportation capacity between two selected partners in adjacent echelons.

5.1 Summary of results and contributions

To solve the complex supply chain network design problem, this research proposed a hybrid model combining a mixed integer linear programming (MILP) model and used Monte Carlo simulation to simulate the stochastic environment. The MILP model was implemented with deterministic customer demands and would generate initial solution for the supply chain network design. Then the outputs of the MILP model, like partner selected in each echelon and production levels at the selected partners, would be set as input values to the Monte Carlo simulation models. Then run the simulation for 1000 iterations to simulate the “real world” customer demand. Results generated included the average values for inventory levels, shipping quantities, customer service level (CSL), and total supply chain cost of the 1000 iterations. Then check whether the resulting CSL was 100% or not, if not, increase the customer demand for the MILP model, resolve the model, then repeat the previous steps.

For the hybrid model, the biggest feature was that it introduces stochastic characteristics in the system by using Monte Carlo simulation, which would be more accurate than discrete event simulation (DES) since it was more close to the required distribution due to large number of replication.
A numerical example was implemented in Chapter 4 with high (CV=0.35) and low (CV=0.05) demand variability to illustrate the hybrid model. The results showed that the MILP result may work well in stochastic environment when the demand variability was low, but not very efficient when the demand variability was high. In both situations, the hybrid model could improve the CSL by 0.8% and 4.6% at a total cost increase of 25.82% and 33.44% respectively, and works better when the demand variability was high. Trade off analysis of the CSL and total supply chain cost would give better suggestions for decision makers. After trade off analysis of CSL and total supply chain cost, a 97% CSL at a 3.57% total cost increase is recommended in this numerical example.

A $2^4$ factorial experimental design with five replicates in each design point was conducted to decide which factor of interest would affect the final response significantly. The factors discussed in this section were customer demand variability, capacity variability for selected partners, transportation capacity variability, and using hybrid method or not. After ANOVA, demand variability and whether or not using hybrid and interactions between them are proved to be significant effects. The demand variability caused a 12.9% decrease when it changed from low level to high level. The factor of whether or not using the hybrid method caused a 11.5% increase when it changed from low level to high level. The interaction between these two factors showed that the CSL increased by 0.05% when demand variability was at a low level going from no hybrid method to using the hybrid, while the CSL increased by 19.8% when the demand variability was at a high level changing from no hybrid method to using the hybrid method. It showed that the difference between two levels of demand variability was stronger when using the hybrid method than no hybrid method was used. Then an efficiency test was conducted to test the efficiency and robustness of the hybrid model taking design point 10 in the experiment design as comparison set and MILP as control set, and both of them are tested using
same customer demand. Twenty replicates are conducted in this efficiency test. The result of the t-test was -2.29, which was smaller than the given value -1.697. It showed that the hybrid model can improve the performances of the supply chain network significantly.

5.2 Future work

This research showed that using a hybrid model in a stochastic environment with big demand variability for supply chain network design for innovative products, can improve CSL significantly. However, there are some limitations of the work and some future work can be done with these aspects.

The model discussed in this research has only one transportation mode, which is capacitated, more than one transportation mode with different charges can be considered in future research. Moreover, the problem contains only four echelons and three cooperating partners in each echelon with only one end customer, larger problem size like more than five partners in each echelon and multiple end customers can be discussed to expend the problem. In addition, this problem only considers one kind of product, so more than one product can also be considered in future research of multi-echelon supply chain network design. The inventory considered in this thesis was only finished goods inventory, in future research, raw material inventory and finished goods inventory can be considered at the same time.
References


Appendix A

Data for Illustrative Example

Table A. 1 Production capacity

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Table A. 5 Transportation capacity: supplier to plant

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Table A. 6 Transportation capacity: plant to warehouse

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Table A. 7 Transportation capacity: warehouse to retailer

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Table A. 8 Transportation cost: supplier to plant

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Table A. 9 Transportation cost: plant to warehouse

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Table A. 10 Transportation cost: warehouse to retailer

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<td>2</td>
</tr>
<tr>
<td>w1</td>
<td>18</td>
<td>11</td>
<td>12</td>
<td>18</td>
<td>14</td>
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<tr>
<td>w2</td>
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<td>14</td>
<td>12</td>
<td>17</td>
<td>13</td>
<td>12</td>
<td>11</td>
<td>14</td>
</tr>
<tr>
<td>w3</td>
<td>17</td>
<td>15</td>
<td>17</td>
<td>13</td>
<td>15</td>
<td>17</td>
<td>13</td>
<td>20</td>
</tr>
</tbody>
</table>
Appendix B

Minitab Result for Factorial Experimental Design

Factorial Fit: ln CSL versus Demand, Capacity, Transportation c, Hybrid

Estimated Effects and Coefficients for ln CSL (coded units)

<table>
<thead>
<tr>
<th>Term</th>
<th>Effect</th>
<th>Coef</th>
<th>SE Coef</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.09274</td>
<td>0.01173</td>
<td>-7.91</td>
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</tr>
<tr>
<td>Demand</td>
<td>-0.10324</td>
<td>-0.05162</td>
<td>0.01173</td>
<td>-4.40</td>
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<tr>
<td>Capacity</td>
<td>-0.04436</td>
<td>-0.02218</td>
<td>0.01173</td>
<td>-1.89</td>
</tr>
<tr>
<td>Transportation capacity</td>
<td>0.00525</td>
<td>0.00263</td>
<td>0.01173</td>
<td>0.22</td>
</tr>
<tr>
<td>Hybrid</td>
<td>0.09567</td>
<td>0.04784</td>
<td>0.01173</td>
<td>4.08</td>
</tr>
<tr>
<td>Demand*Capacity</td>
<td>-0.01025</td>
<td>-0.00513</td>
<td>0.01173</td>
<td>-0.44</td>
</tr>
<tr>
<td>Demand*Transportation capacity</td>
<td>0.00435</td>
<td>0.00217</td>
<td>0.01173</td>
<td>0.19</td>
</tr>
<tr>
<td>Demand*Hybrid</td>
<td>0.06396</td>
<td>0.03198</td>
<td>0.01173</td>
<td>2.73</td>
</tr>
<tr>
<td>Capacity*Transportation capacity</td>
<td>-0.00546</td>
<td>-0.00273</td>
<td>0.01173</td>
<td>-0.23</td>
</tr>
<tr>
<td>Capacity*Hybrid</td>
<td>0.01516</td>
<td>0.00758</td>
<td>0.01173</td>
<td>0.65</td>
</tr>
<tr>
<td>Transportation capacity*Hybrid</td>
<td>-0.01226</td>
<td>-0.00613</td>
<td>0.01173</td>
<td>-0.52</td>
</tr>
</tbody>
</table>

S = 0.104925    PRESS = 1.02115
R-Sq = 41.03%   R-Sq(pred) = 20.73%   R-Sq(adj) = 32.49%

Analysis of Variance for ln CSL (coded units)

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Seq SS</th>
<th>Adj SS</th>
<th>Adj MS</th>
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<tbody>
<tr>
<td>Main Effects</td>
<td>4</td>
<td>0.43615</td>
<td>0.436145</td>
<td>0.109036</td>
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<tr>
<td>Demand</td>
<td>1</td>
<td>0.21317</td>
<td>0.213173</td>
<td>0.213173</td>
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<tr>
<td>Capacity</td>
<td>1</td>
<td>0.03936</td>
<td>0.039355</td>
<td>0.039355</td>
</tr>
<tr>
<td>Transportation capacity</td>
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<td>0.00055</td>
<td>0.000551</td>
<td>0.000551</td>
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<tr>
<td>Hybrid</td>
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<td>0.18307</td>
<td>0.183066</td>
<td>0.183066</td>
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<tr>
<td>Demand*Capacity</td>
<td>6</td>
<td>0.09248</td>
<td>0.092484</td>
<td>0.092484</td>
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<tr>
<td>2-Way Interactions</td>
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<td>0.00210</td>
<td>0.002102</td>
<td>0.002102</td>
</tr>
<tr>
<td>Term</td>
<td>Coef</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>------</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.00076989</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Demand</td>
<td>-3.84567E-04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capacity</td>
<td>-1.49606E-04</td>
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<td></td>
<td></td>
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<tr>
<td>Transportation capacity</td>
<td>0.000036322</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>0.0031051</td>
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</tr>
<tr>
<td>Demand*Capacity</td>
<td>-5.30006E-07</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Demand*Transportation capacity</td>
<td>1.89431E-07</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

R denotes an observation with a large standardized residual.
Effects Plot for In CSL

Alias Structure
I
Demand
Capacity
Transportation capacity
Hybrid
Demand*Capacity
Demand*Transportation capacity
Demand*Hybrid
Capacity*Transportation capacity
Capacity*Hybrid
Transportation capacity*Hybrid
## Appendix C

### Result for Efficiency Test

<table>
<thead>
<tr>
<th>Run</th>
<th>Demand</th>
<th>MILP</th>
<th>Hybrid</th>
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</thead>
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<tr>
<td></td>
<td></td>
<td>CSL</td>
<td>Total cost</td>
</tr>
<tr>
<td>1</td>
<td>914.02</td>
<td>0.908</td>
<td>22706</td>
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<tr>
<td>2</td>
<td>926.27</td>
<td>0.896</td>
<td>22677</td>
</tr>
<tr>
<td>3</td>
<td>1067.7</td>
<td>0.763</td>
<td>22733</td>
</tr>
<tr>
<td>4</td>
<td>987.95</td>
<td>0.840</td>
<td>22683</td>
</tr>
<tr>
<td>5</td>
<td>1258.0</td>
<td>0.659</td>
<td>22688</td>
</tr>
<tr>
<td>6</td>
<td>640.67</td>
<td>1.000</td>
<td>22690</td>
</tr>
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<td>7</td>
<td>753.71</td>
<td>1.000</td>
<td>22619</td>
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<td>8</td>
<td>874.46</td>
<td>0.949</td>
<td>22630</td>
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<td>9</td>
<td>731.13</td>
<td>1.000</td>
<td>22633</td>
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<tr>
<td>10</td>
<td>389.77</td>
<td>1.000</td>
<td>22920</td>
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<td>11</td>
<td>932.45</td>
<td>0.890</td>
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<td>12</td>
<td>1324.0</td>
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<td>13</td>
<td>1386.2</td>
<td>0.598</td>
<td>22667</td>
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<td>14</td>
<td>862.59</td>
<td>0.962</td>
<td>22611</td>
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<td>15</td>
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<td>1.000</td>
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<td>16</td>
<td>840.83</td>
<td>0.987</td>
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<td>17</td>
<td>1063.2</td>
<td>0.780</td>
<td>22700</td>
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<td>18</td>
<td>576.84</td>
<td>1.000</td>
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<tr>
<td>19</td>
<td>1403.0</td>
<td>0.591</td>
<td>22700</td>
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<tr>
<td>20</td>
<td>608.32</td>
<td>1.000</td>
<td>22827</td>
</tr>
</tbody>
</table>

Table A. 11 Comparison between design point 10 and MILP model
Appendix D

MATLAB Code

% D (t) ------ customer demand for period t
% W(i) ------ node i is chosen
% Y(i,j) ------ alliance between i and j is built
% F(i,j) ------ fixed cost for alliance between i and j
% U(i,t) ------ unit processing cost for i at period t
% H(i,t) ------ inventory holding cost for i at period t
% CAP(i,t) ------ capacity for i at period t
% pro(i,t) ------ production amount in i at period t
% inven(i,t) ------ inventory in i at period
% TRANS(i,j,t) ------ transportation cost from i to j at period t
% s(i,j,t) ------ shipping amount from i to j at period t
% i ------ node index
% j ------ node index
% t ------ period index
%-------------------------------------------------------------
cclc;clear;close all
tic;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
define input data%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Nsupplier =3;
Nplant = 3;
Nwarehouse = 3;
Nretailer = 3;
Nperiod = 7;
T=Nperiod-4;

% initialize data sets
D=zeros(Nperiod,1);
M=200000000000;
re=0;
avrgCSL=0;
avrgCSL1=0.1;
iter=0;
U=0.99;
L=0.1;
ddl=1;
% sumx=0;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
fixed cost%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% fixed cost settings from supplier to plant
Fsp=[4367 1050 1601;
    1117 1296 3641;
    1174 2246 2970];
% fixed cost settings from plant to warehouse
Fpw=[1790 1148 1601;
     1931 3378 2525;
     4735 2260 2393];
% fixed cost settings from warehouse to retailer
Fwr=[4353 3260 2816];
% fixed cost for node selection
fs = [2473 1893 3106; 2440 2542 1142; 2523 3985 2623; 4195 1800 2862];
fp = [4318 2886 1142; 2523 3985 2623; 4195 1800 2862];
w = [3432 2150 1957; 1620 2344 1638; 2202 4940 2539];
fr = [3641 4215 2170; 3533 2213 2364; 2317 3183 3222];

% transportation cost
% transportation cost from supplier to plant
TRANSsp(:,:,1)=[12 15 11; 14 15 15; 10 13 19];
TRANSsp(:,:,2)=[16 11 20; 17 13 16; 19 13 13];
TRANSsp(:,:,3)=[14 18 15; 12 12 11; 18 12 13];
TCsp(:,:,1)=[513 774 469; 793 432 673; 639 557 552];
TCsp(:,:,2)=[632 680 647; 442 620 564; 552 459 678];
TCsp(:,:,3)=[694 722 690; 666 763 707; 437 455 782];

% transportation cost from plant to warehouse
TRANSpw(:,:,2)=[20 15 18; 14 19 18; 15 13 19];
TRANSpw(:,:,3)=[14 17 18; 10 17 16; 15 15 14];
TRANSpw(:,:,4)=[12 17 20; 13 13 12; 19 17 17];
TCpw(:,:,2)=[732 710 481; 715 683 657; 687 516 750];
TCpw(:,:,3)=[568 555 785; 532 678 676; 631 493 546];
TCpw(:,:,4)=[783 672 606; 569 682 443; 438 605 489];

% transportation cost from warehouse to retailer
TRANSwr(:,:,3)= [18 11 12;
17 14 12;
17 15 17];
TRANSwr(:,:,4)= [18 14 15;
17 13 12;
13 15 17];
TRANSwr(:,:,5)= [19 17 17;
11 14 15;
13 20 17];
TCwr(:,:,3)= [561 635 422;
712 791 794;
707 419 667];
TCwr(:,:,4)= [689 497 558;
603 572 536;
604 495 689];
TCwr(:,:,5)= [764 619 659;
709 767 582;
615 636 478];

% unit processing cost, holding cost, and capacity
% unit processing cost, holding cost and capacity for supplier
Us = [47 27 36;
37 26 57;
23 25 49];
Hs = [10 7 11;
9 13 9;
14 12 10];
Cs = [435 602 522;
556 364 672;
537 380 463];

% unit processing cost, holding cost and capacity for plant
Up = [0 38 24 47;
0 23 52 44;
0 25 46 57];
Hp = [0 14 14 5;
0 8 15 15;
0 12 13 10];
Cp = [0 693 442 688;
0 492 652 652;
0 372 668 476];

% unit processing cost, holding cost and capacity for warehouse
Uw = [0 0 50 41 47;
0 0 52 56 42;
0 0 31 42 40];
Hw = [0 0 14 7 14;
0 0 9 13 11;
0 0 12 10 6];
Cw = [0 0 368 363 627;
0 0 530 606 644;
0 0 472 523 398];

% unit processing cost, holding cost and capacity for retailer
Ur = [0 0 0 45 50 39;
0 0 0 52 39 25;
0 0 0 31 23 31];
Hr = [0 0 0 7 12 6];
0 0 0 12 8 6;
0 0 0 6 6 10]; % holding
Cr = [0 0 353 660 423;
0 0 560 471 406;
0 0 406 653 566]; % capacity

% demand for period t
for t=4+1:Nperiod
    D(t)= 830; % demand (deterministic)
end

while avrgCSL<0.99
    avrgCSL1=avrgCSL;
    iter=iter+1;
    % build model
    cplex = Cplex('MILP');
    cplex.Model.sense = 'minimize';

    % objective function
    % company selection
    a=1;
    for i=1:Nsupplier
        obj(a)=fs(i);
        ctype(a)=char('B'); % variable type set to binary
        lofxs(i)=a; % location of Xs
        a=a+1;
    end
    for i=1:Nplant
        obj(a)=fp(i);
        ctype(a)=char('B'); % variable type set to binary
        lofxp(i)=a; % location of Xp
        a=a+1;
    end
    for i=1:Nwarehouse
        obj(a)=fw(i);
        ctype(a)=char('B'); % variable type set to binary
        lofxw(i)=a; % location of Xw
        a=a+1;
    end
    for i=1:Nretailer
        obj(a)=fr(i);
        ctype(a)=char('B'); % variable type set to binary
        lofxr(i)=a; % location of Xr
        a=a+1;
    end

    % fixed cost from supplier to plant
    for i=1:Nsupplier
        for j=1:Nplant
            % fixed cost
        end
    end
obj(a)=Fsp(i,j);
cctype(a)=char('B'); %variable type set to binary
lofysp(i,j)=a; %location of Ysp
a=a+1;
end
end
% fixed cost from plant to warehouse
for i=1:Nplant
  for j=1:Nwarehouse
    obj(a)=Fpw(i,j);
cctype(a)=char('B'); %variable type set to binary
lofypw(i,j)=a; %location of Ypw
a=a+1;
  end
end
% fixed cost from warehouse to retailer
for i=1:Nwarehouse
  for j=1:Nretailer
    obj(a)=Fwr(i,j);
cctype(a)=char('B'); %variable type set to binary
lofywr(i,j)=a; %location of Ywr
a=a+1;
  end
end

% transportation cost from supplier to plant
for t=1:T
  for i=1:Nsupplier
    for j=1:Nplant
      obj(a)=TRANSsp(i,j,t);
cctype(a)=char('C'); %variable type set to continous
lofssp(i,j,t)=a; %location of ssp
a=a+1;
    end
  end
end
% transportation cost from plant to warehouse
for t=2:T+1
  for i=1:Nplant
    for j=1:Nwarehouse
      obj(a)=TRANSpw(i,j,t);
cctype(a)=char('C'); %variable type set to continous
lofspw(i,j,t)=a; %location of spw
a=a+1;
    end
  end
end
% transportation cost from warehouse to retailer
for t=3:T+2
  for i=1:Nwarehouse
    for j=1:Nretailer
      obj(a)=TRANSwr(i,j,t);
cctype(a)=char('C'); %variable type set to continous
lofswr(i,j,t)=a; %location of swr
a=a+1;
    end
  end
end
a=a+1;
end
end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% unit processing cost for supplier at period t
for t=1:T
  for i=1:Nsupplier
    obj(a)=Us(i,t);
    ctype(a)=char('C');%variable type set to continuous
    lofqs(i,t)=a;  %location of ps
    a=a+1;
  end
end

% unit processing cost for plant at period t
for t=2:T+1
  for i=1:Nplant
    obj(a)=Up(i,t);
    ctype(a)=char('C');%variable type set to continuous
    lofqp(i,t)=a;  %location of pp
    a=a+1;
  end
end

% unit processing cost for warehouse at period t
for t=3:T+2
  for i=1:Nwarehouse
    obj(a)=Uw(i,t);
    ctype(a)=char('C');%variable type set to continuous
    lofqw(i,t)=a;  %location of pw
    a=a+1;
  end
end

% unit processing cost for retailer at period t
for t=4:T+3
  for i=1:Nretailer
    obj(a)=Ur(i,t);
    ctype(a)=char('C');%variable type set to continuous
    lofqr(i,t)=a;  %location of pr
    a=a+1;
  end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% inventory holding cost for supplier at period t
for t=1:T
  for i=1:Nsupplier
    obj(a)=Hs(i,t);
    ctype(a)=char('C');%variable type set to continuous
    lofis(i,t)=a;  %location of is
    a=a+1;
  end
end

% inventory holding cost for plant at period t
for t=2:T+1
    for i=1:Nplant
        obj(a)=Hp(i,t);
        ctype(a)=char('C'); % variable type set to continuous
        lofip(i,t)=a; % location of ip
        a=a+1;
    end
end
% inventory holding cost for warehouse at period t
for t=3:T+2
    for i=1:Nwarehouse
        obj(a)=Hw(i,t);
        ctype(a)=char('C'); % variable type set to continuous
        lofiw(i,t)=a; % location of iw
        a=a+1;
    end
end
% inventory holding cost for retailer at period t
for t=4:T+3
    for i=1:Nretailer
        obj(a)=Hr(i,t);
        ctype(a)=char('C'); % variable type set to continuous
        lofir(i,t)=a; % location of ir
        a=a+1;
    end
end

% shipping from retailer to customer
% transportation cost from warehouse to retailer
for t=4:T+3
    for i=1:Nretailer
        obj(a)=0;
        ctype(a)=char('C'); % variable type set to continuous
        lofsrc(i,t)=a; % location of src
        a=a+1;
    end
end
a=a-1;

% constraints

A=zeros(nofcon,a);
rs=zeros(nofcon,1);
lhs=-inf*ones(nofcon,1);

% network structure constraints
for i=1:Nsupplier
    for j=1:Nplant
        Y(i,j)<= X(i); Y(i,j)<= X(j); parameters for X, Y
    end
end
\begin{verbatim}
A(i+Nsupplier*(j-1),lofxs(i))=-1;
A(i+Nsupplier*(j-1),lofys(i,j))=1;
end

for i=Nsupplier*Nplant+1:Nsupplier*Nplant+Nplant
for j=1:Nsupplier
    A(i+Nsupplier*(j-1),lofxp(i-Nsupplier*Nplant))=-1;
    A(i+Nsupplier*(j-1),lofysp(j,i-Nsupplier*Nplant))=1;
end
end

for i=2*Nsupplier*Nplant+1:2*Nsupplier*Nplant+Nplant+Nplant
for j=1:Nwarehouse
    A(i+Nwarehouse*(j-1),lofxp(i-2*Nsupplier*Nplant))=-1;
    A(i+Nwarehouse*(j-1),lofypw(i-2*Nsupplier*Nplant,j))=1;
end
for i=2*Nsupplier*Nplant+Nplant*Nwarehouse+1:2*Nsupplier*Nplant*Nplant+Nplant*Nwarehouse+Nwarehouse
for j=1:Nplant
    A(i+Nplant*(j-1),lofxw(i-2*Nsupplier*Nplant-Nplant*Nwarehouse))=-1;
    A(i+Nplant*(j-1),lofypw(j,i-2*Nsupplier*Nplant-Nplant*Nwarehouse))=1;
end
end

for i=2*Nsupplier*Nplant+2*Nplant*Nwarehouse+1:2*Nsupplier*Nplant+2*Nplant*Nwarehouse+Nwarehouse+Nwarehouse
for j=1:Nretailer
    A(i+Nretailer*(j-1),lofxw(i-2*Nsupplier*Nplant-2*Nplant*Nwarehouse))=-1;
    A(i+Nretailer*(j-1),lofywr(i-2*Nsupplier*Nplant-2*Nplant*Nwarehouse,j))=1;
end
end

for i=2*Nsupplier*Nplant+2*Nplant*Nwarehouse+Nwarehouse*Nretailer+1:2*Nsupplier*Nplant+2*Nplant*Nwarehouse+Nwarehouse*Nretailer+Nretailer
for j=1:Nwarehouse
    A(i+Nwarehouse*(j-1),lofxr(i-2*Nsupplier*Nplant-2*Nplant*Nwarehouse-Nwarehouse*Nretailer))=-1;
    A(i+Nwarehouse*(j-1),lofywr(j,i-2*Nsupplier*Nplant-2*Nplant*Nwarehouse-Nwarehouse*Nretailer))=1;
end
end

con1=2*Nsupplier*Nplant+2*Nplant*Nwarehouse+2*Nwarehouse*Nretailer;
\end{verbatim}
% sum(Y(i,:))>=X(j);  sum(Y(:,j))>=X(i); parameters for X,Y
for i=con1+1:con1+Nsupplier
    A(i,lofxs(i-con1))=-1;
    A(i,lofysp(i-con1,:))=-1;
end
for i=i+1:i+Nplant
    A(i,lofxp(i-Con1-Nsupplier))=-1;
    A(i,lofypw(i-Con1-Nsupplier,:))=-1;
end
for i=i+1:i+Nwarehouse
    A(i,lofxw(i-Con1-Nsupplier-2*Nplant))=-1;
    A(i,lofypw(i-Con1-Nsupplier-2*Nplant,:))=-1;
end
for i=i+1:i+Nretailer
    A(i,lofxr(i-Con1-Nsupplier-2*Nplant-2*Nwarehouse))=1;
    A(i,lofywr(i-Con1-Nsupplier-2*Nplant-2*Nwarehouse,:))=-1;
end
con2=con1+Nsupplier+2*Nplant+2*Nwarehouse+Nretailer;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%capacity constraints%%%%%%%%%%%%%%%%%%%%%
%    qs(i,t)+is(i,t)<=Cs(i,t)*Xs(i);  % parameters for q, X
for t=1:T
    for i=con2+1:con2+Nsupplier
        A(i+T*(t-1),lofqs(i-con2,t))=1;
        A(i+T*(t-1),lofis(i-con2,t))=1;
        A(i+T*(t-1),lofxs(i-con2))=-Cs(i-con2,t);
    end
end
%    qp(i,t)<=Cp(i,t)*Xp(i);
for t=2:T+1
    for i=con2+T*Nsupplier+1:con2+T*Nsupplier+Nplant
        A(i+T*(t-2),lofqp(i-con2-T*Nsupplier,t))=1;
        A(i+T*(t-2),lofip(i-con2-T*Nsupplier,t))=1;
        A(i+T*(t-2),lofxp(i-con2-T*Nsupplier))=-Cp(i-con2-T*Nsupplier,t);
    end
end
%    qw(i,t)<=Cw(i,t)*Xw(i);
for t=3:T+2
    for i=con2+T*Nsupplier+T*Nplant+1:con2+T*Nsupplier+T*Nplant+Nwarehouse
        A(i+T*(t-3),lofqw(i-con2-T*Nsupplier-T*Nplant,t))=1;
        A(i+T*(t-3),lofiw(i-con2-T*Nsupplier-T*Nplant,t))=1;
        A(i+T*(t-3),lofxw(i-con2-T*Nsupplier-T*Nplant))=-Cw(i-con2-T*Nsupplier-T*Nplant,t);
    end
end
%    qr(i,t)<=Cr(i,t)*Xr(i);
for t=4:T+3
    for i=con2+T*Nsupplier+T*Nplant+T*Nwarehouse+1:con2+T*Nsupplier+T*Nplant+T*Nwarehouse+Nwarehouse+Nretailer
        A(i+T*(t-4),lofqr(i-con2-T*Nsupplier-T*Nplant-T*Nwarehouse,t))=1;
        A(i+T*(t-4),lofir(i-con2-T*Nsupplier-T*Nplant-T*Nwarehouse,t))=1;
        A(i+T*(t-4),lofxr(i-con2-T*Nsupplier-T*Nplant-T*Nwarehouse))=-Cr(i-con2-T*Nsupplier-T*Nplant-T*Nwarehouse,t);
    end
end
con3=con2+T*Nsupplier+T*Nplant+T*Nwarehouse+Nwarehouse+Nretailer;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%shipping constraints%%%%%%%%%%%%%%%%%%%%%%%
\% s(i,j,t)<=TC(s,p,t)*Y(i,j)
for t=1:T
    for j=1:Nplant
        for i=con3+1:con3+Nsupplier
            A(i+Nsupplier*(j-1)+Nsupplier*Nplant*(t-1),lofssp(i-con3,j,t))=1;
            A(i+Nsupplier*(j-1)+Nsupplier*Nplant*(t-1),lofysp(i-con3,j))=-TCsp(i-con3,j,t);
        end
    end
end
for t=2:T+1
    for j=1:Nwarehouse
        for i=con3+Nsupplier*Nplant*T+1:con3+Nsupplier*Nplant*T+Nplant
            A(i+Nplant*(j-1)+Nplant*Nwarehouse*(t-2),lofspw(i-con3-Nsupplier*Nplant*T,j,t))=1;
            A(i+Nplant*(j-1)+Nplant*Nwarehouse*(t-2),lofypw(i-con3-Nsupplier*Nplant*T,j))=-TCpw(i-con3-Nsupplier*Nplant*T,j,t);
        end
    end
end
for t=3:T+2
    for j=1:Nretailer
        for i=con3+Nsupplier*Nplant*T+Nplant*Nwarehouse*T+1:con3+Nsupplier*Nplant*T+Nplant*Nwarehouse*T+Nwarehouse
            A(i+Nwarehouse*(j-1)+Nwarehouse*Nretailer*(t-3),lofswr(i-con3-Nsupplier*Nplant*T-Nplant*Nwarehouse*T,j,t))=1;
            A(i+Nwarehouse*(j-1)+Nwarehouse*Nretailer*(t-3),lofywr(i-con3-Nsupplier*Nplant*T-Nplant*Nwarehouse*T,j))=-TCwr(i-con3-Nsupplier*Nplant*T-Nplant*Nwarehouse*T,j,t);
        end
    end
end
con4 = con3 + Nsupplier * Nplant * T + Nplant * Nwarehouse * T + Nwarehouse * Nretailer * T;

% src(i,t) <= M * x_r
for t = 4:T + 3
    for i = con4 + 1:con4 + Nretailer
        A(i,lofsrc(i-con4,t)) = 1;
        A(i,lofsrc(i-con4,Nretailer+3)) = 1;
        A(i,lofxr(i-con4)) = -M;
    end
end

demand constraints

% sum(src(i,t)) = D(t);
for t = 4:T + 3
    for i = 1 + con4 + Nretailer:con4 + Nretailer + Nretailer
        for j = 1:Nretailer
            A(i,lofsrc(j,i-con4-Nretailer+3)) = 1;
            rhs(i) = D(i-con4-Nretailer+4);
            lhs(i) = D(i-con4-Nretailer+4);
        end
    end
end
con5 = con4 + Nretailer + T;

inventory constraints

% inven(i,t) = inven(i,t-1) + q(i,t) - sum(s(i,:,t));
for t = 1:T
    for i = con5 + 1:con5 + Nsupplier
        A(i + T * (t-1),lofis(i-con5,t)) = 1;
        A(i + T * (t-1),lofis(i-con5,Nsupplier+1)) = 1;
        if t > 2
            A(i + T * (t-1),lofis(i-con5,T(t-1))) = -1;
        end
        for j = 1:Nplant
            A(i + T * (t-1),lofssp(i-con5,j,t)) = 1;
        end
        rhs(i + T * (t-1)) = 0;
        lhs(i + T * (t-1)) = 0;
    end
end

for t = 2:T + 1
    for i = con5 + Nsupplier + T + 1:con5 + Nsupplier + Nsupplier * T + Nplant
        A(i + T * (t-2),lofip(i-con5-Nsupplier*T,t)) = 1;
        A(i + T * (t-2),lofip(i-con5-Nsupplier*T,t-1)) = 1;
        if t > 3
            A(i + T * (t-2),lofip(i-con5-Nsupplier*T,t-1)) = -1;
        end
        for j = 1:Nplant
            A(i + T * (t-2),lofspw(i-con5-Nsupplier*T,j,t)) = 1;
        end
        rhs(i + T * (t-2)) = 0;
        lhs(i + T * (t-2)) = 0;
    end
end
for t=3:T+2
for i=con5+Nsupplier*T+Nplant*T+1:con5+Nsupplier*T+Nplant*T+Nwarehouse
    A(i+T*(t-3),lofiw(i-con5-Nsupplier*T-Nplant*T,t))=1;
    A(i+T*(t-3),lofqw(i-con5-Nsupplier*T-Nplant*T,t))=-1;
    if t>=4
        A(i+T*(t-3),lofiw(i-con5-Nsupplier*T-Nplant*T,t-1))=-1;
    end
    for j=1:Nplant
        A(i+T*(t-3),lofswr(i-con5-Nsupplier*T-Nplant*T,j,t))=1;
    end
end
rhs(i+T*(t-3))=0;
lhs(i+T*(t-3))=0;
end
for t=4:T+3
for i=con5+Nsupplier*T+Nplant*T+Nwarehouse*T+1:con5+Nsupplier*T+Nplant*T+Nwarehouse*T+Nretailer
    A(i+T*(t-4),lofir(i-con5-Nsupplier*T-Nplant*T-Nwarehouse*T,t))=1;
    A(i+T*(t-4),lofqr(i-con5-Nsupplier*T-Nplant*T-Nwarehouse*T,t))=-1;
    A(i+T*(t-4),lofsrc(i-con5-Nsupplier*T-Nplant*T-Nwarehouse*T,t))=1;
    if t>=5
        A(i+T*(t-4),lofir(i-con5-Nsupplier*T-Nplant*T-Nwarehouse*T,t-1))=-1;
    end
    rhs(i+T*(t-4))=0;
lhs(i+T*(t-4))=0;
end
end
con6=con5+Nsupplier*T+Nplant*T+Nwarehouse*T+Nretailer*T;
%inven(i,1)=0; % initial inventory is 0;
for i=con6+1:con6+Nsupplier
    A(i,lofis(i-con6,1))=1;
rhs(i)=0;
lhs(i)=0;
end
for i=con6+Nsupplier+1:con6+Nsupplier+Nplant
    A(i,lofip(i-con6-Nsupplier,2))=1;
rhs(i)=0;
lhs(i)=0;
end
for i=con6+Nsupplier+Nplant+1:con6+Nsupplier+Nplant+Nwarehouse
    A(i,lofiw(i-con6-Nsupplier-Nplant,3))=1;
rhs(i)=0;
\[ \text{lhs}(i) = 0; \]
\[ \text{end} \]
\[ \text{for} \]
\[ i = \text{con6+Nsupplier+Nplant+Nwarehouse+1:con6+Nsupplier+Nplant+Nwarehouse+Nretailer} \]
\[ A(i, \text{lofir}(i-\text{con6-Nsupplier-Nplant-Nwarehouse}, 4)) = 1; \]
\[ \text{rhs}(i) = 0; \]
\[ \text{lhs}(i) = 0; \]
\[ \text{end} \]
\[ \text{con7} = \text{con6+Nsupplier+Nplant+Nwarehouse+Nretailer}; \]

\\
\text{%%%%%%%%%%%%%%%%%%%%%%%%%demand for each echelon%%%%%%%%%%%%%%%%%%%%%%%%%}

\%qp(i,t)-ip(i,t-1)=\text{sum}(\text{ssp}(i,j,t-1))
\[ \text{for} \ t = 2:T+1 \]
\[ \text{for} \ i = \text{con7+1:con7+Nretailer} \]
\[ A(i+3*(t-2), \text{lofqp}(i-\text{con7}, t)) = 1; \]
\[ A(i+3*(t-2), \text{lofip}(i-\text{con7}, t)) = 1; \]
\[ \text{if} \ t > 2 \]
\[ A(i+3*(t-2), \text{lofip}(i-\text{con7}, t-1)) = -1; \]
\[ \text{end} \]
\[ \text{for} \ j = 1: \text{Nplant} \]
\[ A(i+3*(t-2), \text{lofssp}(j, i-\text{con7}, t-1)) = -1; \]
\[ \text{end} \]
\[ \text{rhs}(i+3*(t-2)) = 0; \]
\[ \text{lhs}(i+3*(t-2)) = 0; \]
\[ \text{end} \]
\[ \text{end} \]

\%qw(i,t)-iw(i,t-1)=\text{sum}(\text{spw}(i,j,t-1))
\[ \text{for} \ t = 3:T+2 \]
\[ \text{for} \ i = \text{con7+Nretailer*3+1:con7+Nretailer*3+Nplant} \]
\[ A(i+3*(t-3), \text{lofqw}(i-\text{con7-3*Nretailer}, t)) = 1; \]
\[ A(i+3*(t-3), \text{lofiw}(i-\text{con7-3*Nretailer}, t)) = 1; \]
\[ \text{if} \ t > 3 \]
\[ A(i+3*(t-3), \text{lofiw}(i-\text{con7-3*Nretailer}, t-1)) = -1; \]
\[ \text{end} \]
\[ \text{for} \ j = 1: \text{Nwarehouse} \]
\[ A(i+3*(t-3), \text{lofspw}(j, i-\text{con7-3*Nretailer}, t-1)) = -1; \]
\[ \text{end} \]
\[ \text{rhs}(i+3*(t-3)) = 0; \]
\[ \text{lhs}(i+3*(t-3)) = 0; \]
\[ \text{end} \]
\[ \text{end} \]

\%qr(i,t)-ir(i,t-1)=\text{sum}(\text{swr}(i,j,t-1))
\[ \text{for} \ t = 4:T+3 \]
\[ \text{for} \ i = \text{con7*3*Nretailer+3*Nplant+1:con7*3*Nretailer+3*Nplant+Nwarehouse} \]
\[ A(i+3*(t-4), \text{lofqr}(i-\text{con7-3*Nretailer-3*Nplant}, t)) = 1; \]
\[ A(i+3*(t-4), \text{lofir}(i-\text{con7-3*Nretailer-3*Nplant}, t)) = 1; \]
\[ \text{if} \ t > 4 \]
\[ A(i+3*(t-4), \text{lofir}(i-\text{con7-3*Nretailer-3*Nplant}, t-1)) = -1; \]
end
for j=1:Nretailer
    A(i+3*(t-4),lofswr(j,i-con7-3*Nretailer-3*Nplant,t-1))=-1;
end
rhs(i+3*(t-4))=0;
lhs(i+3*(t-4))=0;
end

%Specifying the upper and lower boundary for the variables
lb=zeros(a,1);
ub=ones(a,1)*Inf;

% Solving using Cplex
cplex.Model.obj   = obj';
cplex.Model.ctype = ctype;
cplex.Model.A     = A;
cplex.Model.lb    = lb;
cplex.Model.ub    = ub;
cplex.Model.lhs   = lhs;
cplex.Model.rhs   = rhs;
cplex.solve();
cplex.writeModel('MILP.lp');
%Various outputs
display(cplex.Solution.status);
if cplex.Solution.status == 101,
    fprintf ('\nMinimum Cost: %f \n', cplex.Solution.objval);
solf=cplex.Solution.x;
b=1;
    %Create the soln. X matrix
    for i= 1:Nsupplier
        Xs(i)=solf(b);
        %
        xcosts(i)=Xs(i)*fs(i);
        b=b+1;
    end
display(Xs);
    for i= 1:Nplant
        Xp(i)=solf(b);
        %
        xcostp(i)=Xp(i)*fp(i);
        b=b+1;
    end
display(Xp);
    for i= 1:Nwarehouse
        Xw(i)=solf(b);
        %
        xcostw(i)=Xw(i)*fw(i);
        b=b+1;
    end
display(Xw);
    for i= 1:Nretailer
        Xr(i)=solf(b);
        %
        xcostr(i)=Xr(i)*fr(i);
        b=b+1;
    end
end
display(Xr);

%Create the soln. Y matrix
for i= 1:Nsupplier
    for j= 1:Nplant
        Ysp(i,j)=solf(b);
        ycostsp(i,j)=Ysp(i,j)*Fsp(i,j);
        b=b+1;
    end
end
display(Ysp);
for i= 1:Nplant
    for j= 1:Nwarehouse
        Ypw(i,j)=solf(b);
        ycostpw(i,j)=Ypw(i,j)*Fpw(i,j);
        b=b+1;
    end
end
display(Ypw);
for i= 1:Nwarehouse
    for j= 1:Nretailer
        Ywr(i,j)=solf(b);
        ycostwr(i,j)=Ywr(i,j)*Fwr(i,j);
        b=b+1;
    end
end
display(Ywr);

%Create the soln. s matrix
for t=1:T
    for i= 1:Nretailer
        for j=1:Nplant
            ssp(i,j,t)=solf(b);
            b=b+1;
        end
    end
end
display(ssp);
for t=2:T+1
    for i= 1:Nplant
        for j=1:Nwarehouse
            spw(i,j,t)=solf(b);
            b=b+1;
        end
    end
end
display(spw);
for t=3:T+2
    for i= 1:Nwarehouse
        for j=1:Nretailer
            swr(i,j,t)=solf(b);
            b=b+1;
        end
    end
end
end
display(swr);

%Create the soln. p matrix
for t = 1:T
    for i = 1:Nsupplier
        qs(i,t) = solf(b);
        b = b + 1;
    end
end
display(qs);
for t = 2:T+1
    for i = 1:Nplant
        qp(i,t) = solf(b);
        b = b + 1;
    end
end
display(qp);
for t = 3:T+2
    for i = 1:Nwarehouse;
        qw(i,t) = solf(b);
        b = b + 1;
    end
end
display(qw);
for t = 4:T+3
    for i = 1:Nretailer;
        qr(i,t) = solf(b);
        b = b + 1;
    end
end
display(qr);

%Create the soln. i matrix
for t = 1:T
    for i = 1:Nsupplier
        is(i,t) = solf(b);
        b = b + 1;
    end
end
display(is);
for t = 2:T+1
    for i = 1:Nplant
        ip(i,t) = solf(b);
        b = b + 1;
    end
end
display(ip);
for t = 3:T+2
    for i = 1:Nwarehouse;
        iw(i,t) = solf(b);
        b = b + 1;
    end
end
display(iw);
for t = 4:T+3
for i=1:Nretailer;
    ir(i,t)=solf(b);
    b=b+1;
end
display(ir);
% create the src matrix
for t=4:T+3
    for i=1:Nretailer
        src(i,t)=solf(b);
        b=b+1;
    end
display(src);
elseif cplex.Solution.status == 102
    break
else
    continue
end
% sumx=sum(Xs)+sum(Xp)+sum(Xw)+sum(Xr);
fixedcost=sum(sum(ycostwr(i,j)))+sum(sum(ycostpw(i,j)))+sum(sum(ycostsp (i,j)));
MILPcost=((cplex.Solution.objval-
fixedcost)/3)+fixedcost;
display(MILPcost);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% stochastic environment
% input data X,q,U,H,C
for i=1:Nsupplier
    if Xs(i)==1||Xs(i)>U
        prods(i)=sum(qs(i,:))/T;
        Unitcosts(i)=sum(Us(i,:))/T;
        Holdcosts(i)=sum(Hs(i,:))/T;
        capacitys(i)=normrnd(sum(Cs(i,:))/T,26);
    else
        prods(i)=0;
        Unitcosts(i)=0;
        Holdcosts(i)=0;
        capacitys(i)=0;
    end
end
for i=1:Npl
    if Xp(i)==1||Xp(i)>U
        prodp(i)=sum(qp(i,:))/T;
        Unitcostp(i)=sum(Up(i,:))/T;
        Holdcostp(i)=sum(Hp(i,:))/T;
        capacityp(i)=normrnd(sum(Cp(i,:))/T,26);
    else
        prodp(i)=0;
        Unitcostp(i)=0;
        Holdcostp(i)=0;
        capacityp(i)=0;
    end
end
for i=1:Nwarehouse
  if Xw(i)==1||Xw(i)>U
    prodw(i)=sum(qw(i,:))/T;
    Unitcostw(i)=sum(Uw(i,:))/T;
    Holdcostw(i)=sum(Hw(i,:))/T;
    capacityw(i)=normrnd(sum(Cw(i,:))/T,26);
  else
    prodw(i)=0;
    Unitcostw(i)=0;
    Holdcostw(i)=0;
    capacityw(i)=0;
  end
end
for i=1:Nretailer
  if Xr(i)==1||Xr(i)>U
    prodr(i)=sum(qr(i,:))/T;
    Unitcostr(i)=sum(Ur(i,:))/T;
    Holdcostr(i)=sum(Hr(i,:))/T;
    capacityr(i)=normrnd(sum(Cr(i,:))/T,26);
  else
    prodr(i)=0;
    Unitcostr(i)=0;
    Holdcostr(i)=0;
    capacityr(i)=0;
  end
end
% Input data TRANS, TC
for i=1:Nsupplier
  for j=1:Nplant
    if Ysp(i,j)==1||Ysp(i,j)>U
      transcostsp(i,j)=sum(TRANSsp(i,j,:))/T;
      transcappsp(i,j)=normrnd(sum(TCsp(i,j,:))/T,26);
    else
      transcostsp(i,j)=0;
      transcappsp(i,j)=0;
    end
  end
end
for i=1:Nplant
  for j=1:Nwarehouse
    if Ypw(i,j)==1||Ypw(i,j)>U
      transcostpw(i,j)=sum(TRANSpw(i,j,:))/T;
      transcappw(i,j)=normrnd(sum(TCpw(i,j,:))/T,26);
    else
      transcostpw(i,j)=0;
      transcappw(i,j)=0;
    end
  end
end
for i=1:Nwarehouse
  for j=1:Nretailer
    if Ywr(i,j)==1||Ywr(i,j)>U
      transcostwr(i,j)=sum(TRANSwr(i,j,:))/T;
      transcapwr(i,j)=normrnd(sum(TCwr(i,j,:))/T,26);
    else
      transcostwr(i,j)=0;
      transcapwr(i,j)=0;
    end
  end
end
transcostwr(i,j)=0;
transcapwr(i,j)=0;
end
end
end
count=1;
d=1;
dd=1;
d1=1;
d2=1;
d3=1;
replicates=1002;
is0=zeros(Nsupplier,replicates);
ip0=zeros(Nplant,replicates);
iw0=zeros(Nwarehouse,replicates);
ir0=zeros(Nretailer,replicates);
is0(:,1)=0;
ip0(:,1)=0;
iw0(:,1)=0;
ir0(:,1)=0;
while count<replicates
  count=count+1;
  % Monte carlo simulation for customer demands
  stochasticd=normrnd(830,290);
  sdemand(d)=stochasticd;
  d=d+1;

  % Min inventory cost + shipping cost + backorder penalty cost
  % Holdcost*inventory + transcost*ship + backorder*M
  z=1;
  % inventory level in obj
  for i=1:Nsupplier
    c(z)=Holdcosts(i);
    lofinventories(i)=z;
    z=z+1;
  end
  for i=1:Nplant
    c(z)=Holdcostp(i);
    lofinventoryp(i)=z;
    z=z+1;
  end
  for i=1:Nwarehouse
    c(z)=Holdcostw(i);
    lofinventoryw(i)=z;
    z=z+1;
  end
  for i=1:Nretailer
    c(z)=Holdcostr(i);
    lofinventoryr(i)=z;
    z=z+1;
  end
  % shipping amount in obj
  for i=1:Nsupplier
    for j=1:Nplant
      c(z)=transcostsp(i,j);
lofshipsp(i,j)=z;
z=z+1;
end
for i=1:Nplant
    for j=1:Nwarehouse
        c(z)=transcostpw(i,j);
        lofshippw(i,j)=z;
        z=z+1;
    end
end
for i=1:Nwarehouse
    for j=1:Nretailer
        c(z)=transcostwr(i,j);
        lofshipwr(i,j)=z;
        z=z+1;
    end
end
for i=1:Nretailer
    c(z)=0;
    lofshiprc(i)=z;
    z=z+1;
end
c(z)=M;
lofback=z;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% constriants %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

numofcon=Nretailer+Nplant+Nwarehouse+Nretailer;
Aeq=zeros(numofcon,z);
beq=zeros(numofcon,1);
A1=zeros(numofcon,z);
b1=zeros(numofcon,1);

% inventory constraints
for i=1:Nretailer
    Aeq(i,lofinventorys(i))=1;
    for j=1:Nplant
        Aeq(i,lofshipsp(i,j))=1;
    end
    beq(i)=prods(i)+is0(i,count-1);
end
for i=Nretailer+1:Nretailer+Nplant
    Aeq(i,lofinventoryp(i-Nretailer))=1;
    for j=1:Nwarehouse
        Aeq(i,lofshippw(i-Nretailer,j))=1;
    end
    beq(i)=prodp(i-Nretailer)+ip0(i-Nretailer,count-1);
end
for i=Nretailer+Nplant+1:Nretailer+Nplant+Nwarehouse
    Aeq(i,lofinventoryw(i-Nretailer-Nplant))=1;
    for j=1:Nretailer
        Aeq(i,lofshipwr(i-Nretailer-Nplant,j))=1;
    end
    beq(i)=prodw(i-Nretailer-Nplant)+iw0(i-Nretailer-Nplant,count-1);
end
for i=Nretailer+Nplant+Nwarehouse+1:Nretailer+Nplant+Nwarehouse+Nretailer
    Aeq(i,lofinventoryw(i-Nretailer-Nplant-Nretailer))=1;
    for j=1:Nretailer
        Aeq(i,lofshiprc(i-Nretailer-Nplant-Nretailer,j))=1;
    end
    beq(i)=ip0(i-Nretailer-Nplant-Nretailer,count-1);
end
\[ Aeq(i,lofshipwr(i-Nretailer-Nplant,j)) = 1; \]
\[ beq(i) = prodw(i-Nretailer-Nplant) + iw0(i-Nretailer-Nplant,count-1); \]
\[ \% inventoryr(i) = ir0(i) + prod(i) - shiprc(i); \]
\[ end \]
\[ i=Nretailer+Nplant+Nwarehouse+1:Nretailer+Nplant+Nwarehouse+Nretailer \]
\[ Aeq(i,lofinventoryr(i-Nretailer-Nplant-Nwarehouse)) = 1; \]
\[ Aeq(i,lofshiprc(i-Nretailer-Nplant-Nwarehouse)) = 1; \]
\[ beq(i) = prod(r(i-Nretailer-Nplant-Nwarehouse) + ir0(i-Nretailer-Nplant-Nwarehouse)); \]
\[ end \]
\[ nofi = Nretailer+Nplant+Nwarehouse+Nretailer; \]
\[ \% sum(shiprc) = stochastic - backorder; \]
\[ Aeq(i+1,lofshiprc(:)) = 1; \]
\[ Aeq(i+1,lofback) = 1; \]
\[ beq(i+1) = stochasticd; \]
\[ numcon = i+1; \]
\[ \% if x(i) = 0, inventory(i) = 0 \]
\[ for i=numcon+1:numcon+Nsupplier \]
\[ if Xs(i-numcon) == 0 || Xs(i-numcon) < L \]
\[ Aeq(i,lofinventorys(i-numcon)) = 1; \]
\[ beq(i) = 0; \]
\[ end \]
\[ end \]
\[ for i=numcon+Nsupplier+1:numcon+Nsupplier+Nplant \]
\[ if Xp(i-numcon-Nsupplier) < L \]
\[ Aeq(i,lofinventorp(i-numcon-Nsupplier)) = 1; \]
\[ beq(i) = 0; \]
\[ end \]
\[ end \]
\[ for i=numcon+Nsupplier+Nplant+1:numcon+Nsupplier+Nplant+Nwarehouse \]
\[ if Xw(i-numcon-Nsupplier-Nplant) == 0 || Xw(i-numcon-Nsupplier-Nplant) < L \]
\[ Aeq(i,lofinventorw(i-numcon-Nsupplier-Nplant)) = 1; \]
\[ beq(i) = 0; \]
\[ end \]
\[ end \]
\[ for i=numcon+Nsupplier+Nplant+Nwarehouse+1:numcon+Nsupplier+Nplant+Nwarehouse+Nretailer \]
\[ if Xr(i-numcon-Nsupplier-Nplant-Nwarehouse) == 0 || Xr(i-numcon-Nsupplier-Nplant-Nwarehouse) < L \]
\[ Aeq(i,lofinventoryr(i-numcon-Nsupplier-Nplant-Nwarehouse)) = 1; \]
\[ beq(i) = 0; \]
\[ end \]
\[ end \]
\[ Ncon = numcon+Nsupplier+Nplant+Nwarehouse+Nretailer; \]
\[ \% if Ysp(i,j) = 0, ship(i,j) = 0 \]
\[ for i=Ncon+1:Ncon+Nsupplier \]
for j=1:Nplant
    if Ysp(i-Ncon,j)==0||Ysp(i-Ncon,j)<L
        Aeq(i+Nplant*(j-1),lofshipsp(i-Ncon,j))=1;
        beq(i+Nplant*(j-1))=0;
    end
end
end
for i=Ncon+Nsupplier*Nplant+1:Ncon+Nsupplier*Nplant+Nplant
    for j=1:Nwarehouse
        if Ypw(i-Ncon-Nsupplier*Nplant,j)==0||Ypw(i-Ncon-
           Nsupplier*Nplant,j)<L
            Aeq(i+Nwarehouse*(j-1),lofshippw(i-Ncon-
               Nsupplier*Nplant,j))=1;
            beq(i+Nwarehouse*(j-1))=0;
        end
    end
end
for i=Ncon+Nsupplier*Nplant+Nplant*Nwarehouse+1:Ncon+Nsupplier*Nplant+Nplant*
   Nwarehouse+Nwarehouse
    for j=1:Nretailer
        if Ywr(i-Ncon-Nsupplier*Nplant-
           Nwarehouse,Nwarehouse,j)==0||Ywr(i-Ncon-Nsupplier*Nplant-
              Nwarehouse,Nwarehouse,j)<L
            Aeq(i+Nretailer*(j-1),lofshipwr(i-Ncon-
               Nsupplier*Nplant-Nplant*Nwarehouse,j))=1;
            beq(i+Nretailer*(j-1))=0;
        end
    end
end
for i=Ncon+Nsupplier*Nplant+Nplant*Nwarehouse+Nwarehouse*Nretailer+1:Ncon+N
   supplier*Nplant+Nplant*Nwarehouse+Nwarehouse*Nretailer-Nretailer
    if Xr(i-Ncon-Nsupplier*Nplant*Nwarehouse-
       Nwarehouse*Nretailer)==0||Xr(i-Ncon-Nsupplier*Nplant*Nwarehouse-
          Nwarehouse*Nretailer)<L
        Aeq(i,lofshiprc(i-Ncon-Nsupplier*Nplant-
           Nwarehouse-Nwarehouse*Nretailer))=1;
        beq(i)=0;
    end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%capacity constraints%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% inventory+production<=capacity
for i=1:Nsupplier
    if Xs(i)==1||Xs(i)>U
        A1(i,lofinventorys(i))=1;
        b1(i)=(capacities(i)-prods(i));
    end
end
% inventory+production<=capacity
for i=Nsupplier+1:Nsupplier+Nplant
    if Xp(i-Nsupplier)==1||Xp(i-Nsupplier)>U
        A1(i,lofinventoryp(i-Nsupplier))=1;
        b1(i)=(capacitiesp(i-Nsupplier)-prodp(i-Nsupplier));
    end
end
end

% inventory+production<=capacity
for i=Nsupplier+Nplant+1:Nsupplier+Nplant+Nwarehouse
  if Xw(i-Nsupplier-Nplant)==1||Xw(i-Nsupplier-Nplant)>U
    A1(i,lofinventoryw(i-Nsupplier-Nplant))=1;
    b1(i)=(capacityw(i-Nsupplier-Nplant)-prodw(i-Nsupplier-Nplant));
  end
end

% inventory+production<=capacity
for i=Nsupplier+Nplant+Nwarehouse+1:Nsupplier+Nplant+Nwarehouse+Nretailer
  if Xr(i-Nsupplier-Nplant-Nwarehouse)==1||Xr(i-Nsupplier-Nplant-Nwarehouse)>U
    A1(i,lofinventoryr(i-Nsupplier-Nplant-Nwarehouse))=1;
    b1(i)=(capacityr(i-Nsupplier-Nplant-Nwarehouse)-prodr(i-Nsupplier-Nplant-Nwarehouse));
  end
end
numcon1=i;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%shipping capacity constraints%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% shipping quantity <=transportation capacity
for i=numcon+1:numcon+Nsupplier
  for j=1:Nplant
    if Ysp(i-numcon,j)==1||Ysp(i-numcon,j)>U
      A1(i+Nplant*(j-1),lofshipsp(i-numcon,j))=1;
      b1(i+Nplant*(j-1))=transcapsp(i-numcon,j);
    end
  end
end
for i=numcon+Nsupplier*Nplant+1:numcon+Nsupplier*Nplant+Nplant
  for j=1:Nwarehouse
    if Ypw(i-numcon-Nsupplier*Nplant,j)==1||Ypw(i-numcon-Nsupplier*Nplant,j)>U
      A1(i+Nwarehouse*(j-1),lofshippw(i-numcon-Nsupplier*Nplant,j))=1;
      b1(i+Nwarehouse*(j-1))=transcappw(i-numcon-Nsupplier*Nplant,j);
    end
  end
end
for i=numcon+Nsupplier*Nplant+Nplant*Nwarehouse+1:numcon+Nsupplier*Nplant+Nplant*Nwarehouse+Nwarehouse
  for j=1:Nretailer
    if Ywr(i-numcon-Nsupplier*Nplant-Nwarehouse)==1||Ywr(i-numcon-Nsupplier*Nplant-Nwarehouse)>U
      A1(i+Nretailer*(j-1),lofshipwr(i-numcon-Nsupplier*Nplant-Nwarehouse,j))=1;
      b1(i+Nretailer*(j-1))=transcapwr(i-numcon-Nsupplier*Nplant-Nwarehouse,j);
    end
  end
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end

numcon2=numcon1+Nsupplier*Nplant+Nplant*Nwarehouse+Nwarehouse*Nretailer;

for i=numcon2+1:numcon2+Nretailer
    if Xr(i-numcon2)==1||Xr(i-numcon2)>U
        A1(i,lofshiprc(i-numcon2))=1;
        b1(i)=capacityr(i-numcon2);
    end
end

numco3=numcon2+Nretailer;

% demand constraints for each echelon

for i=numcon3+1:numcon3+Nsupplier
    for j=1:Nplant
        if Ysp(i-numcon3))==1||Ysp(i-numcon3)>U
            A1(i+Nplant*(j-1),lofshipsp(i-numcon3,j))=-1;
            A1(i+Nplant*(j-1),lofinventoryp(i-numcon3))=1;
            b1(i+Nplant*(j-1))=-prodp(i-numcon3)+ip0(i-numcon3,count-1);
        end
    end
end

for i=numcon3+Nsupplier*Nplant+1:numcon3+Nsupplier*Nplant+Nplant
    for j=1:Nwarehouse
        if Ypw(i-numcon3-Nsupplier*Nplant,0)==1||Ypw(i-numcon3-Nsupplier*Nplant,0)>U
            A1(i+Nwarehouse*(j-1),lofshippw(i-numcon3-Nsupplier*Nplant,0))=-1;
            A1(i+Nwarehouse*(j-1),lofinventoryw(i-numcon3-Nsupplier*Nplant))=1;
            b1(i+Nwarehouse*(j-1))=-prodw(i-numcon3-Nsupplier*Nplant)+iw0(i-numcon3-Nsupplier*Nplant,count-1);
        end
    end
end

for i=numcon3+Nsupplier*Nplant+Nplant*Nwarehouse+1:numcon3+Nsupplier*Nplant+
     Nplant*Nwarehouse+NWarehouse
    for j=1:Nretailer
        if Ywr(i-numcon3-Nsupplier*Nplant-Nplant*Nwarehouse,0)==1||Ywr(i-numcon3-Nsupplier*Nplant-Nplant*Nwarehouse,0)>U
            A1(i+Nretailer*(j-1),lofshipwr(i-numcon3-Nsupplier*Nplant-Nplant*Nwarehouse,0))=-1;
            A1(i+Nretailer*(j-1),lofinventoryr(i-numcon3-Nsupplier*Nplant-Nplant*Nwarehouse))=1;
            b1(i+Nretailer*(j-1))=-prodr(i-numcon3-Nsupplier*Nplant-Nplant*Nwarehouse,count-1);
        end
    end
end
numcon4=numcon3+Nsupplier*Nplant+Nplant*Nwarehouse+Nwarehouse*Nretailer;

lb=zeros(z,1);
options=optimset('display','off');
[x, fval, exitflag, output, lambda] = linprog(c, A1, b1, Aeq, beq, lb, [], [], options);
z1=1;
% inventory level
for i=1:Nsupplier
    inventorys(i)=x(z1);
    is0(i,count)=x(z1);
    z1=z1+1;
end
for i=1:Nplant
    inventoryp(i)=x(z1);
    iw0(i,count)=x(z1);
    z1=z1+1;
end
for i=1:Nwarehouse
    inventoryw(i)=x(z1);
    iw0(i,count)=x(z1);
    z1=z1+1;
end
for i=1:Nretailer
    inventoryr(i)=x(z1);
    ir0(i,count)=x(z1);
    z1=z1+1;
end
% shipping amount
for i=1:Nsupplier
    for j=1:Nplant
        shipsp(i,j)=x(z1);
        shipsp0(i,j,count)=x(z1);
        z1=z1+1;
    end
end
for i=1:Nplant
    for j=1:Nwarehouse
        shippw(i,j)=x(z1);
        shippw0(i,j,count)=x(z1);
        z1=z1+1;
    end
end
for i=1:Nwarehouse
    for j=1:Nretailer
        shipwr(i,j)=x(z1);
        shipwr0(i,j,count)=x(z1);
        z1=z1+1;
    end
end
end
for i=1:Nretailer
    shiprc(i)=x(z1);
    shiprc0(i,j,count)=x(z1);
    z1=z1+1;
end
invens(:,dd)=inventorys;
invenp(:,dd)=inventoryp;
invenw(:,dd)=inventoryw;
invenr(:,dd)=inventoryr;
dd=dd+1;
% backorder amount
backorder=x(z1);
border(d1)=backorder;
shortages(d1)=1-(backorder/stochastic);
CSL(d2)=shortages(d1);
d2=d2+1;
d1=d1+1;
% fixed costs arc
for i=1:Nsupplier
    for j=1:Nplant
        Fcostsp(i,j)=Fsp(i,j)*Ysp(i,j);
    end
end
for i=1:Nplant
    for j=1:Nwarehouse
        Fcostpw(i,j)=Fpw(i,j)*Ypw(i,j);
    end
end
for i=1:Nwarehouse
    for j=1:Nretailer
        Fcostwr(i,j)=Fwr(i,j)*Ywr(i,j);
    end
end
for i=1:Nsupplier
    Pcosts(i)=Unitcosts(i)*prods(i);
end
for i=1:Nplant
    Pcostp(i)=Unitcostp(i)*prodp(i);
end
for i=1:Nwarehouse
    Pcostw(i)=Unitcostw(i)*prodw(i);
end
for i=1:Nretailer
    Pcostr(i)=Unitcostr(i)*prodr(i);
end

totalcost=fval-
M*backorder+sum(sum(Fcostsp))+sum(sum(Fcostpw))+sum(sum(Fcostwr))+sum(P
costs)+sum(Pcostp)+sum(Pcostw)+sum(Pcostr);
tcost(d2)=totalcost;
d3=d3+1;
end
avrgCSL=mean(CSL);
display(avrgCSL)
aCSL(dd1)=avrgCSL;
dd1=dd1+1;
for t=4+1:Nperiod
    D(t)= 1.05*D(t); %demand (deterministic)
end
if iter>100&&avrgCSL<aCSL(dd1)
    break
end

% display simulation result
avrgdemand=mean(sdemand);
stddemand=std(sdemand);
avrginvens=mean(invens,2);
avrginvenp=mean(invenp,2);
avrginvenw=mean(invenw,2);
avrginvenr=mean(invenr,2);
avrgborder=mean(border);
avrgCSL=max(aCSL);
startCSL=min(aCSL);
avrgtcost=mean(tcost);
display(avrgdemand);
display(stddemand);
display(avrginvens);
display(avrginvenp);
display(avrginvenw);
display(avrginvenr);
display(avrgborder);
display(avrgCSL);
display(startCSL);
display(avrgtcost);
% end