A STOCHASTIC PROGRAMMING APPROACH FOR OPTIMIZING CRYOPRECIPITATE COLLECTION SCHEDULES

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ABSTRACT

A STOCHASTIC PROGRAMMING APPROACH FOR OPTIMIZING CRYOPRECIPITATE COLLECTION SCHEDULES

In this thesis, we investigate the problem of generating weekly collection schedules for cryoprecipitate, a vital blood product as the main source of fibrinogen. As cryoprecipitate requires special equipment for collection, a two-day notice is needed before a mobile site can be assigned to cryoprecipitate collection. Due to the perishable nature of cryoprecipitate, we consider its eight hours collection-to-completion time constraint, in addition to the daily processing capacity of host sites. We aim to minimize the total collection cost while determining which mobile sites should be assigned as cryoprecipitate collection sites to satisfy weekly collection targets. We formulate the problem as an integer programming problem and propose a robust and a stochastic programming approach to model the uncertain nature of blood supplies. We analyze these two approaches in which the first one focuses on feasibility by meeting the weekly demand and the second approach aims to minimize the expected penalty due to the unsatisfied demand. Our results show that stochastic approach performs better with lower total collection cost, whereas robust approach presents a more cautious schedule with less amount of unsatisfied demand. Furthermore, we compute the value of the stochastic solution, which results in a significant improvement in the results as the weight assigned to the penalty of unmet demand amount increases.

ÖZET

KRİYOPRESİPİTAT TOPLAMA ÇİZELGELERİNİN ENİYİLENMESİ İÇİN RASSAL PROGRAMLAMA YAKLAŞIMI

Bu tezde, fibrinojenin ana kaynağı olarak hayati bir kan ürünü olan kriyopresipitat için haftalık toplama çizelgelerinin oluşturulması problemi araştırılmıştır. Kriyopresipitat toplanımı özel ekipmanlar gerektirdiği için, bir kan toplama ziyaretinin kriyopresipitat toplanımına atanması için iki gün önce haber verilmesi gerekmektedir. Kriyopresipitatın bozulabilir doğası sebebiyle, günlük kriyopresipitat işleme kapasitesine ek olarak sekiz saatlik toplanmadan işlenene kadar geçen süreyi kapsayan zaman kısıtı da göz önüne alınmıştır. Hangi kan toplama ziyaretlerinin kriyopresipitat toplama ziyareti olarak atanacağına karar vererek ve haftalık kriyopresipitat toplama hedefine ulaşarak kriyopresipitat toplama maliyetlerinin minimize edilmesi amaçlanmıştır. Problem tamsayı programlama ile ifade edildikten sonra kan arzının belirsizliğini göz önüne alan gürbüz ve rassal programlama yaklaşımları önerilmiştir. İlk yaklaşım haftalık talebin karşılanmasını sağlayarak olabirliğe odaklanmıştır. İkinci yöntem ise karşılanmayan talep nedeniyle oluşan beklenen ceza maliyetini minimize etmeyi amaçlamıştır. Sonuçlar, rassal yaklaşımın daha az toplam toplama maliyeti ile daha iyi sonuçlar elde edebildiğini göstermiştir. Gürbüz yaklaşım ise daha tedbirli bir çizelge sunarak daha az karşılanmayan talep bulunmasını sağlamıştır. Bununla birlikte, rassal çözümün değeri hesaplanmıştır. Bulunan değerler, yardım eylemine verilen değerin artması ile birlikte belirgin katkılar sağlanabileceğini göstermiştir.

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LIST OF SYMBOLS

c_i	Transportation cost from host site to mobile site i
D	Weekly cryo collection target
I	Set of mobile sites
k	Parameter denoting the day of planning in the rolling time horizon
$\widetilde{L}_i$	Random variable denoting the amount to be collected from mobile site i
m_i	Binary parameter denoting whether mobile site i requires mid-day pick-up
N_t	Cryo processing capacity for day t
Q	Set of scenarios
R_i	Collected supply amount for mobile site i
S_i	Projected supply amount for mobile site i
T	Set of days of planning horizon
w	Cost of turning a previously announced cryo collection site to a non-cryo collection site, per package
x_i	Binary variable denoting whether mobile site i is assigned for cryo collection
$\bar{x}_i$	Binary parameter as an upper bound on x_i
z	Duration of the committed time window
μ	Multiplier for computing mean of the distribution of $\widetilde{L}_i$
σ	Multiplier for computing standard deviation of the distribution of $\widetilde{L}_i$

LIST OF ACRONYMS/ABBREVIATIONS

DM	Deterministic Model
DRTM	Deterministic Rolling Time Horizon Model
EMVS	Expected Mean Value Solution
MDP	Markov Decision Process
MVS	Mean Value Solution
RBC	Regional Blood Center
RRTM	Robust Rolling Time Horizon Model
RRTWP	Robust Rolling Time Horizon Model with Penalty
RM	Robust Model
RMWP	Robust Model with Penalty
SM	Stochastic Model
SRTM	Stochastic Rolling Time Horizon Model
SS	Stochastic Solution
VRP	Vehicle Routing Problem
VSS	Value of Stochastic Solution

1. INTRODUCTION

Despite technological advancements and new discoveries in the field of medicine, there exists an inevitable demand for blood. As the limited and unknown supply of blood is combined with the perishable nature of blood products, efficient management of blood becomes an important concern in healthcare delivery.

Blood collection is an essential process for generating blood supply. Most preferred method for collecting blood is through whole blood donation [1]. In this method, blood is collected from donors in its whole form, and then it can be decomposed into different components, such as red blood cells, plasma, platelets, and cryoprecipitate. In addition to this, some components can be acquired from the donor without drawing blood. This method is called apheresis and generally used for obtaining blood platelets. Apheresis is accomplished by connecting a donor to a machine that circulates donor's blood continuously while extracting the necessary components and returning the remaining blood to the donor. This process is more costly compared to whole blood donation and hence less preferred [2].

Cryoprecipitate (in the remainder of this thesis referred to as 'cryo') is a vital blood component that is obtained from plasma. It is prepared by centrifuging thawed fresh frozen plasma (FFP) and collecting its precipitate. The precipitated proteins that constitute cryo are fibrinogen, factor VIII, von Willebrand factor, factor XIII and fibronectin [3]. Cryo is most useful in the treatment of massive hemorrhaging as the main source of fibrinogen, which plays a crucial role in clotting.

Each of the blood components has its own collection, production conditions, and shelf lives. Cryo has a strict collection-to-completion time constraint, which requires the total time needed to transport, process and freeze cryo to be less than or equal to 8 hours from the time of collection [4]. Consequently, this circumstance increases the complexity of cryo collection and production planning in practice.

Additionally, cryo is stored in special bags that are called triple bags. For all other blood products, less expensive double bags are sufficient and they have 24 hour collection-to-completion time constraint. Another operational constraint is the cryo processing capacity of the host site. Since the host site has a certain limit, cryo collected for each day should not exceed this capacity.

For the supply chain management of blood products, Regional Blood Centers (RBCs) play an essential role by satisfying the demands of the hospitals in the region using the blood supplies of that geographical area. In order to accomplish this process, locations of the blood collection sites and the corresponding collection time windows are determined months in advance depending on several factors such as demand forecasts, visit frequencies of the locations and availability to the host site. Although whole blood can be collected at fixed and mobile collection sites, mobile sites constitute most of the mobile sites in the US [5]. Each mobile site departs from its host site, collects cryo or non-cryo products within its collection time window and returns back to the center when its collection time window finishes.

Transportation from mobile sites to the host site is accomplished with blood collection vehicles at the end of the day. This type of transportation is called an end-of-day delivery. Nevertheless, if an end-of-day delivery is not enough for meeting the collection-to-completion time constraint, an additional transportation from the mobile site to the host site is provided with an extra expense. This kind of delivery is called a mid-day pickup. A mid-day pickup vehicle visits a mobile site and return to the host site for processing, therefore there is no need for routing the mid-day pickups. Additionally, before arriving from the host site, a mobile site packed with triple bags can be determined as a non-cryo collection site, then the associated mid-day pickup can be excluded although the extra expense of bags will be incurred.

In addition to these, cryo to be collected from mobile sites are uncertain as most of the donors are walk-ins, meaning that they do not have appointments. Furthermore, some donors with scheduled appointments may not show up. Thus, it becomes important to take into consideration the uncertain blood supply while scheduling the collection plan.

In this thesis, we aim to optimize the weekly cryo collection schedules of a region by minimizing the total collection cost while determining which blood collection sites should be assigned as cryo collection sites. We incorporate cryo collection-to-completion time constraint and operational constraints in our optimization models, and ensure that weekly cryo targets are satisfied. In addition to these, we use a scenario-based robust programming approach and a stochastic programming approach for incorporating the uncertainties into our optimization models. We analyze and compare the performances of the proposed approaches using real data obtained from the American Red Cross, under different blood collection plan characteristics.

The rest of this thesis is organized as follows: In Chapter 2, we present a literature review that focuses on supply chain management of blood products and solution methodologies of existing studies. In Section 3.1, we formulate the problem as an integer program with deterministic collection amounts. Then, we introduce the uncertainty on the collected blood amount and propose a robust programming approach and a stochastic programming approach in Sections 3.2 and 3.3, respectively. Furthermore in Section 3.4, we present rolling time horizon models corresponding to each approach. In Chapter 4, we analyze computational results of the different models. Finally in Chapter 5, we present the concluding remarks and investigate the potential research areas.

2. LITERATURE REVIEW

We conduct the literature review in two sections. In the first section, we investigate the related problems in the supply chain management of blood products and in the second section, we focus on the methodological aspects of these issues by examining the applications of stochastic programming approaches in the related literature.

2.1. Supply Chain Management of Blood Products

Supply chain management of blood products is a widely studied area in literature. Pierskalla [2] provides a general overview of this line of research. Various aspects of this topic are discussed in this paper such as selecting blood donation areas, assigning these areas to blood centers, deciding number of blood centers in a region, locating these centers, and matching supply and demand. Additionally, author points out important concerns to be taken into consideration for blood collection, inventory management, blood allocation to hospitals, and blood delivery.

Although the blood supply chain consists of many stages, most of the work concentrates on inventory management. Nahmias [6] provides one of the first literature reviews on inventory management by discussing ordering policies for perishable inventories and the applications of these policies in blood bank management. In perishable inventory problems, the main concern of the studies is the short shelf lives of the blood products. Another literature review on this issue is conducted by Prastacos [7]. He examines the operational, tactical and strategic level decisions in inventory management. Additionally, Karaesmen *et al.* [8] conduct a review on the perishable inventories by covering some work on the blood inventory management.

Belien *et al.* [9] present the most recent and comprehensive literature review on the supply chain management of blood products by classifying the related problems into groups with respect to their problem focuses and solution strategies. They firstly discern the studies according to the type of the blood products and point out the fact that most of the recent studies focus problems for specific blood products instead of whole blood. In terms of the solution methods, they explain that most popular methods in recent studies are simulation, dynamic programming and queuing models. Moreover, they discuss all stages of the blood supply chain and present the corresponding studies for each stage.

An important area for blood supply chains is the distribution of the processed blood products. Hemmelmayr *et al.* [10] work on the problem of the Austrian Red Cross by planning delivery of the blood products to the hospitals in a cost-effective way. They work on a variant of the Vehicle Routing Problem (VRP) by satisfying the demands of the hospitals, keeping spoilage of the hospitals at a low level and aiming to minimize the delivery cost in a two-week planning horizon. They study two solution methods: an integer programming approach and a variable neighborhood search approach. They compare the performances of these two approaches and an approach that is similar to the current practice. In variable neighborhood search approach, the problem is considered as a periodic VRP, and instead of searching for a single neighborhood, a larger set of neighborhoods of the current solution is explored. Additionally, they investigate the effects of changing from a vendee-managed inventory environment to a vendor-managed inventory system on delivery routing.

Hemmelmayr *et al.* [10] state that it is not possible to redistribute the unused products between hospitals due to the regulations. However, this approach could be plausible in some cases in order to enhance the blood distribution processes, and it is named as reverse logistics. This method is studied by Alshamrani *et al.* [11] in a research initiated by American Red Cross. In this problem, the blood that is previously distributed to a customer can become available for picking-up in the next period. Therefore, they need to simultaneously decide for vehicle routes and picking up actions by considering the pick-up amounts in a probabilistic manner. Their aim is to minimize the total cost of the routes and the expected cost of not picking up the returning products immediately over the multi-period planning horizon. They model the problem as a Markov Decision Process (MDP). As the resulting dynamic program is computationally intense, a decomposition heuristic is introduced for practical purposes.

Şahin *et al.* [12] work on a location-allocation problem for the regionalization process of the Turkish Red Crescent. They divided the problem into three subproblems. The first one is formulated as an integer program by adopting a pq-median location model. It focuses on locating RBCs and blood centers, assigning blood centers to RBCs and ensuring that the demand points are assigned to one RBC-blood center pair by minimizing the weighted distances from demand points to blood centers and from blood centers to RBCs. The second subproblem aims to minimize the additional blood stations to be opened if it is not covered by the blood centers, which is modeled as a set covering problem. Finally, the third subproblem is related with allocating fleets to RBCs.

Blood collection is an important part of the blood supply chain. Cumming *et al.* [13] present a collection planning model for decreasing seasonal imbalances between supply and demand in regional blood suppliers using a Markovian population model. This problem is modeled as an inventory management problem over a planning horizon by forecasting the amounts to be collected. Additionally, an overall view to blood collection process with solution methods for blood transportation are presented in [14].

Yi *et al.* [15] work on a blood collection problem of American Red Cross. In this problem, vehicles collect blood from predetermined collection sites with an eight hour collection-to-completion time constraint. Additionally, different from VRP with time windows (VRPTW), there is not a fixed reward for visiting each collection site as the reward, which is the amount to be collected from a site, is dependent to the the time the site is visited. Therefore, if a site is visited later, more blood could be collected due to its accumulated behavior over time. Consequently, predetermined and constant donation rates are used for each site, which neglects the uncertainty on the amount to be collected. Their objective is to minimize the sum of the length of the tours while collecting blood more than the required production level and allowing at most one pickup from a site. They model the problem in four stages. Firstly, all the feasible routes are constructed, then arrival and departure times of each route is optimized in order to maximize the amount to be collected by utilizing a search method. Thirdly, some of the inferior routes are eliminated. Finally, an integer program is constructed for selecting the best subset of routes, and cutting planes are introduced for solving the problem in a faster way.

Doerner *et al.* [16] work on a project that is initiated by Austrian Red Cross. They introduce VRP with multiple interdependent time windows (VRPmiTW) for collecting perishable products. In this problem, each customer has multiple interdependent time windows as multiple visits to a customer is allowed which is different than [15]. Similar to our problem, the collected products from customers are perishable and they should arrive to the central depot within a specified time after collection. However, pickups of different customers are combined on tours, thus routing of the vehicles is necessary. Additionally, uncertainty on the number of collected products and the weekly targets are not considered within the scope of this study. They model this problem as a mixed integer program and compare the results of the exact and heuristic solution methods.

In addition to these, there are more studies that construct the variants of the VRP for blood collection. Özener *et al.* [17] define Maximum Blood Collection Problem (MBCP), which aims to maximize the collected blood amount by taking into consideration the six hours time limit to deliver the collected blood to the processing center and allowing multiple pickups from a collection point. Similar to [15, 16], it is assumed that blood is continuously donated at collection sites and therefore the pickup times of the sites are important as it affects the amount to be collected. Additionally, multiple visits to a collection site is allowed in the model. For the solution of this problem, firstly, a special case of MBCP with a single vehicle is investigated, then several other special cases of MBCP are explored in order to develop a heuristic for the overall problem. Yücel *et al.* [18] work on a similar problem by addressing clinical specimen collection. They introduce the Collection for Processing Problem (CfPP) in which it is aimed to balance the collected product amount and the processing capabilities by determining the routes for collection. Similar to previous studies [15–17], the amount to be collected from collection sites have an accumulated behavior over time with given donation rates. In addition to that, the processing rate of the host site is also taken into consideration. However, the collection-to-completion time constraint is not considered in the study. They model the problem in two stages. The objective of the first stage is to maximize the daily amount of processed products. Then, in the second model, optimal objective function value of the first model is added as a lower bound on the daily amount of processed products, and the model is solved with a new objective of minimizing the transportation cost. A heuristic is presented for eliminating suboptimal solutions. Additionally, methods for finding upper bounds on the daily amount of processed products and lower bounds on the daily transportation cost are investigated.

Ghandforoush *et al.* [19] study a platelet collection problem, which could be considered as a similar work to our problem of concern. It is aimed to determine the daily platelet collection schedule by minimizing the total cost, which includes platelet production cost, transportation costs and costs due to the loss of platelet at the blood center. Like cryo, production of platelet concentrates require a tight collection-to-completion time constraint. In order to satisfy this constraint, shuttling of blood back to the blood center within the collection time window is necessary. Moreover, there is no need for routing as a shuttle is assigned for each collection site and a shuttle can visit its site multiple times per day. The optimization model is first formulated as a non-convex integer model, and then converted into a linear 0-1 problem using a two step conversion process. Blood collected from each site per shuttle trip is considered as a decision variable, which is between predetermined lower and upper bounds that correspond to the minimum and maximum collection capacity of the associated site. The model determines the number of shuttle trips to and the amount to be collected from each site by taking into account the daily demand to be satisfied, the production loss, the limit on the number of shuttle trips per site, and the limit on the number of platelets produced per shuttle trip.

In the most recent study on this issue, Mobashera *et al.* [20] work on maximizing the collected platelet amount by considering six hours collection-to-completion time constraint and synchronizing the collection and appointment schedules of the blood collection sites. They refer to this problem as Integrated Collection and Appointment Scheduling Problem (ICASP). Unlike [15–18], the authors do not assume a constant donation rate throughout the collection window. In ICASP, blood donors arrive to the collection sites with an appointment, and each collection site has a certain capacity in terms of the number of available appointments. As the time of the appointments play an important role in determining the pickup schedules, they determine the appointment schedules within the capacity of each site, in coordination with the pickup routes. Additionally, more than one visit to the collection sites are considered in the problem. They model this as a mixed integer program and propose a heuristic that divides the collection sites into clusters and then the single vehicle version of ICASP is solved for each cluster.

2.2. Stochastic Programming Approaches in Modeling

A relevant class of problems to our study is Stochastic VRP (SVRP), which integrates uncertainty to the VRP. SVRPs are mostly modeled using MDPs or stochastic integer programs, and a general review on these set of problems can be found in a study conducted by Gendreau *et al.* [21]. The most relevant SVRP to our study is VRP with Stochastic Demands (VRPSD). In this problem, customer demands are considered as random variables. Additionally, the planned routes may not always be traced since if a failure occurs on the route, due to not satisfying the customer demand, a new route may need to be constructed with a penalty. Moreover, it is critical to determine whether reoptimization throughout the plan is allowed and when the demand information becomes available, which could be at the time the customer is visited or after the visit. Dror *et al.* [22] review VRPSD studies and present MDPs and stochastic programs with chance constraints and recourse policies from the literature for modelling this problem. For instance, Stewart *et al.* [23] work on such a problem where the customer demands are random variables with known probability distributions. They first model this as a stochastic program with chance constraints. These constraints imply that the probability of failure for each route, which occurs when the total demand of the route exceeds the vehicle capacity, should be less than the maximum allowed violation probability. Then, these probabilistic constraints are converted into their deterministic equivalents under given circumstances by utilizing a theorem proposed in the study. As the problem turns into a variant of VRP, existing VRP heuristics are used to solve the model. Additionally, stochastic programs with penalty functions are investigated which add the expected cost of route failures to the objective.

Dealing with uncertainty is an important concern in problems that involve blood supply chain management. This is mostly due to the stochasticity in blood supply and demand. Integrating this to modelling is generally achieved by using MDP or stochastic programming. Federgruen *et al.* [24] present an allocation model and a VRP for perishable products, which are distributed from a regional center to a set of locations with random demands. Cumulative distribution functions of the demands are used in the linear programs and the expected transportation, shortage and spoilage costs are minimized. They plan the allocation of the available inventory at the center while determining how it could be delivered. An exact solution and a heuristic solution with two phases are examined. Sapountzis [25] study optimal allocation of blood from a regional blood transfusion center (RBTS) to the hospitals of its area, with respect to the types and quantities demanded by hospitals. A utility function is used for describing the policy of the RBTS regarding the allocation of blood units. The problem is modelled as a stochastic program, however by using the properties of the statistical distributions, it is converted into a linear program in order to be solved in an easier manner.

Hemmelmayr *et al.* [26] extend their studies in [10] by introducing stochastic blood product usage at hospitals. As product usage becomes stochastic, it is not certain to obtain a feasible solution throughout the two-week planning horizon. Thus, recourse policies are adopted for dealing with product shortfalls and the most effective one is selected based on its performance. They work on a two-stage stochastic program with recourse. Four recourse actions are discussed and the cost of these actions are computed by drawing samples and averaging their costs. The same two solution methods as in [10] (an integer programming approach and a variable neighborhood search approach) are studied by introducing external sampling to turn the stochastic optimization problem into a deterministic optimization problem. As the number of product usage realization samples increases, the integer programming approach becomes computationally intractable. The authors observe that variable neighborhood search approach works with larger number of realizations. Finally, the two approaches are compared under different delivery plan characteristics, recourse actions, and realization sizes.

Gunpinar [27] works on different stages of the blood supply chain in his PhD thesis. In the first part, he focuses on a system that consists of a hospital and a blood center. His aim is to determine the optimal order levels of the hospital by minimizing the cost of the ordered blood, holding, wastage and shortage through the planning horizon. He considers blood demands of hospitals as random variables as it is hard to estimate the demand due to the emergency situations and safety issues. He first examines the problem as a stochastic program, and then converts it into an integer program under different demand scenarios. Linearization methods are applied for the non-linear terms in the model. Additionally, he extends the model by considering blood demands for two types of patients and crossmatch to transfusion ratio. The results are examined under different number of scenarios and order plan characteristics. In the second part, he focuses on a supply chain with a single blood center and multiple hospitals and the optimal distribution policies are investigated by formulating an integer program. In the last section, a blood collection problem is studied. In this problem, each blood collection location has a certain demand and a blood mobile can visit at most two or three locations per day. This turns into a VRP that determines the route of each blood mobile and minimizes the travel cost while satisfying the daily demand of the blood center and capacity constraint of the blood mobiles. Different than our problem, collection-to-completion time constraint and the uncertainty on the collected blood amount are not investigated. The problem is solved with CPLEX solver, branch & bound algorithm and column generation algorithm, and the results are compared.

In conclusion, our study differs from the existing blood collection work as a schedule that determines the collection sites to be visited and considers the uncertainty on the amount to be collected is not investigated within a rolling time horizon. Additionally, we haven't encountered any study that specifically focuses on cryo collection in the literature. As a pioneer work for our thesis, Ayer *et al.* [5] work on the optimization of cryo collection schedules with a collaboration with the American Red Cross. Their aim is to minimize the total collection cost and determine which collection sites should be assigned as cryo collection sites by taking into account the collection-to-completion time constraint for cryo and weekly production targets. Non-split case is studied initially, which is the current practice. In non-split case, a site is determined as a cryo or a non-cryo site throughout the whole collection window for that day. As an alternate approach, split-case is suggested. In this case, the collection window of each site is divided into two intervals in which whole blood can be collected for cryo or non-cryo products in either one of these intervals. These problems are modeled using MDPs with large state and action spaces. In order to make problems computationally tractable, an action elimination procedure with constraint relaxation is applied which results in a sub-optimal policy with upper and lower bounds. Finally, a simple heuristic is presented by ranking collection intervals that leads to a sub-optimal solution. In this thesis, we model this problem with a different perspective and propose robust and stochastic programming approaches.

3. PROBLEM FORMULATION

Recall that our objective is to plan the weekly cryo collection schedule by minimizing the total collection cost and determining which mobile sites should be selected as cryo collection sites as the weekly collection targets, daily capacity constraints and cryo completion to time constraint are satisfied. In this chapter, we first focus on the case with deterministic collection amounts. We present an integer programming model to be used at the beginning of the planning horizon and extend the model for integrating uncertainty on the collected blood amount by proposing a robust programming approach and a stochastic programming approach that are based on scenarios. Furthermore, for operational purposes, we propose rolling time horizon models to be used through the planning horizon.

3.1. Deterministic Model

Notations of the sets, parameters and decision variables in our Deterministic Model (DM) can be defined as in Table 3.1.

Length of the collection time window is crucial in determining whether a mobile site requires a mid-day pickup. In addition to the 8 hours collection-to-completion time constraint of cryo, maximum duration of the round-trip from host site to collection sites is assumed to be 2 hours. Thus, if a collection time window is longer than 6 hours, the corresponding mobile site would require a mid-day pickup.

Table 3.1. Sets, parameters, and decision variables for the model.

Sets:	
I	Set of mobile sites, $I = \{1,2,...,\bar{I}\}$
T	Set of days of planning horizon, $T = \{1,2,...,\bar{T}\}$
$I(t)$	Set of mobile sites on day t
Parameters:	
c_i	Cost of round-trip from host site to mobile site i, $\forall i \in I$
S_i	Projected supply for mobile site i, $\forall i \in I$
N_t	Cryo processing capacity for day t, $\forall t \in T$
m_i	Binary parameter which takes value of 1 if the mobile site i requires a mid-day pickup and 0 otherwise, $\forall i \in I$
D	Weekly cryo collection target
Decision variables:	
x_i	Binary variable which takes value of 1 if mobile site i is assigned as cryo collection site and 0 otherwise, $\forall i \in I$

Our DM formulation is as follows:

DM:

$$\min \sum_{i \in I} c_i(1 + m_i)x_i \tag{3.1}$$

$$\text{s.t.} \sum_{i \in I(t)} S_i x_i \leq N_t \qquad \forall t \in T \tag{3.2}$$

$$\sum_{i \in I} S_i x_i \geq D \tag{3.3}$$

$$x_i \in \{0, 1\} \qquad \forall i \in I \tag{3.4}$$

The objective function (3.1) minimizes the total transportation cost by considering the end of day deliveries and mid-day pickups. The constraint (3.2) ensures that the total collected cryo for each day does not exceed the cryo processing capacity of that day. Second constraint (3.3) assures that weekly target demand is satisfied. Lastly, the constraint (3.4) defines the decision variables as binary variables.

Although the deterministic approach presents a schedule for the expected case, it neglects considering uncertain collection amounts at different collection sites. Thus, we propose two different approaches in order to incorporate uncertainty in blood collection amounts.

3.2. Robust Programming Approach

In the previous section, deterministic versions of the optimization models are considered by planning according to the projected supply of the mobile sites. Nevertheless, in reality, cryo amounts to be collected from each site is uncertain and it is realized after the site has been designated as a cryo collection site and cryo collection of that day has been made. Thus, it might be not possible to satisfy the weekly cryo collection target by using the deterministic approach.

In order to incorporate the uncertain nature of blood supplies, we define $\widetilde{L}$, which is a random vector that represents the cryo amounts to be collected from mobile sites. It is shown statistically by Ayer *et al.* [5] that $\widetilde{L_i}$ follows normal distribution with mean equal to $\mu * S_i$ and variance equal to $\sigma^2 * S_i$, where μ and σ are known constants.

For handling this uncertainty, we need to consider different cryo collection assignments with various supply amounts. Therefore, we adopt a scenario approximation approach such that various scenarios are constructed by considering independent and identically distributed (i.i.d.) realizations of cryo amounts to be collected from each site. As $\widetilde{L}$ represents the random vector of cryo amounts to be collected for each mobile site with a known distribution, we generate an i.i.d. sample of $\widetilde{L}$ denoted by $\{L^q\}_{q \in Q}$ where $|Q|$ corresponds to the number of scenarios. Consequently, L_i^q can be defined as the cryo amount to be collected from mobile site i in scenario q. The scenario approximation for the Robust Model (RM) can then be constructed as follows:

RM:

$$\min \sum_{i \in I} c_i(1+m_i)x_i \tag{3.5}$$

$$\text{s.t.} \sum_{i \in I(t)} L_i^q x_i \leq N_t \qquad \forall t \in T, \forall q \in Q \tag{3.6}$$

$$\sum_{i \in I} L_i^q x_i \geq D \qquad \forall q \in Q \tag{3.7}$$

$$x_i \in \{0,1\} \qquad \forall i \in I \tag{3.8}$$

In RM, the objective function (3.5) aims to minimize the total collection cost. The constraint (3.6) ensures that the collected cryo amount for each scenario and each day is less than the cryo processing capacity of that day. Second constraint (3.7) enforces satisfying the weekly collection target under each scenario.

We observe that RM may become infeasible as the number of scenarios increases. Nevertheless, in practice, it is important to find a solution that satisfies the weekly collection target as much as possible. For this purpose, we introduce a decision variable u and a penalty per package parameter p to the model. By adding a single decision variable, we target minimizing maximum unmet demand amount over all scenarios. In order to accomplish this, the maximum unmet demand amount over all scenarios is punished in the objective function with the given penalty parameter p. The resulting Robust Model with Penalty (RMWP) can be found below.

RMWP:

$$\min \sum_{i \in I} c_i(1+m_i)x_i + pu \tag{3.9}$$

$$\text{s.t.} \sum_{i \in I(t)} L_i^q x_i \leq N_t \qquad \forall t \in T, \forall q \in Q \tag{3.10}$$

$$\sum_{i \in I} L_i^q x_i + u \geq D \qquad \forall q \in Q \tag{3.11}$$

$$x_i \in \{0,1\} \qquad \forall i \in I \tag{3.12}$$

$$u \geq 0 \tag{3.13}$$

In objective (3.9), total transportation cost and expected penalty of unmet demand associated with the maximum unmet demand over all scenarios are minimized. Constraint (3.10) is same with the constraint (3.6) in RM. Constraint (3.11) guarantees that demand is satisfied over all scenarios as a decision variable corresponding to the maximum unmet demand amount is penalized in the objective. Lastly, constraint (3.13) enforces non-negativity on the decision variable u.

3.3. Stochastic Programming Approach

While it is important to obtain a schedule that satisfies all of the scenarios, a drawback of the robust programming method may arise when there exists an outlier case. For instance in the robust approach, although the cryo collection target constraint is satisfied by most of the scenarios, the solver may fail to obtain a plan that satisfies the outlier scenario. Thus, a high penalty could be incurred for coping with this situation. In order to handle such cases, we propose a stochastic programming approach that takes into consideration the expected penalty amount over all scenarios.

In the stochastic programming approach, we permit the violation of the weekly cryo collection target constraint by assigning a penalty for each unit of unmet demand. Similar to the robust models, we adopt a scenario based approach. We define decision variables corresponding to the unmet demand amount of each scenario. Let p be the unit cost of not satisfying the weekly demand and y^q be the decision variable that represents units of unmet demand under the scenario q. The weekly problem can be formulated as follows in the Stochastic Model (SM):

SM:

$$\min \sum_{i \in I} c_i(1+m_i)x_i + \frac{1}{|Q|}\sum_{q \in Q} py^q \tag{3.14}$$

$$\text{s.t.} \sum_{i \in I(t)} L_i^q x_i \leq N_t \qquad \forall t \in T, \forall q \in Q \tag{3.15}$$

$$\sum_{i \in I} L_i^q x_i + y^q \geq D \qquad \forall q \in Q \tag{3.16}$$

$$x_i \in \{0, 1\} \qquad \forall i \in I \tag{3.17}$$

$$y^q \geq 0 \qquad \forall q \in Q \tag{3.18}$$

The objective function (3.14) minimizes the total transportation cost and the expected penalty for the unmet demand over all scenarios. The first constraint (3.15) ensures that the collected cryo for each day does not exceed the daily processing capacity for each scenario. The second constraint (3.16) enables the violation of the weekly collection target by introducing a decision variable for each scenario that is penalized in the objective. Finally, constraint (3.17) defines the first stage decisions as binary variables and constraint (3.18) ensures that the decision variables corresponding to the unmet demand amounts are nonnegative.

3.4. Rolling Time Horizon Models

An operational constraint is when to determine the mobile sites as cryo collection sites. At least a two-day notice is required to pack vehicles with the suitable bags and boxes depending on the type of blood collection. Therefore, two days prior to actual collection, each mobile site is chosen as a cryo site or a non-cryo site so that vehicles can be equipped with either triple or double bags, with associated boxes. Moreover, excess storage is not possible, which prevents mobile sites from carrying additional boxes for the same-day determination of what blood products should be collected. In addition to these, collected blood amount at the end of the day could be different than the values considered in planning. Therefore, it may cause significant changes in the upcoming collection plan. In order to handle these cases, the cryo collection schedule should be updated through the rolling time horizon. Thus, we propose rolling time horizon models for each approach presented.

The rolling time horizon models start to be used two days prior to the beginning of the planning horizon. Due to the operational conditions, weekly schedule for the upcoming days should be reoptimized at the beginning of each day. In this stage, we add another parameter to the model for holding the information regarding the start date of the planning. k is used for this purpose where k can take values from 2 to $\bar{T}$. The special case $k = 1$ is ignored as it is equal to the original model.

Starting from the first day's planning output, there exists a committed time window. For instance, if a mobile site is assigned for cryo collection within the commited time window, this mobile site can only be turned into a non-cryo collection site with a cost w that represents the cost of turning a previously announced cryo site to a non-cryo site, per bag. This is the cost difference between a triple bag and a double bag as triple bags would be unnecessarily used for storing non-cryo products. The committed time window is equal to 2 days for the American Red Cross.

Note that if a mobile site is not announced as a cryo collection site, then it cannot be turned into a cryo collection site within the committed time window. In order to satisfy this constraint, we introduce a new parameter $\bar{x}_i$ to the model, which is an upper bound for the decision variable. It is 1 if mobile site i has been announced as a cryo collection site within the committed time window and 0 otherwise. This comes from the output of the previous planning model, as $\bar{x}_i$ values within the committed time window are updated throughout the rolling horizon, prior to the start of a new planning day. Note that for days that are not within this committed time window, this turns into a redundant parameter which is equal to 1.

New parameters added to the model can be summarized in Table 3.2.

Table 3.2. New parameters for the rolling time horizon models.

Parameters:	
k	starting day of the planning horizon
R_i	collected supply amount from mobile site i, $\forall i \in \bigcup_{t=1}^{k-1} I(t)$
z	length of the committed time window (in terms of days)
w	cost of turning a previously announced cryo site to a non-cryo site, per package
$\bar{x}_i$	binary parameter as the upper bound for the decision variable, $\forall i \in I$

Then, the Deterministic Rolling Time Horizon Model (DRTM) with start date k can be formulated as the following program:

DRTM(k):

$$\min \sum_{i \in I} c_i(1+m_i)x_i + w \sum_{t=k}^{min(k+z-1,\bar{T})} \sum_{i \in I(t)} S_i(\bar{x}_i - x_i) \tag{3.19}$$

$$\text{s.t.} \sum_{i \in I(t)} S_i x_i \leq N_t \qquad \forall t \in T \tag{3.20}$$

$$\sum_{t=1}^{k-1} \sum_{i \in I(t)} R_i x_i + \sum_{t=k}^{\bar{T}} \sum_{i \in I(t)} S_i x_i \geq D \tag{3.21}$$

$$x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=k}^{\bar{T}} I(t) \tag{3.22}$$

$$\bar{x}_i \leq x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=1}^{k-1} I(t) \tag{3.23}$$

$$x_i \in \{0,1\} \qquad \forall i \in I \tag{3.24}$$

The objective function (3.19) aims to minimize the total collection cost, in which the first part corresponds to the transportation cost and the second part is the schedule change cost that is related with the cost of turning announced cryo sites to non-cryo sites within the committed time window. First constraint (3.20) is same with the associated constraint (3.2) of DM, which ensures that the total collected cryo for each day does not exceed the daily cryo processing capacity. Second constraint (3.21) assures that the target demand is satisfied by considering the collected supply values before the start date and the projected supply values after the start date of the planning. Finally, constraint (3.22) is necessary, as it is an upper bound on the decision variable that prevents assigning the corresponding collection site as a cryo collection site without a two days notice. Note that constraint (3.23) guarantees that decision variables that are prior to the start day of planning are fixed.

Rolling time horizon model can be formulated as follows in the Robust Rolling Time Horizon Model (RRTM) with start date k:

RRTM(k):

$$\min \sum_{i \in I} c_i(1+m_i)x_i + w * \frac{1}{|Q|} \sum_{t=k}^{min(k+z-1,\bar{T})} \sum_{i \in I(t)} \sum_{q \in Q} L_i^q(\bar{x}_i - x_i) \tag{3.25}$$

$$\text{s.t.} \sum_{i \in I(t)} L_i^q x_i \leq N_t \qquad \forall t \in T, \forall q \in Q \tag{3.26}$$

$$\sum_{t=1}^{k-1} \sum_{i \in I(t)} R_i x_i + \sum_{t=k}^{\bar{T}} \sum_{i \in I(t)} L_i^q x_i \geq D \qquad \forall q \in Q \tag{3.27}$$

$$x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=k}^{\bar{T}} I(t) \tag{3.28}$$

$$\bar{x}_i \leq x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=1}^{k-1} I(t) \tag{3.29}$$

$$x_i \in \{0,1\} \qquad \forall i \in I \tag{3.30}$$

Unlike RM, objective function (3.25) minimizes the total collection cost and the expected cost of turning announced cryo sites to non-cryo sites within the committed time window over all scenarios, assuming that each scenario has an equal probability of occurrence. The rest of the constrains are organized in a similar way as in the deterministic model, however in this formulation, the resulting cryo collection schedule should satisfy all possible scenarios considered in the model.

Furthermore, we can apply this method to the Robust Rolling Time Horizon Model with Penalty (RRTWP) with start date k as follows:

RRTWP(k):

$$\min \sum_{i \in I} c_i(1+m_i)x_i + w * \frac{1}{|Q|} \sum_{t=k}^{min(k+z-1,\bar{T})} \sum_{i \in I(t)} \sum_{q \in Q} L_i^q(\bar{x}_i - x_i) + pu \tag{3.31}$$

$$\text{s.t.} \sum_{i \in I(t)} L_i^q x_i \leq N_t \qquad \forall t \in T, \forall q \in Q \tag{3.32}$$

$$\sum_{t=1}^{k-1} \sum_{i \in I(t)} R_i x_i + \sum_{t=k}^{\bar{T}} \sum_{i \in I(t)} L_i^q x_i + u \geq D \qquad \forall q \in Q \tag{3.33}$$

$$x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=k}^{\bar{T}} I(t) \tag{3.34}$$

$$\bar{x}_i \leq x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=1}^{k-1} I(t) \tag{3.35}$$

$$x_i \in \{0,1\} \qquad \forall i \in I \tag{3.36}$$

$$u \geq 0 \tag{3.37}$$

In objective function (3.31), we aim to minimize the penalty due to the maximum unmet demand over all scenarios in addition to the transportation cost and the expected schedule change cost. Rest of the constraints are organized in a similar way as in RRTM, except the constraint (3.33), as a decision variable is introduced to the model for handling the cases when collected cryo of a scenario cannot meet the demand.

Stochastic Rolling Time Horizon Model (SRTM) with start date k can be similarly formulated as the following.

SRTM(k):

$$\min \sum_{i \in I} c_i(1+m_i)x_i + w * \frac{1}{|Q|} \sum_{t=k}^{min(k+z-1,\bar{T})} \sum_{i \in I(t)} \sum_{q \in Q} L_i^q(\bar{x}_i - x_i) + \frac{1}{|Q|} \sum_{q \in Q} py^q \tag{3.38}$$

$$\text{s.t.} \sum_{i \in I(t)} L_i^q x_i \leq N_t \qquad \forall t \in T, \forall q \in Q \tag{3.39}$$

$$\sum_{t=1}^{k-1} \sum_{i \in I(t)} R_i x_i + \sum_{t=k}^{\bar{T}} \sum_{i \in I(t)} L_i^q x_i + y^q \geq D \qquad \forall q \in Q \tag{3.40}$$

$$x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=k}^{\bar{T}} I(t) \tag{3.41}$$

$$\bar{x}_i \leq x_i \leq \bar{x}_i \qquad \forall i \in \bigcup_{t=1}^{k-1} I(t) \tag{3.42}$$

$$x_i \in \{0,1\} \qquad \forall i \in I \tag{3.43}$$

$$y^q \geq 0 \qquad \forall q \in Q \tag{3.44}$$

In SRTM, transportation cost, expected schedule change cost and expected penalty over all scenarios are minimized in the objective (3.38). The remaining constraints are same as in SM, however, the collected cryo amount is used in constraint (3.40) for days prior to the start date of the planning.

Cryo collection problem need to be solved at the beginning of every planning day in order to achieve a better result for the remaining planning horizon. Thus, an algorithm to obtain the weekly collection schedule using the proposed formulations over the rolling time horizon is presented in Figure 3.1.

Set upper bound $\bar{x}_i := 1$, $\forall i \in I$

Set $k := 1$

while $k \leq \bar{T}$

  if $k == 1$

    Solve DM or RMWP or SM

  else

    Solve DRTM(k) or RRTWP(k) or SRTM(k)

  Obtain an optimal solution x^*

  $k := k + 1$

  Set $\bar{x}_i := x_i^*$, $\forall i \in \bigcup_{t=1}^{min(k+z-1,\bar{T})} I(t)$

end

Figure 3.1. Pseudocode of the Rolling Time Horizon Algorithm.

Firstly, the upper bounds on the decision variables are assigned to 1, which are redundant for the initial model. Then, the model is solved for the first planning day and the resulting optimal solution is obtained. Next in order, $\bar{x}_i$ values within the committed time window are updated using the current optimal solution. Consequently, if an $\bar{x}_i$ value becomes 0, the corresponding mobile site i may not be assigned as a cryo collection site if it is in the committed time window. mobile sites corresponding to the day of planning are set to the current schedule for the subsequent models, as it would not be possible to change the schedule for the days prior to the day of planning. Therefore, earlier decisions becomes fixed for the upcoming models. Then, the problem is solved for the next planning day using the rolling time horizon models by following the same steps. This procedure continues until the last day of the planning period.

4. COMPUTATIONAL RESULTS

In this chapter, we first discuss computational and experimental settings for our analyses. Then, we compare the results of robust and stochastic approaches under different collection plan characteristics, and analyze the value of the stochastic solution.

4.1. Computational and Experimental Settings

In order to analyze our models, we use real data obtained from the American Red Cross. This data consists of the zip codes, collection windows, days of the mobile sites in addition to the projected and collected supply amounts corresponding to each visit. Zip codes are used for determining the travel cost from the host site to the mobile sites. The data belongs to the first week of March 2012, which exhibits a typical blood collection plan. The data set contains 53 mobile sites of which 12 visits are for Monday, 11 for Tuesday, 10 for Wednesday, 13 for Thursday and 7 for Friday. All in all, we work on a weekly collection schedule with 5 working days for all of the models.

As we adopt scenario-based approaches, we generate scenarios corresponding to the each mobile site by generating independent and identically distributed values using the projected supply amounts with given distributions as explained in Section 3.2. The statistical analysis in [5] indicates that $\mu = 0.93$ and $\sigma = 0.75$ in the fitted distributions that represent the cryo amounts to be collected. We initialize random number generators with 5 different seeds. Consequently, the models are computed under 5 different sets of scenarios generated by each seed. Additionally, for each different seed, we examine the approaches under 1 scenario, 10, 100 and 1000 scenarios.

Weekly demand D is equal to 1000 in all models, whereas the daily processing capacity N_t can take values 200, 250 and 300. As each day has an equal processing capacity, the capacity/demand ratios for a weekly schedule with 5 working days are examined under three different settings 1, 1.25 and 1.5. Furthermore, penalty parameter p is examined with three different values \$1, \$10 and \$100. The reference experimental setting is considered as the case when the capacity/demand ratio = 1.25 and $p = \$10$.

We implement our formulations using Java programming language in Eclipse environment with CPLEX 12.5. The models are computed on a Windows Vista PC with a 2.53 GHz CPU and 4 GB RAM. Ultimately, we aim to compare the proposed approaches under different experimental settings and assess the value of the stochastic solution.

4.2. Analysis of Robust and Stochastic Approaches

First, we conduct experiments to analyze the robust and stochastic approaches under different penalty settings. For this purpose, we examine the three different penalty parameters under the reference capacity/demand ratio.

Table 4.1 shows the results of this situation when the penalty parameter is equal to \$10. Results correspond to the models which are computed prior to the beginning of the week. In this table, column "$CPU\ Time$" represents the working time of the program in terms of seconds. Column "$TotalC$" gives the total cost of the weekly schedule. Column "$TransportC$" shows the transportation cost and column "$PenaltyC$" represents the expected penalty cost. All the costs are reported in terms of dollars. As this output is the result of first day's planning, there isn't any cost associated with the schedule change. Column "$UnsatisfiedD$" points out the unsatisfied demand amount at the end of the planning horizon when all of the collections are realized with the current solution. This amount is computed by Equation 4.1.

$$UnsatisfiedD = D - \sum_{i \in I} x_i R_i \tag{4.1}$$

Each row corresponds to a model with different number of scenarios. First part of the model name shows the number of scenarios and the second part represents the modeling approach. For instance, row "$1 - RMWP$" implies RMWP model under 1 scenario and row "$1000 - SM$" shows SM model under 1000 scenarios. In addition to these, each row corresponds to the average of the 5 outputs whose scenarios are generated by 5 different seeds. We examine the average results in order to eliminate the differences due to the randomness and obtain a more reliable result. In order to stay consistent in our analysis, we generate scenarios in an inclusive manner. More precisely, for each seed, generated 1000 scenarios contain the 100 scenarios, 100 scenarios contain the 10 scenarios and 10 scenarios contain the single scenario that are taken into consideration in the models. In addition to these, RMWP and SM models are run with the same set of scenarios for all of the cases. Note that the naming and reporting conventions of the tables and outputs are same throughout this section. Additionally, the experimental results of the all models with different seeds can be found in Appendix A.

Table 4.1. Robust and stochastic approaches when penalty parameter = \$10 and capacity/demand ratio = 1.25.

Model	**CPU Time(s)**	**TotalC(\$)**	**TransportC(\$)**	**PenaltyC(\$)**	**UnsatisfiedD**
1 - RMWP	0.19	809.57	809.57	0.00	-54.60
1- SM	0.19	809.57	809.57	0.00	-54.60
10 - RMWP	0.22	919.20	919.20	0.00	-110.80
10 - SM	0.25	905.99	877.79	28.20	-91.00
100 - RMWP	0.46	952.57	950.57	2.00	-132.80
100 - SM	0.33	897.51	868.87	28.64	-95.20
1000 - RMWP	24.23	1072.81	1066.81	6.00	-113.20
1000 - SM	1.83	899.49	870.57	28.93	-84.80

We notice that robust approach and stochastic approach have the same results when the number of scenarios is 1. This is due to the fact that RMWP and SM reduce to the same model when there exists a single scenario. As the number of scenarios increases, CPU time increases since new constraints are added to the model. For models with 10, 100 and 1000 scenarios, robust approach has higher total cost. Additionally, it has lower unsatisfied demand, which implies that collected cryo amount in robust approach is more than stochastic approach. As RMWP tries to minimize the maximum unmet demand in all scenarios, total cost and penalty cost increases when the number of scenarios increases. In order to measure the effect of penalty parameter, we aim to compare this reference results with the other penalty parameter values.

From Table 4.2, we observe the situation when the penalty parameter is equal to $1 and capacity/demand ratio is 1.25. In this case, neither approach focuses on satisfying the demand with the cryo collected from the mobile sites, as the penalty parameter is low. Thus, this results in a higher penalty cost compared to the reference situation. Additionally, unsatisfied demand is positive and high due to the same reason as the models consider that demand could be met with penalty actions.

Table 4.2. Robust and stochastic approaches when penalty parameter = $1 and capacity/demand ratio = 1.25.

Model	**CPU Time(s)**	**TotalC($)**	**TransportC($)**	**PenaltyC($)**	**UnsatisfiedD**
1 - RMWP	0.21	747.33	505.13	242.20	181.80
1- SM	0.17	747.33	505.13	242.20	181.80
10 - RMWP	0.23	792.21	458.21	334.00	224.20
10 - SM	0.17	758.81	477.33	281.48	194.20
100 - RMWP	0.34	801.19	476.19	325.00	193.00
100 - SM	0.22	757.34	442.63	314.71	216.60
1000 - RMWP	1.31	819.87	445.87	374.00	233.00
1000 - SM	0.44	757.30	435.05	322.25	219.00

In Table 4.3, we examine the case when the penalty parameter is high. CPU Time is highest in this setting, compared to the previous tables. Moreover, RMWP takes more time than SM in all scenarios. Robust approach does not incur any penalty cost, even with the highest number of scenarios, as any violation of the demand constraint could add a high penalty cost to the objective. Additionally, we observe that this setting has the most similar results for the two approaches in terms of the total cost and unsatisfied demand amounts at the end of the week.

In our next experiment, we examine the models under different capacity/demand

Table 4.3. Robust and stochastic approaches when penalty parameter = \$100 and capacity/demand ratio = 1.25.

Model	**CPU Time(s)**	**TotalC(\$)**	**TransportC(\$)**	**PenaltyC(\$)**	**UnsatisfiedD**
1 - RMWP	0.20	809.57	809.57	0.00	-54.60
1- SM	0.20	809.57	809.57	0.00	-54.60
10 - RMWP	0.24	919.20	919.20	0.00	-107.60
10 - SM	0.25	919.20	919.20	0.00	-107.60
100 - RMWP	0.47	953.15	953.15	0.00	-124.80
100 - SM	0.41	943.23	930.63	12.60	-123.40
1000 - RMWP	31.25	1075.53	1075.53	0.00	-105.60
1000 - SM	6.64	972.25	924.95	47.30	-104.40

ratios. In order to accomplish this, we first assess the performance of the two approaches for the three ratios under the reference penalty parameter value. In Table 4.4, we analyze the situation when the capacity is 1.5. As the capacity increases, it becomes easier to solve the problem since the daily processing capacity constraint becomes less tight. Thus, compared to Table 4.1, we observe a decline in CPU time and total cost. Moreover, total cost and collected cryo amount in robust approach are higher than stochastic approach in all of the models.

Table 4.4. Robust and stochastic approaches when penalty parameter = \$10 and capacity/demand ratio = 1.5.

Model	**CPU Time(s)**	**TotalC(\$)**	**TransportC(\$)**	**PenaltyC(\$)**	**UnsatisfiedD**
1 - RMWP	0.16	809.57	809.57	0.00	-54.60
1- SM	0.16	809.57	809.57	0.00	-54.60
10 - RMWP	0.19	907.49	907.49	0.00	-111.60
10 - SM	0.18	899.59	877.99	21.60	-97.20
100 - RMWP	0.28	925.11	925.11	0.00	-128.20
100 - SM	0.24	882.53	859.61	22.92	-94.60
1000 - RMWP	0.97	955.69	955.69	0.00	-157.80
1000 - SM	1.15	880.19	858.65	21.54	-93.00

Following that, we examine the situation when the capacity/demand ratio is 1 in Table 4.5. In this case, we observe that CPU Time of the robust approach is significantly higher than the stochastic approach in all of the cases. Additionally, stochastic approach is able to collect more cryo with lower cost in all sets of scenarios. As the capacity constraint becomes more restrictive, collecting cryo more than the weekly demand in all scenarios is harder to satisfy. Therefore, it is plausible to expect more increase in total cost and penalty cost for the robust models as the maximum unsatisfied demand amount over all scenarios increases. From this observation, we could investigate this situation when the capacity/demand ratio remains 1 and the penalty parameter is either $1 or $100 in Table 4.6 and Table 4.7, respectively.

Table 4.5. Robust and stochastic approaches when penalty parameter = $10 and capacity/demand ratio = 1.

Model	**CPU Time(s)**	**TotalC($)**	**TransportC($)**	**PenaltyC($)**	**UnsatisfiedD**
1 - RMWP	0.22	952.10	872.10	80.00	-48.80
1- SM	0.20	952.10	872.10	80.00	-48.80
10 - RMWP	0.60	1811.31	1031.31	780.00	1.00
10 - SM	0.29	1553.64	941.44	612.20	-5.60
100 - RMWP	4.14	2486.31	902.31	1584.00	72.00
100 - SM	1.48	2064.91	879.13	1185.78	63.60
1000 - RMWP	103.33	2925.32	739.32	2186.00	94.40
1000 - SM	16.58	2305.14	738.33	1566.81	84.40

When the penalty parameter is low in the minimum capacity setting as in Table 4.6, we observe that stochastic models are less successful in satisfying the weekly demand compared to Table 4.5 in which SM performs better with lower costs and more satisfied demand for all scenarios. However, in this case, RMWP could collect more cryo for 100 and 1000 scenario cases although it has higher total cost. As we investigate the results in Table 4.7, robust approach could collect more cryo for 10 scenarios, and less in 100 and 1000 scenario cases, which is the reverse of what we obtain when the penalty parameter is $1 in terms of the unsatisfied demand. Consequently, we could not conclude that stochastic approach could collect more cryo when the capacity is low for all of the penalty parameter values. Additionally, compared to the corresponding outputs with capacity/demand ratio equal to 1.25, total cost increases for all models due to the decrease in capacity. In addition to these, when the penalty parameter is high and capacity is low, the solver requires highest computational time for both approaches compared to the other experiments with 100 and 1000 scenarios.

Table 4.6. Robust and stochastic approaches when penalty parameter = $1 and capacity/demand ratio = 1

Model	**CPU Time(s)**	**TotalC($)**	**TransportC($)**	**PenaltyC($)**	**UnsatisfiedD**
1 - RMWP	0.17	748.17	489.97	258.20	199.00
1- SM	0.16	748.17	489.97	258.20	199.00
10 - RMWP	0.25	794.11	422.91	371.20	267.60
10 - SM	0.16	763.23	424.27	338.96	262.20
100 - RMWP	0.28	805.95	407.75	398.20	277.00
100 - SM	0.21	763.41	381.99	381.42	291.60
1000 - RMWP	1.18	823.99	400.39	423.60	282.00
1000 - SM	0.43	766.20	359.25	406.95	308.00

Table 4.7. Robust and stochastic approaches when penalty parameter = $100 and capacity/demand ratio = 1.

Model	**CPU Time(s)**	**TotalC($)**	**TransportC($)**	**PenaltyC($)**	**UnsatisfiedD**
1 - RMWP	0.37	1216.33	1076.33	140.00	-40.20
1- SM	0.36	1216.33	1076.33	140.00	-40.20
10 - RMWP	1.06	7613.44	1293.44	6320.00	-10.80
10 - SM	0.63	6027.21	1259.21	4768.00	0.00
100 - RMWP	12.35	15668.51	1108.51	14560.00	94.20
100 - SM	5.29	11688.09	1140.09	10548.00	61.60
1000 - RMWP	986.16	21437.02	1057.02	20380.00	109.80
1000 - SM	214.52	15619.50	1059.52	14559.98	71.00

Furthermore, we report the results of the models with low and high penalty settings when the capacity/demand ratio is 1.5. In Table 4.8, stochastic approach is preferable for 10 and 1000 scenarios and robust approach is better for 100 scenarios with respect to the unsatisfied demand amount. Nevertheless, stochastic approach achieves obtaining the schedules with less cost and less computational time. Table 4.9 presents the results with high penalty parameter. In this situation, as in the other results with the same penalty parameter and different capacity/demand ratios, we observe that robust approach avoids penalizing since it results in a higher cost compared to stochastic approach. Consequently, it achieves collecting more cryo by assigning more mobile sites for cryo collection.

Table 4.8. Robust and stochastic approaches when penalty parameter = $1 and capacity/demand ratio = 1.5.

Model	**CPU Time(s)**	**TotalC($)**	**TransportC($)**	**PenaltyC($)**	**UnsatisfiedD**
1 - RMWP	0.15	747.33	505.13	242.20	181.80
1- SM	0.16	747.33	505.13	242.20	181.80
10 - RMWP	0.17	792.21	464.61	327.60	219.60
10 - SM	0.17	758.81	477.33	281.48	194.20
100 - RMWP	0.22	801.19	476.19	325.00	193.00
100 - SM	0.21	757.34	442.63	314.71	216.60
1000 - RMWP	0.89	819.87	445.87	374.00	233.00
1000 - SM	0.52	757.30	435.05	322.25	219.00

Table 4.9. Robust and stochastic approaches when penalty parameter = $100 and capacity/demand ratio = 1.5.

Model	**CPU Time(s)**	**TotalC($)**	**TransportC($)**	**PenaltyC($)**	**UnsatisfiedD**
1 - RMWP	0.16	809.57	809.57	0.00	-54.60
1- SM	0.16	809.57	809.57	0.00	-54.60
10 - RMWP	0.19	907.49	907.49	0.00	-111.60
10 - SM	0.21	907.49	907.49	0.00	-111.60
100 - RMWP	0.27	925.11	925.11	0.00	-128.20
100 - SM	0.28	919.07	911.87	7.20	-118.20
1000 - RMWP	1.11	955.69	955.69	0.00	-157.80
1000 - SM	1.74	926.01	907.81	18.20	-115.60

4.3. Value of Stochastic Solution

In order to handle the uncertainties in modeling, one can prefer solving the problem using the mean values of the random variates. In our problem, the mean value can be computed by taking average of the generated scenarios. Therefore Mean Value Solution (MVS) can be obtained by running DM under the expected scenario. Thus, we find a solution that is optimal for the mean case. Nevertheless, this approach lacks obtaining a solution that considers all scenarios. For dealing with this situation, we solve the model for each scenario by fixing the first stage variables, that is to say the decision variables x_i, to their value at MVS. Finally, we compute the expected result of using MVS by utilizing objective values of each scenario, named as Expected Mean Value Solution ($EMVS$). We compare this result with the Stochastic Solution (SS), and obtain the Value of the Stochastic Solution (VSS). Methodology for computing VSS can be summarized in Figure 4.1.

Generate an i.i.d. sample of $\{L^q\}_{q \in Q}$
Obtain the mean scenario $\bar{L}$
Solve DM using $\bar{L}_i$ *in place of* S_i, $\forall i \in I$
Let x^* *denote optimal solution of MVS*
Fix x *values to* x^*
Compute projected unmet demand amount y^q, $\forall q \in Q$
Compute optimal scenario objective values using x *and* y^q, $\forall q \in Q$
Find EMVS by averaging the optimal objective values of each scenario
Solve SM and obtain the objective value SS
$VSS := EMVS - SS$

Figure 4.1. Pseudocode of Computing the Value of the Stochastic Solution.

We examine VSS under the reference capacity/demand ratio with 3 penalty parameter settings for 1, 10, 100 and 1000 scenarios. In Table 4.10, column "$\#ofScenarios$" refers to these models, where the penalty parameter can take these 3 values, and the problem can be modeled with the presented scenario numbers. Column "$EMVS$" and

"SS" shows the corresponding $EMVS$ and SS values, respectively. Column "VSS" presents their difference and column "% *Improvement*" denotes the percentage improvement by means of the stochastic approach. Rows with penalty parameter values show the average results of all scenarios. Additionally, as in the previous section, the presented results are average of the models that are run by 5 different sets of scenarios. Outputs of the all solutions can be found in Table A.10 in Appendix A.

Table 4.10. Value of the stochastic solution.

# of Scenarios	**EMVS($)**	**SS($)**	**VSS($)**	**% Improvement**
penalty parameter p = $1	755.20	755.19	0.01	0.00
1	747.33	747.33	0.00	0.00
10	758.85	758.81	0.04	0.01
100	757.34	757.34	0.00	0.00
1000	757.30	757.30	0.00	0.00
penalty parameter p = $10	884.46	878.14	6.32	0.71
1	809.57	809.57	0.00	0.00
10	924.19	905.99	18.20	1.97
100	900.67	897.51	3.16	0.35
1000	903.40	899.49	3.91	0.43
penalty parameter p = $100	1281.79	911.06	370.72	28.92
1	809.57	809.57	0.00	0.00
10	1613.59	919.20	694.39	43.03
100	1342.89	943.23	399.66	29.76
1000	1361.09	972.25	388.84	28.57

We first observe that both models become deterministic if there exists a single scenario. Therefore, there is no improvement between the solutions for this case. Moreover, as penalty parameter increases, stochastic program becomes more preferable in modeling uncertainties since it improves the process in a significant amount. For instance, when the penalty parameter equals to 100 and problem is modeled with 10 scenarios, the average improvement is 43.03%. This is due to the fact that increase in penalty parameter results in paying more attention to the penalty of unmet demand associated with each scenario. Consequently, for small penalty parameter values, VSS is relatively small, as expected.

In addition to these, we notice that VSS is highest for 10 scenario cases among all of the penalty parameter settings. This may be related with the weight that is assigned to the penalty actions. As the number of scenarios increases, each unmet demand amount corresponding to a scenario starts to have less effect on objective as their average result is taken into consideration for computing the expected penalty. Therefore, increase in the number of scenarios may not positively affect the improvement percentage of the solution.

5. CONCLUSION AND FUTURE REMARKS

In this thesis, we investigated the problem of generating weekly cryo collection schedules by considering daily cryo processing capacities and collection-to-completion time constraint. Our aim was to minimize the total collection cost while satisfying the weekly cryo collection target and determining which mobile sites should be assigned for cryo collection. We first modeled the problem using the deterministic collection amounts. In order to incorporate the uncertain nature of blood supplies, we proposed robust and stochastic programming approaches. Additionally, we extended our formulations for generating models that are applicable in a rolling time horizon basis. We compared the proposed approaches under different blood collection plan characteristics. Furthermore, we investigated the value of the stochastic solution in order to measure the improvement amount in reply for adopting a stochastic approach.

Our experimental results indicate that robust approach has higher total cost and less unsatisfied demand in most of the cases. This may be related with the fact that robust approach gives more importance to the worst case scenarios as it focuses on satisfying all cases. Additionally, this implies that robust approach is more cautious compared to the stochastic approach in return for higher total costs.

Another observation is that, stochastic approach tends to penalize easier as it penalizes the expected penalty amount. In contrast with stochastic approach, robust approach avoids not satisfying the weekly demand constraint by considering the maximum unmet demand amount over all scenarios in the objective. Furthermore, our results show that, as the number of scenarios increases, total cost of the robust approach increases since the models need to consider a larger set of scenarios while deciding the maximum unmet demand amount. On the contrary, in the stochastic approach, total cost may not increase as the average unmet demand amount over all scenarios are considered in the objective. In addition to these, we observe that when penalty parameter increases or capacity decreases, both approaches require more computational time compared to the reference experimental settings.

All in all, we can conclude that stochastic approach outperforms in most of the cases with a lower total cost and CPU time. However, if the decision makers prefer being more prudent, they could select robust approach as it could collect more cryo despite of its higher cost. Additionally, our VSS analysis indicates that stochastic programming approach is necessary since it significantly contributes to the solution quality when various scenarios are considered.

As a future work, we may extend our analysis by examining different penalty functions associated with the unmet demand amounts. Instead of the proposed linear increase in penalty amount, we could evaluate how the solutions are affected when quadratic or piecewise linear penalty functions are used. In addition to these, we may investigate modeling approaches with chance constraints that enables satisfying the demand constraint with at least a given probability.

APPENDIX A: EXPERIMENTAL RESULTS

Note that for the tables in Appendix, Column "*Seed*" represents the seed for initializing the random number generator. The results are presented for 5 different seeds that are used throughout this study.

Table A.1. All experiments for robust and stochastic approaches when penalty parameter = $10 and capacity/demand ratio = 1.25.

Seed	**Model**	**CPU Time(s)**	**TotalC($)**	**TransportC($)**	**PenaltyC($)**	**UnsatisfiedD**
1	1 - RMWP	0.15	797.85	797.85	0	-59
1	10 - RMWP	0.24	917.15	917.15	0	-88
1	100 - RMWP	0.42	955.75	945.75	10	-159
1	1000 - RMWP	5.54	1045.50	1045.50	0	-152
2	1 - RMWP	0.18	841.45	841.45	0	-68
2	10 - RMWP	0.17	955.75	955.75	0	-135
2	100 - RMWP	0.51	975.05	975.05	0	-186
2	1000 - RMWP	88.36	1181.49	1181.49	0	-108
3	1 - RMWP	0.15	785.75	785.75	0	-35
3	10 - RMWP	0.19	906.6	906.6	0	-91
3	100 - RMWP	0.49	933.65	933.65	0	-84
3	1000 - RMWP	9.77	1071.40	1051.40	20	-135
4	1 - RMWP	0.28	815.75	815.75	0	-49
4	10 - RMWP	0.24	915.15	915.15	0	-120
4	100 - RMWP	0.53	966.65	966.65	0	-128
4	1000 - RMWP	14.65	1067.95	1057.95	10	-100
5	1 - RMWP	0.16	807.05	807.05	0	-62
5	10 - RMWP	0.27	901.35	901.35	0	-120
5	100 - RMWP	0.38	931.75	931.75	0	-107
5	1000 - RMWP	2.81	997.69	997.69	0	-71
1	1 - SM	0.18	797.85	797.85	0.00	-59
1	10 - SM	0.38	897.35	864.35	33.00	-71
1	100 - SM	0.36	900.95	871.85	29.10	-89
1	1000 - SM	1.53	897.91	871.85	26.06	-96
2	1 - SM	0.18	841.45	841.45	0.00	-68
2	10 - SM	0.22	942.85	920.85	22.00	-122
2	100 - SM	0.39	895.95	861.55	34.40	-75
2	1000 - SM	2.37	901.10	868.64	32.46	-75
3	1 - SM	0.16	785.75	785.75	0.00	-35
3	10 - SM	0.22	891.55	874.55	17.00	-76
3	100 - SM	0.31	895.35	873.75	21.60	-114
3	1000 - SM	1.45	897.23	871.85	25.38	-89
4	1 - SM	0.18	815.75	815.75	0.00	-49
4	10 - SM	0.20	909.64	868.64	41.00	-79
4	100 - SM	0.31	906.95	873.75	33.20	-105
4	1000 - SM	2.10	902.12	871.85	30.27	-89
5	1 - SM	0.29	807.05	807.05	0.00	-62
5	10 - SM	0.23	889	861	28.00	-107
5	100 - SM	0.27	888.35	863.45	24.90	-93
5	1000 - SM	1.68	899.11	868.64	30.47	-75

Table A.2. All experiments for robust and stochastic approaches when penalty parameter = $1 and capacity/demand ratio = 1.25.

Seed	Model	CPU Time(s)	TotalC($)	TransportC($)	PenaltyC($)	UnsatisfiedD
1	1 - RMWP	0.18	746.85	499.85	247.00	194
1	10 - RMWP	0.21	786.95	472.95	314.00	207
1	100 - RMWP	0.24	815.95	524.95	291.00	169
1	1000 - RMWP	1.00	823.05	467.05	356.00	196
2	1 - RMWP	0.35	763.85	555.85	208.00	122
2	10 - RMWP	0.20	802.05	455.05	347.00	246
2	100 - RMWP	0.48	804.95	492.95	312.00	192
2	1000 - RMWP	1.24	816.15	397.15	419.00	273
3	1 - RMWP	0.19	742.95	529.95	213.00	126
3	10 - RMWP	0.42	784.05	435.05	349.00	241
3	100 - RMWP	0.23	792.05	455.05	337.00	204
3	1000 - RMWP	1.17	822.05	455.05	367.00	246
4	1 - RMWP	0.19	740.05	467.05	273.00	238
4	10 - RMWP	0.16	788.95	492.95	296.00	192
4	100 - RMWP	0.28	792.05	435.05	357.00	219
4	1000 - RMWP	1.15	817.95	492.95	325.00	192
5	1 - RMWP	0.15	742.95	472.95	270.00	229
5	10 - RMWP	0.17	799.05	435.05	364.00	235
5	100 - RMWP	0.49	800.95	472.95	328.00	181
5	1000 - RMWP	2.01	820.15	417.15	403.00	258
1	1 - SM	0.17	746.85	499.85	247.00	194
1	10 - SM	0.18	746.25	512.75	233.50	172
1	100 - SM	0.30	760.36	472.95	287.41	207
1	1000 - SM	0.45	758.66	435.05	323.61	219
2	1 - SM	0.17	763.85	555.85	208.00	122
2	10 - SM	0.18	760.85	510.85	250.00	169
2	100 - SM	0.21	757.36	435.05	322.31	219
2	1000 - SM	0.45	757.41	435.05	322.36	219
3	1 - SM	0.18	742.95	529.95	213.00	126
3	10 - SM	0.16	759.65	455.05	304.60	204
3	100 - SM	0.19	755.72	435.05	320.67	219
3	1000 - SM	0.44	757.21	435.05	322.16	219
4	1 - SM	0.16	740.05	467.05	273.00	238
4	10 - SM	0.17	764.05	472.95	291.10	207
4	100 - SM	0.20	757.03	435.05	321.98	219
4	1000 - SM	0.44	756.63	435.05	321.58	219
5	1 - SM	0.15	742.95	472.95	270.00	229
5	10 - SM	0.16	763	435	328.20	219
5	100 - SM	0.20	756.21	435.05	321.16	219
5	1000 - SM	0.44	756.57	435.05	321.52	219

Table A.3. All experiments for robust and stochastic approaches when penalty parameter = $100 and capacity/demand ratio = 1.25.

Seed	Model	CPU Time(s)	TotalC($)	TransportC($)	PenaltyC($)	UnsatisfiedD
1	1 - RMWP	0.19	797.85	797.85	0	-59
1	10 - RMWP	0.28	917.15	917.15	0	-88
1	100 - RMWP	0.50	958.65	958.65	0	-136
1	1000 - RMWP	6.22	1045.50	1045.50	0	-138
2	1 - RMWP	0.16	841.45	841.45	0	-68
2	10 - RMWP	0.23	955.75	955.75	0	-135
2	100 - RMWP	0.51	975.05	975.05	0	-169
2	1000 - RMWP	113.79	1181.49	1181.49	0	-108
3	1 - RMWP	0.18	785.75	785.75	0	-35
3	10 - RMWP	0.19	906.6	906.6	0	-92
3	100 - RMWP	0.49	933.65	933.65	0	-84
3	1000 - RMWP	22.52	1080.10	1080.10	0	-105
4	1 - RMWP	0.16	815.75	815.75	0	-49
4	10 - RMWP	0.19	915.15	915.15	0	-120
4	100 - RMWP	0.51	966.65	966.65	0	-128
4	1000 - RMWP	10.99	1072.85	1072.85	0	-106
5	1 - RMWP	0.31	807.05	807.05	0	-62
5	10 - RMWP	0.30	901.35	901.35	0	-103
5	100 - RMWP	0.37	931.75	931.75	0	-107
5	1000 - RMWP	2.72	997.69	997.69	0	-71
1	1 - SM	0.18	797.85	797.85	0.00	-59
1	10 - SM	0.20	917.15	917.15	0.00	-88
1	100 - SM	0.29	946.75	945.75	1.00	-159
1	1000 - SM	3.73	961.75	924.65	37.10	-106
2	1 - SM	0.19	841.45	841.45	0.00	-68
2	10 - SM	0.21	955.75	955.75	0.00	-135
2	100 - SM	0.52	963.25	952.25	11.00	-143
2	1000 - SM	14.89	1002.95	937.05	65.90	-105
3	1 - SM	0.25	785.75	785.75	0.00	-35
3	10 - SM	0.39	906.60	906.60	0.00	-92
3	100 - SM	0.37	923.45	910.45	13.00	-83
3	1000 - SM	5.63	971.14	918.74	52.40	-127
4	1 - SM	0.22	815.75	815.75	0.00	-49
4	10 - SM	0.22	915.15	915.15	0.00	-120
4	100 - SM	0.52	958.25	936.25	22.00	-120
4	1000 - SM	3.61	964.35	923.75	40.60	-110
5	1 - SM	0.18	807.05	807.05	0.00	-62
5	10 - SM	0.20	901	901	0.00	-103
5	100 - SM	0.37	924.44	908.44	16.00	-112
5	1000 - SM	5.35	961.04	920.54	40.50	-74

Table A.4. All experiments for robust and stochastic approaches when penalty parameter = \$10 and capacity/demand ratio = 1.5.

Seed	**Model**	**CPU Time(s)**	**TotalC(\$)**	**TransportC(\$)**	**PenaltyC(\$)**	**UnsatisfiedD**
1	1 - RMWP	0.16	797.85	797.85	0	-59
1	10 - RMWP	0.17	899.15	899.15	0	-83
1	100 - RMWP	0.24	937.35	937.35	0	-135
1	1000 - RMWP	0.76	972.35	972.35	0	-198
2	1 - RMWP	0.16	841.45	841.45	0	-68
2	10 - RMWP	0.19	940.3	940.3	0	-139
2	100 - RMWP	0.28	940.3	940.3	0	-139
2	1000 - RMWP	1.06	946.65	946.65	0	-152
3	1 - RMWP	0.15	785.75	785.75	0	-35
3	10 - RMWP	0.23	884.4	884.4	0	-99
3	100 - RMWP	0.37	905.4	905.4	0	-110
3	1000 - RMWP	1.35	971.25	971.25	0	-160
4	1 - RMWP	0.16	815.75	815.75	0	-49
4	10 - RMWP	0.17	915.15	915.15	0	-120
4	100 - RMWP	0.27	930.05	930.05	0	-127
4	1000 - RMWP	0.87	946.65	946.65	0	-159
5	1 - RMWP	0.16	807.05	807.05	0	-62
5	10 - RMWP	0.18	898.45	898.45	0	-117
5	100 - RMWP	0.26	912.45	912.45	0	-130
5	1000 - RMWP	0.80	941.54	941.54	0	-120
1	1 - SM	0.16	797.85	797.85	0	-59
1	10 - SM	0.19	894.25	867.25	27	-81
1	100 - SM	0.24	889.15	858.65	30.5	-82
1	1000 - SM	1.19	880.74	858.65	22.09	-89
2	1 - SM	0.16	841.45	841.45	0	-68
2	10 - SM	0.19	927.85	920.85	7	-126
2	100 - SM	0.23	879.55	858.65	20.9	-98
2	1000 - SM	1.03	878.42	858.65	19.77	-98
3	1 - SM	0.15	785.75	785.75	0	-35
3	10 - SM	0.19	877.65	872.65	5	-93
3	100 - SM	0.25	879.05	858.65	20.4	-98
3	1000 - SM	1.20	881.07	858.65	22.42	-98
4	1 - SM	0.16	815.75	815.75	0	-49
4	10 - SM	0.18	909.64	868.64	41	-79
4	100 - SM	0.27	888.35	860.55	27.8	-107
4	1000 - SM	1.13	882.6	858.65	23.95	-82
5	1 - SM	0.17	807.05	807.05	0	-62
5	10 - SM	0.16	888.55	860.55	28	-107
5	100 - SM	0.23	876.55	861.55	15	-88
5	1000 - SM	1.20	878.12	858.65	19.47	-98

Table A.5. All experiments for robust and stochastic approaches when penalty parameter = \$10 and capacity/demand ratio = 1.

Seed	Model	CPU Time(s)	TotalC($)	TransportC($)	PenaltyC($)	UnsatisfiedD
1	1 - RMWP	0.21	955.40	845.40	110.00	-26
1	10 - RMWP	0.32	1868.29	1028.29	840.00	58
1	100 - RMWP	9.28	2543.55	943.55	1600.00	108
1	1000 - RMWP	31.37	2895.25	725.25	2170.00	63
2	1 - RMWP	0.34	1023.85	923.85	100.00	-57
2	10 - RMWP	0.40	2077.65	1007.65	1070.00	20
2	100 - RMWP	2.78	2604.19	884.19	1720.00	43
2	1000 - RMWP	37.18	2911.04	701.04	2210.00	129
3	1 - RMWP	0.20	913.65	873.65	40.00	-30
3	10 - RMWP	0.98	1758.04	1118.04	640.00	5
3	100 - RMWP	4.06	2425.24	755.24	1670.00	68
3	1000 - RMWP	256.33	2983.20	803.20	2180.00	125
4	1 - RMWP	0.17	922.95	862.95	60.00	-52
4	10 - RMWP	0.78	1778.45	1008.45	770.00	-39
4	100 - RMWP	2.21	2456.54	956.54	1500.00	77
4	1000 - RMWP	98.28	2958.15	728.15	2230.00	61
5	1 - RMWP	0.18	944.65	854.65	90.00	-79
5	10 - RMWP	0.50	1574.10	994.10	580.00	-39
5	100 - RMWP	2.38	2402.05	972.05	1430.00	64
5	1000 - RMWP	93.51	2878.94	738.94	2140.00	94
1	1 - SM	0.22	955.40	845.40	110.00	-26
1	10 - SM	0.27	1619.49	910.49	709.00	44
1	100 - SM	2.23	2133.80	954.80	1179.00	98
1	1000 - SM	15.92	2320.89	709.25	1611.64	61
2	1 - SM	0.23	1023.85	923.85	100.00	-57
2	10 - SM	0.28	1655.95	991.95	664.00	4
2	100 - SM	1.21	2125.69	840.29	1285.40	30
2	1000 - SM	10.12	2283.27	701.04	1582.23	129
3	1 - SM	0.21	913.65	873.65	40.00	-30
3	10 - SM	0.32	1580.05	982.05	598.00	22
3	100 - SM	1.55	2048.49	865.59	1182.90	70
3	1000 - SM	29.30	2329.85	872.05	1457.80	35
4	1 - SM	0.18	922.95	862.95	60.00	-52
4	10 - SM	0.29	1510.70	903.70	607.00	-55
4	100 - SM	0.95	2068.20	945.90	1122.30	65
4	1000 - SM	15.75	2315.48	708.25	1607.23	68
5	1 - SM	0.19	944.65	854.65	90.00	-79
5	10 - SM	0.29	1402.00	919.00	483.00	-43
5	100 - SM	1.48	1948.35	789.05	1159.30	55
5	1000 - SM	11.81	2276.20	701.04	1575.16	129

Table A.6. All experiments for robust and stochastic approaches when penalty parameter = \$1 and capacity/demand ratio = 1.

Seed	**Model**	**CPU Time(s)**	**TotalC(\$)**	**TransportC(\$)**	**PenaltyC(\$)**	**UnsatisfiedD**
1	1 - RMWP	0.18	746.85	499.85	247.00	194
1	10 - RMWP	0.19	790.15	430.15	360.00	288
1	100 - RMWP	0.26	824.15	449.15	375.00	258
1	1000 - RMWP	1.18	829.05	487.05	342.00	220
2	1 - RMWP	0.16	767.95	517.95	250.00	176
2	10 - RMWP	0.18	804.15	397.15	407.00	296
2	100 - RMWP	0.24	810.15	398.15	412.00	311
2	1000 - RMWP	0.92	819.25	359.25	460.00	308
3	1 - RMWP	0.16	742.95	529.95	213.00	126
3	10 - RMWP	0.18	785.15	397.15	388.00	273
3	100 - RMWP	0.25	794.15	397.15	397.00	273
3	1000 - RMWP	0.96	826.15	417.15	409.00	281
4	1 - RMWP	0.16	740.05	467.05	273.00	238
4	10 - RMWP	0.26	792.05	455.05	337.00	246
4	100 - RMWP	0.24	800.25	359.25	441.00	308
4	1000 - RMWP	0.87	823.25	379.25	444.00	293
5	1 - RMWP	0.19	743.05	435.05	308.00	261
5	10 - RMWP	0.46	799.05	435.05	364.00	235
5	100 - RMWP	0.44	801.05	435.05	366.00	235
5	1000 - RMWP	1.96	822.25	359.25	463.00	308
1	1 - SM	0.19	746.85	499.85	247	194
1	10 - SM	0.16	755.15	436.95	318.2	261
1	100 - SM	0.21	769.26	397.15	372.11	296
1	1000 - SM	0.46	767.25	359.25	408	308
2	1 - SM	0.15	767.95	517.95	250	176
2	10 - SM	0.16	769.65	435.05	334.6	258
2	100 - SM	0.21	766.72	359.25	407.47	308
2	1000 - SM	0.42	766.48	359.25	407.23	308
3	1 - SM	0.15	742.95	529.95	213	126
3	10 - SM	0.16	761.45	417.15	344.3	258
3	100 - SM	0.22	757.53	397.15	360.38	273
3	1000 - SM	0.43	766.3	359.25	407.05	308
4	1 - SM	0.15	740.05	467.05	273	238
4	10 - SM	0.15	766.55	435.05	331.5	261
4	100 - SM	0.21	765.18	359.25	405.93	308
4	1000 - SM	0.43	765.32	359.25	406.07	308
5	1 - SM	0.16	743.05	435.05	308	261
5	10 - SM	0.16	763.35	397.15	366.2	273
5	100 - SM	0.19	758.34	397.15	361.19	273
5	1000 - SM	0.44	765.63	359.25	406.38	308

Table A.7. All experiments for robust and stochastic approaches when penalty parameter = \$100 and capacity/demand ratio = 1.

Seed	Model	CPU Time(s)	TotalC($)	TransportC($)	PenaltyC($)	UnsatisfiedD
1	1 - RMWP	0.29	1327.95	1127.95	200.00	1
1	10 - RMWP	0.35	7897.74	1397.74	6500.00	-30
1	100 - RMWP	30.64	15833.09	1133.09	14700.00	101
1	1000 - RMWP	1233.45	21402.60	1102.60	20300.00	87
2	1 - RMWP	0.41	1298.85	1098.85	200.00	-81
2	10 - RMWP	0.41	9564.05	1364.05	8200.00	42
2	100 - RMWP	4.42	16214.50	1214.50	15000.00	89
2	1000 - RMWP	904.93	21897.80	997.80	20900.00	179
3	1 - RMWP	0.66	1137.75	937.75	200.00	-17
3	10 - RMWP	2.11	6769.29	1369.29	5400.00	2
3	100 - RMWP	15.80	15620.85	1020.85	14600.00	68
3	1000 - RMWP	881.06	21107.10	1107.10	20000.00	124
4	1 - RMWP	0.18	1108.90	1008.90	100.00	-51
4	10 - RMWP	1.46	7504.70	1204.70	6300.00	-56
4	100 - RMWP	7.23	15869.44	969.44	14900.00	86
4	1000 - RMWP	818.52	21324.55	1124.55	20200.00	87
5	1 - RMWP	0.30	1208.20	1208.20	0.00	-53
5	10 - RMWP	0.99	6331.40	1131.40	5200.00	-12
5	100 - RMWP	3.67	14804.65	1204.65	13600.00	127
5	1000 - RMWP	1092.83	21453.05	953.05	20500.00	72
1	1 - SM	0.28	1327.95	1127.95	200.00	1
1	10 - SM	0.49	6370.34	1360.34	5010.00	16
1	100 - SM	7.08	12115.30	1146.30	10969.00	11
1	1000 - SM	119.50	15792.10	1114.10	14678.00	93
2	1 - SM	0.45	1298.85	1098.85	200.00	-81
2	10 - SM	0.47	6754.50	1164.50	5590.00	1
2	100 - SM	2.72	12394.04	1240.04	11154.00	129
2	1000 - SM	299.12	16144.25	1068.75	15075.50	102
3	1 - SM	0.64	1137.75	937.75	200.00	-17
3	10 - SM	0.71	5810.89	1340.89	4470.00	15
3	100 - SM	8.82	11662.20	1104.20	10558.00	58
3	1000 - SM	306.98	15221.30	1004.90	14216.40	70
4	1 - SM	0.20	1108.90	1008.90	100.00	-51
4	10 - SM	0.67	5868.34	1338.34	4530.00	-15
4	100 - SM	5.28	11606.39	1125.39	10481.00	103
4	1000 - SM	123.20	15211.90	1073.70	14138.20	42
5	1 - SM	0.22	1208.20	1208.20	0.00	-53
5	10 - SM	0.81	5332.00	1092.00	4240.00	-17
5	100 - SM	2.57	10662.50	1084.50	9578.00	7
5	1000 - SM	223.78	15727.95	1036.15	14691.80	48

Table A.8. All experiments for robust and stochastic approaches when penalty parameter = $1 and capacity/demand ratio = 1.5.

Seed	Model	CPU Time(s)	TotalC($)	TransportC($)	PenaltyC($)	UnsatisfiedD
1	1 - RMWP	0.17	746.85	499.85	247.00	194
1	10 - RMWP	0.18	786.95	504.95	282.00	184
1	100 - RMWP	0.21	815.95	524.95	291.00	169
1	1000 - RMWP	0.92	823.05	467.05	356.00	196
2	1 - RMWP	0.15	763.85	555.85	208.00	122
2	10 - RMWP	0.20	802.05	455.05	347.00	246
2	100 - RMWP	0.23	804.95	492.95	312.00	192
2	1000 - RMWP	0.97	816.15	397.15	419.00	273
3	1 - RMWP	0.14	742.95	529.95	213.00	126
3	10 - RMWP	0.15	784.05	435.05	349.00	241
3	100 - RMWP	0.23	792.05	455.05	337.00	204
3	1000 - RMWP	0.80	822.05	455.05	367.00	246
4	1 - RMWP	0.15	740.05	467.05	273.00	238
4	10 - RMWP	0.16	788.95	492.95	296.00	192
4	100 - RMWP	0.22	792.05	435.05	357.00	219
4	1000 - RMWP	0.75	817.95	492.95	325.00	192
5	1 - RMWP	0.15	742.95	472.95	270.00	229
5	10 - RMWP	0.17	799.05	435.05	364.00	235
5	100 - RMWP	0.23	800.95	472.95	328.00	181
5	1000 - RMWP	1.00	820.15	417.15	403.00	258
1	1 - SM	0.18	746.85	499.85	247	194
1	10 - SM	0.17	746.25	512.75	233.5	172
1	100 - SM	0.29	760.36	472.95	287.41	207
1	1000 - SM	0.49	758.66	435.05	323.61	219
2	1 - SM	0.15	763.85	555.85	208	122
2	10 - SM	0.20	760.85	510.85	250	169
2	100 - SM	0.18	757.36	435.05	322.31	219
2	1000 - SM	0.58	757.41	435.05	322.36	219
3	1 - SM	0.16	742.95	529.95	213	126
3	10 - SM	0.15	759.65	455.05	304.6	204
3	100 - SM	0.19	755.72	435.05	320.67	219
3	1000 - SM	0.53	757.21	435.05	322.16	219
4	1 - SM	0.16	740.05	467.05	273	238
4	10 - SM	0.16	764.05	472.95	291.1	207
4	100 - SM	0.18	757.03	435.05	321.98	219
4	1000 - SM	0.51	756.63	435.05	321.58	219
5	1 - SM	0.16	742.95	472.95	270	229
5	10 - SM	0.16	763.25	435.05	328.2	219
5	100 - SM	0.20	756.21	435.05	321.16	219
5	1000 - SM	0.48	756.57	435.05	321.52	219

Table A.9. All experiments for robust and stochastic approaches when penalty parameter = \$100 and capacity/demand ratio = 1.5.

Seed	**Model**	**CPU Time(s)**	**TotalC(\$)**	**TransportC(\$)**	**PenaltyC(\$)**	**UnsatisfiedD**
1	1 - RMWP	0.15	797.85	797.85	0	-59
1	10 - RMWP	0.18	899.15	899.15	0	-83
1	100 - RMWP	0.24	937.35	937.35	0	-135
1	1000 - RMWP	0.82	972.35	972.35	0	-198
2	1 - RMWP	0.17	841.45	841.45	0	-68
2	10 - RMWP	0.23	940.3	940.3	0	-139
2	100 - RMWP	0.27	940.3	940.3	0	-139
2	1000 - RMWP	1.41	946.65	946.65	0	-152
3	1 - RMWP	0.15	785.75	785.75	0	-35
3	10 - RMWP	0.17	884.4	884.4	0	-99
3	100 - RMWP	0.26	905.4	905.4	0	-110
3	1000 - RMWP	1.33	971.25	971.25	0	-160
4	1 - RMWP	0.16	815.75	815.75	0	-49
4	10 - RMWP	0.17	915.15	915.15	0	-120
4	100 - RMWP	0.30	930.05	930.05	0	-127
4	1000 - RMWP	1.06	946.65	946.65	0	-159
5	1 - RMWP	0.17	807.05	807.05	0	-62
5	10 - RMWP	0.20	898.45	898.45	0	-117
5	100 - RMWP	0.26	912.45	912.45	0	-130
5	1000 - RMWP	0.92	941.54	941.54	0	-120
1	1 - SM	0.16	797.85	797.85	0	-59
1	10 - SM	0.18	899.15	899.15	0	-83
1	100 - SM	0.28	935.75	923.75	12	-116
1	1000 - SM	1.93	930.65	909.75	20.9	-112
2	1 - SM	0.15	841.45	841.45	0	-68
2	10 - SM	0.19	940.3	940.3	0	-139
2	100 - SM	0.22	927.85	920.85	7	-126
2	1000 - SM	1.58	921.65	910.55	11.1	-121
3	1 - SM	0.15	785.75	785.75	0	-35
3	10 - SM	0.34	884.4	884.4	0	-99
3	100 - SM	0.33	900.45	898.45	2	-126
3	1000 - SM	1.74	929.95	913.45	16.5	-111
4	1 - SM	0.17	815.75	815.75	0	-49
4	10 - SM	0.20	915.15	915.15	0	-120
4	100 - SM	0.33	925.75	919.75	6	-113
4	1000 - SM	1.67	929.05	906.85	22.2	-115
5	1 - SM	0.19	807.05	807.05	0	-62
5	10 - SM	0.17	898.45	898.45	0	-117
5	100 - SM	0.25	905.55	896.55	9	-110
5	1000 - SM	1.81	918.75	898.45	20.3	-119

Table A.10. All experiments for computing the value of the stochastic solution.

Seed	**# of Scenarios**	**EMVS($)**	**SS($)**
	penalty parameter p = $1	755.20	755.19
1	1	746.85	746.85
1	10	746.25	746.25
1	100	760.36	760.36
1	1000	758.66	758.66
2	1	763.85	763.85
2	10	760.85	760.85
2	100	757.36	757.36
2	1000	757.41	757.41
3	1	742.95	742.95
3	10	759.85	759.65
3	100	755.72	755.72
3	1000	757.21	757.21
4	1	740.05	740.05
4	10	764.05	764.05
4	100	757.03	757.03
4	1000	756.63	756.63
5	1	742.95	742.95
5	10	763.25	763
5	100	756.21	756.21
5	1000	756.57	756.57
	penalty parameter p = $10	884.46	878.14
1	1	797.85	797.85
1	10	919.05	897.35
1	100	896.45	900.95
1	1000	901.89	897.91
2	1	841.45	841.45
2	10	950.55	942.85
2	100	900.35	895.95
2	1000	902.23	901.10

Table A.10. All experiments for computing the value of the stochastic solution. (cont.)

Seed	**# of Scenarios**	**EMVS($)**	**SS($)**
	penalty parameter p = $10	884.46	878.14
3	1	785.75	785.75
3	10	901.95	891.55
3	100	897.85	895.35
3	1000	902.06	897.23
4	1	815.75	815.75
4	10	917.65	909.64
4	100	909.95	906.95
4	1000	911.62	902.12
5	1	807.05	807.05
5	10	931.75	889
5	100	898.75	888.35
5	1000	899.22	899.11
	penalty parameter p = $100	1281.79	911.06
1	1	797.85	797.85
1	10	1693.05	917.15
1	100	1263.65	946.75
1	1000	1335.15	961.75
2	1	841.45	841.45
2	10	1778.55	955.75
2	100	1426.65	963.25
2	1000	1348.45	1002.95
3	1	785.75	785.75
3	10	1513.95	906.60
3	100	1294.75	923.45
3	1000	1346.75	971.14
4	1	815.75	815.75
4	10	1448.65	915.15
4	100	1415.75	958.25
4	1000	1449.55	964.35
5	1	807.05	807.05
5	10	1633.75	901
5	100	1313.65	924.44
5	1000	1325.55	961.04

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