EMERGENCY OPERATIONS SCHEDULING OF A SUPPLY CHAIN NETWORK IN DISASTER RELIEFS

By

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ABSTRACT OF THE DISSERTATION

SOLVING THE EMERGENCY OPERATIONS SCHEDULING PROBLEM WITH MULTI-STAGE LEAD TIMES AND TARDINESS PENALTIES

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The present study works on the operations scheduling problem of an emergency supply chain that provides relief goods to affected areas after a disaster. Specifically, we focus on the production and distribution of the disaster relief kit, an emergency package used in disaster relief which includes critical resources for coping with the situation after a disaster.

The whole dissertation includes three essays and a simulation chapter. In the first essay, a thorough literature review is conducted which includes two parts. The first part investigates general integrated distribution and production problems (IPDP), and models/solution approaches used to solve these problems. The second part of the literature review is on the emergency supply chain in disaster relief specifically. In this part, both survey papers and papers dealing with specific problems in this field are reviewed. Based on the review, we compare the commercial supply chain and the emergency supply chain in disaster relief, and identify gaps in the research and practice of disaster relief supply chain management.

The second and third essays study the specific supply chain network that produces and distributes the disaster relief kits. First of all, a structure is proposed for the supply chain network, assumptions are made, and the general problem of optimally scheduling and operating the supply chain is defined which is NP hard. Following that, the second essay investigates a special variation of the general problem and proves it to be strongly polynomial solvable. In the third essay, the structural properties of the general problem are analyzed, and an LP relaxation based heuristic is proposed to solve the general problem efficiently. The performance of the heuristic is tested through extensive numerical experiments. Finally, we evaluate two policies on the strategic level of the supply chain through simulation. Observations obtained through the simulation studies are used to support the development of managerial policies for the future disaster relief.

In this dissertation, the three essays are structured to form a coherent body as described above on the topic of the emergency scheduling operations of a supply chain in disaster relief considering lead time and tardiness penalties.

Preface

The thesis entitled "Solving the Emergency Operations Scheduling Problem with Multi-stage Lead Times and Tardiness Penalties" is prepared by Hui Dong through her Ph.D. program from 2009 to 2014, at the department of Supply Chain Management and Marketing Sciences at Rutgers University.

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CHAPTER 1 INTRODUCTION

Natural disasters, such as hurricanes, earthquakes, wildfires and tornados, have occurred frequently in recently years. According to the National Earthquake Information Centre of the US Geological Survey (http://www.usgs.gov/), the number of earthquakes above the magnitude 4.0 exceeded 158,000 worldwide between 2000 and 2012. Emergency supply chains, which are formed to meet the needs of disaster relief, are responsible for the collection and distribution of rescue supplies to affected areas. Holguín-Veras et al. (2012) compare the commercial supply chain and humanitarian supply chain in emergencies from multiple perspectives, including 1) different objectives: the commercial supply chain focuses on reducing cost while the emergency supply chain emphasizes responsiveness; 2) information: the commercial supply chain has better information transparency while in disasters, information is usually fractional; 3) demand patterns: the commercial supply chain has known or well-forecasted demand, but it is very difficult to forecast demands in disasters, and 4) commercial logistics are large in volume but have a stable and repeating pattern, while emergency logistics spike right after the disaster and taper off as time goes by, etc. These major differences make the operations of the emergency supply chain and logistics a more challenging task.

This dissertation is devoted to studying the effective operations of emergency supply chain that provides relief supplies to the affected areas after a disaster. According to Sheu (2007a), the goal of emergency logistics is to meet the urgent needs of the affected people under emergency conditions. Therefore, coordinated and integrated operations planning and scheduling is particularly critical during an emergency situation for timely provision of life-saving supplies to people in the affected areas. Besides the high expectation of responsiveness, emergency supply chains also need to confront challenges such as poor information/communication, uncertainties in network capacity, limited resource availability, lack of coordination, and frequent last-minute priority change in the content, quantity, and destinations of shipments.

Gaps exist in the current literature of emergency supply chain operations. Altay and Green (2006) mention that the organizational and network structures are not well defined, and that many assumptions about disaster relief are not realistic, which is emphasized again later on by Galindo and Batta (2013). Caunhye et al. (2012) point out there is a lack of comprehensive models for the disaster relief supply chain because of the potential computational inefficiency. Therefore, the motivation of this study is to provide meaningful tools for the practice of emergency operations scheduling and potentially contribute to bridging the gaps in this field.

The relief product studied in this dissertation is called an *emergency rescue kit*. It has been commonly used in various real-life disaster relief operations. A rescue kit typically consists of multiple components (e.g., emergency trauma dressing, latex gloves, blood-stoppers, bandages, alcohol wipes, etc.) from various suppliers. Since different areas hit by a natural disaster may experience different levels/types of damage, both common-purpose (i.e., standard) rescue kits and area-dependent (i.e., customized) rescue kits are usually needed. In general, only standard kits are inventoried in advance in the network, while various customized kits are provisioned during and after a disaster since the contents of customized kits are highly dependent on the types of disasters, damage, seasons, and areas, and are therefore not built to inventory.

In this study, we consider and analyze an integrated replenishment, production and distribution problem defined upon an emergency supply chain for both *standard* and *customized* rescue kits. The hypothetical supply chain network consists of component suppliers, manufacturers, regional distribution centers, and customer demand points. The bill of materials for assembling standard kits is identical regardless of customers, while the bills of materials for assembling customized kits are customer/area-dependent. Each customer orders standard kits, or customized kits, or both, and specifies the preferred time and quantity for orders to be fulfilled. The order for the standard kit may be fulfilled by either existing inventories in the network or a newly produced batch by a manufacturer. There is no inventory for customized kits which are usually ordered by the customers according to their local needs after the disaster. The order lead time, including shipping time, assembly time and waiting time (for the component supplies) must be explicitly considered and modeled. The optimization problem is to find an integrated inventory allocation and a production/assembly plan together with a shipping schedule for inbound component supplies and outbound product deliveries so that the total tardiness in customer order fulfillment is minimized.

The main difference between the focus of our study and those considered in the literature for the integrated operations planning is that our problem involves the multi-stage lead time of a supply chain network and our objective is to minimize the delivery tardiness instead of cost minimization, the two of which together introduce new challenges in modeling and algorithm design.

In general, the problem is a complicated integrated production and distribution problem in an emergency supply chain in disaster relief. Before we start working on the specific problem, we conduct an extensive literature review which includes two parts: the first part is about models and methodologies in the general integrated production and distribution problem, and the other part is specifically about emergency operations of relief goods supply chains in disaster relief.

The rest of the dissertation is organized as follows. In Chapter 2, a thorough literature review is given on both general integrated production and distribution problems and emergency operations of relief goods supply chains. In Chapter 3, the key problem of this dissertation is defined and the general mathematical model is presented which is NP-hard to solve. In Chapter 4, a special variation of the general model is investigated which is strongly polynomial solvable and practically meaningful. We propose an LP-relaxation based heuristic to solve the general problem efficiently in Chapter 5 and test its performance through numerical experiments. Chapter 6 uses simulation to evaluate strategies in emergency supply chains under the general model structure. Finally, conclusions and future research directions are discussed in Chapter 7.

CHAPTER 2 LITERATURE REVIEW

In this chapter, we present an extensive literature review for our study in this dissertation. The literature review includes two parts: Section 2.1 is about the general integrated production and distribution problems (IPDP), and Section 2.2 is about emergency supply chain in disaster relief specifically. We give discussions for both parts and propose research motivations and topics based on the survey.

2.1 Integrated Production and Distribution Problems (IPDP)

A supply chain is defined as an integrated business process with bidirectional flows of products, information, cash, and services, between tiers of suppliers, manufacturers, logistics partners, distributors, retailers, and customers. Due to fast changes in the marketplace and the rapid expansion of supply chains (Eksioglu et al., 2007), ensuring highly coordinated production, inventory, and distribution over a multi-echelon supply chain network is vital, and has an immediate impact on customer service and profit margins. This importance will continue to increase along with the following trends:

Globalization: All functions in a supply chain network, such as procurement, production, distribution and consumptions, have now become more globalized. Most multi-national firms have business facilities located over multiple continents, with many local markets to serve; face the need for emerging market penetration and the challenge of capacity shortages and rising shipping costs; and are constantly confronting environmental/sustainability concerns. At the same time, the promises and flexibility of third-party logistics and subcontracting opportunities offer a great incentive to expand supply chains globally. As supply chains expand, the need to ensure a more precise match between demand and supply increases the importance of integrated operations planning.

Pressure on lead time reduction and profit margin improvement: Since customer demand for both products and services typically changes over time, time-to-market is more important than ever in order to meet the expectations of demanding customers. For most supply chains, production is not the only major process to be considered; there are many other stages, such as sourcing, distribution, inventory, packaging, and order processing that together could account for a significant portion of the lead time. A less-coordinated supply chain process could easily diminish or eliminate the profit margin and lead to poor customer service.

Advances in information technology: Advances in information technology during the past two decades have significantly improved data visibility (e.g., inventory visibility and shipping status) and information accessibility along the supply chain. Data can be automatically collected, retrieved, and manipulated in various ways and shared by many supply chain partners (e.g., through RFID). Furthermore, today’s computing power allows us to solve some larger-scale integrated operations planning problems relatively easily and more rapidly, which were difficult, if not impossible, only a few decades ago when optimization problems of a combinatorial nature were considered computationally intractable.

Serving the needs of emerging non-commercial supply chains: A network for disaster relief operations is a typical illustration of a non-commercial supply chain. Disaster relief and emergency logistics (e.g., in response to Hurricane Katrina in Louisiana in 2005, the tsunami in Japan in 2011, and Hurricane Sandy in New Jersey and

New York in 2012) usually cannot be effectively handled by a single state or a single local government. Today's internet allows the need for disaster relief to be communicated cross-country and internationally within minutes of an event, and the rapid formation of disaster relief supply chains for quick response to people in the affected areas. A highly effective and fully integrated production and distribution operation that pulls supplies from different industries and states to ensure delivery of these resources to the people in an affected area is critical to human well-being.

In this study we focus on the solution methodologies for solving various *integrated/coordinated* production and distribution operations planning problems reported in the current literature. This survey does not focus on results related to decisions for supply chain designs (e.g., facility location and/or facility capacity, which will be briefly mentioned in Chapter 6 below), or on those results that only deal with a single operation such as inventory, or routing, or production scheduling, but rather addresses issues unique to process integration.

There have been several survey papers dealing with integrated operations problems, each with its own focus. Among these, the pioneering review by Thomas and Griffin (1996) defines a generic structure for a supply chain network, and classifies published results at both the strategic planning level and the operational planning level, where the latter falls into our scope. The models related to operational planning are classified into buyer and vendor coordination, production-distribution coordination, and inventory-distribution coordination; up to the time of this study, most researchers, because of limitations on computational capability, have decomposed such multi-stage problems into several two-stage problems which are then solved separately. Erenguc et al.

(1999) review the studies on managing supply chain networks with three distinct stages consisting of suppliers, plants, and distribution centers, and focus on the results for joint operational decision-making across the three stages. Decisions that need to be made jointly regarding optimizing production/distribution planning are discussed. Sarmiento and Nagi (1999) consider integrated production/distribution planning systems at both the strategic and tactical levels with an explicit consideration of transportation. They classify the problems based on the type of decisions being modeled (e.g. decisions on production, distribution, or inventory management) and on the number of locations per echelon in the model. Three categories of two-echelon models are identified, and the differences between such models and those in classical Inventory Routing studies are discussed. Fahimnia et al. (2008b) review existing production/distribution planning models and provide a table summarizing 19 papers according to problem attributes (e.g. numbers of plants, distribution centers, and customers, multi-periods, multi-products, routing), types of modeling approaches (e.g. mathematical programming, optimization, simulation and combinations of these), and the solution methods applied.

There are also two recent survey papers on integrated operations planning: Mula et al. (2010) and Fahimnia et al. (2013). Mula et al. (2010) cite 44 papers published since 1985 among the 54 references, and classify these works based on the decision levels (e.g. strategic, tactical, and operational), modeling approach (e.g., linear programming, and multi-objective integer linear programming), objective (e.g., total cost, and customer satisfaction), level of information sharing (e.g., production cost, lead time, inventory level, and demand), and solution methodologies. Fahimnia et al. (2013) cite 139 papers related to integrated operations planning, and classify these papers by two criteria:

complexity of the network structure and solution methodologies. Interestingly, in spite of the large number of references listed in these surveys, only 19 papers were common to both surveys. However, there is no analysis in either survey on the relationship between problem structures and the methodologies reported in these works.

Unlike the existing surveys, we focus here on the relationships between the problem structures and solution methodologies. Such a survey provides information to the researchers on the solution approaches, developed for solving problems defined over different types of network structures, and their effectiveness. We classify the integrated operations planning problems into two categories. For each category, we present a basic mathematical model and, based upon the properties of the respective network structure, analyze the existing solution methodologies. We define the two categories by deciding whether there is *time constraint* in the model. Most integrated operations planning problems involve multiple time periods. For each period, the ending inventory level, production quantity, and distribution amount must be determined. Since a continuous time scale within a period has to be considered in some studies to describe time constraints like arbitrary delivery deadlines or travel times, there is a need to model the time constraints explicitly. Note that without such explicit modeling of time constraints, as many studies in the past have done, we often have to assume that any quantity produced in one period is delivered to customers in the same period, which leads to a gap between the models and real-world practice. We categorize the problems into two categories in Table 2.1.

Table 2.1 Categories of the Integrated Operations Planning Problems

Issues in the Literature / Problem Categories	Production issues	Distribution issues	Time constrains
Production and Distribution Problem (PDP)	X	X	
PDP with Time Constraints (PDPT)	X	X	X

We also refer readers to another survey by Yossiri et al. (2012), in which the authors categorize the studies according to their inclusion of decision variables related to the flow quantity of production, inventory, distribution and routing.

The first part of the literature review about the IPDP is organized as follows: in Section 2.1.1, we introduce the basic assumptions of the integrated operations planning problems. In particular, the assumptions of two categories shown in Table 2.1, PDP and PDPT, will be presented. In Section 2.1.2, we focus on the studies and solution approaches for the integrated production and distribution problems (PDPs) that involve no time constraint; most of the papers from the related literature belong to this class of problems. In Section 2.1.3, we extend PDP to include time constraints. Discussions and future research directions for IPDP will be presented in Section 2.1.4.

2.1.1 Assumptions and preliminaries

In this section, we introduce the common assumptions and notation used to define the four categories of problems (PDP and PDPT). For each assumption, we then discuss the extensions or variations that are found in literature.

Product and Time Dimension:

- We consider the multi-product problem (i.e., with multiple commodities) over a given planning horizon of multiple time periods.

Network Structure and Material Flow:

- The supply chain network has three stages: manufacturers, distribution centers (DCs) and customers, as shown in Figure 2.1. Each customer has a certain demand to be fulfilled in each period. Both manufacturers and DCs hold inventories of products. Manufacturers produce and fill their own inventories, and send products to DCs, which in turn send the products to customers.

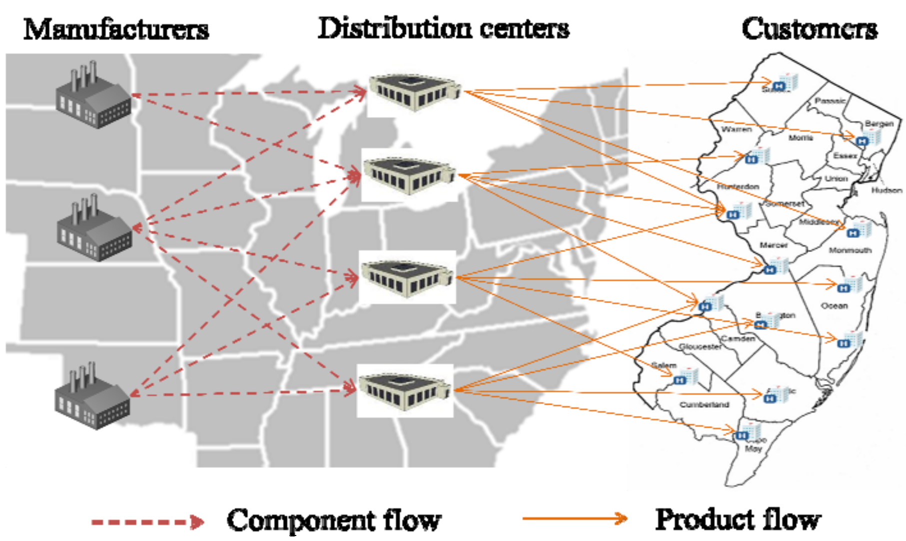


Figure 2.1 Network structure and material flows.

- *Extensions or variations in the literature*:
    - There exist suppliers to provide manufacturers with raw material.
    - There exist third parties that serve as contract manufacturers or DCs. The third parties usually charge higher prices than regular players.
    - In some cases, manufacturers may deliver the product directly to customers.

Production and Transportation Capacity:

- Each manufacturer has a maximum production capacity (i.e., the maximum quantity that it is able to produce) in each period. Both manufacturers and DCs have a maximum transportation capacity (i.e., the maximum outgoing flow quantity) in each period.
- *Extensions or variations in the literature*:
    - Manufacturer's production capacity can be increased at an additional fixed and/or variable cost (e.g., overtime work).
    - Transportation capacity can be defined by the vehicle attributes (e.g., the fleet size, the vehicle loading capacity, the maximum number of trips, and the total working hours in one period, etc.).

Customer Demand Fulfillment and On-time Delivery:

- All customer orders must be fulfilled on time, and no customer carries inventory.
- *Extensions or variations in the literature*:
    - If an order is not fulfilled on-time, it is lost (called a *lost-sale*).
    - If an order is not fulfilled on-time, it can be fulfilled later with a penalty cost (either as a backorder delivered in a subsequent period, or as a late shipment within the same period).

Cost Components:

- Each manufacturer has a fixed, and variable, cost of production, and each DC has a fixed, and variable, cost for handling the product. Both manufacturers and DCs incur inventory holding costs. The shipments from manufacturers to DCs, and from DCs to customers, result in a shipping cost.
- *Extensions or variations in the literature*:

- When raw materials are required, the purchase cost is considered.
- When a third party is involved, the respective costs (e.g., contract fees) are included.
- If a late delivery (backorder) is allowed, the relevant penalty cost is included.
- If a lost-sale is allowed, the shortage penalty is included.

While a representative mathematical model for each of the following sections is built upon these basic assumptions, its variations are introduced as we discuss individual papers.

Throughout this survey, we will use the following notation: let $M=\{m\}$, $B=\{i\}$, $J=\{j\}$ and $K=\{k\}$ denote the set of manufacturing facilities, the set of distribution/transshipment centers (DCs), the set of customers, and the set of products ordered by customers, respectively. When routing decisions are involved, let $V(m)$ denote the set of vehicles of manufacturer *m*. Let $T = \{t\}$ denote the set of periods. For simplicity, $\forall m$, $\forall i$, $\forall j$, $\forall k$, $\forall v$ and $\forall t$ may be used instead of $\forall m \in M$, $\forall i \in B$, $\forall j \in J$, $\forall k \in K$, $\forall v \in V(m)$ and $\forall t \in T$.

2.1.2 The production and distribution problem (PDP)

The **production and distribution problem**, or **PDP**, is primarily concerned with coordinating production and outbound distributions to minimize the total costs associated with production, inventory, and transportation over a discrete multi-period planning horizon. Since PDP does not explicitly include the routing and shipping times, the models for PDP involve only inventory flow balance, facility capacity and transportation capacity constraints (e.g., see Thomas and Griffin, 1996).

To formally define the mathematical model for the PDP, we introduce the following notation: for any given period t, let $C_{m,t}^{k}$ be the production capacity of manufacturer m for product k, $C_{a,b,t}$ be the transportation capacity from location a to location b for $(a,b) \in M \times B \cup B \times J$, and $d_{j,t}^{k}$ be the demand for product k by customer j. Let $I_{a,0}^{k}$ be the initial inventory of product k at location a for $a \in M \cup B \cup J$. For decision variables, let $W_{a,b,t}$ and $Z_{m,t}^{k}$, respectively, be the binary variables denoting the decision for a flow from location a to location b for $(a,b) \in M \times B \cup B \times J$ in period t, and the decision for a production batch for product k by manufacturer m in period t. Let S, Q, P, and I, each with proper superscript and subscript indices, be continuous variables denoting the shortage amount, flow quantity, production quantity, and inventory level, respectively. For example, $Q_{m,i,t}^{k}$ denotes the flow quantity of product k from manufacturer m to DC i in period t. In addition, we use $M||J$, and $B||J$, to denote a network involving only manufacturers and customers, and distribution centers and customers, respectively, and $M||B||J$ to denote a network involving all three stages. A basic PDP model can then be described as follows:

Minimize: $\quad \boldsymbol{G}(W_{m,i,t}, W_{i,j,t}, Z_{m,t}^{k}, S_{j,t}^{k}, Q_{m.i.t}^{k}, Q_{i,j,t}^{k}, P_{m,t}^{k}, I_{m,t}^{k}, I_{i,t}^{k}, I_{j,t}^{k})$ (2.1.2.1)

s.t.

$$I_{m,t-1}^{k} + P_{m,t}^{k} - \sum_{\forall i} Q_{m,i,t}^{k} = I_{m,t}^{k}, \qquad \forall m,k,t \tag{2.1.2.2}$$

$$I_{i,t-1}^{k} + \sum_{\forall m} Q_{m,i,t}^{k} - \sum_{\forall j} Q_{i,j,t}^{k} = I_{i,t}^{k}, \qquad \forall i,k,t \tag{2.1.2.3}$$

$$I^k_{j,t-1} + \sum\nolimits_{\forall i} Q^k_{i,j,t} - (d^k_{j,t} - S^k_{j,t}) = I^k_{j,t}, \qquad \forall j,k,t \qquad (2.1.2.4)$$

$$P^k_{m,t} \le C^k_{m,t} \cdot Z^k_{m,t}, \qquad \forall m,k,t \qquad (2.1.2.5)$$

$$\sum\nolimits_{\forall k} Q^k_{m,i,t} \le C_{m,i,t} \cdot W_{m,i,t}, \qquad \forall m,i,t \qquad (2.1.2.6)$$

$$\sum\nolimits_{\forall k} Q^k_{i,j,t} \le C_{i,j,t} \cdot W_{i,j,t}, \qquad \forall i,j,t \qquad (2.1.2.7)$$

$$W_{m,i,t}, W_{i,j,t}, Z^k_{m,t} \in \{0,1\}, \;\; S^k_{j,t}, Q^k_{m,i,t}, Q^k_{i,j,t}, P^k_{m,t}, I^k_{m,t}, I^k_{i,t}, I^k_{j,t} \ge 0 \qquad \forall m,i,j,k,t \qquad (2.1.2.8)$$

The objective function (2.1.2.1) minimizes the total operations cost, consisting of raw materials, facility setup, production, inventory, and transportation costs. Constraints (2.1.2.2) - (2.1.2.4) ensure the flow balances at the manufacturing facilities, DCs and customer sites, respectively, while constraints (2.1.2.5) - (2.1.2.7) are network capacity constraints.

While special cases of PDP, such as the classical transportation problem and the transshipment problem, can be solved in strongly polynomial time, the general version of the PDP is difficult to solve. More precisely, the multi-product PDP defined by (2.1.2.1) - (2.1.2.8) is strongly NP-hard, because a special case of this PDP is a multi-product multi-period lot-sizing problem which has been proved to be strongly NP-hard by Chen and Thizy (1990). Therefore, a general version of PDP could require an excessive amount of computational time to verify the solution optimality when the network size becomes large.

In this section, we focus on the existing solution methodologies for variations of the PDP defined by (2.1.2.1) - (2.1.2.8), and classify them into three categories. The first one is *heuristic and metaheuristic algorithms*, in which a solution (or a set of solutions) is constructed according to relatively simple rules and then improved through an iterative process. The other two are both mathematical programming-based solution approaches, and differ on how the PDP model is relaxed: *constraints relaxation approaches* and *variables relaxation approaches*. Note that while the routing decision is not considered in this section, we do include those problems that assume fixed routing.

Heuristic and Meta-heuristic Algorithms

Because of the intractability of the general PDP, feasible solutions with acceptable quality and minimal solution time have been commonly discussed in the literature. Representative solution approaches in this category are *greedy heuristics* and *genetic algorithms*.

Park (2005) proposes a two-phase heuristic for solving a multi-product PDP defined upon an $M||J$ network to maximize the total profit. The Phase I problem is formed by aggregating the demand of all customers in each period, defined by $D_t^k = \sum_{\forall j} d_{j,t}^k$ and then replacing constraint (2.1.2.4) by $I_{t-1}^k + Q_t^k - D_t^k = I_t^k$, $\forall k, t$, in the model, which reduces the problem to a single-customer multi-period model and allows one to quickly determine the values of $P_{m,t}^k$ by solving a production lot-sizing problem (Fumero and Vercellis, 1999) with constant production capacity. All unsatisfied demand is penalized as shortage and no backorder is considered. Given $P_{m,t}^k$, the author then solves a distribution problem in phase II to determine the values of $Q_{m,j,t}^k$, by applying a bin-packing heuristic together with local improvement procedures which consolidate partial loads by shifting shipping periods and reducing the level of stock-out using leftover production capacity. Through computational experiments on 21 test problems of three sizes, this heuristic achieves an error gap, or a difference between the optimal and heuristic solutions, of 5.6~6.8% for small-size cases and no more than 9.2% for all the test cases. The computation time is less than 3 seconds for small cases and no more than 1200 seconds for large cases.

Ahuja et al. (2007) study a two-echelon $M||J$ single product PDP with *single sourcing* constraint, which means that each customer receives shipment from at most one supplier in each period. In addition to constraints (2.1.2.2) - (2.1.2.7), the authors also include a constraint on inventory perishability, so that the maximum inventory time for the product is bounded by a given constant N. Thus, at any period t, the ending inventory at DC i, $i \in I$, cannot exceed its future demand from all customers in the next N periods, or $I_{i,t} \leq \sum_{n=1}^{N} \sum_{\forall j} Q_{i,j,t+n}$. The resulting PDP is decomposed into two sub-problems. One includes only binary facility-customer assignment variables, and the other includes variables for transportation flow and inventory levels. A proposed greedy heuristic is used to assign the facility-customer pairs, upon which a very-large-scale-neighborhood (VLSN) search heuristic is applied to improve the quality of the solution. Extensive tests on randomly generated problem sets are conducted, and the error gap obtained by comparing the heuristic with the best lower bound obtained by CPLEX within 15 minutes of CPU time is less than 3% in all cases. The authors also report that their error gaps have a decreasing tendency as the number of customers is increased, and it is less than 0.1 % in the largest size case. The computation time is less than 40 seconds in all cases.

Some researchers consider PDP with extensions such as fixed routes for transportation or direct shipment. Lei et al. (2006) investigate an integrated production, inventory and distribution routing problem encountered from the practices of after-merge operations of a chemical company. A two-phase approach is proposed, where the Phase I problem is defined by assuming direct shipment between manufacturing plants and customers. The assumptions on direct shipments allow the authors to solve an optimization problem with a significantly reduced complexity, which yields a feasible solution to the original problem. The problem in Phase II is to improve the solution from Phase I, and is modeled as a shortest path problem on a directed acyclic graph. An empirical study that evaluates the computational performance of this solution approach is also reported. Liu et al. (2008) study a multi-product packing and delivery problem with a single capacitated truck and a fixed sequence of customer locations. The authors first apply a network flow-based polynomial time algorithm to solve the problem assuming no split deliveries, and then allow the split delivery to improve the truck efficiency by using a greedy heuristic with a time complexity of $O(|J|^3 \log|J|)$. In both papers, optimal solutions of the special cases (with restriction) are modified to obtain feasible solutions to the original problems.

During the past two decades, the *genetic algorithm* (GA), inspired by the process of natural evolution, has been quickly gaining in popularity. In Jang et al. (2002), the problem of production and distribution planning over a three-echelon $M||B||J$ network is considered. Constraints similar to (2.1.2.1) - (2.1.2.7) are included and a material transform factor Γ is used to define the rate of raw materials consumption: $I_{m,t-1} + P_{m,t} - \sum_{\forall i} \Gamma_{mi} \cdot Q_{m,i,t} = I_{m,t}$, $\forall m,t$. The solution of the proposed GA algorithm is compared with that obtained by CPLEX. Among randomly generated test problems, the solution time of GA is quite stable, averaging from 334 to 546 seconds, while that required by the CPLEX solver exhibits exponential growth with respect to problem size, from 32 to 67,854 seconds to obtain the optimal solutions. The proposed GA also demonstrates strong performance, with an average error gap of 0.2%. Gen and Syarif (2005) propose a GA-based approach for their $M||J$ network. A new solution approach called the *spanning-tree-based genetic algorithm* is presented together with the fuzzy logic controller concept for auto-tuning the GA parameters. The proposed method is also compared with a traditional spanning-tree-based approach. This comparison shows that the proposed approach achieves a better result in every experiment, with an average improvement from 0.05% to 0.65% for six different settings. Kannan et al. (2010) develop an $M||B||J$ network model for battery recycling. Besides production, inventory and transportation cost, the objective function contains additional cost factors for recycling such as collection, disposal and reclaiming cost. The authors introduce a heuristic-based genetic algorithm to solve the problem and compare the result with that obtained by GAMS, a commercial solver. In experiments with different problem sizes and heuristic parameters (population and iteration), the maximum error observed is 7.4% compared with the results from GAMS. Moreover, the average computation time of the GA-based approach is less than 315 seconds for the largest problem while that by GAMS is at least 2800 seconds for the smallest problem.

Constraints Relaxation-Based Approaches

Another popular solution approach to PDP in the current literature is to relax a subset of constraints in order to make the relaxed problem easier to solve. The major approach in this regard is the well-known *Lagrangian relaxation,* by which difficult constraints are placed into the objective function with coefficients called Lagrangian multipliers so that the resulting problem is "easily solvable". One example of such an easily solvable problem is a network flow problem (Ahuja et al., 1993). Another important approach is based upon problem decomposition, by which a subset of constraints is temporarily simplified or removed from the original model to make the remaining problem decomposable. When a Lagrangian relaxation is adapted to achieve the decomposition, the resulting process is called *Lagrangian decomposition*. In constraints relaxation-based approaches, identifying the constraints to be relaxed and ensuring that the search converges to the optimal or near-optimal solution quickly are two critical steps for achieving the quality and effectiveness of such solution approaches. For example, in the basic model defined by (2.1.2.1) – (2.1.2.8), when we relax constraint (2.1.2.3) and incorporate it in the objective function with penalty factors, the problem is decomposed into two problems as follows:

- ***Minimize***: $\boldsymbol{G^1}(W_{m,i,t}, Z^k_{m,t}, Q^k_{m.i.t}, P^k_{m,t}, I^k_{m,t})$ s.t. (2.1.2.2), (2.1.2.5), (2.1.2.6)
- ***Minimize***: $\boldsymbol{G^2}(W_{i,j,t}, S^k_{j,t}, Q^k_{i,j,t}, I^k_{i,t}, I^k_{j,t})$ s.t. (2.1.2.4), (2.1.2.7), (2.1.2.8)

where both $\boldsymbol{G^1}$ and $\boldsymbol{G^2}$ include the penalty terms for violating constraint (2.1.2.3).

Yung et al. (2006) use constraints relaxation to solve a multi-product single-period PDP, and thus the time index t is dropped from all the notations, defined upon an $M||J$ network. Their study involves decisions on production and transportation, as well as on lot-sizing and order quantity. The average inventory level is used to define the inventory cost, and variables z^k_m and x^k_{mj} are added to denote production lot size and shipping quantity for product k. The model contains flow balance constraints similar to (2.1.2.2) – (2.1.2.4), and capacity constraints similar to (2.1.2.5) – (2.1.2.7). However, the objective function includes terms P_m^k / z_m^k as the number of production lots for product k at manufacturer m and terms Q_{mj}^k / x_{mj}^k as the number of shipments of product k from m to j, which lead to a non-linear objective function that is neither convex nor concave. In order to apply Lagrangian relaxation, an artificial variable R_{mj}, where:

$$\sum_k Q_{mj}^k = R_{mj} \tag{2.1.2.9}$$

is utilized, and redundant constraints $\sum_k P_m^k = \sum_j R_{mj}$, $\sum_k d_j^k = \sum_m R_{mj}$, and $0 \le R_{mj} \le \sum_k d_j^k$ are added to the model. By relaxing constraint (2.1.2.9), the original model is decomposed into two independent sub-models. The first one deals with joint decisions on production and lot-sizing and thus contains variables P_m^k , z_m^k and the aggregated transportation flow, R_{mj} . In the second model, the constraints for transportation planning involving Q_{mj}^k and ordering quantity x_{mj}^k are included. By continuously updating the Lagrangian multipliers and the artificial variables, two sub-problems are iteratively solved. The test result is compared with that obtained by Fmincon, a non-linear programming tool box in MATLAB 6.1. Among seven problem settings, Fmincon cannot terminate for three cases while the proposed algorithm is able to solve all the cases. In terms of the solution performance, the proposed algorithm saves 1.5% to 8% in cost, with less CPU time, over what Fmincon achieves for all the cases solved.

Eksioglu et al. (2007) consider a variation of multi-product multi-period PDP on an $M||J$ network where only the production facility carries an inventory and there are no capacity limits for inventory and transportation. The model contains flow balance constraints:

$$I^k_{m,t-1} + P^k_{m,t} - \sum\nolimits_{\forall j} Q^k_{m,j,t} = I^k_{m,t} \tag{2.1.2.10}$$

instead of (3.1) and (3.2). Since the model does not allow shortages, it has:

$$\sum\nolimits_{\forall m} Q^k_{m,j,t} = d^k_{j,t} \tag{2.1.2.11}$$

instead of (2.1.2.4), and capacity constraint (2.1.2.5) with binary indicator variables for production. Unlike the previous solution approach, which uses redundant aggregated variables, this approach introduces redundant disaggregated variables. The authors reformulate the original model by introducing a new variable $Q^k_{mjt\tau}$, which defines the amount of product k from manufacturer m to customer j to satisfy demand in period τ using the quantity produced in period t, where $t \le \tau$. Thus, the original variables can be expressed by new variables as follows:

$$P^k_{mt} = \sum\nolimits_{j=1}^{J} \sum\nolimits_{\tau=t}^{T} Q^k_{mjt\tau} \text{ , } \forall m,k,t \tag{2.1.2.12}$$

$$Q^k_{mjt} = \sum\nolimits_{s=1}^{t} Q^k_{mjst} \text{ , } \forall m, j, k, t \tag{2.1.2.13}$$

$$I^k_{mt} = \sum\nolimits_{j=1}^{J} \sum\nolimits_{s=1}^{t} \sum\nolimits_{\tau=t+1}^{T} Q^k_{mjs\tau} \text{ , } \forall m,k,t \tag{2.1.2.14}$$

By using constraints (2.1.2.12) – (2.1.2.13), the original model becomes a facility location problem. The authors then show that the linear programming (LP) relaxation of the location model provides a tighter lower bound than the LP relaxation of the original model. Lagrangian decomposition is applied to the resulting location problem by introducing $z^k_{mjt\tau}$, clone or copy of $Q^k_{mjt\tau}$:

$$Q^k_{mjt\tau} = z^k_{mjt\tau} \tag{2.1.2.15}$$

Accordingly, redundant constraints for $z^k_{mjt\tau}$:

$$\sum_{m=1}^{M}\sum_{t=1}^{\tau} z^k_{mjt\tau} = d^k_{j\tau} \tag{2.1.2.16}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{\tau=1}^{T} z^k_{mjt\tau} \le C_{mt} \tag{2.1.2.17}$$

$$z^k_{mjt\tau} \ge 0 \tag{2.1.2.18}$$

are then added into the model. By relaxing (2.1.2.15) using a Lagrangian multiplier, the model is decomposed into two sub-problems. The first one containing $Q^k_{mjt\tau}$ is an uncapacitated multi-product problem and is further decomposed into $|K|$ single product sub-sub-problems which are NP-hard but solvable by dynamic programming. On the other hand, the second one containing $z^k_{mjt\tau}$ can be modeled as an LP problem. For test problems of large sizes, the sub-problems are solved by using the primal-dual algorithm and the total running times vary from 4 to 87 CPU seconds with empirical error gaps no more than 5%.

Karakitsiou and Migdalas (2008) consider a single product PDP defined on an $M||J$ network. The model has flow balance constraints similar to (2.1.2.2) – (2.1.2.4), and capacity constraints similar to (2.1.2.5) – (2.1.2.7). Defining a new variable:

$$r_{m,t} = \sum_j Q_{m,j,t} \tag{2.1.2.19}$$

the inventory flow balance constraint at m is replaced by:

$$I_{m,t-1} + P_{m,t} - r_{m,t} = I_{i,t} \tag{2.1.2.20}$$

and the transportation capacity constraint is replaced by:

$$0 \le r_{m,t} \le C^S_{m,t} \tag{2.1.2.21}$$

where $C^S_{m,t}$ is the maximum outbound shipping quantity. Moreover, a redundant constraint:

$$\sum_m r_{m,t} = \sum_j d_{j,t} \tag{2.1.2.22}$$

is added. In order to apply Lagrangian decomposition, a clone variable of $r_{m,t}$, denoted as $z_{m,t}$, is introduced:

$$r_{m,t} = z_{m,t} \tag{2.1.2.23}$$

so that constraint (3.20) can be replaced by:

$$I_{m,t-1} + P_{m,t} - z_{m,t} = I_{i,t} \tag{2.1.2.24}$$

$$0 \le z_{m,t} \le C^S_{m,t} \tag{2.1.2.25}$$

By relaxing (2.1.2.23) and using Lagrangian multipliers, the original model is decomposed into two independent parts: the first one deals with variables $P_{m,t}$, $I_{i,t}$ and $z_{m,t}$ along with constraints (2.1.2.5), (2.1.2.24), and (2.1.2.25), while the second one deals with $Q_{m,j,t}$ and $r_{m,t}$ along with constraints (2.1.2.4), (2.1.2.19), (2.1.2.21) and (2.1.2.22). The first sub-problem can be further decomposed, over the manufacturing facilities, into $|M|$ sub-sub-problems that can each be modeled as a linear programming problem. The second sub-problem can also be further decomposed, over the time horizon, into $|T|$ sub-sub-problems, each as a network flow problem. In order to check the quality of the solutions produced by the Lagrangian relaxation, the results are compared with the optimal solution obtained by GLPK solver, a free and open source piece of software. For six randomly generated problems involving 30 to 1200 nodes, the empirical error gaps are no more than 6% and the required computation time is no more than 350 seconds.

Variables Relaxation-Based Approaches

During the past decade, the *variables relaxation*-based approaches, in which a selected subset of integer variables is relaxed so that the reduced problem can be relatively easy to solve, have gained a significant amount of attention from researchers. While the Lagrangian relaxation procedures aim at reducing the duality gaps, most variables relaxation-based approaches focus on reducing the sub-optimality due to rounding linear values to integers.

Dogan and Goetschalckx (1999) introduce a multi-product multi-period PDP model involving strategic decisions on the network and detailed production planning on the machine level along with deterministic seasonal customer demands. The network under consideration includes candidates for suppliers, potential manufacturing facilities, and DCs with multiple possible configurations and customers. The manufacturing facilities have alternative facility types, which introduce binary variables for the facility selections, and integer variables are used to define the number of machines used in each facility during each period. In addition to the ending inventory, the authors also consider the work-in-process inventory which defines part of the inventory holding cost. Replenishment of raw material may happen more than once during each period. Transportation flow quantities and production quantities on each machine at each facility are also decision variables. Benders decomposition is used as the solution methodology. In the mixed integer master problem, the status of the facilities, the production lines, and the production and inventory quantities are determined. The reduced problem becomes a minimum-cost transportation flow problem, and its optimal cost is added to the mixed integer master problem to find a feasible schedule satisfying the obtained flow cost. The search terminates when the master problem can find no lower cost solutions. For the real life problem that motivated this study, the proposed approach saves the company an additional 2% over the hierarchical approach, where optimal strategic and tactical decisions are made sequentially. The Benders decomposition solution method with acceleration techniques utilizing disaggregated cuts, dual variables and the LP relaxation in the initial iterations reduces the running time by a factor of 480, versus a standard Benders decomposition algorithm.

Yilmaz and Catay (2006) consider a variation of PDP involving a single product, multiple suppliers, multiple producers, and multiple distributors, with an option of capacity expansion at additional fixed and variable costs. New continuous variables representing increased capacity, and binary variables indicating capacity expansion decisions for transportation and facility, are introduced. Only manufacturers are allowed to carry inventory, and thus the inventory balance is only considered at the manufacturers' sites. Three different LP relaxation-based heuristics are used to solve the problem, and the relaxed variables are then adjusted to 0 or 1 according to different search mechanisms. The results are then compared with CPLEX solutions obtained with a 300-second time limit.

Another representative study on variables relaxation-based approaches is performed by Lei et al. (2009). The authors consider a single product multi-period PDP defined upon a $M||B||J$ network with both forward and reverse flows. Because of the need to model the reverse flow in the supply chain network, new constraints such as

$$H_{i,t-1} + \sum_{\forall j} R_{i,j,t} - \sum_{\forall m} R_{m,i,t} = H_{i,t}, \quad \forall i,t$$

are added, where variable *R* refers to the reverse flow quantity, and *H* refers to the reverse product inventory levels. A partial LP relaxation-based rolling horizon method is proposed. With this approach, a given multi-period planning horizon is partitioned into three intervals: the current period, the immediate next period, and a consolidated period covering all future time periods. In the first interval, all the original constraints and the integer requirements remain unchanged. For the second and the third intervals, only the integer requirements on the number of truck trips between the DC and customers are relaxed. To reduce the computational effort of each iteration, the forward and backward demands in the third interval are equal to the sum of the forward and backward demands of all the time periods in that interval, respectively. The ending inventories obtained from the solution to the first interval are then fixed as the beginning inventories for the second interval, and this process repeats by redefining intervals until all the time periods achieve integer solutions. Randomly generated test cases are used to benchmark the computational performance of the proposed algorithm against that obtained by the CPLEX within one-hour CPU time. Over 70 test cases are randomly generated, and the largest error gap observed is 0.16%, and the required computation time is less than 5 seconds; the average computation time required by CPLEX for solving these cases far exceeds 700 CPU seconds.

Remarks on PDP

In general, if the particular PDP problem being studied has a relatively simple structure, the well-known solution methodologies from the literature can often be effectively adapted. For example, when a PDP problem is defined on a two-stage supply chain network and the constraints are limited to those defined by (2.1.2.2) - (2.1.2.8), the original problem can be decomposed by either a sequential decomposition or Lagrangian decomposition, which allows the decomposed problem to be modeled as an easy-to-solve problem such as the lot-sizing problem, or a linear programming or network flow problem.

While not included in this survey, it should be pointed out that there has also been a significant amount of work in the literature focusing on production and distribution involving uncertainty in demand, processes, and/or supplies, for which stochastic and fuzzy models have been applied extensively. The difference between stochastic and fuzzy models is that a stochastic model usually follows a known probabilistic distribution, while a fuzzy model is described by a simple distribution, such as a triangular distribution, based on expert knowledge. Representative work in stochastic PDP can be found in studies by Park (2005), Aliev et al. (2007), Lejeune and Ruszczynski (2007), and Liang and Cheng (2009). Also note that while the exact methods have rarely been discussed in the literature for solving PDP problems, they could be appropriate if the problem has a special structure, such as that given by Wang et al. (2010).

2.1.3 The production and distribution problem with time constraints (PDPT)

PDP with time constraints (PDPT) is a natural extension of the PDP model, which explicitly takes into account production and transportation time and usually assumes a deadline for the shipment arrival to the customer. To define the shipment arrival times, additional notation must be introduced. Let r_m^k be the production rate for product k at manufacturer *m*. Let $\tau_{m,i}$ and $\tau_{i,j}$ be the transportation times from manufacturer *m* to DC *i,* and from DC *i* to customer *j,* respectively. Let $L_{j,t}$ be the deadline at customer site *j* in period *t,* by which time the shipment of commodities should have arrived at *j*; otherwise a shortage or tardiness cost would be incurred. Let *MM* be a very large positive number. The deadline constraints are defined as follows.

$$\frac{P_{m,t}^{k}}{r_{m}^{k}}+\tau_{m,i}+\tau_{i,j}-(3-Z_{m,t}^{k}-W_{m,i,t}-W_{i,j,t})MM\le L_{j,t}\quad \forall m,i,j,k,t \tag{2.1.3.1}$$

The basic PDPT model is defined by (2.1.2.1) - (2.1.2.8) and (2.1.3.1).

Some papers study PDPT problems involving production lead times and delivery lead times over a multi-period planning horizon. Let $l_{m,i}$ and $l_{i,j}$ represent lead times from manufacturer *m* to DC *i*, and from DC *i* to customer *j*, respectively. In this case, (2.1.2.2) – (2.1.2.4) should be replaced by the following constraints.

$$I_{m,t-1}^{k}+P_{m,t}^{k}-\sum\nolimits_{\forall i}Q_{m,i,t}^{k}=I_{m,t}^{k}, \qquad \forall m,k,t \tag{2.1.3.2}$$

$$I_{i,t-1}^{k}+\sum\nolimits_{\forall i}Q_{m,i,t-l_{m,i}}^{k}-\sum\nolimits_{\forall i}Q_{i,j,t}^{k}=I_{i,t}^{k}, \qquad \forall i,k,t \tag{2.1.3.3}$$

$$I_{j,t-1}^{k}+\sum\nolimits_{\forall i}Q_{i,j,t-l_{i,j}}^{k}-(d_{j,t}^{k}-S_{j,t}^{k})=I_{j,t}^{k}, \qquad \forall j,k,t \tag{2.1.3.4}$$

Due to the complexity of PDPT, using a single methodology, such as a Lagrangian relaxation or a simple heuristic algorithm, may not be effective enough to solve the problem. In the literature, two major approaches have been discussed. One is iteration-based, and starts with an initial solution (or a group of solutions), and then continuously improves the solution (or a set of solutions) iteratively by a relatively simple procedure; most metaheuristic-based algorithms belong to this category. The other is to formulate the original problem into a mathematical model and then use optimization software to derive the optimal or near-optimal solutions. The latter approach has typically been used for solving some case-specific problems.

There are also several papers using simulations to deal with PDPT involving uncertainty. Most such studies (e.g., Lee et al., 2002; Lee and Kim, 2002; and Safaei et al., 2010) start with a deterministic version of the problem and solve it to find an initial solution. Through simulation, the solution is evaluated and the parameters of the respective deterministic problem are modified until the solution stabilizes. In this survey, we only include such simulation studies that report on the approaches to solve respective deterministic versions of the PDPT problem.

In this section, we focus on the existing solution methodologies for solving PDPT. Two categories of solution approaches are reviewed: 1) *metaheuristic and iterative approach,* and 2) *mathematical modeling and the use of an optimization solver*. Again, we do not consider detailed routing decisions in this section, and hence we treat all transportation operations as direct shipping or fixed routing.

Metaheuristic and Iterative Approach

Naso et al. (2007) consider the integrated problem of finding an optimal schedule for the just-in-time (JIT) production and delivery of ready-mixed concrete with manufacturers and customers. The study involves a single product in a single period with no inventory permitted. Times required for the loading, unloading and shipping operations of each truck must be explicitly modeled. In addition, outsourcing options of production and third-party (or overtime) trucks are permitted at an additional cost. All decision variables are binary, where $x_{jvr} = 1$ if job *j* is assigned to truck *v* as the *r*-th task: $y_{mj} = 1$ if job *j* is produced at manufacturer *m*, and $y_{oj} = 1$ if job *j* is outsourced. The scheduling algorithm combines a GA and a set of constructive heuristics, which are guaranteed to terminate in a feasible schedule for any given set of jobs.

Gebennini et al. (2009) consider a multi-period strategic and operational planning problem for a single manufacturer that offers a single product with uncertain demand on an *M*||*B*||*J* network. Production lead times and delivery lead times are considered, where lead time may be an integer multiple of one time period, and inventory and stockout costs are considered with safety stock (SS) determination. Thus, the problem to minimize the total cost is modeled as a mixed-integer non-linear programming problem in which the objective function includes a non-linear term representing the SS cost, $\sum_{i \in B} c_i^s \hat{k} \sqrt{\sum_{j \in J} \hat{\sigma}_{ij}^2 \vartheta_{ij}}$ where c_i^s is the inventory cost for DC *i*, $\hat{k}$ is a safety factor to control the customer service level, $\hat{\sigma}_{ij}^2$ is the combined variance at DC *i* serving customer *j*, and ϑ_{ij} is a 0-1 decision variable equal to 1 if DC *i* supplies customer *j* in any time period. This non-linear term is linearized to $\sum_{i \in B} \sum_{j \in J} c_i^s \frac{1}{SS_i} \hat{k}^2 \hat{\sigma}_{ij}^2 \vartheta_{ij}$ where SS_i is a lower bound on the optimal amount of SS carried at DC *i,* because the closer SS_i is to the optimal SS level at DC *i*, the closer the formula is to the optimal SS cost. A recursive procedure based on the modified linear model is developed in order to find an admissible solution to the non-linear model and quantify the minimized global logistic cost, while also taking the effect of safety-stock management into consideration. Since the optimal safety-stock level is unknown, the value is initially set to a lower bound on the effective safety-stock quantity for each DC. It is claimed that the proposed recursive procedure converges to the global optimal solution of the original non-linear problem in a finite number of iterations.

Yimer and Demirli (2010) address a multi-period, multi-product scheduling problem in a multi-stage build-to-order supply chain manufacturing system with consideration of lead times for production and delivery. For the sake of efficient modeling performance, the entire problem is first decomposed into two sub-problems: 1) an upstream part: from suppliers through fabricators to manufacturers, and 2) a downstream part: from manufacturers through distributors and retailers to customers. Both sub-problems are then formulated as MIP models with the objective of minimizing the associated aggregate costs while improving customer satisfaction. A GA-based heuristic is proposed with a chromosome of three parts: 1) product ID, total production quantity at each plant, and inventory level at each DC in the period; 2) flow proportion floating values; and 3) status values for feasibility. If a candidate solution is infeasible, it is revised by a proposed repairing heuristic. The fitness value is measured by the original objective function value and the degree of infeasibility. Using some test instances, the best solutions obtained from GA are of high quality compared with the lower bounds obtained from LINGO, a non-linear programming solver.

Sabri and Beamon (2000) develop an integrated multi-objective supply chain model that facilitates simultaneous strategic and operational planning using an iterative method in a four-tier network. They consider stochastic demand and capacity constraints in all layers of the supply chain, and shortages are allowed but penalized, while a fixed setup production cost is incurred. Total production lead time at manufacturer m for product k is $g_m^k + \frac{Q_m^k}{r_m^k} + l_m^k + \theta_m^k$ where $g_m^k, Q_m^k, r_m^k, l_m^k$ and θ_m^k are production setup time, production quantity, production rate, waiting time, and material delay time respectively. θ_m^k is determined by the bill of material of product k and customer service level. They first find a solution for the strategic model and then use the solution as an input to solve the operational model. New parameters determined in solving the operational model are used to solve the strategic model, and this iteration terminates when all binary variables no longer change. LINGO is used in solving each sub-problem.

Mathematical Modeling and the Use of Optimization Solver

While some researchers try to develop effective solution methodologies to solve the PDPT, others put more effort into the modeling process. In this subsection, we summarize research in which the models are solved by mathematical optimization software such as CPLEX. The common feature of the following papers is that the authors concentrate on the models rather than the design of methodologies. The size of the computational testing instances is small enough for the solver to handle, or the problem comes from real world practice so that the solution by a solver is applicable.

Rizk et al. (2006) examine a multiple-product production–distribution planning problem with a single manufacturer and a single destination. The manufacturer operates a serial production process with a bottleneck stage, subject to a predetermined production sequence. The manufacturing cost consists of the changeover cost of intermediate products and the inventory holding cost of final products. The transportation cost is characterized by a general piecewise linear function of transportation quantity with break points of Λ_h with $\Lambda_0 = 0$. In the h-th interval $(\Lambda_{h-1}, \Lambda_h]$, let v_h be the slope of its straight line, A_h be the discontinuity gap at the beginning of the interval and E_h be the ending value. Thus, the transportation cost is $z(\Lambda) = (E_{h-1} + A_h) + v_h \lambda_h$, $\lambda_h = \Lambda - \Lambda_{h-1}$. Valid inequalities to strengthen these formulations are proposed and the strategy of adding extra 0–1 variables to improve the branching process is examined.

Chen and Lee (2004) investigate a multi-period simultaneous optimization of multiple conflict objectives with market demand uncertainties and uncertain product prices in a supply chain network consisting of manufacturers, DCs, retailers and customers. The scenario-based approach is adopted for modeling uncertain market demands, and the product prices are taken as fuzzy variables where the incompatible preference on prices for different participants are handled simultaneously. The whole model becomes a mixed-integer non-linear programming problem to compromise fair profit distribution, safe inventory levels, maximum customer service levels, and decision robustness to uncertain product demands. Incompatible preference of product prices for all participants will be determined by applying the fuzzy multi-objective optimization method. Non-linear MIP solvers, DICOPT and CONOPT, are used for the numerical example.

Dhaenens-Flipo and Finke (2001) provide a multiple period model on an $M||B||J$ network which comes from a practical case at the European industrial division of the manufacturer. Since switching from one product to another on a production line may take a long time, it is assumed that at most one switching per period and per production line is allowed. There are three aggregated products and three line types according to capability to handle these products. All possible sequences in each manufacturing line are enumerated, and they are used in a mixed integer programming model. The set of available product sequences of the line m is denoted by $S(m)$ and these sequences are indexed by s. At this stage, the data involved concerns the total production time (B_m) available on line m, the production time (TP_m^k) and cost (CP_m^k) of product k on line m, the changeover time (TC_{sm}) and the cost (CC_{sm}) associated with the products of sequence s on line m. Let p_m^k be a quantity of product k manufactured on line m, and let y_{sm} be 1 if sequence s is chosen for the line m. Thus, we need to add the following constraints:

$$\sum_{s \in S(m)} y_{sm} = 1 \qquad \forall m \tag{2.1.3.5}$$

$$p_m^k - \sum_{s \in S(m): k \in s} y_{sm} \times B_m / TP_m^k \leq 0 \quad \forall m, \forall k \tag{2.1.3.6}$$

$$\sum_k p_m^k \times TP_m^k + \sum_{s \in S(m)} y_{sm} \times TC_{sm} \leq B_m \qquad \forall m \tag{2.1.3.7}$$

The proposed MIP has constraints (2.1.3.5) - (2.1.3.7), flow balance equations similar to (2.1.2.2) - (2.1.2.4), and domain constraints. For problems of industrial sizes, the model is able to provide a sub-optimal solution in less than 2 hours (23 minutes on the average) by CPLEX.

Fahimnia et al. (2008a) survey 20 papers and define a representative mixed integer program formulation for the integration of an aggregate production and distribution plan on an $M||B||J$ network. Three production alternatives are considered: regular-time production, overtime production, or outsourcing. They illustrate with an example to show that considering production alternatives can give a more accurate and better schedule than considering average production cost.

Remarks on PDPT

Lagrangian relaxations and decomposition-based techniques are not effective for solving the general PDPT problems because newly added time constraints often change the model structure significantly. The production and transportation time as well as the incurred deadline constraints all add more complexities to the original PDP, since a feasible solution for a PDP may violate the deadline constraint in PDPT. Even after a PDPT is decomposed, the resulting sub-problems may still be NP-hard and therefore make Lagrangian relaxation and decomposition-based solution approaches fail to function effectively. Therefore, most literature results reported are either customized solution approaches for specific PDPTs or efficient algorithms for solving some special cases of PDPT.

2.1.4 Discussion

In a realistic situation, such as multi-product, multi-echelon production and distribution, the problem under consideration has a complicated structure with a huge size. Moreover, each problem surveyed has its unique assumptions and definitions. Various approaches are considered and analyzed for different problems, and therefore it is very difficult to propose an integrated view of the entire set of methodologies. In this section, we provide three different perspectives. The first is to classify the solution approaches with a perspective on the decomposition framework, and solution methodologies applied to the decomposed sub-problems. The second is to relate the problem structure to the utilized solution approaches. The last is to address future research directions.

Structure of Solution Approach

Most problems in the literature are computationally difficult to solve optimally, and thus different decomposition approaches are utilized. When the problem is decomposed, the optimality of the problem may not be guaranteed, but each decomposed problem is much easier to solve and can sometimes be solved effectively (e.g., optimally or near-optimally) and efficiently (e.g., in polynomial time or in pseudo-polynomial time). Moreover, after the original problem is decomposed into sub-problems, each sub-problem can be further decomposed according to the structure of the sub-problem. The overall framework of the solution methodology in terms of decomposition has the following three categories.

1) *No Decomposition*: The entire problem is solved at once.
2) *Mathematical Decomposition*: The original problem is decomposed according to mathematical properties. Two representative decompositions are *Lagrangian decomposition* and *Benders decomposition*. In Lagrangian decomposition, some of the constraints are relaxed by Lagrangian relaxation and the problem under consideration can be decomposed into independent sub-problems. In Benders decomposition, some of the variables are fixed and the problem can be decomposed.
3) *Heuristic Decomposition*: The original problem is decomposed according to problem-specific properties. A common method is to decompose the problem with respect to layers. Thus, the upstream problem and the downstream problem are separately defined. Another method is to decompose the original problem into a strategic problem and an operational problem.

When the problem (or decomposed sub-problem) cannot be further decomposed, or is going to be solved directly, several approaches are utilized. The major solution approaches in the literature can be summarized:

1) *Exact Algorithm Development*: When the problem (or sub-problem) can be formulated as a problem which has a known optimal algorithm in polynomial time (or pseudo-polynomial time), it can be solved optimally. Typical examples are Network Flow Problems, Linear Programming (LP), and Dynamic Programming.
2) *Modeling with an Optimization Solver*: Some papers describe the problem with an exact mathematical formulation, such as Linear Programming (LP), Non-linear Programming (NLP), and Mixed Integer Programming (MIP), and solve it with an optimization solver. When the problem size is small enough or the problem has unique properties, optimal solutions can be obtained in a reasonable time frame. Various optimization solvers are found in the literature, such as CPLEX, GAMS, AMPL, LINGO, and GLPK. In order to strengthen the formulation, additional constraints, such as valid inequalities, can be inserted. In most cases, an approximate solution by an optimization solver is acceptable, given the error limit or running time limit.
3) *Mathematical Programming Approach*: When the sub-problem is still too hard to be solved optimally, there are several approaches utilizing mathematical programming techniques. Representative methods are Lagrangian relaxation and LP relaxation.
4) *Metaheuristic*: Metaheuristics iteratively improve a candidate solution with regard to a given measure of quality. A metaheuristic makes few or no assumptions

about the problem being optimized and can search very large spaces of candidate solutions. However, it does not guarantee that an optimal solution is ever found. The solution quality and running times are highly dependent on the setup parameters for the metaheuristic approach. Examples are Local Search (e.g., Tabu Search, Simulated Annealing), Evolutionary Algorithms (e.g., Genetic Algorithm), and Swarm Intelligence (e.g., Particle Swarm Optimization, Ant Colony Optimization).

5) *Problem-Specific Algorithms*: According to the problem-specific property, an algorithm can be developed only for the particular problem. In many cases, values of variables are sequentially decided. A representative one is a greedy algorithm, which makes a locally optimal choice at each stage with the hope of finding a global optimum. After obtaining a solution, a local improvement procedure may be applied.

Figure 2.2 gives an overview of the existing procedures for solving the integrated problem. If a problem is directly solvable, it can be solved using an exact method. Otherwise, we may try to decompose it into multiple sub-problems with minor changes from the original problem, or try to use other solution approaches. If the problem is decomposed, sub-problems can be solved separately and each of them is considered as an independent problem. Then, we can iteratively check whether the sub-problems are directly solvable or further decomposable. If the problem (or sub-problem) is not decomposable or we do not attempt to further decompose it, several solution approaches are applicable.

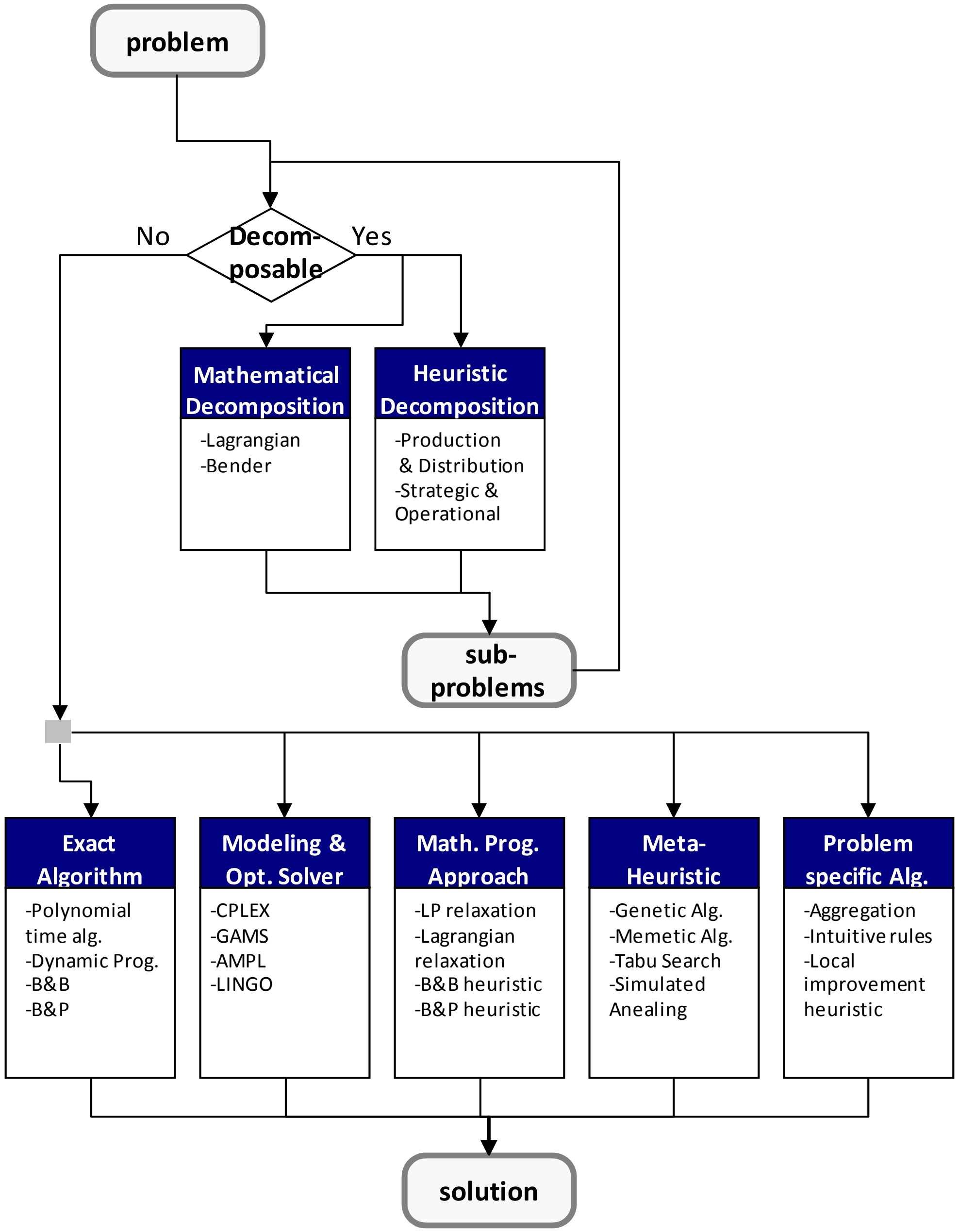


Figure 2.2 An overview of existing procedures for solving the integrated problem.

Based on the above classification, the solution approaches used in the literature surveyed in this paper can be classified in Table 2.2. We make the following observations:

- When the problem is solved without decomposition, the two major methodologies are modeling with an optimization solver, and a metaheuristic, in which the structural property is not well-utilized.
- When a mathematical decomposition is utilized as an overall framework, the sub-problem is always solved by mathematical programming methods for optimal or approximate solutions. In other words, if one would like to apply mathematical decomposition, sub-problems should be able to be well-handled by mathematical programming methods.
- When the problem is heuristically decomposed, metaheuristic and problem-specific heuristics are frequently used.

Table 2.2 Summary of solution approaches.

Overall framework / ***Sub-problem Methodology***	***No Decomposition***	***Mathematical Decomposition***	***Heuristic Decomposition***
Modeling with Optimization Solver	Rizk et al. (2006) Chen and Lee (2004) Dhaenens-Flipo and Finke (2001) Fahimnia et al. (2008a)		Sabri and Beamon (2000)
Exact Algorithm Development		Yung et al. (2006) Eksioglu et al. (2007) Karakitsiou and Migdalas (2008) Dogan and Goetschalckx (1999)	
Mathematical Programming Approach	Yilmaz and Catay (2006) Lei et al. (2009)	Fumero and Vercellis (1999)	
Metaheuristic	Jang et al. (2002) Gen and Syarif (2005)		Ahuja et al. (2007) Yimer and Demirli (2010)

	Kannan et al. (2010) Naso et al. (2007)	Yossiri et al. (2012)
Problem-Specific Algorithm	Lei et al. (2006) Liu et al. (2008) Gebennini et al. (2009)	Park (2005) Lei et al. (2006)

Problem Structure and Solution Approaches

In the reviewed papers, along with their problem structure and methodologies used, when routing is involved as a part of the decision, the problem includes a vehicle routing problem (VRP), which is one of the well-known difficult combinatorial optimization problems. Thus, we separately discuss the problems where routing is considered, and those where it is not.

The methodologies for PDP and PDPT are different.

- The major solution methodology for PDP is to use Lagrangian decomposition as a framework and mathematical programming for the decomposed problems. Especially when the PDP is defined on a supply chain network with two stages, Lagrangian decomposition works very well, because the sub-problems can be solved optimally. However, when PDP is defined on a network with three or more stages, Lagrangian decomposition is rarely used.
- The major methodology of PDPT is to establish a mathematical model without decomposition and use an optimization solver. Half of the papers dealing with PDPT use an optimization solver, even though some mathematical models are non-linear, while no papers use mathematical programming for overall or decomposed problems. The reason is that the problem with time constraints can be clearly defined in a mathematical model, but the time constraints make it

difficult to utilize the mathematical structure for mathematical programming-type algorithm development.

In addition, we observe the following relationships between problem structure and methodologies used:

- The mathematical programming approach works better for problems without time constraints.
- When the problem structure is complicated, problem-specific algorithms and local improvement heuristics are frequently used.
- Metaheuristics can be applied for most problem structures.

Future Research Directions

The trend in solution approaches for modern supply chain operations is to use a hybrid methodology, by combining the aforementioned methods and the use of a simulation as a framework, especially for practical and large-scale problems. When a simulation is used as a framework for solving the problem, a mathematical model is first established by relaxing some uncertain factors and solved with a variety of approaches. Its solution is then used as the input to the simulation model, then incorporated with different uncertainty sources such as demand, facility failure, delivery time, etc., and the output of the simulation model gives feedback for the parameters of the mathematical model to be revised accordingly. This procedure can be repeated until the obtained solution is efficient and robust.

In most of the literature, we find that stochastic factors are seldom incorporated in the models with time constraints and routing issues. Most papers dealing with routing issues only consider a supply chain with at most two or three echelons. A third party is not considered by most models, and when it is considered, it usually has unlimited or very large capacity and zero or very short lead time. Thus, future research may be directed towards an extension of the models to cover more general cases.

One of most promising directions is to construct a general framework to deal with an integrated problem of a practical size. Each component of the framework should be separately modeled and possible solution methodologies should be proposed; the decision process, including information granularity and the decision period, should be carefully designed. We may need to consider more qualitative decisions beyond the total cost. A big company may prefer amicable small companies as its partners even though they are not currently cost-effective. Alternatively, an industry-dependent framework is a possible direction. For example, the supply chain network in electronic manufacturing might have a general framework to handle various operations-level decisions.

In this literature review, the focus has been on a collaborative environment such that all information is shared and a decision is made by a central authority and applied to all players in the supply chain. In practice, each player (or group of players) may pursue its own objective and all players may not try to achieve the global optimal. Even though all or some try to collaborate together, information sharing can be a critical issue. Each entity may have a different management policy in terms of a given information item, sharing scheme, updating period, etc. Although a competitive supply chain has been studied in the past decade, researchers have generally assumed only two echelons: either suppliers and manufacturers or manufacturers and retailers. In the case where competition exists across the entire supply chain, or in a part of the supply chain, the global optimum may differ significantly from the local optimum. Thus, a game-theoretic approach to modeling and solving competitive but integrated supply chain problems may also be a promising area for future research.

2.2 Emergency Operations Scheduling of Relief Supply Chain

In the second part of the literature review, we survey recent work in the field of emergency operations scheduling in disaster relief specifically, based on which we will then compare commercial supply chain operations and emergency operations of relief supply chain, discuss gaps in this field, and propose directions for related research. The literatures will be reviewed in Section 2.2.1 and the discussion presented in Section 2.2.2.

2.2.1 Literatures

There have been significant efforts devoted by researchers to emergency operations of relief supply chains during the past two decades. Altay and Green (2006) discuss the potential applications of operations research (OR) in the field of disaster operations management. They reviewed related literatures and categorized the results through four programmatic phases in emergency management: mitigation, preparedness, response and recovery. According to their report, a majority of the papers were on mitigation while fewer were on the remaining categories. Caunhye et al. (2012) conduct a comprehensive review on the applications of operations research to emergency logistics. The scope of their review includes pre-disaster planning about facility locations, stock pre-positioning, evacuations, and short-term post-disaster planning about resource allocations, commodity flows, and a combination of both. They also categorize the literature into those related to facility locations and those related to relief distribution and casualty transportation. They point out the lack of models for explicit response time minimization because of the potential complexity for tracking response time, and that computation efficiency is a main reason for the absence of comprehensive operations models for emergency logistics. The review by Galindo and Batta (2013) is a continuation of Altay and Green (2006) which evaluates how research in disaster operations management has evolved since then.

There have been quite a few studies on specific disaster relief operations in practice. Haghani and Oh (1996) study a logistics problem encountered in disaster relief management. In their paper, a logistics network with multi-commodity, multi-modal and time constraints is transformed into a time-space network, upon which a mixed integer programming model was formulated. Two heuristics are proposed: one resorts to Lagrangian decomposition by exploring the network structure property, and the other uses linear programming relaxation. Barbarosoglu et al. (2002) develop a mathematical model for helicopter mission planning during disaster relief operations. The planning includes both tactical decisions and operations decisions. The authors propose a two-level framework including two mixed integer programming models: the top level covers helicopter fleet determination, helicopter crew assignment and tour numbers determination to minimize the total cost, while the bottom level covers the helicopter routing, transportation and refueling to minimize the make span. An iterative coordination process is used to generate non-dominant solutions for the multi-objective problem and then an interactive procedure is proposed for decision-making to choose the best feasible solution. Özdamar et al. (2004) study the dynamic time-dependent transportation problem that is solved repetitively at given time intervals during emergency logistics planning. Their model integrates the multi-commodity network flow problem and the vehicle routing problem (VRP). The authors also discuss the differences between the VRP in a regular scenario and that in an emergency situation. Vehicles are treated as commodities in their study. Therefore the problem is modeled as a multi-period multi-commodity network flow problem with arc capacities as variables instead of parameters (imposed by the capacity of vehicles). A Lagrangian decomposition based iterative methodology is proposed to solve the problem. Sheu (2007) works on relief distribution in the crucial rescue periods after a disaster, and proposes a three-tier network with relief suppliers, urgent relief distribution centers and relief-demanding areas. The affected areas are grouped according to the urgency extent, where the urgency attribute is measured by a fuzzy method. A two-stage demand-driven multi-objective (demand fill rate and time-varying distribution cost) dynamic programming optimization model is proposed, with one stage for the distribution between relief suppliers and distribution centers and the other for the distribution between distribution centers and the affected areas. Yi and Özdamar (2007) consider the evacuation planning of wounded people and location selection for temporary medical centers. By further extending the model of Özdamar et al. (2004), the authors treat vehicles as commodities to avoid individual tracking of each vehicle. After the initial solution is obtained, they solve a system of linear equations to extract from the optimal solution an exact schedule for each vehicle in pseudo-polynomial time. The location problem is also coped with implicitly by allocating optimal service rates to medical centers. The two-stage procedure is shown to be computationally more efficient comparing to a VRP based single-stage formulation. More recently, Lee et al. (2013a) presents a structural analysis for an emergency logistics optimization problem involving both renewable resources (medical teams that perform treatments to the patients in shelters after a disaster) and non-renewable resources (medical and emergency supplies).

2.2.2 Discussion

Based on the literature we surveyed, there are some major differences between the operations of commercial supply chains and emergency supply chains for disaster relief. First of all, the two have different goals. The main purpose of the commercial supply chain operations is to reduce the operations cost. Compared to that, the emergency supply chain operations emphasize responsiveness after a disaster and aims to provide timely supplies of relief resources. Second, commercial supply chains have relatively complete information regarding the supporting system including highway, truck capacity, facility status, etc, but emergency supply chains frequently deal with fragmented and limited information after a disaster. For example, planned shipping could be seriously delayed because of disruptions in the transportation system. Also, the demands of commercial supply chain are more stable and predictable: as a result, the volume of commercial logistical activities is usually large but has a repeating pattern. On the other hand, the demands in disaster relief are highly uncertain, and it is hard to forecast them effectively. The volume of logistical activities typically spikes up after the disaster hits, and tapers off as time goes by.

These differences lead to changes in the modeling and solution methodology for emergency supply chain operations, and open up new research topics. Several research gaps are mentioned in the literature. Altay and Green (2006) point out that the organizational and network structure in emergency supply chains are not well defined, and some assumptions in the current literature are not realistic or reasonable. Later on, the survey by Galindo and Batta (2013) further discuss these gaps. Also, there is a lack of a comprehensive model for the overall emergency supply chain, as many of them only focus on a part of the whole supply chain, either relief goods distributions, inventory preposition/management, or helicopter/truck scheduling and routing, etc. Caunhye et al. (2012) suggest that the reason for this is the potential computational complexity of a large comprehensive model. Therefore, proposing efficient and practical solution methodologies is also of great interest for further research. Our work in this dissertation aims to contribute to one or more of the topics discussed above.

CHPATER 3 A FORMAL DEFINITION OF PROBLEM P

The key problem for the present study is defined upon a three-stage supply chain network (see Figure 3.1) encountered in a real life project performed by Rutgers Center for Supply Chain Management (Lei, et al., 2012). The network consists of customer demand points, regional distribution centers (DC), manufacturers, and suppliers of components used in the rescue kit assemblies. The network produces and delivers both *standard* and *customized* rescue kits subject to non-negligible lead times and order delivery deadlines. All rescue kits are assembled according to their respective bill of materials (BOMs).

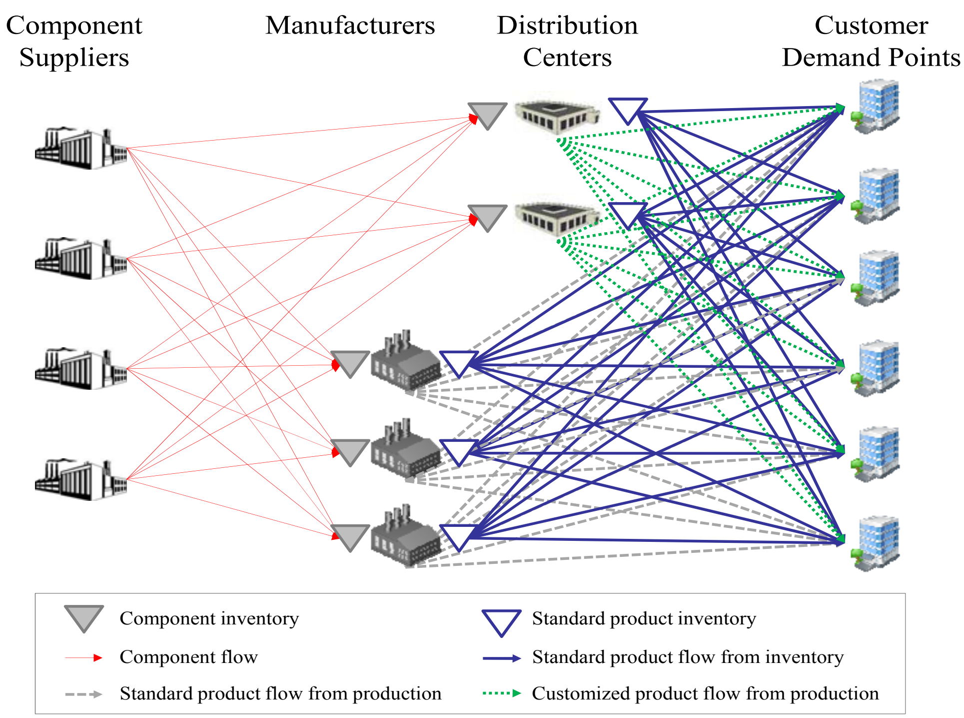


Figure 3.1 A hypothetical three-stage supply chain network of problem P.

Customer demand points that, without loss of generality, each customer *h* has two orders, one is for the standard rescue kits with order quantity $D_h \geq 0$, and the other is for customized rescue kits with order quantity $\widetilde{D}_h \geq 0$. When $\widetilde{D}_h = 0$, $D_h > 0$, $\forall h$, our problem reduces to the one with a single product and customer-dependent order sizes. However, when $\widetilde{D}_h > 0$, $D_h = 0$, $\forall h$, our problem becomes the one with heterogeneous products and customer-dependent order sizes. Let T_h be the delivery deadline specified by customer *h* so that any delivery after T_h will result in a penalty proportional to the tardiness and the order quantity. The order for standard rescue kits can be fulfilled by existing inventories at manufacturers and DCs, and newly produced batches by manufacturers. The network does not carry any inventory for customized kits, so orders for customized rescue kits can only be fulfilled by make–to–order assembly operations performed at DCs. Let H be the set of customers.

Capacitated manufacturers that each is able to assemble standard rescue kits and ship directly to customers (without going through any DC) because of the urgency of shipments. Each manufacturer carries an outbound inventory of standard rescue kits as well as inbound inventories of raw materials (i.e., components for the assembly operations) that can be used to make more standard kits. When the outbound inventory is not enough to fulfill the customer orders, a manufacturer may produce a new batch of standard rescue kits. When the inbound inventories for certain components are not enough for the new batch, additional shipments from the suppliers must be made which imposes, however, additional lead times. Let M be the set of manufacturers.

Regional Distribution centers (DCs) have the responsibility to produce and deliver customized rescue kits (because they are closer to affected areas and have more information about local needs). In practices, such DCs could also be manufacturers for customized products who donate directly or collaborate with a NGO. For example, during Typhoon Haiyan, Amway at Manila assembled 10,000 disaster relief kits and designated them for the Philippines (Source:http://chiefexecutive.net/typhoon-haiyan-corporate-donations-list). Whenever the inbound inventory of components is not enough for a new assembly operation, a DC places orders of additional supplies from respective component suppliers, which again results in additional lead times. Each DC only carries an inventory of standard rescue kits (which were pre-positioned before the disaster), and does not produce standard rescue kits. Let K denote the set of regional DCs in the network.

Capacitated component suppliers that each produces, inventories, and delivers a particular component to support the assembly needs of manufacturers (for standard rescue kits) and DCs (for customized rescue kits). Each supplier has an outbound inventory of a particular finished component. Whenever the outbound inventory is not enough, a new batch of a component will be produced by the supplier, which however extends the lead time to fulfill the replenishment orders from manufacturers and/or DCs. Let S be the set of component suppliers.

Our problem is to 1) allocate the outbound inventories for standard kits, at both manufacturers and DCs, to customers; 2) assign customized orders to DCs; 3) decide the batch size, and which customers will be served by the new batch of standard kits produced by each manufacturer, so that the total weighted tardiness in customer order fulfillment is minimized. Note that while we introduced these assumptions for an emergency operation, our study can also be generalized to a non-emergency situation. For example, the regional DCs can be considered as a subset of manufacturers that are designated to customize the products. Also note that each customer (e.g., a hospital) may submit multiple orders over the period of disaster relief. What we consider in this study is the operations scheduling for a given set of customer orders under a given availability of inventory supplies together with a given shipping time status at a particular time point during disaster relief.

To define this problem more formally, we introduce the following notations.

r_s The production rate of supplier *s* to produce the component *s*, $s \in S$;

r_m The production rate of manufacturer *m* to produce the standard rescue kit, $m \in M$;

r_{kh} The production rate of DC *k* to produce the customized rescue kit for customer *h*, $k \in K$, $h \in H$;

τ_{sm} Shipping time from supplier *s* to manufacturer *m*, $s \in S$, $m \in M$;

τ_{sk} Shipping time from supplier *s* to DC k , $s \in S$, $k \in K$;

τ_{mh} Shipping time from manufacturer *m* to customer *h*, $m \in M$, $h \in H$;

τ_{kh} Shipping time from DC *k* to customer *h*, $k \in K$, $h \in H$;

I_s Available outbound inventory for component *s* at supplier *s*, $s \in S$;

I_m^s Available inbound inventory for component *s* at manufacturer *m*, $s \in S$, $m \in M$;

I_k^s Available inbound inventory for component *s* at DC *k*, $s \in S$, $k \in K$;

I_m Available outbound inventory for the standard rescue kit at manufacturer *m*, $m \in M$;

I_k Available outbound inventory for the standard rescue kit at DC *k*, $k \in K$;

D_h Order quantity for the standard rescue kit by customer *h*, $h \in H$;

$\widetilde{D}_h$ Order quantity for the customized rescue kit by customer *h*, $h \in H$;

T_h The order due date of customer *h*, $h \in H$;

B^s Bill of materials for the standard rescue kit (i.e., the conversion ratio from component *s* to the standard rescue kit) , $s \in S$;

B_h^s Bill of materials for the customization rescue kit ordered by customer *h* (i.e., the conversion ratio from component *s* to the customization rescue kit for customer *h*) , $s \in S$, $h \in H$;

F_{ab} An upper bound on the flow quantity between location *a* and location *b*, $(a,b) \in S \times M \cup S \times K \cup M \times H \cup K \times H$ where

$$F_{sm} = \max\left\{0, \left[B^s \cdot \max\left\{0, \sum_h D_h - I_m\right\}\right] - I_m^s\right\},$$

$$F_{sk} = \max\left\{0, \sum_h \left(B_h^s \cdot \widetilde{D}_h\right) - I_k^s\right\} \text{ and}$$

$$F_{mh}^i = D_h,\ F_{mh} = D_h,\ F_{kh}^i = D_h,\ F_{kh} = \widetilde{D}_h$$

where F_{ab}^i stands for an upper bound on the flow quantity from the *inventory* prepositioned at location *a* to location *b*.

G^{upper} An upper bound on the total weighted tardiness.

Decision variables:

Q_s Quantity of component *s* produced by supplier *s*, $s \in S$;

q_{sm} Quantity of component *s* shipped from supplier *s* to manufacturer *m*, $s \in S$, $m \in M$;

q_{sk} Quantity of component *s* shipped from supplier *s* to DC *k*, $s \in S$, $k \in K$;

q_{mh} Quantity of standard rescue kits shipped to customer *h* from the new batch produced by manufacturer *m*, $m \in M$, $h \in H$;

q_{mh}^i Quantity of standard rescue kits shipped to customer *h* from the outbound inventory of manufacturer *m*, $m \in M$, $h \in H$;

q_{kh}^i Quantity of standard rescue kits shipped to customer *h* from the outbound inventory of DC *k*, $k \in K$, $h \in H$;

q_{kh} Quantity of customized rescue kits shipped to customer *h* from DC *k*, $k \in K$, $h \in H$;

PS_m Production starting time at manufacturer m, $m \in M$;

PS_k Production starting time at DC k, $k \in K$;

TD_h Tardiness of delivering the standard rescue kit to customer h , $h \in H$;

$\widetilde{T}D_h$ Tardiness of delivering the customized rescue kit to customer h , $h \in H$;

y_m^s Binary variable indicating whether replenishment of component s is needed at manufacturer m, $s \in S$, $m \in M$;

y_k^s Binary variable indicating whether replenishment of component s is needed at DC k, $s \in S$, $k \in K$;

y_{mh} Binary variable indicating whether there are standard rescue kits from the new batch

produced by manufacturer m to customer h, $m \in M$, $h \in H$;

y_{mh}^i Binary variable indicating whether there are standard rescue kits from the outbound inventory manufacturer m to customer h, $m \in M$, $h \in H$;

y_{kh}^i Binary variable indicating whether there are standard rescue kits from the outbound inventory of DC k to customer h, $k \in K$, $h \in H$;

y_{kh} Binary variable indicating whether there are customized rescue kits from DC k to customer h, $k \in K$, $h \in H$;

Problem P:

Minimize: $\sum_h (TD_h \cdot D_h + \widetilde{T}D_h \cdot \widetilde{D}_h)$ (3.0)

Subject to:

1. *Production and inventory capacity constraints*

$$\sum_m q_{sm} + \sum_k q_{sk} \le I_s + Q_s \qquad s \in S \qquad (3.1)$$

$$\sum_h q^i_{mh} \le I_m \qquad m \in M \qquad (3.2)$$

$$\sum_h q^i_{kh} \le I_k \qquad k \in K \qquad (3.3)$$

$$(B^s \cdot \sum_h q_{mh} - I^s_m) \le y^s_m \cdot MM \qquad s \in S,\ m \in M \qquad (3.4)$$

$$(\sum_h \left(B^s_h \cdot q_{kh}\right) - I^s_k) \le y^s_k \cdot MM \qquad s \in S,\ k \in K \qquad (3.5)$$

2. *Flow capacity constraints*

$$q_{sm} \le y^s_m \cdot F_{sm} \qquad s \in S,\ m \in M \qquad (3.6)$$

$$q_{sk} \le y^s_k \cdot F_{sk} \qquad s \in S,\ k \in K \qquad (3.7)$$

$$q_{kh} \le y_{kh} \cdot F_{kh} \qquad k \in K,\ h \in H \qquad (3.8)$$

$$q_{mh} \le y_{mh} \cdot F_{mh} \qquad m \in M,\ h \in H \qquad (3.9)$$

$$q^i_{mh} \le y^i_{mh} \cdot F^i_{mh} \qquad m \in M,\ h \in H \qquad (3.10)$$

$$q^i_{kh} \le y^i_{kh} \cdot F^i_{kh} \qquad k \in K,\ h \in H \qquad (3.11)$$

3. *Demand-supply balance constraints*

$$\sum_m q_{mh} + \sum_m q^i_{mh} + \sum_k q^i_{kh} = D_h \qquad h \in H \qquad (3.12)$$

$$\sum_k q_{kh} = \widetilde{D}_h \qquad h \in H \qquad (3.13)$$

4. Constraints that define lead times and tardiness

$$TD_h \geq (\tau_{mh} - T_h) - MM \cdot (1 - y^i_{mh}) \qquad m \in M\,,\ h \in H \qquad (3.14)$$

$$TD_h \geq (\tau_{kh} - T_h) - MM \cdot (1 - y^i_{kh}) \qquad k \in K\,,\ h \in H \qquad (3.15)$$

$$PS_m \geq \frac{Q_s}{r_s} + \tau_{sm} - MM \cdot (1 - y^s_m) \qquad s \in S\,,\ m \in M \qquad (3.16)$$

$$TD_h \geq (PS_m + \frac{\sum_h q_{mh}}{r_m} + \tau_{mh}) - MM \cdot (1 - y_{mh}) - T_h \qquad m \in M\,,\ h \in H \qquad (3.17)$$

$$PS_k \geq \frac{Q_s}{r_s} + \tau_{sk} - MM \cdot (1 - y^s_k) \qquad s \in S\,,\ k \in K \qquad (3.18)$$

$$\widetilde{T}D_h \geq (PS_k + \frac{q_{kh}}{r_{kh}} + \tau_{kh}) - MM \cdot (1 - y_{kh}) - T_h \qquad k \in K\,,\ h \in H \qquad (3.19)$$

5. Domain constraints

y^s_m, y^s_k, y_{mh}, y_{kh}, y^i_{mh}, y^i_{kh} are binary constraints (3.20)

All other variables are non-negative continuous variables (3.21)

Note that each binary variable in **P** corresponds to a link in the respective supply chain network. If a binary variable is assigned to be 1, then the corresponding link is referred to as *open*. Otherwise, the link is referred to as *closed* and allows no flows between the two locations connected by that link. Computationally, **P** is a difficult one and can be shown to be NP-hard in strong sense (see Lee et al. (2013)).

CHPATER 4 A SOLVABLE CASE OF P

As stated in Chapter 3, the general problem **P** is NP hard to solve. Before we propose an efficient methodology to solve **P**, we investigate a variation of **P** that is both practically meaningful and solvable in strongly polynomial time. In this section, we will define this special case, propose a strongly polynomial algorithm and demonstrate it on a numerical example. Applications and possible extensions of the solvable case are discussed in the end of the chapter.

The real life operations scheduling problem that motivated the special case was encountered from the practice of assembling, packaging, and delivery of *rescue packs* to support disaster relief efforts during and after natural disasters (e.g., earthquakes, flooding, and hurricanes). In particular, we focus in this chapter on a four-stage supply chain process (see Figure 4.1) for a *single product* (e.g., the standard rescue pack for a particular affected area). The bill-of-material (BOM) for the product is given. For example, each unit of product requires 100 units of Certi-Strip Adhesive Bandages, 50 units of Ammonia Inhalants, 25 units of Certi-Burn Cream, 10 units of Trauma Dressing, and 10 units of medical gloves, etc. Depending on the type of natural disaster and the specific needs for local disaster relief, the BOM composition for the product may vary from case to case (Ferris, 2010).

This supply chain consists of component suppliers, a single packaging contractor (the PC), distribution centers (DCs), and many customer demand points (e.g., hospitals, rescue shelters, or local offices of non-profit organizations). Each customer order is defined by its quantity, due date, and a lateness penalty. During and after a disaster, different locations in an affected area suffering from different levels of damage may request rescue supplies with different levels of urgency, which leads to a heterogeneity in order due dates and late penalties. In this study we assume that all customer orders are of identical size (i.e., the unit size) and each order can be fulfilled by either the existing inventory of DCs or a new assembly operation at the PC. Each DC carries a limited inventory for the product (supplied by various external sources that participate in the disaster relief) and takes a DC-dependent time for handling the orders (e.g., for information processing, order validation, packaging/labeling, waiting for the local vehicles, and loading the shipments, etc.). However, DCs do not perform assembly operations and thus are only responsible for allocating existing inventories to fulfill the customer orders. On the other hand, the PC is capable of assembling/packaging additional supplies of the product when needed. As a contracted manufacturer, the PC only carries an inbound inventory of components to be used in various final products (i.e., various medical packs), instead of an outbound inventory for any particular disaster-dependent finished product. Depending on the number of orders to be fulfilled, the PC may require its suppliers to send additional component supplies. Whenever this is the case, the PC′s operation will halt until all the new shipments from its suppliers arrive, which further delays the assembly and shipping operations. Note that DCs do not have their own assembly function, and thus no replenish flows to DCs from upstream suppliers are required.

The problem is to assign customer orders to DCs and the PC, which in turn determines whether and how long the PC has to wait for the additional supplies of components from its suppliers, so that the total weighted tardiness in delivering the shipments to the customers is minimized. Furthermore, the shipping times between DCs and customers, and that between each component supplier and the PC, must be explicitly considered. Orders to be fulfilled by the new assembly/packaging operation must be sequenced at the PC due to the packaging requirement. In general, the inventory allocation plus production sequencing to minimize the total weighted tardiness is a very difficult optimization problem, especially when multi-stage lead/shipping times are involved. In this paper, we propose a search algorithm that finds the optimal operations schedule to this problem in strongly polynomial time when the customer order sizes are identical (e.g., one truck load). Such an algorithm can be used as a subroutine embedded in a heuristic for solving general versions of the problem such as those with multiple PCs in the network or order-dependent bill-of-materials. To our knowledge, the result presented in this paper is among very few, if not the first, that efficiently solves a sub-problem of emergency logistics optimally.

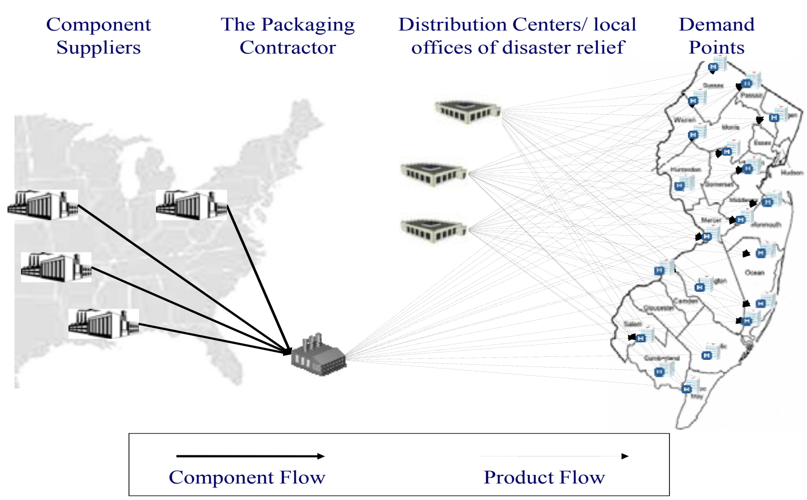


Figure 4.1 Network structure for the special case of the emergency supply chain.

4.1 Definition of the Special Case

For a formal definition of the special case problem, we introduce the following notations.

***Components*:** Let N be the set of components needed for the product according to the given BOM. Each unit of the final product requires B_n units of component n, $n \in N$. Note that if each customer order requires a customer-dependent BOM, then the proposed solution approach must be revised, which will lead to a different level of time complexity of the solution process (see Lee et al. 2013b).

***Customer demand points*:** The set of demand points is denoted by H. Each demand point h, $h \in H$, places an order together with a due date T_h and a penalty w_h for each time unit of delay, which measure the urgency of the order. Since all the customer order sizes are identical, without loss of generality, we assume *unit size* orders.

***Distribution centers* (*DCs*):** The set of DCs in the network is denoted by K, where DC k, $k \in K$, has a given inventory of the final product, I_k, which can fulfill at most I_k orders (since order sizes are of unit-size). Let a_{kh} stand for the time for DC k to process the order of customer h, and τ_{kh} stand for the shipping time from k to h. Note that the maximum supply quantity of a DC′s inventory and the lead time from a DC to a customer are constants, while the maximum supply quantity of the PC and the lead time from the PC to a customer depend on whether the suppliers are involved. Thus, when the PC is involved, which in turn introduces the order sequencing at PC together with the lead times for shipping from component suppliers, this is no longer a simple assignment problem.

***The packaging contractor* (*PC*):** The PC takes R time units to produce (i.e., assemble and package) an order. That is, the production time needed for each order is a constant. The PC carries an inbound inventory $\bar{I}_n$ for component n, $n \in N$, but does not carry any outbound inventory of the final product. Let $\bar{\tau}_h$ be the shipping time from the PC to customer h. Depending on the orders assigned to the PC, additional supplies of components may need to be shipped in from respective suppliers. When this is the case, the lead time between suppliers and the PC must be considered. Note that the PC will not start its production until sufficient supplies of the required components are ready.

***Suppliers*:** There are multiple suppliers for each component n. Let J_n be the set of suppliers for component n and $\hat{\tau}_{nj}$ be the shipping time from the j-th supplier in J_n to the PC. Without loss of generality, we assume that $\hat{\tau}_{nj} \le \hat{\tau}_{n,j+1}$ for all $j = 1,...,|J_n| - 1$. Let $\hat{I}_{nj}$ be the inventory level for component n at the j-th supplier in J_n. Let J be the set of all suppliers, i.e. $J := \bigcup_{n \in N} J_n$.

Note that, if we know the number of orders to be produced by the PC, then the total required production time (for assembly and packaging operations) is known since the production time for each order is a given constant R. Furthermore, if the starting time of the production (i.e., the time at which all the required component supplies are ready) is given, say S, then the first order in the production sequence will be completed, and depart for the respective customer, at time $S + R$. Similarly, the second order will be completed and depart at time $S + 2R$, etc. Let a *time slot* denote a time period of duration R that is needed for processing an order at the PC. We now introduce the following decision variables:

x_{kh} Binary variable, and $x_{kh} = 1$ if demand point h is served by DC k, and 0 otherwise, $\forall k \in K$, $\forall h \in H$;

$\bar{x}_{ih}$ Binary variable, and $\bar{x}_{ih} = 1$ if the order of demand point h is produced during the i-th time slot at the PC, and 0 otherwise, $\forall i, 1 \leq i \leq |H|, \forall h \in H$;

q_{nj} The flow quantity from the j-th supplier of component n to the PC, $\forall n \in N$, $\forall j \in J_n$;

y_{nj} Binary variable, and $y_{nj} = 1$ if there is a flow quantity from the j-th supplier of component n to the PC, and 0 otherwise, $\forall n \in N$, $\forall j \in J_n$;

Q Total quantity produced (or the total number of orders fulfilled) by the PC;

t_h Arrival time of the shipment at the demand point h, $\forall h \in H$;

TD_h The tardiness in delivery to demand point h, $\forall h \in H$;

S Production starting time at the PC;

The mathematical model that formally defines our problem is as follows, where M is a sufficiently large number.

Model $\boldsymbol{P}^{s}$

Minimize $$Z = \sum_{h \in H} w_h TD_h \tag{4.1}$$

Subject to

1) Capacity and flow balance constraints

All the customer orders must be fulfilled

$$\sum_{k \in K} x_{kh} + \sum_{i=1}^{|H|} \bar{x}_{ih} = 1 \qquad \forall h \in H \tag{4.2}$$

The total outflow quantity (i.e., the number of unit-size orders) from DC k to customers cannot exceed the inventory at DC k

$$\sum_{h \in H} x_{kh} \le I_k \qquad \forall k \in K \tag{4.3}$$

Each time slot in the PC's operations can be assigned to at most one order

$$\sum_{h \in H} \bar{x}_{ih} \le 1 \qquad \forall i, 1 \le i \le |H| \tag{4.4}$$

Total number of orders produced by the PC equals to the total number of assigned time slots (because of the unit order sizes)

$$Q = \sum_{h \in H} \sum_{i=1}^{|H|} \bar{x}_{ih} \tag{4.5}$$

The shortage in component inventory must be provided by its suppliers

$$\sum_{j \in J_n} q_{nj} \geq B_n \times Q - \bar{I}_n \qquad \forall n \in N \tag{4.6}$$

Constraints that establish the relationships between linear and binary variables

$$q_{nj} \leq M \cdot y_{nj} \qquad \forall n \in N \;, \forall j \in J_n \tag{4.7}$$

2) Lead time constraints

The PC's production must wait until the latest arrival of components from suppliers (if any)

$$S \geq \hat{\tau}_{nj} y_{nj} \qquad \forall n \in N \qquad , \; \forall j \in J_n \tag{4.8}$$

Constraints that define the earliest possible arrival time at each demand point

$$t_h \geq x_{kh} \cdot \left(a_{kh} + \tau_{kh}\right) \qquad \forall k \in K \;, \forall h \in H \tag{4.9}$$

$$t_h \geq S + i \cdot R + \bar{\tau}_h - M(1 - \bar{x}_{ih}) \quad \forall h \in H \;, \; \forall i, 1 \leq i \leq |H| \tag{4.10}$$

Constraints that define the delivery tardiness at each demand point

$$TD_h \geq t_h - T_h \qquad \forall h \in H \tag{4.11}$$

3) Domain constraints

$$x_{kh}, \; \bar{x}_{ih}, \; y_{nj} \in \{0,1\} \tag{4.12}$$

All other variables are non-negative.

In the following discussion, we shall use $\mathbf{P^s}$ to denote this optimization problem, and show that problem $\mathbf{P^s}$ is solvable in strongly polynomial time.

Our study contributes to the literature of emergency logistics in three aspects. First, we explicitly model the total weighted tardiness in the objective function for the optimization. As pointed out by Caunhye et al. (2012), there were very few models dealing with the objective concerning delivery times in the current literature because of potential complexity of tracking multi-stage lead time. The need to track the network lead time in this study also makes the existing literature results not directly applicable to our case. Second, our analysis on the structural properties of the emergency logistics optimization problem identifies a special case that can be solved in strongly polynomial time, and facilitates the design of heuristics for the general cases of supply chain operations scheduling problems. Third, to our knowledge, this is the first result on supply chain operations scheduling that involves sequencing customer orders together with multi-stage lead times.

4.2 A Decomposition-based Algorithm for Solving $\mathbf{P}^{\mathbf{s}}$

In this section, we propose a strongly polynomial time algorithm for solving $\mathbf{P}^{\mathbf{s}}$. To start, we decompose $\mathbf{P}^{\mathbf{s}}$ into two sub-problems with the single PC as the disjunction point. Note that the customer orders can be fulfilled by either the inventory of local DCs or those newly produced by the PC, and that decision variable Q denotes the total quantity (or the total number of orders) produced by the PC. Since $|H|$ is the total demand quantity and $\sum_{k \in K} I_k$ is the total inventory from all DCs, $\max\left\{0, |H| - \sum_{k \in K} I_k\right\}$ is the minimum production quantity (or the minimum number of orders fulfilled) by the PC. Thus, while the optimal value of Q will be determined by the search process of the algorithm to be proposed, its lower and upper bounds are known *a priori*, and are given as $\left[\max\left\{0, |H| - \sum_{k \in K} I_k\right\},\ |H|\right]$.

Let **P(*Q*)** denote $\mathbf{P^s}$ under a given production quantity *Q*, and the basic idea of our proposed algorithm is outlined as follows. For any given *Q* value, we decompose problem **P(*Q*)** into an *upstream problem,* denoted as $P^A(Q)$, and a *downstream problem*, denoted as $P^B(Q)$. Problem $P^A(Q)$ is concerned with the selection of suppliers that supplies enough components (i.e., supplies) for producing *Q* units of the product (i.e., *Q* orders) so that the production starting time at the PC can be as early as possible. After solving $P^A(Q)$ optimally, we obtain the earliest feasible starting time at the PC, from which ensues the lead times, denoted as $S(Q)$. Upon the given *Q* and $S(Q)$, $P^B(Q)$ is about how to assign customer orders to inventory of DCs and to the time slots of the PC to minimize the total weighted tardiness in delivery to the customers. In the following analysis, we shall show that for any given *Q*, the two sub-problems, $P^A(Q)$ and $P^B(Q)$, can both be solved in strongly polynomial time. Since the number of possible values of *Q* is bounded by constant $|H|$, the original problem $\mathbf{P^s}$ is strongly polynomial time solvable. A flow chart describing the solution procedure is presented in Figure 4.2. In the rest part of this section, we will elaborate on how to solve problems $P^A(Q)$ and $P^B(Q)$, respectively.

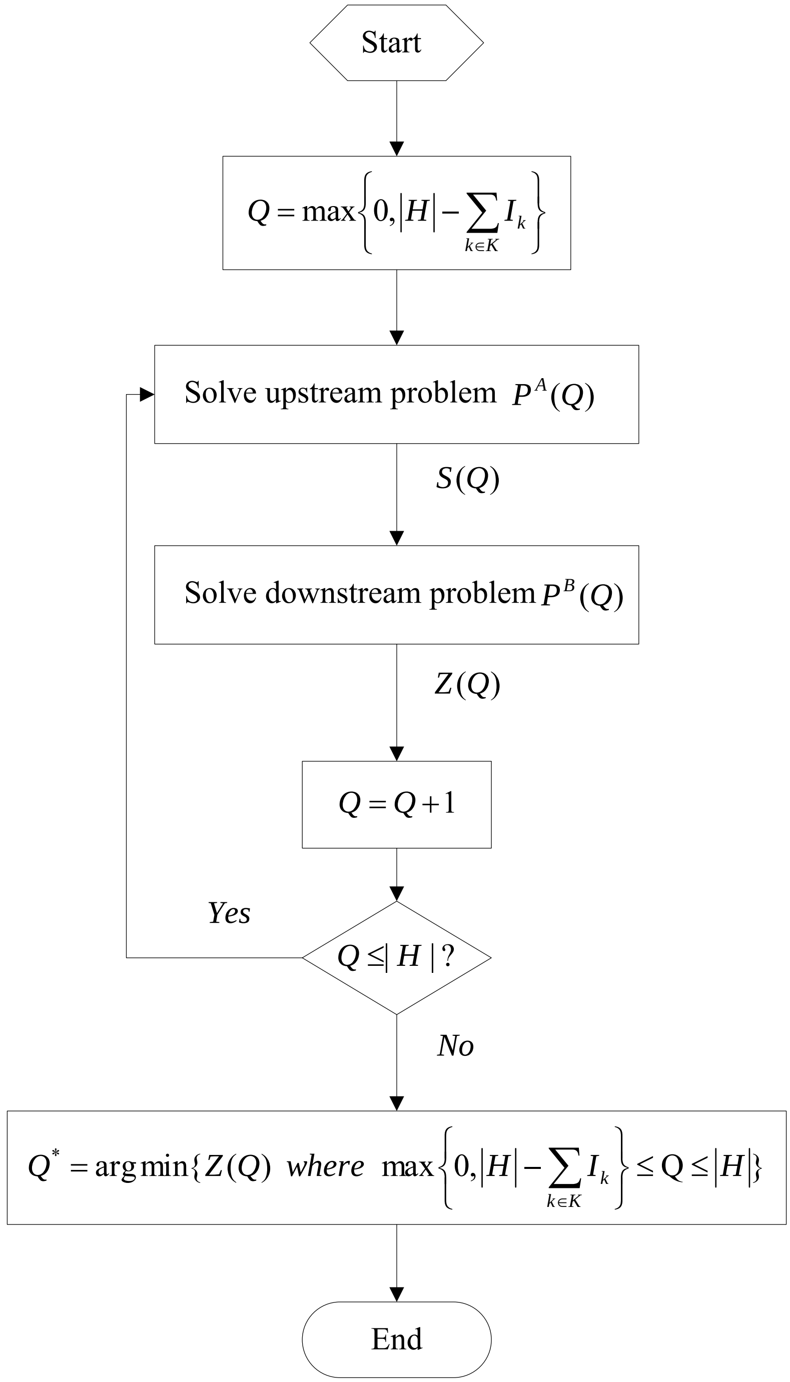


Figure 4.2 Decomposition-based optimal solution procedure of the special case P^s .

4.2.1 Solving the upstream problem under a given Q value, $P^A(Q)$

First, we consider the upstream network that consists of $|J|$ component suppliers and the PC. Given that the production quantity (or the total number of orders of unit size) is Q, our objective for optimization here is to find the schedule to minimize the latest arrival time of the components at the PC.

In order to calculate the lead time from component suppliers, we need to check whether the existing inbound inventory for components at the PC is enough for producing Q orders. If yes, then the production at PC may start at time zero. Otherwise, the production starting time equals the longest lead time from the suppliers who need to send out additional supplies of components. Therefore, the production starting time is a function of production quantity Q, denoted as $S(Q)$, and is defined as

$$S(Q) := \max_{n \in N}\{S_n(Q)\}$$

where $S_n(Q)$ is the earliest possible ready time of component n for production quantity Q. Note that, for any given Q, additional quantity of component n to be shipped in from suppliers in J_n is defined by $\max\{0, B_n Q - \bar{I}_n\}$. If $\max\{0, B_n Q - \bar{I}_n\} > 0$, then $S_n(Q) > 0$ implying a positive lead time for component n. Since suppliers for component n are ordered in the increasing order of their shipping time to the PC (i.e., $\hat{\tau}_{nj} \le \hat{\tau}_{n,j+1}$ for all $j = 1,...,|J_n| - 1$), $S_n(Q)$ is defined as follows;

$$S_n(Q) = \begin{cases} 0 & \text{if } C_n Q \le \bar{I}_n \\ \hat{\tau}_{nj} \ \text{ for } j := \min\limits_{l' \in \{1,\ldots,|J_n|\}} \left\{ \sum\limits_{l=1}^{l'} \hat{I}_{nl} \ge C_n Q - \bar{I}_n \right\} & \text{if } C_n Q > \bar{I}_n \end{cases} \tag{4.13}$$

Now, we consider the time complexity to solve $P^A(Q)$ for $Q \ge 0$. Equation (4.13) shows that the value of $S_n(Q)$ can be determined in $O(|J_n|)$ time. Thus, it takes $O(|J|)$ time to compute $S(Q)$.

We can also consider an extension to the situation where each component *n* has, instead of a set of suppliers with finite inventory, a set of candidate suppliers with heterogeneous production rates and inventory levels. Each supplier for component *n* may have a finite inventory or a production facility with a non-zero production rate or both. Let $\hat{I}_{nj}$ and $\hat{r}_{nj}$ be the inventory level and the production rate for component *n* of the *j*-th supplier in J_n, respectively.

Now, let $Q_n(t)$ be the maximum quantity of component *n* to be available at the PC in time *t*. Then, $Q_n(t)$ can be defined as follows:

$$Q_n(t) = \begin{cases} \hat{I}_n & \text{if } 0 \le t < \hat{\tau}_{n1} \\ \hat{I}_n + \sum\limits_{l=1}^{j} \left(\hat{I}_{nl} + \hat{r}_{nl}(t - \hat{\tau}_{nl}) \right) & \text{if } \hat{\tau}_{nj} \le t < \hat{\tau}_{n,j+1} \end{cases} \tag{4.14}$$

Figure 4.3 shows an example where there are three suppliers for component *n*, where supplier 1 carries inventory but does not have production facility, supplier 2 has a production facility but no inventory, and supplier 3 has both.

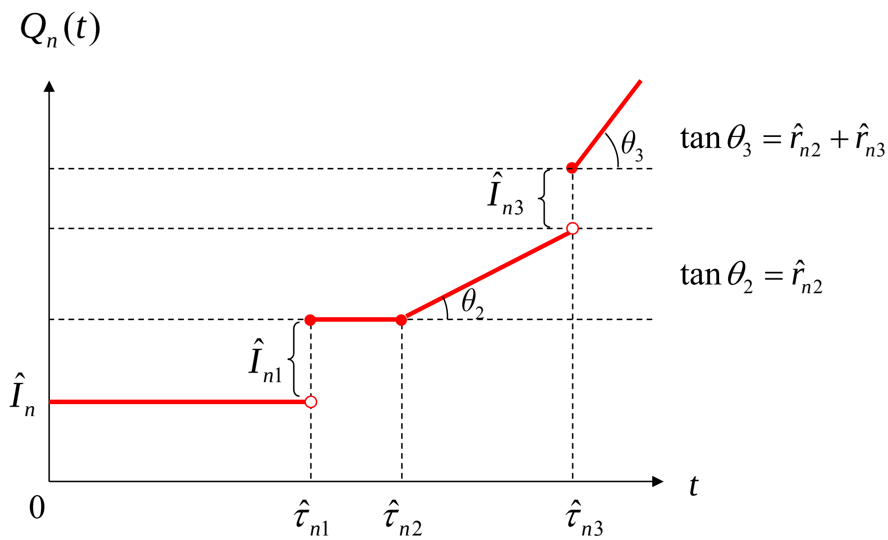


Figure 4.3 An example of $Q_n(t)$.

$S_n(Q)$, which denotes the minimum lead time needed to replenish the right quantity of component n for producing quantity Q at the PC, can be defined as follows:

$$S_n(Q) = \begin{cases} 0 & \text{if } C_n Q \le \bar{I}_n \\ \arg\min\limits_{t \ge 0} \{Q_n(t) \ge C_n Q\} & \text{if } C_n Q > \bar{I}_n \end{cases} \tag{4.15}$$

Since $Q_n(t)$ is a non-decreasing piece-wise linear function of time t with $O(|J_n|)$ non-differential points, $S_n(Q)$ can be calculated in $O(|J_n|)$ time. Therefore, in this extended model, since we have $S(Q) := \max_{n \in N} \{S_n(Q)\}$, it still takes a linear time of the number of suppliers for all components, $O(|J|)$, to compute $S(Q)$.

4.2.2 Solving the downstream problem under given Q and S(Q), $P^B(Q)$

For any given pair of Q and $S(Q)$, we now show that the respective downstream problem, $P^B(Q)$, can be formulated as a minimum cost flow problem. To do so, let us construct a directed network $G = (V, A)$ with a source node $SRC \in V$ and a sink node $SNK \in V$. With any given Q, let the set of time slots at the PC be $L := \{1, ..., Q\}$, where each time slot will be assigned to one of the Q orders. The node set V and the arc set A can then be defined as follows (see Figure 4.4).

The node set is defined as $V := \bigcup_{\alpha=0}^{5} V_\alpha$ where

$V_0 = \{SRC\}$: The set of the source node, and $|V_0|=1$;

$V_1 = \{TSlt_i \mid i \in L\}$: The set of nodes representing the Q time slots at the PC;

$V_2 = \{PInv\}$: The set of a dummy node representing the total amount of DC inventory used to fulfill the customer orders;

$V_3 = \{KInv_k \mid k \in K\}$: The set of nodes each representing a DC′s inventory used to fulfill the customer orders;

$V_4 = \{HDmd_h \mid h \in H\}$: The set of nodes representing demand points;

$V_5 = \{SNK\}$: The set of the sink node, and $|V_5|=1$.

The arc set is defined as $A := A_{01} \cup A_{02} \cup A_{14} \cup A_{23} \cup A_{34} \cup A_{45}$ where each subset of arcs is defined below along with each arc flow's lower bound (*LB*) and upper bound (*UB*).

Set	An arc in the set	[*LB*, *UB*] of an arc flow	Range of indices
A_{01}	$(SRC, TSlt_i)$	$[1,1]$	$i \in L$
A_{02}	$(SRC, PInv)$	$[\lvert H\rvert - Q, \lvert H\rvert - Q]$	
A_{14}	$(TSlt_i, HDmd_h)$	$[0,1]$	$i \in L$,
A_{23}	$(PInv, KInv_k)$	$[0, I_k]$	$k \in K$
A_{34}	$(KInv_k, HDmd_h)$	$[0,1]$	$k \in K$, $h \in H$
A_{45}	$(HDmd_h, SNK)$	$[1,1]$	$h \in H$

The costs of arcs in this network are defined as follows:

- The cost of an arc in A_{14} is $a(TSlt_i, HDmd_h) = w_h \max\{0, S(Q) + iR + \bar{\tau}_h - T_h\}$
- The cost of an arc in A_{34} is $a(KInv_k, HDmd_h) = w_h \max\{0, a_{kh} + \tau_{kh} - T_h\}$
- The costs of the other arcs are equal to zero.

For each arc $(u, v) \in A$, we have flow $f(u, v)$ as a decision variable subject to upper bound $UB(u, v)$ and lower bound $LB(u, v)$, and cost $a(u, v)$. The cost of sending this flow over arc (u, v) is $a(u, v) \cdot f(u, v)$. Therefore, $P^B(Q)$ becomes the one to find flows minimizing the total cost:

$$Z(Q) = \sum_{(u,v)\in A} a(u,v) \cdot f(u,v)$$

subject to the following constraints:

1) Flow capacity constraint

$$LB(u,v) \leq f(u,v) \leq UB(u,v) \text{ for } (u,v) \in A,$$

2) Flow conservation constraint

$$\sum_{(u,v)\in A} f(u,v) = \sum_{(w,u)\in A} f(w,u) \text{ for } u \in V \setminus \{SRC, SNK\},$$

3) Flow requirement constraint

$$\sum_{(SRC,u)\in A} f(SRC,u) = |H| \text{ and } \sum_{(u,SNK)\in A} f(u,SNK) = |H|.$$

Note that this network model can also be extended to handle additional constraints. For example, if there is a flow capacity limit for each arc between a particular DC and a demand point, we can revise the upper bound of the arc accordingly.

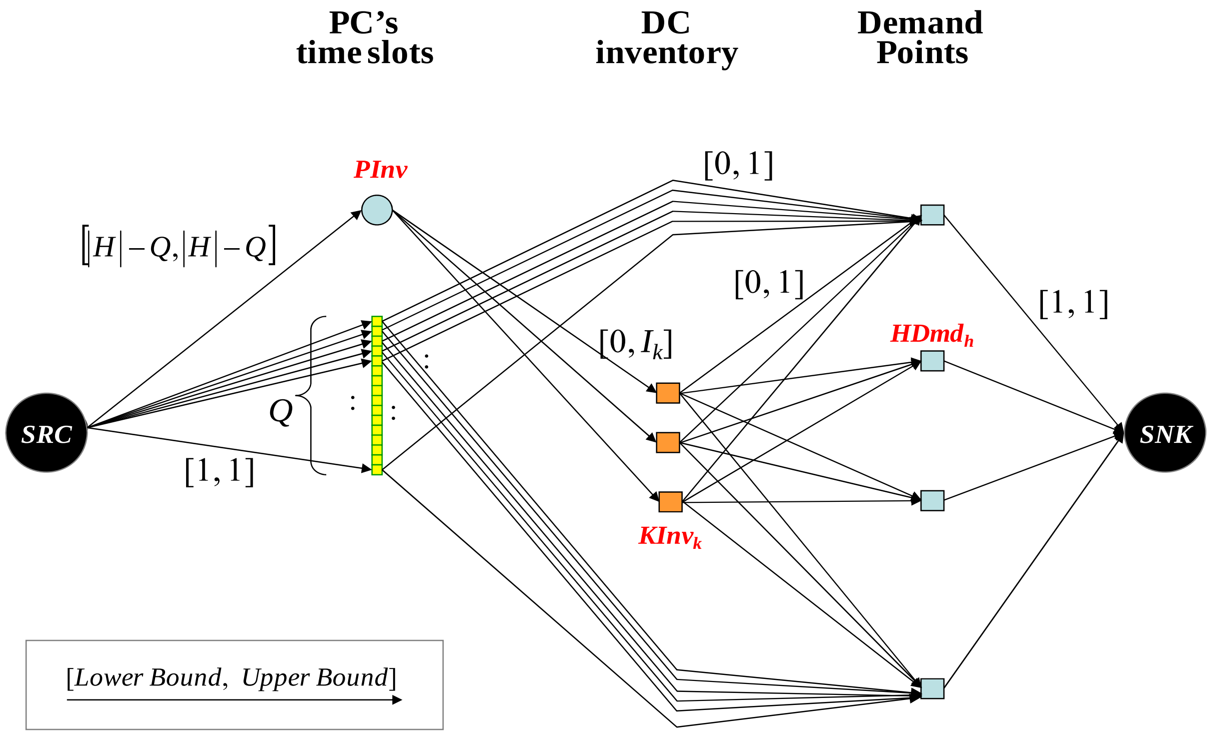


Figure 4.4 The network flow model for $P^B(Q)$.

Note that this network formulation gives a precise description of $P^B(Q)$. First of all, the number of time slots equals exactly to the production quantity at the PC. From the discussion above, we see that a customer order can be served by either i) a time slot at the PC, or ii) the inventory of a DC. If the *i*-th time slot at the PC serves demand point *h*, then the arrival time at demand point *h* equals to the summation of the starting time of the initial production at the PC, $S(Q)$, the total waiting time in sequence of the *i-th* time slot including its production time, $i \cdot R$, and the shipping time from the PC to demand point *h*, $\bar{\tau}_h$, or $S(Q)+iR+\bar{\tau}_h$. If DC *k* serves demand point *h*, then the arrival time at demand point *h* is the summation of the loading time at DC *k* for demand point *h*, a_{kh}, and the shipping time from DC *k* to demand point *h*, τ_{kh}, or $a_{kh}+\tau_{kh}$. In the optimal solution, if the flow over arc $\left(TSlt_i, HDmd_h\right)$ equals 1 then it implies that the *i*-th time slot serves demand point *h,* and if the flow over arc $\left(KInv_k, HDmd_h\right)$ equals 1 then it implies the inventory of DC *k* serves demand point *h*.

Also note that the number of time slots is bounded from above by the total number of customer orders, or $|L| = Q \le |H|$, and thus the total number of nodes in the network is bounded by $O(|K|+|H|)$ and the total number of arcs is bounded by $O(|H|(|H|+|K|))$. The minimum cost flow problem defined on $G=(V', E')$ can be solved in $O\left(|E'|\log|V'| \times \left(|E'| + |V'|\log|V'|\right)\right)$ time according to Orlin (1988). Thus, $P^B(Q)$ can be solved in $O\left(|H|\left(|K| + |H|\right)^2 \log\left(|K| + |H|\right)\left\{|H| + \log\left(|K| + |H|\right)\right\}\right)$ time.

Recall that $P^A(Q)$ can be solved in $O\left(|J|\right)$ time. Therefore, for each given production quantity Q, $\mathbf{P}(Q)$ can be solved in $O\left(|J| + |H|\left(|K| + |H|\right)^2 \log\left(|K| + |H|\right)\left\{|H| + \log\left(|K| + |H|\right)\right\}\right)$ time. Furthermore, since the production quantity is bounded by $\left[\max\left\{0, |H| - \sum_{k \in K} I_k\right\}, |H|\right]$, the total number of the possible values of Q is bounded from above by $|H|$. By enumerating all possible values for production quantity Q and solving all the respective sub-problems $P^A(Q)$ and $P^B(Q)$, we can determine the optimal production quantity to minimize the objective function value (1) of $\mathbf{P}^{\mathbf{s}}$. Therefore, the time complexity of the proposed algorithm for solving $\mathbf{P}^{\mathbf{s}}$ is bounded from above by $O\left(|J||H| + |H|^2\left(|K| + |H|\right)^2 \log\left(|K| + |H|\right)\left\{|H| + \log\left(|K| + |H|\right)\right\}\right)$.

4.3 A Numerical Example of the Proposed Algorithm

Since our proposed algorithm solves $\mathbf{P^s}$ optimally in polynomial time, as discussed in Section 4.2, we will not perform any empirical study in this paper. Instead, we shall demonstrate the step-by-step solution process by this proposed algorithm in deriving the optimal solution to an example of $\mathbf{P^s}$. In this numerical example, the network consists of six component suppliers for three components such that $|J_1| = 1$, $|J_2| = 2$ and $|J_3| = 3$, a single PC, three local DC, and ten demand points. Assuming the time needed for the PC to produce an order is $R = 2$, and other parameter values are given in Tables 4.1-4.3.

Table 4.1 Parameters of demand points.

h	T_h	w_h	$\bar{\tau}_h$	τ_{kh}		
				$k=1$	$k=2$	$k=3$
1	8	5	7	3	3	2
2	3	6	6	2	2	3
3	3	8	1	10	10	10
4	1	7	1	12	10	10
5	3	6	6	3	2	3
6	5	6	1	10	10	10
7	1	10	5	2	2	2
8	6	4	1	10	11	10
9	6	1	8	3	3	4

10	3	3	6	3	2	1

Table 4.2 Parameters of the component suppliers and the PC.

n	B_n	$\bar{I}_n$	$\hat{I}_{nj}$			$\hat{\tau}_{nj}$		
			$j=1$	$j=2$	$j=3$	$j=1$	$j=2$	$j=3$
1	1	6	8	-	-	3	-	-
2	2	6	8	6	-	1	5	-
3	1	2	6	1	3	2	4	8

Table 4.3 Parameters of DCs.

k	I_k	a_{kh}									
		$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$	$h=9$	$h=10$
1	3	1	1.5	1	2	0.5	3	4	5	0.5	1
2	2	2	3	0.5	1	1	4	3	6	2	2
3	4	0.5	2	0.5	1	1.5	2.5	4	5	2	1

As shown in Tables 4.1-4.3, $|H|-\sum_{k\in K} I_k = 1 > 0$, and the range for the possible production quantity at the PC, Q, is $\left[\max\left\{0,|H|-\sum_{k\in K} I_k\right\},|H|\right]=[1,10]$. For each possible value of Q, we apply the decomposition algorithm to solve the respective sub-problems. For example, when Q = 3, the sub-problems $P^A(Q)$ and $P^B(Q)$ are defined and solved, step-by-step, as follows.

For $P^A(3)$, we have $S_1(3)=0$, $S_2(3)=0$ and $S_3(3)=\hat{\tau}_{31}=2$. Therefore, the earliest possible production starting time at the PC is $S(3)=\max\{0,0,2\}=2$.

For $P^B(3)$, flow cost $a(TSlt_i, HDmd_h) = w_h \max\{0,\ 2+i2+\bar{\tau}_h-d_h\}$ is calculated and its values for i = 1, 2, 3, and h = 1, ..., 10 are summarized as below.

$i \setminus h$	1	2	3	4	5	6	7	8	9	10
1	15	42	16	28	42	0	80	0	6	21
2	25	54	32	42	54	12	100	4	8	27
3	35	66	48	56	66	24	120	12	10	33

By solving $P^B(3)$, we have the optimal value of 153 when Q = 3. Similarly, we solve all the sub-problems with respect to Q = 1, 2, ..., 10. Table 4.4 summarizes the results.

Table 4.4 Numerical example results.

Q	$P^A(Q)$	$P^B(Q)$

	$S_1(Q)$	$S_2(Q)$	$S_3(Q)$	$S(Q)$	$Z(Q)$
1	0	0	0	0	194
2	0	0	0	0	149
3	0	0	2	2	153
4	0	1	2	2	145
5	0	1	2	2	159
6	0	1	2	2	206
7	3	1	2	3	301
8	3	5	2	5	488
9	3	5	4	5	622
10	3	5	8	8	952

As we can see from the results listed in Table 4.4, the optimal production quantity (or the number of orders) produced by the PC is $Q^* = 4$. Note that the total tardiness is not a unimodal function of the production quantity and thus we need to enumerate all sub-problems with possible production quantities. The optimal assignment plan is summarized in Table 4.5, where DC *k* stands for the *k*-th DC and TS *i* stands for the *i*-th time slot at the PC.

Table 4.5 Optimal assignment of plan ($Q^* = 4$).

h	1	2	3	4	5	6	7	8	9	10
Assign-ment	DC 3	DC 1	TS 1	TS 2	DC 2	TS 3	DC 2	TS 4	DC 3	DC 3

4.4 Conclusions and Future Extensions

We studied the integrated production and transportation scheduling problem of a capacitated supply chain network consisting of component suppliers, a PC, DCs, and many customer demand points, with multi-stage lead times. The objective is to minimize the total weighted tardiness in the delivery to customers, which is a widely adapted industry performance measure for supply chains involved in disaster reliefs and emergency logistics. Assuming the customer orders are unit-sized, a decomposition-based algorithm for assigning customer orders to DCs and the PC (and then the selection of suppliers) is proposed, which finds the optimal solution to the respective integrated operations scheduling problem in strongly polynomial time. A numerical example that shows the step-by-step solution process of this proposed search algorithm is also presented.

There are several extensions from this study. First, a heuristic that uses the proposed polynomial time algorithm as a subroutine to solve a more general integrated operations scheduling problem is of great interest, such as the one with customer-dependent order quantities where an order of size $D_h > 1$ can be treated as D_h orders of unit size. Each shelter or hospital has a different capacity for accommodating affected people or patients, which lead to a different order size. The other one is to extend the proposed solution approach to allow each customer to place multiple orders, allowing an inventory at each customer site, over a given interval of multiple time periods. Each customer demand point places a sequence of orders over time, which is also a common practice in disaster relief. Hospitals in an affected area usually place an order before the strike of an anticipated natural disaster and then few subsequent orders after the disaster has arrived, depending on their local needs. When multiple shipments to a customer are allowed, we can extend the proposed algorithm directly to this case as well.

CHAPTER 5 AN LP-RELAXATION BASED SOLUTION APPROACH FOR SOLVING P

In this section, we propose an LP-relaxation based heuristic for solving the general problem **P** defined in Chapter 3. First of all, we will conduct a structure analysis of the problem by studying two solvable sub-problems of **P**. Then the LP-relaxation based heuristic is described in detail and presented in a flowchart. Finally, an extensive numerical study is conducted to test the performance of the heuristic. Using the proposed heuristic, properties of two important parameters in the model are studied.

5.1 Two Solvable Cases of P

While the general version of **P** is difficult to solve optimally, there exist special cases that can be solved efficiently. The optimal solutions to such special cases can be used to construct heuristics for **P** in future studies. In this section, we examine two such solvable cases.

5.1.1 Solving P with a single customer and sufficient inbound inventories

This case holds when the network contains only a single customer (e.g., an NGO center dedicated to a particular affected area), and all the manufacturers and DCs each carries a sufficient large amount of inbound inventory of components. When this is the case, component suppliers in the original model can be omitted, and the problem can be decomposed into two sub-problems, P_s and P_c, where sub-problems P_s, and P_c, are concerned with the provision of standard kits and customized kits respectively.

Since we have only a single customer, subscript h can be dropped for convenience. Let τ_m and $\tilde{\tau}_k$ denote the shipping times from manufacturer m to the customer and from DC k to the customer, respectively. Without loss of generality, we assume that manufacturers and DCs are sequenced in the increasing order of shipping times to the customer, i.e. $\tau_m \le \tau_{m+1}$ for $m = 1,...,|M|-1$ and $\tilde{\tau}_k \le \tilde{\tau}_{k+1}$ for $k = 1,...,|K|-1$. For convenience, let $\tau_{|M|+1} = \infty$ and $\tilde{\tau}_{|K|+1} = \infty$, and the due date of the customer be zero ($T = 0$), which can be relaxed later without affecting the result.

a). Solving sub-problem P_c

Let $\widetilde{TD}^*$ stand for the minimum tardiness for the customized product.

Lemma 1. If $\tilde{\tau}_{k^*} < \widetilde{TD}^* \le \tilde{\tau}_{k^*+1}$ for some $k^* \in K$, then

i) $\tilde{q}_k > 0$ for $k = 1,...,k^*$ and $\sum_{k=1}^{k^*} \tilde{q}_k = \tilde{D}$ and $\tilde{q}_k = 0$ for $k = k^* + 1,...,|K|$;

ii) $\dfrac{\tilde{q}_k}{\tilde{r}_k} + \tilde{\tau}_k = \widetilde{TD}^*$ for $k = 1,...,k^*$

Lemma 1 i) can be easily verified by contradiction. If there is any $\tilde{q}_{k'} = 0$ where $k' \in \{1,...,k^*\}$, one can always improve $\widetilde{TD}^*$ by letting the DC k' share a certain amount of production from other $k \in \{1,...,k^*\}$, $k \ne k'$. If there is any $\tilde{q}_{k'} > 0$ where $k' \in \{k^* + 1,...,|K|\}$, then $\widetilde{TD} > \tilde{\tau}_{k^*+1}$. Lemma 1 ii) can be verified similarly.

By Lemma 1 ii), we have $\tilde{q}_k = \widetilde{TD}^* \tilde{r}_k - \tilde{\tau}_k \tilde{r}_k$ for $k = 1,\dots,k^*$ and by $\sum_{k=1}^{k^*} \tilde{q}_k = \tilde{D}$, we have

$$\widetilde{TD}^* = \left(\tilde{D} + \sum_{k=1}^{k^*} \tilde{\tau}_k \tilde{r}_k \right) \Big/ \sum_{k=1}^{k^*} \tilde{r}_k .$$

Since $\widetilde{TD}^* \le \tilde{\tau}_{k^*+1}$, the optimal k^* value for the minimum tardiness is as follows:

$$k^* = \min \left\{ k' \in K \,\middle|\, \left(\tilde{D} + \sum_{k=1}^{k'} \tilde{\tau}_k \tilde{r}_k \right) \Big/ \sum_{k=1}^{k'} \tilde{r}_k \le \tilde{\tau}_{k'+1} \right\} .$$

By pre-calculating $\sum_{k=1}^{k'} \tilde{\tau}_k \tilde{r}_k$ and $\sum_{k=1}^{k'} \tilde{r}_k$ for $k' \in K$, the minimum k^* can be obtained in $O(|K|)$ time.

b). Solving sub-problem P_s

Let TD^* be the minimum tardiness for the standard product. Let

$$\Gamma = \{\tau_m \mid m \in M\} \cup \{\tilde{\tau}_k \mid k \in K\} = \{t_1, t_2, \dots, t_{|\Lambda|}\}$$

such that $t_i < t_{i+1}$ for $i = 1,\dots,|\Gamma|-1$ and let $t_{|\Gamma|+1} = \infty$. Let $M(t_i) = \{m \in M \mid \tau_m \le t_i\}$ and $K(t_i) = \{k \in K \mid \tilde{\tau}_k \le t_i\}$.

Lemma 2. If $t_{i^*} \le TD^* < t_{i^*+1}$, then we shall use up all the outbound inventory of $M(t_{i^*})$ and $K(t_{i^*})$ to partially fulfill the demand. Let $D'(t_i) = D - \sum_{m\in M(t_i)} I_m - \sum_{k\in K(t_i)} \widetilde{I}_k$ stand for the quantity to be fulfilled by the production of manufacturers. Then,

i) $\sum_{m\in M(t_{i^*})} q_m = D'(t_{i^*})$ and $q_m = 0$ for $m \in M \setminus M(t_{i^*})$

ii) $\dfrac{q_m}{r_m} + \tau_m = TD^*$ for $m \in M(t_{i^*})$

The proof of Lemma 2 is similar to that of Lemma 1. Assume outbound inventories at $M(t_{i^*})$ and $K(t_{i^*})$ are not used up, the TD^* can always be improved by using the residual outbound inventories. Therefore, as stated in Lemma 2 i), there is $\sum_{m\in M(t_{i^*})} q_m = D'(t_{i^*})$, and for $m \in M \setminus M(t_{i^*})$, if $q_m > 0$, then $TD \ge t_{i^*+1}$ which leads to a contradiction. Lemma 2 ii) can also be easily verified by contradiction.

By Lemma 2 ii), we have $TD^* = \left(D'(t_i) + \sum_{m\in M(t_i)} \tau_m r_m \right) \Big/ \sum_{m\in M(t_i)} r_m$. Therefore,

$$t_{i^*} = \min\left\{ t_i \in \Gamma \,\middle|\, \left(D'(t_i) + \sum_{m\in M(t_i)} \tau_m r_m \right) \Big/ \sum_{m\in M(t_i)} r_m < t_{i+1} \right\}.$$

By pre-calculating Γ and $M(t_i)$, $K(t_i)$, $\sum_{m\in M(t_i)} \tau_m r_m$ and $\sum_{m\in M(t_i)} r_m$ for $t_i \in \Gamma$, the minimum i^* can be obtained in $O(|K| + |M|)$ time.

Thus, both sub-problems P_s and P_c can be solved in linear time of $O(|K|+|M|)$. Note that if we are given an arbitrary delivery deadline, the results and the solution procedures discussed above shall remain the same since we aim at minimizing the latest arrival time at the customer. One potential use of this special case result is to develop a greedy heuristic that obtains a feasible solution to **P** by handling the orders of one customer at a time. The quality of such a heuristic, however, depends on how the sequence of customers is constructed.

5.1.2 Solving P assuming constant production times

Another solvable case of **P** holds when the production schedule at manufacturers and DCs are fixed in advance. In other words, PS_m and PT_m for all $m \in M$, and PS_k and PT_k for all $k \in K$, are given constants, where PT_m and PT_k stand for the production durations at *m* and *k* respectively. This allows us to drop constraints (3.16) and (3.18) completely. The total production quantities at manufacturer *m* and DC *k* are now fixed as $PT_m r_m$ and $PT_k r_k$, respectively, which require $\sum_h q_{mh} \le PT_m r_m$ for $m \in M$, (5.1) and $\sum_h q_{kh} \le PT_k r_k$ for $k \in K$ (5.2).

We assume that the outbound inventory of component suppliers is sufficient, which implies that there is no need to produce more by the component suppliers and the lead time between each supplier and each manufacturer (or a DC) equals to respective transportation time between the two locations. Because the production starting times at manufacturers and DCs are fixed in advance in this case, whenever the lead time from suppliers are greater than the given production starting time, the inbound shipment cannot be used for the production. That is, if $\tau_{sm} > PS_m$ then $y_m^s = 0$ and if $\tau_{sm} \le PS_m$ then $y_m^s = 1$ for $s \in S$, $m \in M$. Similarly, if $\tau_{sk} > PS_k$ then $y_k^s = 0$ and if $\tau_{sk} \le PS_k$ then $y_k^s = 1$ for $s \in S$, $k \in K$. Therefore, constraints for all binary variables indicating flow from suppliers to manufacturers and DCs (3.6) and (3.7) are taken out and constraints (3.4) and (3.5) can be simplified by plugging in appropriate binary variables, which can be denoted by (3.4)′ and (3.5)′ as follows.

$$(B^s \cdot \sum_h q_{mh} - I_m^s) \le 0 \qquad \text{if } y_m^s = 0,\ s \in S,\ m \in M \qquad (3.4)'$$

$$(\sum_h \left(B_h^s \cdot q_{kh}\right) - I_k^s) \le 0 \qquad \text{if } y_k^s = 0,\ s \in S,\ k \in K \qquad (3.5)'$$

We can approximate the objective function by minimizing the sum of weighted tardiness of shipments. For example, suppose that customer *h* has an order with a due date 24 and quantity 120, and the solution yields the following schedule: 50 units arriving at time 20, 40 units arriving at time 26, and 30 units arriving at time 30. Then, the resulting sum of weighted tardiness is given by 50 × max (0, 20 – 24) + 40 × max (0, 26 – 24) + 30 × max (0, 30 – 24) = 0 + 80 + 180 = 260. For supply chain networks with |H| >> |M|+|K|, such approximation could be promising because many customers are supplied by a single source. More precisely, when we consider the standard product, the number of customers that are supplied by multiple sources is bounded from above by |*M*| + |*K*| because the links with non-zero flows will construct a tree structure. If the number of customers supplied by multiple sources is more than |*M*| + |*K*|, then we can define links with non-zero flows between customers and suppliers (manufacturers and DCs), identify a loop consisting of links with non-zero flows alternating customers and suppliers, and change the flow quantities in the loop by $+\theta$ and $-\theta$ alternatively for some θ to improve the objective function value until the flow of one link in the loop becomes zero. By repetition of this process, the number of customers that are supplied by multiple sources cannot exceed $|M| + |K|$. Thus, the number of customers served by a single source is at least $|H| - (|M| + |K|)$.

For the shipment of standard product for customer h, the tardiness may be defined as

(i) Shipment from the outbound inventory of manufacturer m, $TD^{i}_{mh} = \max\{\tau_{mh} - T_h, 0\}$

(ii) Shipment from the outbound inventory of DC k, $TD^{i}_{kh} = \max\{\tau_{kh} - T_h, 0\}$

(iii) Shipment from the production of manufacturer m, $TD_{mh} = \max\{PS_m + PT_m + \tau_{mh} - T_h, 0\}$

For customer h, the total weighted tardiness for the standard product is then given by

$$WTD_h = \sum_{m \in M}\left(TD^{i}_{mh} q^{i}_{mh}\right) + \sum_{k \in K}\left(TD^{i}_{kh} q^{i}_{kh}\right) + \sum_{m \in M}\left(TD_{mh} q_{mh}\right). \tag{5.3}$$

Similarly, for the customized product for customer h, the tardiness may only be caused by the shipment from the production of DC k, or

$$TD_{kh} = \max\{PS_k + PT_k + \tau_{kh} - T_h, 0\},$$

which leads to the tardiness of customer h for customized product

$$W\tilde{T}D_h = \sum_{k \in K} \left(TD_{kh} q_{kh} \right) \tag{5.4}$$

Note that parameters TD^i_{mh}, TD^i_{kh}, TD_{mh}, and TD_{kh} are all constants. The resulting optimization problems can then be defined as follows

Minimize $\sum_h (WTD_h + W\tilde{T}D_h)$

Subject to (3.1), (3.2), (3.3), (3.4)′, (3.5)′, (3.12), (3.13), (3.21), (5.1), (5.2), (5.3), (5.4)

$$q^i_{mh}, q^i_{kh}, q_{mh}, q_{kh} \geq 0, \ \forall k, m, h$$

It is a linear programming problem and can be solved quickly even with very large networks.

While this special case has a slightly different objective function from that of **P**, the resulting LP problem can be solved easily and its optimal solution is always a feasible solution to **P**. Using such a LP solution as an initial feasible solution to **P**, we can then design a heuristic that focuses on generating production schedules for improved feasible solutions.

5.2 A LP-Relaxation Based Heuristic for P

We introduce in this section an iterative algorithm for solving **P**, by which the search process is guided by a sequence of linear programming (LP) relaxation solutions. Each iteration starts with a given feasible solution as an incumbent solution which defines the values of binary variables and the flow quantity between locations. During an iteration, the shipment arriving at a hospital that results in the greatest tardiness under the current solution is identified, and the respective binary variable, called the *target variable*, is penalized in the objective function (3.0), which results in a new problem called $\mathbf{P_1}$. The LP relaxation of $\mathbf{P_1}$ is then solved optimally, and the respective LP solution is rounded heuristically to obtain a new feasible solution to **P** together with a new objective function value Z_1. If the value of Z_1 improves that of the given incumbent solution, we replace the incumbent solution by the new feasible solution and permanently fix the value of the *target variable* as it is for remaining iterations. Otherwise, we fix the value of the target variable to be one for the remaining iterations, without replacing the given incumbent solution. Doing so, the number of integer variables monotonically decreases through the iterations. This process continues until the values of all the binary variables are determined. The algorithm can also be implemented differently by using more than one target variable per iteration. The resulting heuristic is denoted as the ***LPR*** algorithm in our remaining discussion, and a traceable numerical example that shows a detailed step-by-step search process of LPR can be found in Dong et al. (2013). A more formal search process by the LPR algorithm is defined in Section 5.2.2 and illustrated in Figure 5.1.

5.2.1 Implementation of the proposed heuristic LPR

The implementation of this proposed heuristic LPR deploys two schemes to improve its solution quality and computational efficiency, which are summarized as follows.

Utilizing the skewed network structure

Most supply chain networks for medical emergency supplies tend to have a skewed structure (i.e., a relatively smaller number of manufacturers and DCs on the supply side, and a very large number of customers or hospitals/shelters on the demand side). For example, Cardinal Health, one of the world’s largest distributors of pharmaceuticals and medical supplies, has only four medical kit manufacturing facilities in the U.S, while in NJ/NY area alone, there are over 300 hospitals (Source: http://cardinalhealth.mediaroom.com/index.php?s=20295&item=22571; http://health.usnews.com/best-hospitals/area/new-york-ny). Such a skewed network often results in a large number of binary variables related to distribution flows to customers in model **P** but fewer binary variables related to the flows in the upstream (i.e., from suppliers to manufacturers and DCs). Such a skewed structure supports us to keep all the binary variables connecting the suppliers and manufacturers/DCs during the search process, at the cost of a marginal increase in the computation time, while achieving a significant improvement in the solution quality. The solution quality is improved by the fact that binary variables defining the upper stream network (consisting of suppliers, manufacturers and DCs) have a ripple effect over the multi-echelon process. Because of the skewed network structure, the *partially* relaxed MIP model solved in iteration handles only a small number of binary variables.

The experiment results reported in Table 5.1 highlight the effectiveness of such a partial LP relaxation approach vs. total LP relaxation approach, which relaxes all the integer variables. The performance is measured by

$$Empirical\ \ Error\ \ Gap(EEG) = \frac{(G^{LPR} - G^{*})}{G^{*}} \times 100\% \tag{5.5}$$

and G^{LPR}, and G^{*}, stand for the objective function value of the proposed LPR algorithm, and the best solution obtained by Gurobi solver (on Intel Core Duo CPU, 2.10GHz) with time limit of 3600 CPU seconds, respectively. A negative error gap means that the heuristic obtained a better solution than the best solution found by the MIP solver within the given time limit. Each data point in Table 5.1 is the average of results from five test cases. While taking a little longer time to terminate the search, the partial LP relaxation consistently achieved a better solution quality.

Table 5.1 The effectiveness of partial LP relaxation vs. total LP relaxation (|*S*|=5, |*M*|=2, |*K*|=3).

Experiment settings	**Total LP relaxation**		**Partial LP relaxation**	
$\lvert H\rvert$	EEG %	CPU Time	EEG%	CPU Time
50	2.51%	3.63 sec.	1.09%	10.88 sec.
80	2.15%	5.71 sec.	0.00%	22.29 sec.
100	1.63%	15.96 sec.	0.35%	37.29 sec.
150	1.53%	20.95 sec.	0.02%	71.84 sec.
200	1.33%	37.03 sec.	-0.03%	144.92 sec.
250	2.09%	78.76 sec.	-0.11%	363.95 sec.

Allowing multiple target variables per iteration

To improve the search efficiency, especially when the network size is large, we penalize a group of target variables, instead of a single target variable, per iteration to reduce the number of iterations. A *convergence coefficient* parameter, α, where $0 \le \alpha \le 50\%$, is therefore introduced to control the percentage of binary variables to be treated as target variables in each iteration. As value of α increases, the values of more binary variables are determined and fixed in each iteration, which allows the search to terminate more quickly at the price , however, of potential the solution quality. A detailed study on the impact of α values on solution quality will be reported in the next section.

5.2.2 A formal description of the search process by LPR

To make a formal description of the search process by LPR, let *link* denote a directed arc between *m* and *h,* or between *k* and *h*, which corresponds to binary variable either y_{mh}, y^i_{mh}, y^i_{kh}, or y_{kh}. Then, upon the results from the immediate previous iteration (or the initial heuristic solution for the search), we can define the following sets of links as the input to the current iteration:

Π Set of links corresponding to y_{mh}, y^i_{mh}, y^i_{kh}, and y_{kh}.

Φ The set of links with binary variable y_{link} permanently fixed at $y_{link} = 1$;

Ω The set of links with binary variable y_{link} permanently fixed at $y_{link} = 0$;

Λ Set of links $\{y_{link}\}$ whose values are not yet permanently determined;

Y Set of *target variables* to be penalized by adding $G^{upper} \cdot \sum_{link \in Y} y_{link}$ to the objective function in the current iteration.

Note that $\Phi \cup \Omega \cup \Lambda = \Pi$ and $Y \subset \Lambda$.

For each iteration, the partial LP relaxation problem, $P^{LP}(\Phi, \Omega, Y)$, is implemented as follows:

Input: Parameter α, and sets of links $\{\Phi, \Omega, \Lambda\}$ as defined by the previous iteration

For $\forall link \in \Phi$, add constraints $y_{link} = 1$;

For $\forall link \in \Omega$, add constraints $y_{link} = 0$;

For $\forall link \in \Lambda$, relax each binary variable corresponding to $link \in \Lambda$ to a continuous variable in [0, 1];

Penalize selected target variables by adding $G^{upper} \cdot \sum_{link \in Y} y_{link}$ to the objective, where G^{upper} is an upper bound of G.

Then, we solve the resulting partial relaxation problem, $P^{LP}(\Phi,\Omega,Y)$, to obtain its optimal solution $X^{LP}(\Phi,\Omega,Y)$. If some of those relaxed binary variables receive non-integer values in the optimal solution to $P^{LP}(\Phi,\Omega,Y)$, then solution $X^{LP}(\Phi,\Omega,Y)$ is not feasible to the original problem **P**. When this is the case, we round up all such $0 < y_{link}^{LP} < 1$ values to $y_{link}^{LP}=1$ to obtain a feasible solution $X(\Phi,\Omega,Y)$ for the iteration. Let $G(X(\Phi,\Omega,Y))$ denote the objective function value of feasible solution $X(\Phi,\Omega,Y)$. If $G(X(\Phi,\Omega,Y))$ does not improve the objective function value of the incumbent solution (i.e., the effort to close the target links does not show a merit), we shall keep the links in Y open, i.e., expand Φ to $\Phi \cup Y$. On the other hand, if $G(X(\Phi,\Omega,Y))$ does show an improvement, we examine the values of target variables as follows: if $y_{link}^{LP} = 0$ then the respective link is no longer needed by the improved solution, and let $\Omega \Leftarrow \Omega \cup \{link \in Y \mid y_{link} = 0\}$; if $y_{link}^{LP} = 1$ then the link should remain open, and let $\Phi \Leftarrow \Phi \cup \{link \in Y \mid y_{link} > 0\}$.

Note that in each iteration set Y is determined upon the value of α and consists of those links from Λ with the largest tardiness. After that, set Λ is updated to $\Lambda \Leftarrow \Lambda \setminus Y$ for the next iteration. This iterative search process by LPR terminates when either set Λ becomes empty or the objective function value can no longer improve in remaining iterations. In the latter case, leftover binary variables in Λ are heuristically rounded based on current values. Then a final LP problem is solved with all binary variables' values fixed. A detailed flowchart of LPR is given in Figure 5.1 below.

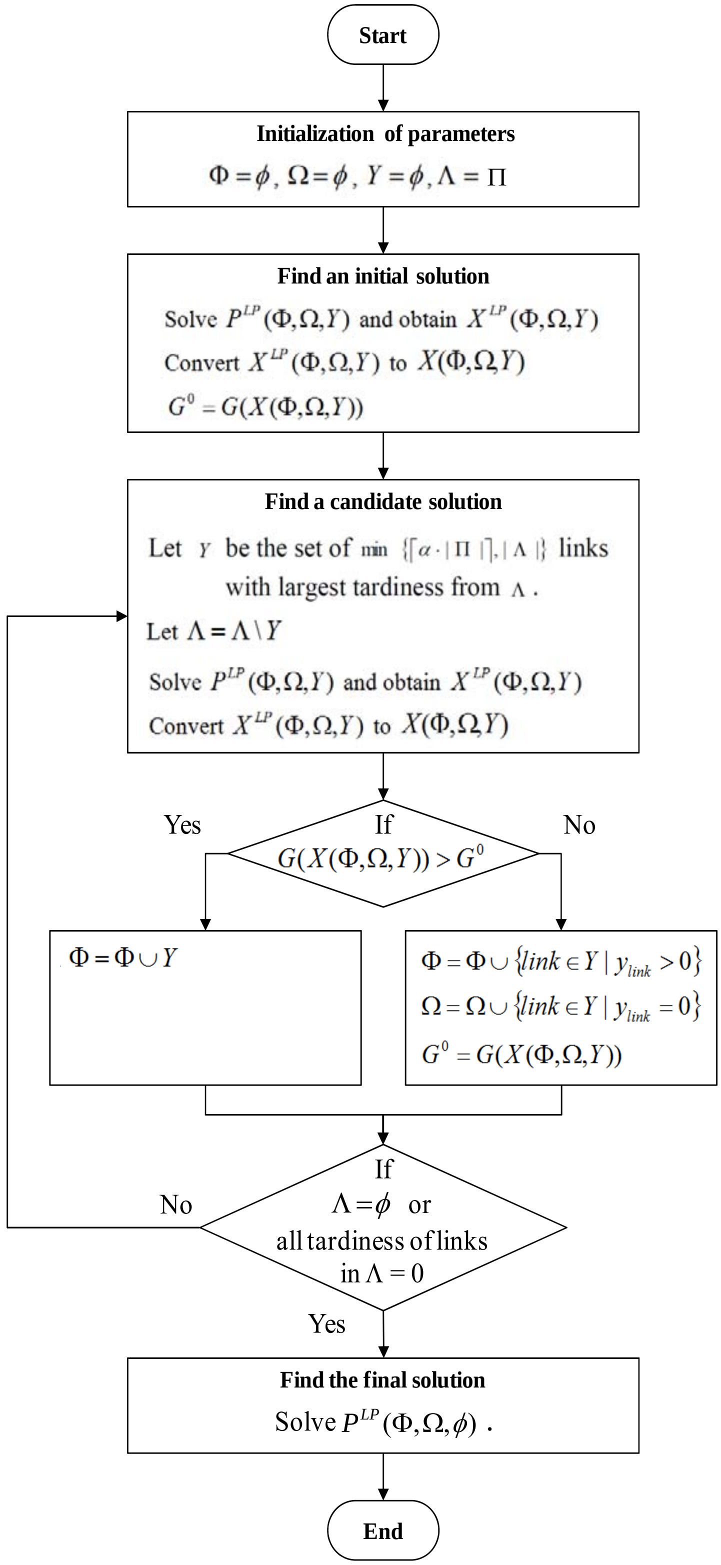


Figure 5.1 Flowchart of the iterative partial LP relaxation based algorithm (LPR).

5.3 The Empirical Study

In this section, we discuss the implementation of **LPR,** and compare its computational performance with the best solutions obtained by commercial optimizer Gurobi (on Intel Core Duo CPU, 2.10GHz). Table 5.2 below summarizes the values of parameters used in our experiments.

Table 5.2 Parameters used in the empirical study.

Parameters	**Values used in the experiments**
Shipping time (hrs)	$\tau_{sm} \sim uniform(10,50)$, $\tau_{sk} \sim uniform(20,50)$
	$\tau_{mh} \sim uniform(20,50)$, $\tau_{kh} \sim uniform(10,30)$
Due date (hrs)	$T_h \sim uniform\ (0,72)$
Inventory (units)	$I_s \sim uniform(3000,5000)$, $I_m^s \sim uniform\ (1000,2000)$
	$I_k^s \sim uniform\ (1000,2000)$, $\sum_m I_m + \sum_k I_k = 10\% \cdot \sum_h D_h$
Production rate (units/hr)	$r_s \sim Normal\ (5000,500)$, $r_m \sim Normal\ (5000,500)$,
	$r_{kh} \sim Normal\ (1000,100)$
Demand (units)	$D_h \sim Normal\ (10000,1000)$, $\widetilde{D}_h \sim Normal(2000,200)$

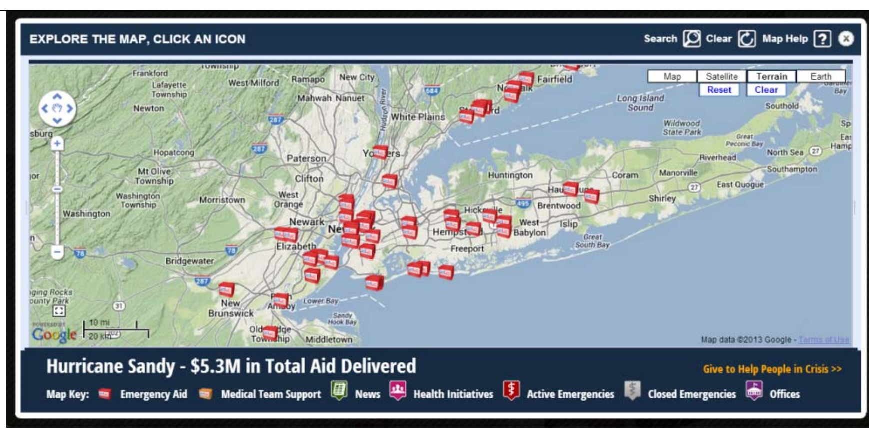


Figure 5.2 The response of AmeriCares to Hurricane Sandy.

(from http://www.americares.org/emergency-response/hurricane-sandy-recovery.html)

In these experiments, the shipping times (see Table 5.2) were randomly generated proportional to the scale of the affected area of Hurricane Sandy (see Figure 5.2), and the order delivery due dates were generated based on the critical 3-day period right after the occurrence of a disaster (Sheu (2007a)). For all the experiments, the sizes of supply chain networks were defined as $|S|=5$, $|M|=2$, $|K|=3$ and $|H| \in \{8, 9, 10, 50, 100, 150, 200, 250\}$.

5.3.1 Choice of the convergence coefficient

When the network sizes were relatively small (*e.g.*,$|H| \leq 10$), the commercial solver (Gurobi) was able to terminate with the optimal solutions. Such optimal solutions can be used to benchmark the computational performance of **LPR** in terms of the *empirical error gaps (EEG)* as defined by equation (5.5). In Table 5.3, we report the EEG values together with the average (and standard deviation) of running times upon each set of 10 randomly generated test cases under $|H|$=8, 9, and 10, respectively. As we can see, the EEG value improves consistently as the value of α decreases. Also, as the network size $|H|$ increases, the running time required by the MIP solver increases quickly, while the changes in computational effort by LPR remain to be minimal. From the observations reported in Table 5.3, we adapted α=0.05 for the remaining experiments in this study.

Table 5.3 Comparison between MIP solver and the proposed heuristic (|*S*|=5, |*M*|=2, |*K*|=3).

$\|H\|$			MIP solver	Heuristic		
				$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.20$
8	EEG	Average (Std. Dev.)	-	2.04% (0.79%)	1.46% (0.78%)	4.84% (1.90%)
	CPU	Average	**82.55**	**1.91**	**1.49**	**0.99**

	Time(sec)	(Std. Dev.)	**(36.59)**	**(0.14)**	**(0.08)**	**(0.09)**
9	EEG	Average (Std. Dev.)	-	1.20% (1.31%)	4.89% (3.91%)	11.42% (3.24%)
	CPU Time(sec)	Average (Std. Dev.)	**302.98** **(218.32)**	**2.22** **(0.54)**	**1.33** **(0.23)**	**1.30** **(0.47)**
10	EEG	Average (Std. Dev.)	-	3.65% (1.17%)	5.31% (1.83%)	11.27% (2.72%)
	CPU Time(sec)	Average (Std. Dev.)	**618.27** **(170.32)**	**2.53** **(0.58)**	**1.47** **(0.25)**	**1.16** **(0.30)**

5.3.2 Performance of LPR against network sizes

We studied the impact of network sizes on the computational performance of **LPR**. In this part of the study, we fixed the numbers of suppliers, DCs, and manufacturers at $|S|$=5, $|M|$=2, and $|K|$=3, respectively, and allowed the number of customers to range between 50 and 300. Since the commercial solver failed to find the optimal solution (within the given CPU limit of 3600 seconds) for all the cases in this part of study, we report (Table 5.4) the gaps between the heuristic solution and the best Gurobi solution, denoted as G^*, obtained within the time limit. In terms of performance measure EEG defined in equation (5.5), the heuristic LPR demonstrated a very competitive and robust performance. Even though its computational time increases as the network size ($|H|$), it is still significantly less than the time required by the commercial solver.

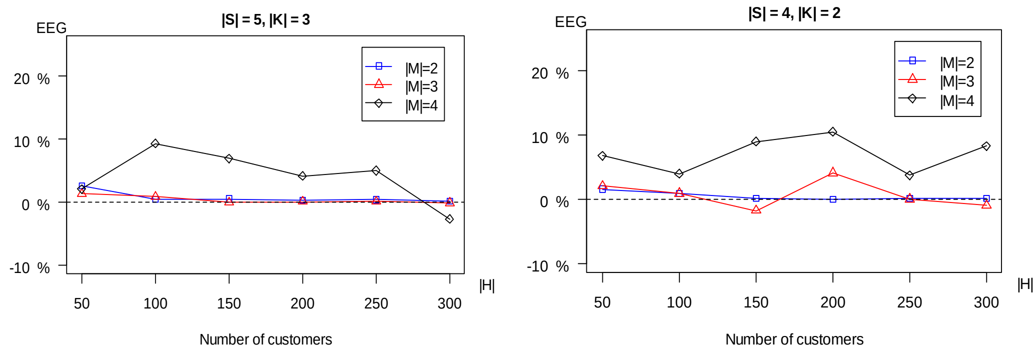
Table 5.4 Performance comparison with larger networks ($|S|$=5, $|M|$=2, $|K|$=3).

$\|H\|$	**EEG**		**CPU time in sec.**	
	Avg.	(Std. Dev.)	Avg.	(Std. Dev.)

50	1.90%	(0.49%)	8.34	(0.75)
100	0.78%	(0.34%)	23.78	(2.79)
150	0.46%	(0.16%)	53.13	(12.33)
200	0.34%	(0.17%)	121.16	(31.09)
250	0.26%	(0.12%)	178.87	(34.36)
300	0.54%	(0.83%)	329.90	(117.65)

We also conducted experiments using networks with (a) $|S| = 5$, $|K| = 3$; and (b) $|S| = 4$, $|K| = 2$ under different numbers of manufacturers ($|M|$) and customers ($|H|$). Figures 5.3 (a) and (b) report the average performance measures (EEG) observed under different network settings, where each data point denotes the average result from five randomly generated test cases. As we can see, the number of DCs does not seem to have a significant impact on the performance of **LPR**. However, as the number of manufacturers becomes larger, EEG tends to increase. Furthermore, the EEG value seems quite stable when $|M| = 2$ or 3, and then becomes less stable when $|M| = 4$. One possible reason for this is that the new batch produced by each manufacturer is more likely to introduce significant delays (through its production time and component sourcing time) to a large number of customers.

It is interesting to note that for the largest upstream network in this study with $|S| = 5$, $|M| = 4$, and $|K| = 3$, the performance of LPR, as measured by EEG, seems to become better as the number of customers increases. One possible explanation is that, as the problem size increases, the commercial solver becomes more unlikely to locate a good feasible solution within the given time limit, which in turn leads to a smaller EEG value. As the empirical results in Figures 5.3 (a) and (b) show, the number of customers does not have a significant impact on the computational performance of LPR algorithm, which is consistent with the observation in Table 5.4. However, the LPR performance (as measured by the EEG values) is more sensitive to the upstream network structures.



(a) EEG value with |*S*|=5, |*K*| =3 **(b) EEG value with |*S*|=4, |*K*| =2**

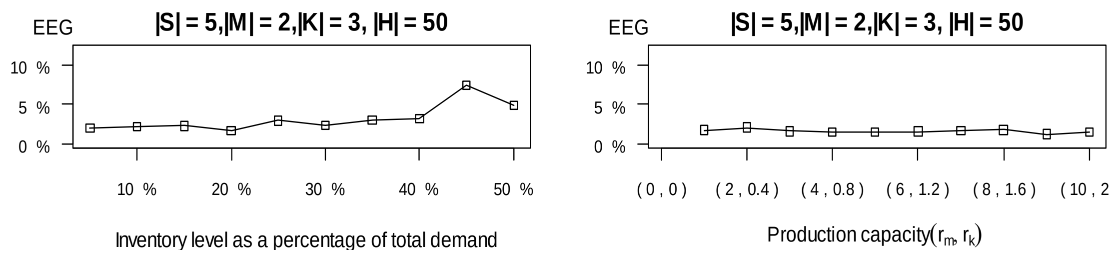
Figure 5.3 EEG value in different network settings.

5.3.3 Performance of LPR against inventory levels and production capacity

We also investigated the impact of inventory levels and production capacity on the computational performance of the proposed LPR algorithm. The inventory here can be regarded as pre-disaster stock, measured by the ratio of the total inventory to the total demand for standard kits. The higher the inventory level, the more customers' demands can be fulfilled directly by existing inventory without the need to produce a new batch. Production capacity at manufacturers and DCs were measured by thousand units produced per hour at the facility.

For this part of the study, we varied the inventory level of standard kits from 5% to 50%. For each given inventory level, five test cases were randomly generated to empirically observe the values of EEG. As one can see from Figure 5.4(a), the resulting EEG values were fairly stable under different inventory levels, with the largest empirical error gap around 7%.

Figure 5.4(b) shows the impact of production capacity on the computational performance of LPR. Different production capacities of manufacturers and DCs were considered in the experiments. As we can see, the average EEGs achieved by LPR under different production capacities of manufacturers and DCs were fairly stable, and all of them fell below 3%.



(a) EEG vs. different inventory levels (b) EEG vs. production capacity

Figure 5.4 Empirical EEG values under different parameter settings.

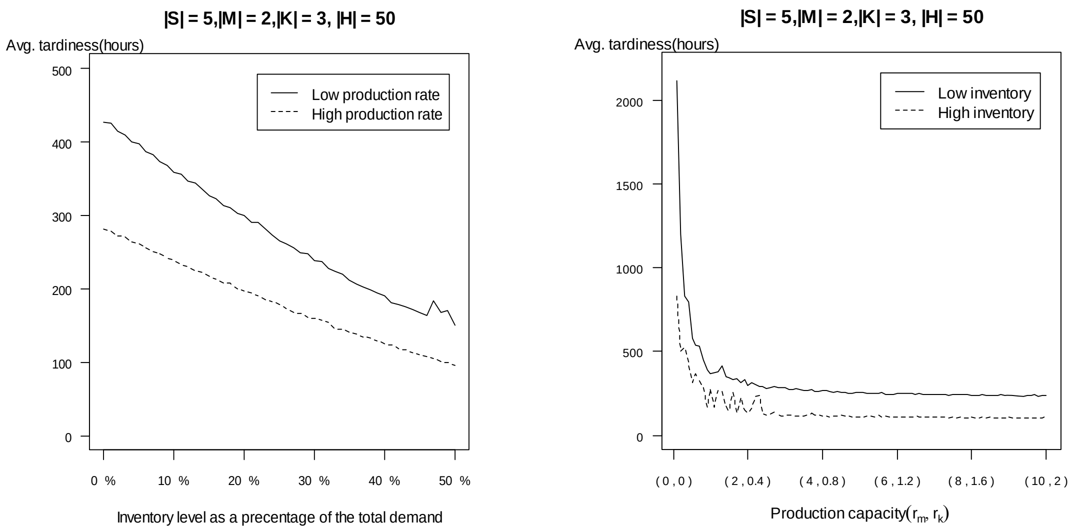
5.3.4 The impact of strategic policies on average tardiness

Another part of our empirical study was devoted to gaining an understanding of the impact of production capacity and pre-positioned inventory, as strategic policies, on the *average tardiness* in customer order fulfillment, which is defined as

$$\sum_h (TD_h \cdot D_h + \widetilde{T}D_h \cdot \widetilde{D}_h) / \sum_h (D_h + \widetilde{D}_h) . \tag{5.6}$$

To do so, we conducted an empirical study with $|H|$=50, as reported in Figures 5.5(a) and 5.5(b). Figure 5.5(a) shows the impact of pre-positioned inventory under two different levels of production capacity, *high* and *low*, where the high capacity level was defined by $r_m = 6000\ units/hr$, $r_k = 1200\ units/hr$ and the low capacity level was defined by $r_m = 2000\ units/hr$, $r_k = 400\ units/hr$. These observations were obtained from 51 randomly generated test cases by changing inventory levels from 0% to 50%. As we can see, the average tardiness decreases linearly as the inventory level increases regardless of the production capacity. We can also see that the average tardiness under the high level of production capacity is proportional to that under the low level of production capacity.

Figure 5.5(b) reports our empirical observations on the relationships between *average tardiness* and *production capacity* under different inventory levels. Two kinds of inventory levels, measured by the ratio of pre-positioned inventory to total demand, were considered, where a ratio of 50% refers to a high inventory level, while a ratio of 10% refers to a low inventory level. As the production capacity decreases, the average tardiness increases rapidly due to the lead time needed for supplies. On the other hand, as the production capacity increases, the average tardiness decreases quickly, and then stabilizes (due to the bottleneck of shipping time). Furthermore, the average tardiness under high inventory level is fairly proportional to that under low inventory level. This empirical observation indicates that prepositioning a sufficient inventory in the network prior to the arrival of a disaster could lead to a significant reduction in the tardiness of delivering emergency supplies. However, as for the production capacity, once it exceeds a certain threshold, then its impact on average tardiness is no longer that significant.



(a) Tardiness vs. inventory levels **(b) Tardiness vs. production capacity**

Figure 5.5 The average tardiness under different strategic policies.

5.4 Concluding remarks

We study the operations scheduling problem defined upon a multi-stage network with non-negligible lead times between the stages, and an objective of minimizing the total tardiness in customer order fulfillment. Two solvable cases of this problem are analyzed, and a heuristic search algorithm is proposed. The proposed heuristic solves a series of partial linear programming relaxation problems, and is able to terminate quickly with a near-optimal solution. Observations from an extensive empirical study are reported.

CHPATER 6 EFFECTIVENESS OF THE MANAGEMENT STRATEGIES FOR THE EMERGENCY OPERATIONS

Supply chain management covers the scope of three levels: the strategic level, the tactical level and the operational level. Our previous work in Chapters 4 and 5 mainly focus on the tactical and operational planning of the disaster relief supply chain, including production planning, allocation of demands and inventories, replenishment of components at manufacturers and distribution centers, etc. In practice, higher level strategic decisions must be made before the execution of emergency operations to improve the agility and capability of a relief process. Examples of such strategic decisions are facility locations, supplier selections, logistics network structure design and inventory prepositions, etc.

In Chapter 1, we have surveyed literatures in both the general integrated production and distribution problems and the production and distribution operations/scheduling in disaster relief. These papers are about the tactical or operational decision of a supply chain. There are also abundant papers about strategic decisions for supply chains. In the field of the emergency supply chain, Wassenhove (2006) discusses the collaboration of humanitarian organizations and private sectors, along with which he also lists five key elements that are essential for better preparedness for disaster response, including human resource, knowledge management, operations and process management, financial resources and the community; Balcik and Beamon (2008) consider a facility location model for a relief supply chain that responds to quick-onset disasters which determines the number, location and amount of relief supplies to stock in each facility;

Balcik et al. (2010) examine the coordination mechanisms in humanitarian relief chains including collaborative procurements, warehousing standardization and transportation. They mention that while coordination mechanisms in the commercial supply chain management have been well studied, the counterpart in humanitarian relief chain is still in its infancy; Horner and Downs (2010) study a warehouse location problem that is used to manage flows of relief goods shipments, and show that the performance measure is affected by the distribution infrastructure and the assumed population in need of aid. In this chapter, we will propose and evaluate management strategies for the general supply chain network defined in Chapter 3.

Both Altay and Green (2006) and Galindo and Batta (2013) mention in their survey that the organizational and network structure in the disaster relief chain is not as well defined as in the commercial supply chain management. The relief chain network can be very complex itself and almost always has uncertain parameters. Because of this feature, we choose simulation as the methodology to effectively study strategies for our emergency supply chain network, which avoids directly modeling the complex network and also takes care of the uncertain factors.

In the rest of the chapter, we will propose two strategies to improve the supply chain performance in Section 6.1, along with the experiment design and result, and give concluding remarks in Section 6.2.

6.1 Two Management Strategies for Emergency Operations

In Chapter5, we conduct an empirical study on the impact of important parameters in the general problem **P**, including the inventory of standard kits and production rates at all manufacturers/distribution centers. We found that the impact of production rates on the system performance has a bottleneck (Figure 5.5 (b)), which we infer is the components inventories at manufacturers/distribution centers. The inference motivates us to develop a strategy that utilizes the influence of components inventories.

Also, in disastrous situation, the outbound shipping to the affected areas could get delayed due to damaged infrastructures (e.g., broken highway) or chaos in transportation resources (e.g., trucks, drivers). These factors will greatly increase the difficulty of serving customers. The problem can be mitigated if we have facilities located near the affected areas with pre-positioned inventories. Along this direction, we propose a strategy that locates a mobile distribution center (DC) near customers that carries standard kit inventories and components inventories for the production of customized kits.

In summary, we will propose two strategies for the general emergency supply chain defined in Chapter 3, including 1) increasing components inventories at manufacturers and distribution centers; 2) setting up a mobile DC which can assemble customized kits and ship them to customers in negligible time. We reflect the two strategies in Figure 6.1 on the basis of the supply chain network presented in Figure 3.1.

The two strategies are evaluated through Monte Carlo simulation: for each of the strategy, we generated *n* independent replications of parameters using distributions defined in Table 5.2, and under each replication, the general problem **P** is solved both with and without applying the strategy and the system performance under both cases are compared. The performance measure used is the *average tardiness* in hours as defined by Equation (5.6) in Chapter 5, and we define *improvement* as the reduced *average* *tardiness* in hours after applying a strategy. We calculate a mean and a 95% confidence interval for the *improvement* in this study. According to the central limit theorem, when the sample size is large enough (n≥30), the sample mean approximately follows a normal distribution $N(\mu,\delta^2)$ with mean μ and variance δ^2. Let $z_{0.025}$ be the 0.975-quantile of a standard normal distribution, a two-tail 95% confidence interval is defined as

$$[\bar{x} - z_{0.025}\sigma/\sqrt{n}, \bar{x} + z_{0.025}\sigma/\sqrt{n}],$$

Where $\bar{x}$ is the sample mean from a sample of size *n* and σ is the corresponding sample standard deviation. In this study, we choose *n*=30.

In the rest of this section, we will introduce details of our strategies and present the results from the simulation study.

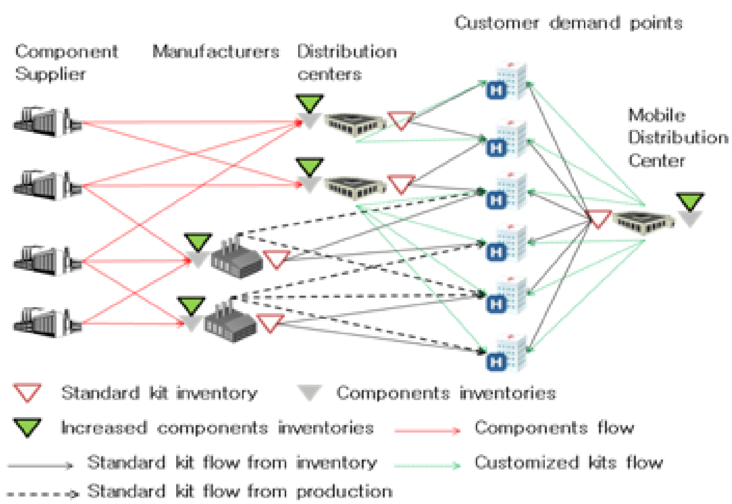


Figure 6.1 The emergency supply chain network after applying strategies.

Strategy 1: Increasing components inventories at manufacturers and distribution centers

A lack of components inventories will force manufacturers and distribution centers to replenish when they have a production task, which will introduce extra lead time to fulfill the customer orders.

In Strategy 1, we will increase the components inventories at manufacturers and distribution centers to several different levels, and compare system performances before and after applying Strategy 1. Figure 6.2 shows the decision process of fulfilling a customer order, and stages affected by Strategy 1 are highlighted in grey.

During the disaster, suppliers face a spike in the demand of the components they provide, which could cause a shortage of transportation resources such as trucks and drivers. In this case, the shipping time from suppliers to manufacturers and distribution centers is longer than the normal situation. We expect that increasing components inventories at manufacturers and distribution centers is more meaningful when such delays happen. Also, because demands are highly uncertain right after a disaster, we also would like to investigate the cross influence of components inventories and demand variability, and see how robust the strategy is to the demand uncertainty.

Therefore, we first study the impact of Strategy 1 on the system performance under different demand variability, and then under different levels of inbound shipping delay. The network we use contains 5 component suppliers, 2 manufacturers, 3 distribution centers (DCs) and 50 customer demand points. We increase the components inventories at manufacturers and distribution centers to 2 times, 5 times and 10 times of the original levels, respectively. For each of the three levels, we vary the standard deviation of the demand distribution from 5% to 50% of the mean and study the cross effect. Independently, we increase the shipping time of components from suppliers to manufacturers and DCs. The increments range from 10% to 100% of the originally generated shipping time. For each scenario, we simulate 30 independent replications, and calculate a mean and a 95% confidence interval for the *improvement*.

Figure 6.3(a)-(c) show the *improvement* by Strategy 1 under different levels of demand variability. The horizontal axis is the standard deviation of demand distribution as a percentage of the mean, and the vertical axis is the *improvement* after applying Strategy 1. The solid line in each figure is the mean of the improvement over 30 independent replications, and the two blue dotted lines are the lower bound and upper bound of a 95% confidence interval, respectively.

Seen from the simulation results, it is obvious that increasing components inventories will improve the performance of the supply chain, and the *improvement* becomes more significant as components inventory levels become higher. However, the impact of increased components inventories is not influenced by the standard deviation of the demand distribution. It means that regardless of the demand variability of the affected areas, increasing component inventories will achieve the same improvements on the *average tardiness* of the supply chain.

Figure 6.4 (a)-(c) present the *improvement* by Strategy 1 under different levels of inbound shipping delay. It shows that overall the *improvement* increases as the level of components inventories increases. However, different from the expectation, the *improvement* is not clearly influenced by the level of inbound shipping delay, since for each components inventory level, the *improvement* stays flat over all levels of inbound shipping delay. This is actually because in the current parameter settings, increasing inbound shipping time by 10% to 100% does not have a significant impact on the final *average tardiness*. In cases where the inbound shipping time plays a more important role in the *average tardiness*, the contribution of increased components inventories will be more and more obvious as the inbound shipping gets delayed longer.

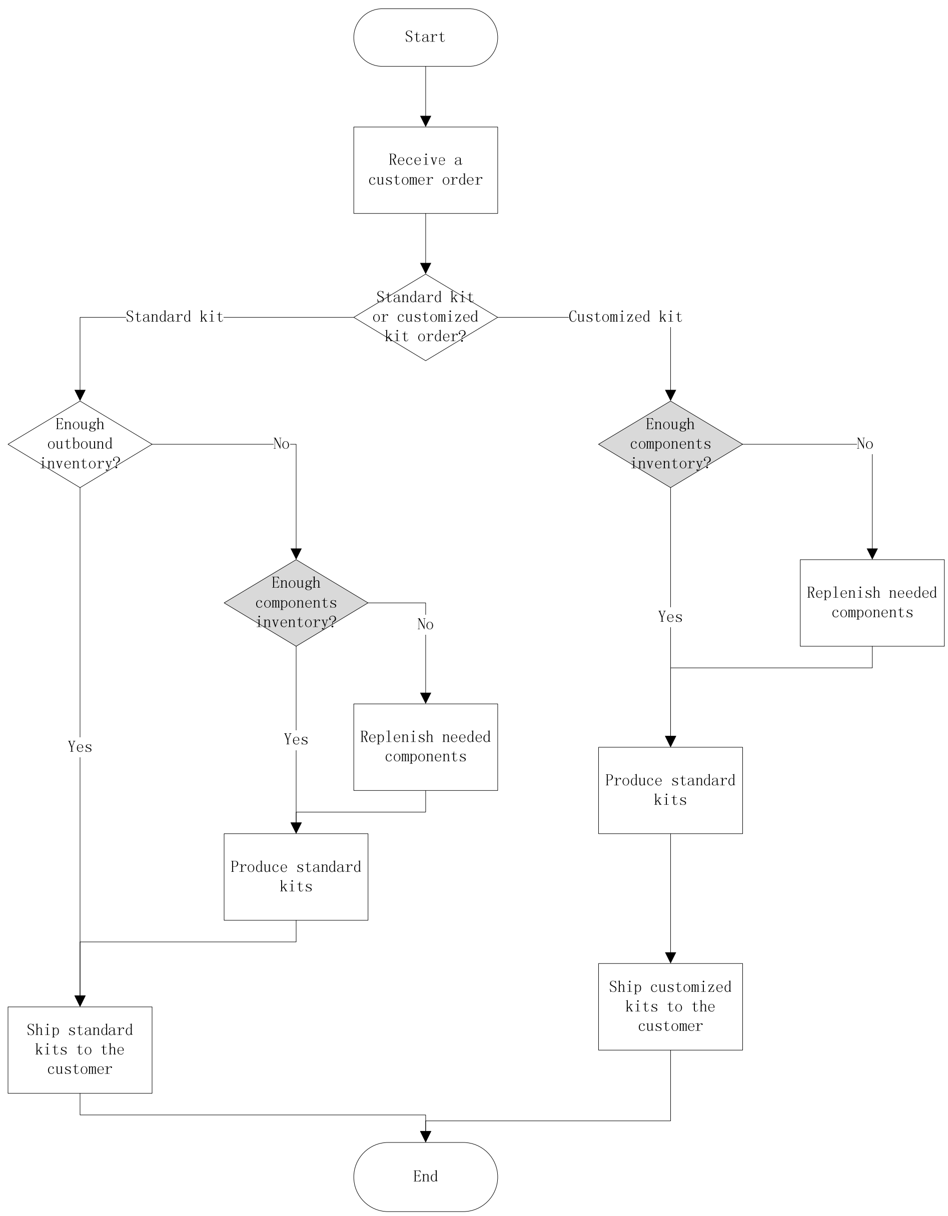
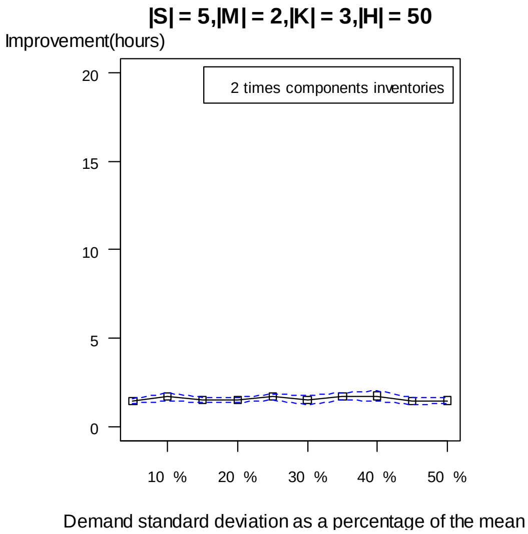
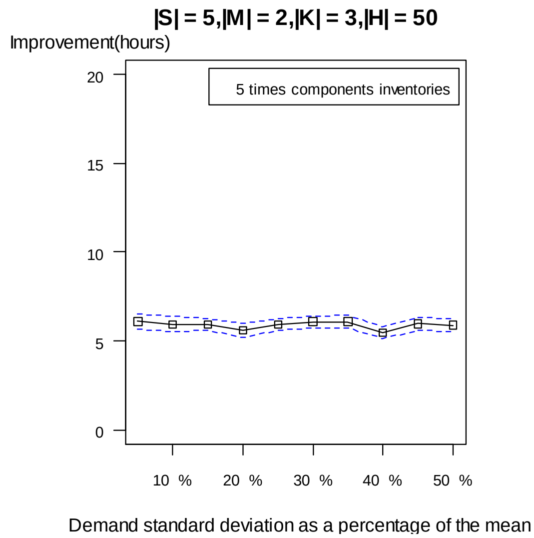


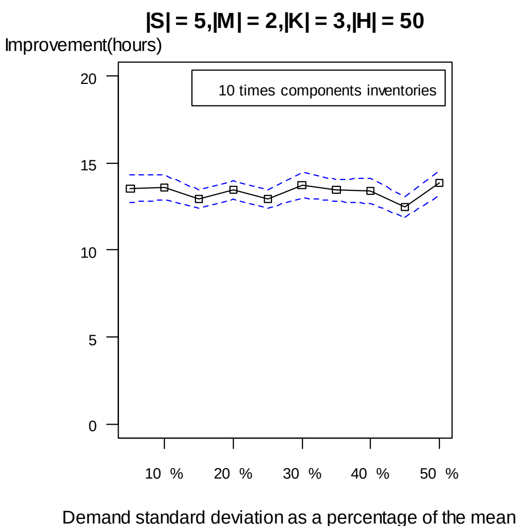
Figure 6.2 Stages affected by Strategy 1 in the decision process.



(a) 2 times components inventories

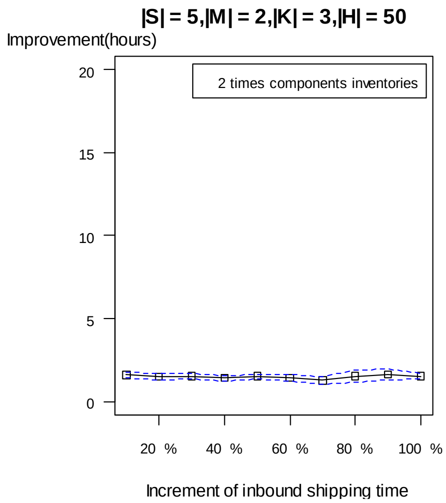


(b) 5 times components inventories

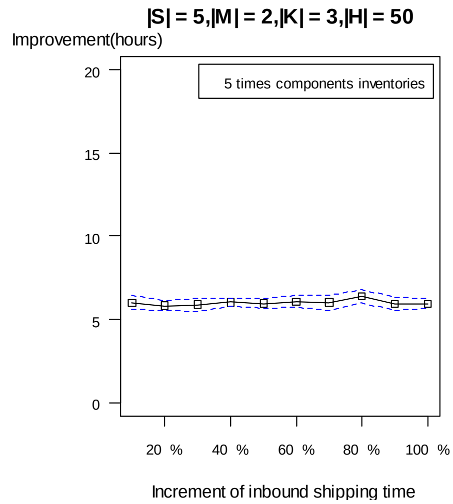


(c) 10 times components inventories

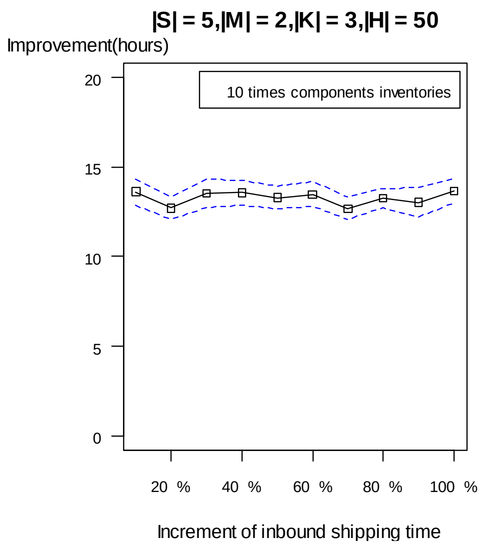
Figure 6.3 Improvements of the *average tardiness* in hours with different demand variability.



(a) 2 times components inventories



(b) 5 times components inventories



(c) 10 times components inventories

Figure 6.4 Improvements of the *average tardiness* in hours with different levels of inbound shipping delay.

Strategy 2: Mobilizing the distribution centers

The bills of materials for customized kits are not known until after the disaster, so it is impossible to prepare the final product inventory of customized kits at either manufacturers/distribution centers or customer demand points. We propose a strategy that sets one of the distribution centers as a mobile DC, which carries certain amount of standard kit inventories, assembles customized kits after the disaster, and ships them to the customer demand points in negligible time. For this purpose, we introduce q_h^{mob} as the amount of customized kits for customer demand point *h* produced at the mobile DC. In addition, we change constraint (3.13) in problem **P** into $\sum_k q_{kh} + q_h^{mob} = \widetilde{D}_h$. To be clearer, we highlight the stages affected by Strategy 2 in the decision process of fulfilling a customer order, as shown in Figure 6.5.

The mobile DC has more components inventories and negligible shipping time to customers compared to regular DCs, but the production time of the customized kit still needs to be considered. Also, if the production requires more components inventories than there are onsite, the mobile DC has to replenish components from the upstream suppliers, which will incur extra waiting time.

The main purpose of such a mobile DC is to hedge the risk of disruption and delay of outbound shipping. Therefore, in our study, we will vary the extent of delays in the outbound shipping, and compare the contribution of the mobile DC under different scenarios. It is reasonable to assume that the more serious the outbound shipping is delayed, the more useful the mobile DC is. Also, to test the robustness of the strategy under demand uncertainly, we also study the impact of Strategy 2 with respect to different levels of demand variability.

The network has 5 suppliers, 2 manufacturers, 3 DCs and 50 customer demand points. In the simulation, we set the components inventories at the mobile DC to be 3 times and 10 times of their originally levels, respectively. We simulate scenarios when the outbound shipping time of all manufacturers and distribution centers increases by 10% - 100%. For each scenario, 30 independent replications are generated, and a mean and a confidence interval are calculated for the *improvement*. Independently, we also vary the standard deviation of the demand distribution from 5% to 50% of the mean, and observe how the *improvement* by Strategy 2 changes.

Figure 6.6 (a) and (b) show the *improvement* in hours with respect to different levels of outbound shipping delay. Again, the solid line is the mean of 30 independent replications and the two blue dotted lines stand for a 95% confidence interval. It is observed that more components inventories in the mobile DC result in greater improvement. Also, note that there is an upward trend of the *improvement* in both figures when the outbound shipping time increments get large. This verifies the assumption that the worse the transportation condition is in the downstream network, the more useful a mobile DC is for the distribution of the relief kits.

Figure 6.7 (a) and (b) show the *improvement* in hours with different levels of demand variability. The results also show that the overall improvement is greater when there are more components inventories, however, for each of the two components inventory levels (3 times or 10 times), the improvement is not impacted by the level of demand variability.

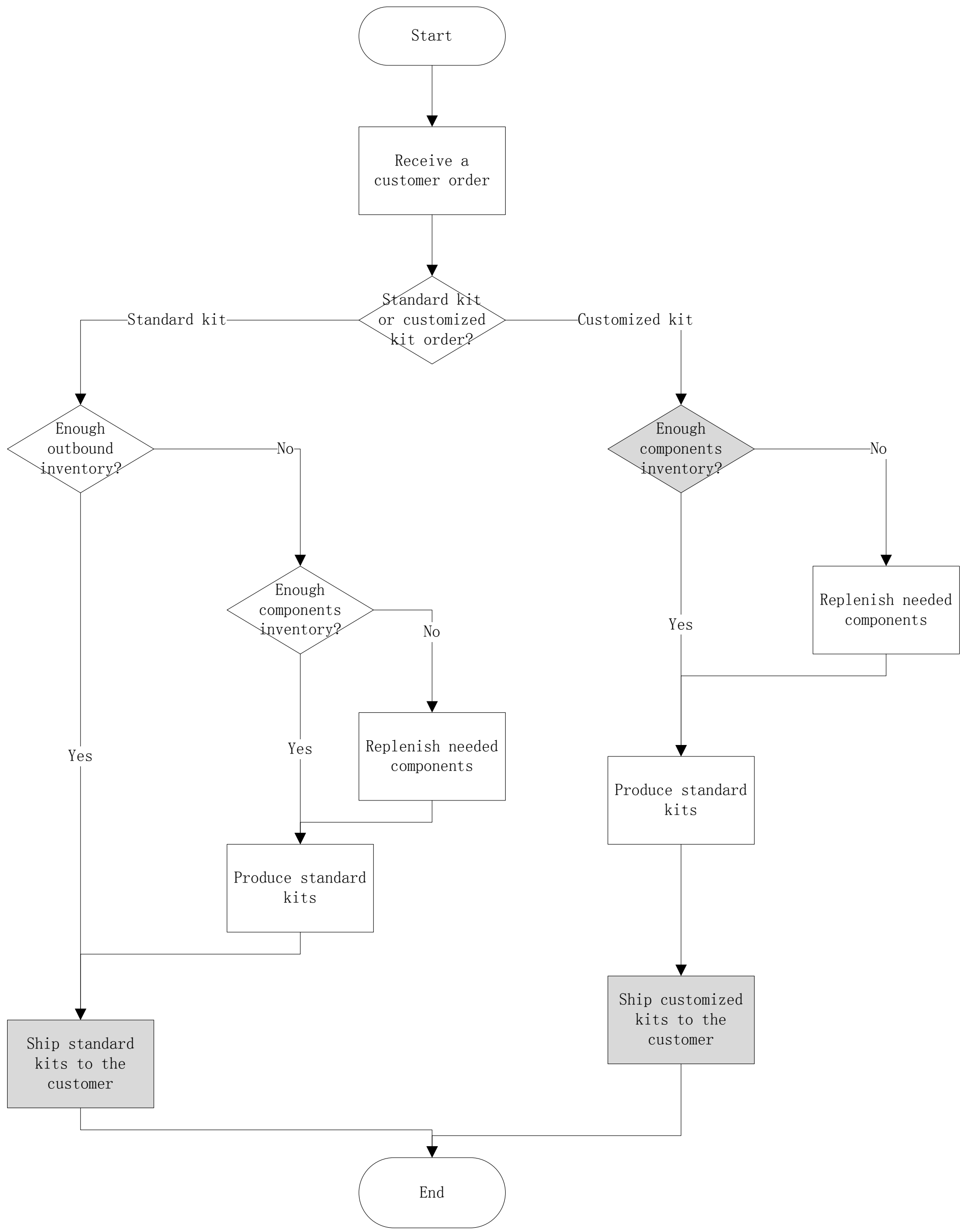
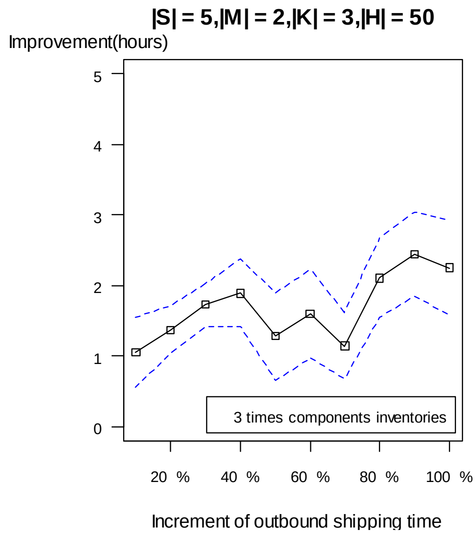
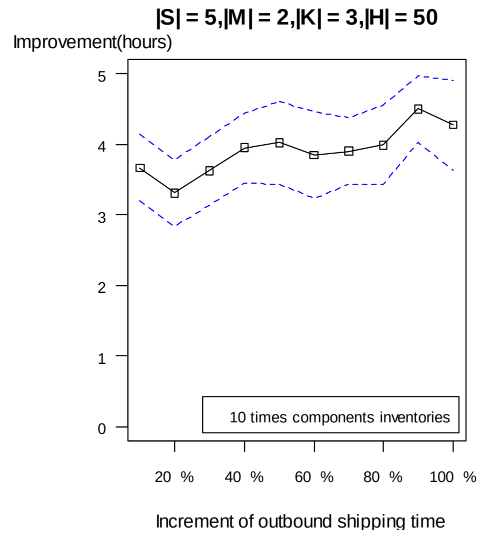


Figure 6.5 Stages affected by Strategy 2 in the decision process.

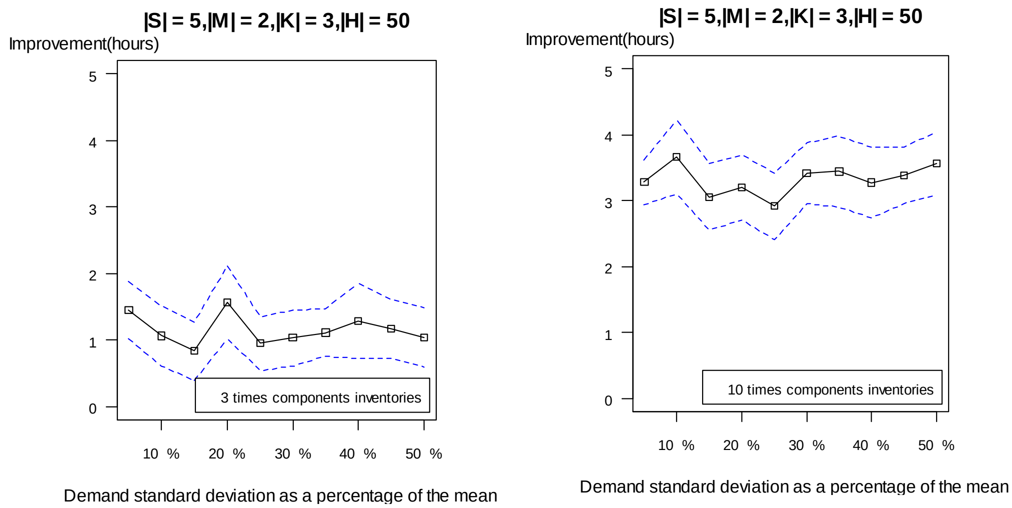




(a) 3 times components inventories at the mobile DC

(b) 10 times components inventories at the mobile DC

Figure 6.6 Improvements of the *average tardiness* in hours with different levels of outbound shipping delay.



(a) 3 times components inventories at the mobile DC

(b) 10 times components inventories at the mobile DC

Figure 6.7 Improvements of the *average tardiness* in hours with different demand variability.

6.2 Concluding Remarks

Based on the indication of the simulation study, the users can choose appropriate strategies according to the situation they are dealing with. For example, if they predict the downstream transportation network will be heavily affected, then it is wise to set up a mobile distribution center near target areas and allocate inventories to it with priority. On the other hand, when the inbound shipping time of components plays a significant role in the supply chain performance (tardiness), increasing components inventories can effectively hedge potential delays in the upstream transportation. Both strategies are robust to the demand uncertainty.

CHAPTER 7 EXTENSIONS AND FUTURE RESEARCH

The research in this study can be extended in both modeling and solution methodologies. There are several interesting extensions for the modeling. For examples, the supply chain network model can be generalized to allow a subset of demand points (hospitals) to serve as the transshipment points, which is fairly common in real life emergency operations. Whenever a hospital has spare supplies during a disaster, it often shares the supplies with other hospitals in the neighborhood area to reduce the patient waiting time. While adding transshipment points to a network increases the complexity, the resulting model is certainly one step closer to what is encountered in practice. In addition to minimizing the weighted tardiness, another meaningful objective is to minimize the maximum deviation from target delivery times. During a real life emergency relief process, minor delays in shipments are common practices and can be usually managed. However, a significant delay which in turn leads to a severe shortage in medical supplies could be damaging and threatening to the patient lives. Furthermore, at the operations planning level, each plan is usually developed and deployed for a particular region of the affected area where multiple regions may compete for bottleneck resources (e.g., ambulances and registered nurses). This leads to the needs for modeling with multiple objectives such as minimizing the total tardiness to the demand points and minimizing the number of ambulances deployed for the shipments. While minimizing the operation cost is not considered as a primary objective in our study, it is certainly interesting to be included in the future studies to develop managerial guidelines for government and NGOs in inventory, supplier contracting, and emergency vehicle deployment for emergencies, under a constrained budget. On this basis, we would like to study multiple shipping options in the network. In emergency disaster relief, it is common to have multiple types of transportation vehicles to assist the logistics. For example, helicopters (Barbarosoglu et al. (2002)) are employed when trucks are not fast enough or when the ground transportation system is severely damaged.

There are also several potential extensions in the solution methodology proposed. First, while we assumed the direct shipments, in this study, between manufacturers/ distribution centers and the demand points, the vehicle routing issues are often foreseeable in the practices (e.g., when some demand points are located in the same neighborhood area and all ordered a less-than-truck-load), which is particularly true when the trucks used for shipments are bottleneck resources in the emergency logistics network. When this is the case, the newly added routing issue may require the inclusion of metaheuristics as subroutines of our proposed solution algorithm. Another meaningful extension of the solution approach is based on problem decomposition via customer-facility-supplier clustering. For each given cluster, the problem size becomes much smaller, which allows our proposed search algorithm to increase the likelihood of locating a near-optimal solution. However, the clustering through network decomposition leads to another optimization issue yet to be solved. Finally, in this study, we only considered the deterministic version of the problem. In reality, both the shipping time and customer demand, even the production capacities, could be random variables. Designing the methodologies that can solve the resulting stochastic optimization problem is certainly more challenging and interesting.

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