An Integrated Logistics System for Effective Resource Distribution in Post-disaster Humanitarian Relief Operations

by

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Abstract

After a disaster, distributing supplies and transferring people are critical operations and should be done quickly and fairly, with consideration to difficulties associated with limited resources.

In this research, more realistic and integrated models are proposed to perform several important logistic operations, including commodity distribution, wounded evacuation, and work–force transfer. To accomplish this, first, an existing model of Yi and Kumar (2007), which considers two logistic operations (e.g., commodity distribution and wounded evacuation), is discussed and corrected.

Second, a new model is developed to incorporate a new logistic operation of work–force transfer. Evaluation of this model shows that it has some of the same limitations as the Yi and Kumar (2007) model such as lacking detailed vehicles routes. Third, an integrated logistics system is developed to incorporate all three logistic operations while considering realistic issues such as the determination of detailed vehicle routes. Tiny-scale problems are solved optimally via CPLEX-Concert Technology, while problems of realistic size require the application of new heuristic approaches based on solving the model iteratively and optimally according to specific routes which are constructed greedily to achieve the maximum resources utilization. Different heuristic versions are considered to solve the model, the performances of which are compared to the CPLEX results for numerous randomly generated data sets, and they show excellent results in an extremely short processing time. Local search is used in conjunction with replacement and insertion to improve the suggested solution approaches. In replacement, one customer visit could be replaced by two customer visits in the existing routes, if possible, to increase the number of visits which improves the distribution system. Using insertion, a node may be added to existing routes, if possible, to improve the efficiency

of vehicles. These searches are applied in different ways and the results show that applying them for each candidate solution with higher numbers of iterations (longer termination time) gives the best results among all ways.

Finally, a more comprehensive, multi-objective model is developed to consider the use of large vehicles as temporary satellite facilities, serving as mobile supply nodes to improve the efficiency of smaller vehicles. The objectives are considered separately which will minimize the total wounded deviation, the total worker deviations, or the total commodities deviations. Different approaches are developed to find a wide range of solutions for more representative Pareto sets. It is found that there are some clusters in both wounded deviations–worker deviations and wounded deviations–commodities deviations Pareto sets, but they decrease in the commodities deviations–worker deviations Pareto set. Despite the problem of clusters, the suggested solution approaches are capable of finding many solutions in different regions of Pareto sets to cover most cases that might be requested from users.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

Each year, natural and man-made disasters result in catastrophic loss of life, critical injuries, and debilitating economic impacts worldwide. In 2010, for example, a total of 385 natural disasters killed more than 297,000 people, affected over 217 million others and caused $123.9 billion in economic damages worldwide (Sapir et al. 2010). In the United States, the Federal Emergency Management Agency (FEMA) reported 99 major and 29 emergency declarations in 2011, FEMA (2013).

In response to the large number of disasters experienced in the last 20 years, an increasing amount of research in engineering, medicine, and social sciences has been conducted to aid in recovery in the aftermath of these events. Logistics is one of the most important research fields that could help save lives, especially when the resources are distributed fairly and in a timely manner. A recent survey by the Fritz Institute investigated the importance of logistics for humanitarian relief after a tsunami. Their findings indicate that 88% of the relief organizations had to reallocate their most experienced logisticians to staff the tsunami relief efforts. Furthermore, without adequate supply chain systems in place, the majority of organizations relied on solutions using Excel spreadsheets or manual processes for tracking goods in the field. Not surprisingly, 62% of the organizations' plans fell short of needs and only 58% of organizations used logisticians in their assessment teams, Firtz Institute (2013).

With many deficiencies existing in humanitarian relief logistics, the focus of this research is to address some of these shortcomings by developing realistic models and constructing solution approaches capable of solving these models with reasonable computational effort.

Altay and Green (2006) divided the disaster operations into four main categories; mitigation, preparedness, response, and recovery. The first two categories are performed before disasters, so they are called pre-disaster operations and include pre-disaster planning (c.f. Chang et al. (2007), Rawls and Turnquist (2010), and Campbell and Jones (2011)) and construction of warehouses (c.f. Widener and Horner (2011)). The second two categories are done after disasters, so they are called post-disaster operations. The goals of post-disaster humanitarian relief logistics are to provide rapid delivery of essential commodities to survivors (e.g. food, water, medicine), to evacuate wounded survivors in the most efficient manner possible, given limited resources and potentially impassable roadways (c.f. Yi and Kumar (2007) and Yi and Ozdamar (2007)), debris removal (c.f. Fetter and Rakes (2011)) and construction of temporary warehouses (c.f. Widener and Horner (2011)).

This research presents optimization models to focus on post-disaster logistic operations such as commodity delivery, wounded evacuation, and assignment of relief workers to regions affected by the event. This problem is complicated by a number of factors. First, workforce transfer is difficult due to operational complexity and the variety of skills required (i.e. doctors, nurses, and drivers). Second, besides demand distribution, vehicles have to evacuate the wounded. Third, demand almost certainly exceeds the available supply. Fourth, vehicles are working in an environment of damaged roads and infrastructure. Fifth, because vehicles are donated from different sources, they have a variety of specifications in size, capacity, and speed. Finally, large vehicles, which can not be used in cases of partially destroyed roadways, require long load, unload, and travel times, and thus require utilization in different ways.

Several existing studies in the literature have proposed approaches to post-disaster humanitarian relief logistics efforts; however, to the best of our knowledge, no study has considered more than two logistic operations (e.g., commodity distribution, wounded evacuation, and workforce transfer) in the same model, and no study has considered workforce assignment and transfer in conjunction with other logistic operations. There are also no studies that utilize large and small vehicles in different ways. Accordingly, new models, and corresponding solution approaches, are proposed to address these shortcomings.

In the proposed models, many vehicle routing problem (VRP) variants are considered, including split deliveries, multiple depots, multiple commodities, heterogeneous vehicles, and multiple periods. Furthermore, the suggested models in this research consider dynamic supply and demand changes, hence they will be solved for multiple time periods and resolved at the beginning of each new time horizon. More details about these models are discussed in later chapters.

The remaining sections of this chapter address the research objectives in Section 1.1, list the research contributions in Section 1.2, and describe all models that are discussed or developed in this dissertation in Section 1.3 .

1.1 Research Objectives

This research considers mixed integer models to optimize the service performance of a post-disaster logistic system and solve the problems that humanitarian agencies encounter during relief work. To do so, we propose different models, each of which offers improvements over previous studies, as follows:

- All studies in the literature consider at most two logistic operations in post–disaster situations while utilizing many unrealistic assumptions. The first research objective is to develop more realistic and efficient models to incorporate more than two logistic operations that can be used efficiently in post-disaster situations. These operations include commodity delivery, wounded evacuation, and assignment of relief workers.

- In post–disaster situations, utilizing large vehicles in distribution is not easy because of blocked roads and substantial loading and unloading times. In the literature of humanitarian relief operations, there are no studies that utilize large vehicles in non-traditional ways. The second research objective is to develop a model to use large vehicles as mobile satellite facilities (SFs) that serve as movable supply nodes to improve the performance of distribution systems. These SFs are used to replenish small vehicles without returning back to supply depots, which saves time and increases the delivered amount.

- With the improved model from previous research objectives, the third research objective is to use multiple objectives instead of a single objective. The objectives used are relevant to the case of post-disaster, including minimizing total commodities deviations, total workers deviations, and total wounded deviations. Deviations are the difference between requested amounts and delivered amounts. These objectives are used because they are the most suitable objectives in case of a disaster. The goal of using multi-objective optimization is to provide a wide range of solutions to the users.

- Create different heuristic approaches to solve these models in a reasonable time. These approaches are supposed to provide full a detailed distribution plan for each individual vehicle based on a given route.

- Suggest different techniques to improve the heuristic approaches to offer different solution platforms with different performances and computation times.

Figure 1.1 shows the flow of research objectives.

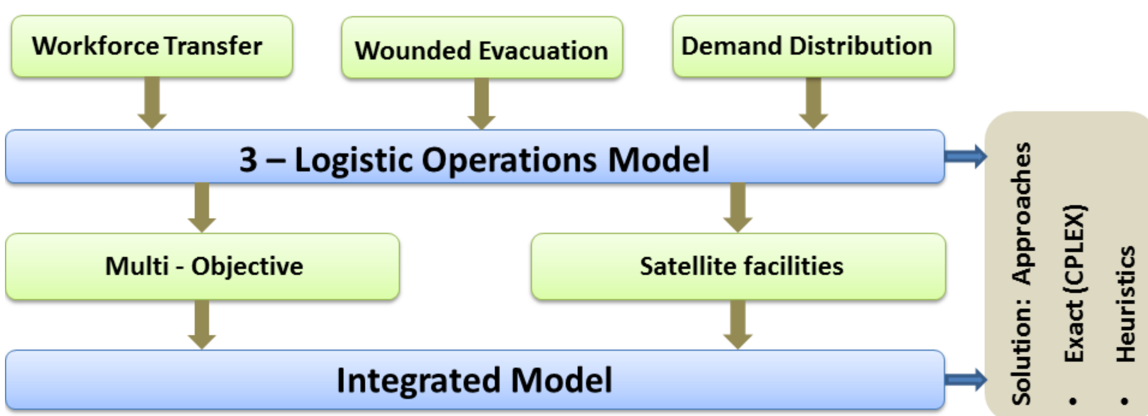


Figure 1.1: Overview of the proposed research objectives

1.2 Research Contributions

This research effort aims to provide many contributions. First, it will provide a corrected formulation of the humanitarian logistics model of Yi and Kumar (2007). This represents an admittedly minor contribution, but enables its use as a basis for future models.

The second contribution of this research is the construction of a humanitarian logistics model incorporating the most important operations that must be performed after a disaster, with consideration of realistic assumptions. The literature in this field shows that the available models incorporate two operations at most (i.e. wounded evacuation and demand distribution). By contrast, the suggested model in this research will incorporate three operations within a single framework by adding the work-force assignment operation to those previously mentioned.

Third, the model in the second contribution has the same limitations as that of Yi and Kumar (2007) such that it does not produce a detailed route for each vehicle, needs a heuristic to build up a detailed solution for each vehicle, and considers vehicles with same speed. A new model is developed to explicitly consider individual vehicle routes, a feature that is noticeably absent from the work of Yi and Kumar (2007). This model represents the first major contribution in this research.

Fourth, the incorporation of larger vehicles as temporary satellite facilities (SF) represents a novel approach to improve humanitarian relief efforts. SFs represent movable supply nodes that can supply distribution vehicles, saving time, and enhancing the distribution system.

Fifth, efficient heuristic approaches will provide high-quality solutions to the model developed in the third contribution with a short computation time. It depends in constructing route for all vehicles using greedy approaches, and then solve complete model at specific routes (fixed binary variables) using CPLEX. This approach allows CPLEX to find an optimal solution for the modified model in extremely short time such that, in large scale problem, it gives a feasible solution in less than 5 minutes whereas CPLEX fails to give any feasible solution in 16 hours. The procedure is repeated iteratively to find different vehicle routes and solutions taking the advantage of some good routes inherited from previous iterations. Furthermore, different local search variants are applied iteratively to this approach to find more improved solutions.

Finally, the heuristic approaches that were developed in previous contribution will be modified to be suitable to solve the model developed in the fourth contribution. Hence the model is using SF and multi-objective, the proposed heuristic is capable to take SFs in consideration and provide representative Pareto sets that include wide range of solutions in short computation time.

1.3 An Overview of Proposed Model Development

In this section, a short description of the five models included in this research is presented which makes the understanding of the following chapters easier. Detailed information about each model is contained in later chapters.

1.3.1 The Baseline Model (YK)

There are many insightful studies related to humanitarian relief in post-disaster operations, including Ozdamar et al. (2004), Yi and Kumar (2007), and Yi and Ozdamar (2007), all of which include two operations and use an objective function well-suited to the problem at hand. Of these, the model of Yi and Kumar (2007), which we will denote as YK, was selected to be the starting point for this research. It incorporates multiple commodity types, split deliveries, differing vehicle capacities, multiple depots, multiple time periods, and wounded evacuation. A complete description of the YK model is presented in Chapter 3.

1.3.2 A Corrected YK Model (YK')

There are some minor errors in the YK model such as missing indices and missing variables in some constraints that cause infeasible solutions. A corrected version of this model, denoted as model YK', is presented in Section 3.2.2.

1.3.3 Adding the Workforce Transfer Operation (YK'+WT):

A new model is built to incorporate one more logistic operation. In the YK' model, there are some potential operations that could be added to make it more robust. The most important operation that could improve it is to use available vehicles to transfer the workforce from the supply nodes or hospitals to the demand nodes to help in distribution, medication, and evacuation of wounded people. Although Dolinskaya et al. (2011) have suggested workforce management as an important area for future research, and Jiang et al. (2012) have suggested a focus on the interdependency of operations and work-flow across different stakeholders, no models exist that incorporate workforce management in humanitarian relief efforts. This model formulation with a numerical example is presented in Chapter 3.3

1.3.4 Incorporating Vehicle Routing (HLVRP)

One drawback of the YK'+WT model is that it neglects vehicle routing. A new model, the *humanitarian logistics vehicle routing problem* (HLVRP), is proposed to incorporate vehicle routing decisions. In particular, solutions to the HLVRP provide detailed vehicle tracking information that is not afforded by the aforementioned models. Details about this model – including differences from previous models, a mathematical formulation, a numerical analysis, and an example – are explained in Chapter 4.

1.3.5 Satellite Facilities and Multiple Objectives (HLVRPSF)

Improving the distribution system is the ultimate goal of this research. A new model is developed to incorporate the operations in the HLVRP model with improved logistics operations. We will call this model *humanitarian logistics vehicle routing problem with satellite facilities* (HLVRPSF). The benefit of this model is to use large vehicles as satellite facilities (SFs) to deliver commodities faster, where using large vehicles as satellite facilities incurs no construction cost or time comparing with construction fixed warehouses.

The model with SF considers three objectives in a truly multi–objective manner. The first objective is to minimize unsatisfied demand, the second objective is to minimize unserved workforce, and the third objective is to minimize unserved wounded evacuees. In the HLVRP model, priorities are defined by users and used in a single objective function to differentiate between wounded, workers, and commodities categories. Whereas, in the HLVRPSF model, considering these objectives separately overcomes the problem of using priorities which could cause undesirable results when unsuitable values are used. Formulation, solution approaches, and numerical analysis of this model are presented in Chapter 5.

1.4 Organization of the Dissertation

This dissertation is organized as follows. In Chapter 2, an extensive literature review of related studies is provided. Chapter 3 includes the model from Yi and Kumar (2007), the corrected model of Yi and Kumar (2007), and develops the first model to incorporate work-force transfer with demand distribution and wounded evacuation.

In Chapter 4, a new model is developed to incorporate all three operations while considering detailed routes for each individual vehicle. To utilize the large vehicles as mobile satellite facilities, the last model is developed in Chapter 5 which includes the formulation, solution approaches, and discussion about different multi-objective treatments. Finally, Chapter 6 concludes this research and suggests future work.

Chapter 2

Review of Related Literature

This section reviews the literature related to this research and is organized as follows. Section 2.1 summarizes related pre-disaster research, while Section 2.2 summarizes and describes relevant post-disaster research. Section 2.3 explains the most relevant VRP variants and how they are related to this research. Finally, Section 2.4 reviews existing satellite facility (SF) research and describes how this research area will be applied to the proposed work.

2.1 Pre-Disaster Research

Pre-disaster research is concerned with all activities performed before a disaster, such as determining facility locations in areas with a high risk of disaster, and determining the quantities of first aid materials, food, and other supplies to store in those facilities. Although this research does not consider pre-disaster planning, the following articles could be helpful for post-disaster cases. For example, most of the permanent suppliers' locations found in pre-disaster models are used in post-disaster activities.

Several optimization models have been developed for pre-disaster planning. For instance, Chang et al. (2007) suggested two models to help relief agencies construct rescue organizations, specify the locations of rescue resource storehouses, allocate rescue resources under capacity restrictions, and distribute rescue resources. They have formulated two stochastic models for the case of a flood disaster. The first model aims to distribute rescue equipment from the distribution centers of minimum distance to the predefined rescue areas under different rainfall levels. The second model determines the quantity of equipment that should be stored at each location before the rainy season. The objective is to minimize the cost of operations, maintenance, and purchases. These models use non-mathematical approaches to divide the disaster area into groups and a sampling-based approximation to address the stochastic nature of the problem.

Similarly, Rawls and Turnquist (2010) proposed an integer programming model to determine the locations and quantities of different commodities that should be prepositioned in areas having a high disaster risk. The objective is to minimize the fixed cost of constructing new facilities plus the cost of quantities that will be stored at these locations. Costs of transportation, holding in case of excess, and a penalty in the case of shortage, were also added, based on the different possible scenarios with different probabilities. The authors assume that the road conditions before and after a disaster are the same (i.e. constant cost), and consider the quantities stored at a supply location to be the only resources for supply.

Other research demonstrates parameter specification. For example, Campbell and Jones (2011) have defined the parameters that could affect the selection of supply points in pre-disaster conditions. These parameters define the probability of the disaster destroying the supply points, the distances between points, restocking costs, salvage values, and other variables. Additional literature related to pre-disaster planning can be found in the recent review article of Caunhye et al. (2012).

2.2 Post-Disaster Research

Post-disaster research is concerned with all activities performed after a disaster, such as commodity distribution, wounded evacuation, and workforce management. In this section, some studies related to this research are presented.

Because the complexity of the post-disaster situation and the limited resources, logistic systems should adopt many important logistical operations. Few studies incorporate more than one operation in the optimization model. For example, Yi and Kumar (2007) suggest a model that includes the objective of minimizing both unsatisfied demand and unserved wounded. It aims to distribute commodities to distribution centers in the affected areas and evacuate the wounded people to medical centers. Similarly, Yi and Ozdamar (2007), Yan and Shih (2009), Ozdamar and Demir (2012), Balcik et al. (2008) and Ozdamar and Yi (2008) have suggested models with two logistical operations.

In Yi and Ozdamar (2007), an integrated capacitated location-routing problem (LRP) is suggested, which is a mixed integer multi-commodity network flow model aimed at the coordination of the transportation of commodities from major supply centers to affected areas and the transportation of wounded people from affected areas to temporary and permanent emergency units. Specifically, the objective is to minimize the total unserved commodities multiplied by their priorities and divided by a standard amount to sustain one wounded, plus the number of unserved wounded people with different level of wounded multiplied by its priority for all time periods. The drawback of this model is neglecting vehicle routes and treating the vehicles as commodities passing along arcs. Similarly, Ozdamar and Yi (2008) have suggested a model with minor differences from the model of Yi and Ozdamar (2007) such as adding limitations to the number of wounded that can be served at each hospital. They used a greedy neighborhood search to solve the model. Because roadway repair affects the supply distribution, Yan and Shih (2009) have suggested a model to perform these operations with respect to the repair schedule. In a similar way, Wex et al. (2013) suggested a model for the problem of rescue unit scheduling and assignment, where the rescue units are scheduled to process different prioritized types of incidents such as fires and building collapse.

Some studies include a model for evacuation only. For example, Baharanchi et al. (2011) have developed bi-objective integer programming models to evacuate wounded persons after an earthquake. The first objective is to minimize the number of unsuccessful vehicle visits, and the second is to minimize the total travel distance. Drawbacks include the assumption of only one level of earthquake (six Richter), incorporating only identical vehicles, and decision variables that indicate only the arcs that should be traveled by each vehicle without sequence. Jotshi et al. (2009) have used data fusion analysis to estimate the number of victims who need transfer. Chiu and Zheng (2007) have suggested a model to evacuate multi-priority groups with minimum travel time.

On the other hand, some studies only include a model for demand distribution. For example, Ozdamar et al. (2004) have presented a model to minimize the amount of unsatisfied demand for all types of commodities at all nodes and time slots. In the model, vehicles do not necessarily return to the depot, assuming the drivers have contact with coordination centers. The first of the two models determines the flow plan or quantity that should be transfered through each road. The second model is an integer program to determine the number of vehicles that should pass through each road. Similarly, Balcik et al. (2008) have suggested a model to find the routes of vehicles with minimum travel cost and unsatisfied demand cost where the route costs are assumed to be known, and Lin et al. (2011) have presented a model to minimize the penalty cost associated with a delay of delivering the demand of different types to the nodes at all periods plus the penalty cost of unsatisfied demand. Finally, Afshar and Haghani (2012) have developed a model to distribute the demand while minimizing the total prioritized unsatisfied demand.

Some studies have used numerical analysis to develop the procedure for performing some post-disaster operations, but they do not include an optimization model. Sheu (2007) has shown a hybrid fuzzy clustering optimization approach to divide the relief supply network into three levels: supply, distribution, and demand areas. His model starts with processing data numerically to forecast the relief demand based on the number of facilities available in the governmental records. A fuzzy clustering approach classifies affected area into groups based on the clustering results. Finally, multi-criteria decision making is applied to rank the priority order of groups. This article does not include an optimization model, and instead is a numerical analysis. Similarly, Sheu (2010) used numerical methods to forecast the relief demand, group the affected areas, and determine the urgency of relief demand; these models do not consider optimization. In the same manner, numerical and statistical analysis are used to determine the bounds and estimations of some parameters and decision variables. For example, Fiedrich et al. (2000) employed statistical methods to find the estimated number of supplier locations to be used among available facilities. Gong and Batta (2007) used numerical techniques to model the clusters in disaster areas and to allocate/re-allocate ambulances into the clusters. Arora et al. (2010) described a resource allocation approach to optimize regional aid during public health emergencies.

Some studies consider models with multiple objectives, such as Liu and Zhao (2007) who have presented a weighted multi-objective model for distributing commodities in emergency logistics. In the model, the objective is to minimize the time needed to move the items from suppliers to distribution centers (DCs) and from DCs to the demand points. The cost of constructing DCs and the cost of unsatisfied demand are also included. In this model, the decision variables represent the demand quantities that should be distributed to each location, without considering the vehicle routes. Using other objectives related to the distribution time, Campbell et al. (2008) have presented a new objective function for relief effort that depends on the maximum and average arrival times, instead of total distance. They used a model with one vehicle, and then approximated values for some bounds. Besides the time, Vitoriano et al. (2010) added more terms to the objective function. They developed a multi-objective model based on equity, reliability, time, cost, security and priority. A target value for each of these objectives is specified, and the deviation variables are defined as the difference between the objective and its target value. They assumed a heterogeneous fleet of vehicles characterized by capacity, velocity, and variable and fixed costs. Two types of nodes were suggested in this single-commodity model: nodes to pick up the commodity and nodes for delivery. A goal programming approach was used to minimize the deviation variables of the objectives.

Yuan and Wang (2009) suggested two models to select the paths during the relief distribution. In the first model, travel speed along each arc was considered while in the second model, chaos, panic and congestion were considered to minimize the number of arcs required to cover all demand locations.

Some studies incorporate location determination in post-disaster relief. For example, Widener and Horner (2011) have suggested a hierarchical model to select the best location for facilities in the event of a hurricane to minimize the total distance of serving the nodes with different service or demand levels. They neglected vehicle routing, multi-commodity considerations, and differing costs of facility construction based on location. Tzeng et al. (2007) constructed a multi-objective model to minimize the total cost and total travel distance and maximize the minimal satisfaction. Total cost includes the fixed costs associated with constructing supply nodes and transportation. Supply nodes are selected from predetermined locations. The drawback with this model is that the best locations to construct the supply nodes are selected after a disaster. Distribution can only begin after construction, creating extremely long delays for post-disaster response where time is a critical factor.

Barbarosoglu et al. (2002) developed a model for a helicopter logistics system. It is divided into six sub problems: fleet consumption, pilot assignment, number of tours for each helicopter, helicopter routing, helicopter transportation (loading and unloading), and refueling scheduling problems. The mathematical model is divided into two models, such that the *top level* model contains the first three sub problems, while the *base level* model contains the last three sub problems. The objective is to minimize the cost of pilots and helicopters in the first model, and the total distance in the second model.

Finally, some researches suggest models that are suitable for small scale problems only. First, Barbarosoglu and Arda (2004) developed a model with two stochastic stages to solve multi-commodity network flow problems. This model was used to solve a small scale problem with 6 demand nodes and 5 supply nodes. Second, Fei et al. (2011) solved a small scale path selection problem for post-disaster situations. The problem solves a 15-node problem using ant colony optimization, with the objective of minimizing the time traveled by all vehicles. Finally, Haghani and Oh (1996) solved two problems, one with 4 nodes and the other with 10 nodes.

A recent review article is by Galindo and Batta (2013) includes a full summary about the studies concerning pre-disaster and post-disaster, as well as a discussion on research gaps in the literature. For example, they note the lack of studies on coordination among humanitarian agencies that are working in the same geographical area. New technologies, such as geographical information system (GIS) ans simulation software, have not yet seen widespread adoption. Furthermore, better performance indicators to measure the effectiveness of proposed models, using interdisciplinary techniques that would be more suitable for the case of disaster, are desirable. Finally, it is suggested that future research should rely upon more realistic assumptions. Another review study has been conducted by Luis et al. (2012), which includes a good summary for the research of disaster relief operations.

The following subsections classify the research according to different criteria. These classifications highlight several gaps in the existing literature.

2.2.1 Humanitarian Logistics Operations

There are many different operations that take place during humanitarian relief efforts. First, demand requirements must be determined, typically via numerical methods to analyze existing demand data and forecast future demands (c.f., Sheu (2007) and Sheu (2010)). Next, emergency resources must be allocated to available facilities (c.f., Fiedrich et al. (2000), Sherali et al. (2004), Gong and Batta (2007), and Arora et al. (2010)). These resources must be distributed to points of demand (c.f., Tzeng et al. (2007), Yuan and Wang (2009), Barbarosoglu and Arda (2004), and Barbarosoglu et al. (2002)). In addition to resource delivery, wounded persons must be evacuated to first aid areas or hospitals (c.f., Jotshi et al. (2009), Han et al. (2006), Chiu and Zheng (2007), Ozdamar and Yi (2008), Ozdamar and Demir (2012) and Tan et al. (2009)).

Most existing research on humanitarian logistics has focused on only one logistic activity at a time. While some research, most notably the works of Ozdamar and Yi (2008), Yi and Kumar (2007), Yi and Ozdamar (2007), Yan and Shih (2009), and Balcik et al. (2008) have incorporated two of these activities within a single model, we are aware of no existing models that have considered three or more of these critical operations within a unified framework. Furthermore, the activities of allocating and transferring relief workers are noticeably absent from the literature.

2.2.2 Objectives in Emergency Logistics

A variety of objectives have been considered in humanitarian relief optimization models, as highlighted in Table 2.1. Most studies employ traditional objectives such as minimizing cost and time while few use emergency-related objectives such as minimizing unsatisfied demand and unserved wounded.

Table 2.1: Common objectives in emergency logistics research.

Objective	**References**
Minimize distribution time	Tzeng et al. (2007), Jotshi et al. (2009), Chiu and Zheng (2007), Ozdamar and Demir (2012) and Yan and Shih (2009)
Minimize maximum completion time	Gong and Batta (2007), Campbell et al. (2008)
Minimize evacuation time	Tan et al. (2009)
Minimize distribution cost	Sheu (2007), Tzeng et al. (2007), Barbarosoglu and Arda (2004), and Balcik et al. (2008)
Maximize vehicle tour duration	Barbarosoglu et al. (2002)
Minimize unsatisfied demand and minimize unserved wounded (in one objective function)	Ozdamar and Yi (2008), Yi and Ozdamar (2007), and Yi and Kumar (2007)
Maximize demand fill rate	Sheu (2007) and Tzeng et al. (2007)
Minimize number of fatalities	Fiedrich et al. (2000)
Multi-objective	Lin et al. (2011) (penalty cost of delayed deliveries, tours cost, and satisfaction), Yan and Shih (2009) (Minmax repairing, Minmax distribution), Liu and Zhao (2007) (overall cost, effectiveness, and satisfaction), Najafi et al. (2013), and Tzeng et al. (2007) (total cost, travel time, satisfaction)

2.2.3 Review of Solution Approaches in Humanitarian Relief Studies

Many previous studies on humanitarian relief relied on commercial integer programming software (e.g. CPLEX, GAMS, LINGO) to solve small-scale problems optimally. For large scale problems, heuristic approaches, such as particle swarm optimization (PSO), modified branch-and-bound (MBAB), ant colony optimization (ACO), tabu search (TS), genetic algorithm (GA), and simulated annealing (SA) were used. A summary of solution approaches applied to previous emergency studies is contained in Table 2.2.

Table 2.2: Solution approaches employed in previous studies.

Solution Approaches	**References**
Commerical software (CPLEX, GAMS, LINGO)	Lin et al. (2011), Yi and Ozdamar (2007), Vitoriano et al. (2010), Yan and Shih (2009), Widener and Horner (2011), Liu and Zhao (2007), Tzeng et al. (2007), Sheu (2007), Barbarosoglu and Arda (2004), and Balcik et al. (2008)
Genetic Algorithm	Lin et al. (2011)
Ant Colony	Yuan and Wang (2009), Yi and Kumar (2007), and Fei et al. (2011)
Simulated Annealing	Baharanchi et al. (2011)
Greedy Neighborhood Search	Ozdamar and Yi (2008)
Lagrangian relaxation based iterative algorithm	Ozdamar et al. (2004)
Insertion algorithm	Campbell et al. (2008)
hierarchical cluster and route procedure	Ozdamar and Demir (2012)

2.3 Vehicle Routing Problem (VRP)

The classical vehicle routing problem (VRP) is an essential part of this research because it forms the basis for many logistic systems. The VRP will be used to construct the integrated logistic system for post-disaster relief, which is the ultimate goal of this research. It should be noted, however, that the VRP must be substantially extended to be applicable to humanitarian relief problems. Such enhancements include incorporating multiple existing VRP variants, considering workforce transfer, and addressing wounded evacuation. In this section, some common VRP variants that are related to this research will be reviewed and explained.

The VRP is a very well-known problem in logistics and operations research, and was first introduced by Dantzig and Ramser (1959). The classical version of the VRP consists of a set of customers with known demands for a single commodity, a fleet of identical vehicles, and a single depot. The objective is to minimize the total cost of distribution, where each customer must be visited exactly once.

Any violation of one or more of the previous assumptions will result in a new VRP variant. In the next subsections, a short review of relevant variants is presented. A comparison of these variants with the proposed research is provided in Table 2.3. There are some other VRP classes of note that incorporate multiple variants simultaneously (c.f. Bettinelli et al. (2011) and Ho and Haugland (2004)). More details about VRP variants can be found in Toth and Vigo (2002) and Chapter 6 of Barnhart and Laporte (2007), while Cordeau et al. (2002) describe many effective algorithms to solve VRP problems.

Table 2.3: A comparison of VRP variants.

Type	**Multi Commodities**	**Split Delivery**	**Time Windows**	**Hetero. Vehicle**	**Multi Depot**	**Periodic**	**Satellite Facilities**
VRP							
CVRP							
VRPTW			✓				
MDVRP					✓		
VRPSD		✓					
PVRP						✓	
VRPSF							✓
This Research	✓	✓		✓	✓	✓	✓

2.3.1 Capacitated VRP (CVRP)

This variant considers identical vehicles and is the simplest extension of the VRP. Although this variant will not be considered in this research, it is explained here because it is an important case that is used for building other variants. It is considered as a modified multiple traveling salesman problem (MTSP). The only difference between the two cases is that in the CVRP the capacity of vehicles is finite, not infinite as in MTSP. The terms *VRP* and *CVRP* are often used interchangeably because vehicle capacities are typically implied within most VRP formulations.

Many studies have considered this variant. For example, Laporte (1992) reviewed the exact and approximate algorithms that have been used to solve the CVRP. The exact algorithms include direct tree search, dynamic programming, and integer programming. The heuristics or approximate algorithms include the nearest neighbor, insertion algorithms, and tour improvement procedures. In recent studies, both Baldacci et al. (2008) and Lysgaard et al. (2004), have presented an exact algorithm based on the branch-and-cut to solve the CVRP. More details about the CVRP can be found in Chapters 1–6 of Toth and Vigo (2002).

2.3.2 VRP with Time Windows (VRPTW)

In the VRPTW, customers must be visited within pre-determined time windows. This variant was first presented by Golden and Assad (1986). Chapter 7 of Toth and Vigo (2002) explains details of this variant. Many articles have suggested algorithms to solve the VRPTW (c.f., Wen and Meng (2008) and Ho and Haugland (2004)).

While the proposed research effort does not explicitly consider customer time windows, the time-critical nature of customer demand is certainly important. For example, in the short period of time immediately following a disaster, the *golden time*, all customers need the demand as soon as possible. For this reason, it is difficult to define a time window for when each customer should be supplied. Instead, in the context of humanitarian relief, some urgency parameters that depend on the customer status are developed to attribute higher priority to the most urgent demand needs.

2.3.3 Multi-Depot VRP (MDVRP)

The MDVRP addresses cases that have more than one depot, such as distribution centers or stores. If the nodes can be clustered around depots, this problem becomes a multi-CVRP; otherwise, it should be treated as a MDVRP.

This problem was first introduced by Tillman (1969). Desaulniers et al. (1998) studied this variant with time windows and waiting costs. Ho et al. (2008) developed a hybrid genetic algorithm to solve the MDVRP with customer grouping. Soeanu et al. (2011) suggested a decentralized heuristic approach to solve the MDVRP with split delivery. Bettinelli et al. (2011) suggested a branch-and-cut-and-price algorithm to solve VRP with a heterogeneous fleet, time windows, and multi depots.

In the proposed research effort, more than one location in the logistic network will be considered as a supply point.

2.3.4 VRP with Split Delivery (VRPSD)

The VRPSD occurs when customers may be supplied by more than one vehicle. The mathematical formulation is the same as that of the CVRP, except the single vehicle constraint, which guarantees that only one vehicle supplies each node, is removed.

This variant was first introduced by Dror and Trudeau (1989). Ho and Haugland (2004) used tabu search to solve VRP with time window and split delivery, and Jin et al. (2007) suggested two stage tabu search to solve VRPSD. In the proposed research, split deliveries are allowed.

2.3.5 Periodic VRP (PVRP)

The PVRP is a general case of the CVRP where the distribution could occur over many days or time periods. Beltrami and Bodin (1979) were the first to describe this case for a waste collection case study. The proposed research may be considered to be a modified PVRP, as each demand node may have a different demand for each time period.

2.3.6 VRP with Satellite Facilities (VRPSF)

In the VRPSF, satellite facilities (SFs) can be used to provide delivery vehicles with additional supplies if needed. In this case, the vehicles could be replenished completely or partially during the distribution without returning back to the depot. At the end of each shift, delivery vehicles may return to the depot. Beltrami and Bodin (1979) were the first to suggest this variant, while Bard et al. (1998a) suggested a branch-and-cut solution approach. This variant is applicable to the proposed research effort, where large vehicles may serve as SFs.

2.4 Satellite Facilities Research

The term *satellite facility* appears to lack a universal definition in the context of logistic networks. Typically, SFs include large vehicles, simple buildings, tents, local stores, or shelters. In the proposed research, large mobile vehicles will be used as satellite facilities whose use affords improved response to affected areas. The remainder of this section describes the use of SFs in other research fields, within the area of humanitarian relief, and as they are applied specifically to the proposed research.

2.4.1 General SF Research

Satellite facilities have been successfully deployed across a variety of applications. For example, military camps operating in remote areas often utilize temporary SFs for both housing and supplies. Other short-duration activities such as blood donation drives and weather monitoring stations typically use mobile vehicles as SFs. In industry, the term SF is commonly used in inventory routing problems and multi-echelon inventory systems where the inventory is transfered from the main warehouses to local stores and then to the final retailers.

Bard et al. (1998b) have suggested the use of satellite facilities around a central supplier to solve the problem of demand uncertainty which could conflict with the objective of minimizing the annual operating cost of the inventory routing problem (IRP). An IRP arises when a set of customers depends on a supplier to provide them with a certain commodity. The solutions of such cases aims to distribute the commodity and specify the amount of supplies that should be maintained at stores to reduce the chance of stock-out.

Bard et al. (1998a) have suggested branch-and-cut to solve the vehicle routing problem with satellite facilities (VRPSF). In this problem vehicles could be replenished at any of the SFs instead of going back to the main depot. In this article, the model consists of n customers with demands from a known distribution, a central depot, and s satellite facilities. Vehicles can be reloaded at the central depot or at any satellite facility.

As with many routing problems, the objective is to minimize the cost of distribution. The model was solved in three main steps: identification of the customers to visit at each time, assignment of customers to vehicles, and construction of routes for each vehicle.

Research on multi-echelon inventory problems often incorporates the use of satellite facilities. Here, inventory is distributed in multiple stages from the main suppliers through multiple levels of transshipment nodes until reaching the end users. Vehicle routing decisions are not always considered within these problems. Clark and Scarf (1960) were the first to present the multi-echelon inventory system to determine optimal purchasing quantities. Rottkemper et al. (2012) suggested a mixed integer model with two objectives to minimize the total unsatisfied demand and distribution cost. The model allows transshipments between regional depots, and was solved by a rolling horizon solution method. The main drawback associated with this model is that it can be used for only a single item. Jaillet et al. (2002) determined distribution cost approximations in an inventory routing problem with fixed satellite facilities. Crainic et al. (2010) proposed a distribution system within a two-echelon-vehicle routing problem. This basic system employs large vehicles that travel from the central depot to a fixed number of capacitated satellite facilities. Smaller vehicles transfer the demand from the SFs to customers with fixed demands. Such a system keeps large vehicles outside of crowded cities. Perboli et al. (2008) presented a two-echelon model with capacitated vehicle routing to minimize the total cost of transferring goods from the first level depot to the predetermined SFs.

Zhao et al. (2008) presented a three-echelon logistics system consisting of a supplier, a central warehouse, and a group of retailers. The objective is to minimize the overall average cost of the system. This model was solved by a large neighborhood search. Jung and Mathur (2007) suggested a heuristic to solve the two-echelon inventory routing problem with a single warehouse and multiple retailers. Gendron and Semet (2009) suggested path- and arc-based formulations for multi-echelon inventory routing problems.

A comprehensive review about this topic can be found in the paper of Paterson et al. (2011). In previous studies, there are many assumptions that limit their use in humanitarian relief efforts. For example, in all existing studies, time is not a critical factor. However, in the proposed research, the primary motivation behind employing SFs is to improve the distribution system and reduce delivery times. Additionally, the previous studies assume that the SF locations are fixed and already constructed, or can be selected from many available locations. In this research, SF locations will be changed after each shift based on the new data concerning demand and road conditions. Other assumptions regarding customers with equal demands and customers with unlimited storage capacities are also inappropriate for humanitarian relief.

2.4.2 SF in Humanitarian Relief Research

To the best of our knowledge, only Azimi et al. (2012) have used the SF term and applied it in the context of humanitarian relief. The authors have suggested a model to deliver multiple commodities to demand locations through multiple fixed SFs. The model results only decide which SFs and node should be visited by each vehicle in a single trip.

Many shortcomings are encountered in this research. First, it is not periodic, as a single trip with only one arc for each vehicle is considered. Second, SF locations are predetermined and each node is assigned to a specific SF with an unknown procedure. Third, it is assumed that the available supply is greater than the overall demand. Finally, the objective function is to minimize the total distance traveled by all vehicles.

Some studies have used multi-phase distribution systems in post-disaster situation such as Clark et al. (2013) who developed a model to distribute demand from main suppliers to regional warehouses and then to the recipients. The objective is to minimize unsatisfied demand, operating cost of the vehicles, amount of inventory, and the number of vehicles used. Similarly, Rottkemper et al. (2012) suggested a model with multi-phase distribution to minimize the cost of distribution demand and the running cost of trucks. Finally, Afshar and Haghani (2012) suggested a single logistic operation and multi-phases supply model for demand distribution. In this study, the term "mobile center" is used to define the locations where the supplies can be stored for a specific time. The objective is to minimize the prioritized unsatisfied demand.

It can be concluded from the literature that no studies consider SF efficiently in a multi-operation model while considering individual plans for each SF and vehicle.

Chapter 3

A Baseline Humanitarian Relief Model with Corrections and Improvement

3.1 Introduction

In this chapter, the model of Yi and Kumar (2007) is studied extensively and corrected to make it usable. For the purposes of the proposed research effort, the so-called YK model was chosen to serve as a baseline model because it is one of the most recent studies that includes two operations (distribution and evacuation), utilizes an objective function related to humanitarian relief. There are some errors in the YK model, so it is corrected and used to solve a simple example. The corrected model is denoted as YK' model.

The second part of this chapter addresses a new model. The YK' model is extended to consider the use of available vehicles for the transfer of relief workers from supply nodes to demand nodes. In post–disaster situation, volunteers and workers are supposed to help people in evacuation and wounded treatment. But the problem with this is that workers come to the regions of where the humanitarian agencies are placed and they request transfer to demand areas. This leads us to extend the YK' model to adopt workforce transfer as a new logistic operation that can improve the whole model.

This chapter is organized as follows: Section 3.2 describes the problem solved by YK model, Section 3.2.1 presents the mathematical formulation, Section 3.2.2 provides some corrections to the YK' model, Section 3.2.3 shows a numeric example of the YK' model. Section 3.3 includes the description, formulation, and a numeric example of the YK'+WT model. Section 3.4 summarizes the chapter.

3.2 The Yi and Kumar Model (YK)-Problem Description

Yi and Kumar (2007) developed a multi-operation logistics model for post-disaster situations. It aims to distribute commodities to affected areas and evacuate wounded persons to medical centers. In such situations, disaster areas are divided into three main categories: supply nodes, demand nodes, and hospital nodes with the distance of the arcs (routes) between nodes being predefined. Vehicles are classified into many types based on capacity but they are assumed to have equal speed. They pick up supplies from the supply nodes and deliver them to the demand nodes. They can then pick up wounded from demand nodes and transfer them to the hospitals.

Demand is classified into many types and prioritized based on its importance where the more important commodities have higher priority. In the same manner, wounded are classified into many categories and prioritized based on the level of injury.

Due to the limitation of resources in a post–disaster situation, vehicles might not be able to deliver the overall demand for each demand node or to pick up all wounded from a node when it is visited. The difference between the requested and the delivered demand for each node at each time period is called deviation or unsatisfied demand, and the difference between the total wounded needing evacuation and the wounded still awaiting transfer is called deviation wounded. Accordingly, this model develops a relevant objective function to minimize the summations of these deviation variables.

The model outputs for each time period are the amount of commodities of each type which are transfered on each arc, number of wounded from each category traveling on each arc, number of unsatisfied demand of each type at each demand node, number of unserved wounded (deviations) from each category, number of vehicles from each types transfer each arc at each time, and the total number of wounded treated at each hospital node.

Many data sets for this model were exactly solved by the authors using CPLEX. These problems were also solved using a two-phase approach. Ant colony optimization (ACO) is applied in the first phase to determine distribution quantities, while the number of vehicles required to deliver goods between pairs of nodes is determined in the second phase.

3.2.1 Notations and Formulation

The YK model employs the following sets and parameters:

- T: Set of discrete time periods comprising the planning horizon, T= $\{1, 2, \ldots, |T|\}$.
- H: Set of severity categories for wounded people,
  $H = \{1(\text{heavy}), 2\ (\text{moderate}), 3\ (\text{light}), \ldots, |H|\}$.
- V: Set of vehicle types, where vehicles are classified based on capacity.
- A: Set of commodity types, $A = \{1, 2, 3, \ldots, |A|\}$.
- CD: Set of demand nodes.
- CS: Set of supply nodes.
- CH: Set of available hospitals.
- C: Set of all nodes in the network, $C = CD \cup CS \cup CH$.
- t_{op}: Number of discrete time intervals required to traverse arc (o, p). This parameter is not vehicle-specific.
- dH_{hot}: Number of wounded people of category $h \in H$ at node $o \in CD$ at time $t \in T$.
- dA_{aot}: Amount of commodity $a \in A$ demanded at node $o \in CD$ at time $t \in T$.
- sup_{aot}: Amount of commodity $a \in A$ that can be supplied at node $o \in CS$ at time $t \in T$.
- av_{ovt}: Number of vehicles of type $v \in V$ assigned to node o at time $t \in T$.
- srv_{ho}: Service rate of node $o \in CH$ for wounded category $h \in H$. This represents the maximum number of wounded category $h \in H$ can be treated at hospital node o.
- wc_a: Unit weight of one unit of commodity $a \in A$.
- ww_h: Average weight of one wounded person of category $h \in H$.
- cap_v: Capacity of vehicles of type $v \in V$.
- PC_a: Priority of commodity type $a \in A$.

- PW_h: Priority of wounded category $h \in H$
- K_{ospt}: Binary parameter such that $K_{ospt} = 1$ if node $p \in C$ is reachable from node $o \in C$ at time $t \in T$, zero otherwise.

The decision variables are given by:

- Z_{aopvt}: Quantity of commodity $a \in A$ traversing arc (o, p) at time $t \in T$ by vehicle type $v \in V$.
- $devC_{aot}$: Amount of unsatisfied demand of commodity $a \in A$ at node $o \in CD$ at time $t \in T$.
- X_{hopvt}: Number of wounded people of category $h \in H$ traversing arc (o, p) at time $t \in T$ by vehicle type $v \in V$.
- $devW_{ht}$: Number of unserved wounded people of category $h \in H$ at time $t \in T$.
- Y_{opvt}: Number of vehicles of type $v \in V$ traversing arc (o, p) at time $t \in T$.
- SP_{hot}: Number of wounded category $h \in H$ served at node $o \in CH$ at time $t \in T$.

The YK model of Yi and Kumar (2007) is given as follows.

$$\text{Minimize} \sum_{a \in A} \sum_{o \in CD} \sum_{t \in T} PC_a \; devC_{aot} + \sum_{h \in H} \sum_{t \in T} PW_h \; devW_{ht} \tag{3.1}$$

subject to

$$\sum_{\substack{s \in T \\ s \leq t}} dA_{aos} - \sum_{p \in C} \sum_{v \in V} \sum_{\substack{s \in T \\ s \leq t}} [K_{psot} Z_{apovs} - Z_{aopvs}] = devC_{aot} \quad \forall \;\; a \in A, \; o \in CD, \; t \in T \tag{3.2}$$

$$\sum_{p \in C} \sum_{v \in V} \sum_{\substack{s \in T \\ s \leq t}} [Z_{aopvs} - K_{psot} Z_{apovs}] \leq \sum_{\substack{s \in T \\ s \leq t}} sup_{aos} \quad \forall \;\; a \in A, o \in CS, t \in T \tag{3.3}$$

$$Y_{opvt} \leq M \sum_{\substack{s \in T \\ s \leq t}} K_{otps} \quad \forall \; o \in C, p \in C, v \in V, t \in T \tag{3.4}$$

$$Y_{opvt} cap_v \geq \sum_{a \in A} wc_a Z_{aopvt} + \sum_{h \in H} ww_h \; X_{hopvt} \quad \forall \;\; o \in C, p \in C, t \in T \tag{3.5}$$

$$\sum_{\substack{s \in T \\ s \leq t}} \sum_{p \in C} [Y_{opvs} - Y_{povs} K_{povs}] \leq \sum_{\substack{s \in T \\ s \leq t}} av_{ovs} \quad \forall \;\; o \in C, v \in V, t \in T \tag{3.6}$$

$$\sum_{v \in V} \sum_{\substack{s \in T \\ s \leq t}} \sum_{p \in C} [X_{hopvs} - K_{psot} X_{hpovs}] \leq \sum_{\substack{s \in T \\ s \leq t}} dw_{hos} \quad \forall \;\; h \in H, o \in CD, t \in T \tag{3.7}$$

$$\sum_{v \in V} \sum_{\substack{s \in T \\ s \leq t}} \sum_{p \in C} [K_{psot} X_{hpovs} - X_{hopvs}] \geq \sum_{\substack{s \in T \\ s \leq t}} SP_{hos} \quad \forall \;\; h \in H, o \in C \backslash CD, t \in T \tag{3.8}$$

$$\sum_{\substack{s \in T \\ s \leq t}} \sum_{o \in C} [dw_{hos} - SP_{hos}] = devW_{ht} \quad \forall \;\; h \in H, t \in T \tag{3.9}$$

$$0 \leq \text{all variables} < \infty, \;\; SP_{hot} \leq srv_{ho} \quad \forall \; h \in H, o \in CH, t \in T \tag{3.10}$$

In this model, the objective is to minimize the total unsatisfied commodity demands (weighted by the priority of each type at all demand nodes, across all time periods) plus the number of unserved wounded people (weighted by their priority) across all time periods. Constraints (3.2) balance the flow and define the unsatisfied demand for each demand node. In other words, the total quantity delivered from node o minus the quantity received by node o in previous periods plus the unsatisfied demand at that node in the current period should equal the total demand for all previous periods. Similarly, constraints (3.3) balance the flow through supply nodes. Constraints (3.4) restrict the itinerary of each vehicle type to existing arcs, while (3.5) restrict the transportation quantities by the capacity of vehicles traversing the arc. Constraints (3.6) balance the vehicle flows at each node and restrict the number of vehicles introduced to the network by their cumulative availability over time. Constraints (3.7) and (3.8) govern the flow of wounded people, whereas constraints (3.9) define the unserved wounded people. Finally, constraints (3.10) define the variable bounds.

Unfortunately, as described in the next section, the YK model contains errors that limit its usefulness.

3.2.2 A Corrected Formulation

The YK' model represents a corrected formulation of the model proposed by Yi and Kumar (2007). The first issue associated with the YK model is encountered in constraints (3.2) and (3.3). They were designed to restrict the quantity delivered from each node by its supply capacity and input. Using only these constraints could result in demand nodes operating as supply nodes with unrealistic quantities being admitted. For example, a demand node could supply 100 units and receive 80 units with both constraints (3.2) and (3.3) still satisfied. To correct this, the following constraint, (3.11), is added to the model:

$$\sum_{v \in V} \sum_{p \in C} [Z_{aopvt} - Z_{apovt}] \leq sup_{aot} \quad \forall \; a \in A, o \in C, t \in T \tag{3.11}$$

Similarly, constraints (3.6) allow infeasible vehicle flows at a given node. For example, suppose that only 6 vehicles are available in the system. As written, these constraints would allow the release of 10 vehicles and the receipt of 5. The net difference of 5 is less than the number of vehicles in the system, but the 10 vehicles released exceeds the system vehicle availability. To solve this issue, constraints (3.12), below, are added to restrict the total number of vehicles that are moving in the system at any time by the actual number of available vehicles in the system.

$$\sum_{o \in C} \sum_{p \in C} Y_{opvt} \leq \sum_{\substack{s \in T \\ s \leq t}} \sum_{o \in C} av_{ovs} \quad \forall \; v \in V, t \in T \tag{3.12}$$

Constraints (3.5) do not properly define the v index, an omission likely due to a typographical error in the YK model. These constraints are easily modified as follows, where $v \in V$ is incorporated into the "for–all ($\forall$)" sets:

$$Y_{opvt} cap_v \geq \sum_{a \in A} ww_a \; Z_{aopvt} + \sum_{h \in H} ww_h \; X_{hopvt} \quad \forall \; o \in C, p \in C, v \in V, t \in T \tag{3.13}$$

Finally, constraints (3.8) and (3.9) utilize variable SP_{hot}, which is defined for hospital nodes only. These constraints are modified by considering node $o \in CH$, rather than $o \in C$ or $o \in \{C \backslash CD\}$. These constraints are rewritten as:

$$\sum_{v \in V} \sum_{\substack{s \in T \\ s \leq t}} \sum_{p \in C} [K_{psot} X_{hpovs} - X_{hopvs}] \geq \sum_{s=0}^{t} SP_{hos} \quad \forall\, h \in H, o \in CH, t \in T \tag{3.14}$$

$$\sum_{\substack{s \in T \\ s \leq t}} \sum_{o \in CH} [devW_{hos} - SP_{hos}] = devW_{ht} \quad \forall\, h \in H, t \in T \tag{3.15}$$

The corrected model, YK', may be represented as:

$$\begin{aligned} \text{Min} \quad & (3.1) \\ \text{s.t.} \quad & (3.2) - (3.4), (3.6), (3.7), (3.11) - (3.15). \end{aligned}$$

3.2.3 An Example

A small example demonstrates the validity of model YK'. This example includes three demand nodes, one supply node, one hospital node, six time periods, and two vehicle types. Two vehicles from each type are available, such that the first (second) vehicle of Type 1 is added at the beginning of time period 1 (2), and the first (second) vehicle of Type 2 is added at the beginning of time period 3 (4). Type 1 vehicles have a capacity of 800 lb and Type 2 vehicles have a capacity of 600 lb. This small example considers only one commodity type with a unit weight of 1.5 lb, and one category of wounded victims with an assumed weight of 200 lb each. Unit travel times between any two nodes are assumed for the sake of simplicity. Periodic supply and demand quantities for each node are shown in Table 3.1, while Table 3.2 contains the number of wounded persons waiting at each demand node over time.

Table 3.1: Commodity supply and demand over time.

Node	**Type**	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
1	Supply	360	460	360	200	240	200
2	Demand	0	260	200	160	210	0
3	Demand	0	190	140	180	192	100
4	Demand	90	160	186	100	160	80
5	Hospital	–	–	–	–	–	–

Table 3.2: Quantity of evacuation requests over time.

Node	**Type**	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
2	Demand	2	3	1	2	1	0
3	Demand	7	3	1	2	0	0
4	Demand	6	2	1	2	2	0

For this small-scale problem, an optimal solution may be obtained directly via CPLEX. This solution, as represented graphically in Figure 3.1, provides the quantities of commodities and wounded persons transported between nodes. A summary of unsatisfied commodity demand and unserved wounded persons is contained in Table 3.3.

Table 3.3: Summary of unsatisfied commodity demand and unserved wounded over time.

Node	**Type**	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
2	Demand	0	0	0	0	0	0
3	Demand	0	0	140	140	192	0
4	Demand	0	160	26	100	130	0
Nodes 2, 3, and 4 (Total)	Wounded	15	8	6	0	1	0

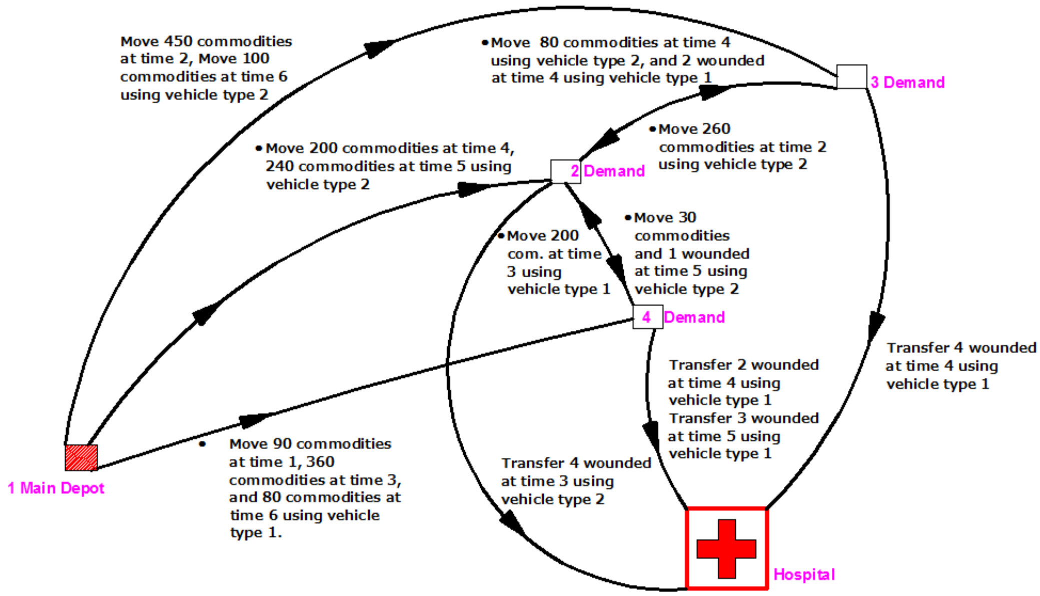


Figure 3.1: Example solution using the YK' model.

3.3 Incorporating Workforce Transfer (YK'+WT)

The YK' model is extended to consider the use of available vehicles for the transfer of relief workers from supply nodes to demand nodes to help in wounded treatment and evacuation. These workers, while vital to relief efforts, can consume valuable vehicle space and impose additional constraints on the system. It is assumed that workers may be classified according to their skills (e.g., doctors or nurses) with many assumptions such as a known number of each category of relief worker at any node in the network at any specific time, a periodic demand for particular worker skills at any node, and a priority for successfully delivering workers of a particular type.

Beside the same assumptions, inputs, and outputs of the YK' model, the YK'+WT model has the number of workers available at supply nodes and the number of workers requested at demand nodes as inputs, and the number of workers from each category transfered at each arcs by each type of vehicles as output.

3.3.1 Notation and Formulation

The following additional parameters are required by this new model which we denote as YK'+WT.

- W: Set of worker categories, $W = \{1 \text{ (nurses)}, 2 \text{ (doctors)}, \ldots, |W|\}$.
- SR_{wot}: Number of workers of category $w \in W$ that are available at node $o \in CS$ at time $t \in T$.
- d_{wot}: Number of workers of category $w \in W$ that are needed at node $o \in CD$ at time $t \in T$.
- wr_w: Average weight of a worker in category $w \in W$.
- PR_w: Priority of workers in category $w \in W$.

Two new decision variables are also required. The first, W_{wopvt}, represents the number of workers of category $w \in W$ traversing arc (o, p) at time $t \in T$ by vehicle type $v \in V$. Second, $devR_{wot}$ denotes the number of workers of category $w \in W$ are requested by all demand nodes at time $t \in T$, but they are not delivered.

The objective function of the YK'+WT model incorporates a third term not found in the YK and YK' models. This term penalizes the number of relief workers waiting for transfer over time:

$$\text{Minimize} \sum_{a \in A} \sum_{o \in CD} \sum_{t \in T} PC_a \ devC_{aot} + \sum_{h \in H} \sum_{t \in T} PW_h \ devW_{ht} + \sum_{w \in W} \sum_{o \in C} \sum_{t \in T} PR_w \ devR_{wot}. \tag{3.16}$$

New constraints related to workforce transfer are as follows:

$$Y_{opvt} cap_v \geq \sum_{a \in A} wc_a Z_{aopvt} + \sum_{h \in H} ww_h X_{hopvt} + \sum_{w \in W} wr_w W_{wopvt} \quad \forall \quad o, p \in C, v \in V, t \in T \tag{3.17}$$

$$\sum_{\substack{s\in T\\ s\leq t}} SR_{wot} + \sum_{v\in V}\sum_{\substack{s\in T\\ s\leq t}}\sum_{p\in C}[W_{wpovs} - K_{ospt}W_{wopvs}] = dev_{wot} \ \ \forall \ \ w, o \in CS, t \in T \tag{3.18}$$

$$\sum_{\substack{s\in T\\ s\leq t}} d_{wos} - \sum_{\substack{s\in T\\ s\leq t}} SR_{wot} - \sum_{v\in V}\sum_{\substack{s\in T\\ s\leq t}}\sum_{p\in C}[W_{wpovs} - K_{ospt}W_{wopvs}] = dev_{wot} \quad \forall \ \ w, o \in CD, t \in T \tag{3.19}$$

$$\sum_{v\in V}\sum_{p\in C}[W_{wopvt} - W_{wpovt}] \leq SR_{wot} \ \ \forall \, w \in W, \ o \in CS, \ t \in T \tag{3.20}$$

Constraints (3.17) incorporate worker weights within vehicle capacity restrictions. As in the YK' model, constraints (3.18) - (3.20) balance the flow of workers, define the deviation variables, and restrict the number of workers that can be moved between nodes.

The YK'+WT model may be represented as corrected model while YK' may be represented as:

$$\begin{aligned} \text{Minimize} \quad & (3.16) \\ \text{s.t.} \quad & (3.2) - (3.4), (3.6), (3.7), (3.11) - (3.15), \ (3.17) - (3.20). \end{aligned}$$

3.3.2 An Example

A small example of the YK'+WT model is presented to demonstrate the differences between the solution to the YK'+WT model and YK' model (where work–force transfer is ignored). The data for this problem are taken from the example of Section 3.2.3, with the addition of workforce parameters, as shown in Table 3.4. This table describes the number of available workers at supply nodes and the number of workers needed at demand nodes. It is assumed that the average weight of workers and wounded people are the same, such that $wr_w = 200$.

Table 3.4: Worker demands and availability at each node over time.

Node	**Type**	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$
1	Available	6	6	4	5	4	0
2	Needed	3	4	1	2	1	0
3	Needed	2	2	2	0	0	1
4	Needed	5	1	0	2	1	0

A graphical representation of the solution to this example is depicted in Figure 3.2, and quantities of unsatisfied demand, unserved wounded, and available workers awaiting transfer are summarized in Table 3.5.

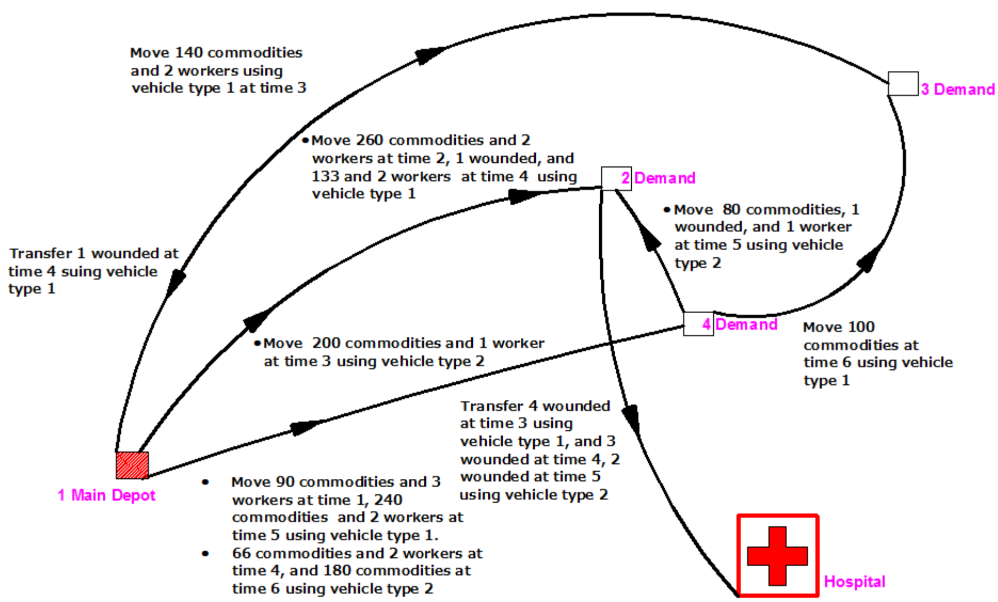


Figure 3.2: Example solution from the YK'+WT model.

Table 3.5: Summary of unsatisfied commodity demand, unserved wounded, and non–delivered workers over time.

Node	**Type**	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$
2	Demand	0	0	0	27	130	0
3	Demand	0	190	0	180	192	0
4	Demand	0	160	186	34	0	0
All nodes	Wounded	15	8	6	5	0	0
All nodes	Workers	7	5	0	0	0	1

In the YK' solution, the total commodities delivered is 1,520 and the number of wounded evacuated is 13. Whereas, in the YK'+WT solution, less commodities are delivered and fewer wounded are evacuated (the total commodities delivered is 1,309 and the number of wounded evacuated is 9). This is because the new logistic operation (work–force transfer) is added to the YK'+WT model and 13 workers are transfered consuming space in vehicles. Accordingly, the benefit of the YK'+WT model is to utilize the available vehicles to perform more logistic operations as requested realistically by the humanitarian agencies in post disaster relief operations.

It can be also noted that the utilization of the vehicles in YK'+WT is better than in YK', as the total mass picked by vehicles in the YK' solution is 4,880 lb and in YK'+WT solution is 6,163 lb. This happens because vehicles in YK'+WT have more options for picking up at supply nodes.

3.4 Summary

To start this research, a good baseline model was studied in this chapter. The model from Yi and Kumar (2007) is selected to be our starting point. For better understanding, the mathematical model from this study is coded in CPLEX to solve a small example, but some errors are found which limit its use. Because of this, some corrections are made to the formulation which represents the first contribution in this research.

Unfortunately, solutions obtained by the corrected model (YK') do not provide actual vehicle routes. They provide the demand quantities and wounded numbers traveled by each type of vehicles as shown in Figure 3.1; such solutions can not be applied directly. Due to this drawback, an additional optimization procedure is required to obtain vehicle assignments to deliver the quantities of goods or people between nodes. This type of post-processing may result in inefficient vehicle routes or the use of excess vehicles which could be avoided if the model were to incorporate individual vehicle assignments. Such an enhancement is described in Chapter 4; however, the YK' model is first extended to consider the transfer of relief workers between nodes.

The new model is developed to incorporate the work-force transfer in YK' model in the same manner of wounded and commodities transfer, i.e. this model provides the number of workers from each category transfered at each arc without providing insight into the actual vehicles route. This shortcoming is addressed in the next chapter.

It is interesting to note the differences between the solutions obtained by the YK' and YK'+WT models. First, the flow quantities of commodities and wounded persons differ, as shown in Figures 3.1 and 3.2. Not surprisingly, the numbers of unserved wounded and unsatisfied demand are greater in the YK'+WT model than in the YK' model. This reduction in service reflects the more realistic nature of the YK'+WT model where the work–force transfer is considered.

The next chapter provides a new model to incorporate work–force transfer and consider individual vehicle routes.

Chapter 4

Humanitarian Logistics Vehicle Routing Problem (HLVRP)

4.1 Introduction

In this chapter, the fourth model which represents the first main contribution of this research is considered. This model, the *humanitarian logistics vehicle routing problem* (HLVRP), is an integrated model for humanitarian relief logistics that offers several distinct advantages over the baseline model of Yi and Kumar (2007), denoted as YK. First, the new model incorporates three logistic operations simultaneously: demand distribution, evacuation of wounded, and workforce transfer. To the best of our knowledge, no other humanitarian logistics model has considered more than two operations. For example, in the models of Yi and Kumar (2007) and Yi and Ozdamar (2007), demand distribution and wounded evacuation, but not workforce transfer, are included.

Second, the HLVRP model provides valid and complete vehicle routes. This is facilitated by the inclusion of a new binary decision variable, x_{vijt}, which determines if a particular vehicle, v, arrives at node j at time t after traversing arc (i, j). Thus, solutions of the HLVRP model indicate the exact sequence of nodes to be visited by each vehicle at particular times. By contrast, while the YK model determines the *quantities* of commodities and wounded traversing each arc, valid vehicle routes to transport these entities are not modeled. This increased granularity of solution information provided by the HLVRP model, as well as detailed vehicle speed characteristics, result in a more practical model. For example, solutions from the HLVRP may indicate exactly which vehicles should be operated to deliver goods, pickup wounded, and transport workers. Conversely, the models of Yi and Kumar (2007) and Yi and Ozdamar (2007) only indicate that a certain number of goods or wounded should be transferred between two nodes by some nondescript vehicle of a particular type.

The final advantage of the proposed HLVRP model is the fact that it considers heterogeneous vehicles, such that each vehicle may have a unique capacity, average travel speed, and capabilities of traveling along certain roadways. The inclusion of this data provides a more realistic representation of the problem, where many of the vehicles employed may be donated from several sources.

Besides the above advantages, this model considers many VRP variants and humanitarian relief features and activities. While many of the individual features of the proposed research effort have been considered in separate existing studies, this model aims to provide a comprehensive unified model that incorporates multiple critical components of humanitarian relief. These variants and features are explained in the next section.

4.2 Problem Description

The problem to be solved in this chapter deals with a logistic system in a post–disaster network requiring coordination of commodity distribution from main distribution centers to areas affected by a disaster, evacuation of wounded people from affected areas to the available emergency centers, and transfer of workers from distribution centers to affected areas to help in medication, evacuation, and repairing the damaged infrastructures. Each separate affected area represents a demand node, where each demand node is characterized by a time based demand for different commodities, such as bottled water, boxed food, medications, and clothes. Commodities have different priority values based on their importance. Besides the demand requested at each demand node, there are a number of wounded persons with differing levels of injuries awaiting transfer to emergency centers or hospitals. To differentiate among the different levels of injury (category), each is given a value of priority such that more severe levels are given a higher value. Because, in the demand nodes, disasters cause different levels of destruction and the number of affected people changes over time, different types of workers are needed at each demand node. Accordingly, different numbers of workers at a given time are requested at each demand node from different professions, such as doctors and nurses who are supposed to help in medication of wounded and electrical technicians who help in repairing power lines.

Supplies and workers are picked up from the supply nodes to fulfill the requests that sent from the demand nodes. Time–based supply for each type of commodity and worker are available in the distribution centers which could be the available warehouses in the affected areas, supply units constructed in pre–disaster planning, non–permanent warehouses built immediately after a disaster, and shelters and tents donated by humanitarian agencies. Despite the kind of supply places, each one is called a supply node.

The last type of node in a post–disaster network is the hospitals and emergency centers. These nodes could be the already available hospitals in the area of the disaster or temporary units constructed by humanitarian agencies after the disaster.

Heterogeneous vehicles are utilized to perform the demand distribution, worker transfer, and wounded evacuation. It is assumed that each vehicle has its own capacity and speed, starts from a depot (one of the supply nodes) and returns to the same depot at the end of the planning period to start from there for the next plan. The logistic operations are performed as follows. Each vehicle, based on its capacity and the availability of supplies and workers, retrieves an amount of commodities and workers from its depot. The vehicle then starts visiting demand nodes to distribute commodities and deliver workers. If sufficient free space is available, a vehicle may pick up wounded people. After some visits, it has many options such as going to a hospital to deliver the wounded and then to another depot to reload, returning directly to another depot if it has no wounded, or returning to its origin depot.

In some cases with special conditions, vehicles perform the logistic plans differently. For example, if some depots have a high number of vehicles compared to others, vehicles from these depots may go directly to the depots with low number of vehicles to pick up supplies and/or workers and then start distribution. In another example, if the available vehicle capacities exceed the available supplies, or if the priority of wounded evacuation is much higher than the demand distribution and work–force transfer, some vehicles may travel empty to demand nodes to evacuate wounded.

Due to the limitation of supplies and transporters in a post–disaster situation, the goal in this problem is to deliver as many commodities as possible, transfer as many workers as possible, and evacuate as many wounded as possible. Thus, these minimizing the unsatisfied demand, non–transfered workers, and non-evacuated wounded.

4.3 An Overview of the HLVRP Model

From the previous description, a mathematical model called HLVRP model, a mixed integer program, is used to model a dynamic routing system. The HLVRP includes many input sets. First, the time horizon set T, which is discretized into a set of integer periods with equal length, where the duration of each depends on the situation and could be any time, (e.g., 5 minutes, 30 minutes, 1 hours, 2 hours). This time horizon makes other parameters, such as demands needed, available supplies, number of workers at each depot, and number of wounded as time based parameters. Second, the set of wounded evacuee categories E includes different qualitative values such as heavy, moderate, and light injuries. For fairness, the priority of these categories is different, where more severe injuries have higher priority values. Third, the set of vehicles, V, includes all vehicles in the system with different speeds and capacities. Fourth, the set of commodities, C, contains all commodity types, such as bottled water, boxed food, medications, and clothes. Fifth, the set of workers, W, defines different professions of the work-force and volunteers, such as doctors, nurses, and first responders. Sixth, the set of nodes N contains all nodes in the networks. This set includes three sub–sets: supply nodes set S, demand nodes set D, and hospital nodes set H.

The given parameters are: starting depot for each vehicle, time needed to pass between nodes by each vehicle, time based demand at each demand node from each type of commodity, time based number of wounded for each level of injury at each demand node, time based number of workers from each category (profession) requested by each demand node, time based supply from different commodities and available workers from each category at each supply node, mass capacity for each vehicle, unit mass for each demand type, unit mass for each worker and wounded, priorities for each demand type, priorities for each work-force category, and priority for each wounded level.

After solving the model, each vehicle will be given a route and the following outputs (decisions) given for the users. For each vehicle and time period, the number of commodities of each type to be picked up from each supply node, the number of commodities of each type to be delivered to each demand node, the number of wounded from each level to be picked up from each demand node, the number of wounded from each level to be delivered to each hospital node, the number of workers from each category to be picked up from each supply node, and the number of workers from each category to be delivered to each demand node will be determined. Accordingly, unsatisfied demand, non–evacuated wounded, and undelivered workers can be determined

The HLVRP model considers many realistic features. First, the existence of multiple depots, where each vehicle starts from a specific depot. Second, split deliveries are allowed, such that each demand node can be supplied by different vehicles. Third, the HLVRP considers multiple commodity types, evacuee categories, and work–force professions. Fourth, the HLVRP provides a detailed route for each vehicle including the nodes that must be visited, the time to visit each node, demand quantities to be picked up and delivered, wounded to be evacuated, and workers to be transfered. Finally, the proposed HLVRP model considers heterogeneous vehicles, such that each vehicle may have a unique capacity, average travel speed, and capabilities of traveling along certain roadways. Table 4.1 contrasts the previous studies with this proposed model according to several key features.

Some assumptions are made in the HLVRP model for practical reasons. First, demand nodes can not operate as transshipment nodes (i.e., excess supply can not be temporarily stored at a demand node). This restriction is considered for the practical reason that it is likely that any excess goods left at a demand node may be consumed (or even stolen) during the chaos of a humanitarian crisis. However, this assumption may be relaxed by modifying some constraints.

Second, workers do not need to return to their starting locations. Instead, it is assumed that they will remain stranded at their last destinations and begin from there on the following day. In the event that it is necessary for each worker to return "home", a constraint may be added to the model, as discussed later. Third, because each vehicle starts from its depot and can not revisit it, a vehicle can pick up commodities and workers from its depot only at the first time period, but vehicles can pick up commodities and workers from other supply nodes. Fourth, each vehicle should return back to its depot where a new plan could be given for the next planning horizon.

To avoid any infeasible activity, many conditions must be satisfied through the model's constraints. First, a vehicle can not reach a node (i) before finishing the travel time on the arc between its current node and node (i). Second, any vehicle that enters a node should also leave that node which balances the vehicle flows. Third, the total picked up commodities and workers from any supply node should be less than or equal to the available quantities. Fourth, the total delivered commodities and workers to any demand node at any time period should be less than or equal to the requested numbers. Fifth, vehicles must visit a node to be able to pick up or deliver commodities, workers, or wounded.

Table 4.1: A comparison between the HLVRP model and the existing literature.

Reference	**Multi Commodity**	**Split Delivery**	**Different Speed**	**Diff. Cap Vehicle**	**Multi Depot**	**Vehicles Routing**	**Multi-Time slots**	**Evacuation**	**Work-force Transfer**
Ozdamar et al. (2004)	✓	✓		✓	✓				
Yi and Kumar (2007)	✓	✓		✓	✓		✓	✓	
Liu and Zhao (2007)	✓			✓	✓				
Yi and Ozdamar (2007)	✓	✓		✓	✓		✓	✓	
Campbell et al. (2008)									
Yuan and Wang (2009)									
Vitoriano et al. (2010)	✓		✓	✓	✓				
Widener and Horner (2011)					✓			✓	
Lin et al. (2011)	✓								
Fei et al. (2011)							✓		
HLVRP	✓	✓	✓	✓	✓	✓	✓	✓	✓

4.4 Notations and Formulation

4.4.1 Notations

In this section, the notations employed by the model are defined. This model requires the definitions of numerous parameters and decision variables, as described below.

- T: Set of discrete time periods in the planning horizon, $T = \{1, 2, 3, \ldots |T|\}$.
- E: Set of different injury severity categories of evacuees (wounded people). For example, E= {1: Heavy, 2: Moderate, 3: Light, ...}.
- W: Set of worker categories. For example, $W = \{1 \text{ (doctors)},\ 2 \text{ (nurses)},\ 3, \ldots, |W|\}$.
- V: Set of individual vehicles, $V = \{1, 2, 3, \ldots |V|\}$.
- C: Set of commodity types $C = \{1, 2, 3, \ldots |C|\}$.
- D: Set of demand nodes.
- S: Set of supply nodes.
- H: Set of available hospitals.
- N: Set of all nodes in the network, $N = \{D \cup S \cup H\}$.
- i_v: Initial depot of vehicle $v \in V$, where each depot is a supply node, i.e. all $i_v \in S$.
- τ_{vij}: Integer time periods needed by vehicle $v \in V$ to travel from node $i \in N$ to node $j \in N$.
- d^E_{eit}: Number of wounded persons, of category $e \in E$, requesting evacuation from node $i \in D$ at time $t \in T$.
- d^W_{wit}: Number of workers of category $w \in W$ requested by node $i \in D$ at time $t \in T$.
- d^C_{cit}: Amount of commodity type $c \in C$ demanded at node $i \in D$ by time $t \in T$.

- s^C_{cit}: Amount of commodity type $c \in C$ that can be supplied from node $i \in S$ at time $t \in T$.
- m^C_c: Unit mass of commodity $c \in C$.
- m^E_e: Average mass of an evacuee of category $e \in E$.
- s^W_{wit}: Number of workers of category $w \in W$ that are available at node $i \in S$ at time $t \in T$.
- m^W_w: Average mass of one worker of category $w \in W$.
- p^W_w: Priority of workers in category $w \in W$.
- m_v: Mass capacity of vehicle $v \in V$.
- p^C_c: Priority of commodity type $c \in C$.
- p^E_e: Priority of wounded evacuees category $e \in E$.

Numerous decision variable types are required to provide the more detailed solutions afforded by the HLVRP model. There are four main variable categories: pick–ups, deliveries, deviations, and binary routing variables. The pick–up variables are used to define the picked up quantities of supplies as in z^P_{civt}, number of workers picked up from the supply nodes as in w^P_{wivt}, and the number of wounded evacuated from the demand nodes as in e^P_{eivt}. Similarly, the delivery variables define the demand deliveries as in z^D_{civt}, workers delivered to demand nodes as in w^D_{wivt}, and the number of wounded delivered to each hospital as in e^D_{eivt}.

The deviation variables depend on the values of picked up and delivery variables. There are three groups of the deviation variables. First, the demand deviation variables v^C_{cit} are defined, at each demand node and time, as the demand requested minus the total value of demand delivery variables to that node by that time. Second, worker–force deviation variables v^W_{wit} are defined, at each demand node and time, as the number of workers requested by that node minus the total value of work–force delivery variables to that node by the same time. Third, the evacuation deviation variables v_{eit}^E are defined, at each demand node and time, as the number of wounded request evacuation by that node minus the total value of wounded picked up variables from that node by the same time.

Finally, binary variables define the vehicle routes and relate to other variables using big–M constraints, such that the picked up and delivery variables for each vehicle can take values greater than zero only if a particular binary variable is equal to one. This is discussed more clearly after the model is formulated. All of these variables are listed below:

- z_{civt}^D: Quantity of commodity type $c \in C$ delivered to node $i \in D$ at time $t \in T$ by vehicle $v \in V$, where $z_{civt}^D \in \left\{0, 1, \ldots, \min\left\{d_{cit}^C, \frac{m_v}{m_c^C}\right\}\right\}$
- z_{civt}^P: Quantity of commodity type $c \in C$ picked up from node $i \in S$ at time $t \in T$ by vehicle $v \in V$, where $z_{civt}^P \in \left\{0, 1, \ldots, \min\left\{\sum_{\substack{s \in T \\ s \leq t}} s_{cis}^C, \frac{m_v}{m_c^C}\right\}\right\}$
- v_{cit}^C: Amount of unsatisfied demand of commodity type $c \in C$ at node $i \in D$ at time $t \in T$, where $v_{cit}^C \in \{0, 1, \ldots, d_{cit}^C\}$
- v_{eit}^E: Number of evacuees of category $e \in E$ that requested transportation from node $i \in D$ at time $t \in T$ but were not transfered, where $v_{eit}^E \in \{0, 1, \ldots, d_{eit}^E\}$
- v_{wit}^W: Number of workers of category $w \in W$ requested by node $i \in D$ at time $t \in T$ but were not satisfied, where $v_{wit}^W \in \{0, 1, \ldots, d_{wit}^W\}$
- e_{eivt}^D: Number of evacuees of category $e \in E$ transfered (delivered) to node $i \in H$ at time $t \in T$ by vehicle $v \in V$, where $e_{eivt}^D \in \left\{0, 1, \ldots, \frac{m_v}{m_e^E}\right\}$
- e_{eivt}^P: Number of evacuees of category $e \in E$ transfered (picked up) from node $i \in D$ at time $t \in T$ by vehicle $v \in V$, where $e_{eivt}^P \in \left\{0, 1, \ldots, \min\left\{d_{eit}^E, \frac{m_v}{m_e^E}\right\}\right\}$
- w_{wivt}^D: Number of workers of category $w \in W$ (e.g., nurses or doctors) transfered (delivered) to node $i \in D$ at time $t \in T$ by vehicle $v \in V$, where $w_{wivt}^D \in \left\{0, 1, \ldots, \min\left\{d_{wit}^W, \frac{m_v}{m_w^W}\right\}\right\}$

- w^P_{wivt}: Number of workers of category $w \in W$ transfered (picked up) from node $i \in S$ at time $t \in T$ by vehicle $v \in V$, where $w^P_{wivt} \in \left\{0, 1, \ldots, \min\left\{s^W_{wit}, \frac{m_v}{m^W_w}\right\}\right\}$
- x_{vijt}: A binary variable, such that $x_{vijt} = 1$ if vehicle $v \in V$ arrives at node $j \in N$, coming from node $i \in N, i \neq j$, at time $t \in T$; $x_{vijt} = 0$ otherwise.

4.4.2 The HLVRP Formulation

In this section, a mathematical formulation of the HLVRP is presented, as follows

$$\text{Min} \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_c \; v^C_{cit} + \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_e \; v^E_{eit} + \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_w \; v^W_{wit} \tag{4.1}$$

$$\sum_{i \in N} \sum_{\substack{j \in N \\ j \neq i}} x_{vijt} \leq 1 \quad \forall\, v \in V,\ t \in T \tag{4.2}$$

$$\sum_{\substack{j \in N \\ j \neq i_v}} \sum_{t \in T} x_{vi_vjt} = 1 \quad \forall\, v \in V \tag{4.3}$$

$$\sum_{\substack{j \in N \\ j \neq i_v}} \sum_{t \in T} x_{vji_vt} = 1 \quad \forall\, v \in V \tag{4.4}$$

$$\sum_{\substack{i \in N \\ i \neq j}} \sum_{t \in T} x_{vijt} \leq 1 \quad \forall\, v \in V,\ j \in N \tag{4.5}$$

$$\sum_{i \in N} \sum_{t \in T} t \;\, x_{vijt} \leq \sum_{k \in N \setminus i_v} \sum_{t \in T} (t - \tau_{jkv}) x_{vjkt} \quad \forall\, v \in V,\ j \in N \tag{4.6}$$

$$\sum_{\substack{i \in N \setminus i_v \\ i \neq j}} \sum_{t \in T} x_{vijt} = \sum_{i \in N \setminus i_v} \sum_{t \in T} x_{vijt} \quad \forall\, v \in V, j \in N \tag{4.7}$$

$$\sum_{i \in N} \sum_{\substack{j \in N \\ i \neq j}} \sum_{t \in T} \;\tau_{ijv} \;\, x_{vijt} \leq |T| \quad \forall\, v \in V \tag{4.8}$$

$$\sum_{\substack{s \in T \\ s \leq t}} v^C_{cis} = \sum_{\substack{s \in T \\ s \leq t}} d^C_{cis} - \sum_{v \in V} \sum_{\substack{s \in T \\ s \leq t}} z^D_{civs} \quad \forall\, c \in C,\ i \in D,\ t \in T \tag{4.9}$$

$$\sum_{\substack{s \in T \\ s \leq t}} v^E_{eis} = \sum_{\substack{s \in T \\ s \leq t}} d^E_{eis} - \sum_{v \in V} \sum_{\substack{s \in T \\ s \leq t}} e^D_{eivs} \quad \forall\, e \in E, i \in D,\ t \in T \tag{4.10}$$

$$\sum_{\substack{s\in T\\ s\le t}} v^W_{wis} = \sum_{\substack{s\in T\\ s\le t}} d^W_{wis} - \sum_{v\in V}\sum_{\substack{s\in T\\ s\le t}} w^D_{wivs} \quad \forall\ w\in W,\ i\in D,\ t\in T \tag{4.11}$$

$$\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in S} z^P_{civs} \ge \sum_{\substack{s\in T\\ s\le t}}\sum_{j\in D} z^D_{cjvs} \quad \forall\ v\in V,\ c\in C,\ t\in T \tag{4.12}$$

$$\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in D} e^P_{eivs} \ge \sum_{\substack{s\in T\\ s\le t}}\sum_{j\in E} e^D_{ejvs} \quad \forall\ v\in V,\ e\in E,\ t\in T \tag{4.13}$$

$$\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in S} w^P_{wivs} \le \sum_{\substack{s\in T\\ s\le t}}\sum_{j\in D} w^D_{wjvs} \quad \forall\ v\in V,\ w\in W,\ t\in T \tag{4.14}$$

$$\sum_{v\in V} z^P_{civt} \le \sum_{\substack{s\in T\\ s\le t}} s^C_{cis} - \sum_{\substack{s\in T\\ s\le t-1}}\sum_{v\in V} z^P_{civt} \quad \forall\ c\in C,\ i\in S, t\in T \tag{4.15}$$

$$\sum_{v\in V} e^P_{eivt} \le d^E_{eit} \quad \forall\ e\in E,\ i\in D,\ t\in T \tag{4.16}$$

$$\sum_{v\in V} w^P_{wivt} \le \sum_{\substack{s\in T\\ s\le t}} s^W_{wis} - \sum_{\substack{s\in T\\ s\le t-1}}\sum_{v\in V} w^P_{wivs} \quad \forall\ w\in W,\ i\in S,\ t\in T \tag{4.17}$$

$$\begin{aligned} m_v \ge &\sum_{a}\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in S} m^C_c\ z^P_{civs} + \sum_{e\in E}\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in D} m^E_e\ e^P_{eivs} \\ &+ \sum_{winW}\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in S} m^W_w\ w^P_{wivs} - \sum_{c\in C}\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in D} m^C_c\ z^D_{civt} \\ &- \sum_{e\in E}\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in H} m^E_e\ e^D_{eivs} - \sum_{w\in W}\sum_{\substack{s\in T\\ s\le t}}\sum_{i\in D} m^W_w\ w^D_{wivs} \quad \forall\ v\in V,\ t\in T \end{aligned} \tag{4.18}$$

$$\sum_{i\in D}\sum_{t\in T}\sum_{v\in V} e^P_{eivt} = \sum_{i\in H}\sum_{t\in T}\sum_{v\in V} e^D_{eivt} \quad \forall\ e\in E \tag{4.19}$$

$$\sum_{c\in C} z^D_{civt} \le M_{4.20}\sum_{j\in N} x_{vjit} \quad \forall\ i\in D,\ v\in V,\ t\in T \tag{4.20}$$

$$\sum_{c\in C} z^P_{civt} \le M_{4.21}\sum_{j\in N} x_{vjit} \quad \forall\ c\in C, i\in S\backslash i_v, v\in V,\ t\in T \tag{4.21}$$

$$z^P_{ci_v vt} = 0 \quad \forall\ c\in C, v\in V,\ t\in T\backslash t=1 \tag{4.22}$$

$$\sum_{e\in E} e^D_{eivt} \le M_{4.23}\sum_{j\in N} x_{vjit} \quad \forall\ e\in E,\ i\in H,\ v\in V,\ t\in T \tag{4.23}$$

$$\sum_{e\in E} e^P_{eivt} \le M_{4.24}\sum_{j\in N} x_{vjit} \quad \forall\ e\in E,\ i\in D,\ v\in V,\ t\in T \tag{4.24}$$

$$\sum_{w\in W} w^D_{wivt} \le M_{4.25} \sum_{j\in N} x_{vjit} \quad \forall\, w \in W,\ i \in D,\ v \in V,\ t \in T \tag{4.25}$$

$$\sum_{w\in W} w^P_{wivt} \le M_{4.26} \sum_{j\in N} x_{vjit} \quad \forall\, w \in W, i \in S\backslash i_v,\ v \in V,\ t \in T \tag{4.26}$$

$$w^P_{ci_vvt} = 0 \quad \forall\, w \in W,\ v \in V,\ t \in T\backslash t = 1 \tag{4.27}$$

The objective function (4.1), seeks to minimize the quantities of unsatisfied demand, unserved wounded, and non-transfered workers. Each of these quantities are scaled by their respective priority values. There are 26 constraint sets: Constraints (4.2) ensure that each vehicle may serve only one node at a given time, whereas Constraints (4.3) ensure that each vehicle starts from its initial depot. To ensure that each vehicle will return to its initial depot after finishing its route and it can not leave the depot again, Constraints (4.4) are used. Constraints (4.5) prevent each vehicle from visiting any node more than once. To maintain feasibility of routes, Constraints (4.6) are used ensure that each vehicle can not reach any node before finishing the arc between the previous and the current nodes, Constraints (4.7) are used to balance flow for each demand node, so each vehicle should enter and leave each node the same number of times. Constraints (4.8) restrict each vehicle's route by the total time available for that vehicle.

Constraints (4.9), (4.10), and (4.11) define the deviation variables, such that Constraints (4.9) address unsatisfied demand, Constraints (4.10) address non–evacuated wounded, and Constraints (4.11) consider undelivered workers. To maintain control of quantities in each vehicle, Constraints (4.12) restrict the quantity of commodities that may be delivered to demand nodes by the quantity that are picked up from supply nodes. Similarly, constraints (4.13) and (4.14) restrict the number workers delivered to demand nodes and the number of wounded delivered to hospitals by the number picked up by each vehicle.

Constraints (4.15), (4.16), and (4.17) restrict the supply and transfer at each time. Constraints (4.15) ensure that each supply node can provide quantities not exceeding the available supply for each type. Constraints (4.16) limit the number of assisted wounded to be no more than the number waiting at a particular demand node. In the same manner, Constraints (4.17) ensure that the number of workers dispatched from any supply node does not exceed the actual number of available workers. Vehicle capacity limitations are included in constraints (4.18), while constraints (4.19) ensure that wounded persons should be transferred from demand nodes to hospital nodes.

Constraints (4.20)–(4.27) ensure that all distribution and transfer variables have a value for any node only if a vehicle visits that node; such that Constraints (4.20) ensure that the delivered quantity from a vehicle to a demand node can be greater than zero only if the vehicle visits that node. Constraints (4.21) ensure that the quantity picked up from a supply node by a vehicle can be greater than zero only if the vehicle visits that node. Constraints (4.22) require that each vehicle can pick up commodities from its depot at time zero but not later. Constraints (4.23) ensure that a vehicle can deliver wounded to a hospital only if it visits that hospital. For wounded pick–ups, Constraints (4.24) ensure that a vehicle can retrieve wounded from a demand node only if it visits that node. Constraints (4.25) allow a vehicle to deliver workers to a demand node only if it visits that node. Similarly, Constraints (4.26) allow a vehicle to pick up workers from a supply node if it visits that node. Finally, Constraints (4.27) ensure that each vehicle can pick up workers from its depot only at the first time period. Because vehicles can leave their depots just once, both Constraints (4.27) and (4.22) are used for the same purpose, which is to allow vehicles to pick up commodities or workers only at the first time.

On of the assumptions discussed before is that workers do not need to return to their starting locations. In the event that it is necessary for each worker to return "home", Constraints 4.28 may be added.

$$\sum_{v \in V} \sum_{t \in T} w^P_{wivt} = \sum_{v \in V} \sum_{t \in T} w^D_{wjvt} \quad \forall i \in S. \tag{4.28}$$

The big–M values in constraints (4.20), (4.21), and (4.23)–(4.26) may be calculated as follows. The definitions of these values have an abuse of notation such that the M values should be defined for each combination of indices, (e.g., $M_{4.20}^{ivt}$), but for simplicity, it is defined without indices (e.g., $M_{4.20}$).

$$M_{4.20} = \min\left\{d_{cit}^{C}, \frac{m_v}{m_c^C}\right\} \qquad \forall\; i \in D,\; v \in V,\; t \in T$$

$$M_{4.21} = \min\left\{\sum_{\substack{s\in T\\ s\leq t}} s_{cis}^{C}, \frac{m_v}{m_c^C}\right\} \qquad \forall\; c \in C, i \in S\backslash i_v, v \in V,\; t \in T$$

$$M_{4.23} = \frac{m_v}{m_e^E} \qquad e \in E,\; i \in H,\; v \in V,\; t \in T$$

$$M_{4.24} = \min\left\{d_{eit}^{E}, \frac{m_v}{m_e^E}\right\} \qquad \forall\; e \in E,\; i \in D,\; v \in V,\; t \in T$$

$$M_{4.25} = \min\left\{d_{wit}^{W}, \frac{m_v}{m_w^W}\right\} \qquad \forall\; w \in W,\; i \in D,\; v \in V,\; t \in T$$

$$M_{4.26} = \min\left\{s_{wit}^{W}, \frac{m_v}{m_w^W}\right\} \qquad \forall\; w \in W, i \in S\backslash i_v,\; v \in V,\; t \in T$$

By defining each value separately, the bounds of the linear program (LP) relaxation may be improved, thus (potentially) saving computational effort.

In the next section, an example verifies this model and demonstrates how the solution represents a detailed plan.

4.5 Model Verification by Example

A small problem is presented to demonstrate the benefits of the proposed HLVRP formulation and to show how the results are understandable and easy to apply. This example includes 12 time periods (15 minutes each), 3 demand nodes, 2 supply nodes, 1 hospital node, 2 commodity types, 1 wounded category, 1 worker category, and 3 vehicles. Table 4.2 contains the commodity demand data over the planning horizon, while Table 4.3 contains the commodity supply data over the planning horizon. Available and requested numbers of relief workers are summarized in Table 4.4. Similarly, Table 4.5 shows the number of wounded requiring evacuation. Finally, Table 4.6 shows other parameter values which are the starting node for each vehicle (i_v), vehicle capacities (m_v^V), unit mass of each commodity type (m_c^C), wounded and worker average mass (m_e^E, m_w^W), commodity priorities (p_c^C), wounded priority (p_e^E), and worker priority (p_w^W), respectively.

Table 4.2: Demand data, d_{cit}^c

Node	**Demand Type**	**Time**											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	1st type	0	0	60	85	96	0	100	0	0	120	0	0
	2nd type	0	0	100	100	30	0	110	0	180	0	0	0
3	1st type	0	0	30	100	0	0	195	0	165	66	0	0
	2nd type	0	0	100	200	0	100	0	120	0	30	0	0
4	1st type	0	0	0	36	112	0	100	0	120	0	0	0
	2nd type	0	0	140	0	112	0	100	200	0	130	0	0

Table 4.3: Supply data, s_{cit}^c

Node	**Demand Type**	**Time**											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2	1st type	400	0	0	60	0	100	0	60	0	0	0	0
	2nd type	230	0	0	0	300	0	0	0	0	0	0	0
6	1st type	400	0	0	60	0	100	0	60	0	0	0	0
	2nd type	566	0	0	220	0	68	0	0	0	0	0	0

Table 4.4: Available and needed workers, s_{wit}^W and d_{wit}^W

Node	**Type**	**Time**											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	Requested	0	1	4	3	5	2	1	4	3	2	2	0
2	Available	6	0	2	0	0	4	0	0	1	0	0	0
3	Requested	0	2	3	1	6	5	5	2	0	2	0	0
4	Requested	0	1	3	3	2	0	2	5	3	2	3	0
6	Available	8	0	0	2	0	0	0	3	0	0	0	0

Table 4.5: Wounded awaiting evacuation, d^E_{eit}

Node	Time											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0	4	2	1	1	0	1	1	0	0	0
3	0	6	4	1	8	0	5	0	1	0	0	0
4	0	0	7	0	4	0	4	0	1	0	0	0

Table 4.6: Parameter values

Parameter	Values
Vehicle depots i_v	[2, 2, 6]
Vehicle capacities (lb) m^V_v	[1400, 1000, 1100]
Commodity mass (lb) m^C_c	[1.5, 2]
Wounded and worker mass m^W_w , m^E_e	200
Commodity priorities p^C_c	[5, 10]
Evacuee priority p^E_e	160
Worker priorities p^W_w	100

4.5.1 Example Results

The deviation variable results of this example are shown in Tables 4.7–4.9. These variables are: unsatisfied demand of commodity type 1 (v^C_{1it}), unsatisfied demand of commodity type 2 (v^C_{2it}), undelivered workers (v^W_{wit}), and unserved wounded (v^E_{eit}). Route variables x_{vijt}, which are used to construct the route for each vehicle, are shown in Table 4.10. To make the solution of this example easier to understand, it is depicted graphically in Figure 4.1.

Table 4.7: Unsatisfied demand (commodity deviation values), v^C_{cit}

Node	**Unsatisfied Demand**	**Time**											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	1st type	0	0	0	85	96	0	100	0	0	120	0	0
	2nd type	0	0	0	100	30	0	110	0	0	0	0	0
3	1st type	0	0	30	7	0	0	195	0	165	66	0	0
	2nd type	0	0	50	170	0	100	0	120	0	30	0	0
4	1st type	0	0	0	36	112	0	0	0	120	0	0	0
	2nd type	0	0	140	0	112	0	0	0	0	130	0	0

Table 4.8: Non–evacuated wounded (wounded deviation values), v^E_{eit}

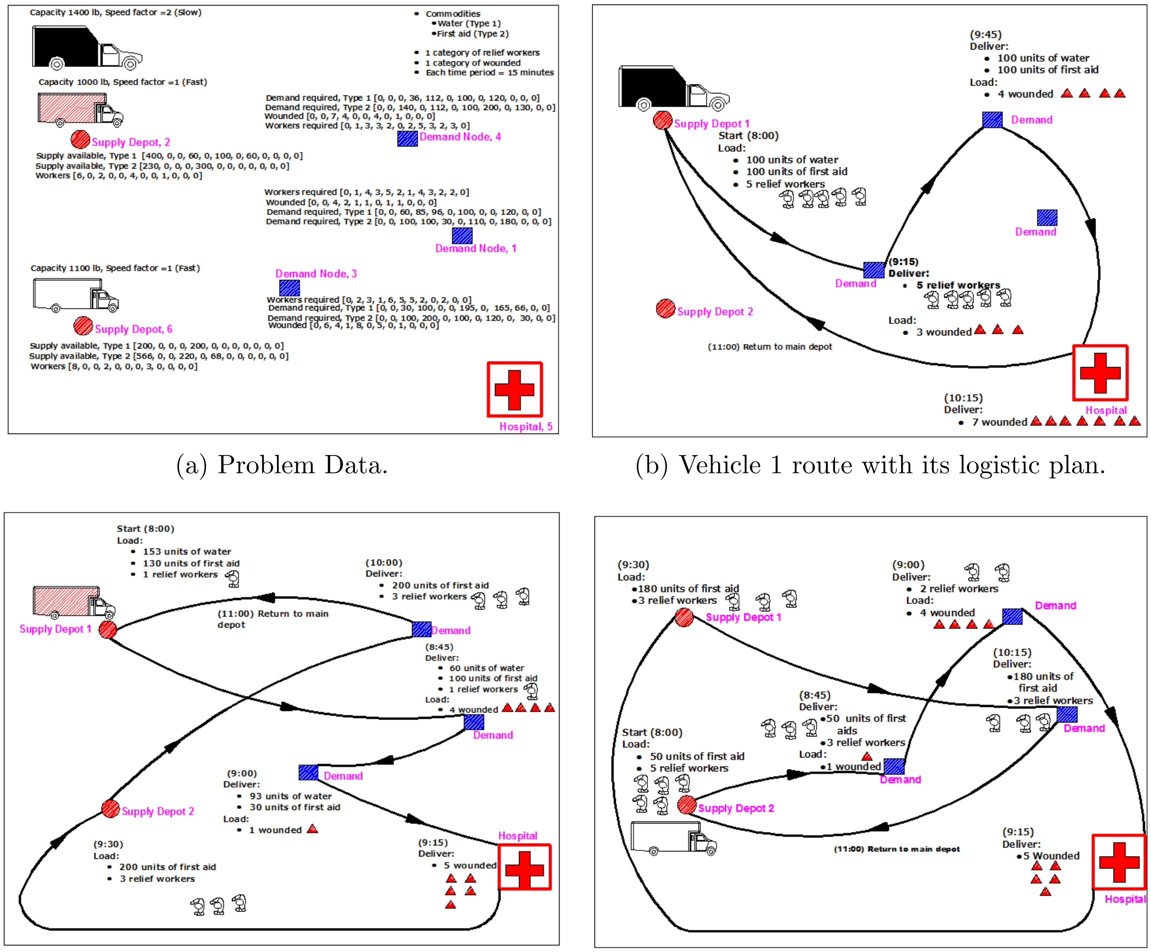
Node	**Time**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0	0	0	2	1	1	0	1	1	0	0	0
3	0	6	3	0	5	0	5	0	1	0	0	0
4	0	0	7	0	0	0	0	0	1	0	0	0

Table 4.9: Undelivered workers (worker–force deviation values), v^W_{wit}

Node	**Time**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0	1	3	3	5	2	1	4	0	2	2	0
3	0	2	0	1	1	5	5	2	0	2	0	0
4	0	1	3	1	2	0	2	2	3	2	3	0

Table 4.10: Vehicle routes

Vehicle	Route, times are listed below						
1		depot → t=1(8:00)	3 → t=5(9:15)	4 → t=7(9:45)	hospital → t=9(10:15)	depot t=12(11:00)	
2	depot → t=1(8:00)	1 → t=3(8:45)	3 → t=4(9:00)	hospital → t=5(9:15)	resupply → t=6(9:30)	4 → t=8(10:00)	depot t=12(11:00)
3	depot → t=1(8:00)	3 → t=3(8:45)	4 → t=4(9:00)	hospital → t=5(9:15)	resupply → t=6(9:30)	1 → t=9(10:15)	depot t=12(11:00)



(a) Problem Data. (b) Vehicle 1 route with its logistic plan.

(c) Vehicle 2 route with its logistic plan. (d) Vehicle 3 route with its logistic plan.

Figure 4.1: Detailed logistic plan for all vehicles

As indicated, the HLVRP provides a full detailed and realistic logistic plan which is easy to apply. For each vehicle, the plan includes the quantities which should be picked up, where they should be delivered, the number of wounded, and where workers should be transfered at each time.

4.6 Solution Approaches

As an extension of the CVRP, it is clear that the HLVRP represents an NP-hard problem. It is particularly challenging because it requires the determination of vehicle routes and delivery quantities that might not meet demand. Additionally, decisions must be made regarding whether to visit a particular hospital, the number of workers to transport, and the number of wounded to evacuate. Although small-scale problems may be solved optimally via CPLEX, larger-scale problems require the use of customized heuristic approaches to obtain high-quality solutions.

The proposed heuristic depends on taking advantage of the model's inherent consideration of individual vehicle routes. Thus, the solution approach will be rooted in a valid, realistic, and complete mathematical model. The first phase will consist of a heuristic vehicle route construction procedure. Preliminary testing indicates that, given a set of vehicle routes, the resulting integer programming problem can be solved surprisingly quickly (i.e., in a few seconds) using CPLEX. The CPLEX solution would provide quantities of commodities, wounded, and workers (again, for a fixed set of vehicle assignments). An iterative procedure will be applied to generate different vehicle routes at each iteration via changing some parameters. Then different local search techniques are used to improve the routes, as discussed later in this section.

4.6.1 Heuristic Description

In this subsection, the proposed heuristic is described. The new notations are defined as follows:

- $Route_v$ is a route for a vehicle v which is constructed from the variables x_{vijt} and is used to facilitate the coding. For example, if a vehicle route is [2, 3, 6, 8, 2], this means the vehicle starts from node 2 and visits 3, 6, and 8, before returning to node 2. The vehicle does not visit any nodes not shown in this array. A function exists to convert between $Route_v$ and x_{vijt}. This function is the `Binaries-Route` and shown in Algorithm 1 in the next point.
- $Route_v^T$ is a row array of the same size as $Route_v$ which contains the time to reach each node. Function `Binaries-Route` in Algorithm 1 shows how $Route_v$ and $Route_v^T$ are generated from the binary variables.

Algorithm 1: `Binaries-Route` converter

Set k = current selected vehicle
Set $counter = 2$
Set $Route_k(1) = i_k$ // starting point is the current vehicle's depot
Set $Route_k^T(1) = 1$ // starting time
for all $t \in T$ **do**
    for all $i \in N$ **do**
        for all $j \in N \backslash i$ **do**
            if $x_{kijt} = 1$ **then**
                $Route_k(counter) = j$
                $Route_k^T(counter) = t$
                $counter = counter + 1$
                Set $i, j > |N|$ Skip loops, impossible to find other visit at the same time.
            end if
        end for
    end for
end for

- *current* is a holder used to save the current location for a vehicle. It changes dynamically during the process.
- $sort^D$ is a two dimensional array of size $|T| \times |D|$ which contains the demand nodes sorted in descending order at each time based on their importance value. The element $sort^D(t, i)$ represents the i^{th} demand node at time t. For example, if the importance values for 5 demand nodes at time t are [1000, 800, 3000, 2100, 1450], then the t^{th} row from $sort^D$ is [3, 4, 5, 1, 2] so the element $sort^D(t, 1) = 3$. In other words, node 3

is placed in the first place because it has the highest preference to be visited by the current selected vehicle.

- $sort^S$ is a two dimensional array of size $|T| \times |S|$ which contains the supply nodes sorted in descending order at each time based on their importance value. The element $sort^S(t,i)$ represents the i^{th} supply node at time t.
- $sort^H$ is a two dimensional array of size $|T| \times |H|$ which contains the hospital nodes sorted in descending order at each time based on their importance value. The element $sort^H(t,i)$ represents the i^{th} supply node at time t.
- Avg_D is a scalar quantity which represents the average commodity and worker masses requested by the demand nodes for the whole time horizon. It can be mathematically calculated as

$$Avg_D = \frac{\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} (d^C_{cit} \times m^C_c) + \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} (d^W_{wit} \times m^W_w)}{|T| \times |D|}$$

- α is a random integer which represents the number of demand nodes that should be visited by a vehicle v before it ends the trip and goes to a hospital or supply node. It is randomly selected from a set of integer values, a set which is created based on the vehicle capacity and node demands. Mathematically, α can be represented as follows

$$\alpha \in \left[\left\lfloor \frac{m_v}{d \times Avg_D} + 0.5 \right\rfloor - 2, \left\lfloor \frac{m_v}{d \times Avg_D} + 0.5 \right\rfloor + 2 \right]. \tag{4.29}$$

Selecting a high number for α, i.e. 8 nodes in the previous example, could result in useless visits such as visiting some nodes while the vehicle is empty. In contrast, visiting a low number of demand nodes could force the vehicle to resupply or go to a hospital while it has some undelivered commodities and workers. d is the percentage of the demand and workers requested expected to be delivered each time the vehicle visits a demand node. Portion of 70% is selected as a value of d because it has been noticed that in many instances, vehicles try to visit demand nodes where 70% of their needs can be supplied. This helps minimize the deviation variables which is the model objective.

For example, in a data instance, if Avg_D is 600 lb and the capacity of a vehicle is 1600, assuming vehicle supplies 70% of node demands each time it visits a node ($d = 0.7$), this means vehicle v can supply 1600 / (0.7*600) = 3.8 nodes. In this case, α is randomly selected from an interval that has a center value of 3.8 (rounded to the closest integer which is 4) nodes. Based on equation 4.29, the interval equals to [2 nodes, 6 nodes]. The value of α is randomly selected from this interval at each time the vehicle v leaves a supply node and begins distribution.

- t_{now} is the current time of the selected vehicle which is used to test the feasibility of any visit done by the vehicle. This time is incremented at each visit but not between visits. For example, one of the feasibility conditions is to test if $t_{now} + \tau_{v,current,i} = t$, where i is a node that the vehicle tries to visit. At the beginning, $t_{now} = t = 1$, if the first visit to node i can be made at time 4 because $\tau_{v,current,i} = 3$, t_{now} is kept at a value of 1 while the value of t incremented to 2, 3, and 4. At time 4, the visit is done and the value of t_{now} is updated to 4.
- ξ_{sup} is a counter used to keep track of the number of supply nodes which are visited by a vehicle. It is incremented by 1 each time the vehicle visits a supply node during the heuristic process.
- ξ_{dem} is a counter used to keep track of the number of demand nodes visited by a vehicle. It is incremented by 1 each time the vehicle visits a demand node during the heuristic process.
- ξ_{hos} is a counter used to keep track of the number of hospital nodes visited by a vehicle. It is incremented by 1 each time the vehicle visits a hospital.
- β is a number selected randomly from the set [1, 2] selected randomly after a vehicle finishes visiting α demand nodes, such that $\beta = 1$ means that the current vehicle must

visit a supply node on the next step while $\beta = 2$ means the vehicle must visit a hospital next.

- PT^D is a two dimensional array, where the element $PT^D(t,i)$ represents the prioritized demand requested, workers needed, and wounded awaiting help at node $i \in D$ at time $t \in T$. It can be calculated as

$$PT^D(t,i) = \sum_{c \in C} d^C_{cit}\ p^C_c + \sum_{e \in E} d^E_{eit}\ p^E_e + \sum_{w \in W} d^W_{wit}\ p^W_w. \tag{4.30}$$

  The whole array appears as follows

$$PT^D(t,i) = \begin{bmatrix} PT^D(1,1), & PT^D(1,2), & \dots & PT^D(1,|D|) \\ PT^D(21), & PT^D(22) & \dots & PT^D(2,|D|) \\ \dots, & \dots, & \dots & \dots \\ PT^D(|T|,1), & PT^D(|T|,2), & \dots & PT^D(|T|,|D|) \end{bmatrix}.$$

- PT^S is a two dimensional array, where the element $PT^S(t,i)$ represents the prioritized available supply and workers at node $i \in S$ at time $t \in T$. It can be calculated as

$$PT^S(t,i) = \sum_{k=2}^{t} \left\{ \sum_{c \in C} s^C_{cik}\ p^C_c + \sum_{w \in W} s^W_{wik}\ p^W_w \right\} \tag{4.31}$$

  In demand nodes, prioritized demand is calculated at each time by using the demand, wounded, and workers at that time. For supply nodes, because picking up workers and supplies left from previous periods is allowed, prioritized supply is calculated cumulatively excluding the first time period. In the first time period, vehicles pick up workers and supplies from their depots, so the information about prioritized supply values at that time is not known. This justifies its exclusion from the prioritized supply calculation. The whole array is given by

$$PT^S(t,i) = \begin{bmatrix} PT^S(1,1), & PT^S(1,2), & \dots & PT^S(1,|S|) \\ PT^S(2,1), & PT^S(2,2) & \dots & PT^S(2,|S|) \\ \dots, & \dots, & \dots & \dots \\ PT^S(|T|,1), & PT^S(|T|,2), & \dots & PT^S(|T|,|S|) \end{bmatrix}.$$

- IM^v is a two dimensional array which contains the importance values, $IM^v(t,i)$, of node $i \in N$ at each time $t \in T$ for vehicle v. This array is calculated for each vehicle at the beginning of the solution approach and is updated each time the vehicle changes its location. Importance is not constant and is a function of the selected vehicle, current location, PT^S, and PT^D. This array looks like:

$$IM^v = \begin{bmatrix} IM^v(1,1), & IM^v(1,2), & \dots & IM^v(1,|N|) \\ IM^v(2,1), & IM^v(2,2), & \dots & IM^v(2,|N|) \\ \dots, & \dots, & \dots & \dots \\ IM^v(|T|,1), & IM^v(|T|,2), & \dots & IM^v(|T|,|N|) \end{bmatrix}.$$

- Z^* is the incumbent objective value, initialized to be ∞.
- ZB^* is an array which contains all variables associated with the incumbent objective value such that

$$ZB^* = \begin{bmatrix} z^D_{civt} & \forall c \in C, i \in D, v \in V, t \in T \\ z^P_{civt} & \forall c \in C, i \in S, v \in V, t \in T \\ v^C_{cit} & \forall c \in C, i \in D, t \in T \\ v^W_{wit} & \forall w \in W, i \in D, t \in T \\ v^C_{cit} & \forall e \in E, i \in D, t \in T \\ e^D_{eivt} & \forall e \in E, i \in H, v \in V, t \in T \\ e^P_{eivt} & \forall e \in E, i \in D, v \in V, t \in T \\ w^D_{wivt} & \forall w \in W, i \in D, v \in V, t \in T \\ w^P_{wivt} & \forall w \in W, i \in S, v \in V, t \in T \\ x_{vijt} & \forall i \in N, j \in N \backslash i, v \in V, t \in T \end{bmatrix}.$$

- Xb_{vijt} is a four dimensional array which contains all binary variable values xb_{vijt} $\forall i \in N,\ j \in \{N \backslash i\},$ and $t \in T$ associated with the best solution ZB^*, so, it contains the last row of matrix ZB^* .
- Z is the objective function value of the current candidate solution.
- ZC is an array which contains all variables associated with the current objective function value. It looks similar to ZB^* but is associated with the current solution.
- XC_{vijt}: is a sub–array from ZC which contains only the binary variables associated with the current objective function value, $XC_{vijt} = xc_{vijt}$ $\forall i \in N,\ j \in \{N \backslash i\},\ t \in T$.
- P_v is the performance of a vehicle $v \in V$ which equals the total mass of commodities, workers, and wounded picked up by v during the whole logistic plan, as in equation 4.32

$$P_v = \sum_{t \in T} \left\{ \sum_{i \in S} \sum_{c \in C} m_c^C z_{civt}^P + \sum_{i \in D} \sum_{e \in E} m_e^E e_{eivt}^P + \sum_{i \in S} \sum_{w \in W} m_w^W w_{wivt}^P \right\} \tag{4.32}$$

- BP_v is the best performance achieved by vehicle $v \in V$. It is initialized to zero for all vehicles.
- Xb_{vijt}^v is a four dimensional array which contains all binary variable values xb_{vijt}^v $\forall i \in N,\ j \in \{N \backslash i\},$ and $t \in T$ associated with the best performance achieved by each vehicle.

  The difference between Xb_{vijt}^v and Xb_{vijt} is that Xb_{vijt}^v used to save the best binary values for each vehicle individually, (i.e., the best binaries for vehicles might come from different solutions and iterations and they only depend on the performance of the vehicle). Conversely, Xb_{vijt} is used to save the best binaries for a complete solutions from a single iteration, depending on the performance of all vehicles together.
- $XI_{vijt}^{initial}$ is a four dimensional array which contains all binary variable values xi_{vijt} $\forall i \in N,\ j \in \{N \backslash i\},$ and $t \in T$. This array is used as a starting solution for the local search

and can take different values based on the type of local search. Local search with initial solutions are further explained later in this section.

- φ is a number, $\varphi \in [0, 1, 2, 3]$, set by the user before the code is run to specify some inputs for the local search where 0 is used when local search is not required, 1 is used for (A) variants of local search, 2 is used for (I) variants of local search, and 3 is used for (B) variants of local search. All of these types are explained later in this section.

This approach begins with calculating the prioritized demand for each demand node and the prioritized supply for each supply node. In the case of demand nodes, the prioritized demand is found based on the demand needed, workers requested, and wounded evacuees who need help, as in equation 4.30. For supply nodes, the prioritized supply is determined by cumulative available supply and workers, as in equation 4.31.

Next, the set of vehicles is randomly partitioned into two sets, large (V^1) and small (V^2), where the number of vehicles in the larger set is about 70% of the total number. The reason of selecting the 70% for the larger set is discussed later. In the larger set, a vehicle is randomly selected, and the importance for all nodes is calculated depending on node type, the selected vehicle, and its current place which is initially its depot. In the case of hospital nodes, vehicles visit closer hospitals, so importance values of hospitals are independent of the node type and they are mainly dependent on the distance from the current node.

The selected vehicle moves to the most beneficial demand node (i.e., the demand node with the highest importance value), given that the node has not yet been visited by the vehicle. After a specific random number of demand nodes α, the vehicle visits the most beneficial (important) supply node or hospital based on the β value. If the vehicle decides to visit a hospital, it goes afterwards to a supply node to be replenished, then visits a new value of α demand nodes. On the other hand, if it visits a supply node, it goes on to visit a new set of α demand nodes. This procedure is repeated until the end of the time horizon. Each time a node is visited, its importance is decreased to avoid being revisited by other vehicles in the same time period unless its importance justifies multiple visits. This procedure is continued until all vehicles in the larger group have been selected. At the end of the time horizon for each vehicle, binary variables are known and set to 0 or 1.

In the smaller set of vehicles (V^2), best binary variables are set to be the current values except the first iteration where no history is available. Vehicles in this set are treated as the vehicles in the larger set. To determine the best binary variable values for each vehicle at the end of each iteration, the total mass of commodities, wounded, and workers picked up by the vehicle is measured; higher mass indicates a better route because this means the vehicle works more efficiently by picking up more commodities, wounded, and/or workers. If the current measure is improved, it is saved as the best performance for this vehicle and binary variables are saved as best binaries.

The selection of 70% of the vehicles to be in the larger group is justified as follows. All the vehicles are working in parallel such that one route could affect other routes and the best routes for the vehicles are created within different complete solutions from different iterations where each solution includes routes for all vehicles. Within the same solution, vehicles have no conflicts such as an important node being visited by two vehicles at the same time while other important nodes are available for visit by that time. This is because the suggested approach prevents conflicts from happening, as the prioritized demand value for visited demand nodes is dropped down. However, the best routes could have some conflicts because they are produced from different solutions. Therefore, selecting many best routes to create a new complete solution could have some conflicts that affect the objective negatively. Accordingly, in the smaller vehicle group (V^2), the best route for each vehicle, achieved in previous iterations is selected to be the current route to take advantage of good inherited history. Preliminary results show that increasing the number of vehicles in (V^2) can worsen results; this why is the smaller group is set to the best routes while routes are constructed in the larger group.

When all binary variables are set using the construction function or selected from the best history, the model is solved optimally in CPLEX where the binaries are set to zeros and ones. The model is solved with CPLEX-Concert technology to determine the other variable values such as quantities picked up, quantities delivered, worker assignments, and wounded evacuation.

Iterations end when the termination criterion is met. Many termination criteria can be used, including the total memory used, processing time, number of iterations, and number of iterations without improvement. In this research, time limit is selected in the numerical analysis because it is easier for users to set based on an actual situation.

The pseudo code of this heuristic is provided in Algorithm 2.

ALGORITHM 2: Main Heuristic

Define the termination criterion

Set $\varphi \in [0, 1, 2, 3]$

Initialize incumbent $Z^* = \infty$

$itr = 1$ //Iterations counter

$BP_v = 0 \; \forall \; v \in V$

while Termination criterion not met **do**

  Calculate the prioritized demand for all demand nodes, as $PT^D(t,i) = \sum_{c \in C} d^C_{cit} \; p^C_c + \sum_{e \in E} d^E_{eit} \; p^E_e + \sum_{w \in W} d^W_{wit} \; p^W_w \quad \forall i \in D, \; t \in T$

  Calculate the cumulative prioritized supply for all supply nodes, as $PT^S(t,i) = \sum_{k=2}^{t} \sum_{c \in C} s^C_{cik} \; p^C_c + \sum_{k=2}^{t} \sum_{w \in W} s^W_{wik} \; p^W_w \quad \forall i \in S, \; t \in T.$

  Randomly divide vehicle set V into 2 groups, V^1 and V^2

  Reorder $v \in V^1$ and $v \in V^2$ to be randomly sequenced.

  for all $v \in V^1$ **do**

    $x_{vijt} = 0 \quad \forall i, j \in N \backslash i, \; t \in T$ // Initialization and clear any 1 values from previous iterations

    $current = i_v$ // Set current location to the depot of the selected vehicle

Calculate time-based importance for all nodes, such that

$IM^v = \texttt{Importance}\left(v, current, N, PT^S, PT^D\right)$

Construct the route (Set the binary variables), $x_{vijt} \ \ \forall i, j \in N,\ i \neq j,\ t \in T = \texttt{Construction}(IM^v,\ v)$

end for

for all $v \in V^2$ **do**

if $itr == 1$ **then** //first iteration, no history is available

$current = i_v$ //Set current location to the depot of the selected vehicle

Calculate the importance for all nodes, such that

$IM^v = \texttt{Importance}\left(v, current, N, PT^S, PT^D\right)$

Specify the binary variables, $x_{vijt}\ \forall i, j \in N,\ i \neq j,\ t \in T = \texttt{Construction}(IM^v,\ v)$

end if

if $itr \geq 2$ **then**

Use the binary variables associated with the best route as current variables, $x_{vijt} = xb^v_{vijt} \quad \forall i \in N,\ j \in N \backslash i,\ t \in T$

end if

end for

Binary variable values = `Construction` function output or set from history

Solve the model using CPLEX// CPLEX determines variable values except x_{vijt}, output Z and ZC

if $Z \leq Z^*$ **then**

$Z^* = Z$

Save the new solution $ZB^* = ZC$

end if

for all $v \in V$ **do**

$P_v = \sum_{i \in D} \sum_{t \in T} \sum_{w \in W} m^W_w w^D_{wivt} + \sum_{i \in D} \sum_{t \in T} \sum_{e \in E} m^E_e e^P_{eivt} + \sum_{i \in D} \sum_{t \in T} \sum_{c \in C} m^C_c z^D_{civt}$

if $P_v \geq BP_v$ **then** // Performance improved

Save the current binary variable values of v as best values, $xb^{v}_{vijt} = x_{vijt} \quad \forall i \in N,\ j \in N\backslash i,\ t \in T$.

end if

end for

if $\varphi = 1$ **then** // (A) local search, performed at each iteration

$XI^{initial}_{vijt} = XC_{vijt}$

`Local search`$\left(XI^{initial}_{vijt}\right)$ // Function call

end if

if $\varphi = 2$ and $Z \leq Z^{*}$ **then** // (I) local search, performed at each iteration if the current solution improved

$XI^{initial}_{vijt} = XC_{vijt}$

`Local search`$\left(x^{initial}_{vijt}\right)$ // Function call

end if

$itr = itr + 1$

end while// End main loop

if $\varphi = 3$ **then** // (B) local search, performed at the end of all iterations

$XI^{initial}_{vijt} = XB_{vijt}$

`Local search`$\left(x^{initial}_{vijt}\right)$ // Function call

end if

The `Importance` function depends on the node type, the current vehicle, and its location. Current location is used to incorporate the travel time between it and other nodes in the importance, where nearer nodes have higher importance. The other parameters are incorporated in the importance based on the node type, such as the demand and workers requested in the case of demand nodes and available supplies and workers in the case of supply nodes. To give more exploration choices, all importance values are slightly randomized by multiplying the value by a random number from the interval of [0.8, 1.2]. Selecting a wider interval to select the random number increases the randomness. This worsens the results because it performs against the main concept of this proposed solution approach which is the greedy concept. This function is shown in Algorithm 3.

ALGORITHM 3: `Importance` Function

for all $t \in T$ **do**
  for all $i \in N$ **do**
    Generate R //Random number [0.8,1.2]

$$IM_{t,i}^{v} = \begin{cases} \dfrac{R}{t_{v,current,i}} PT_{ti}^{D} & \text{if } i \in D \\ \dfrac{R}{t_{v,current,i}} PT_{ti}^{S} & \text{if } i \in S \\ \dfrac{R}{\tau_{v,current,i}} & \text{if } i \in H \end{cases}$$

  end for
end for
Return IM^{v}

Route construction is used to set the binary variables to zero or one which is a major part of this solution approach. The pseudo code of the `Construction` function is shown in Algorithm 4. There are many important steps in this function. First, nodes from each type are sorted based on their importance value (IM^{v}). Next, the time loop begins considering three possibilities for the current selected vehicle; demand node visits, supply node visits, and hospital visits. Only one of these possibilities can be performed at a given time, and each has two conditions. The first is whether a possibility is selected or not, as in lines 12, 35, and 55. The second tests if this visit is feasible or not by satisfying many sub–conditions, such as determining if this node has been visited before by this vehicle, if it is reachable by the vehicle at time t which is done by check the equation $t_{now} + \tau_{v,\ current,\ sort(t,i)} = t$, and if the vehicle can return back to its depot before the end of time horizon if the node is visited which is done by checking the inequality $t_{now} + \tau_{v,\ current,\ sort(t,i)} + \tau_{v,\ sort(t,i),\ i_v} \leq |T|$. These conditions are in lines 14, 37, and 57.

If the demand node visit condition is satisfied, as in line 12, both t–loop in line 11 and demand nodes loop in line 13 are working in parallel to find the nearest and most important demand node to visit. When a demand node is visited, its prioritized demand by the visiting time is decreased by dividing by 3. As prioritized demand values were calculated at the beginning of while loop in line 7 in Algorithm 2, the new reduced value of the visited demand will be used to calculate the importance values for the next selected vehicles. Reducing the prioritized demand value by a large amount causes the visited demand node to not be visited by other vehicles. After testing many reduction values, it is found dividing by 3 is the most proper value.

In case of hospital node visits, as in line 35, a vehicle selects the most important hospital where the hospital importance values are calculated based on travel time with some randomness. Supply node visits, as in line 55, are similar to demand node visits; the sub–conditions inside the supply node loop find the nearest and most important supply node excluding its depot. Once a supply node is visited, its prioritized supply value is reduced for a period from the second time period to the current time. This is because vehicles can pick supplies from previous periods. To explain this, suppose that a supply node is visited by a vehicle at time t, and the next vehicle wants to visit the same supply node at an earlier time. It should be warned that the importance of this node is reduced. The first time is excluded from prioritized supply value reduction because vehicles start picking up supplies and workers from the supply nodes at the first time period. No information will be available about the remaining supplies and workers from the first time and we can not depend on the first time to recalculate the importance values.

After the time loop ends, the selected vehicle returns back to its depot and the `Construction` function returns the binary values.

Algorithm 4: `Construction` Function

$\xi_{dem} = 0$ //Set demand node visits to zero

$\xi_{sup} = 1$ //Set supply node visits to one because the current vehicle leaves from its depot which is supply node.

$\xi_{hos} = 0$ //Set hospital node visits to zero

$t_{now} = 1$

for all $t \in T$ **do**

  Sort demand nodes in descending order based on their total importance to get $sort^D$.

  Sort supply nodes in descending order based on their total importance to get $sort^S$.

  Sort hospital nodes in descending order based on their total importance to get $sort^H$.

end for

Select a random integer number $\alpha \in \left[\left\lfloor \frac{c_v}{0.7 \times Avg_D} + 0.5 \right\rfloor - 2, \left\lfloor \frac{c_v}{0.7 \times Avg_D} + 0.5 \right\rfloor + 2\right]$ // Based on vehicle capacity and average masses of workers and demand

for all $t \in T$ **do**

  if $\xi_{dem} \leq \alpha$ **then**

    for all $i \leq |D|$ **do**

      if it is feasible to visit demand node $sort^D(t, i)$ **then**

        $\hat{x}_{v,\ current,\ sort^D(t,i),\ t} = 1$

        $t_{now} = t$

        Update $current = sort^D(t, i)$

        Reduce the prioritized demand of $sort^D(t, i)$, such that

        $PT^D(t, i) = PT^D(t, i)/3$ //to avoid revisiting by other vehicles

        Recalculate importances for all nodes: // Because the current is updated

        $IM^v =$ `Importance` $\left(v, current, N, PT^S, PT^D\right)$

        for all $k \in T$ **do** // New sorting because importance values are updated

Sort demand nodes in descending order based on their total importance to get $sort^D$.

Sort supply nodes in descending order based on their total importance to get $sort^S$.

Sort hospital nodes in descending order based on their total importance to get $sort^H$.

end for

$\xi_{dem} = \xi_{dem} + 1$

i = big number $> |D|$ // end loop to avoid infeasibility due to visiting more than one node at the same time.

if $\xi_{dem} = \alpha$ **then**

Select β randomly from [1,2] // To decide the next step

end if

end if// End if feasible to visit

end for

end if

if $\beta == 2$ And $\xi_{hos} < |H|$ And $\xi_{dem} \geq \alpha$ **then**

for all $i \leq |H|$ **do**

if it is feasible to visit hospital node $sort^H(t,i)$ **then**

$\hat{x}_{v,\ current,\ sort^H(t,i),\ t} = 1$

Set $t_{now} = t$

Update $current = sort^H(t,i)$

Recalculate importance of all nodes, // Current updated

$IM^v = \texttt{Importance}\left(v, current, N, PT^S, PT^D\right)$

for all $s \in T$ **do**

Sort demand nodes in descending order based on their total importance to get $sort^D$.

Sort supply nodes in descending order based on their total importance to get $sort^S$.

Sort hospital nodes in descending order based on their total importance to get $sort^H$.

end for

$t_{now} = t$

$\xi_{hos} = \xi_{hos} + 1$ // Hospital visits counter updated

$\beta = 1$ //next step must be re-supply

$i =$ big number $> |H|$ // to exit the for loop

end if// End if feasible to visit

end for

end if// End hospital visit

if $\beta == 1$ And $\xi_{sup} < |S|$ And $\xi_{dem} \geq \alpha$ **then**

for all $i \leq |S|$ **do**

if If it is feasible to visit supply node $sort^S(t, i)$ **then**

$\hat{x}_{v,\ current,\ sort^S(t,i),\ t} = 1$

Set $t_{now} = t$

Update $current = sort^S(t, i)$

Reduce the prioritized supply of $sort^S(t, i)$ node, such that

for all $k \in [2, t]$ **do**

$PT^S = PT^S(k, current)/2$

end for

Recalculate importance of all nodes,

$IM^v = \texttt{Importance}\left(v, current, N, PT^S, PT^D\right)$

for all $s \in T$ **do**

Sort demand nodes in descending order based on their total importance to get $sort^D$.

69: Sort supply nodes in descending order based on their total importance to get $sort^S$.

70: Sort hospital nodes in descending order based on their total importance to get $sort^H$.

71: **end for**

72: $\xi_{sup} = \xi_{sup} + 1$

73: $i =$ big number $> |S|$ // to exit the for loop

74: Generate new value of α // As in line 10, next steps must be demand nodes visits

75: **end if**// End if feasible to visit

76: **end for**

77: **end if**// End supply visit

78: **end for**// End t-loop

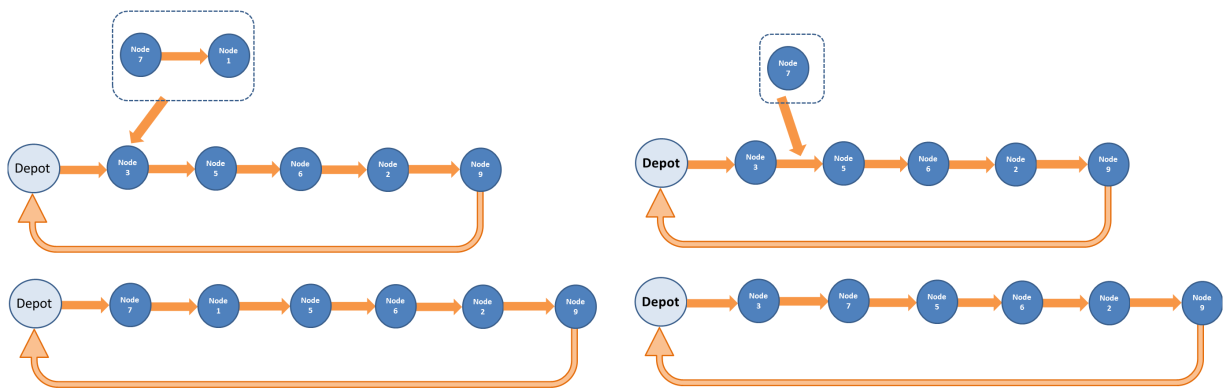
79: $t_{now} = t_{now} + \tau v, current, i_v$ // time to return back

80: $x_{v\ current\ i_v\ t_{now}} = 1$

81: Return $x_{vijt}\ \ \forall i, j \in N,\ i \neq j,\ t \in T$

The previous approach with $\varphi = 0$ (no local search) is called `Heuristic-0`. Preliminary tests show that the main advantage of this approach is the short computation time, such as 1 minute to perform 100 iterations to solve small scale instance. This good attribute allows for further improvements by spending more time on computational efforts. Two kinds of local search are iteratively applied to improve `Heuristic-0`. First, if a node in a vehicle route is selected and is then found to be far from the previous or next node in the route, it could waste vehicle time. To solve this problem, an extensive search can be performed to find two nearer nodes to replace it. In this case, a neighborhood is defined as any solution which can be constructed by replacing a node with two nodes. This search is called a `Replacement local search heuristic`.

Second, in some routes, vehicles might have an idle time. For example, if three time periods are available to a vehicle, and it can not find a node to visit before the end of the time horizon, it could return to its depot in one time period and sit idle for the next two. In this event, local search is performed to find a node which can be inserted in earlier route steps without affecting the feasibility of the route. In this case, a neighborhood is defined as any solution which can be constructed by inserting a node at any point in the route. This is called an `Insertion local search heuristic`. Figure 4.2 provides an explanation of both replacement and insertion.



(a) Replacement (b) Insertion

Figure 4.2: Local search operations

The pseudo codes for both searches are provided in Algorithm 5, where γ_1 is the number of iterations each local search is repeated using the same starting solution, and γ_2 is the number of trials used to perform insertions or replacements inside each local search iteration. In other words, each iteration of γ_1 starts with the same initial solution, and γ_2 is the number of trials performed inside each iteration of γ_1.

Different values of γ_1 and γ_2 were tested, and results show that in most data sets the number of local searches required for at least one success is 4, so both γ_1 and γ_2 are fixed at 2. Let γ_3 represent the number of random nodes generated and tested for feasibility of use in replacement or insertion; this number is selected to be a large value such as 100 because the chance of success for replacement or insertion using random nodes is very low, and the calculations can be done in a very short time.

These local searches start from an initial solution, $XI_{vijt}^{initial}$, which is a four dimensional array that contains the value of all binary variables, such that it contains the elements $xi_{vijt}^{initial}$ $\forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T$. It could be the current solution ($XI_{vijt}^{initial} = XC_{vijt}$), the current solution if improved compared with previous solutions ($XI_{vijt}^{initial} = XC_{vijt}$ and $ZC \leq Z^*$), or the best solution at the end of all iterations ($XI_{vijt}^{initial} = XB_{vijt}$). The variable array ($\hat{x}_{vijt}^{n'}$ $\forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T$) is used to save the updated binary variable values after replacement in the n^{th} iteration, whereas $\hat{x}_{vijt}^{n}$ $\forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T$ is used to save the updated binary variable values after insertion in the nth iteration. At the end of local search, $\hat{x}_{vijt}^{\gamma_2}$ $\forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T$ is used to save the last updated binary values after replacement and insertion have been performed γ_2 times.

ALGORITHM 5: `Local search` function

for $y = 1 : \gamma_1$ **do**
    $\hat{x}_{vijt}^{0} = x_{vijt}^{initial}$ // Initialization
    `success` $= 0$
    for $n = 1 : \gamma_2$ **do**
        Try Replacement, $\hat{x}_{vijt}^{n'}$ $\forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T =$ `Replacement` $\{V, \hat{x}_{vijt}^{n-1}\}$
        if replacement succeeded **then**
            `success = 1`
        end if

        Try Insertion, $\hat{x}_{vijt}^{n}$ $\forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T =$ `Insertion` $\{V, \hat{x}_{vijt}^{n'}\}$
        if insertion succeeded **then**
            `success = 1`
        end if

if `success = 1` **then**

Solve the model at specific $\hat{x}^{\gamma_2}_{vijt}$ $\forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T$ variables using CPLEX // Determine all variables except x_{vijt}, output Z and ZC

if $Z \leq Z^*$ **then**

$Z^* = Z$

Save the new solution $ZB^* = ZC$

end if

end if// end if success = 1

end for// end for loop of γ_2

end for// end for loop of γ_1

The `Replacement` function is performed using the following approach. `Replacement` function starts with vehicle loop, creating a route for the current vehicle by putting the nodes that have binary variables of value 1 in ascending order of time index. The benefit of creating routes from the binaries is to facilitate the coding process. A loop for the nodes in the route starts. If the travel time between a node and the next node in the route is greater than or equal to twice the minimum travel time in the network, this means there is a chance of finding two nodes for replacement. Once this condition is satisfied, two random nodes of any type are generated many times (e.g., 100 times) and determined if they can be placed in the route by testing if they are visited anywhere in the route and if the travel times needed to visit them can be satisfied. After this procedure, we might have updated binary variable values or we might not find any possibilities for replacement.

Algorithm 6: Replacement local search function

1: **for all** $v \in V$ **do**
2: Create route using binary variable values
3: **for all** $i \in Route_v$ **do**
4: **if** node $\tau_{v,i-1,i}$ or $\tau_{v,i,i+1} \geq$ 2× the shortest time needed by v to pass between any two nodes in the system **then**
5: **while** Stopping criterion is not met **do** // γ_3 trials
6: Generate two nodes randomly $x,\ y$
7: **if** Feasible to replace i by these two nodes **then**
8: Replace i by $x,\ y$
9: **end if**
10: **end while**
11: **end if**
12: **end for**
13: **end for**
14: Return $\hat{x}^{n'}_{vijt}\ \ \forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T$

`Insertion` is demonstrated in the next approach. The `Insertion` function starts the vehicle loop that takes the binary variable values from the replacement function as an input. If the time for the current vehicle is less than the total time available, this means there is idle time somewhere in the route and a chance to insert a node or more. A random node is selected and tested to determine if it can be inserted in the route. If the travel time between it and any two nodes in the route is less than or equal to the idle time and if it is not visited by the same vehicle in the route, then it is viable insertion. The condition at line 6 is done by a loop to insert the random node anywhere in the route. After the `Insertion` function, a new update of binaries might be available.

Algorithm 7: Insertion local search function

for all $v \in V$ **do**
  Create route using binary variable values
  if Total time needed for $Route_v < |T|$ **then**
    while Stopping criterion is not met **do**// γ_3 iterations
      Generate a node randomly x
      if Feasible to insert x at any place in $Route_v$ **then**
        Insert it //
        `success = 1`
      end if
    end while
  end if
end for
Return $\hat{x}^n_{vijt}\ \ \forall v \in V,\ i,j \in N,\ i \neq j,\ t \in T$

As shown in Algorithm 2, lines 42, 46, and 52, previous versions of local searches can be applied in different ways using different initial solutions. First, they can be applied after the main heuristic to improve the best known solution `Heuristic-B`, in line 42. The main advantage of this variant is the short computation time, as it could improve the incumbent solution while spending very limited additional time after `Heuristic-0`. The disadvantage is the small neighborhood structure which produces no improvement in many cases. its

The second method is to apply the local search to each candidate solution of the main algorithm (i.e. in each iteration), line 46. Three different versions are considered for this variant: short computation time limit `Heuristic-A1`, medium computation time limit `Heuristic-A2`, and long computation time limit `Heuristic-A3`. Time limits are different based on the problem size which is explained more in the numerical analysis section. This variant is expected to give the best solution because it has the largest neighborhood.

In the third method, local searches can be applied at each iteration if a solution is better than the previous iteration's solution (better than the incumbent). Two versions are considered for this method: `Heuristic-I1`, and `Heuristic-I2`. `Heuristic-I2` is performed by running `Heuristic-I1` many times (4 times in this research), and then selecting the best solution from all runs. Testing Heuristic-I1 shows that stagnation problems appear frequently, which means no improvement on the incumbent for many iterations because the local search is applied to improved solutions only. This is why `Heuristic-I2` is performed by running Heuristic-I1 many times, where each time all parameters are re–initialized and more search space is explored. Similar to `Heuristic-A`s variants, time limits vary between data sets based on their size, as discussed in the next section. Table 4.11 summarizes the suggested approaches.

Solution approach	**Time limit**	**Where LS applied**	**LS starting solution**
`Heuristic-0`	The shortest	No local search	——
`Heuristic-B`	Slightly longer than `Heuristic-0`	After `Heuristic-0`	$XI_{vijt} = XB_{vijt}$
`Heuristic-A1`	The shortest among `Heuristic-A1,2,3`	At each iteration	$XI_{vijt} = XC_{vijt}$
`Heuristic-A2`	Medium compared with `Heuristic-A1,3`	At each iteration	$XI_{vijt} = XC_{vijt}$
`Heuristic-A3`	The longest among `Heuristic-A1,2,3`	At each iteration	$XI_{vijt} = XC_{vijt}$
`Heuristic-I1`	= `Heuristic-A1`	At each iteration, if $ZC \leq Z^*$	$XI_{vijt} = XC_{vijt}$
`Heuristic-I2`	=`Heuristic-I1` $\times$ 3	At each iteration, if $ZC \leq Z^*$	$XI_{vijt} = XC_{vijt}$

Table 4.11: Solution approach variants

4.7 Numerical Analysis

To test the effectiveness of the suggested approaches, different data sets are solved using them and using CPLEX with a six hour time limit. CPLEX solutions are produced using CPLEX–Concert Technology 12.2 MIP solver on an HP Compaq 8100 Elite SSF PC, with a quad-core Intel i7-860 processor running Ubuntu Linux 10.10 in 64-bit mode. Data sets are classified as tiny, small, medium, and large scale. This classification is developed based on available data and the literature. For example, Red Cross stated that in a disaster, it has about 30 vehicles and more than 20 regions, Red-Cross (2013). These specifications, which are considered for large scale problems, are suitable for a relief agency. All data sets are generated randomly, with about 20%-30% of nodes specified as supply and hospital nodes, while the remaining are considered to be demand nodes. This portioning of nodes has been used in many studies, such as Yi and Ozdamar (2007).

Preliminary testing shows that CPLEX can give optimal results for tiny scale data sets and sub-optimal results for small scale instances, but it fails to solve medium and large scale problems in six hours. The scale of problem instances are decided based on the parameters described in Section 4.7.1. Sections 4.7.2, 4.7.3, 4.7.4, and 4.7.5 show and analyze the results of CPLEX and the heuristic approaches for tiny, small, medium, and large scale sets. Finally, Section 4.8 analyzes the performance of different heuristics with respect to the data set scales.

4.7.1 Experimental Design

Some parameters, such as time intervals, number of nodes, number of vehicles, commodity types, and work–force and evacuee categories influence computation time greatly. These parameters are used to classify the data sets into different scales. In Table 4.12, these parameters are shown along with their suggested values. Other parameters, such as vehicle capacities and commodity masses, have less influence over computation time. These parameters are fixed and do not depend on the disaster scale, as shown in Table 4.13

Parameter	**Tiny Scale Range**	**Small Scale Range**	**Medium Scale Range**	**Large Scale Range**
Time Intervals $\|T\|$	∼Unif(5,8)	∼Unif(7,10)	∼Unif(10,16)	∼Unif(16,48)
Vehicles $\|v\|$	∼Unif(2,4)	∼Unif(3,5)	∼Unif(5,15)	∼Unif(10,40)
Demand Nodes $\|D\|$	∼Unif(3,6)	∼Unif(4,8)	∼Unif(8,15)	∼Unif(10,30)
Supply Nodes $\|S\|$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(3,7)	∼Unif(5,10)
Hospital Nodes $\|H\|$	∼Unif(1,2)	∼Unif(1,2)	∼Unif(2,4)	∼Unif(3,6)
Commodities Types $\|C\|$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(2,5)	∼Unif(3,7)
Workers categories $\|W\|$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(2,5)	∼Unif(3,7)
Evacuees categories $\|E\|$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(2,5)	∼Unif(3,7)

Table 4.12: HLVRP - design of experiment

Parameter	**All Scales Range**
Capacity of each vehicles m_v	∼Unif(600 lb,1400b)
Speed of each vehicles	∼Unif(1,3)
Mass of each commodity m_c^C	∼Unif(1 lb,10 lb)
Mass of one worker m_w^W	200 lb
Mass of one evacuee m_e^E	200 lb
Demand of each demand node d_{cit}^C	∼Unif(0,350)
Workers needed d_{wit}^W	∼Unif(0,8)
Available workers s_{wit}^W	∼Unif(70%,100%)
Available supply s_{cit}^C	∼Unif(70%,100%)

Table 4.13: HLVRP - fixed parameters

In Table 4.12, the parameter ranges are displayed for the four different problem scales. This means the total number of sets to cover all possible combinations is $4^8 = 65536$ sets. It could take 16384 days if each one was run in CPLEX using a six hour limit. Accordingly, 75 sets are generated for the tiny scale to compare the results with optimal solutions which allows us to evaluate the proposed heuristic approaches fairly. Fifty sets are randomly generated in the small scale to compare with near optimal results, and 50 sets are generated randomly for medium and large scales to compare different heuristic approaches and to test the scalability of the proposed heuristic. CPLEX is not used in the medium and large scales because it fails to give results in a 6–hour time limit.

The last five parameters have the same range for all scales because they are independent of the disaster scale. The capacity of each vehicle is selected to be between 600 lb and 1400 lb, which covers most available vehicles suitable to work in such cases. The other vehicle parameter is speed, which is selected from one of three factors: one means fast, two means medium, and three means slow speeds. Quantitatively, if a vehicle with a speed factor of one takes three time units to pass from node i and node j, another vehicle with a speed factor of two would take six time units to pass between the same nodes, while one with a speed factor of three would require nine time units.

Mass of commodities is generated between 1 and 10 lbs, which covers most commodities such water bottles, food bags, and blankets. Workers and wounded mass is considered to be a fixed value of 200 lb. This is approximately the body mass of an average person in the USA when clothes and other personal effects are taken into account, (McDowell et al. 2006).

Demand at each node is selected to be between 0 and 350 units from each type at each time period, and the supply is generated as a percentage of the demand. In other words, the total supply at all supply nodes and time periods equals 70-100% of the total demand. In the same way, the total number of available workers at all supply nodes and time periods equals 70-100% of the total workers requested by the demand nodes. It is assumed that 30-50% of the available supply and workers is ready in the first time period for several reasons. First, undistributed commodities and non-transferred workers from previous plans are collected at time zero of the current plan. Second, plans are usually started when the planning agencies have a large enough amount of supplies that they can use vehicles efficiently. Finally, if prepositioned amounts exist, they can be used at time zero.

4.7.2 Tiny Scale Problems

In this subsection, all data sets that CPLEX can produce optimal solutions for in 6 hours are tested versus the proposed heuristic. For the sake of comparison, a gap between the objective function value (OFV) of the CPLEX solution (which is the best or minimum one in case of tiny scale problems) and the OFV of the heuristic solution is defined as:

$$gap = \frac{\texttt{Heuristic OFV - CPLEX OFV}}{\texttt{CPLEX OFV}} 100\%$$

Tables 4.14, 4.15, and 4.16 summarize the results of these sets. The second and third columns show the results given by CPLEX with time limits equal to 6 hours (21600 seconds). Tiny scale sets are considered as special cases because CPLEX can solve some of them in 1 second. Because of this, a new variant of (A) heuristic with time limit 1 second is considered only for tiny problems and is called `Heuristic-A0`. Time limits are 5 seconds for `Heuristic-0`, 6 seconds for `Heuristic-B`, 10 seconds for `Heuristic-A1`, 20 seconds for `Heuristic-A2`, 30 seconds for `Heuristic-A3`, 10 seconds for `Heuristic-I1`, and 10 seconds repeated three times for `Heuristic-I2`

Data	**CPLEX**		**H-0 (5s)**	**H-B (5.5s)**	**H-A0 (1s)**	**H-A1 (10s)**	**H-A2 (20s)**	**H-A3 (30s)**	**H-I1 (10s)**	**H-I2 (30s)**
Set	Time	OFV	gap	gap	gap	gap	gap	gap	gap	gap
1	647	125666	1.10%	1.10%	2.06%	2.06%	1.79%	1.79%	2.02%	1.74%
2	1	42280	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
3	2	83070	0.82%	0.82%	1.93%	0.82%	0.63%	0.00%	1.42%	0.82%
4	1	126700	0.24%	0.00%	0.24%	0.24%	0.00%	0.00%	0.24%	0.00%
5	3	120350	1.99%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
6	1040	178041	2.61%	2.61%	2.33%	1.57%	1.57%	1.57%	1.97%	1.71%
7	247	147557	0.30%	0.00%	1.59%	0.30%	0.30%	0.30%	0.00%	0.00%
8	1	60490	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
9	1	26232	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
10	1	93096	0.00%	0.00%	0.40%	0.46%	0.46%	0.00%	2.67%	0.00%
11	1	98315	3.17%	2.30%	2.37%	2.30%	2.30%	1.66%	2.30%	2.30%
12	1	37760	4.13%	4.13%	0.00%	0.00%	0.00%	0.00%	4.13%	4.13%
13	6	166660	1.68%	1.26%	1.26%	1.23%	1.23%	1.23%	1.68%	1.23%
14	1	46288	0.00%	0.00%	1.97%	0.00%	0.00%	0.00%	5.25%	0.00%
15	1	149880	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
16	80	140850	0.67%	0.00%	2.17%	0.00%	0.00%	0.00%	0.67%	0.67%
17	11	52550	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.61%	0.00%
18	162	174310	0.00%	0.00%	0.06%	0.00%	0.00%	0.00%	0.00%	0.00%
19	2	132299	0.06%	0.00%	0.15%	0.11%	0.00%	0.00%	0.24%	0.11%
20	48	127330	0.42%	0.31%	2.02%	0.63%	0.42%	0.31%	0.31%	0.31%
21	1	36944	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.52%	0.00%
22	1	74750	0.00%	0.00%	0.07%	0.00%	0.00%	0.00%	0.00%	0.00%
23	5	53150	12.74%	6.65%	2.86%	2.86%	2.86%	1.51%	6.65%	4.08%
24	3566	74650	0.00%	0.00%	0.07%	0.00%	0.00%	0.00%	0.00%	0.00%
25	6	76610	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.22%	0.00%

Table 4.14: Tiny scale data set results (sets 1-25)

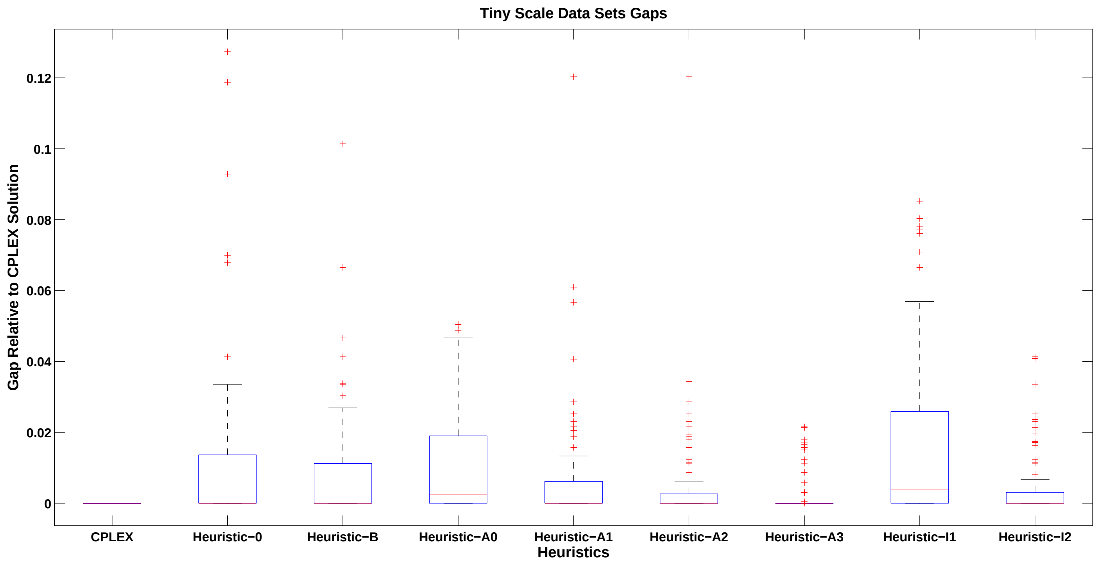
Data	**CPLEX**		**H-0 (5s)**	**H-B (5.5s)**	**H-A0 (1s)**	**H-A1 (10s)**	**H-A2 (20s)**	**H-A3 (30s)**	**H-I1 (10s)**	**H-I2 (30s)**
Set	Time	OFV	gap	gap	gap	gap	gap	gap	gap	gap
26	1	52517	2.40%	1.41%	3.12%	1.14%	1.14%	0.00%	1.98%	1.98%
27	46	303962	1.32%	0.00%	0.05%	0.00%	0.00%	0.00%	0.03%	0.00%
28	2	126800	0.00%	0.00%	0.35%	0.00%	0.00%	0.00%	0.00%	0.00%
29	14	204134	0.00%	0.00%	0.78%	0.00%	0.00%	0.00%	0.00%	0.00%
30	177	125946	0.00%	0.00%	0.09%	0.00%	0.00%	0.00%	0.00%	0.00%
31	1	27886	6.99%	4.66%	4.66%	6.10%	0.00%	0.00%	7.71%	0.00%
32	1	98035	0.00%	0.00%	1.53%	0.00%	0.00%	0.00%	0.00%	0.00%
33	53	104700	0.00%	0.00%	1.43%	0.00%	0.00%	0.00%	0.00%	0.00%
34	1	59060	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
35	35	103700	6.78%	1.72%	1.53%	0.58%	0.58%	0.58%	5.69%	1.14%
36	1	95615	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
37	302	157550	0.00%	0.00%	0.54%	0.00%	0.00%	0.00%	1.37%	0.00%
38	1	51570	3.30%	1.07%	5.04%	2.52%	2.52%	0.29%	3.18%	2.52%
39	1	32862	0.05%	0.05%	0.00%	0.00%	0.00%	0.00%	0.05%	0.00%
40	2	86534	0.92%	0.00%	0.00%	0.09%	0.00%	0.00%	0.00%	0.00%
41	1	27580	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.61%	0.00%
42	1	35540	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.04%	0.00%
43	3	50466	11.87%	10.14%	2.36%	5.67%	1.95%	1.58%	7.09%	2.36%
44	8	62470	0.00%	0.00%	0.70%	0.16%	0.16%	0.00%	0.16%	0.13%
45	1	62018	3.03%	3.03%	2.85%	0.00%	0.00%	0.00%	3.61%	0.00%
46	143	29753	0.28%	0.28%	0.28%	2.52%	0.87%	0.87%	0.87%	0.28%
47	1	153910	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
48	1	75370	0.00%	0.00%	0.00%	0.16%	0.16%	0.00%	0.11%	0.00%
49	1	26690	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
50	1	113562	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.75%	0.00%

Table 4.15: Tiny scale data set results (sets 26-50)

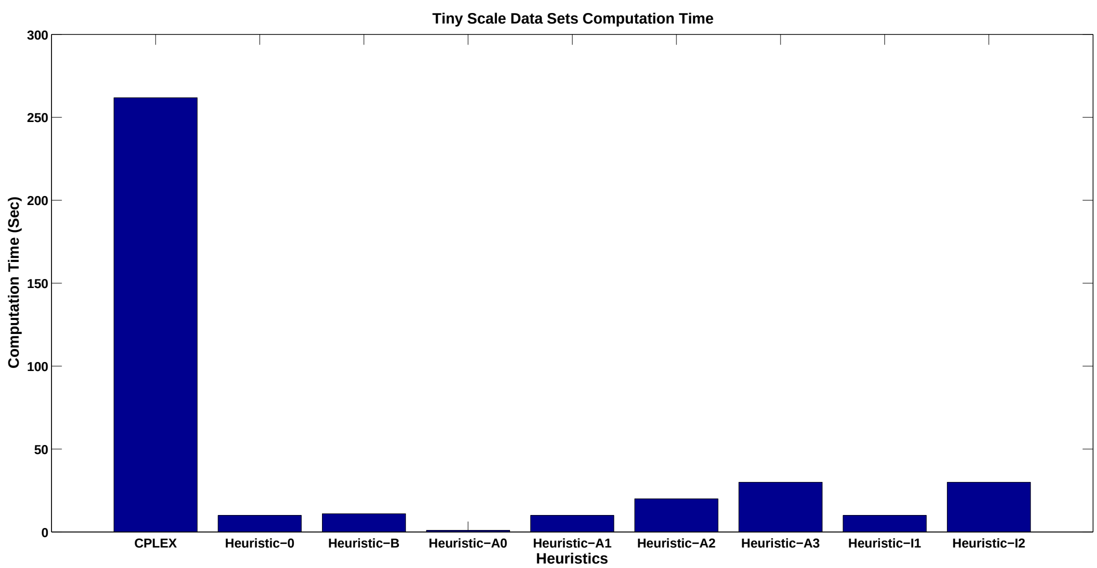
Data	**CPLEX**		**H-0 (5s)**	**H-B (5.5s)**	**H-A0 (1s)**	**H-A1 (10s)**	**H-A2 (20s)**	**H-A3 (30s)**	**H-I1 (10s)**	**H-I2 (30s)**
Set	Time	OFV	gap	gap	gap	gap	gap	gap	gap	gap
51	2	23620	0.00%	0.00%	0.56%	0.00%	0.00%	0.00%	2.34%	0.00%
52	1	25150	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
53	1	99430	1.13%	1.13%	1.13%	1.13%	1.13%	1.13%	2.35%	1.13%
54	33	145987	0.41%	0.41%	1.67%	0.00%	0.00%	0.00%	0.01%	0.00%
55	4	120490	0.40%	0.00%	1.22%	0.00%	0.00%	0.00%	0.40%	0.00%
56	8	120998	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
57	1	42810	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
58	2	144274	0.00%	0.00%	1.39%	0.00%	0.00%	0.00%	0.00%	0.00%
59	2	86580	1.70%	1.70%	2.43%	1.88%	1.88%	1.70%	1.70%	1.70%
60	8	128918	0.00%	0.00%	1.63%	0.00%	0.00%	0.00%	0.00%	0.00%
61	3	32000	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	8.03%	0.00%
62	1	34130	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
63	4	28394	2.11%	2.11%	2.11%	0.00%	0.00%	0.00%	0.00%	0.00%
64	345	70260	9.29%	3.38%	2.13%	4.06%	3.43%	2.13%	2.13%	2.13%
65	1	46360	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	8.52%	0.00%
66	2	46180	3.36%	3.36%	0.00%	0.69%	0.00%	0.00%	3.36%	3.36%
67	1	56214	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
68	2	19682	0.00%	0.00%	0.00%	12.03%	12.03%	0.00%	7.81%	0.00%
69	2	74316	0.00%	0.00%	2.56%	0.00%	0.00%	0.00%	3.54%	0.00%
70	1	80019	0.00%	0.00%	2.12%	0.00%	0.00%	0.00%	0.00%	0.00%
71	4	198890	2.69%	2.69%	0.00%	0.00%	0.00%	0.00%	2.69%	0.35%
72	12552	132200	1.40%	1.40%	4.88%	2.16%	2.16%	2.16%	3.82%	1.63%
73	12	101200	1.38%	1.38%	1.83%	1.33%	0.00%	0.00%	1.73%	0.00%
74	2	110793	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%
75	6	86590	1.15%	1.15%	0.00%	0.00%	0.00%	0.00%	0.69%	0.00%

Table 4.16: Tiny scale data set results (sets 51-75)

Heuristic approaches give competitive results for tiny scale problems. The mean gap for `Heuristic-0` equals 1.23% and the standard deviation is 0.0252. Low improvement is achieved with `Heuristic-B` with a mean gap 0.83% and standard deviation of 0.0168. `Heuristic-A0` with a 1 second time limit gives good results with a mean gap of 0.94% and standard deviation of 0.0125. With longer time limits, solutions are improved as seen in `Heuristic-A1` which has a mean gap of 0.73% and standard deviation of 0.018, `Heuristic-A2` which has a mean gap of 0.38% and standard deviation of 0.0154, and `Heuristic-A3` which has a mean gap of 0.25% and standard deviation of 0.006. As expected, `Heuristic-I1` gives good results with high variation in gaps, the mean gap equals 1.72% and standard deviation is .0235. Finally, `Heuristic-I2` improves the results of `Heuristic-I1` producing a mean gap of only 0.48% and standard deviation of 0.0097. Figure 4.3 shows the box plot of tiny problem gaps and the bar plot of computation times.



(a) Gap



(b) Computation time

Figure 4.3: Gap and computation time for tiny scale sets

Many advantages and recommendations can be obtained from previous tables and figures. `Heuristic-A0` gives 0 gap and finds optimal solution for 29 sets out of 75 in 1 second, and `Heuristic-A3` produces 0 gap and finds optimal solution for 56 out of 75 sets. `Heuristic-I1` is not recommended for tiny scale because compared to `Heuristic-0` and `Heuristic-B` variants, it produces the worst results and takes longer to do it. Finally, the main aim of tiny problems is to test the heuristics versus optimal solutions, and the results show that the heuristics give very competitive results.

4.7.3 Small Scale Problems

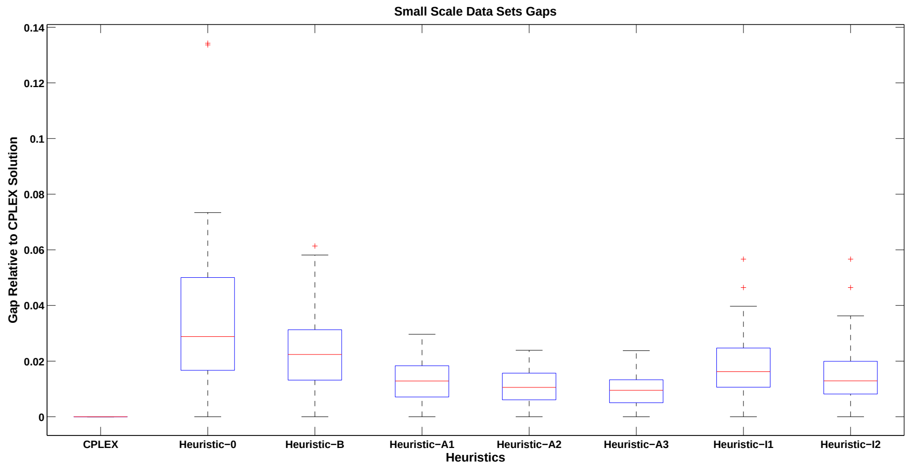
In this subsection, data sets which CPLEX can produce near optimal solutions for in 6 hours are considered. The same definition of gap from Section 4.7.2 is used. Tables 4.17 and 4.18 summarize the results of these sets. Figure 4.4 shows the box–plot of the gaps and the bar plot of the computation times. Time limits are 10 seconds for `Heuristic-0`, 11 seconds for `Heuristic-B`, 20 seconds for `Heuristic-A1`, 40 seconds for `Heuristic-A2`, 60 seconds for `Heuristic-A3`, 20 seconds for `Heuristic-I1`, and 20 seconds repeated three times for `Heuristic-I2`

Data	**CPLEX**		**Heur-0 (10sec)**	**Heur-B (11sec)**	**Heur-A1 (20sec)**	**Heur-A2 (40sec)**	**Heur-A3 (60sec)**	**Heur-I1 (20sec)**	**Heur-I2 (60sec)**
Set	Time	OFV	gap	gap	gap	gap	gap	gap	gap
1	21600	738520	3.20%	3.11%	1.61%	1.26%	1.26%	2.14%	1.72%
2	17232	232860	3.50%	3.50%	2.05%	1.89%	1.70%	2.48%	2.19%
3	21600	851796	2.90%	1.78%	1.57%	1.30%	1.12%	2.14%	1.42%
4	21600	204539	3.59%	3.13%	1.15%	1.15%	1.15%	3.32%	2.53%
5	21600	251515	1.67%	1.67%	1.39%	0.00%	0.00%	1.57%	1.11%
6	21600	530080	6.43%	2.23%	1.00%	1.00%	1.00%	1.03%	1.03%
7	21600	456744	0.50%	0.50%	0.00%	0.00%	0.00%	0.00%	0.00%
8	21600	736496	3.66%	1.96%	1.59%	1.10%	1.10%	2.00%	1.38%
9	21600	720756	1.56%	1.56%	1.52%	0.85%	0.85%	1.30%	1.28%
10	21600	670375	1.97%	0.61%	0.01%	0.01%	0.00%	0.84%	0.22%
11	21600	776360	2.62%	2.62%	0.95%	0.88%	0.88%	1.64%	1.27%
12	21600	135922	13.43%	6.14%	1.96%	1.96%	1.96%	5.67%	5.67%
13	21600	559040	0.61%	0.56%	0.36%	0.36%	0.00%	0.00%	0.00%
14	21600	123850	13.36%	5.81%	2.18%	2.18%	1.98%	4.64%	4.64%
15	21600	329630	4.88%	2.76%	1.89%	1.19%	0.89%	2.68%	2.18%
16	21600	606340	0.75%	0.75%	0.75%	0.75%	0.75%	0.75%	0.75%
17	21600	791170	2.50%	1.34%	0.65%	0.65%	0.65%	1.45%	0.87%
18	21600	493312	6.28%	2.85%	2.96%	2.02%	2.02%	3.97%	3.54%
19	21600	553610	5.50%	2.63%	1.23%	1.06%	1.06%	2.64%	1.74%
20	21600	920500	0.83%	0.83%	0.49%	0.49%	0.00%	0.68%	0.50%
21	21600	827490	2.75%	1.72%	1.25%	1.25%	1.25%	2.00%	1.43%
22	21600	537284	2.11%	1.64%	1.87%	1.40%	1.40%	2.36%	0.64%
23	21600	404205	5.17%	3.42%	1.83%	1.73%	0.93%	1.39%	1.39%
24	21600	451491	1.27%	1.27%	0.63%	0.32%	0.32%	1.06%	1.06%
25	21600	451760	6.93%	3.81%	0.99%	0.99%	0.99%	3.11%	2.07%

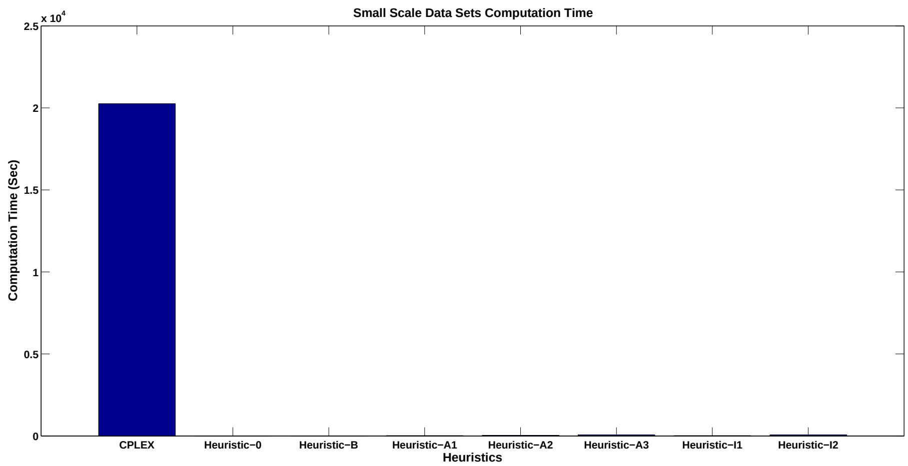
Table 4.17: Small scale data set results (sets 1-25)

Data Set	CPLEX		Heur-0 (10sec)	Heur-B (11sec)	Heur-A1 (20sec)	Heur-A2 (40sec)	Heur-A3 (60sec)	Heur-I1 (20sec)	Heur-I2 (60sec)
	Time	OFV	gap	gap	gap	gap	gap	gap	gap
26	21600	560862	5.52%	4.02%	1.98%	1.98%	1.57%	1.72%	1.72%
27	21600	442150	7.17%	5.38%	2.17%	2.17%	2.17%	2.38%	2.38%
28	21600	241736	4.98%	3.35%	1.41%	1.05%	1.05%	2.59%	1.70%
29	21600	287875	4.40%	2.78%	0.71%	0.61%	0.00%	1.20%	0.89%
30	21600	636080	2.78%	2.25%	1.15%	1.08%	1.08%	1.51%	1.51%
31	21600	511150	3.22%	2.93%	1.54%	1.27%	0.50%	2.53%	1.29%
32	21600	391509	3.64%	3.18%	0.94%	0.94%	0.94%	2.14%	0.82%
33	21600	723720	2.09%	1.72%	1.32%	0.66%	0.66%	1.22%	1.05%
34	21600	231540	0.84%	0.84%	1.12%	0.84%	0.84%	1.12%	0.84%
35	21600	732652	2.34%	1.32%	0.99%	0.99%	0.90%	1.14%	1.09%
36	21600	140640	7.34%	4.25%	2.39%	2.39%	2.37%	3.63%	3.63%
37	21600	613290	5.77%	3.32%	2.11%	2.11%	1.79%	2.38%	2.10%
38	21600	533797	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
39	5	354152	0.20%	0.20%	0.20%	0.20%	0.20%	0.14%	0.14%
40	21600	251622	2.86%	2.54%	0.36%	0.24%	0.00%	0.52%	0.52%
41	1687	393260	1.91%	1.69%	1.22%	0.96%	0.96%	1.30%	1.30%
42	21600	440309	3.73%	2.46%	2.41%	1.49%	1.49%	2.19%	2.19%
43	21600	432990	5.15%	3.50%	2.01%	1.94%	1.94%	3.54%	3.29%
44	21600	681130	2.59%	2.23%	1.57%	1.57%	1.33%	1.60%	1.50%
45	21600	458146	2.85%	2.13%	1.57%	1.57%	1.26%	1.97%	1.39%
46	21600	280662	1.10%	0.96%	0.66%	0.60%	0.60%	0.66%	0.00%
47	21600	456218	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
48	21600	853630	5.00%	2.64%	1.81%	1.81%	1.81%	2.47%	1.99%
49	21600	221014	0.24%	0.24%	0.20%	0.07%	0.07%	0.66%	0.31%
50	21600	387540	4.56%	2.35%	1.34%	1.34%	0.15%	1.17%	1.17%

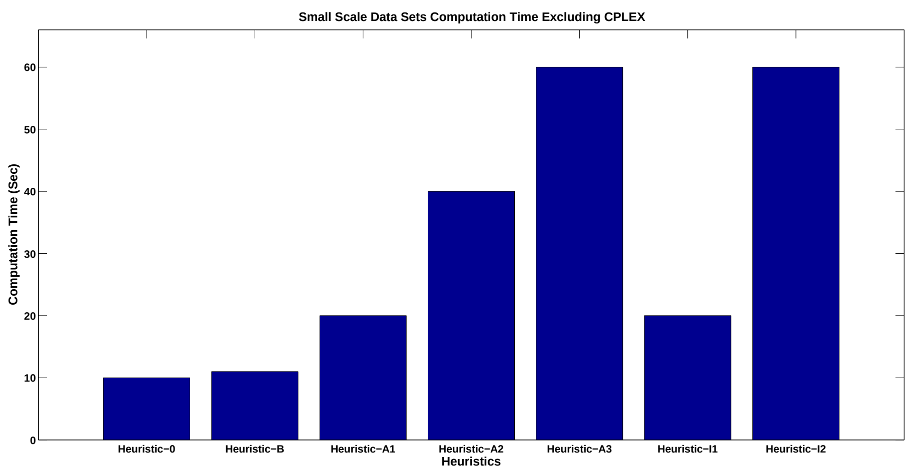
Table 4.18: Small scale data set results (sets 26-50)



(a) Gap



(b) Computation time



(c) Computation time excluding CPLEX

Figure 4.4: Gap and computation time for small scale sets

As shown in the results, `Heuristic-0` produces results with a mean gap of 3.57% and standard deviation of 0.0281 in a short computation time. `Heuristic-B` improves the solution with gap average of 2.29% and standard deviation of 0.014.

Because `Heuristics-A1`, `Heuristics-A2`, and `Heuristics-A3` have a larger neighborhood structure than `Heuristics-0` and `Heuristics-B`, they produce better solution as in `Heuristic-A1` with a mean gap of 1.26% and standard deviation of 0.007, `Heuristic-A2` with a mean gap of 1.08% and standard deviation of 0.00647, and `Heuristic-A3` with a mean gap of 0.94% and standard deviation 0.006. `Heuristic-I1` has better results than the `Heuristic-0` and `Heuristic-B` variants with a mean gap of 1.82% and standard deviation of 0.01174, while `Heuristic-I2` gives solutions with a mean gap of 1.49% and standard deviation of 0.01128.

In small data sets, the proposed heuristics are highly recommended because in one minute they can give results with a gap less than 1% in many instances, while CPLEX takes 6 hours to determine near optimal solutions. `Heuristic-A3` is recommended because it gives the best results in a short time while other variants give worse results without saving valuable time. For example, the `Heuristics-0` has mean gap of 3.57%, but spending 50 seconds more improves the solutions greatly to a mean gap of 0.94%.

4.7.4 Medium Scale Problems

In this subsection, larger data sets are considered. CPLEX does not give any solution to this size in 6 hours. Because of this, gap is redefined to be the gap between the solution and the minimum solution among all versions. The gap of a solution S is

$$gap_s = \frac{\texttt{OFV of S - Minimum OFV}}{\texttt{Minimum OFV}} 100\%$$

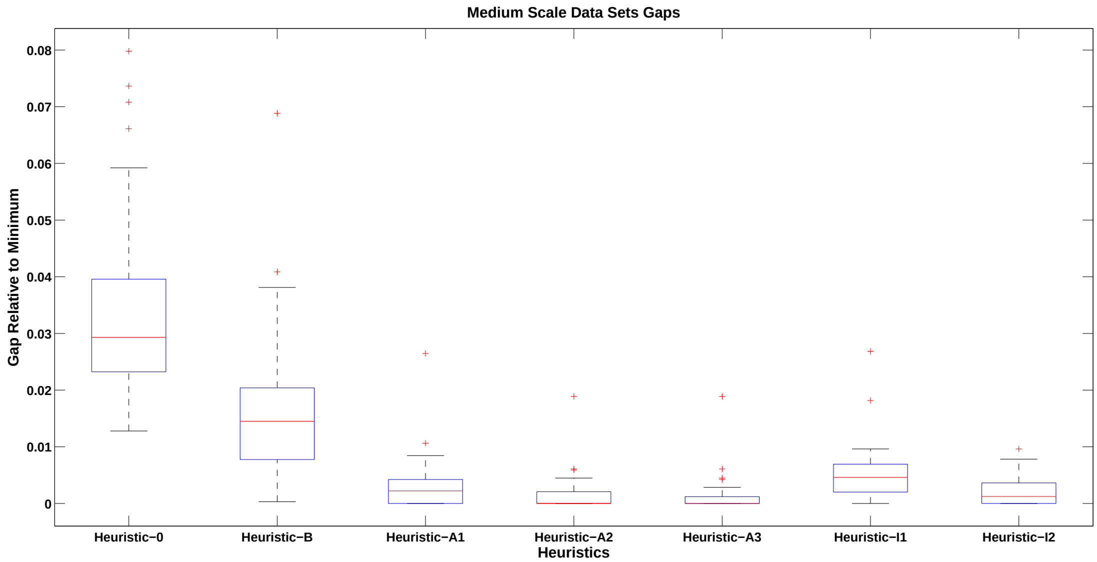
Tables 4.19 and 4.20 show the results of these data sets, and Figure 4.5 shows the box-plot of the gap and the bar plot of the computation time. Time limits are 60 seconds for `Heuristic-0`, 66 seconds for `Heuristic-B`, 600 seconds for `Heuristic-A1`, 1200 seconds for `Heuristic-A2`, 1800 seconds for `Heuristic-A3`, 600 seconds for `Heuristic-I1`, and 600 seconds repeated three times for `Heuristic-I2`

Data	Min. Obj.	**CPLEX**		**Heur-0 (60 sec)**	**Heur-B (66 sec)**	**Heur-A1 (600 sec)**	**Heur-A2 (1200 sec)**	**Heur-A3 (1800 sec)**	**Heur-I1 (600 sec)**	**Heur-I2 (1800 sec)**
Set	Value	Time	OFV	gap	gap	gap	gap	gap	gap	gap
1	928858	21600	No Soln	3.69%	3.69%	0.49%	0.13%	0.00%	0.51%	0.51%
2	1529400	21600	No Soln	2.37%	1.63%	0.24%	0.24%	0.22%	0.43%	0.00%
3	2805420	21600	No Soln	1.35%	0.17%	0.10%	0.00%	0.00%	0.37%	0.00%
4	1906670	21600	No Soln	3.61%	0.83%	0.42%	0.12%	0.12%	0.37%	0.00%
5	801382	21600	No Soln	5.92%	2.18%	0.00%	0.00%	0.00%	0.93%	0.56%
6	1683350	21600	No Soln	2.51%	2.51%	0.00%	0.00%	0.00%	0.08%	0.08%
7	1310170	21600	No Soln	3.17%	1.53%	0.19%	0.19%	0.19%	0.28%	0.00%
8	986323	21600	No Soln	3.33%	2.96%	0.01%	0.01%	0.00%	0.58%	0.32%
9	2697340	21600	No Soln	1.67%	0.59%	0.38%	0.24%	0.24%	0.31%	0.00%
10	2795330	21600	No Soln	2.97%	1.06%	0.17%	0.17%	0.17%	0.37%	0.00%
11	1772760	21600	No Soln	2.20%	2.04%	0.18%	0.18%	0.18%	0.71%	0.00%
12	2258300	21600	No Soln	2.61%	1.48%	0.23%	0.00%	0.00%	0.51%	0.39%
13	1051940	21600	No Soln	5.05%	1.90%	0.03%	0.03%	0.00%	0.87%	0.78%
14	1766640	21600	No Soln	2.52%	1.53%	0.00%	0.00%	0.00%	0.59%	0.08%
15	2654650	21600	No Soln	2.00%	1.04%	0.00%	0.00%	0.00%	0.25%	0.18%
16	966704	21600	No Soln	2.66%	1.20%	0.00%	0.00%	0.00%	0.66%	0.59%
17	2931340	21600	No Soln	1.28%	0.36%	0.00%	0.00%	0.00%	0.31%	0.25%
18	1792000	21600	No Soln	3.68%	1.23%	0.45%	0.00%	0.00%	0.41%	0.22%
19	2177910	21600	No Soln	2.72%	1.66%	0.79%	0.00%	0.00%	0.13%	0.13%
20	2492010	21600	No Soln	3.96%	1.43%	0.46%	0.20%	0.00%	0.58%	0.27%
21	2492800	21600	No Soln	2.92%	1.55%	0.73%	0.59%	0.00%	0.72%	0.63%
22	1488200	21600	No Soln	2.32%	0.47%	0.04%	0.00%	0.00%	0.79%	0.08%
23	1485120	21600	No Soln	2.88%	1.97%	0.84%	0.00%	0.00%	0.92%	0.34%
24	755301	21600	No Soln	7.37%	2.81%	0.63%	0.00%	0.00%	0.20%	0.20%
25	1442420	21600	No Soln	2.58%	0.91%	0.36%	0.31%	0.28%	0.52%	0.00%

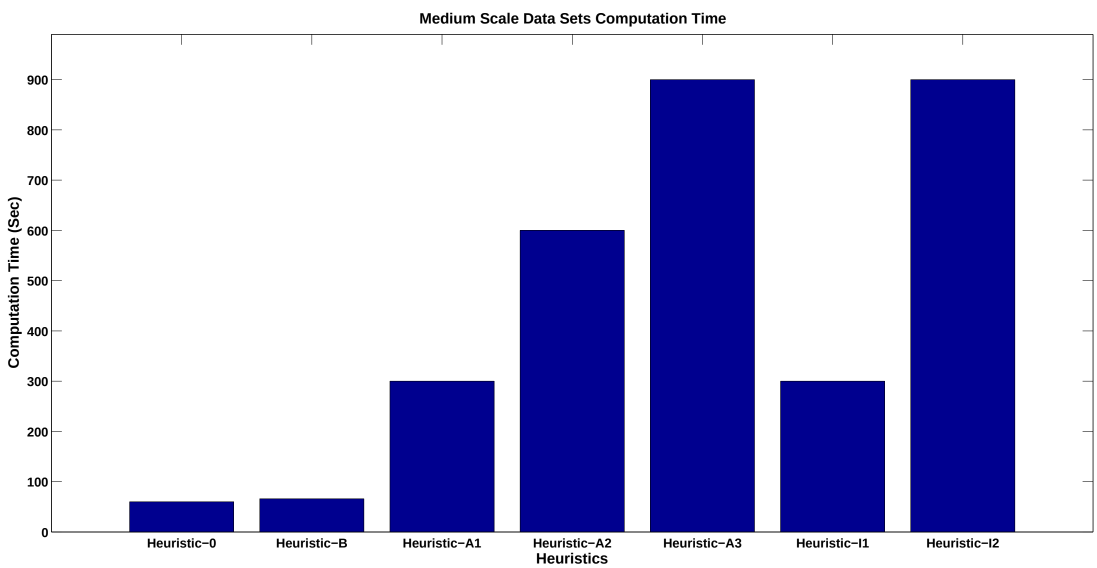
Table 4.19: Medium scale data set results (sets 1-25)

Data	Min. Obj.	**CPLEX**		**Heur-0 (60 sec)**	**Heur-B (66 sec)**	**Heur-A1 (600 sec)**	**Heur-A2 (1200 sec)**	**Heur-A3 (1800 sec)**	**Heur-I1 (600 sec)**	**Heur-I2 (1800 sec)**
Set	Value	Time	OFV	gap	gap	gap	gap	gap	gap	gap
26	1801260	21600	No Soln	4.55%	2.11%	0.55%	0.39%	0.00%	0.50%	0.39%
27	1151870	21600	No Soln	6.61%	3.80%	0.61%	0.61%	0.61%	1.82%	0.00%
28	1407980	21600	No Soln	4.85%	0.98%	0.15%	0.15%	0.15%	0.00%	0.00%
29	1525910	21600	No Soln	1.50%	0.51%	0.11%	0.00%	0.00%	0.17%	0.12%
30	1435790	21600	No Soln	3.30%	0.77%	0.40%	0.00%	0.00%	0.08%	0.08%
31	2077950	21600	No Soln	3.10%	1.64%	0.26%	0.10%	0.10%	0.16%	0.00%
32	2142580	21600	No Soln	4.19%	2.02%	1.07%	0.00%	0.00%	0.75%	0.75%
33	1433270	21600	No Soln	4.65%	2.84%	0.28%	0.28%	0.04%	0.85%	0.00%
34	2029990	21600	No Soln	2.12%	1.34%	0.00%	0.00%	0.00%	0.61%	0.40%
35	1361960	21600	No Soln	2.83%	1.09%	0.00%	0.00%	0.00%	0.56%	0.55%
36	1760760	21600	No Soln	3.81%	3.81%	0.00%	0.00%	0.00%	0.36%	0.24%
37	3687690	21600	No Soln	2.87%	0.51%	0.00%	0.00%	0.00%	0.42%	0.04%
38	2770330	21600	No Soln	1.36%	0.77%	0.00%	0.00%	0.00%	0.14%	0.14%
39	1209690	21600	No Soln	4.45%	0.03%	0.26%	0.21%	0.00%	0.50%	0.27%
40	1490920	21600	No Soln	5.28%	2.37%	0.42%	0.42%	0.42%	0.69%	0.00%
41	3571340	21600	No Soln	2.07%	0.75%	0.00%	0.00%	0.00%	0.20%	0.11%
42	3132370	21600	No Soln	3.71%	1.11%	0.22%	0.22%	0.01%	0.00%	0.00%
43	4502810	21600	No Soln	1.70%	0.38%	0.14%	0.14%	0.00%	0.13%	0.13%
44	1246840	21600	No Soln	3.51%	0.98%	0.62%	0.45%	0.45%	0.04%	0.00%
45	2606130	21600	No Soln	2.94%	0.67%	0.23%	0.18%	0.00%	0.55%	0.36%
46	1132090	21600	No Soln	7.08%	6.88%	0.00%	0.00%	0.00%	0.96%	0.96%
47	998599	21600	No Soln	7.98%	4.09%	2.65%	1.89%	1.89%	2.69%	0.00%
48	1729040	21600	No Soln	1.85%	1.57%	0.28%	0.28%	0.28%	0.11%	0.00%
49	1685150	21600	No Soln	1.75%	0.48%	0.28%	0.00%	0.00%	0.23%	0.02%
50	1901940	21600	No Soln	2.47%	1.74%	0.00%	0.00%	0.00%	0.77%	0.47%

Table 4.20: Medium scale data set results (sets 26-50)



(a) Gap



(b) Computation time

Figure 4.5: Gap and computation time for medium scale sets

CPLEX fails to find any feasible solutions for medium–scale problems, even with a time limit longer than 6 hours. The `Heuristic-0` solutions have a mean gap of a 3.36% and standard deviation of 0.0157. `Heuristic-B` improves the solutions to a mean gap of 1.64% and standard deviation of 0.0122. `Heuristic-A1` has results with a mean gap of 0.31% and standard deviation of 0.004. `Heuristic-A2` improves the solution even further with mean gap of 0.16% and standard deviation of 0.0029. `Heuristic-A3` gives the best solution in most sets with a mean gap of 0.11% and standard deviation of 0.0028. `Heuristic-I1` produces results with a mean gap of 0.51% and standard deviation of 0.0045, and `Heuristic-I2` improves the results of `Heuristic-I1` to a mean gap of 0.21% and standard deviation of of 0.00244.

4.7.5 Large Scale Problems

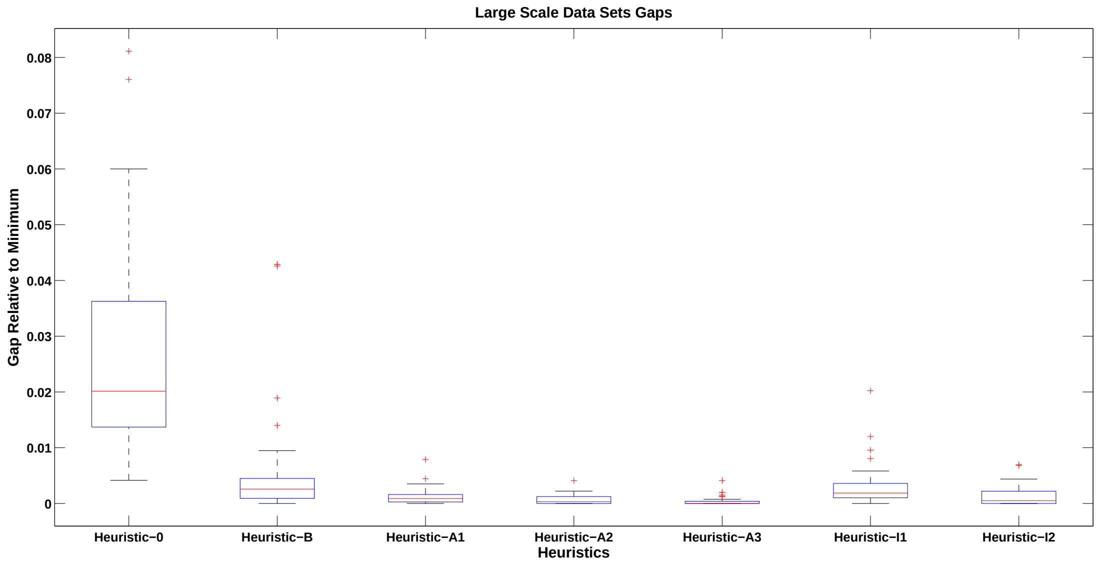
In this subsection, large scale data sets are considered to test the scalability of the proposed heuristics and show that they are suitable for this type of data sets. No solutions are obtained from CPLEX in 6 hours, so creating a feasible integer solution is a challenging problem. The suggested heuristics are used to solve these sets with a time limit of 600 seconds for `Heuristic-0`, 660 seconds for `Heuristic-B`, 1200 seconds for `Heuristic-A1`, 2400 seconds for `Heuristic-A2`, 3600 seconds for `Heuristic-A3`, 1200 seconds for `Heuristic-I1`, and 1200 seconds with three `Heuristic-I1` replications for `Heuristic-I2`. The same gap definition from section 4.7.4 is used. Tables 4.21 and 4.22 show the results of these sets and Figure 4.6 shows the box-plot of the gap and bar plot of the time.

Data	Min. Obj.	**CPLEX**		**Heur-0 (600sec)**	**Heur-B (660sec)**	**Heur-A1 (1200sec)**	**Heur-A2 (2400sec)**	**Heur-A3 (3600sec)**	**Heur-I1 (1200sec)**	**Heur-I2 (3600sec)**
Set	Value	Time	OFV	gap	gap	gap	gap	gap	gap	gap
1	5199930	21600	No Soln	5.16%	0.16%	0.05%	0.05%	0.04%	0.14%	0.00%
2	9102900	21600	No Soln	1.69%	0.60%	0.13%	0.13%	0.00%	0.30%	0.29%
3	9261110	21600	No Soln	2.96%	0.00%	0.15%	0.15%	0.06%	0.29%	0.29%
4	6760140	21600	No Soln	2.72%	0.47%	0.29%	0.00%	0.00%	0.38%	0.37%
5	12433200	21600	No Soln	2.77%	0.00%	0.28%	0.02%	0.02%	0.21%	0.04%
6	3938800	21600	No Soln	4.66%	0.69%	0.79%	0.04%	0.04%	0.00%	0.00%
7	4508870	21600	No Soln	5.32%	0.43%	0.00%	0.00%	0.00%	1.20%	0.70%
8	8657580	21600	No Soln	4.29%	4.26%	0.00%	0.00%	0.00%	0.96%	0.34%
9	4328400	21600	No Soln	2.95%	1.40%	0.00%	0.00%	0.00%	0.51%	0.41%
10	6349750	21600	No Soln	3.07%	0.00%	0.35%	0.12%	0.12%	0.54%	0.07%
11	3473970	21600	No Soln	5.49%	0.95%	0.16%	0.16%	0.00%	0.19%	0.19%
12	8520220	21600	No Soln	3.63%	0.28%	0.26%	0.20%	0.20%	0.00%	0.00%
13	2722880	21600	No Soln	8.11%	1.89%	0.00%	0.00%	0.00%	2.02%	0.68%
14	14113300	21600	No Soln	3.07%	0.00%	0.44%	0.41%	0.41%	0.34%	0.19%
15	18787200	21600	No Soln	1.68%	0.29%	0.00%	0.00%	0.00%	0.17%	0.17%
16	9586200	21600	No Soln	2.01%	0.33%	0.00%	0.00%	0.00%	0.44%	0.18%
17	20355600	21600	No Soln	0.45%	0.01%	0.03%	0.00%	0.00%	0.11%	0.05%
18	4090640	21600	No Soln	7.60%	0.42%	0.16%	0.16%	0.00%	0.44%	0.44%
19	19053200	21600	No Soln	1.64%	0.11%	0.09%	0.08%	0.00%	0.09%	0.03%
20	19171800	21600	No Soln	1.22%	0.08%	0.13%	0.13%	0.00%	0.04%	0.03%
21	5976030	21600	No Soln	4.14%	4.29%	0.00%	0.00%	0.00%	0.58%	0.26%
22	24445800	21600	No Soln	0.42%	0.42%	0.00%	0.00%	0.00%	0.05%	0.00%
23	15692900	21600	No Soln	1.45%	0.23%	0.00%	0.00%	0.00%	0.14%	0.14%
24	18946000	21600	No Soln	1.11%	0.19%	0.11%	0.00%	0.00%	0.15%	0.02%
25	4331500	21600	No Soln	4.03%	0.44%	0.00%	0.00%	0.00%	0.41%	0.41%

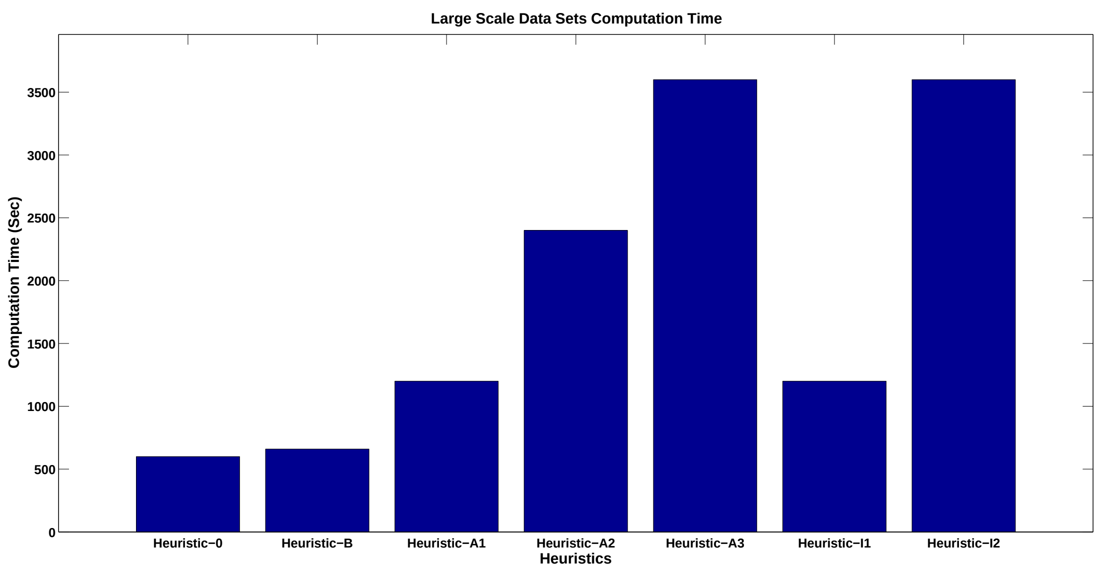
Table 4.21: Large scale data set results (sets 1-25)

Data	Min. Obj.	CPLEX		**Heur-0 (600sec)**	**Heur-B (660sec)**	**Heur-A1 (1200sec)**	**Heur-A2 (2400sec)**	**Heur-A3 (3600sec)**	**Heur-I1 (1200sec)**	**Heur-I2 (3600sec)**
Set	Value	Time	OFV	gap	gap	gap	gap	gap	gap	gap
26	11707600	21600	No Soln	2.38%	0.27%	0.16%	0.15%	0.00%	0.22%	0.07%
27	12358200	21600	No Soln	1.61%	0.45%	0.21%	0.15%	0.15%	0.33%	0.00%
28	10995800	21600	No Soln	1.70%	0.31%	0.03%	0.02%	0.02%	0.05%	0.00%
29	6044960	21600	No Soln	3.63%	0.78%	0.21%	0.18%	0.00%	0.81%	0.22%
30	8457880	21600	No Soln	1.71%	0.47%	0.27%	0.12%	0.00%	0.36%	0.36%
31	7092580	21600	No Soln	4.50%	0.43%	0.22%	0.22%	0.08%	0.36%	0.00%
32	29186200	21600	No Soln	0.42%	0.14%	0.04%	0.04%	0.03%	0.12%	0.00%
33	9516200	21600	No Soln	1.60%	0.46%	0.08%	0.08%	0.06%	0.24%	0.00%
34	13883100	21600	No Soln	2.28%	0.09%	0.09%	0.00%	0.00%	0.18%	0.05%
35	22829800	21600	No Soln	1.37%	0.00%	0.18%	0.17%	0.13%	0.25%	0.11%
36	12748400	21600	No Soln	2.77%	0.24%	0.00%	0.00%	0.00%	0.28%	0.00%
37	12705600	21600	No Soln	2.02%	0.23%	0.04%	0.00%	0.00%	0.16%	0.05%
38	15699000	21600	No Soln	1.63%	0.00%	0.07%	0.07%	0.07%	0.14%	0.14%
39	12719400	21600	No Soln	2.31%	0.01%	0.16%	0.00%	0.00%	0.01%	0.01%
40	4006900	21600	No Soln	6.00%	0.88%	0.00%	0.00%	0.00%	0.36%	0.12%
41	31674500	21600	No Soln	0.75%	0.07%	0.09%	0.03%	0.03%	0.11%	0.00%
42	21076300	21600	No Soln	0.54%	0.16%	0.05%	0.03%	0.03%	0.10%	0.00%
43	13002700	21600	No Soln	1.32%	0.23%	0.19%	0.10%	0.00%	0.27%	0.27%
44	24388600	21600	No Soln	1.01%	0.11%	0.09%	0.03%	0.02%	0.10%	0.00%
45	9321270	21600	No Soln	2.46%	0.17%	0.15%	0.11%	0.07%	0.10%	0.00%
46	23020700	21600	No Soln	0.66%	0.00%	0.03%	0.03%	0.00%	0.08%	0.05%
47	12763300	21600	No Soln	1.73%	0.07%	0.12%	0.02%	0.02%	0.00%	0.00%
48	13673200	21600	No Soln	0.88%	0.34%	0.05%	0.05%	0.05%	0.00%	0.00%
49	14635000	21600	No Soln	1.38%	0.25%	0.11%	0.09%	0.04%	0.17%	0.00%
50	19091900	21600	No Soln	1.02%	0.28%	0.14%	0.00%	0.00%	0.16%	0.16%

Table 4.22: Large scale data set results (sets 26-50)



(a) Gap



(b) Computation time

Figure 4.6: Gap and computation time for large scale sets

As seen, `Heuristic-0` gives the worst results with an average gap of 2.59% and standard deviation of 0.0178, but also using the shortest time. `Heuristic-B` improves the results greatly compared to the `Heuristic-0` variant with a 0.49% gap average and 0.0085 standard deviation. `Heuristic-A1`, `Heuristic-A2`, and `Heuristic-A3` give better results such as `Heuristic-A1` with a mean gap of 0.12% and standard deviation of 0.0014, `Heuristic-A2` with a mean gap of 0.07% and standard deviation of 0.0008, and the best solutions are obtained by `Heuristic-A3` which has mean gap of 0.03% and standard deviation of 0.00069. For (I) variants, `Heuristic-I1` has better solution than `Heuristic-B` but takes 9 minutes longer time. The average gap of `Heuristic-I1` results is only 0.029% and standard deviation is 0.0034% which are almost the same as those of `Heuristic-A1` and are produced in a slightly shorter time. `Heuristic-I2` produces better results with a mean gap of 0.14% and standard deviation of 0.00174.

In large scale sets, time becomes more important and choosing between variants becomes a trade off problem. If very short time is available for the users, `Heuristic-B` can be used, while `Heuristic-A1` or `Heuristic-I1` can be used if more time is available. `Heuristic-A2` and `Heuristic-A3` would be the best choices if time is not an issue.

4.8 Numerical Analysis with Respect to Scales

In this section, a brief analysis is presented to show the performance of the proposed approaches versus the set scales. First, to see the effect of `Heuristic-B`, the average of the gaps is drawn with `Heuristic-0` versus the data set scales as in Figure 4.7. In the figure, the amount of improvement achieved by `Heuristic-B` increases with increasing set size. It can be concluded that `Heuristic-B` becomes more beneficial as the size of a set increases because the chance of finding suitable nodes for replacement or insertion is higher with larger sets.

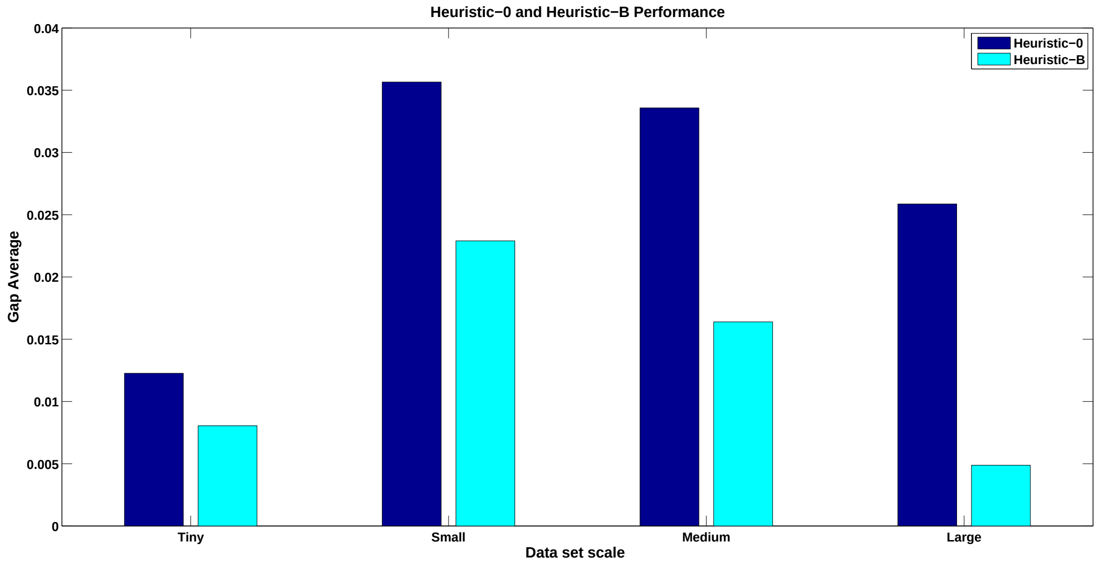


Figure 4.7: `Heuristic-0` and `Heuristic-B` vs. scale

Second, if a long computation time limit is available for users, it is better to use `Heuristic-A` with time limit equal to the available time in the termination criterion. As described in the numerical analysis, giving a longer time limit to `Heuristic-A` improves the results. Figure 4.8 shows the results of `Heuristic-A1`, `Heuristic-A2`, and `Heuristic-A3` with different set scales. As seen, `Heuristic-A3` is always the best, and it is better in the cases of large and medium scale than in those of tiny and small scales. This is because CPLEX results are not available for medium and large scales which allows the results of `Heuristic-A3` to be the best in the most sets. Since gaps are calculated based on the best solution, the gap average of `Heuristic-A3` is better for medium and large scales than for tiny and small scales.

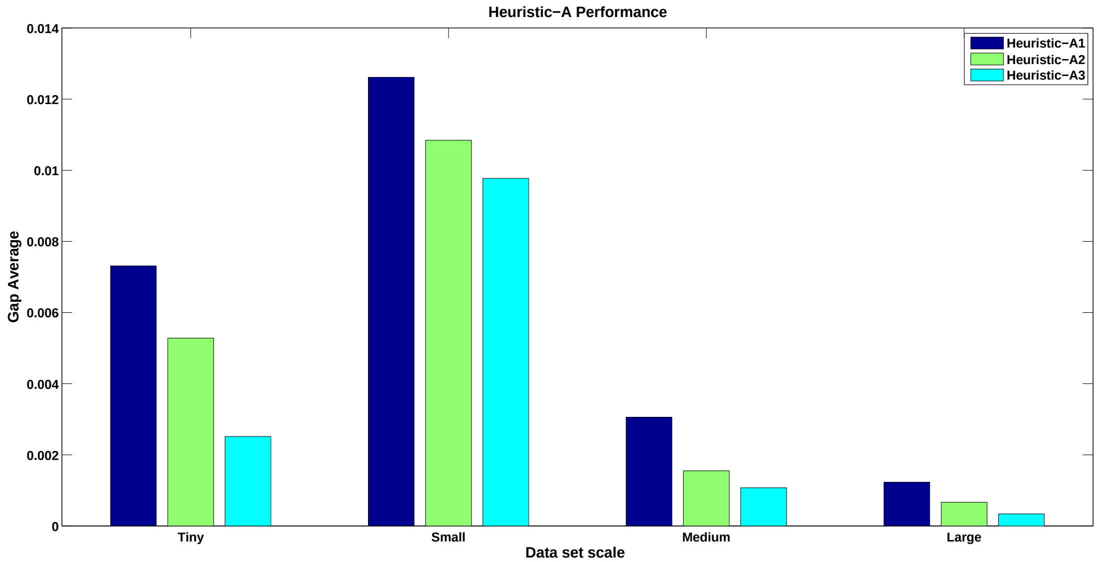


Figure 4.8: Gap averages produced by `Heuristics-A` vs. size scales

Third, `Heuristic-I` variants fail to compete with other heuristics. Figure 4.8 shows the results of `Heuristic-I` variants with all other results in one figure with different scales. As seen, `Heuristic-I2` is defeated by `Heuristic-A3` in all scales. One of the unexpected results is that `Heuristic-0` and `Heuristic-B` are better than `Heuristic-I1` in tiny scale. This can be justified by the fact that the time limit in tiny scale is short and the chance of finding candidate nodes for replacement and insertion is low; `Heuristic-I1` consumes time for local search without any improvement which reduces the number of iterations which can be performed. `Heuristic-0` and `Heuristic-B` perform more iterations because they do not consume time for local search which allows them to find more solutions and finds better incumbents at the end.

In general from Figure 4.9, `Heuristic-A3` shows the best results among all heuristics, `Heuristic-B` is always better than `Heuristic-0`, and `Heuristics-A` is better than `Heuristics-I`.

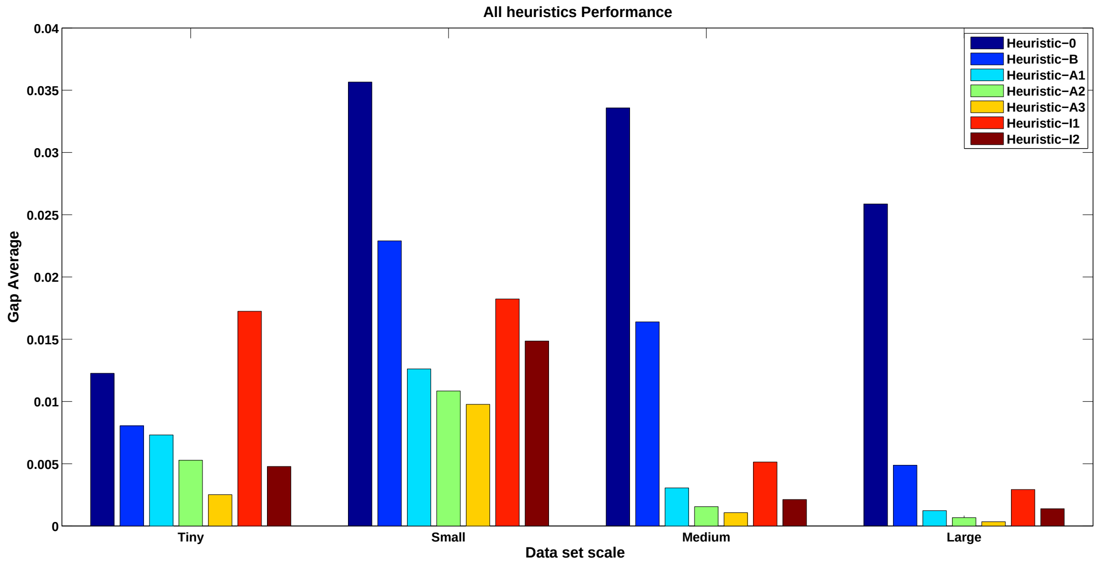


Figure 4.9: Gap average comparison for all proposed heuristics at different size scales

The other comparison which can be made is how many times each heuristic produces the best results compared to the other heuristics. Because 75 sets were solved for tiny scale and 50 sets for other scales, the percentage, instead of using the numbers, of how many times each heuristic produces the best results is drawn in Figure 4.10. It can be noticed that `Heuristic-A3`, which gives the best gap average in all scales, gives the most best solutions for scales. Even the number of best solutions for `Heuristic-A3` in small scale sets is low, it does very well for other sets as shown in Figure 4.8 which shows that a mean gap of 0.98% for small scale sets, and the analysis of Figure 4.4 shows a narrow spread of `Heuristic-A3` gaps for small scale sets.

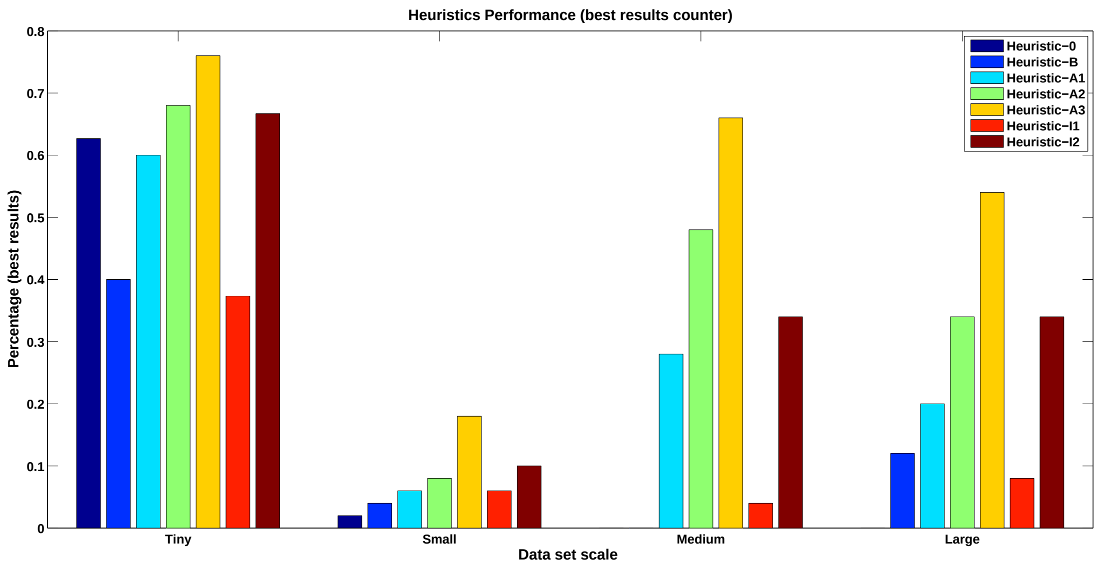


Figure 4.10: Percentages of how many times best solution is produced

4.9 Summary

In this chapter, a new model (HLVRP model) is developed to incorporate vehicle routing and three logistic operations in a single framework, which improves resource utilization in post–disaster situations. In this model, incorporating work–force transfer with the demand distribution and wounded evacuation in a single logistic system represents the first contribution. Considering detailed vehicle routes overcomes the main shortcoming of YK'+WT model and represents another contribution. Finally, creating novel solution approaches represents the last contribution of the work discussed in this chapter.

The HLVRP is an NP–hard problem and can not be solved in a reasonable time using commercial packages. Hence, a new heuristic approach is created to solve the model. The proposed approach depends on building a route for each vehicle using a greedy approach, then solving the model using CPLEX at specific binary variable values to determine for each vehicle the quantities which should be picked up, amount which should be delivered to each node, number of workers which should be transfered, and the number of wounded which should be evacuated. All of these decisions are made for each time period. This approach is iterated many times by changing the routes to explore more choices and ultimately select the best one.

Different local searches are added to the proposed approach to improve the results. These are replacement and insertion applied to replace one node by two other nodes or to insert one or more nodes into the vehicle routes. These local searches use initial routes to start so they can be applied in different places in the heuristic using different initial routes. First, `Heuristic-B` is performed at the end of the approach to improve the best routes achieved. In this type, the initial routes to start the local searches are taken from the best routes achieved after finishing the basic run ($XI_{vijt} = XB_{vijt}$). Second, `Heuristic-A1`, `Heuristic-A2`, and `Heuristic-A3` are applied at the end of each iteration of the approach to improve the current candidate routes. In this case, the initial routes are taken as the current iteration routes ($XI_{vijt} = XC_{vijt}$). The difference between the three variants of this type is the time limit. Short time limit is given for `Heuristic-A1`, medium time limit is given for `Heuristic-A2`, and long time limit is given for `Heuristic-A3`. Finally, `Heuristic-I1` and `Heuristic-I2` are applied at the end of each iteration of the approach if the solution of the this iteration is improved. In this type, the initial routes are the current routes and the condition of improved solution should be satisfied ($XI_{vijt} = XC_{vijt}$ and $ZC \leq Z^*$).

To test the performance of the approaches, an extensive numerical analysis has been preformed on four different data set scales: tiny, small, medium, and large. The results show that `Heuristic-B` is highly recommended in cases of limited waiting time because it can improve the results of `Heuristic-0` with very little time added.

`Heuristic-A` has different termination criteria and is recommended in non-urgent cases where a longer computation time limit is available. Because this variant is applied for each candidate solution, it gives the best results among all other heuristics, which is expected due to the larger exploration space available in this case. `Heuristic-A` is recommended for tiny and small scales because it does not take a long time to give excellent results. For example, in small scale problems, it takes 10 seconds to produce results with a mean gap of 3.57%

using `Heuristic-0` and 60 seconds to improve the results to a mean gap of 0.98%. In the case of medium and large scale sets, it is hard to differentiate between the heuristics because it depends on how much computation time is available.

`Heuristic-I1` and `Heuristic-I2` are not recommended because they are always defeated by one of the `Heuristic-A` variants. `Heuristic-I1` is used with a short time limit and gives results with high variation (i.e., high standard deviations compared to `Heuristic-A` variants). This is because `Heuristic-I1` performs local search when the current candidate solution is improved which shrinks the search space. However, when `Heuristic-I1` finds good candidates for replacement and insertion, it could improve the solution greatly in some instances. This results in low gaps in many instances and bad gaps in others. Some tests show that increasing the time limit for `Heuristic-I1` is not helpful, because continuing to perform local search for only improved solutions could not lead to better results. To overcome this problem, `Heuristic-I2` is performed by repeating `Heuristic-I1` four times which allows it to reinitialize the best routes and start local search in different spaces. `Heuristic-I2` shows a good improvement over `Heuristic-I1`, but `Heuristic-A3`, which has the same time limit of `Heuristic-I2`, gives better results than `Heuristic-I2`. It can be concluded that even through applying local search to the improved solution is recommended in many research fields, it fails to give competitive results in this research and is not recommended.

The next chapter addresses the last model which improves and overcomes some limitations of the HLVRP model. The first limitation of the HLVRP model is that it does not consider any special care for using large vehicles where they can not be used efficiently in many cases in post–disaster situations; the next model suggests a novel use for them. Second, using a single objective function in the HLVRP model requires the specification of priority values which could lead to bad results if improper values are used. Thus, the next model uses multiple objective functions to avoid this problem.

Chapter 5

Incorporating Satellite Facilities and Multiple Objectives

5.1 Introduction

Employing large vehicles to serve as satellite facilities (SFs) may help to improve distribution efforts. Additionally, it is clear that there are multiple objectives relevant to post-disaster relief efforts, for example, minimizing unsatisfied demand, minimizing the number of non–evacuated wounded, and minimizing the number of non–transfered workers. In the HLVRP model, a single objective function is used, where it is noted that the humanitarian logistic models are quite sensitive to changes in the coefficients of the objective function. Because of this, using multiple objective functions leads to more realistic solutions and will be adopted in this chapter.

In this chapter, a new model is developed to incorporate the use of SFs and multiple objectives. Knowledge obtained through the development of the aforementioned models will be applied to the construction of this new model. With appropriate modifications to consider SFs and multiple objectives, the same concepts of heuristic approaches under development for the HLVRP are applicable to the new model.

This chapter is organized as follows. Section 5.2 describes the problem to be solved in the chapter. Section 5.3 describes the mathematical model used to solve the problem. Section 5.4 includes the formulation of the model. Section 5.5 provides a small example to verify the formulation and demonstrate the benefits of using SFs. Section 5.6 explains the proposed solution approaches. Section 5.7 provides the suggested approaches for route construction and solution generation. Section 5.8 shows some numerical results for specific data sets obtained by the proposed solution approaches. Section 5.9 discusses the advantages and disadvantages of the suggested solution approaches and suggests a new solution approach.

Section 5.10 solves a case study and proposes a procedure to compare between single and multi–objective models. Section 5.11 summarizes the chapter.

5.2 Problem Description

In post–disaster relief operations, many humanitarian agencies work together to allocate available resources to areas affected by a disaster, transfer relief workers to areas affected by a disaster, and evacuate wounded to hospitals. Each agency has a set of vehicles provided by different donors; consequently, vehicles have different specifications for speed, capacity, and starting location. Some of these vehicles can not be utilized efficiently in post–disaster situations because of destroyed infrastructure and the low speed of some large vehicles. This chapter solves a post–disaster humanitarian relief logistic problem where small and large vehicles are utilized differently. In this problem, large vehicles are called satellite facilities (SFs). The reasons for and importance of utilizing large vehicles in a unique manner is discussed in Section 5.2.1.

Unlike the network in the HLVRP model, nodes in this problem's network are classified into four main groups: demand nodes, supply nodes, candidate SF locations, and hospital nodes. Demand nodes represent the affected areas where people request demand from supply nodes and wounded people await evacuation. Supply nodes represent the warehouses or temporary stores built after disasters. Candidate SF locations are empty nodes representing candidate locations for SF parking. Once SFs park at the candidate SF locations, these locations serve as supply nodes. Finally, hospital nodes represent medical facilities in the area of a disaster which were not destroyed by the disaster, or any non-permanent emergency center built by humanitarian agencies.

The same operations considered in the HLVRP model are also considered here. These include demand dispatching, wounded evacuation, and work-force transfer. Demand is classified into different types, such as food and medical supplies, where each type has its own priority value which varies among nodes. Similarly, workers are classified into different categories based on their professions, such as doctors, nurses, drivers, and maintenance technicians. Every worker requested by a demand node has a priority based on his profession and the node which requests him. Wounded waiting at demand nodes are classified into different categories (levels) based on their injury level. Each level has a priority value dependent on the seriousness of the injury and the demand node where the wounded are waiting. Sometimes, wounded with a given injury level will have a higher priority at one node than wounded of the same injury level at another node. This is because the lack of medications and doctors at some nodes makes the wounded evacuation more urgent.

Logistic operations are performed as follows: both vehicles and SFs are filled with commodities and workers from the main depots (supply nodes). Vehicles then begin distributing the demand and workers to the demand nodes, while the SFs select the best SF locations to park based on vehicle movement. SFs select to park in some of SF locations to minimize the distance traveled by vehicles to these locations for resupply. After a vehicle has completed its first trip, it has many choices. It can travel to a hospital to drop wounded people, travel to a SF (which functions as a mobile supply node in this problem), or visit a supply node to replenish and restart distribution. This procedure continues for the reminder of the available time. It is assumed that vehicles can revisit hospitals to perform evacuation as often as necessary, and visit candidate SF locations to pick up supplies and workers from SFs instead of going back to supply nodes if this saves time. However, they must return to their depots before the end of time horizon. In the case of SF routes, SFs can only visit the candidate SF locations and can revisit any of the SF locations or spend more than one time period there. These activities can be understood more in the numeric example shown in Section 5.5.

In some cases, vehicles and SFs may perform the logistic operations different than what is described above. For example, some vehicles can arrive at demand nodes empty to evacuate wounded in the event evacuation is more important than other operations. In case a depot has limited resources, vehicles start from that depot can go directly to other depots (supply nodes) or SF locations to pick up commodities or workers. Finally, some SFs can pick up only commodities or only workers.

The goals of this problem are to deliver the maximum possible commodities to demand nodes, transfer the maximum possible workers to demand nodes, and evacuate as many wounded as possible.

5.2.1 Satellite Facilities in Post–Disaster Relief

Due to the impracticality of constructing permanent facilities immediately after a disaster, temporary mobile satellite facilities are suggested to help in distribution efforts. The benefits of using SFs in humanitarian relief operations may be observed in a variety of ways. For example, many regions of the world do not have any prepositioned facilities available in case of a disaster. In this situation, temporary mobile facilities (SFs, in this case) can be dispatched quickly to help in logistic operations. Additionally, due to a lack of *a priori* information about demands and supplies, SFs could be used to replenish vehicles in remote locations, away from primary depots.

Other benefits of using SFs are related to the availability of warehouses. For example, warehouses that exist in other cities or near airports could be used as main depots because they are already constructed and are the easiest places to receive supplies. Using these depots as main suppliers will result in a long travel time, so temporary depots (candidate SF locations) may be located closer to affected regions. Another reason for incorporating SFs is that using large vehicles (LVs) in humanitarian relief could cause problems such as road blocking and long times for unloading and dispatching commodities during distribution operations. It is, therefore, preferable to keep SFs off of major roadways and to use them as intermediate suppliers with low setup cost and time. These large vehicles can be loaded and parked at candidate locations to avoid problems.

Candidate locations are selected based on accessibility, distance from depots, and availability of security. Figure 5.1 shows an example of a system containing 1 large vehicle, 1 small vehicle, 1 hospital, 1 depot, and 10 demand nodes. Both vehicles are positioned at the depot, and four candidate SF locations are identified. It is necessary to determine a location for the large vehicle to serve as a SF, and to construct vehicle routes for the small vehicle.

A notional example demonstrating a scenario in which the large vehicle serves as a temporary supply point is described by Figure 5.2. If the large vehicle is not dispatched to a candidate satellite location, the small vehicle must make frequent return visits to the depot to re-supply (Figure 5.2a). If, as in Figure 5.2b, the large vehicle is loaded and moved to a more centralized location, the small vehicle can more efficiently deliver goods to demand nodes.

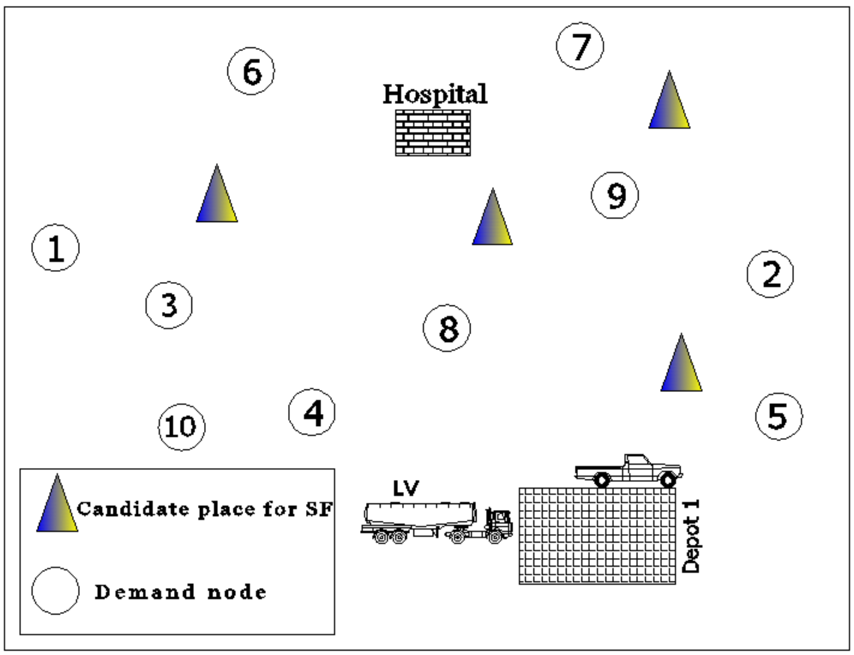
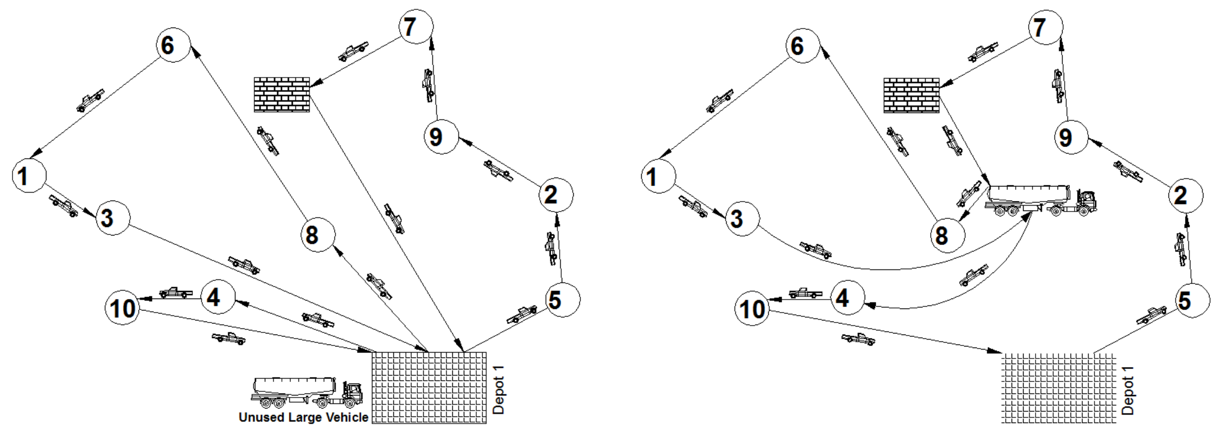


Figure 5.1: A humanitarian relief network including candidate locations for a large vehicle (LV) to serve as a satellite facility.



(a) Longer vehicle routes are required without the SF.

(b) A SF allows more efficient and timely delivery.

Figure 5.2: A comparison of vehicle routes when SFs are considered.

To better demonstrate how the humanitarian relief problem is solved used our suggested model by using SFs, Section 5.5 shows an example which will be discussed extensively later in this chapter. The next section provides an overview of the mathematical model which is used to solve the problem of this chapter.

5.3 An Overview of the HLVRPSF Model

A mixed integer linear model, called HLVRPSF model, is constructed to formulate the described problem. As with the HLVRP, the HLVRPSF includes the same input sets. First, the time horizon set T includes all discrete time slots. The time set makes all parameters, such as supplies, demand, wounded, and workers as time based parameters. Second, the set of wounded evacuee categories or levels, E, includes different injury levels such as heavy, moderate, and light. Higher injury level is given a higher priority value. Third, the set of available vehicles, V, contains all small vehicles in the network, but not the SFs. Each vehicle has its capacity, speed, and starting node. Fourth, the set of commodities C contains the different types of commodities, such as boxed food, bottled water, and clothes. Each commodity type is given a priority value varies between demand nodes. Fourth, the set of workers, W, contains all types of professions requested by the demand nodes such as nurses, doctors, and technicians. Fifth, the set of demand nodes, D, represents the areas where the demand is requested and wounded are awaiting evacuation. Sixth, the set of supply nodes S includes all nodes that have supplies such as warehouses and non–permanent stores built by the humanitarian agencies. Seventh, the set of hospital nodes, H, includes all hospitals and emergency centers. Eighth, the set of nodes, N, includes all nodes. Additionally, the HLVRPSF considers a set of satellite facilities F and a set of candidate SF locations where SFs can park L.

In this model, the set of nodes (N) contains the subsets of candidate SF locations (L), demand (D) nodes, supply (S) nodes, and hospital (H) nodes (i.e., $N = L \cup D \cup S \cup H$). Candidate SF locations are not a part of the supply node set, because a SF location can work as a supply node at time t only if SF(s) park at that location by that time.

The parameters that are assumed to be known for each time period $t \in T$ are the supplies of each type available at each supply node, demand for each type requested by each demand node, number of workers for each category available at each supply node or requested at each demand node, and the number of each level of wounded waiting at each demand node. Additionally, the average mass for each commodity type, worker category, and wounded level are assumed to be known. Specifications for speed, capacity, and starting points for all vehicles and SFs are known. Finally, priorities for each commodity type, work–force category, and wounded level are specified at each demand node.

There are many outputs (decision variable values) for this model. First, the number of commodities of each type and workers of each category to be picked up by each vehicle at each time from each supply node or SF location. Second, the number of commodities and workers to be picked up by each SF and vehicle from its depot at the first time period. Third, the number of wounded of each level to be picked up from each demand node at each time and which hospital they are delivered and when to. Fourth, a route for each vehicle. Fifth, a route for each SF which represents which SF locations to be visited and when each SF location is visited.

As discussed earlier, the HLVRPSF considers the objectives of minimizing unsatisfied commodities, non-transfered workers, and unserved wounded separately as a multiple objective model. In single objective models, a single solution is produced after solving the model and the decision variable values depend on the coefficients (priority values in this research) used in the objective function, which could lead to inappropriate solutions. For example, if relatively high priorities are applied to commodities (compared to the priorities of wounded and workers), a single solution could be available which has an excellent performance for demand distribution and poor performance for worker transfer and wounded evacuation. In contrast, the multi–objective models, as will be considered in this chapter, eliminate the effect of priority values between the objective functions and produce multiple solutions with different performance for the logistic operations.

This model considers many features. First, multiple depots are considered, each of which serve as supply node. Each vehicle begins its route at one of these depots. Second, split delivery is allowed, such that each demand node can be supplied by different vehicles. Third, heterogeneous vehicles with different speeds and capacities are used. Fourth, the HLVRPSF model considers multiple commodity types, evacuee categories, and workforce professions.

Fifth, a solution of the HLVRPSF provides a route for each vehicle, including the nodes must be visited, supplies of each type should be picked up from the SFs and supply nodes, the demand of each type to be delivered to each visited demand node, wounded of each category to be evacuated from each visited demand node, and workers of each category to be transfered to each visited demand node.

Sixth, hospitals can be visited more than once by the same vehicle which makes the HLVRPSF model more realistic. In some actual cases of the HLVRPSF, the objective of minimizing evacuation deviations becomes the main objective and there may be few hospital nodes available in the network. In this way, vehicles can perform the evacuation operation as much as necessary by revisiting the same hospitals. Seventh, SFs can revisit candidate SF locations and spend more than one time period in the same place which is easily done in practice and could cause the logistic system to become more efficient. Eighth, the HLVRPSF model considers priority values depending on the node and type or category, while the HLVRP model considers priority values depending on the category only.

The HLVRPSF relies on some practical assumptions. First, candidate SF locations are selected in discrete positions and are not part of decisions made by the model. This is because in disaster areas, the locations for delivering demand from one vehicle to another must be secured by police or security agencies. Second, each SF starts from a depot, which is one of the supply nodes, and must return to the same depot before the end of the time horizon. Third, SFs can visit only the candidate SF locations to deliver supplies and workers to vehicles. This is for the same reason (availability of security) that discrete locations are chosen. Fourth, demand nodes can not operate as transshipment nodes because leaving supplies at demand nodes could be unsafe. Fifth, workers stay at the last point they reach, and do not need to return to their starting locations. If it is necessary that they return home, a constraint set may be added to the model which is the same set discussed in the HLVRP model (Constraint 4.28). Sixth, vehicles can not revisit supply nodes, candidate SF locations, and demand nodes. Because of this, they can pick up supplies and workers from their depots only at the first time period before they leave. Seventh, each vehicle should return back to its depot to start a new plan from the same depot.

Section 5.4 contains the notations and formulation of the mixed integer linear programming model developed to solve the HLVRPSF.

5.4 Notations and Formulation

This model requires the definitions of numerous parameters and decision variables described as follows. All sets, parameters, and variables are shown in this section. Some of them have the same definition as in the HLVRP model of Chapter 4.

- List of new notations for the HLVRPSF model

- F: Set of individual large vehicles that can be used as satellite facilities (SF), $F = \{1, 2, 3, \ldots |F|\}$. $F \cap V = \phi$
- L: Set of candidate SF locations, $L = \{1, 2, 3, \ldots |L|\}$.
- N: Set of all nodes and locations, $N = \{D \cup S \cup H \cup L\}$.
- i^F_f: Initial depot of satellite vehicle $f \in F$, all $i^F_f \in S$.
- τ^F_{fij}: Integer time periods needed by SF $f \in F$ to travel from node $i \in i^F_f \cup L$ to $j \in i^F_f \cup L$.
- m^F_f: Mass capacity of SF $f \in F$.
- p^W_{wi}: Priority of workers in category $w \in W$ at node $i \in D$.
- p^C_{ci}: Priority of commodity type $c \in C$ at node $i \in D$.
- p^E_{ei}: Priority of wounded evacuees category $e \in E$ at node $i \in D$.

• List of notations that have the same definitions as in the HLVRP

- T: Set of discrete time periods in the planning horizon, $T = \{1, 2, 3, \ldots |T|\}$.
- V: Set of individual vehicles, $V = \{1, 2, 3, \ldots |V|\}$.
- E: set of different categories of evacuees (wounded) people, E= {Heavy, Moderate, Light, ...}.
- C: Set of commodity types $C = \{1, 2, 3, \ldots |C|\}$.
- W: Set of worker categories $W = \{1 \text{ (doctors)},\ 2 \text{ (nurses)},\ 3, \ldots, |W|\}$.
- D: Set of demand nodes.
- S: Set of supply nodes.
- H: Set of available hospitals.
- N: Set of all nodes and locations, $N = \{D \cup S \cup H \cup L\}$.
- i^V_v: Initial depot of vehicle $v \in V$, all $i^V_v \in S$.

- τ^V_{vij}: Integer time periods needed by vehicle $v \in V$ to travel from node $i \in N$ to $j \in N$.
- d^E_{eit}: Number of wounded of category $e \in E$ requesting evacuation from node $i \in D$ at time $t \in T$.
- d^C_{cit}: Amount of commodity type $c \in C$ demanded at node $i \in D$ at time $t \in T$.
- s^C_{cit}: Amount of commodity type $c \in C$ that can be supplied from node $i \in S$ at time $t \in T$.
- m^C_c: Unit mass of commodity $c \in C$.
- m^E_e: Average mass of an evacuee of category $e \in E$.
- s^W_{wit}: Number of workers of category $w \in W$ that are available at node $i \in S$ at time $t \in T$.
- d^W_{wit}: Number of workers of category $w \in W$ requested at node $i \in D$ at time $t \in T$.
- m^W_w: Average mass of one worker of category $w \in W$.
- m^V_v: Mass capacity of vehicle $v \in V$.

Numerous decision variable types are required to provide the more detailed solutions afforded by the HLVRPSF model. Decision variables can be grouped into different categories; pick–up, delivery, deviation, and routing. Pick–up variables define, for each vehicle at each time period, the picked up commodities of each supply type, the picked up workers of each work–force category, and the picked up wounded of each wounded level. For SFs, pick–up variables represent the commodities of each supply type and the number workers of each work–force category picked up by each SF from its depot. There are seven variables types used to define all pick–up variables, as explained below.

Delivery variables define all deliveries in the logistic system, such as the quantity of each demand type delivered by each vehicle during all time periods to demand nodes z^D_{civt}, the number of workers of each work–force category delivered by each vehicle during all time periods to demand nodes w^D_{wivt}, and the number of wounded of each level delivered by each vehicle at each time period to each hospital node e^D_{eivt}. Both z^{PL}_{cflvt} and z^{PL}_{cflvt} are considered to be picked up variables, but they can be also be regarded as delivery variables because the quantity of demand or number of workers delivered by each SF at candidate SF locations during all time periods are picked up by the vehicles.

Deviation variables represent the shortage or unsatisfied demand v^C_{cit}, unserved wounded e^D_{eivt}, and non–transfered workers v^W_{wit}. Routing variables are binary variables used to define a route for each vehicle x^V_{vijt} and for each SF x^F_{fijt}. All variables are listed below.

- Decision variables having the same definitions and notations as in the HLVRP model:
  - z^D_{civt}: Amount of commodity type $c \in C$ delivered to node $i \in D$ at time $t \in T$ by vehicle $v \in V$, where $z^D_{civt} \in \left\{0, 1, \ldots, \min\left\{d^C_{cit}, \dfrac{m^V_v}{m^C_c}\right\}\right\}$
  - v^C_{cit}: Amount of unsatisfied demand of commodity type $c \in C$ at node $i \in D$ at time $t \in T$, where $v^C_{cit} \in \left\{0, 1, \ldots, d^C_{cit}\right\}$
  - v^E_{eit}: Number of wounded of category $e \in E$ at node $i \in D$ that requested evacuation at time $t \in T$ which were not evacuated. $v^E_{eit} \in \left\{0, 1, \ldots, d^E_{eit}\right\}$
  - v^W_{wit}: Number of workers of category $w \in W$ requested by node $i \in D$ at time $t \in T$ which were not assigned. $v^W_{wit} \in \left\{0, 1, \ldots, d^W_{wit}\right\}$
  - e^D_{eivt}: Number of evacuees of category $e \in E$ transfered (delivered) to node $i \in H$ at time $t \in T$ by vehicle $v \in V$, where $e^D_{eivt} \in \left\{0, 1, \ldots, \dfrac{m^V_v}{m^E_e}\right\}$
  - e^P_{eivt}: Number of evacuees of category $e \in E$ transfered (picked up) from node $i \in D$ at time $t \in T$ by vehicle $v \in V$, where $e^P_{eivt} \in \left\{0, 1, \ldots, \min\left\{d^E_{eit}, \dfrac{{m_v}^V}{m^E_e}\right\}\right\}$
  - w^D_{wivt}: Number of workers of category $w \in W$ (e.g., nurses or doctors) transfered (delivered) to node $i \in D$ at time $t \in T$ by vehicle $v \in V$, where $w^D_{wivt} \in \left\{0, 1, \ldots, \min\left\{d^W_{wit}, \dfrac{m^V_v}{m^W_w}\right\}\right\}$

- Decision variables having the same definitions as in the HLVRP model, but using different notations:

  - z^{PS}_{civt}: Amount of commodity type $c \in C$ picked up from node $i \in S$ at time $t \in T$ by vehicle $v \in V$, where $z^{PS}_{civt} \in \left\{0, 1, \ldots, \min\left\{s^C_{cit}, \frac{m^V_v}{m^C_c}\right\}\right\}$
  - w^{PS}_{wivt}: Number of workers of category $w \in W$ transfered (picked up) from node $i \in S$ at time $t \in T$ by vehicle $v \in V$, where $w^P_{wivt} \in \left\{0, 1, \ldots, \min\left\{s^W_{wit}, \frac{m^V_v}{m^W_w}\right\}\right\}$
  - x^V_{vijt}: Binary variables used to define the small vehicles movement, such that $x^V_{vijt} = 1$ if vehicle $v \in V$ arrives at node $j \in N$ coming from node $i \in N, i \neq j$ at time $t \in T$; otherwise, $x^V_{vijt} = 0$.

- New decision variables created for the HLVRPSF:

  - z^{PL}_{cflvt}: Amount of commodity type $c \in C$ picked up by vehicle $v \in V$ at time $t \in T$ from satellite facility $f \in F$ that parks at node $l \in L$, where $z^{PL}_{cflvt} \in \left\{0, 1, \ldots, \min\left\{\sum_{f \in F} C_{cf}, \frac{m^V_v}{m^C_c}\right\}\right\}$
  - C_{cf}: Amount of commodity type $c \in C$ picked up by SF $f \in F$ from its depot, where $C_{cf} \in \left\{0, 1, \ldots, \min\left\{s^C_{cit}, \frac{m^F_f}{m^C_c}\right\}\right\}$
  - W_{wf}: Number of workers of category $w \in W$ (e.g., nurses or doctors) picked up by SF $f \in F$ from its depot, where $W_{wf} \in \left\{0, 1, \ldots, \min\left\{s^W_{wit}, \frac{m^F_f}{m^W_w}\right\}\right\}$
  - w^{PL}_{wflvt}: Number of workers of category $w \in W$ transfered (picked up) from satellite facility $f \in F$ while it is parked at node $l \in L$ at time $t \in T$ by vehicle $v \in V$, where $w^P_{wflvt} \in \left\{0, 1, \ldots, \min\left\{W_{wf}, \frac{m^V_v}{m^W_w}\right\}\right\}$
  - x^F_{fijt}: Binary variables to define SFs movement, such that $x^F_{vijt} = 1$ if satellite vehicle $f \in F$ arrives at node $j \in L \cup i^F_f$ coming from node $i \in L \cup i^F_f$ at time $t \in T$; otherwise, $x^F_{fijt} = 0$.

5.4.1 The HLVRPSF Formulation

In this section, a mathematical formulation of the HLVRPSF model is presented.

$$\text{Min} \sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p^C_{ci}\ v^C_{cit} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\ x^F_{fli^F_f t} \tag{5.1}$$

$$\text{Min} \sum_{w\in W}\sum_{i\in D}\sum_{t\in T} p^W_{wi}\ v^W_{wit} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\ x^F_{fli^F_f t} \tag{5.2}$$

$$\text{Min} \sum_{e\in E}\sum_{i\in D}\sum_{t\in T} p^E_{ei}\ v^E_{eit} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\ x^F_{fli^F_f t} \tag{5.3}$$

$$\sum_{j\in N}\sum_{\substack{i\in N\\ i\neq j}} x^V_{vijt} \leq 1 \quad \forall\ v\in V,\ t\in T \tag{5.4}$$

$$\sum_{\substack{i\in N\\ i\neq i^V_v}}\sum_{t\in T} x_{vi^V_v it} = 1 \quad \forall\ v\in V \tag{5.5}$$

$$\sum_{\substack{i\in N\\ i\neq i^V_v}}\sum_{t\in T} x^V_{vii^V_v t} = 1 \quad \forall\ v\in V \tag{5.6}$$

$$\sum_{\substack{j\in N\\ j\neq i^V_v}} x^V_{vi^V_v jt} = 0 \quad \forall\ v\in V\ t\in \{T,\ t\leq t_{ji^V_v}\} \tag{5.7}$$

$$\sum_{i\in N}\sum_{\substack{j\in N\\ j\neq i}}\sum_{t\in T}\ \tau^V_{ijv}\ x^V_{vijt} \leq |T| \ \ \forall\ v\in V \tag{5.8}$$

$$\sum_{\substack{i\in N\\ i\neq j}}\sum_{t\in T} x^V_{vijt} \leq 1 \quad \forall\ v\in V,\ j\in N\backslash H \tag{5.9}$$

$$\sum_{\substack{i\in N\\ i\neq j}}\ \sum_{\substack{s\in T\\ s+t^V_{vjk}\leq t}}\ x^V_{vijs} \geq x^V_{vjkt} \ \ \forall\ v\in V,\ j\in H,\ k\in N\backslash j,\ t\in T \tag{5.10}$$

$$\sum_{\substack{i\in N\\ i\neq j}}\sum_{\substack{s\in T\\ s\leq t}} x^V_{vijs} \geq \sum_{\substack{k\in N\\ k\neq j}}\ \sum_{\substack{s\in T\\ s\leq t+t^v_{vjk}}}\ x^V_{vjks} \ \ \forall\ v\in V, j\in H,\ t\in T \tag{5.11}$$

$$\sum_{i\in N\backslash i^V_v}\ \sum_{t\in T} t\ x^V_{vijt} \leq \sum_{i\in N\backslash i^V_v}\ \sum_{t\in T}(t-\tau^V_{ijv})x^V_{vijt} \quad \forall\ v\in V,\ j\in N \tag{5.12}$$

$$\sum_{\substack{i\in N\setminus i_v^V\\ i\neq j}}\sum_{t\in T} x_{vijt}^V = \sum_{\substack{i\in N\setminus i_v^V\\ i\neq j}}\sum_{t\in T} x_{vjit}^V \quad \forall\ v\in V, j\in N \tag{5.13}$$

$$\sum_{j\in L}\sum_{t\in T} x_{fi_f^F jt}^F = 1 \quad \forall\ f\in F \tag{5.14}$$

$$\sum_{j\in L}\sum_{t\in T} x_{fji_f^F t}^F = 1 \quad \forall\ f\in F \tag{5.15}$$

$$\sum_{i\in i_f^F\cup L}\ \sum_{j\in i_f^F\cup L} x_{fijt}^F \leq 1 \quad \forall\ f\in F,\ t\in T \tag{5.16}$$

$$\sum_{\substack{t\in T\\ t\leq \tau_{fji_f^F}^F}} x_{fi_f^F jt}^F = 0 \quad \forall\ f\in F,\ j\in L \tag{5.17}$$

$$\sum_{\substack{i\in L\cup i_f^F\\ i\neq k}}\ \sum_{\substack{s\in T\\ s+\tau_{fjk}^F\leq t}} x_{fijs}^F \geq x_{fjkt}^F \ \ \forall\ f\in F,\ j\in L,\ k\in L,\ t\in T \tag{5.18}$$

$$\sum_{i\in L\cup i_f^F}\sum_{\substack{s\in T\\ s\leq t}} x_{fijt}^F \geq \sum_{k\in L}\ \sum_{\substack{s\in T\\ s\leq t+\tau_{fjk}^F}} x_{fjks}^F\ \forall\ f\in F, j\in L,\ t\in T \tag{5.19}$$

$$\sum_{j\in L}\sum_{t\in T}\ \tau_{ji_f^F f}^F\ x_{fji_f^F t}^F \leq |T| \quad \forall\ f\in F \tag{5.20}$$

$$\sum_{\substack{s\in T\\ s\leq t}} v_{cis}^C = \sum_{\substack{s\in T\\ s\leq t}} d_{cis}^C - \sum_{v\in V}\sum_{\substack{s\in T\\ s\leq t}} z_{civs}^D \quad \forall\ c\in C,\ i\in D,\ t\in T \tag{5.21}$$

$$\sum_{\substack{s\in T\\ s\leq t}} v_{eis}^E = \sum_{\substack{s\in T\\ s\leq t}} d_{eis}^E - \sum_{v\in V}\sum_{\substack{s\in T\\ s\leq t}} e_{eivs}^D \quad \forall\ e\in E, i\in D,\ t\in T \tag{5.22}$$

$$\sum_{\substack{s\in T\\ s\leq t}} v_{wis}^W = \sum_{\substack{s\in T\\ s\leq t}} d_{wis}^W - \sum_{v\in V}\sum_{\substack{s\in T\\ s\leq t}} w_{wivs}^D \quad \forall\ w\in W,\ i\in D,\ t\in T \tag{5.23}$$

$$\sum_{\substack{s\in T\\ s\leq t}}\sum_{i\in S} z_{civs}^{PS} + \sum_{\substack{s\in T\\ s\leq t}}\sum_{f\in F}\sum_{k\in L} z_{cfkvs}^{PL} \geq \sum_{\substack{s\in T\\ s\leq t}}\sum_{j\in D} z_{cjvs}^D \quad \forall\ v\in V,\ c\in C,\ t\in T \tag{5.24}$$

$$\sum_{\substack{s\in T\\ s\leq t}}\sum_{i\in D} e_{eivs}^P \geq \sum_{\substack{s\in T\\ s\leq t}}\sum_{j\in H} e_{ejvs}^D \quad \forall\ v\in V,\ e\in E,\ t\in T \tag{5.25}$$

$$\sum_{\substack{s\in T\\ s\leq t}}\sum_{i\in S} w_{wivs}^{PS} + \sum_{\substack{s\in T\\ s\leq t}}\sum_{j\in L}\sum_{f\in F} w_{wfjvs}^{PL} \leq \sum_{\substack{s\in T\\ s\leq t}}\sum_{k\in D} w_{wkvs}^D \quad \forall\ v\in V,\ w\in W,\ t\in T \tag{5.26}$$

$$\sum_{v \in V} z^{PS}_{civt} \leq \sum_{\substack{s \in T \\ s \leq t}} s^{C}_{cis} - \sum_{\substack{s \in T \\ s \leq t-1}} \sum_{v \in V} z^{PS}_{civt} - \sum_{f \in \{F: i^F_f = i\}} C_{cf} \quad \forall\, c \in C,\ i \in S, t \in T \tag{5.27}$$

$$\sum_{v \in V} e^{P}_{eivt} \leq d^{E}_{eit} \quad \forall\, e \in E,\ i \in D,\ t \in T \tag{5.28}$$

$$\sum_{v \in V} w^{PS}_{wivt} \leq \sum_{\substack{s \in T \\ s \leq t}} s^{W}_{wis} - \sum_{\substack{s \in T \\ s \leq t-1}} \sum_{v \in V} w^{PS}_{wivs} - \sum_{f \in \{F: i^F_f = i\}} W_{wf} \quad \forall\, w \in W,\ i \in S,\ t \in T \tag{5.29}$$

$$\begin{aligned} m^{V}_{v} \geq & \sum_{c \in C} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in S} m^{C}_{c}\ z^{PS}_{civs} + \sum_{c \in C} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in L} \sum_{f \in F} m^{C}_{c}\ z^{PL}_{cfivs} + \sum_{e \in E} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in D} m^{E}_{e}\ e^{P}_{eivs} \\ & + \sum_{w \in W} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in S} m^{W}_{w}\ w^{PS}_{wivs} + \sum_{w \in W} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in L} \sum_{f \in F} m^{W}_{w}\ w^{PL}_{wfivs} - \sum_{c \in C} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in D} m^{C}_{c}\ z^{D}_{civt} \\ & - \sum_{e \in E} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in H} m^{E}_{e}\ e^{D}_{eivs} - \sum_{w \in W} \sum_{\substack{s \in T \\ s \leq t}} \sum_{i \in D} m^{W}_{w}\ w^{D}_{wivs} \quad \forall\, v \in V,\ t \in T \end{aligned} \tag{5.30}$$

$$m^{F}_{f} \geq \sum_{w \in W} m^{W}_{w}\ W_{wf} + \sum_{c \in C} m^{C}_{c}\ C_{cf} \qquad \forall\, f \in F,\ t \in T \tag{5.31}$$

$$\sum_{t \in T} \sum_{v \in V} \sum_{l \in L} z^{PL}_{cflvt} \leq C_{cf} \quad \forall\, f \in F,\ c \in C \tag{5.32}$$

$$\sum_{t \in T} \sum_{v \in V} \sum_{l \in L} w^{PL}_{wflvt} \leq W_{wf} \quad \forall\, f \in F,\ w \in W \tag{5.33}$$

$$\sum_{i \in D} \sum_{t \in T} \sum_{v \in V} e^{P}_{eivt} = \sum_{i \in H} \sum_{t \in T} \sum_{v \in V} e^{D}_{eivt} \quad \forall\, e \in E \tag{5.34}$$

$$\sum_{i \in S} \sum_{t \in T} \sum_{v \in V} z^{PS}_{civt} + \sum_{l \in L} \sum_{f \in F} \sum_{t \in T} \sum_{v \in V} z^{PL}_{cflvt} = \sum_{i \in D} \sum_{t \in T} \sum_{v \in V} z^{D}_{civt} \quad \forall\, c \in C \tag{5.35}$$

$$\sum_{i \in S} \sum_{t \in T} \sum_{v \in V} w^{PS}_{wivt} + \sum_{l \in L} \sum_{f \in F} \sum_{t \in T} \sum_{v \in V} w^{PL}_{wflvt} = \sum_{i \in D} \sum_{t \in T} \sum_{v \in V} w^{D}_{wivt} \quad \forall\, w \in W \tag{5.36}$$

$$\sum_{c \in C} z^{D}_{civt} \leq M_{5.37} \sum_{\substack{j \in N \\ j \neq i}} x^{V}_{vjit} \quad \forall\, i \in D,\ v \in V,\ t \in T \tag{5.37}$$

$$\sum_{c \in C} z^{PS}_{civt} \leq M_{5.38} \sum_{j \in N} x^{V}_{vjit} \quad \forall i \in S \backslash i_v, v \in V,\ t \in T \tag{5.38}$$

$$\sum_{c \in C} z^{PL}_{cfivt} \leq M_{5.39} \sum_{j \in N} x^{V}_{vjit} \quad \forall\, v \in V, i \in L, c \in C,\ t \in T \tag{5.39}$$

$$\sum_{c \in C} w^{PL}_{wfivt} \leq M_{5.40} \sum_{j \in N} x^{V}_{vjit} \quad \forall\, v \in V, i \in L, w \in W,\ t \in T \tag{5.40}$$

$$\sum_{c \in C} z^{PL}_{cfivt} \leq M_{5.41} \sum_{j \in L \cup i^F_f} x^F_{fjit} \quad \forall\, c \in C, i \in L, f \in F,\ t \in T \tag{5.41}$$

$$\sum_{c \in C} w^{PL}_{wfivt} \leq M_{5.42} \sum_{j \in L \cup i^F_f} x^F_{fjit} \quad \forall\, w \in W, i \in L, f \in F,\ t \in T \tag{5.42}$$

$$z^{PS}_{ci^V_v vt} = 0 \quad \forall\, c \in C, v \in V,\ t \in \{T : t > 1\} \tag{5.43}$$

$$\sum_{e \in E} e^D_{eivt} \leq M_{5.44} \sum_{j \in N} x^V_{vjit} \quad \forall\, e \in E,\ i \in H,\ v \in V,\ t \in T \tag{5.44}$$

$$\sum_{e \in E} e^P_{eivt} \leq M_{5.45} \sum_{j \in N} x^V_{vjit} \quad \forall\, e \in E,\ i \in D,\ v \in V,\ t \in T \tag{5.45}$$

$$\sum_{w \in W} w^D_{wivt} \leq M_{5.46} \sum_{j \in N} x^V_{vjit} \quad \forall\, w \in W,\ i \in D,\ v \in V,\ t \in T \tag{5.46}$$

$$\sum_{w \in W} w^{SP}_{wivt} \leq M_{5.47} \sum_{j \in N} x^V_{vjit} \quad \forall\, w \in W, i \in S \backslash i_v,\ v \in V,\ t \in T \tag{5.47}$$

$$w^P_{wi^V_v vt} = 0 \quad \forall\, w \in W,\ v \in V,\ t \in \{T : t > 1\} \tag{5.48}$$

$$\sum_{j \in N} x^V_{vjit} \leq M_{5.49} \sum_{f \in F} \sum_{j \in L \cup i^F_f} x^F_{fjit} \quad \forall\, v \in V, i \in L, f \in F,\ t \in T \tag{5.49}$$

The objective functions (5.1)–(5.3), seek to minimize the quantities of unsatisfied demand, non-transfered workers, and unserved wounded, respectively. Each of these quantities are scaled by their respective priority values which vary between nodes. The second term in each function is a very small value used to ensure the SFs return to their depot, once they finish distribution. The value of this term should be small compared to the first term (deviation term) so that it does not affect the distribution quantities.

Constraints (5.4)–(5.13) are used to construct the vehicle routes in the following ways. Constraints (5.4) ensure that each vehicle may serve only one node at each time. Constraints (5.5) ensure that each vehicle starts from its initial depot, while Constraints (5.6) ensure that it returns to its initial depot after finishing its route. Constraints (5.7) prevent the creation of infeasible initial visits (e.g., reaching a node in less time than is needed) for the vehicles. Constraints (5.8) restrict each vehicle's route by the total time available for that vehicle. Constraints (5.9) restrict each vehicle from visiting any node more than once.

Hospital nodes are excluded because they can be revisited by the same vehicle multiple times, so Constraints (5.10) and (5.11) are added to ensure the feasibility of revisiting hospitals. Constraints (5.10) ensure that if a vehicle leaves a hospital node it must have traveled to this hospital from another node, and Constraints (5.11) balance the vehicle flows at each hospital node. To maintain feasibility of routes, Constraints (5.12) ensure that no vehicle can reach any node before finishing the arc between that node and the current node. Constraints (5.13) balance the flow of each demand node so each vehicle enters and leaves each node the same number of times.

Satellite facilities are routed differently because they can revisit the same node and stay more than one time period at a given SF location; consequently, variables x^F_{fijf}, where $i = j$, are defined and can take a value of 1. Constraints (5.14) and (5.15) ensure that each SF leaves from and returns to its depot only once. Constraints (5.16) ensure that each SF can be in only one location at a given time. Constraints (5.17) prevent each SF from making any infeasible initial visit, such as reaching the first node in the route in less time than is needed. Constraints (5.18) maintain the feasibility of the route series by ensuring that if a SF visits a SF location node, it must come from its depot or another SF location. Constraints (5.19) ensure that the number of SFs leaving a node is less than the number to enter the same node, this balances the SF flows at each node. Similar to the constraints for small vehicles, Constraints (5.20) ensure that each SF must return to its depot before the end of the available time slots.

Constraints (5.21), (5.22), and (5.23) define the deviation variables: (5.21) address unsatisfied demand, (5.22) address non–evacuated wounded, and (5.23) consider non–transfered workers.

Vehicle supply restrictions are found in Constraints (5.24)–(5.26). Constraints (5.24) restrict the delivered commodities to the quantity picked up from suppliers and SFs. Constraints (5.25) restrict the delivered wounded to the number picked up from demand nodes. Constraints (5.26) restrict the delivered workers to the number picked up from suppliers and

SFs. Constraints (5.34) ensure that wounded persons picked up from demand nodes are transferred to hospital nodes.

Similarly, Constraints (5.27), (5.28), and (5.29) restrict the nodes supply and transfer at each time. Constraints (5.27) ensure that each supply node can provide quantities not exceeding the available supply of each commodity type. Constraints (5.28) limit the number of assisted wounded to be no more than the number waiting at a particular demand node. In the same manner, Constraints (5.29) ensure that the number of workers dispatched from any supply node does not exceed the actual number of available workers.

In Constraints (5.27) and (5.29), it is assumed that SFs can pick up commodities and workers only once from their depots and perform one trip to deliver commodities and workers to small vehicles. This assumption can be relaxed by adding new time–based variables representing the amount of commodities and the number of workers that picked up from other supplies nodes ($W_{wift},\ C_{cift}$ instead of $W_{wf},\ C_{cf}$). This complicates the model and makes it hard to be mathematically solved and to be accomplished in practice.

Constraints (5.32) prohibit each SF from providing quantities of a commodity type exceeding what was picked up at its depot. Similarly, Constraints (5.33) ensure that SFs can not provide a number of workers from each category exceeding the number picked up by the same SF. Vehicle capacity limitations are included in Constraints (5.30), while Constraints (5.31) consider the SFs' capacity limitations. Constraints (5.34)–(5.36) ensure that any picked up commodity, worker, or wounded person must be delivered.

Constraints (5.37)–(5.48) ensure that all distribution and transfer variables have a value for any node only if a vehicle or SF visits that node. Constraints (5.37) allow for the delivery of commodity type c to a demand node i at time t by vehicle v only if the vehicle visits that node at that time. Constraints (5.38) allow vehicle v to pick up commodities of type c from supply node i if it visits the node at that time; vehicle depots are excluded from this constraint set. For candidate SF locations, Constraints (5.39) ensure that a vehicle can pick up from a SF location only if it visits the SF location. Constraints (5.40) ensure that vehicle v can pick up workers from SF location l only if it visits the SF location at time t. Constraints (5.41) ensure that SF f can deliver commodities to a candidate SF location l if it visits the location at time t. For workers, Constraints (5.42) ensure that SF f can deliver workers to vehicles at candidate SF location l if it visits the location at time t. Constraints (5.43) ensure that each vehicle can pick up commodities from its depot only at the beginning of the time horizon; once it leaves the depot, it can not revisit the depot again until it is finished. Constraints (5.44) allow vehicles to deliver wounded to a hospital only if they visit the hospital. For wounded pick–ups, Constraints (5.45) ensure that a vehicle can pick up wounded from a demand node only if the vehicle visits the demand node. Constraints (5.46) ensure that if a vehicle visits a demand node, then it can deliver workers. Constraints (5.47) ensure that a vehicle can pick up workers only if it visits a supply node which is not its depot. Constraints (5.48) ensure that each vehicle can pick up workers from its depot only at the beginning of a plan series since it can not revisit the depot during the time horizon.

The big-M values in Constraints (5.37)–(5.42), (5.44)–(5.47), and (5.49) are defined as follows. By using the lowest possible value for each M, the computation effort is potentially saved because the solver may start with better bound for the linear program relaxation. Value of M in each constraint should be defined for all indices of the constraint. For simplicity, the notations are slightly abused and big-M values are defined just once for each constraint. For example, $M_{5.37}$ is defined instead of the definition of $M_{5.37}^{ivt}$.

$$
\begin{aligned}
M_{5.37} =& \min\left\{d_{cit}^{C}, \frac{m_v^V}{m_c^C}\right\} \qquad \forall\, i \in D,\ v \in V,\ t \in T \\
M_{5.38} =& \min\left\{\sum_{\substack{s\in T\\ s\leq t}} s_{cis}^{C}, \frac{m_v^V}{m_c^C}\right\} \qquad \forall\, c \in C, i \in S \backslash i_v^V, v \in V,\ t \in T \\
M_{5.39} =& \frac{m_v^V}{m_c^C} \qquad c \in C,\ i \in L,\ v \in V,\ t \in T \\
M_{5.40} =& \frac{m_v^V}{m_w^W} \qquad \forall\, w \in W,\ i \in L,\ v \in V,\ t \in T
\end{aligned}
$$

$$
\begin{aligned}
M_{5.41} =& \frac{m_f^F}{m_c^C} \qquad c \in C,\ i \in L,\ f \in F,\ t \in T \\
M_{5.42} =& \frac{m_f^F}{m_w^W} \qquad \forall\ w \in W,\ i \in L,\ f \in F,\ t \in T \\
M_{5.44} =& \frac{m_v^V}{m_e^E} \qquad \forall\ e \in E, i \in H,\ v \in V,\ t \in T \\
M_{5.45} =& \min\left\{d_{eit}^E, \frac{m_v^V}{m_e^E}\right\} \qquad \forall\ e \in E, i \in D, v \in V,\ t \in T \\
M_{5.46} =& \min\left\{d_{wit}^W, \frac{m_v^V}{m_w^W}\right\} \qquad \forall\ w \in W, i \in D, v \in V,\ t \in T \\
M_{5.47} =& \min\left\{s_{wit}^W, \frac{m_v^V}{m_e^E}\right\} \qquad \forall\ w \in W, i \in D, v \in V,\ t \in T \\
M_{5.49} =& |F| \qquad \forall\ v \in V, i \in L, f \in F,\ t \in T
\end{aligned}
\tag{5.50}
$$

Finally, Constraints (5.49) allow vehicles to visit a candidate SF location only if a SF visits the same SF location at that time, otherwise, such visitations are useless.

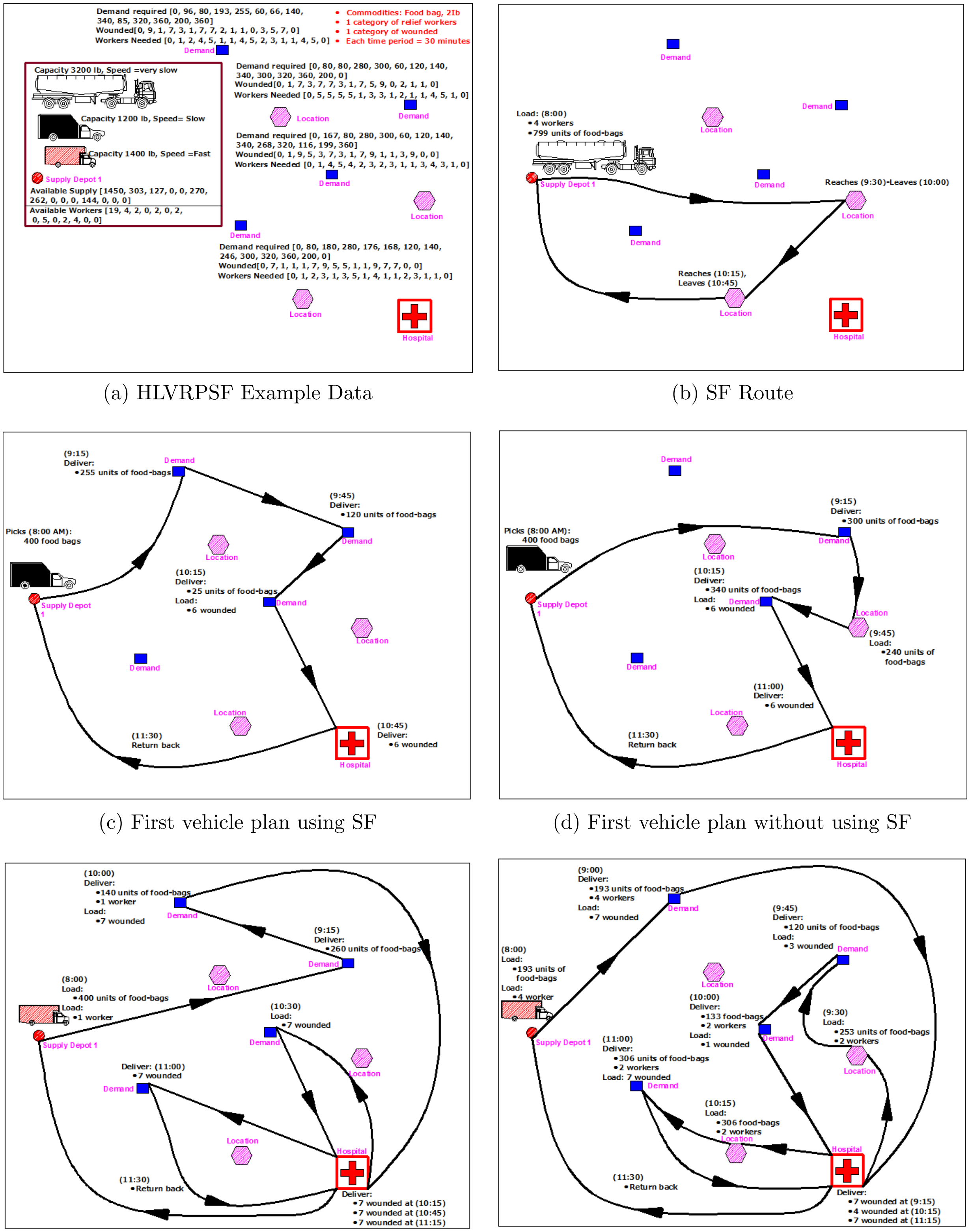
In the next section, a small example is used to verify this model.

5.5 Numerical Example

The goal of the small example presented here is to verify the model, not to discuss how it is solved. Solution approaches are developed and fully explained in the next section. This example is solved by CPLEX–Concert technology using a single objective function that includes all logistic operations, as follows

$$
\text{Min} \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^C\ v_{cit}^C + \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p_{wi}^W\ v_{wit}^W + \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p_{ei}^E\ v_{eit}^E \tag{5.51}
$$

Two regular vehicles, each of different capacity and travel speed are used together, with a single SF. There are four demand nodes, one supply node, and one hospital node. Three candidate SF locations for the SF have been pre–determined. A single commodity type is considered. Similarly, wounded persons are classified as being of the same category, as are workers. Additional problem details, including the commodity demands over time, are shown in Figure 5.3a. This example is solved twice: once using the available SF, and again without utilizing the SF. Figure 5.3b shows the route of the SF. Figure 5.3c shows the plan of the first vehicle while the use of the SF is allowed, and Figure 5.3d shows the plan when the use of the SF is prohibited. Similarly, Figure 5.3e shows the plan of the second vehicle using the SF and Figure 5.3f shows the plan of the second vehicle without using the SF.



(a) HLVRPSF Example Data

(b) SF Route

(c) First vehicle plan using SF

(d) First vehicle plan without using SF

(e) Second vehicle plan using SF

(f) Second vehicle plan without using SF

Figure 5.3: Solution of the HLVRPSF model example for both options: with and without using the available SF

The first vehicle visits 3 demand nodes when the SF is not used and only 2 when it is used, as shown in Figures 5.3a and 5.3b. Nevertheless, it delivers less demand quantity (400 food bags) when the SF is not used compared to the other case (640 food bags). This is because when using the SF, the first vehicle visits a location and loads 240 food bags from the SF which allows it to deliver more quantity, even with a smaller number of demand nodes visited. In both cases, the vehicle evacuates 6 persons and does not transfer any workers.

The second vehicle delivers 752 food bags when using the SF (as in Figure 5.3e) and only 400 food bags otherwise (as in Figure 5.3f). In both cases, this vehicle visits the hospital 3 times, but in case when not using the SF, the vehicle visits 2 of the demand nodes empty to pick up wounded without delivering any workers or food bags because no more supplies are available. This results in fewer efficient visits. If more demand nodes were available in the example and the time horizon was longer, this vehicle, when not using a SF, is expected to perform more evacuations. This is not preferable in some actual cases such as if hospitals have limited work capacity and if the demand distribution is much important than evacuation. To quantify the comparison, Table 5.1 summarizes the total numbers of commodities, workers, and wounded in both cases.

	Using SF	**Without using SF**
Food bags delivered	1,392	800
Workers transfered	8	1
Wounded evacuated	24	27
Total mass (lb)	10,576	8,000

Table 5.1: Summary of the HLVRPSF example solution for both options: with and without using the available SF

In Table 5.1, it can be obtained that when using a SF, vehicles are more fully utilized since they load 10,576 lb using the SF compared to 8,000 lb when not using the SF. In this particular example, worker priorities are low, and it can be noticed that only 1 worker is transfered when not using a SF. When using a SF, because vehicles know ahead of time that resupplies are allowed during the route, the second vehicle picks up 4 workers at the beginning which improves the operation of work–force transfer. This is another benefit of using a SF in this example.

The previous comparisons show that the using SFs improves the logistics system with a single objective. However, using a single objective in the HLVRPSF is not appropriate. Consequently, one of the main ideas of the HLVRPSF is to incorporate multiple objectives. To check how the SFs improve the HLVRPSF with multiple objectives, the next section will solve many instances, where each instance is solved three times considering a single objective function each time.

5.5.1 Examples to Demonstrate SF Benefits

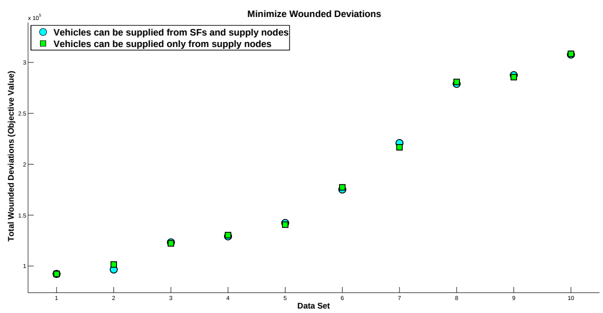
In this section, different examples are solved in different ways to show the benefits of using SFs in humanitarian logistic systems.

Allowing small vehicles to be resupplied from SFs at SF locations offers more choices and flexibility for resupply operations. This saves time for vehicles and allows them to visit more nodes which results in more commodity delivery, worker transfer, and wounded evacuation. To show an example of such logistic system enhancement, 10 different data sets are randomly generated. Each of the 10 sets is solved 6 times using CPLEX–Concert technology with a time limit equal to 3 hours. They are solved 6 times to cover all possible combinations of objective functions and SF utilization options.

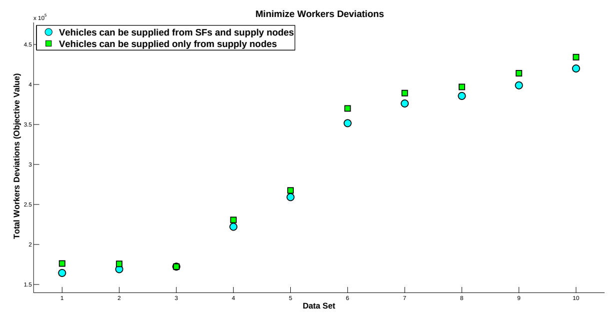
First, using objective function 5.3 to minimize the total wounded deviation variables and vehicles can be resupplied only from supply nodes. Second, using objective function 5.3 to minimize the total wounded deviation variables and vehicles can be resupplied from supply nodes or from SFs at SF locations. The results of both options are plotted in in Figure 5.4a.

Third, using objective function 5.2 to minimize the total worker deviation variables and vehicles can be resupplied only from supply nodes. Fourth, using objective function 5.2 to minimize the total worker deviation variables and vehicles can be resupplied from supply nodes or from SFs at SF locations. The results of the third and fourth options are shown in Figure 5.4b.

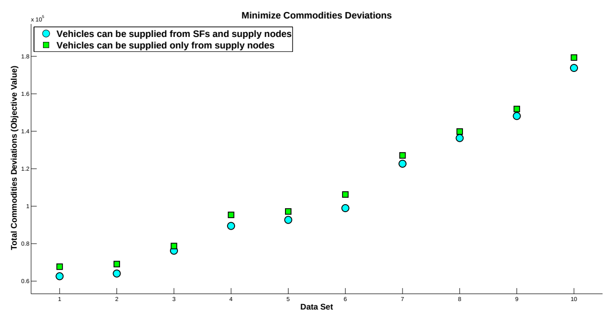
Fifth, using objective function (5.1) to minimize the total commodity deviation variables and vehicles can be resupplied only from supply nodes. Sixth, using objective function 5.1 to minimize the total commodity deviation variables and vehicles can be resupplied from supply nodes or from SFs at SF locations. Results of these options are shown in Figure 5.4c.



(a) Objective Function is to Minimize Wounded Evacuation Deviations



(b) Objective Function is to Minimize Workers Transfer Deviations



(c) Objective Function is to Minimize Commodity Delivery Deviations

Figure 5.4: HLVRPSF model, with SFs vs. without SFs

In Figure 5.4, there are no significant differences in part (a) which is expected because in minimizing the wounded evacuation deviations, vehicles are not resupplied, but they are utilized for evacuation only. The small differences are because some data sets are not solved optimally in 3 hours which causes very tiny differences between the options of using SFs and not using SFs. In parts (b) and (c), there is an improvement because there are more locations added for resupply instead of depending only on supply nodes. The improvement average in part (b), where the objective is to minimize the worker transfer deviations, is

3.7%. In part (c), where the objective is to minimize the commodity delivery deviations, the improvement average is 5%. These improvement values are expected to be higher in medium and large scale sets where longer time horizons are available, more vehicles are considered, and more replenishments are needed by each vehicle. As shown in the previous section, the improvements are achieved by visiting more nodes and/or delivering higher quantities of demand and workers.

In this section, an example was solved using CPLEX with a single objective function includes the objective functions (5.1), (5.2), and (5.3) in a linearly weighted manner. Since a single objective function was used in this example, only one solution is provided containing all logistic operations (i.e., demand distribution, work–force transfer, and wounded evacuation). After that, in the sub–section 5.5.1, ten data instances were solved using exact solution procedure by CPLEX three times (considering only the cases of using SFs) where one of the objective functions (5.1), (5.2), and (5.3) is used each time. Three solutions are provided for each data set where each solution contains only one logistic operation based on which objective function was used. For example, if the objective function (5.1) is used, only demand distribution is performed. Based on this, depending on a single objective function includes all functions in a weighted form is not useful because it provides only a single solution, and solving the model three times where one objective function is used each time is not also useful because only three solutions are provided and each solution contains only one logistic operation. Additionally, exact solutions using CPLEX require a very long time.

The HLVRPSF model is suggested to be a multiple objective model, and multiple solutions should be provided after solving the model with different combinations of the logistic operations. In the next sections, different solution approaches are suggested to provide a wide range of solutions in a reasonable amount of time.

5.6 Description of the HLVRPSF Solution Approach

In multi-objective models, many solutions should be provided after solving the models to offer a wide variety of solution options where some of them are excellent for some of objective functions and bad for others. In the case of competing objectives, decision makers seek solutions that are acceptable for all objectives. Before proceeding, some important definitions and explanations should be considered.

Consider a problem with K objectives, and let X represent a solution vector with objective function values equal to $z(X) = z_1(X), z_2(X), \ldots, z_k(X)$. Solution X is said to dominate some other solution Y in a minimization problem if $z_i(X) \leq z_i(Y) \ \forall \ i = 1, \ldots, k$ and $z_i(X) < z_i(Y)$ for at least one objective. A Pareto optimal set is a set containing all solutions that are not dominated by other solutions. The corresponding objective function values are called a Pareto front. The aim of this section is to provide a representative subset from the Pareto optimal set by using good solution approaches.

Finding feasible solution for the HLVRPSF is a challenging problem because it is an NP–hard problem and includes many decision variables such as the variables that define the vehicle and SF routes, amount of pick–ups and deliveries, number of workers to transfer, and number of wounded to evacuate. Commercial solvers such as CPLEX can give sub–optimal solutions for very small problems while it fails to produce any feasible solution for larger problems in a reasonable amount of time. Accordingly, a solution approach is suggested to provide multiple and representative solutions for the HLVRPSF instances in a reasonable time.

The suggested heuristic is an iterative approach. In each iteration, it starts by selecting an objective function to be active for the iteration and builds a route for each vehicle in a greedy approach depending on which objective function is activated. The next phase is to use the information available from the constructed vehicle routes to create the SF routes. Vehicle and SF route construction are in Section 5.7.1. The final phase is to use a proper procedure to find some candidate solutions as discussed in Section 5.7.2. The common step in these procedures is to solve the integer HLVRPSF problem using CPLEX while considering the pre–specified SF and vehicle routes (fixed binary variables) which can be performed in a short computation time.

It can be noticed that the suggested approach is similar to the approach used to solve the single (weighted) objective HLVRP but with some modifications to address multiple objectives in a more robust manner. First, the suggested method depends on an iterative greedy solution approach where only one objective function is randomly selected for each iteration to find a set of candidate solutions. Depending on one objective function for each iteration to find a set of candidate solutions has been used by Kulturel-Konak et al. (2006). In Kulturel-Konak et al. (2006), multi-objective tabu search (MOTS) using a multinomial probability mass function is used to solve the redundancy allocation problem (RAP) with three objective functions: maximizing the reliability, minimizing the cost, and minimizing the weight. To perform MOTS to solve the RAP, the objectives have equal chance of being activated which is similar to the approach suggested here to solve the HLVRPSF. However, in RAP, special moves suitable for the problem are used to create a set of candidate solutions while different procedures are used to create candidate solutions for the HLVRPSF as explained in Section 5.7.2. Second, routes are constructed with some dependency on which objective function is active.

Third, best routes are not used in this approach despite their use to solve the HLVRP. In the HLVRP approach, the best route for each vehicle represents the route that has the highest utilization (highest mass picked up during the planning horizon) among all iterations and it is found based on the single objective function. Best routes will potentially produce a high quality solution every iteration they are used because the same single objective is used. In the approach suggested for the HLVRPSF with multiple objective functions, if a best route for a vehicle is found when a specific objective function is active, it can give a high quality solution in the next iterations if the same objective function is used; however, they will not give a good objective function value with other objective functions. For example, if a best route for a vehicle is found when the function of minimizing commodity deviations is active, it is expected to contain many demand node visits with commodities as the main load while visiting the hospital a minimum number of times. In the next iteration, if the function of minimizing wounded deviations is activated, this route will produce a very bad results in term of evacuation because of the few hospital visits. Fourth, local search phase is not used because, in multi-objective HLVRPSF, local searches of replacements or insertions cause deterioration of some objective function values though they can improve others. For example, it is found in some preliminary testing that the replacement of a hospital by two demand nodes deteriorates the wounded deviation objective and will not necessarily improve the others. Consequently, relying on the fact that the multi-objective approaches should provide diverse solution sets makes these types of local search unhelpful to solve the HLVRPSF.

The next Section 5.7 describes the overall approach. Section 5.7.1 describes new route construction procedures, and candidate solution approaches are proposed and discussed in Section 5.7.2.

5.7 Solution Approach for the HLVRPSF

The overall approach to solve the HLVRPSF is shown in Algorithm 8. The algorithm starts with the definitions of the termination criterion which could be time, number of iterations, or number of different solutions produced. In this research, specific time based on the data scale is used as the termination criterion, as shown in the numerical analysis section. Then, a number ψ is selected from a set of [1, 2, 3] to specify which option of SF route construction is used. One of three options can be used to construct the SF routes, as explained in Section 5.7.1.

Once the iteration loop starts, a number ϕ is selected randomly at the beginning of each iteration from a set of [1, 2, 3] to define which objective function is active for the current iteration. One means the current activated objective is to minimize the wounded deviations (Objective 5.1), two means the current objective is to minimize the commodity deviations (Objective 5.2), and 3 indicates the current objective is to minimize the worker deviations (Objective 5.3). After this, prioritized demand is calculated. Prioritized demand is defined as a two dimensional array, where the element $PT^D(t,i)$ represents the prioritized demand requested, workers needed, and wounded awaiting help at node $i \in D$ at time $t \in T$. This array depends on the activated function. If the current activated objective function is to minimize the commodity deviations, PT^D is calculated based in requested demand. If the current activated objective function is to minimize the workforce deviations, PT^D is calculated based in requested workers. If the current activated objective function is to minimize the wounded deviations, PT^D is calculated based in the number of wounded waiting evacuation. Calculations of the prioritized demand are in line 6 of the Algorithm 8. The whole array appears as follows

$$PT^D(t,i) = \begin{bmatrix} PT^D(1,1), & PT^D(1,2), & \dots & PT^D(1,|D|) \\ PT^D(21), & PT^D(22) & \dots & PT^D(2,|D|) \\ \vdots, & \vdots & \ddots & \vdots \\ PT^D(|T|,1), & PT^D(|T|,2), & \dots & PT^D(|T|,|D|) \end{bmatrix}.$$

Similarly, prioritized supply is calculated for each supply node and SF location. Prioritized supply is defined as a two dimensional array, where the element $PT^{SL}(t,i)$ represents the prioritized available supply and workers at node $i \in S \cup L$ at time $t \in T$. It depends on the node type (Supply node or SF locations) and the current activated objective function. It can be calculated as in line 7 of the Algorithm 8. The whole array appears as follows

$$PT^{SL}(t,i) = \begin{bmatrix} PT^{SL}(1,1), & PT^{SL}(1,2), & \dots & PT^{SL}(1,|S|+|L|) \\ PT^{SL}(2,1), & PT^{SL}(2,2) & \dots & PT^{SL}(2,|S|+|L|) \\ \vdots, & \vdots & \ddots & \vdots \\ PT^{SL}(|T|,1), & PT^{SL}(|T|,2), & \dots & PT^{SL}(|T|,|S|+|L|) \end{bmatrix}.$$

In demand nodes, prioritized demand is calculated at each time by using the demand, wounded, and workers at that time with dependency on current activated objective function. For supply nodes, because picking up workers and supplies left from previous periods is allowed, prioritized supply is calculated cumulatively considering which objective function is active and excluding the first time period. In the first time period, vehicles pick up workers and supplies from their depots, so the information about prioritized supply values at that time is not known. This justifies its exclusion from the prioritized supply calculation. In SF locations, since SFs pick up workers and commodities from supply nodes at the first time period, their prioritized supply are calculated as the average of available supply and workers at the first time and based on the current activated objective function, as shown in as in line 7 of the Algorithm 8. The whole array of prioritized supply is shown below. This array can be divided into two sub–arrays; PT^S which includes the prioritized supply values for only the supply nodes, and PT^L which includes the prioritized supply values for only the SF locations.

After that, a vehicle is randomly selected, and the importance value is calculated for each node using the `Importance` function as shown in Algorithm 9. Importance array for each vehicle (IM^v) is a two dimensional array where the element $IM^v(t,i)$ represents the importance value of node $i \in N$ at time $t \in T$ for vehicle v. This array is calculated for each vehicle at the beginning of the solution approach and is updated each time the vehicle changes its location. This array looks like:

$$IM^v = \begin{bmatrix} IM^v(1,1), & IM^v(1,2), & \dots & IM^v(1,|N|) \\ IM^v(2,1), & IM^v(2,2), & \dots & IM^v(2,|N|) \\ \vdots & \vdots & \ddots & \vdots \\ IM^v(|T|,1), & IM^v(|T|,2), & \dots & IM^v(|T|,|N|) \end{bmatrix}.$$

Demand and supply node importances are not constants and depend on the prioritized demand and supply values, the selected vehicle, the activated objective function, and the current location of the selected vehicle which is its depot at the beginning. Dependency on the activated objective function is already included in the calculation of the prioritized values such that if the activated objective is the wounded deviations, the importance is calculated using only the total prioritized wounded with some randomness. If the activated objective is the commodities deviations, the importance is calculated using only the total prioritized commodities. Similarly, if the activated objective is the workers deviations, the importance is calculated using only the total prioritized workers. This ensures that vehicles visit nodes in such a way as to minimize the activated objective. Relying on the fact that the route construction, which will be accomplished in the next step, is performed in a greedy way and vehicles should visit the most important nodes, closer hospitals are more beneficial to vehicles because they can be visited in a shorter time. Hence, importance values for hospital nodes depend on the travel time from the current node of the selected vehicle.

Both supply and SF location nodes are considered as one type because both of them are responsible for the supply of small vehicles with commodities and workers. In the case of supply nodes, importance depends on the activated objective function in cases of commodity deviations and worker deviations, but does not depend on the activated objective function for wounded deviations. In the case of candidate SF locations where the SFs may deliver commodities and workers to the smaller vehicles, the best way to find representative importance values is to initially assign the averages of workers, commodities, or both to each SF location. These assignments will be updated as discussed later.

After all importance values are calculated, the construction function is performed to construct a route for the current selected vehicle by giving a specific value, 0 or 1, for all binary variables related to this vehicle, as discussed later in Section 5.7.1. The same procedure is repeated many times until all vehicles are selected and a route is created for each vehicle.

After constructing routes for all vehicles, a route for each SF is constructed. The updated values of the prioritized supply (produced after vehicle routes construction) for SF locations are used to calculate the importance values as in function `SF-Importance`. In the same manner, a SF is randomly selected and `SF-construction` route function is performed to set all binary variables that relate to the selected SF to 0 or 1. This procedure is repeated until all SFs are selected. SF routes construction is explained in Section 5.7.1.

When all routes for vehicles and SFs are constructed and all variables are set, candidate solutions are found next. The HLVRPSF model has a characteristic that complicates the model and makes finding candidate solutions difficult. Specifically, using one objective function, the variables that do not relate to this function will acquire the value of zero. For example, if objective (5.1), which is to minimize the total commodity–delivery deviations, is used, the number of workers transfered and the number of wounded evacuated are zero because they do not affect the objective value. In this case, vehicles only work for commodity delivery (i.e., $Z^D_{civt} \geq 0, \quad \forall c \in C,\ i \in D,\ v \in V,\ t \in T$) to minimize the deviation variables, d^C_{cit}, because they are part of the objective function. While other variables such as e^D_{eivt} and $w^D_{wivt} = 0, \quad \forall e \in E,\ w \in W,\ i \in D,\ v \in V,\ t \in T$ because they are not a part of the objective function.

Similarly, if objective (5.2), minimizing the total workforce transfer deviations, is used, the number of commodities distributed and wounded evacuated are zero, and if objective (5.3), which is to minimize the total wounded–evacuation deviations, is used, the number of commodities distributed and number of workers transfered are zero. This means that finding candidate solution or solutions in line 24 of the Algorithm 8 is an important phase and as such will be extensively discussed in Section 5.7.2 where proper procedures for treatment of multi-objective are developed.

Every candidate solution generated has an objective value Z which includes 3 elements for the three objective functions as

$$Z = \left[\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci}\ v^C_{cit} \quad \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi}\ v^W_{wit} \quad \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei}\ v^E_{eit} \right].$$

Associated with the objective value vector Z, an array ZC is defined which contains all variables associated with the current objective function value. It looks as

$$ZC = \begin{bmatrix} z^{D}_{civt} & \forall c \in C, i \in D, v \in V, t \in T \\ z^{PS}_{civt} & \forall c \in C, i \in S, v \in V, t \in T \\ z^{PL}_{cflvt} & \forall c \in C, l \in L, v \in V, f \in F, t \in T \\ v^{C}_{cit} & \forall c \in C, i \in D, t \in T \\ v^{W}_{wit} & \forall w \in W, i \in D, t \in T \\ v^{C}_{cit} & \forall e \in E, i \in D, t \in T \\ C_{cf} & \forall c \in C, f \in F \\ W_{wf} & \forall w \in W, f \in F \\ e^{D}_{eivt} & \forall e \in E, i \in H, v \in V, t \in T \\ e^{P}_{eivt} & \forall e \in E, i \in D, v \in V, t \in T \\ w^{D}_{wivt} & \forall w \in W, i \in D, v \in V, t \in T \\ w^{PS}_{wivt} & \forall w \in W, i \in S, v \in V, t \in T \\ w^{PL}_{wflvt} & \forall w \in W, l \in L, v \in V, f \in F, t \in T \\ x^{V}_{vijt} & \forall i \in N, j \in N \backslash i, v \in V, t \in T \\ x^{F}_{fijt} & \forall i \in N,\ j \in N \backslash i,\ t \in T \end{bmatrix}.$$

Another array (Z_{all}) is defined to contain all objective values for all candidate solutions, as follows. To save all solution candidate details, an array(ZC_{all}) is constructed to contain all variables associated with all solutions. Keeping track of all solution details consumes the memory. CPLEX-Concert technology has a good feature which allows to save each solution in a separate data file with small memory. Sizes of these arrays depend on the termination criterion used and is dynamically changed when any solution added.

$$Z_{all} = \begin{bmatrix} Soln_1 = & \left[\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^{C}_{ci}\ v^{C}_{cit} \quad \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^{W}_{wi}\ v^{W}_{wit} \quad \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^{E}_{ei}\ v^{E}_{eit} \right] \\ Soln_2 = & \left[\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^{C}_{ci}\ v^{C}_{cit} \quad \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^{W}_{wi}\ v^{W}_{wit} \quad \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^{E}_{ei}\ v^{E}_{eit} \right] \\ Soln_3 = & \left[\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^{C}_{ci}\ v^{C}_{cit} \quad \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^{W}_{wi}\ v^{W}_{wit} \quad \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^{E}_{ei}\ v^{E}_{eit} \right] \\ Soln_4 = & \left[\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^{C}_{ci}\ v^{C}_{cit} \quad \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^{W}_{wi}\ v^{W}_{wit} \quad \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^{E}_{ei}\ v^{E}_{eit} \right] \\ \vdots & \quad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \end{bmatrix}$$

In line 26 of the Algorithm 8, 4 types of Pareto sets are found. Three of them are two dimensional: wounded evacuation deviations versus commodities deviations (EC), evacuation deviations versus worker deviations (EW), workers deviations versus commodities deviations (WC). The fourth set is three dimensional and contains all objectives together. Finding Pareto sets from available solutions is done by testing each solution to determine if it is dominated by others. If it is not, it is added to the Pareto set.

ALGORITHM 8: Main Heuristic

1: Define the termination criterion

2: $itr = 1$ //Iterations counter

3: Set ψ //Which option is considered for SF route construction

4: **while** Termination criterion not met **do**

5: Randomly select ϕ

6: Calculate the prioritized demand for all demand nodes

$$PT^D(t,i) = \begin{cases} PT^D(t,i) = \sum_{e \in E} d^E_{eit}\; p^E_e & \text{if } \phi = 1 \\ PT^D(t,i) = \sum_{c \in C} d^C_{cit}\; p^C_c & \text{if } \phi = 2 \\ PT^D(t,i) = \sum_{w \in W} d^W_{wit}\; p^W_w & \text{if } \phi = 3 \end{cases}$$

7: Calculate the cumulative prioritized supply for all supply nodes and SF locations

$$PT^{SL}(t,i) = \begin{cases} PT^{SL}(t,i) = \sum_{k=2}^{t} \left\{ \sum_{c \in C} s^C_{cik}\; p^C_c + \sum_{w \in W} s^W_{wik}\; p^W_w \right\} & \text{if } \phi = 1 \text{ and } i \in S \\ PT^{SL}(t,i) = \dfrac{\sum_{c \in C} s^C_{ci1}\; p^C_c + \sum_{w \in W} s^W_{wi1}\; p^W_w}{|S|} & \text{if } \phi = 1 \text{ and } i \in L \\ PT^{SL}(t,i) = \sum_{k=2}^{t} \sum_{c \in C} s^C_{cik}\; p^C_c & \text{if } \phi = 2 \text{ and } i \in S \\ PT^{SL}(t,i) = \dfrac{\sum_{c \in C} s^C_{ci1}\; p^C_c}{|S|} & \text{if } \phi = 2 \text{ and } i \in L \\ PT^{SL}(t,i) = \sum_{k=2}^{t} \sum_{w \in W} s^W_{wik}\; p^W_w & \text{if } \phi = 3 \text{ and } i \in S \\ PT^{SL}(t,i) = \dfrac{\sum_{w \in W} s^W_{wi1}\; p^W_w}{|S|} & \text{if } \phi = 3 \text{ and } i \in L \end{cases}$$

Reorder the vehicle set (lV) to be randomly sequenced.
for all $v \in V$ **do**
$x^V_{vijt} = 0 \;\; \forall i, j \in N \backslash i, \;\; t \in T$ // Initialization and clear any 1 values from previous iterations
$current = i^V_v$ // Set current location to the depot of the selected vehicle
Calculate time-based importance for all nodes, such that
$IM^v =$ `Importance` $\left(v, current, N, PT^{SL}, PT^D\right)$
Construct the route (Set the binary variables), $x^V_{vijt} \;\; \forall i, j \in N, \;\; i \neq j, \;\; t \in T =$ `Construction`$(IM^v, \; v)$
end for
Reorder the SF set (F) to be randomly sequenced.
for all $f \in F$ **do**
$x^F_{fijt} = 0 \;\; \forall i \in \{L \cup i^F_f\}, j \in \{L \cup i^F_f\}, \;\; t \in T$ // Initialization and clear any 1 values from previous iterations
$current = i^F_f$ // Set current location to the depot of the selected vehicle
Calculate time-based importance for all SF locations, such that
$IM^f =$ `SF-Importance` $\left(f, current, L, PT^L\right)$
Construct the route (Set the binary variables), $x^F_{fijt} \;\; \forall i, j \in N, \;\; i \neq j, \;\; t \in T =$ `SF-Construction`$\left(IM^f, \; f\right)$
end for
Find one or more candidate solutions and save them. // Call one of the functions `LWCO, SOWP, SOSMS, SOIMRUC, SOAMRUC2`, as explained in Section 5.7.2
end while// End main loop
Find Pareto sets.

Algorithm 9 shows the pseudo code of the `Importance` function which is used to calculate the importance values for all nodes based on the current selected vehicle, its current location, the activated objective function, and the prioritized demand and supply value. Importances are slightly randomized by using a multiplier R close to 1. Using a wider range for R produces higher randomness which works against the use of the greedy approach; using a narrower range of R decreases the effect of randomness. Preliminary testing indicates that $R \in [0.8, 1.2]$ works well.

ALGORITHM 9: `Importance` Function

for all $t \in T$ **do**
  for all $i \in N$ **do**
    Generate R //Random number [0.8,1.2]

$$IM^v_{t,i} = \begin{cases} \dfrac{R}{\tau^V_{v,current,i}} PT^D_{ti} & \text{if } i \in D \\ \dfrac{R}{\tau^V_{v,current,i}} PT^S_{ti} & \text{if } i \in S \\ \dfrac{R}{\tau^V_{v,current,i}} & \text{if } i \in H \end{cases}$$

  end for
end for
Return IM^v

Finally, the importance values for SFs are calculated for SF locations in the same manner of importances of vehicles, as in the next function.

ALGORITHM 10: `SF-Importance` Function

for all $t \in T$ **do**
  for all $i \in L$ **do**
    Generate R //Random number [0.8,1.2] $IM^f_{t,i} = \dfrac{R}{\tau^F_{f,current,i}} PT^L_{ti}$
  end for
end for

6: Return IM^f

The next section explains the `Construction` and `SF-Construction` functions that used to construct vehicle and SF routes.

5.7.1 Route Construction for Various Objectives

In this section, a proposed approach is suggested to construct the vehicle and SF routes. A set of notations used in this approach are defined as follows:

- $current$ is a holder used to save the current location for a vehicle. It changes dynamically during the process.
- $sort^D$ is a two dimensional array of size $|T| \times |D|$ which contains the demand nodes sorted in descending order at each time based on their importance. The element $sort^D(t, i)$ represents the i^{th} demand node at time t. For example, if the importance values for 5 demand nodes at time t are [1000, 800, 3000, 2100, 1450], then the t^{th} row from $sort^D$ is [3, 4, 5, 1, 2] so the element $sort^D(t, 1) = 3$. In other words, node 3 is placed in the first place because it has the highest preference to be visited by the current selected vehicle.
- $sort^S$ is a two dimensional array of size $|T| \times |S|$ which contains the supply nodes sorted in descending order at each time based on their importance. The element $sort^S(t, i)$ represents the i^{th} supply node at time t.
- $sort^L$ is a two dimensional array of size $|T| \times |L|$ which contains the candidate SF locations sorted in descending order at each time based on their importance. The element $sort^L(t, i)$ represents the i^{th} SF location at time t.
- $sort^{SL}$ is a two dimensional array of size $|T| \times (|S| + |L|)$ which contains the supply nodes and the candidate SF locations sorted in descending order at each time based on their importance. The element $sort^{SL}(t, i)$ represents the i^{th} SF location or supply node at time t.

- $sort^H$ is a two dimensional array of size $|T| \times |H|$ which contains the hospital nodes sorted in descending order at each time based on their importance. The element $sort^H(t, i)$ represents the i^{th} supply node or SF locations at time t.
- Avg_D is a scalar quantity which represents the average commodity and worker masses requested by the demand nodes for the whole time horizon. It can be mathematically calculated as

$$Avg_D = \frac{\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} (d^C_{cit} \times m^C_c) + \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} (d^W_{wit} \times m^W_w)}{|T| \times |D|}$$

- α is a random integer which represents the number of demand nodes that should be visited by a vehicle v before it ends the trip and goes to a hospital or supply node. It is randomly selected from a set of integer values, a set which is created based on the vehicle capacity and node demands, Mathematically, α can be represented as follows

$$\alpha \in \left[\left\lfloor \frac{m_v}{d \times Avg_D} + 0.5 \right\rfloor - 2, \left\lfloor \frac{m_v}{d \times Avg_D} + 0.5 \right\rfloor + 2 \right].$$

Selecting a high number for α, i.e. 8 nodes in the previous example, could result in useless visits such as visiting some nodes while the vehicle is empty. In contrast, visiting a low number of demand nodes could force the vehicle to resupply or go to a hospital while it has some undelivered commodities and workers. d is the percentage of the demand and workers requested expected to be delivered each time the vehicle visits a demand node. Portion of 70% is selected as a value of d because it has been noticed that in many instances, vehicles try to visit demand nodes where 70% of their needs can be supplied. This helps minimize the deviation variables which is the model objective.

For example, in a data instance, if Avg_D is 600 lb and the capacity of a vehicle is 1600, assuming a vehicle supplies 70% of node demands each time it visits a node, this means vehicle v can supply 1600 / (0.7*600) = 3.8 nodes. In this case, α is randomly selected from an interval that has a center value of 3.8 (rounded to the closest integer which is

4) nodes. The interval equals to [2 nodes, 6 nodes]. This value of α is generated each time the vehicle v leaves a supply node and begins distribution.

- t_{now} is the current time of the selected vehicle which is used to test the feasibility of any visit done by the vehicle. This time is incremented at each visit but not between visits. For example, one of the feasibility conditions is to test if $t_{now} + \tau_{v,current,i} = t$, where i is a node that the vehicle tries to visit. At the beginning, $t_{now} = t = 1$, if the first visit to node i can be made at time 4 because $\tau_{v,current,i} = 3$, t_{now} is kept at a value of 1 while the value of t incremented to 2, 3, and 4. At time 4, the visit is done and the value of t_{now} is updated to 4.
- ξ_{sl} is a counter used to keep track of the number of supply nodes and SF locations which are visited by a vehicle. It is incremented by 1 each time the vehicle visits a supply node during the heuristic process.
- ξ_{dem} is a counter used to keep track of the number of demand nodes visited by a vehicle. It is incremented by 1 each time the vehicle visits a demand node during the heuristic process.
- β is a number from the set [0, 1, 2] selected randomly after a vehicle finishes visiting a supply, SF location node, or set of α demand nodes, such that $\beta = 0$ means that the current vehicle must visit α demand nodes on the next step, $\beta = 1$ means that the current vehicle must visit a supply node or SF location on the next step, and $\beta = 2$ means the vehicle must visit a hospital next.

Route construction is performed using the `Construction` function. In this function, β does not have the same definition as in the approach suggested to solve the HLVRP model where only two values are considered. In the HLVRP, routes are constructed using the same procedure with some differences, by visiting a set of demand nodes and then visiting a hospital or resupply node. The difference in the HLVRPSF is that routes are constructed based on which objective function is active for the current iteration. Thus, in the HLVRPSF, vehicles may make visits that are not common in the HLVRP. For example, a vehicle may visit two SF locations consecutively to collect more supplies if the current objective function is to minimize the commodity deviations, or it may visit a hospital to transfer wounded people and then go to demand nodes while it is empty to evacuate more wounded if the current objective function is to minimize the non–evacuated wounded. Such visits are not common in the HLVRP model. Because of this, β has three values and is updated at the end of each loop in the `Construction` function to decide what the next visit should be.

Because unusual visits, such as visiting two supply nodes or SF locations, are not common, β is selected from the numbers [0,1,2] with different chances. For example, at the beginning when a vehicle leaves its depot, there is no need to visit a hospital, so the chance of selecting $\beta = 2$ is set to 0. After visiting supply node or SF locations, demand visits ($\beta = 0$) is given higher chance because this was observed to be more effective in preliminary testing.

The `Construction` function is used to construct a route, by setting all binary variables to 0 and 1, for the current selected vehicle and it is recalled (executed) for each vehicle. This function starts by sorting all node types in descending order based in their importance value to create the $Sort^D$, $Sort^{SL}$, and $Sort^H$ sets. Then the time loop begins and three types of visit are allowed: demand node visits, supply node and SF location visits, and hospital node visits. Only one of these visit types can be performed at a time because only one of the if–conditions in lines 14, 37, and 58 can be satisfied at a given time. Once one of these if–conditions is satisfied and becomes the current choice of visits, other loop begins to test which node is reachable (feasible to visit) by this time and has the highest importance value, as in lines 15, 38, 59. A feasibility test is performed by two sub–tests which are if the node can be reached by the current time loop value and if the current selected vehicle can return to its depot if this suggested visit is performed.

In the case of demand node visits, the prioritized demand of the visited node is decreased by dividing by 3. Prioritized demand values are calculated at the beginning of each iteration and are not reinitialized inside the while loop, so, this decreased value is used to calculate the importance values for the next vehicles. Experimental works show that 3 is the best number to divide by because using a larger number may make the visited nodes not preferable for future visits even if they are worth more visits, and using a smaller value renders the reduction not useful as the visited nodes remain preferable for more visits.

For hospital node visits, vehicles select the nearest hospital, so hospital importance values are calculated based on travel time with some randomness and it is not necessary to decrease them when a hospital is visited. Both supply and candidate SF location nodes are grouped in one category because they perform the same job, resupplying small vehicles with workers and commodities, but supply nodes are treated differently than SF locations when they are visited.

In case a vehicle visits a supply node at time t, its prioritized supply value is decreased from the second time period to the current time t. This is because picking up commodities and workers that are left from previous periods is allowed and it can not be determined if the next selected vehicles will visit this supply node at an earlier time or not. The next vehicles should know that this supply node was visited at time t and some of its supplies at any time before t might already be picked up. The first time period is excluded because the supplies and workers left at that time period is not known. Thus, it can not be used in the calculations.

In contrast, when a vehicle visits a candidate SF location node at time t, the prioritized supply value of this SF location is increased for three time slots: $t-1$, t, $t+1$. This is to make the visited SF location more preferable to other small vehicles and to SFs which facilitates and improves the distribution system by decreasing diversity. To explain this, consider a data instance with 10 vehicles, 2 SFs, and 20 SF locations. If the importance of SF locations is updated in the same way as of supply nodes by decreasing the values, the vehicles could visit 15 different SF locations because vehicle prefer to visit higher important SF location nodes, and most unvisited SF locations have higher importance value than reduced SF locations.

If many SF locations are visited, SFs would not be available at these SF locations to provide small vehicles with demand. By using the proposed importance update technique to increase the importance of visited SF locations, vehicles visit the SF locations with higher importance values, SF locations which have already been visited. In this example, vehicles could visit only 5 SF locations, and SFs can easily find a feasible solution to be available at these 5 different SF locations. Additionally, importances are increased for three periods to eliminate non-important movements which could be performed by SFs. For example, if a SF visits the location node l at time t, where other small vehicles will visit a location at time $t+1$, it is much easier for the SF to stay at l while the vehicles come to that location. This is why the importance of a location is increased for multiple time periods. On the other hand, allowing only one visit by each vehicle to each SF location encourages diversity and randomness of location visits. Increasing the prioritized supply value of visited SF locations is done by multiplying the current value by 1.5, this value is selected empirically through some observations performed in preliminarily test. First, SF route construction can be skipped in small scale instances and when CPLEX is used to find a complete candidate solution, it finds the best values for the x^F_{fijt} variables. This approach produces the best solution for the SF routes in short computation time using the pre–specified small vehicle routes.

ALGORITHM 11: `Construction` Function for Small Vehicle Routes

1: $\xi_{dem} = 0$ //Set demand node visits to zero
2: $\xi_{sl} = 1$ //Set supply node visits to one because the current vehicle leaves from its depot which is a supply node.
3: $t_{now} = 1$
4: **for all** $t \in T$ **do**
5:     Sort demand nodes in descending order based on their total importance to get $sort^D$.

Sort supply nodes and SF locations in descending order based on their total importance to get $sort^{SL}$.

Sort hospital nodes in descending order based on their total importance to get $sort^{H}$.

end for

Select $\beta = [0, 1]$ // First visit(s) could be demand node, SF locations, or supply node. But not hospital

if $\beta == 0$ **then** //Demand node visits are selected.

Select a random integer number $\alpha \in \left[\left\lfloor \dfrac{c_v}{0.7 \times Avg_D} + 0.5 \right\rfloor - 2, \left\lfloor \dfrac{c_v}{0.7 \times Avg_D} + 0.5 \right\rfloor + 2 \right]$ // Based on vehicle capacity and average masses of workers and demand

end if

for all $t \in T$ **do**

if $\xi_{dem} \leq \alpha$ and $\beta = 0$ **then**

for all $i \leq |D|$ **do**

if it is feasible to visit demand node $sort^{D}(t, i)$ **then**1stif2-hlvrpsf

$x^{V}_{v,\ current,\ sort^{D}(t,i),\ t} = 1$

$t_{now} = t$

Update $current = sort^{D}(t, i)$

Reduce the prioritized demand of $sort^{D}(t, i)$, such that

$PT^{D}(t, i) = PT^{D}(t, i)/3$ //to avoid revisiting by other vehicles

Recalculate importances for all nodes: // Because the current is updated

$IM^{v} = \texttt{Importance}\left(v, current, N, PT^{SL}, PT^{D}\right)$

for all $k \in T$ **do** // New sorting because importance values are updated

Sort demand nodes in descending order based on their total importance to get $sort^{D}$.

Sort supply nodes and SF locations in descending order based on their total importance to get $sort^{SL}$.

Sort hospital nodes in descending order based on their total importance to get $sort^H$.

end for

$\xi_{dem} = \xi_{dem} + 1$

i = big number $> |D|$ // end for loop to avoid infeasibility due to visiting more than one node at the same time.

if $\xi_{dem} = \alpha$ **then**

Select $\beta = [1, 2]$ randomly // To decide the next step (visits supply node, SF location, or hospital)

end if

end if// End if feasible to visit

end for

end if

if $\beta == 2$ And $\xi_{dem} \geq \alpha$ **then**

for all $i \leq |H|$ **do**

if it is feasible to visit hospital node $sort^H(t, i)$ **then**

$x^V_{v,\ current,\ sort^H(t,i),\ t} = 1$

Set $t_{now} = t$

Update $current = sort^H(t, i)$

Recalculate importance of all nodes, // Current updated

$IM^v = \texttt{Importance}\left(v, current, N, PT^{SL}, PT^D\right)$

for all $s \in T$ **do**

Sort demand nodes in descending order based on their total importance to get $sort^D$.

Sort supply nodes and SF locations in descending order based on their total importance to get $sort^{SL}$.

Sort hospital nodes in descending order based on their total importance to get $sort^H$.

end for

$\beta = random[0, 1]$ //next step could be re-supply or demand node visits

if $\beta = 0$ **then**

Generate new value of α // Next steps are demand node visits

end if

$i =$ big number $> |H|$ // to exit the for loop

end if// End if feasible to visit

end for

end if// End hospital visit

if $\beta == 1$ And $\xi_{sl} < |S| + |L|$ And $\xi_{dem} \geq \alpha$ **then**

for all $i \leq |S| + |L|$ **do**

if If it is feasible to visit supply or location node $sort^{SL}(t, i)$ **then**

$x^V_{v,\ current,\ sort^{SL}(t,i),\ t} = 1$

Set $t_{now} = t$

Update $current = sort^{SL}(t, i)$

if $sort^{SL}(t, i) \in S$ **then**

Reduce the prioritized supply of $sort^{SL}(t, i)$ node, such that

for all $k \in [2, t]$ **do**

$PT^{SL}(t, i) = PT^{SL}(t, i)(k, current)/2$

end for

if $i \in L$ **then**

Increase the prioritized supply of $sort^{SL}t, i$, such that:

$PT^{SL}(t, i) = 1.5 * PT^{SL}(t, i)$

$PT^{SL}(t - 1, i) = 1.5 * PT^{SL}(t - 1, i)$

$PT^{SL}(t + 1, i) = 1.5 * PT^{SL}(t + 1, i)$

end if

Recalculate importance of all nodes,

$IM^v = \texttt{Importance}\left(v, current, N, PT^{SL}, PT^{D}\right)$

end if

for all $s \in T$ **do**

Sort demand nodes in descending order based on their total importance to get $sort^D$.

Sort supply nodes and SF locations in descending order based on their total importance to get $sort^{SL}$.

Sort hospital nodes in descending order based on their total importance to get $sort^H$.

end for

$\xi_{sl} = \xi_{sl} + 1$

$i =$ big number $> |S| + |L|$ // to exit the for loop

Select new value of $\beta = [0, 0, 1, 2]$ randomly // decide next step, higher chance to 0 (visit demand node)

if $\beta = 0$ **then**

Generate new value of α

end if

end if// End if feasible to visit

end for

end if// End supply visit

end for// End t-loop

$x^V_{v\ current\ i^V_v\ t_{now}} = 1$

Return $x^V_{vijt}\ \ \forall i, j \in N,\ i \neq j,\ t \in T$

After execution of the vehicle routes `construction` function, some information is produced such as which SF locations were visited by the small vehicles, when they were visited, and the prioritized values of the SF locations. This information is used to construct the SF routes in different ways.

As discussed earlier, the common step to generate any candidate solution is to solve the model by CPLEX at specific binary variable values. The first option to construct the SF routes is to keep their binary variables as free (without setting them to 0 or 1) and use CPLEX to solve the model at specific vehicle binary variable values. In this case, CPLEX is used to find a complete candidate solution, it finds the best values for the x^F_{fijt}, variables besides the picked–up and delivery variable values. This approach produces the best solution for the SF routes in short computation time using the pre–specified small vehicle routes.

The second approach for SF routes construction is to eliminate, for all time periods, the unvisited SF locations from the network by setting some x^F_{fijt} variables to zero and keeping the others as free binary. If a SF location l is visited at time t by one or more small vehicles, variables $x^F_{fil\ t-1}, x^F_{fil\ t},\ x^F_{fil\ t+1} \forall f \in F$ remain free binary while others variables related to this SF location are set to 0. Three time periods are considered to select the free binary variables to add flexibility to the model and reduce the chance of infeasibility. To explain this, consider a SF location which is visited by small vehicles at times t and $t+2$. Only the variables at these times are kept free (e.g., only $x^F_{fil\ t}, x^F_{fil\ t+2}\ \forall f \in F$ are kept free, and $x^F_{fil\ t+1} = 0\ \forall f \in F$). This means that if a SF visits l at time t, it can not stay until $t+2$ because the binary variables at $t+1$ are set to 0. So, adding free binary conditions to three time periods provides more choices for SFs.

After setting some binary variables to 0 and keeping others as free binary, the `SF-construction` function can be skipped, allowing CPLEX to find the optimal SF routes, but only the free binary variables are available. This becomes much easier for CPLEX and this approach is suitable for medium scale instances.

In the third approach, the updated SF location prioritized value matrix (which is part of the whole prioritized matrix) that produced at the end of small vehicle routes construction can be used to construct SF routes in the same manner as those of small vehicles. In this approach, SFs are randomly sequenced, then selected one by one. For each SF, the current location is set to its depot, then the time loop starts in line 22 of Algorithm 12. Time loop and the feasibility test at line 27 are working in parallel to find the most important SF location which has the highest importance value and can be reached by the current time value.

In the `SF-construction` function, the SF location prioritized values are no longer treated as in the `Construction` function by increasing the importance value of the visited SF locations as discussed earlier. Instead they are treated as supply nodes by decreasing the importance value of the visited SF locations to break ties and allow other important SF locations to be visited. Accordingly, once a SF location is visited by a SF, its prioritized value decreased by divided by 1.5 which the same multiplication number used in `Construction` function to increase the prioritized value of visited SF locations. Then, the current selected SF stays at the same SF location if necessary or visits another. This procedure continues up to the end of the planning horizon.

The third approach produces a complete set of routes for SFs, so it is suitable for large scale instances. Because solving the model with complete specified routes for both SFs and small vehicles saves much computational effort and time. Pseudo code 12 shows the SF route construction.

To allow the code run without any input from the users, some conditions can be added to select one of these choice. For example, if the number of vehicles is greater than 20, the code will select the third choice.

Algorithm 12: `SF-Construction` Routes Function

if $\Psi == 1$ **then**
  First case, Skip the `SF-Construction` function
end if//End the first case if
if $\Psi == 2$ **then**
  Case two: some of the x^F_{fijt} variables are free, such that
  for all $l \in L,\ t \in T$ **do**
    if $\sum_{v \in V} \sum_{i \in N} \hat{x}^V_{vilt} \geq 1$ **then** //Check if the location is visited
      for all $f \in F, j \in L \cup i^F_f$ **do**
        Add condition: x^F_{fjlt} is binary.
        Add condition: $x^F_{fjl(t+1)}$ is binary.
        Add condition: $x^F_{fjl(t-1)}$ is binary.
      end for
    end if
  end for
end if//End the second case if
if $\Psi == 3$ **then**
  Case three: construct routes
  Sort location nodes in descending order based on their total importance
  for all $f \in F$ **do**
    $t_{now} = 1$
    Set $current = i^F_f$
    for all $t \in T$ **do**
      Sort SF location nodes in descending order based on their total importance to get $sort^L$
    end for

for all $t \in T$ **do**
for all $i \leq |L|$ **do**
if it is feasible to visit SF location $sort^L(t, i)$ **then**
$x^F_{f,\ current,\ sort_{t,i},\ t} = 1$
$t_{now} = t$
Update $current = sort^L(t, i)$
Reduce the the prioritized value of $sort^L(t, i)$, such that $PT^L(sort^L(t, i)) = sort^L(t, i)/1.5$ //to avoid revisiting many times by other SF
Recalculate importances for all SF locations,
$IM^f = \texttt{SF-Importance}\left(f, current, L, PT^L\right)$
for all $k \in T$ **do**
Sort SF location nodes in descending order based on their total importance to get $sort^L$
end for
i = big number $> |L|$ // end for loop to avoid infeasibility due to visiting more than one node in the same time.
end if// End if feasible to visit
end for//End for i
end for//End for t
end for//End for f
end if//End the third case if
$x^F_{f\ current\ i^F_f\ t_{now}} = 1$
Return $x^F_{fijt}\ \ \forall i, j \in L \cup i^F_f,\ i \in L \cup i^F_f,\ t \in T$

After finishing the construction of small vehicle and SF routes, the set of candidate solutions should be developed considering these routes, in line 24 of pseudo code 8, to get Pareto optimal at the end of all iterations. This is discussed next in Section 5.7.2.

5.7.2 Generating Candidate Solutions for a Particular Objective

As discussed in Section 5.6, using a single objective causes many variables to have a value of zero. In this section, six different approaches are developed to generate representative candidate solutions that include all logistic operations.

Multiple approaches are developed and evaluated because each approach has some limitations that prevent it from being suitable for all cases. So, the six approaches aim to overcome the limitations and cover all possible cases. All proposed approaches are compared in terms of the number of solutions generated in a specific computation time, variety of solutions, and quality of solutions to find the most suitable approach. Some of these approaches depend on a single objective function without adding any constraints, as in Sections 5.7.2.1 and 5.7.2.6. On the other hand, some approaches depend on a single objective function as well as the addition of new constraints, as in Sections 5.7.2.2, 5.7.2.3, and 5.7.2.4. Finally, in Section 5.7.2.5, a multi–stage approach is proposed, where a single objective function is used in each stage.

5.7.2.1 A Linearly–Weighted Combination of Objectives (LWCO)

This is the easiest approach where all objectives are used in a single objective with different weights, $W_1, W_2,$ and W_3, which are generated randomly in the range of [0,1]. The single objective function is in 5.52.

$$\text{Min } W_1 \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^C \ v_{cit}^C + W_2 \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p_{wi}^W \ v_{wit}^W + W_3 \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p_{ei}^E \ v_{eit}^E \tag{5.52}$$

In line 24 of Algorithm 8, the `LWCO` function is called and performed as shown in Algorithm 13. The termination criterion in this algorithm is a specific number γ which represents how many candidate solutions are created in each iteration using the same routes (same binary variable values). Because the termination criterion for the overall main code is time (as discussed in the Algorithm 8), using a high number for γ decreases the number of iterations which can be performed in a specific time. On the other hand, using a low number for γ decreases the chance of getting different candidate solutions for different objective function values at each iteration using the same binary variables. After extensive experiments, it is found that finding four candidate solutions ($\gamma = 4$) at each iteration is appropriate to produce the best diverse set of solutions at the end.

To generate each candidate solution, weights are randomly generated, binary variable values for vehicles are taken from the `Construction` function, and binary variable values for SFs are taken from the `SF-construction` function. In the case of $\Psi = 1$, where the `SF-construction` function is skipped, binary variables are used without any conditions, as defined originally. Then, CPLEX can solve the model to create a complete solution for the HLVRPSF. This procedure is repeated γ times.

ALGORITHM 13: `LWCO` Function

Set $Counter = 1$
while $Counter \leq \gamma$ **do**
    Generate $W_1, W_2,$ and $W_3 \in [0, 1]$ randomly
    Use the objective function
        $\text{Min } W_1 \sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p^C_{ci}\ v^C_{cit} + W_2 \sum_{w\in W}\sum_{i\in D}\sum_{t\in T} p^W_{wi}\ v^W_{wit} + W_3 \sum_{e\in E}\sum_{i\in D}\sum_{t\in T} p^E_{ei}\ v^E_{eit}$
    Vehicle binary variable values = `Construction` function output
    SF binary variable values = `SF-Construction` function output
    Solve the model using CPLEX
    Save the value of all objective functions in Z_{obj}
    Save the complete solution in Z_{all}
    Update $Counter = Counter + 1$
end while

This approach has many advantages and produces representative results as will be shown in the numerical analysis; however, it has the disadvantage that created solutions depend on the generated weights. It is supposed that using different weights to build different objective functions to generate many candidate solutions at each iteration can overcome the problem of using a single objective. In some cases, the priorities that are used in each single objective function can dominate the effect of the generated weights and similar candidate solutions are produced regardless of the weight values.

The next approach uses only the current activated objective function to generate a candidate solution and overcome the potential problems due to the use of a weighted single objective.

5.7.2.2 Single Objective with Individual Minimum Resource Usage Constraints (SOIMRUC)

Using a single objective function which includes all objective functions in a weighted manner could cause a problem due to the priority values while using only one of the three objective functions causes the problem of producing many variables with a value of 0. Because of this, a new approach is suggested in this section to use the current activated objective function with some added constraints to overcome these problems.

In this approach, the total load of each vehicle picked up during the whole plan is divided into three almost equal parts for the three logistic operations, i.e. commodities, workers, and wounded. This is achieved by adding three constraints, as follows

$$\begin{aligned}
&0.3 \Bigg(\sum_{t \in T} \sum_{c \in C} \sum_{i \in S} m_c^C z_{civt}^{PS} + \sum_{t \in T} \sum_{f \in F} \sum_{c \in C} \sum_{i \in L} m_c^C z_{cfivt}^{PL} \\
&+ \sum_{t \in T} \sum_{f \in F} \sum_{w \in W} \sum_{l \in L} m_w^W w_{wflvt}^{PL} + \sum_{t \in T} \sum_{w \in W} \sum_{i \in S} m_w^W w_{wivt}^{PS} + \sum_{t \in T} \sum_{e \in E} \sum_{i \in D} m_e^E e_{eivt}^{P} \Bigg) \\
&\le \sum_{t \in T} \sum_{c \in C} \sum_{i \in S} m_c^C z_{civt}^{PS} + \sum_{t \in T} \sum_{f \in F} \sum_{c \in C} \sum_{l \in L} m_c^C z_{cflvt}^{PL} \quad \forall v \in V
\end{aligned} \tag{5.53}$$

$$
\begin{aligned}
&0.3\Bigg(\sum_{t\in T}\sum_{c\in C}\sum_{i\in S} m_c^C z_{civt}^{PS} + \sum_{t\in T}\sum_{f\in F}\sum_{c\in C}\sum_{i\in L} m_c^C z_{cfivt}^{PL} \\
&+ \sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{i\in L} m_w^W w_{wfivt}^{PL} + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} + \sum_{t\in T}\sum_{e\in E}\sum_{i\in D} m_e^E e_{eivt}^{P}\Bigg) \\
&\leq \sum_{t\in T}\sum_{e\in E}\sum_{i\in D} m_e^E e_{eivt}^{P} \quad \forall v \in V
\end{aligned} \tag{5.54}
$$

$$
\begin{aligned}
&0.3\Bigg(\sum_{t\in T}\sum_{c\in C}\sum_{i\in S} m_c^C z_{civt}^{PS} + \sum_{t\in T}\sum_{f\in F}\sum_{c\in C}\sum_{i\in L} m_c^C z_{cfivt}^{PL} \\
&+ \sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{i\in L} m_w^W w_{wfivt}^{PL} + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} + \sum_{t\in T}\sum_{e\in E}\sum_{i\in D} m_e^E e_{eivt}^{P}\Bigg) \\
&\leq \sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{i\in L} m_w^W w_{wfivt}^{PL} + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} \quad \forall v \in V
\end{aligned} \tag{5.55}
$$

Using these constraints ensures that the vehicles perform all logistic operations almost equally regardless of which objective is used. Suppose that the total mass of commodities, workers, and wounded picked up by a vehicle v equals M. Constraints (5.53) ensure that at the end of the plan the total mass of commodities picked up by the vehicle v greater than or equal to 30% of M. In the same manner, Constraints (5.54) ensure that the total mass of wounded picked up by the vehicle v greater than or equal to 30% of M, and Constraints (5.55) ensure that the total mass of workers picked up by the vehicle v greater than or equal to 30% of M.

Ten percent of the total mass picked up is assigned as free space to reduce the chance of producing infeasible solutions due to the integer condition of some variables. To understand the benefit of using 0.3 but not 0.33, the following example is created. Assume a vehicle v, with capacity 1300 lb, performs only one simple trip by visiting two demand nodes and one hospital. Using 0.33 means that this vehicle should pick up more than 433 lb of wounded, workers, and commodities. Knowing that the average mass of people is 200 lb, the vehicle can pick up only 400 lb or 600 lb. By picking 600lb of workers and wounded, no more space will be available to pick up 433lb of commodities, making the model infeasible. If 0.3 is used, the vehicle can pick up 400 lb of workers, 400 lb of wounded, 390 lb of commodities, and 110 lb of other commodities.

This approach is performed by calling the `SOIMRUC` function in line 24 of the Algorithm 8. This function is presented in Algorithm 14. Because only one objective function is used, γ is set to 1 which means only one candidate solution is created at each iteration using this approach.

Algorithm 14: `SOIMRUC` Function

Set $Counter = 1$

while $Counter \leq \gamma$ **do**

  Add constraints (5.53)–(5.55) to the HLVRPSF model

  if $\varphi = 1$ **then**

    Use objective function 5.1

    $\text{Min} \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci} \; v^C_{cit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \; x^F_{fli^F_f t}$

  end if

  if $\varphi = 2$ **then**

    Use objective function 5.2

    $\text{Min} \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi} \; v^W_{wit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \; x^F_{fli^F_f t}$

  end if

  if $\varphi = 3$ **then**

    Use objective function 5.3

    $\text{Min} \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei} \; v^E_{eit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \; x^F_{fli^F_f t}$

  end if

  Vehicle binary variable values = `Construction` function output

  SF binary variable values = `SF-Construction` function output

  Solve the model using CPLEX

  Save the value of all objective functions in Z_{obj}

Save the complete solution in Z_{all}

Update $Counter = Counter + 1$

end while

This procedure is tested for many data sets and shows limitations of use. One limitation is that it is only suitable for long planning horizons where the vehicles can perform many trips by resupplying and revisiting hospitals. For short planning horizon, vehicles will work at less than full capacity to satisfy Constraints (5.53)–(5.55). To explain this more fully, consider Figure 5.5 which shows a simple route performed by a slow vehicle where the current activated objective function is to minimize the wounded deviations.

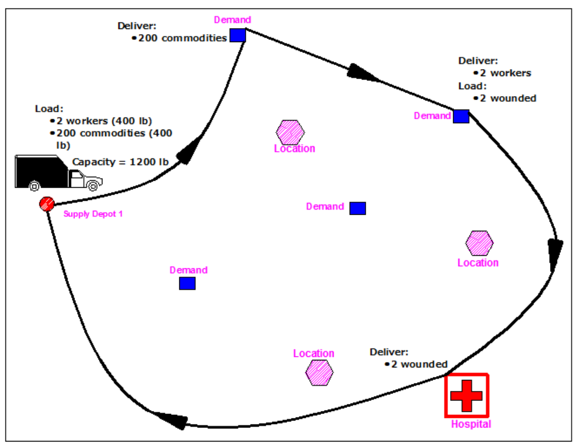


Figure 5.5: Slow vehicle route in HLVRPSF model- first approach

In the figure, the vehicle picks up 400 lb of commodities from its depot, 400 lb of workers from its depot, and 400 lb of wounded from one of the demand nodes. Because it starts with a load of 800 lb, it also has 400 lb of free space. Furthermore, it picks up only 400 lb of wounded from one of the demand nodes to transfer them to the hospital which leaves 800 lb of free space. After the hospital visit, because of the limited planning horizon, it returns to its depot.

Other solution can be constructed by picking up 600 lb of commodities and 600 lb of workers from its depot, and 1200 lb of wounded from the demand nodes. This solution is wanted because it provides higher vehicle utilization and better objective function values. The wanted solution was not created by this approach, even it is possible, because picking up full loads violates Constraints (5.53)–(5.55) as happens if this vehicle picks up a full load of 600 lb of commodities and 600 lb of workers from its depot, and 1200 lb of wounded from the demand nodes. The total mass is 2400 lb; the quantities of 600 lb are not greater than or equal 30% of 2400. According to the proposed example, it can be concluded that this procedure is suitable if the plan is long and the vehicles can make many visits to resupply and deliver wounded to hospitals, so any shortages of mass that violate the constraints in the first trip can be satisfied in the following trips.

Beside the one above, another limitation of this approach is that the number of solutions in each Pareto set is low (2-3 solutions), because the value of each objective would not be changed greatly no matter what objective is activated. This is not always considered a limitation. In some cases where the three logistic operations have the same care or importance to be performed, this approach can be used efficiently without any worries concerning the priority values hence it produces a few solutions with almost the same deliverables.

In Section 5.7.2.3, a similar procedure is suggested to use the current activated objective function with some added constraints but with better source utilizations in the cases of a short planning horizon.

5.7.2.3 Single Objective with Aggregate Minimum Resource Usage Constraints (SOAMRUC1)

It can be noticed from the network system that commodities and workers have the same sources, the supply and SF location nodes, and the same destinations, the demand nodes. On the other hand, wounded are picked up from the demand nodes and delivered to the hospital nodes. Relying on this, a new set of constraints are added to give equal opportunities for commodity distribution and workers transfer with wounded evacuation. In other words, the total loads that can be picked up by a vehicle is divided into two almost equal parts. The first part is used for commodity distribution and worker transfer while the second part is used for wounded evacuation. This allows vehicles to pick up a full load, if resources are available, of commodities and workers each time they visit supply nodes, and pick up a full load of wounded before they visit hospitals without violating the added constraints. These constraints are presented below.

$$\sum_{t\in T}\sum_{c\in C}\sum_{i\in S} m_c^C z_{civt}^{PS} + \sum_{t\in T}\sum_{f\in F}\sum_{c\in C}\sum_{i\in L} m_c^C z_{cfivt}^{PL} \geq 0.45 \left(\sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{l\in L} m_w^W w_{wflvt}^{PL} \right.$$
$$\left. + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} + \sum_{t\in T}\sum_{c\in C}\sum_{i\in S} m_c^C z_{civt}^{PS} + \sum_{t\in T}\sum_{f\in F}\sum_{c\in C}\sum_{l\in L} m_c^C z_{cflvt}^{PL} \right) \quad \forall v \in V \tag{5.56}$$

$$\sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{l\in L} m_w^W w_{wflvt}^{PL} + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} \geq 0.45 \left(\sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{l\in L} m_w^W w_{wflvt}^{PL} \right.$$
$$\left. + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} + \sum_{t\in T}\sum_{c\in C}\sum_{i\in S} m_c^C z_{civt}^{PS} + \sum_{t\in T}\sum_{f\in F}\sum_{c\in C}\sum_{l\in L} m_c^C z_{cflvt}^{PL} \right) \quad \forall v \in V \tag{5.57}$$

$$\sum_{t\in T}\sum_{c\in C}\sum_{i\in S} m_c^C z_{civt}^{PS} + \sum_{t\in T}\sum_{f\in F}\sum_{c\in C}\sum_{i\in L} m_c^C z_{cfivt}^{PL}$$
$$+ \sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{i\in L} m_w^W w_{wfivt}^{PL} + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} \geq 0.9 \sum_{t\in T}\sum_{e\in E}\sum_{i\in D} m_e^E e_{eivt}^{P} \quad \forall v \in V \tag{5.58}$$

$$\sum_{t\in T}\sum_{e\in E}\sum_{i\in D} m_e^E e_{eivt}^{P} \geq 0.9 \left(\sum_{t\in T}\sum_{c\in C}\sum_{i\in S} m_c^C z_{civt}^{PS} + \sum_{t\in T}\sum_{f\in F}\sum_{c\in C}\sum_{i\in L} m_c^C z_{cfivt}^{PL} \right.$$
$$\left. + \sum_{t\in T}\sum_{f\in F}\sum_{w\in W}\sum_{i\in L} m_w^W w_{wfivt}^{PL} + \sum_{t\in T}\sum_{w\in W}\sum_{i\in S} m_w^W w_{wivt}^{PS} \right) \quad \forall v \in V \tag{5.59}$$

Constraints (5.56) and (5.57) are always added to the model, regardless of which objective function is active in the current iteration. In these constraints, the right hand side represents the total mass of commodities and workers without considering the wounded mass. They balance the first part of the load between workers and commodities.

Constraints (5.58) are used only if Objective (5.3) is activated to force the vehicles to perform commodity distribution and worker transfer even though the objective is to minimize the wounded deviations. Constraints (5.59) are used only if either Objectives (5.1) or (5.2) are activated to force vehicles to perform wounded evacuation while the current objective function is to minimize the commodities deviations or work-force deviations. As in the previous approach, 10% of vehicle capacity is not assigned to one type of load to avoid infeasible solutions due to integer condition of some variables. This free space is partially or completely filled up when it is needed to satisfy the added constraints.

This approach is performed by calling the function `SOAMRUC1` in the main Algorithm 8 at line 24. `SOAMRUC1` is presented in Algorithm 15. As in the previous approach, because one of the objective functions is used at each iteration, γ is set to one and one candidate solution is created.

ALGORITHM 15: `SOAMRUC1` **Function**

Set $Counter = 1$
while $Counter \leq \gamma$ **do**
  Add constraints (5.53)–(5.55) to the HLVRPSF model
  if $\varphi = 1$ **then**
    Use objective function 5.1
    Min $\sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p^C_{ci}\ v^C_{cit} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\ x^F_{fli^F_f t}$
    Add constraints 5.56, 5.57, and 5.59
  end if
  if $\varphi = 2$ **then**
    Use objective function 5.2

Min $\sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi} \; v^W_{wit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \; x^F_{fli^F_f t}$

Add constraints 5.56, 5.57, and 5.59

end if

if $\varphi = 3$ **then**

Use objective function 5.3

Min $\sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei} \; v^E_{eit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \; x^F_{fli^F_f t}$

Add constraints 5.56, 5.57, and 5.58

end if

Vehicle binary variable values = `Construction` function output

SF binary variable values = `SF-Construction` function output

Solve the model using CPLEX

Save the value of all objective functions in Z_{obj}

Save the complete solution in Z_{all}

Update $Counter = Counter + 1$

end while

Testing this approach shows marked improvement in the performance of vehicles. In this case, vehicles pick up almost full loads of commodities and workers each time they visit a supply or SF location node, and pick up almost full loads of wounded before visiting a hospital, but, as in the previous approach, the number of solutions in each Pareto set is low because the objective values do not depend on the current activated function. Consequently, this approach is recommended when the actual case requests equal care for both commodity distribution and worker transfer on one side and wounded evacuation on the other side.

The limitation with this approach is the unassigned 10% space which is not fully used in most of cases and which reduces the efficiency of vehicles. In Section 5.7.2.4, a modified approach is presented to utilize this free space.

5.7.2.4 Single Objective with Aggregate Minimum Resource Usage Constraints to Fill Free Space (SOAMRUC2)

The following approach is used overcome the problem of 10% unassigned space in the previous approach. This free space is not utilized in most cases which decreases the amount of commodities delivered, workers transfered, and/or wounded evacuated. For this reason, in this approach, beside adding Constraints (5.56) – (5.59), the original objective functions (5.1) – (5.3) are changed as follows.

$$\text{Min} \sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p_{ci}^{C}\ v_{cit}^{C} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\ x_{fli_f^F t}^{F} + \left(\sum_{w\in W}\sum_{i\in D}\sum_{t\in T} p_{wi}^{W}\ v_{wit}^{W} + \sum_{e\in E}\sum_{i\in D}\sum_{t\in T} p_{ei}^{E}\ v_{eit}^{E}\right)/\Omega \tag{5.60}$$

$$\text{Min} \sum_{w\in W}\sum_{i\in D}\sum_{t\in T} p_{wi}^{W}\ v_{wit}^{W} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\ x_{fli_f^F t}^{F} + \left(\sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p_{ci}^{C}\ v_{cit}^{C} + \sum_{e\in E}\sum_{i\in D}\sum_{t\in T} p_{ei}^{E}\ v_{eit}^{E}\right)/\Omega \tag{5.61}$$

$$\text{Min} \sum_{e\in E}\sum_{i\in D}\sum_{t\in T} p_{ei}^{E}\ v_{eit}^{E} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\ x_{fli_f^F t}^{F} + \left(\sum_{w\in W}\sum_{i\in D}\sum_{t\in T} p_{wi}^{W}\ v_{wit}^{W} + \sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p_{ci}^{C}\ v_{cit}^{C}\right)/\Omega \tag{5.62}$$

Where $\Omega = \left(\sum_{w\in W}\sum_{i\in D}\sum_{t\in T} p_{wi}^{W}\ d_{wit}^{W} + \sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p_{ci}^{C}\ d_{cit}^{C} + \sum_{e\in E}\sum_{i\in D}\sum_{t\in T} p_{ei}^{E}\ d_{eit}^{E}\right)$ represents the maximum possible total deviations if all requested demands and workers are not satisfied and all wounded are not evacuated. The third term in each function is very small compared to the first term and is always less than one. This term motivates vehicles to fill up any free space without affecting the main objective (first term). Another benefit of using the third term in each objective function is that the vehicles perform the logistic operations, not related to the current activated objective (first term), with respect to priority values. For example, if the current activated objective function is to minimize the wounded deviations, if the third term is not used, vehicles pick up commodities and workers without preference.

When the third term is used, vehicles pick up commodities and workers with higher priority to satisfy the added constraints and minimize the value of the third term in the objective function.

To execute this approach, the `SOAMRUC2` function is called in the main Algorithm 8 at line 24. `SOAMRUC2` is presented in Algorithm 16. Again, because one of the objective functions is used at each iteration, γ is set to one and one candidate solution is created.

ALGORITHM 16: `SOAMRUC2` Function

Set $Counter = 1$

while $Counter \leq \gamma$ **do**

  Add constraints (5.53)–(5.55) to the HLVRPSF model

  if $\varphi = 1$ **then**

    Use objective function 5.60

$$\text{Min} \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci} \, v^C_{cit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \, x^F_{fli^F_f t} + \left(\sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi} \, v^W_{wit} + \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei} \, v^E_{eit} \right) / \Omega$$

    Add constraints 5.56, 5.57, and 5.59

  end if

  if $\varphi = 2$ **then**

    Use objective function 5.61

$$\text{Min} \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi} \, v^W_{wit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \, x^F_{fli^F_f t} + \left(\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci} \, v^C_{cit} + \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei} \, v^E_{eit} \right) / \Omega$$

    Add constraints 5.56, 5.57, and 5.59

  end if

  if $\varphi = 3$ **then**

    Use objective function 5.62

$$\text{Min} \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei} \, v^E_{eit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \, x^F_{fli^F_f t} + \left(\sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi} \, v^W_{wit} + \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci} \, v^C_{cit} \right) / \Omega$$

    Add constraints 5.56, 5.57, and 5.58

  end if

  Vehicle binary variable values = `Construction` function output

  SF binary variable values = `SF-Construction` function output

Solve the model using CPLEX

Save the value of all objective functions in Z_{obj}

Save the complete solution in Z_{all}

Update $Counter = Counter + 1$

end while

The vehicle in Figure 5.5, produced by the SOIMRUC approach, is re-drawn after solving the model using the SOAMRUC2 approach; Figure 5.6 shows the solution. It can be observed that the total mass of evacuated wounded is improved from 400 lb to 1200 lb, and the total mass for both transfered workers and distributed commodities are increased from 400 lb to 600 lb, as summarized in Table 5.2.

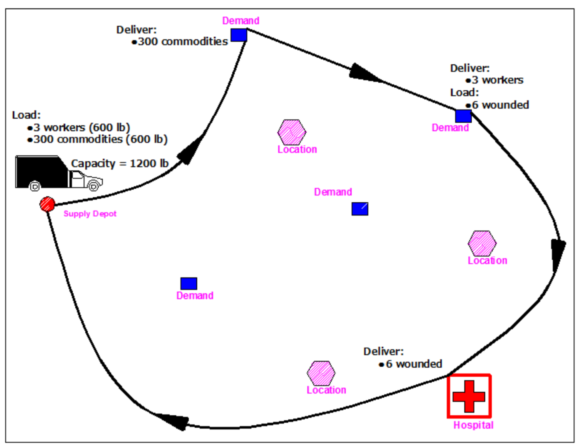


Figure 5.6: A vehicle route in the HLVRPSF model obtained by the SOAMRUC2 approach

Logistic Operation	**SOIMRUC Solution**	**SOAMRUC2 Solution**
Commodities distribution	400 lb	600 lb
Workers transfer	400 lb	600 lb
Wounded evacuation	400 lb	1,200 lb
Total mass	1,200 lb	2,400 lb

Table 5.2: SOAMRUC2 vs. SOIMRUC

Similarly, the SOIMRUC approach in Section 5.7.2.4 can be modified slightly to solve the problem of the 10% unassigned space. To do so, the same third term in each objective function in this section can be added to the objective functions used in the SOIMRUC approach and Algorithm 14 can be used again but with modified objective functions.

The approach defined in this Section 5.7.2.4 keeps the vehicles at full capacity as the supplies are available, but the limitation is that these procedures give the same importance to commodities and workers as they do to wounded. This might not be reasonable in some cases and fails to find the extreme cases determined using a single objective. The next section presents a new approach that uses multiple stages to find candidate solutions at each iteration.

5.7.2.5 Single Objective Solved in Multiple Stages (SOSMS)

In this section, a new approach is suggested to create candidate solutions. A similar approach has been suggested by Najafi et al. (2013) to solve a humanitarian relief problem considering demand distribution and wounded evacuation. The objective functions considered in Najafi et al. (2013) are to minimize unsatisfied demand, minimize non–evacuated wounded, and minimize the number of vehicles used.

SOSMS begins by solving the model with one objective function. Then, a constraint set derived from the first solution is added to the model which is solved using the first objective function with the next objective function in the next stage. In the final stage, the model is solved again using the first two functions and the third objective function while considering two constraint sets. There is no clear rule of how to select the arrangement of the objective functions. In the HLVRPSF, because 3 objective functions are used, there are 6 different possibilities, as in Table 5.3.

Fist stage objective function	**Second stage objective function**	**Third stage objective function**
Minimize commodity deviations 5.1	5.1+Minimize workers deviations 5.1+5.2	5.1+5.2+Minimize wounded deviations 5.1+5.2+5.3
Minimize commodity deviations 5.1	5.1+Minimize wounded deviations 5.1+5.3	5.1+5.3+Minimize workers deviations 5.1+5.3+5.2
Minimize workers deviations 5.2	5.2+Minimize commodity deviations 5.2+5.1	5.2+5.1+Minimize wounded deviations 5.2+5.1+5.3
Minimize workers deviations 5.2	5.2+Minimize wounded deviations 5.2+5.3	5.2+5.3+Minimize commodity deviations 5.2+5.3+5.1
Minimize wounded deviations 5.3	5.3+Minimize commodity deviations 5.3+5.1	5.3+5.1+Minimize workers deviations 5.3+5.1+5.2
Minimize wounded deviations 5.3	5.3+Minimize workers deviations 5.3+5.2	5.3+5.2+Minimize commodity deviations 5.3+5.2+5.1

Table 5.3: Different possibilities of SOSMS

Suppose the first possibility is arbitrarily selected to construct the approach of SOSMS. This procedure is performed by calling the `SOSMS` function in line 24 of the main Algorithm 8. The `SOSMS` function is presented in Algorithm 17. In this function, the model is first solved considering only the first objective function which is to minimize the commodity deviations. The first solution includes only demand distribution, and vehicles are expected to work with full load of commodities if the supplies are available. Suppose that the objective function value of this solution is Z_1^* which is the best value of total commodity deviations which can be achieved because it is produced when vehicles only perform the logistic operation of demand distribution. Then the constraint in line 12 is added to the model where the left hand side is the total commodity deviations and the right side is δ_1 (a number greater than 1) multiplied by Z_1^*. Because Z_1^* is the best value which can be achieved for commodity deviations, using this constraint forces vehicles to have free space depending on the value of δ_1. This free space is used to transfer workers which is part of the second objective function.

After the model is solved using the updated objective function that includes two functions (commodity and worker deviations), a new solution is produced with only commodity distribution and worker transfer. Suppose the objective function value of the second solution is Z_2^*, which is the best value can be achieved for total commodity and worker deviations. Another constraint is added to the model as in line 16 with the left hand side being total commodity and worker deviations. The value δ_2 is randomly generated with a value greater than 1 and Z_2^* is the best objective value for commodity and worker deviations; this constraint forces vehicles to have free space to use for wounded evacuation because evacuation is added to the third objective function. Finally, the model is solved with the third objective function, which includes all deviation variables, and with added constraints to find the complete candidate solution.

As this approach requires solving the model three times to get one complete candidate solution, γ is set to one to allow the generation of more candidate solutions using different routes.

ALGORITHM 17: `SOSMS` Function

1: Set $Counter = 1$

2: **while** $Counter \leq \gamma$ **do**

3: Vehicle binary variable values = `Construction` function output

4: SF binary variable values = `SF-Construction` function output

5: Use objective function 5.1

6: Min $\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^{C} \, v_{cit}^{C} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \, x_{fli_f^F t}^{F}$

7: Solve the model using CPLEX

8: Assume the solution has an objective value of $Z_1^* = \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^{C} \, v_{cit}^{C}$

9: Second step: modify the first objective function to add other objective function 5.2+5.1

10: Min $\sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p_{wi}^{W} \, v_{wit}^{W} + \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^{C} \, v_{cit}^{C} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \, x_{fli_f^F t}^{F}$

11: Generate $\delta_1 \in (1, 1.5]$ randomly

12: Add a constraint $\sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^{C} \, v_{cit}^{C} \geq \delta_1 \; Z_1^*$

13: Solve the model using CPLEX

14: Assume the solution has an objective value of $Z_2^* = \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^{C} \, v_{cit}^{C} + \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p_{wi}^{W} \, v_{wit}^{W}$

15: Third step: modify the previous objective function to add other objective function 5.1+5.2+5.1

16: $$\text{Min} \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p_{wi}^{W} \, v_{wit}^{W} + \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^{C} \, v_{cit}^{C} + \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p_{ei}^{E} \, v_{eit}^{E} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|} \, x_{fli_f^F t}^{F}$$

17: Generate $\delta_2 \in (1, 1.5]$ randomly.

18: Keep constraint in line 12, add the constraint

19: $$\sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p_{wi}^{W} \, v_{wit}^{W} + \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p_{ci}^{C} \, v_{cit}^{C} \geq \delta_2 \; Z_2^*$$

20: Solve the model using CPLEX

21: Save the value of all objective functions obtained from the previous step in Z_{obj}

22: Save the complete solution obtained from the previous step Z_{all}

23: Update $Counter = Counter + 1$

24: **end while**

The ranges of δ_1 and δ_2 are defined by the users. Based on some experimental work, (1,1.5] seems to be a reasonable range. The problem with this approach is that three stages are required to generate one candidate solution which takes more time. Another problem demonstrated during experimental work is that no solution is produced during many iterations because vehicles can not always satisfy the added constraints.

The final approach is suggested in the next section and adopts different features from the previous approaches. First, it can create a candidate solution in one stage. Second, it uses single objective function without adding constraints. Finally, it incorporates the other objective functions with the current activated function in a way different than the weighted method.

5.7.2.6 Single Objective with Weighted Penalties (SOWP)

In previous approaches, the LWCO approach, which uses weighted objective functions, depends on the priority values and might not be a proper approach if the priority values are not selected carefully. Both SOIMRUC and SOAMRUC2, which use a single objective function with added constraints, make selection of the current activated objective function not important because the added constraints force the vehicles to always perform all logistic activities regardless of which objective function is activated. SOSMS needs to solve the model three times to create one candidate solution. Consequently, the approach suggested in this section uses the current activated objective function without adding constraints to create a candidate solution in one stage. To let vehicles to perform all logistic operations without adding constraints, small weights (penalties) are used to add the other objective functions to the current selected function.

This new objective equals the active plus the other two objectives multiplied by random penalties to create other candidate solutions around the solution of the activated objective. Assume the current activated function is ϕ_1, and the other two functions are ϕ_2 and ϕ_3, as in Objective 5.63. The generated objective function is as follows, where R_1 and R_2 are random ratios. Many penalty ranges were tested, such as $R_1,\ R_2 = [0.1, 0.6]$, $R_1,\ R_2 = [0, 0.6]$, $R_1,\ R_2 = [0.1, 0.8]$, $R_1,\ R_2 = [0.1, 0.4]$, and $R_1 = [0, 0.3],\ R_2 = 1 - R_1$. Preliminary tests show that the last choice ($R_1 = [0, 0.3],\ R_2 = 1 - R_1$) is the best one to generate a wider range of less clustered Pareto sets.

$$\text{Objective} = \phi_1 + R_1 \times \phi_2 + R_2 \times \phi_3 \tag{5.63}$$

This approach is performed by the function `SOWP` which is presented in Algorithm 18. This function is called at line 24 in the main Algorithm 8. As in the LWCO, four candidate solutions are created in each iterations using the same routes ($\gamma = 4$).

Algorithm 18: `SOWP` Function

Set $Counter = 1$

Vehicle binary variable values = `Construction` function output

SF binary variable values = `SF-Construction` function output

while $Counter \leq \gamma$ **do**

  Generate $R_1 \in [0, 0.3]$ randomly

  Calculate $R_2 = 1 - R_1$

  if $\varphi = 1$ **then**

    Use objective function

$$\text{Min} \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci}\, v^C_{cit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|}\, x^F_{fli^F_f t} + \left(R_1 \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi}\, v^W_{wit} + R_2 \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei}\, v^E_{eit} \right) / \Omega$$

  end if

  if $\varphi = 2$ **then**

    Use objective function

$$\text{Min} \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi}\, v^W_{wit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|}\, x^F_{fli^F_f t} + \left(R_1 \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci}\, v^C_{cit} + R_2 \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei}\, v^E_{eit} \right) / \Omega$$

  end if

  if $\varphi = 3$ **then**

    Use objective function

$$\text{Min} \sum_{e \in E} \sum_{i \in D} \sum_{t \in T} p^E_{ei}\, v^E_{eit} + \sum_{f \in F} \sum_{l \in L} \sum_{t \in T} \frac{t}{|T|}\, x^F_{fli^F_f t} + \left(R_1 \sum_{w \in W} \sum_{i \in D} \sum_{t \in T} p^W_{wi}\, v^W_{wit} + R_2 \sum_{c \in C} \sum_{i \in D} \sum_{t \in T} p^C_{ci}\, v^C_{cit} \right) / \Omega$$

  end if

  Solve the model using CPLEX

  Save the value of all objective functions in Z_{obj}

  Save the complete solution in Z_{all}

  Update $Counter = Counter + 1$

end while

In this approach, we know the current routes are constructed to minimize the function ϕ_1, whereas the generated objective function contains ϕ_1 and the other two functions are penalized. Extreme cases can be found such that vehicles are allowed to work with 90% of their capacity for doing only one logistic operation. This allows us to find a wide range of different solutions which really represent the subset of Pareto optimal. However, its ability to produce solutions which have good objective values for all functions is not guaranteed because one of the objective functions always slightly dominates the others.

Table 5.4 summarizes the good and bad attributes that obtained during preliminary tests for all approaches.

Approach	**How it is performed**	**Advantages**	**Limitations**
LWCO	Single objective function that includes all three objective functions in linearly weighted manner, no constraints are added	Short computation time which allows to create more candidate solutions	Improper weights and priority values could produce bad solutions
SOIMRUC	Uses only the current activated objective function, constraints are added to perform all logistic operations almost equally	Suitable for the cases that request equal care for the three logistic operations	Not suitable for the problems with a short planning horizon, needs longer computation time compared to LWCO, and few different solutions are produced for the Pareto set because the effect of objective function is decreased
SOAMRUC1	Uses only the current activated objective function, constraints are added to give equal care for both commodity distribution and workers transfer as wounded evacuation	Better utilization of vehicles compared to SOIMRUC in short plan problems	Needs longer computation time compared to LWCO, and few different solutions are produced for the Pareto set because the effect of objective function is decreased
SOAMRUC2	Uses the current activated objective function plus a term that gives very small care to other functions, constraints are added to give equal care for both commodity distribution and workers transfer as wounded evacuation	Solves the limitation of unassigned space, better vehicles utilization compared to SOAMRUC1	Needs longer computation time compared to LWCO, and few different solutions are produced for the Pareto set because the effect of objective function is decreased
SOSMS	Solves the model 3 times. The first solution is obtained by using single objective function without adding constraints. Then, the second and third solutions are obtained using a new objective function plus the previous one adding a constrain built using information from previous solutions	–	Take longer computation time than others, no solutions appear in many iterations because of the interaction complexity between different objectives and added constraints
SOWP	Uses the current activated objective function plus the other functions	Short computation time as in LWCO, able to create solutions in most of Pareto's optimal regions	Ability to produce solutions with good objective value for all functions

Table 5.4: HLVRPSF – compare all approaches

In the next section, some results using these approaches are shown and discussed.

5.8 Numerical Analysis

In this section, different data sets are randomly generated and solved by using the proposed approaches. As in the HLVRP, model solving is conducted using CPLEX–Concert Technology 12.2 MIP solver on an HP Compaq 8100 Elite SSF PC, with a quad-core Intel i7-860 processor running Ubuntu Linux 10.10 in 64-bit mode. This section is organized as follows. Section 5.8.1 describes the data sets classification based on scales. Sections 5.8.2, 5.8.3, 5.8.4, and 5.8.5 show the results of a tiny, small, medium, and large data set, respectively.

5.8.1 Experimental Design

As in the HLVRP model, different data sets of different sizes are randomly generated. They are classified as tiny scale, small scale, medium scale, or large scale. All parameters have the same ranges as in the HLVRP model except for the time periods. As the SFs are assumed to be slower than the vehicles and the benefits of using them becomes more noticeable when the small vehicles have longer time for resupply, longer planning horizons are used for the HLVRPSF sets. Table 5.5 shows all parameter ranges for the HLVRPSF model. Other parameters are fixed for all scales and have the same values as in the HLVRP model (Table 4.13).

As stated in the HLVRP model, the large scale ranges are suitable for an agency and they are larger than many sets considered in the literature. For example, the analysis has been done by Yi and Kumar (2007) includes sets up to 55 vehicles, 80 nodes, and with only 10 time periods.

To test the effectiveness of the solution approaches, one data set is randomly selected from each scale and solved using the suggested approaches – LWCO, SOIMRUC, SOAM-RUC2, and SWOP – to find the Pareto sets. SOSMS is not considered because of the

Parameter	Tiny Scale	Small Scale Range	Medium Scale Range	Large Scale Range
Time Intervals $\lvert T\rvert$	∼Unif(12,16)	∼Unif(15,22)	∼Unif(20,28)	∼Unif(25,48)
Vehicles $\lvert v\rvert$	∼Unif(2,4)	∼Unif(3,5)	∼Unif(5,15)	∼Unif(10,40)
SFs $\lvert F\rvert$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(2,8)	∼Unif(5,20)
Demand Nodes $\lvert D\rvert$	∼Unif(3,6)	∼Unif(4,8)	∼Unif(8,15)	∼Unif(10,30)
Supply Nodes $\lvert S\rvert$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(3,7)	∼Unif(5,10)
Location Nodes $\lvert S\rvert$	∼Unif(2,4)	∼Unif(3,5)	∼Unif(5,10)	∼Unif(10,20)
Hospital Nodes $\lvert H\rvert$	∼Unif(1,2)	∼Unif(1,2)	∼Unif(2,4)	∼Unif(3,6)
Commodities Types $\lvert C\rvert$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(2,5)	∼Unif(3,7)
Workers categories $\lvert W\rvert$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(2,5)	∼Unif(3,7)
Evacuees categories $\lvert E\rvert$	∼Unif(1,2)	∼Unif(1,3)	∼Unif(2,5)	∼Unif(3,7)

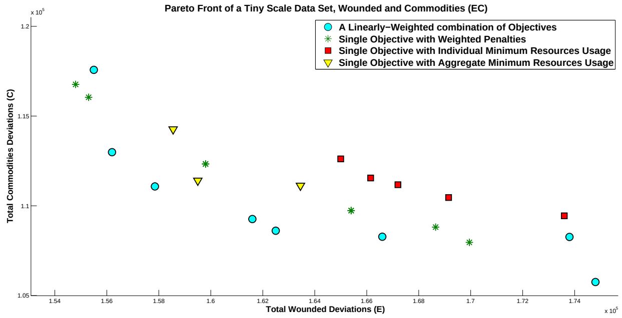
Table 5.5: HLVRPSF - design of experiment

limitations discussed earlier and because testing this approach shows that it is very sensitive to the constants used in the constraints shown in lines (12) and (19) of Algorithm 17. Consequently, there are many iterations with no solution when using this procedure.

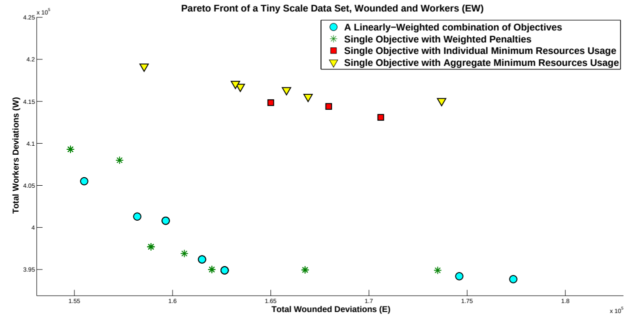
5.8.2 Tiny Scale Problem

In this section, a tiny scale set is selected and solved with the proposed solution approaches. Data of this set is shown in Appendix D . The termination criterion is the time limit which is set to 60 seconds. Figure 5.7 shows the Pareto sets of this set.

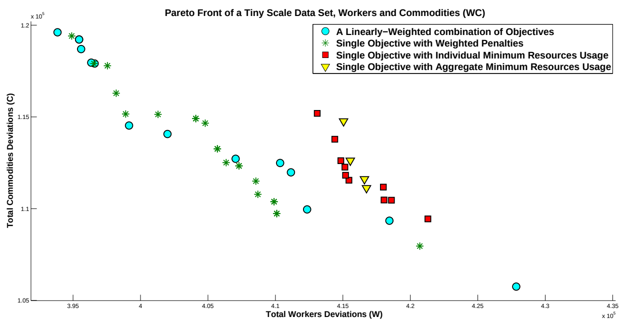
In Figure 5.7a, the 2-dimensional Pareto optimal of the total deviations of wounded evacuation, denoted as (E) on the x–axis, and the total deviations of commodities, denoted as (C) on the y–axis, is drawn. In Figure 5.7b, the 2-dimensional Pareto optimal of the total deviations of wounded evacuation, denoted as (E) on the x–axis, and the total deviations of workers, denoted as (W) on the y–axis, is drawn. In Figure 5.7c, the 2-dimensional Pareto optimal of the total deviations of workers, denoted as (W) on the x–axis, and the total deviations of commodities, denoted as (C) on the y–axis, is drawn. In Figure 5.7d, the 3-dimensional Pareto optimal of the total deviations of commodities, denoted as (C) on the x–axis, the total deviations of wounded evacuation, denoted as (E) on the y–axis, and the total deviations of workers, denoted as (W) on the z–axis, is drawn.



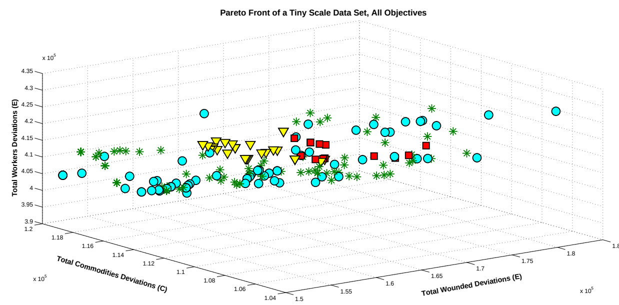
(a) Wounded-Commodities Pareto Front



(b) Wounded-Workers Pareto Front



(c) Workers-Commodities Pareto Front



(d) Wounded-Workers-Commodities Pareto Front

Figure 5.7: Detailed Pareto front for a tiny scale set

In Figure 5.7, some small clusters are obtained in figures (a), (b), and (c) using all approaches. The LWCO and SWOP approaches produce clusters more clearly in figures (a) and (b) because the wounded deviations is one of the axes. In these cases, wounded have the hospitals as destinations, whereas commodities and workers have the demand nodes as destinations. This makes finding alternative solutions for the latter case harder and causes clusters. In figure (c), the clusters are less frequent because both workers and commodities have the same sources and destinations.

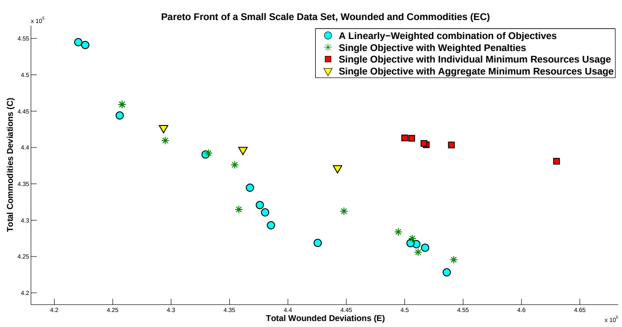
Both SOIMRUC and SOAMRUC2 have bad results in terms of the number of solutions for each Pareto optimal sets and the objective value of the solutions. This is because in both approaches, evacuation composes a portion of the total vehicle loads which prevents worker and commodity deviations from obtaining a wide range values. Additionally, in tiny scale sets, SOIMRUC has the fewest number of solutions clustered in the middle of the figures which is a good example of its inefficient use of resources in short planning horizons, as mentioned earlier.

It can be concluded that there is no clear winner which can be considered for all Pareto sets.

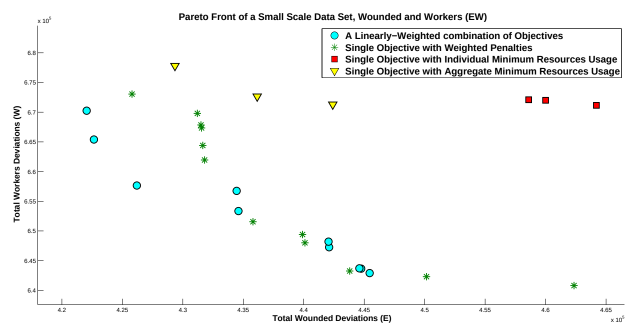
5.8.3 Small Scale Problem

In this section, the larger data set shown in Appendix C is considered; the results are shown in Figure 5.8. Time limit is set to 300 seconds.

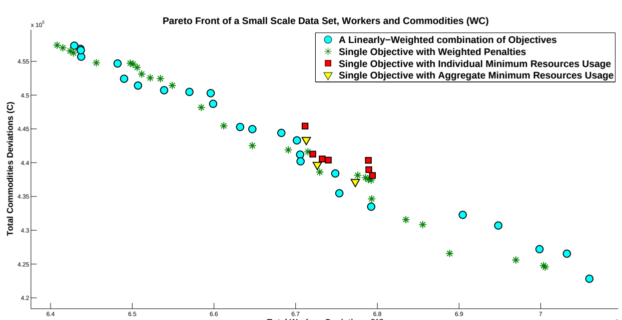
As in the previous section, Figure 5.8 contains four sub–figures. Figure 5.8a represents the Pareto optimal of wounded evacuation (E) versus commodity distribution (C), Figure 5.8b shows the Pareto optimal of wounded evacuation (E) and workers transfer (W), Figure 5.8c shows the Pareto optimal of wounded evacuation (E) and workers transfer (W), and 5.8d represent the Pareto optimal of all logistic operations in one 3-dimensional figure.



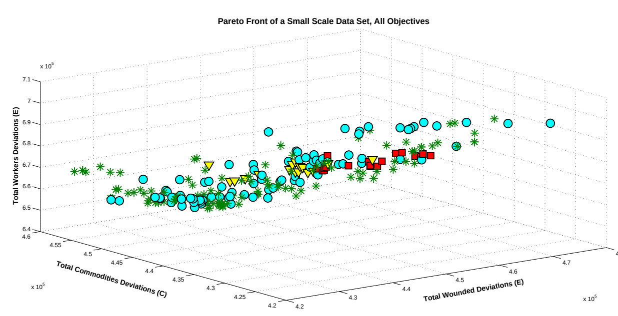
(a) Wounded-Commodities Pareto Front



(b) Wounded-Workers Pareto Front



(c) Workers-Commodities Pareto Front



(d) Wounded-Workers-Commodities Pareto Front

Figure 5.8: Detailed Pareto front for a small scale set

As in the tiny scale set, all approaches produce some clusters in both the wounded evacuation–workers transfer (EW) and wounded evacuation–commodities distribution (EC) Pareto sets, while fewer clusters are obtained in the workers-commodities (WC) Pareto set.

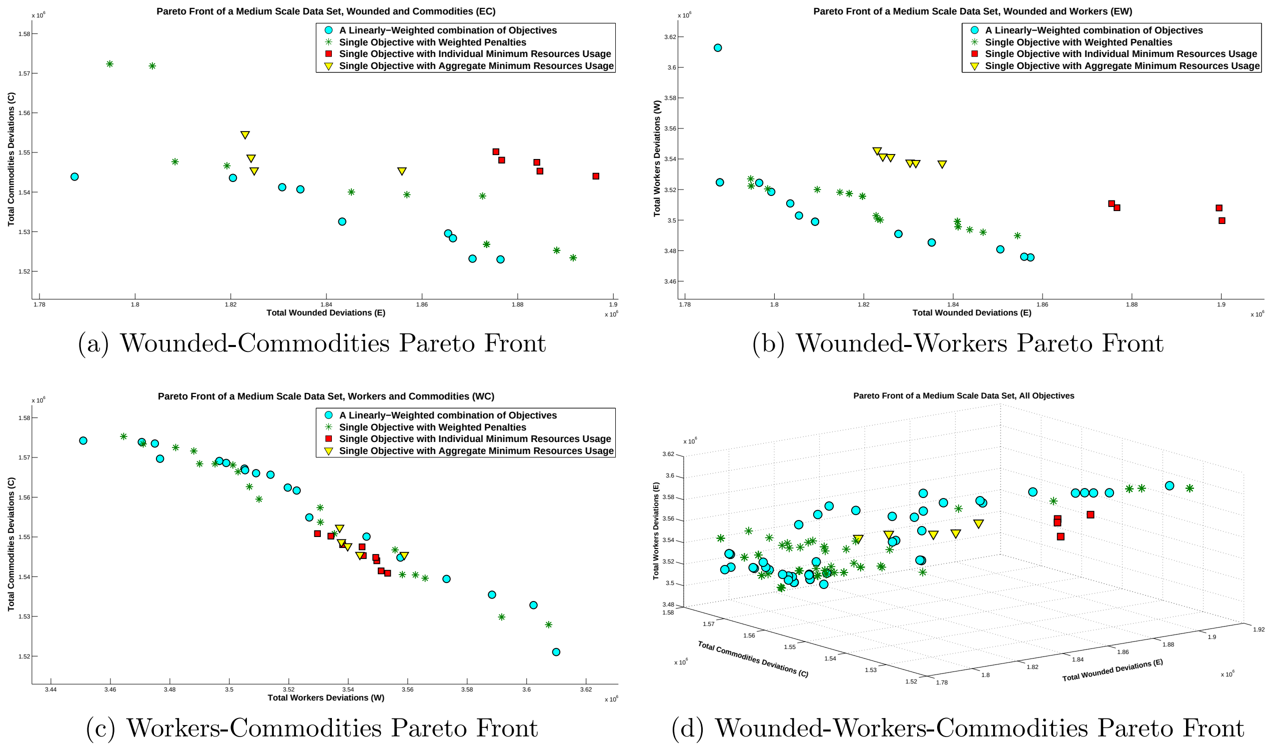
SOIMRUC produces few solutions on the right side of the EC and EW figures which limits its use. This happens because this approach gives both logistic operations the same chance to be performed by forcing vehicles to load the same mass of wounded as commodities in case of EC and the same mass of wounded as workers in case of EW. On the other hand, SOAMRUC2 produces few solutions on the left hand side of EC and EW figures because the wounded evacuation is in the x–axis and it consumes around 50% of the vehicle loads in this approach. Both SOAMRUC2 and SOIMRUC produce few solutions in the middle of the WC figure because they give workers transfer and commodity distribution equal care.

Both LWCO and SWOP produce better results than SOAMRUC2 and SOIMRUC in terms of the number and variety of the solutions, overall we can not find a single approach that always produces better results than others.

5.8.4 Medium Scale Problem

The medium data set shown in Appendix B is considered in this section. Figure 5.9 shows the Pareto sets of this set. The time limit is set to 1800 seconds. Similar to the previous sections, 4 sub–figures are included in Figure 5.9. First, wounded evacuation and commodity distribution (EC) is included in Figure 5.9a. Second, wounded evacuation and workers transfer (EW) is shown in Figure 5.9b. Third, workers transfer and commodity distribution (WC) is presented in Figure 5.9c. Fourth, the Pareto optimal that shows all logistic operations is drawn in Figure 5.9d.

It seems that clusters in the cases of wounded–workers (EW) and wounded–commodities (EC) can not be eliminated, but even with the problem of clusters, the LWCO and SOWP approaches are capable of finding solutions in extreme regions where one objective is good and the other is bad, and solutions in the middle regions where both objectives are good.



(a) Wounded-Commodities Pareto Front

(b) Wounded-Workers Pareto Front

(c) Workers-Commodities Pareto Front

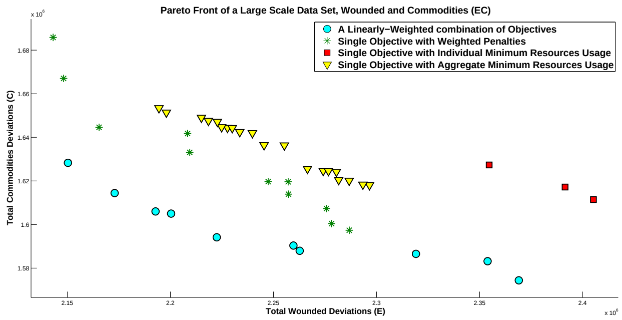
(d) Wounded-Workers-Commodities Pareto Front

Figure 5.9: Detailed Pareto front for a medium scale set

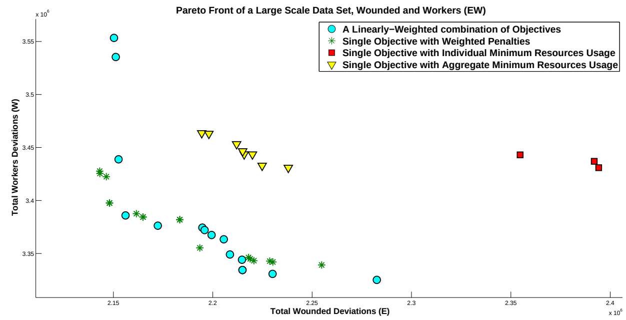
It can be determined that some SOIMRUC and SOAMRUC2 solutions have better objective values than some of SOWP and LWCO solutions in the middle of the WC Pareto set; whereas, in EC and EW Pareto sets, bad results are produced in terms of objective values, variety of solutions, and number of different solutions. Similar to small and tiny sets, there is no approach that has an advantage over the other approaches. Although LWCO gives the best results in most regions of EC and EW Pareto sets, it does not in many places in the WC Pareto set.

5.8.5 Large Scale Problem

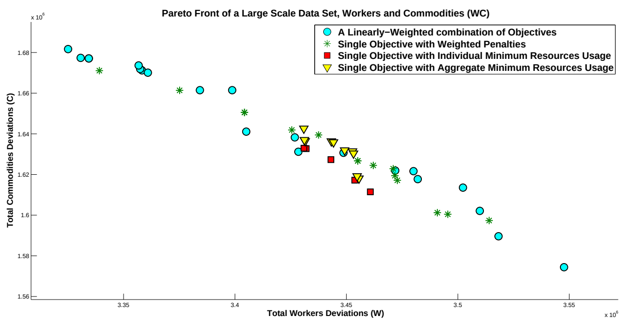
In this section, a large scale set shown in Appendix A is considered, and the time limit is set to 3600 seconds. Figure 5.10 shows the results of this set. Figure 5.10 includes the Pareto optimal of wounded evacuation and commodity distribution (EC) in Figure 5.9a, wounded evacuation and workers transfer (EW) in Figure 5.9b, workers transfer and commodity distribution (WC) in Figure 5.9c, and all logistic operations in Figure 5.9d.



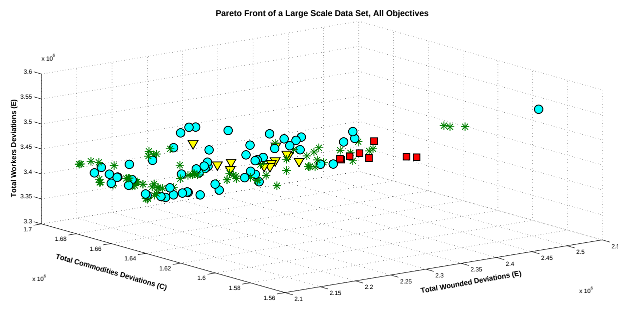
(a) Wounded-Commodities Pareto Front



(b) Wounded-Workers Pareto Front



(c) Workers-Commodities Pareto Front



(d) Wounded-Workers-Commodities Pareto Front

Figure 5.10: Detailed Pareto front for a large scale set

Several things can be noted in this section. First, clusters are obtained in Figure 5.10 using LWCO and SWOP approaches, but there is a wide range of solutions available in different regions of the figures. Second, SOIMRUC and SOAMRUC2 have good results in term of objective values only in the WC Pareto sets. Third, LWCO is a clear winner in the EC Pareto set, but not in the EW and the WC Pareto sets.

Because of the previous notes and conclusions, a new approach involving all previous approaches is suggested to provide us a clear winner. The next section discusses this in detail.

5.9 Hybrid Approach

In this section, a new approach is developed as a combination of all approaches and it takes all approaches into consideration based on their advantages and disadvantages as obtained from previous analysis. To get the Pareto optimal using the hybrid approach, the following steps should be followed

- Run the main code in Algorithm 8, call the `SOIMRUC` function in line 24. This produces Pareto optimal using the SOIMRUC approach. As noted in the previous analysis, the SOIMRUC approach produces good results, in term of objective values, only in the middle of the WC Pareto set. So, shorter time is considered as the termination criterion, as shown in Table 5.6.

- Similarly, run the main code in Algorithm 8, call the `SOAMRUC2` function in line 24. For the same reason above, short time is considered as the termination criterion for this run.

- Run the main code in Algorithm 8, call the `LWCO` function in line 24. Because LWCO produces good results in all Pareto sets, this run is given longer time as the termination criterion as shown in Table 5.6.

- Run the main code in Algorithm 8, call the `SOWP` function in line 24. Similar to the previous run, this run is given a longer time as the termination criterion.

- Run the main code in Algorithm 8, call the `EXTR` function in line 24. The EXTR approach is a modified version of the SOWP version, as explained below. The aim of this approach is to produce solutions in the extreme areas, so this run is given a short time as termination criterion.

- Five different Pareto sets are found at the end of these runs, where each approach has its own Pareto set, then a Pareto of Pareto sets is found which represents our final solution.

SOWP is modified to construct a new approach with a new objective function, as follows (denoted as EXTR)

$$\text{Min} \quad R_1 \times obj_1 + R_2 \times obj_2 + R_3 \times obj_3$$

Where one of the numbers R_1, R_2, and R_3 is randomly selected to take the value of 1, and the other two numbers take a random value from [0, 0.2]. This approach helps in finding extreme points which are hard to locate using LWCO and SOWP. The EXTR is performed by using the `EXTR` function as shown below in Algorithm 19. Value of γ is set to 4 as in LWCO and SOWP approaches.

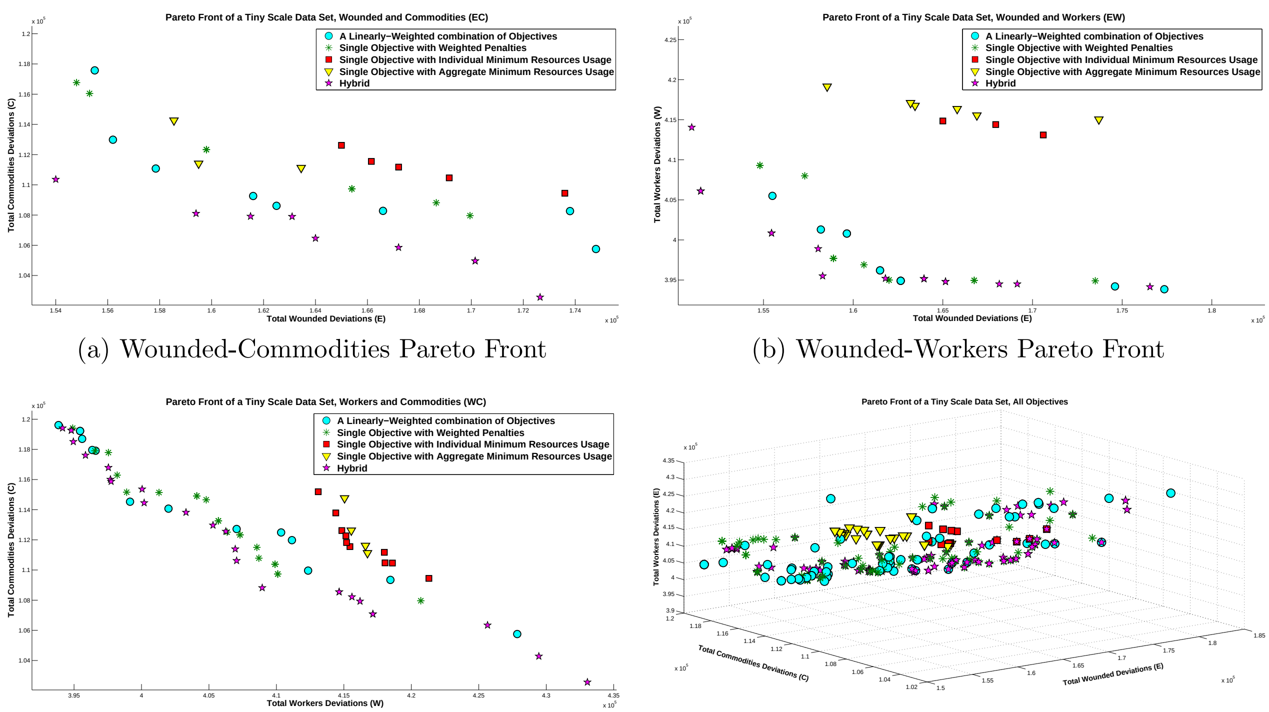
ALGORITHM 19: `EXTR` Function

Set $Counter = 1$
Vehicle binary variable values = `Construction` function output
SF binary variable values = `SF-Construction` function output
while $Counter \leq \gamma$ **do**
    Randomly select one of the $R_1,\ R_2,$ or R_3 to be 1
    Generate others $Rs \in [0, 0.2]$ randomly
    Use objective function
    $\text{Min } R_1 \sum_{c\in C}\sum_{i\in D}\sum_{t\in T} p^C_{ci}\, v^C_{cit} + R_2 \sum_{w\in W}\sum_{i\in D}\sum_{t\in T} p^W_{wi}\, v^W_{wit} + R_3 \sum_{e\in E}\sum_{i\in D}\sum_{t\in T} p^E_{ei}\, v^E_{eit} + \sum_{f\in F}\sum_{l\in L}\sum_{t\in T} \frac{t}{|T|}\, x^F_{fli^F_f t}$
    Solve the model using CPLEX
    Save the value of all objective functions in Z_{obj}
    Save the complete solution in Z_{all}
    Update $Counter = Counter + 1$
end while

Table 5.6 shows that the hybrid approach does not take more time to produce the Pareto sets than the previous methods, Figure 5.11 shows the results of the same tiny scale set in Section 5.8.2.

Time Limit (sec)	Data Set Scale			
	Tiny Scale	**Small Scale**	**Medium Scale**	**Large Scale**
LWCO	20	100	600	1200
SWOP	20	100	600	1200
SOAMRUC2	5	25	150	300
SOIMRUC	5	25	150	300
EXTR	10	50	300	600
Total	60	300	1800	3600

Table 5.6: Hybrid approach time limits



(a) Wounded-Commodities Pareto Front

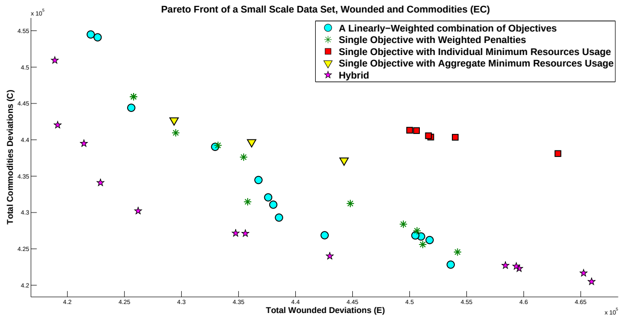
(b) Wounded-Workers Pareto Front

(c) Workers-Commodities Pareto Front

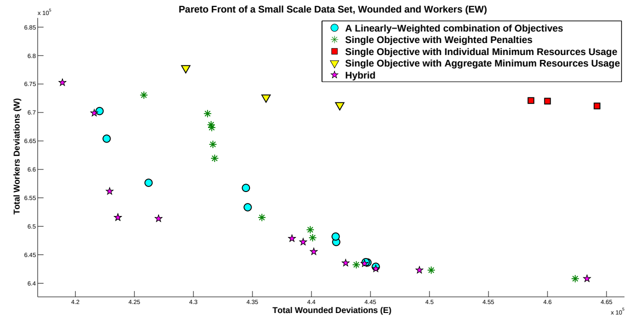
(d) Wounded-Workers-Commodities Pareto Front

Figure 5.11: Detailed Pareto front for a tiny scale set with hybrid approach

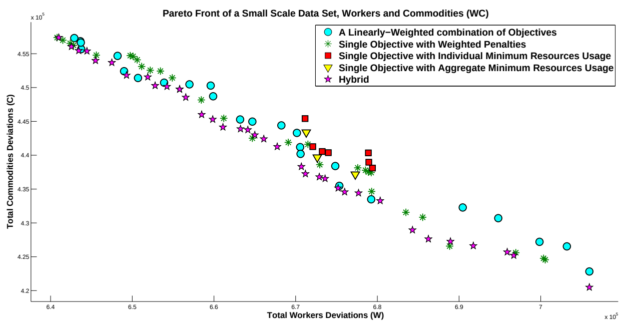
Now, we can see that the hybrid approach gives the best results in all Pareto sets. Clusters in the hybrid approach become wider which is expected because this approach is designed to find the good solutions at all regions. The good solutions dominate the others and cause the clusters. Next, Figure 5.12 shows the results of the same small scale set in Section 5.8.3.



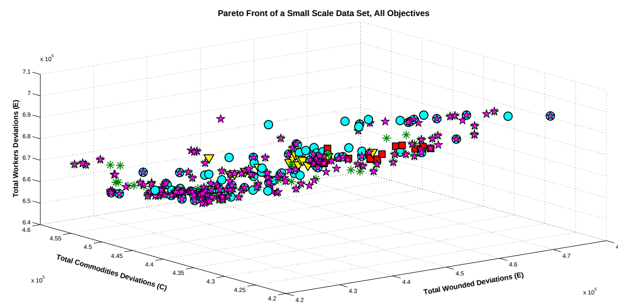
(a) Wounded-Commodities Pareto Front



(b) Wounded-Workers Pareto Front



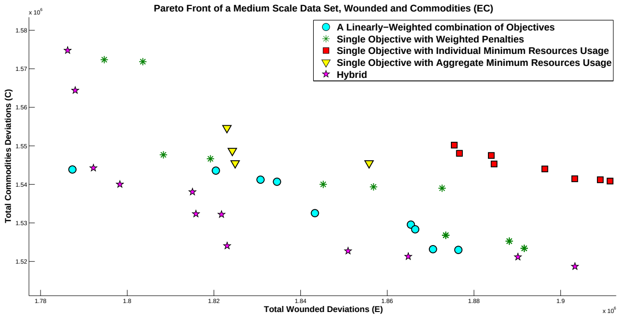
(c) Workers-Commodities Pareto Front



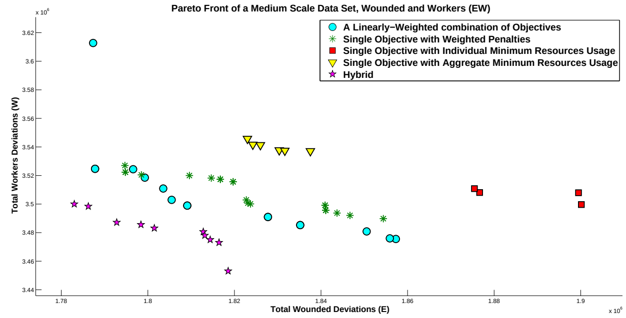
(d) Wounded-Workers-Commodities Pareto Front

Figure 5.12: Detailed Pareto front for a small scale set with hybrid approach

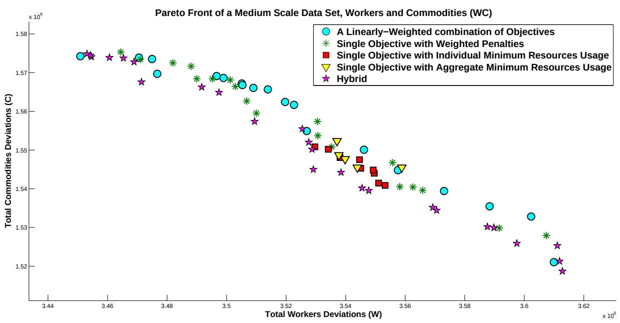
Figure 5.12 shows some clusters in the EW and EC Pareto sets, and less in the WC Pareto set. A noticeable solution enhancement achieved by the hybrid approach is obtained in the first half of the EW Pareto set. It is hard to explain this enhancement, but it could be because the extreme approach, with some help from the LWCO and SOWP approaches, produces these good results. Figure 5.13 shows the results of the medium scale set.



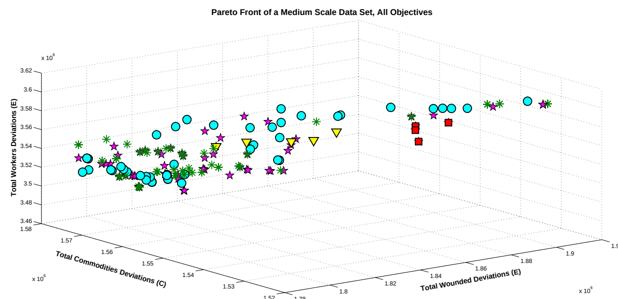
(a) Wounded-Commodities Pareto Front



(b) Wounded-Workers Pareto Front



(c) Workers-Commodities Pareto Front

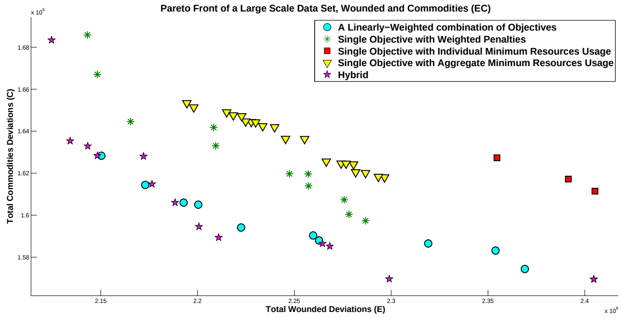


(d) Wounded-Workers-Commodities Pareto Front

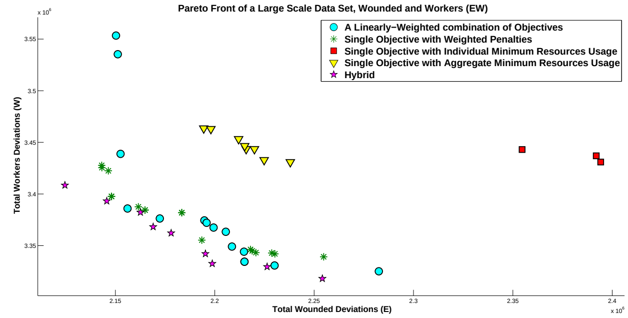
Figure 5.13: Detailed Pareto front for a medium scale set with hybrid approach

In Figure 5.13, the hybrid approach gives good results for the EC Pareto set and can be considered the clear winner although it losses in one point. In the EW Pareto set, the hybrid approach results in amazingly improved solutions on the left side of the figure, while the right side has no solutions because they are dominated by the good solutions on the left. In the WC Pareto set, solutions appear in a more uniform style.

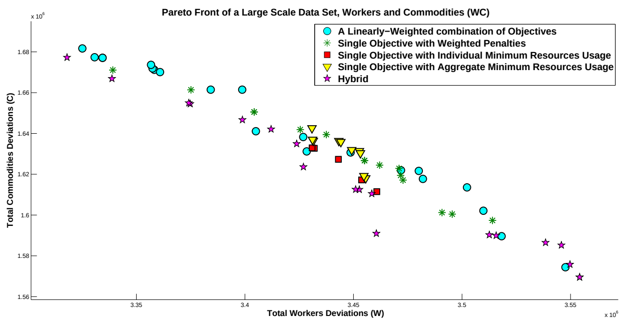
For the medium scale set, the hybrid approach improves the results in the EW Pareto set more than for tiny and small sets. This is might be a data set specific. Several medium sets are solved similarly and the results show different improvement ranges. Figure 5.14 shows the results of the large scale set.



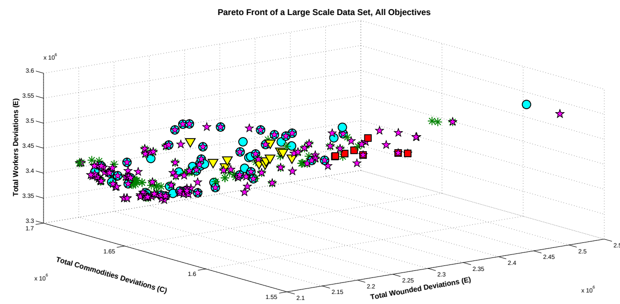
(a) Wounded-Commodities Pareto Front



(b) Wounded-Workers Pareto Front



(c) Workers-Commodities Pareto Front



(d) Wounded-Workers-Commodities Pareto Front

Figure 5.14: Detailed Pareto front for a large scale set with hybrid approach

The hybrid approach results in solutions dominant over those from other approaches, and it can be seen that it gives more solutions in extreme regions. For example, in the EC Pareto set, there are many solutions with extreme good objective values in wounded deviations and two solutions with extreme commodities deviation values. Similarly in the EW Pareto set, there is a solution with a very good wounded deviation value and one solution with very good worker deviations. In the WC Pareto set, the hybrid approach loses in two places, where other approaches result in slightly better solutions, but it can still be considered as the clear winner.

The next section provides a simple case study solved by the proposed solution approaches for the HLVRP and HLVRPSF models.

5.10 Case Study

One of the problems encountered in this research is how to estimate real data. All data sets used in this research are randomly generated, but with dependence on some parameters from previous studies, such as the number of nodes and the number of vehicles.

In this section, a case study is generated based on some real data to reflect a real life scenario. This case is considered to solve an example as HLVRPSF and HLVRP models using the suggested approaches.

5.10.1 Case Study Data

FEMA developed software called HAZUS to help generate real data[1]. This software also needs some realistic inputs such as the expected earthquake scales in case of earthquake estimation, the actual population in the region, the number of schools and universities in the region, available hospitals, and the regions which can be used as supply nodes such airports and warehouses.

In 2008, MMI engineering group prepared a full HAZUS earthquake simulation for a region in California containing 8 counties with about 19 million in population and about 5 million houses with a value of 2 trillion dollars, (MMI Engineering Group (2013)).

The number of casualties is estimated according to the time the expected earthquake will occur. The time of 2 AM is expected to cause the highest number of casualties because most people at this time will be in the houses. The most extreme case is considered in this section.

Casualties are classified into four groups (levels). The first, require medical attention but hospitalization is not needed. The second, require hospitalization but are not considered life-threatening. The third, require hospitalization and can become life threatening if not

[1] `http://www.fema.gov/hazus`

promptly treated. The fourth are killed victims. The first group is used to estimate the number of workers needed because this group can be treated in the demand nodes. The second and third groups are considered as wounded needing evacuation with different priorities.

An extra large scale problem is generated based on this HAZUS simulation results and used to solve the HLVRPSF and HLVRP model. Some parameters are missing, such as the number of vehicles needed by agencies. Such variables are generated randomly as follows.

- The total number of vehicles and SFs is estimated to be 65 which is the highest number considered by Yi and Kumar (2007).
- The number of time periods is set to 10 to cover one day, where each period is 2.4 hour. This is the same number considered by Yi and Kumar (2007).
- The maximum nodes considered by Yi and Kumar (2007) is 80 which is the same number considered in this case study, where 30% of the nodes are hospitals, supply nodes, and locations. The other 70% of the nodes are considered to be demand nodes.
- The number of wounded is taken from HAZUS results which equals 2,154 for the second level, and 140 for the third level. As resulted from HAZUS, wounded in level one do not need evacuation, but they need attention at demand nodes.
- The number of wounded for the first level is taken from HAZUS results which equals 11,303. These wounded do not request evacuation, but need care and supplies at demand nodes.
- The number of workers is assumed to be 3000 ± 200 which equals to one fourth of the total people awaiting help in shelter areas. This data is taken from HAZUS.
- Three commodity categories are selected: bottled water, boxed food, and medication and first aid bags. These are the most common categories needed. Water bottles are expected to be needed every 2 time periods by each person, so the total number

$11,303$ person $\times$ 5 times $= 56,515$. A food box is needed every 3 time periods by each person, so the total number $11,303$ person $\times$ 3 times $= 33,909$. One medications and first aid bag is needed by every 10 persons at the beginning of each day, so the total number $11,303$ person$/10 = 1,190$. Availability of supplies is assumed to be $80 \pm 5\%$ of total requested demand.

Table 5.7 shows a summary of the case study parameters and data.

Parameter	Notes and Description
Time Periods	10, 2.4 hours each
Vehicles and SFs	65
Nodes	80, 30% are supply nodes, locations, and hospitals
Commodities	3 types: bottled water, boxed food, and medication bags
Bottled water	demand is uniformly distributed with average of 56,515
Boxed food	demand is uniformly distributed with average of 33,909
Medication bags	demand is uniformly distributed with average of 1,190
Workers	2 Categories, uniformly distributed with average of 3000
Evacuees	2 levels, uniformly distributed with average of 2154 and 140 respectively

Table 5.7: Case study parameters and Data

A data set is randomly generated depending on the parameters described above in Table 5.7. Then it is solved twice. First, it is considered as HLVRP problem and solved using `Heuristic-A3` approach (discussed in Chapter 4) with a time limit of two hours as a termination criterion. Second, it is considered as HLVRPSF problem and solved using the suggested approach suggested in Chapter 5 with the options of $\psi = 3$ for SF route construction, two hours time limit as a termination criterion, and the hybrid approach to create candidate solutions.

The next section, provides a procedure to compare between multi–objective and single objective models. This procedure will be used in Section 5.10.3 to compare between the HLVRP and HLVRPSF models.

5.10.2 Comparison between Multi–objective and Single Objective Models

Multi–objective models are solved to provide different solutions that can cover wide ranges in Pareto fronts. Single objective models are solved to create only one solution. According to this, it is not easy to compare the quality of the single solution created by a single objective model with multiple solutions created by a multi–objective model. In this subsection, to perform a fair comparison between multi–objective and single objective models, a two phase comparison procedure is suggested.

In the first phase, the objective function value of the single solution, which is obtained from the single objective model, is split into many values. Each of those values represents a single objective function value of the single objective model if it is solved as multiple objectives. For further explanation, consider the following example for how this procedure is applied in the HLVRP. When the HLVRP is solved, a single objective function value is produced. This value is split into three values where the first value represents the total commodity deviations, the second value represents the total work–force deviations, and the third value represents the total wounded deviations. After this, the single solution produced by the single objective model (HLVRP) can be easily plotted in the Pareto optimal sets obtained by the multiple objective model (HLVRPSF). The benefit of this phase is to compare the performance of the single objective model versus the multiple objective in two dimensional objectives.

Two–dimensional Pareto sets include only the non–dominated solutions of two objective function values without knowing the performance of the third objective function value. From the Pareto front sets, in the previous sections, when a solution appears in a Pareto front set, it will potentially have a bad objective function value of the third dimension that is not shown in this Pareto set. For example, any point in EC figures has a good objective function value for one or both commodity distribution and wounded evacuation; however, it likely has a bad objective function value of the work–force transfer which is not shown in the EC figures. This makes depending on only the Pareto sets (the first phase) for comparison not fair for the single objective function model. Consequently, the second phase is suggested, as follows.

In the second phase, objective function values of each solution produced by the multi–objective model are summed to create a single value. In our case study, a total objective function value is calculated for each solution obtained by the HLVRPSF as the sum of the three individual objective values. Then the summed objective values of the HLVRPSF are plotted with the single objective value obtained by the HLVRP in a single figure. The benefit of this phase is that the multi–objective model can be compared with single objective while considering all objective function values.

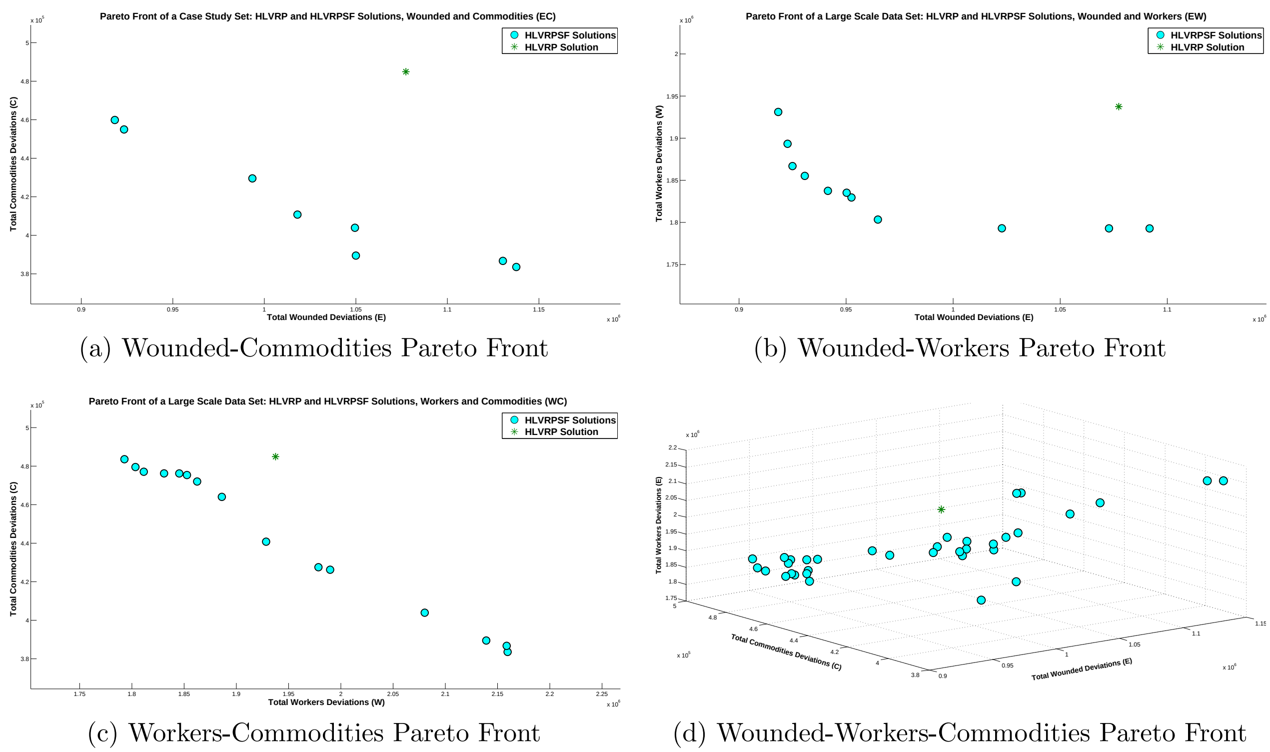
5.10.3 Case Study Results

The first phase of comparison is to plot the single solution obtained by the HLVRP in the Pareto front plots of the multi–objective HLVRPSF. Figure 5.15 shows these Pareto sets. The HLVRP solution will fail to be in any Pareto sets if it competes with the HLVRPSF solutions. This is because of two reasons.

First, as discussed earlier, HLVRP is a single objective function model which produces a single solution that has a moderate objective function value in all logistic operations based on the priority values used. In the HLVRPSF, the two dimensional Pareto sets include the solutions that have good objective function values in two logistic operations and bad in the other operation. This makes the objective function values for any two logistic operations, from the single HLVRP solution, are not competitive to the corresponding objective function values from the HLVRPSF solutions which appear in Pareto sets. For example, the HLVRPSF solutions appear in the wounded-commodity Pareto front have good objective function values in both wounded and commodity deviations and bad objective function value in worker deviations. If the wounded and commodity deviations of the HLVRP solution is plotted in this Pareto front, they will potentially lose the competition with the HLVRPSF solutions, as the worker transfer in the HLVRP solution consume a good portion from the vehicle capacities and prevent wounded and commodity to have a good value.

Second, SFs are used in the HLVRPSF which makes small vehicles more efficient. This results in better operational performance in the HLVRPSF compared to the HLVRP solution.

In the wounded–commodity deviations Pareto set, the HLVRP solution has a better objective function value for wounded evacuation than two solutions of the HLVRPSF. In the wounded–worker deviations Pareto set, the HLVRP solution has a better objective function value for wounded evacuation than one solution of the HLVRPSF. In the wounded–commodity deviations Pareto set, the HLVRP solution has a better objective function value for commodity distribution than one solution of the HLVRPSF and a better objective function value for work–force transfer than six solutions of the HLVRPSF.



(a) Wounded-Commodities Pareto Front

(b) Wounded-Workers Pareto Front

(c) Workers-Commodities Pareto Front

(d) Wounded-Workers-Commodities Pareto Front

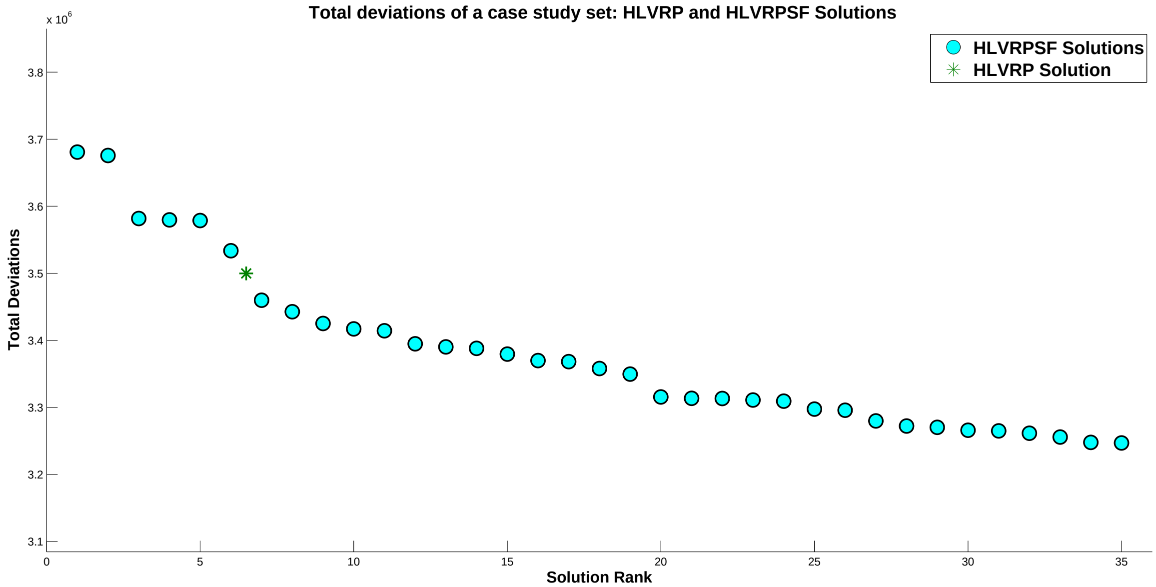
Figure 5.15: Detailed Pareto Front for a Case Study Set

The second phase of comparison is to compare the HLVRP solution versus the HLVRPSF solutions while considering all logistic operations. Table 5.8 shows the objective function values for 35 solutions produced by the HLVRPSF and the objective function value for the solution resulted by the HLVRP. In the fifth column, the objective function values are summed in a single objective function value for the sake of performing the second phase of comparison. These values are sorted in descending order and plotted in Figure 5.16.

Before proceeding to the second phase of comparison, other strong point can be derived from the table to validate the first phase. Table 5.8 includes 35 solutions that are produced by the HLVRPSF, whereas only 8 solutions appear in the EC Pareto front, 11 solutions appear in the EW Pareto set, and 15 solutions appear in the WC Pareto set. This provides a good example that the two dimensional Pareto sets include the solutions that have a bad objective function value in the hidden dimension.

Solution #	Wounded Deviations	Commodity Deviations	Worker Deviations	Total Deviations
1	1021500	475379	1852700	3349579
2	923350	454950	1935200	3313500
3	1036500	427520	1978550	3442570
4	952500	479276	1829600	3261376
5	1018100	410761	2150800	3579661
6	964850	475727	1874900	3315477
7	1081750	478589	1819050	3379389
8	924950	480358	1866850	3272158
9	1004800	473696	1879400	3357896
10	925350	467260	1920550	3313160
11	1064100	464033	1886100	3414233
12	1049500	403905	2080250	3533655
13	930700	479911	1855250	3265861
14	1022750	431100	1793050	3246900
15	922650	481387	1893350	3297387
16	959300	477510	1833400	3270210
17	1022600	411295	2147850	3581745
18	918300	459869	1931100	3309269
19	941500	476646	1837500	3255646
20	1083150	476222	1830800	3390172
21	950250	479353	1835250	3264853
22	958250	476201	1845350	3279801
23	1072800	445210	1792900	3310910
24	1047800	440786	1928450	3417036
25	964850	479517	1803400	3247767
26	1053550	472006	1862450	3388006
27	942650	476086	1876900	3295636
28	993450	429544	2002100	3425094
29	1091750	483574	1792850	3368174
30	1137650	383550	2159600	3680800
31	1106250	477071	1811400	3394721
32	1043850	426232	1989750	3459832
33	1061600	478976	1829200	3369776
34	1050000	389485	2139150	3578635
35	1130300	386726	2158700	3675726
HLVRP Solution	1077350	484932	1937500	3499782

Table 5.8: Objective function values for the HLVRPSF and HLVRP solutions



(a) Wounded-Commodities Pareto Front

Figure 5.16: Objective function value for HLVRPSF and HLVRP solutions

In Figure 5.16, the objective function value of the HLVRP solution is better than the objective function value of 6 HLVRPSF solutions and worse than 29 solutions. Again, this shows that using SFs improves the post–disaster relief operations by providing more supply points which enhances the resource utilizations. Even with SF utilization, the HLVRP was able to defeat six of the HLVRPSF solutions.

5.11 Summary

In this chapter, a new model is developed for post–disaster logistic systems which incorporates three logistic operations and multiple objectives while utilizing satellite facilities as movable supply nodes. The three logistic operations are wounded evacuation, demand distribution, and workers transfer. Considering these operations in a single logistic system represents the first contribution of this model because it has not been done before. Considering multiple objectives eliminates the problem of scaling the objectives by arbitrary weights. Finally, using large vehicles as mobile satellite facilities allows small vehicles to be resupplied more quickly which improves the efficiency of the logistic system.

In multiple objective models, different solutions should be found to cover most possible cases. Accordingly, different solution approaches are developed in this chapter to create different candidates, after which one of these approaches is selected to be the best approach based on the objective values of the created solutions. These candidate solutions are used to create three main Pareto sets: wounded–commodities deviations (EC), wounded–worker deviations (EW), and worker–commodities deviations (WC).

In all data set sizes, some clusters appear in some Pareto plots and can not be eliminated. They occur because of the integer condition of many variables with different ranges. For example, both workers and wounded have mass considered to be very large compared to commodities, and with smaller ranges. This makes finding many different solutions complicated; however, the suggested solution approaches have the advantage of covering a wide range of solutions.

The following points can be concluded for all sets in general. First, in the commodities–wounded (EC) deviations Pareto front, SOAMRUC2 gives few solutions with good objective function values in wounded evacuation and bad objective function values in commodity distribution (solutions on the upper left side of the EC figure); whereas SOIMRUC2 gives a wider range of solutions on the upper right side of EC figure with bad objective values in both wounded evacuation and commodity distribution. There is an overlap in commodities deviations objective values between SOIMRUC2 and SOAMRUC2, but SOAMRUC2 gives a better value of wounded deviations. This is expected, because SOIMRUC2 gives only 30% of total vehicles loads to the wounded while SOAMRUC2 allocates about half to this purpose. Both SOIMRUC and SOAMRUC2 give a very bad commodities deviations objective value because they always force vehicles to pick up workers having total masses almost equal to commodity masses which effect the commodities quantity negatively.

Second, SOWP gives the widest range of solutions and LWCO gives the second widest solutions range with better objective values in some cases, especially on to the evacuation operation (on the left side of the EC figure). The wider range of SOWP is due to its ability to find extreme cases. The better objective values of LWCO has no clear argument, but might be because all objectives have equal chances to be in the weighted single objective.

Third, SOSMS is not considered in the analysis because it is sensitive to the constants used in each step. This causes the problem of no solutions in most iterations after the first step. Accordingly, this approach is removed because it might cause confusion for users.

Fourth, in worker–commodity deviations Pareto front, a more uniform mix is obtained from SOWP and LWCO, because both workers and commodities have the same sources and destinations which allows for more solutions. Both SOIMRUC and SOAMRUC2 are clustered in the middle of the figure because these approaches have limited solution choices and do not depend on which objective is used. Finally, a hybrid approach which uses all approaches is suggested to find the best results.

If we need only some solutions in the extreme areas, different ratios can be used to produce them with shorter run times. For example, if we need very good solutions for wounded deviations, this objective can be given a higher chance of being selected in the SOWP approach instead of uniform random selection at the beginning of the code. The ratios can be $R_1 = [0,\ 0.25]$, $R_2 = 1 - R_1$. In these cases, good solutions for wounded deviations can be obtained in a shorter time.

A data set is generated using some real parameter values as a case study. This case study is solved as a HLVRP and as a HLVRPSF. Two phase comparison is used to compare between the single solution produced by the HLVRP and multiple solutions produced by the HLVRPSF. It is found that the HLVRPSF is able to produce many solutions with better objective function values than the HLVRP solution. This is because the utilization of the available resources is improved in the HLVRPSF by using SFs.

The next chapter provides conclusions for this research and suggests future research opportunities.

Chapter 6

Conclusion and Opportunities for Future Research

6.1 Conclusion

This research proposes different mixed integer models to perform post-disaster logistic operations in an integrated, efficient, and realistic manner. In doing so, the HLVRP model is developed to perform the logistics operations involving commodities distribution, wounded evacuation, and work–force transfer, while considering detailed individual vehicle routes. This is an NP-hard problem which requires an extremely long time to solve optimally using commercial solvers such as CPLEX and can not be solved optimally in cases of large scale problems. Because of this, a new greedy local search heuristic depends on building a feasible route for each vehicle based on the node visit beneficiary, and then solves the model optimally for these specific routes to determine other details. This procedure is repeated in an iterative fashion using some good route attributes determined in previous iterations to avoid bad moves as possible. In the end, the best solution is the one associated with the minimum objective value. The suggested approach is denoted as `Heuristic-0`. This heuristic is improved by replacement and insertion local search algorithms. These algorithms are applied in different ways. First, they can be applied for the best solution achieved from the main heuristic, as in `Heuristic-B`. Second, they can be applied for each solution, as in the `Heuristic-A1`, `Heuristic-A2`, and `Heuristic-A3`. Third, they can be applied for each improved solution, as in `Heuristic-I1` and `Heuristic-I2`.

The proposed heuristics' results are compared with CPLEX results for tiny, small, medium, and large data sets. Comparing the results shows that the proposed heuristics are effective and can produce competitive results in an extremely short processing time, an advantage in the case of a post-disaster situation. `Heuristic-A1`, `Heuristic-A2`, and

`Heuristic-A3` shows the best results among all local search variants but requires more time, whereas `Heuristic-B` gives good results in a very short time, but is not guaranteed to always improve the best solution. Finally, `Heuristic-I1` produces high variations in results if it is run just once, but improves results in a moderate processing time if the run repeated many times, as in `Heuristic-I2`.

For most tiny scale sets, CPLEX can be used to solve the model. Users can run CPLEX with a short time limit such as 5 minutes, but if they fail to get a solution, can switch to the heuristic to get a solution in less than a minute. Tiny sets are used in this study to compare optimal solutions versus the proposed heuristics. Such comparison shows excellent solutions with an average gap of 0.25% in 30 seconds. The proposed heuristics become more important in small scale problems where CPLEX takes a long time to give sub-optimal solutions. In medium and large scale sets, CPLEX can not be used, and the heuristics are utilized to efficiently solve these problems.

`Heuristic-0` is not recommended in all sets because `Heuristic-B` may give the same or better results with very little time added and is considered a free benefit. It is found that `Heuristic-B` becomes more efficient when the size of sets increases. For example, `Heuristic-B` decreases the average gap from 2.59% to 0.49% when it is added to `Heuristic-0` for large scale problems, and it drops the average gap from 3.57% to 2.29% in small scale problems. `Heuristic-A1`, `Heuristic-A2`, and `Heuristic-A3` are highly recommended for tiny and small sets because they give a better results in short time although this time is longer than the time needed for `Heuristic-0` and `Heuristic-B`. For example, it is worth while to wait only up to 50 seconds more to get better solutions. `Heuristic-I1` variants are not recommended for tiny, small, and medium sets because there are other variants with better results in the same or shorter time; however, in large problems, `Heuristic-I1` has an advantage over `Heuristic-A1`. The selection between the variants in medium and large scale problems depends on the available time for the users; `Heuristic-B` is recommended in cases of short time, `Heuristic-I1` or `Heuristic-A1` can be used when more time is available, and `Heuristic-A2` or `Heuristic-A3` are good for long time.

The research is extended by developing the new model HLVRPSF which incorporates satellite facilities as mobile supply nodes and considers multi-objective. To solve this model, a new solution approach similar to that suggested to solve the HLVRP model, is recommended to construct the vehicle routes, then many solution approaches are suggested to provide a wide range of candidate solutions to cover most combinations of objective values. Eight different approaches were used to generate candidate solutions.

First, the linearly weighted combination of objectives (LWCO) uses a single objective function without adding any constraint. This approach produce a wide range of solutions with better objective functions compared with other approaches. Second, the single objective with individual minimum resources usage constraints (SOIMRUC) uses a single objective function with adding some constraints to provide each logistic operation an equal opportunity. This approach is found not suitable for short time horizons and it is able to produce only few solutions. Third, the single objective with aggregate minimum resources usage constraints (SOAMRUC1) uses a single objective function with adding some constraints to give equal opportunities for commodity distribution and workers transfer with wounded evacuation. This approach overcomes the limitation of the (SOIMRUC) in short time horizons, but it also produces few solutions. Fourth, the single objective with aggregate minimum resources usage constraints to fill free space (SOAMRUC2) adds small terms to the objective functions used in the (SOAMRUC1) to fill the free space. This improve the vehicle utilizations. Fifth, the single objective solved in multiple stages (SOSMS) utilizes many steps to generate a single candidate solution. It is found that this approach is not recommended because it needs to define many constants by users and it can not generate solutions in may iterations. Sixth, the single objective with weighted penalties (SOWP) uses single objective without adding any constraint. Similar to the LWCO, this approach produces wide range of solution with good objective function values. Seventh, the extreme approach (EXTR) is used to find solution in extremed regions of Pareto fronts. These solutions usually have an excellent objective function value in one logistic operation and bad objective function values in others. Eighth, the hybrid approach utilizes all previous approaches, except the SOSMS, to find the best representative Pareto fronts.

Four data sets are solved using the suggested approaches. These data sets cover all size scales; tiny, small, medium, and large. The results shows that there are some clusters in the wounded–commodities and workers–wounded Pareto front sets, but these clusters are reduced in the commodities–workers Pareto set. It is also found that the hybrid approach can be considered as a clear winner to provide the Pareto fronts.

A case study is included in Chapter 5 to create a data set with some real parameter values. A procedure is suggested to compare between single objective and multi–objective models. This procedure is used to compare the results of the cases study when it is solved as HLVRP and as HLVRPSF. The comparison concludes that the HLVRPSF produces better solutions than the single solution produced by the HLVRP. In spite of this, the HLVRP solution is able to defeat some of the HLVRPSF solutions in term of total objective values.

As stated in the literature review, no studies have suggested models with three logistic operations; consequently, the performance of the solution approaches can not be compared to existing solutions from the literature in terms of quality and computation time. In the case of the HLVRP model, solutions obtained from the proposed approaches are compared with CPLEX results in tiny and small scale problems. In case of the HLVRPSF model, results are evaluated based on some properties such as clusters, regions covered in the Pareto plots, and computation time.

6.2 Future Research

This research is the first attempt to consider three logistic operations and satellite facilities in post–disaster humanitarian relief and many of future works can be suggested to improve it. First, more than three logistic operations could be incorporated in the logistic system. For example, vehicles could pick up debris when they have idle time to open important blocked roads. Second, although the suggested solution approaches are capable of providing solutions in a reasonable amount of time for large scale sets, more research could address solutions for cases with extra-large scale sets by dividing the set into sub problems and solving while sharing some information and activities between sub-sets.

One apparent improvement opportunity is to define conditions or cost for using SFs. In some cases where the ratio between the number of vehicles and SFs is low (i.e. 4 vehicles, 3 SFs), SFs could work at low efficiency such as making a trip with 20% of its capacity. This would be beneficial because there is no cost associated with using SFs.

If commodities have different sizes (i.e. cots, blankets, first aids bags, and insulin bottles) and weights, vehicle loads have two restrictions: weight and volume. This can make finding the optimum load for each vehicle more complex. All studies in this field have considered only the weight of commodities. Which, when ignoring the size restriction, could result in infeasible solutions.

In the proposed models, workforce transfer is considered from a logistic perspective. Workforce management can be also studied using the humanitarian relief logistic, which includes scheduling, jobs distribution, finding the optimum number of each profession to stay at each node, and work time management.

Another opportunity for future research might be an investigation of the effect of data randomness either by considering a stochastic or a robust model. Due to the inherent uncertainty associated with humanitarian logistics, the idea of robust optimization (RO) may be introduced to consider a worst-case situation, especially when unmet demand may result in the loss of someone's life.

RO can be defined as an optimization approach that attempts to solve problems with uncertain parameters by using the worst possible scenario associated with the data sets, or by using an approximate value of uncertain parameters for defined intervals of time. In the linear program, the uncertain set could be the cost matrix, right hand side matrix

(RHS), and/or coefficients matrix. RO has been extensively studied in different fields such as communication and control systems, but less so in industrial engineering and humanitarian relief logistics. For example, BenTal and Nemirovski (1999) introduced uncertain ellipsoidal sets where the uncertain parameters could have any value inside an ellipse rather than box. BenTal et al. (2004) have talked about adjustable RO with application for uncertain RHS. In this article, the variables were divided into two groups, first the adjustable variables which can be determined based on the previous realizations, and second the non-adjustable variable which should be determined before the realization. BenTal et al. (2011) have used the same concept of adjustable RO to solve emergency logistics that have uncertain demand, and Sungur et al. (2008) have shown a solution for a vehicle routing problem (VRP) with uncertain demand.

Another extension may incorporate the use of communication devices and feedbacks from social media. Using these devices is so important in humanitarian relief, and the model with communication devices is different from the model without them. For example, assume that a road is blocked and the driver has a communication device to communicate this to the control at depot. In this case, it is easy for the vehicle to be redirected with little time loss; however, if the driver does not have the communication device, he may redirect himself or go back to the supply node which will cause a high loss of time. The model should take this issue into consideration and give different results (alternatives) such as leaving roads with high blocking probability until the last step of the routes in case there is a lack of communication devices. Using the same model to find logistic plans for both cases could lead to very bad results. For example, consider the network depicted in Figure 6.1, where arc $(2, 3)$ is suddenly blocked. In this case, the driver must decide which alternative route should be followed, two of which are suggested in Figure 6.2.

If the driver has a communication device, he will be redirected to 4, and then go back to node 3; however, if he does not have a communication device, he could decide to go back

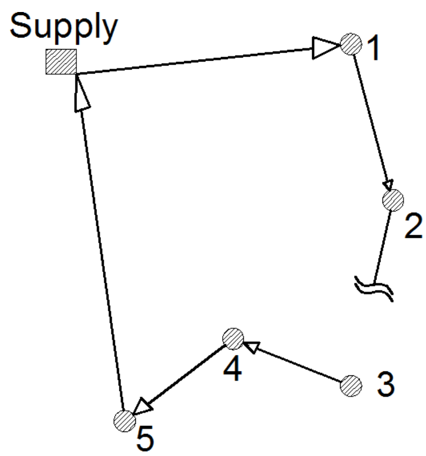


Figure 6.1: Communication device effect

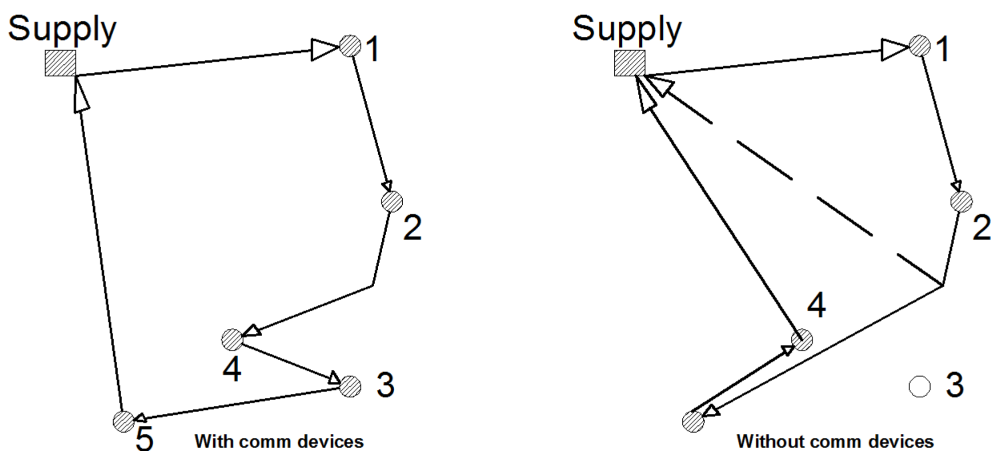


Figure 6.2: Communication device: with and without cases

directly to the depot as depicted by the doted line or he could go to the node 5 then 4 , missing number 3 and traveling a much longer distance.

Finally, because detrimental behaviors such as stealing could exist on roads or at nodes and delivery could exceed demand at some nodes, some additions could be used to overcome these problems. For example, chance constraints could be studied to model the human behavior. For example, these constraints could add a probability for the successful delivery of commodities, where the nodes with low probability should take precautionary measures. Sungur et al. (2008) compare between chance-constrained at different level of chances. The importance of the chance constraints is to determine the expected quantity to be distributed by each vehicle or received at each node which may not be equal to the planned quantity, i.e if a vehicle is supposed to deliver 100 items to a specific node, this quantity could be only 95 units or, in extreme cases, zero.

Bibliography

Abbas Afshar and Ali Haghani. Modeling integrated supply chain logistics in real time large-scale disaster relief operations. *Socio Economic Planning Sciences*, 38:1–12, 2012.

N. Altay and W. G. Green. Or/ms research in disaster operations management. *European Journal of Operational Research*, 175:475–493, 2006.

H. Arora, T.S. Raghu, and A. Vinze. Resource allocation for demand surge mitigation during disaster response. *Decision Support Systems*, 50:304–315, 2010.

N. Azimi, J. Renaud, A. Ruiz, and M. Salari. A covering tour approach to the location of satellite distribution centers to supply humanitarian aid. *European Journal of Operational Research*, 222:596–605, 2012.

S. R. Baharanchi, M. M. Khah, and G. Jandaghi. Design a routing-allocation model for relief transportation of the earthquake wounded using simulated annealing method. *European Journal of Economics, Finance and Administrative Sciences*, 30:1450–2275, 2011.

B. Balcik, B. M. Beamon, and K. Smilowitz. Last mile distribution in humanitarian relief. *Journal of Intelligent Transportation Systems*, 12(2):51–63, 2008.

R. Baldacci, N. Christofides, and A. Mingozzi. An exact algorithm for the vehicle routing problem based on the set partitioning formulation with additional cuts. *Math. Program., Ser. A*, 115:351–385, 2008.

G. Barbarosoglu and Y. Arda. A two-stage stochastic programming framework for transportation planning in disaster response. *Journal of the Operational Research Society*, 55:43–53, 2004.

G. Barbarosoglu, L. Ozdamar, and A. Cevik. An interactive approach for hierarchical analysis of helicopter logistics in disaster relief operations. *European Journal of Operational Research*, 140:118–133, 2002.

J. F. Bard, L. Huang, M. Dror, and P. Jaillet. A branch and cut algorithm for the vrp with satellite facilities. *IIE Transactions*, 30:821–834, 1998a.

J. F. Bard, L. Huang, P. Jaillet, and M. Dror. A decomposition approach to the inventory routing problem with satellite facilities. *Tansportation Science*, 32 No. 2: 189–204, 1998b.

C. Barnhart and G. Laporte, editors. *HandBook in Operations Research and Management Science*. North Holland, 2007.

E.J. Beltrami and L.D. Bodin. Networks and vehicle routing for municipal waste collection. *Networks*, 4:65–94, 1979.

A. BenTal and A. Nemirovski. Robust solutions of uncertain linear programs. *OR Letters*, 25:1–13, 1999.

A. BenTal, A. Goryashko, E. Guslitzer, and A. Nemirovski. Adjustable robust solutions of uncertain linear programs. *Math. Program., Ser. A*, 99:351 – 376, 2004.

A. BenTal, B. D. Chung, S. R. Mandala, and T. Yao. Robust optimization for emergency logistics planning: Risk mitigation in humanitarian relief supply chains. *Transportation Research Part B*, 45:1177–1189, 2011.

A. Bettinelli, A. Ceselli, and G. Righini. A branch-and-cut-and-price algorithm for the multi-depot heterogeneous vehicle routing problem with time windows. *Transportation Research Part C*, 19:723–740, 2011.

A. M. Campbell and P. C. Jones. Prepositioning supplies in preparation for disasters. *European Journal of Operational Research*, 209:156–165, 2011.

A. M. Campbell, D. Vandenbussche, and W. Hermann. Routing for relief efforts. *Transportation Science*, 42 No. 2:127–145, 2008.

A. M. Caunhye, X. Nie, and S. Pokharel. Optimization models in emergency logistics: A literature review. *Socio-Economic Planning Sciences*, 46:4–13, 2012.

M. S. Chang, Y. L. Tseng, and J. W. Chec. A scenario planning approach for the flood emergency logistics preparation problem under uncertainty. *Transportation Research*, Part E 43:737754, 2007.

Y. C. Chiu and H. Zheng. Real-time mobilization decisions for multi-priority emergency response resources and evacuation groups: Model formulation and solution. *Transportation Research*, Part E 43:710–736, 2007.

Clark, Alistair, and Bernadette Culkin. A network transshipment model for planning humanitarian relief operations after a natural disaster. *Decision Aid Models for Disaster Management and Emergencies*, 2013:233–257, 2013.

A. J. Clark and H. Scarf. Optimal policies for a multi-echelon inventory problem. *Management Science*, 6, No. 4:475–490, 1960.

J. F. Cordeau, M. Gendreau, G. Laporte, J. Y. Potvin, and F. Semet. A guide to vehicle routing heuristics. *The Journal of the Operational Research Society*, 53:512–522, 2002.

T. G. Crainic, G. Perboli, S. Mancini, and R. Tadei. Two-echelon vehicle routing problem: A satellite location analysis. *Procedia Social and Behavioral Sciences*, 2:5944–5955, 2010.

Dantzig and Ramser. The truck dispatching problem. *Management Science*, 6:80–91, 1959.

G. Desaulniers, J. Lavigne, and F. Soumis. Multi-depot vehicle scheduling problems with time windows and waiting costs. *European Journal of Operational Research*, 111: 479–494, 1998.

I. S. Dolinskaya, Z. E. Shi, and K. R. Smilowitz. Decentralized approaches to logistics coordination in humanitarian relief. In *Proceedings of the 2011 Industrial Engineering Research Conference*, 2011.

M. Dror and P. Trudeau. Savings by split delivery routing. *Transportation Science*, 23: 141–145, 1989.

T. Fei, H. W. Ren, L. Y. Zhang, J. Zhang, and Q. Li. The research about emergency logistics path optimization based on max - min ant colony algorithm. In *Seventh International Conference on Natural Computation*, 2011.

FEMA. Disaster declarations by year, 05 2013. URL `http://www.fema.gov/disasters/grid/year`.

G. Fetter and T. Rakes. A self-balancing cusum approach for the efficient allocation of resources during post-disaster debris disposal operations. *Operation Managment Research*, 4:51–60, 2011.

F. Fiedrich, F. Gehbauer, and U. Rickers. Optimized resource allocation for emergency response after earthquake disasters. *Safety Science*, 35:41–57, 2000.

G. Galindo and R. Batta. Review of recent developments in or/ms research in disasteroperations management. *European Journal of Operational Research*, 230:201–211, 2013.

B. Gendron and F. Semet. Formulations and relaxations for a multi-echelon capacitated locationdistribution problem. *Computers and Operations Research*, 36:1335–1355, 2009.

Golden and Assad. Perspectives on vehicle routing: Exciting new developments. *Operations Reseach*, 34:803–809, 1986.

Q. Gong and R. Batta. Allocation and reallocation of ambulances to casualty clusters in a disaster relief operation. *IIE Transactions*, 39:27–39, 2007.

MMI Engineering Group. Hazus enhancements and implementation for the shakeout scenario earthquake, 11 2013. URL `www.colorado.edu/hazards/shakeout/hazus.pdf`.

A. Haghani and S. C. Oh. Formulation and solution of a multi-commodity, multi-modal network flow model for disaster relief operations. *Transportation Research A*, 30:231–250, 1996.

L. D. Han, F. Yuan, S. M. Chin, and H. Hwang. Global optimization of emergency evacuation assignments. *Informs*, 36, No. 6:502–513, 2006.

S. Ho and D. Haugland. A tabu search heuristic for the vehicle routing problem with time windows and split deliveries. *Computers & Operations Research*, 31:1947–1964, 2004.

W. Ho, G. Ho, P. Ji, and H. Lau. hybrid genetic algorithm for the multi-depot vehicle routing problem. *Engineering Applications of Artificial Intelligence*, 21 (4):548–557, 2008.

Frtiz Institute. Logistics and the effective delivery of humanitarian relief, 09 2013. URL `www.fritzinstitute.org/PDFs/Programs/tsunamiLogistics0605.pdf`.

P. Jaillet, J. F. Bard, L. Huang, and M. Dror. Delivery cost approximations for inventory routing problems in a rolling horizon framework. *Transportation Science*, 36, No.3:292–300, 2002.

Y. Jiang, Y. Yuan, K. Huang, and L. Zhao. Logistics for large-scale disaster response: Achievements and challenges. In *2012 45th Hawaii International Conference on System Sciences*, 2012.

M. Jin, K. Liu, and R. Bowden. A two-stage algorithm with valid inequalities for the split delivery vehicle routing problem. *International Journal Of Production Economics*, 105 (1):228–242, 2007.

A. Jotshi, Q. Gong, and R. Batt. Dispatching and routing of emergency vehicles in disaster mitigation using data fusion. *Socio-Economic Planning Sciences*, 43:1–24, 2009.

J. Jung and K. Mathur. An efficient heuristic algorithm for a two-echelon joint inventory and routing problem. *Transportation Science*, 41, No. 1:55–73, 2007.

S. Kulturel-Konak, A. E. Smith, and B. A. Norman. Multi-objective tabu search using a multinomial probability mass function. *European Journal of Operational Research*, 169:918–931, 2006.

G. Laporte. The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, 59:345–358, 1992.

Y. H. Lin, R. Batta, P. A. Rogerson, A. Blatt, M. Flanigan, and K. Lee. A logistics model for emergency supply of critical items in the aftermath of a disaster. *Socio-Economic Planning Sciences*, 45:132–145, 2011.

M. Liu and L. Zhao. A composite weighted multi-objective optimal approach for emergency logistics distribution. *IEEE IEEM*, 2007.

T. Luis, I. Dolinskaya, and k. Smilowitz. Disaster relief routing: Integrating research and practice. *Socio-Economic Planning Sciences*, 46:88–79, 2012.

J. Lysgaard, A. N. Letchford, and R. W. Eglese. A new branch-and-cut algorithm for the capacitated vehicle routing problem. *Mathematical Programming*, 100:423–445, 2004.

M. McDowell, C. Fryar, C. Ogden, and K. Flegal. Anthropometric reference data for children and adults: United states 20032006. Technical report, U.S. Department of Health and Human Services, 2006.

M. Najafi, K. Eshghi, and W. Dullaert. A multi-objective robust optimization model for logistics planning in the earthquake response phase. *Transportation Research Part E 49 (2013) 217249*, Part E 49:217–249, 2013.

L. Ozdamar and O. Demir. A hierarchical clustering and routing procedure for large scale disaster relief logistics planning. *Transportation Research*, E48:591–602, 2012.

L. Ozdamar and W. Yi. Greedy neighborhood search for disaster relief and evacuation logistics. *IEEE*, 23 No.1:14–23, 2008.

L. Ozdamar, E. Ekinci, and B. Kucukyazici. Emergency logistics planning in natural disasters. *Annals of Operations Research*, 129:217245, 2004.

C. Paterson, G. Kiesmuller, R. Teunter, and K. Glazebrook. Inventory models with lateral transshipments: A review. *European Journal of Operational Research*, 210:125–136, 2011.

G. Perboli, R. Tadei, and D. Vigo. *The Two-Echelon Capacitated Vehicle Routing Problem: Models and Math-Based Heuristics*. CIRRELT, 2008.

C. G. Rawls and M. A. Turnquist. Pre-positioning of emergency supplies for disaster response. *Transportation Research Part B*, 44:521–534, 2010.

Red-Cross. Isaac: Red cross changes method of disaster relief supply delivery to ensure they go to real victims, 05 2013. URL `http://blog.gulflive.com/mississippi-press-news/2012/09/isaac_red_cross_disaster_relie.html`.

B. Rottkemper, K. Fischer, and A. Blecken. A transshipment model for distribution and inventory relocation under uncertainty in humanitarian operations. *Socio-Economic Planning Sciences*, 46:98–109, 2012.

D. G. Sapir, F. Vos, R. Below, and S. Ponserre. Annual disaster-statistical review 2010-the numbers and trends. Technical report, Centre for Research on the Epidemiology of Disasters - CRED, 2010.

H. D. Sherali, J. Desai, and T. S. Glickman. Allocating emergency response resources to minimize risk with equity. *Mathematical and Management Sciences*, 24:367–410, 2004.

J. B. Sheu. An emergency logistics distribution approach for quick response to urgent relief demand in disasters. *Transportation Research, Part E 43*, pages 687–709, 2007.

J. B. Sheu. Dynamic relief-demand management for emergency logistics operations under large-scale disasters. *Elsevier - Transportation Research*, Part E 46:117, 2010.

A. Soeanu, S. Ray, M. Debbabi, J. Berger, A. Boukhtouta, and A. Ghanmi. A decentralized heuristic for multi-depot split-delivery vehicle routing problem. In *Proceeding of the IEEE International Conference on Automation and Logistics*, 2011.

I. Sungur, F. Ordonez, and M. Dessouky. A robust optimization approach for the capacitated vehicle routing problem with demand uncertainty. *IIE Transactions*, 40: 509523, 2008.

Q. Tan, G. H. Huang, C. Wu, Y. Cai, and X. Yan. Development of an inexact fuzzy robust programming model for integrated evacuation management under uncertainty. *Journal of Urban Planning and Development*, 135 No, 1:39–49, 2009.

F. Tillman. The multiple terminal delivery problem with probabilistic demands. *Transportation Science*, 3:192–204, 1969.

P. Toth and D. Vigo. *The Vehicle Routing Problem*. Society for Industrial and Applied Mathmatics, 2002.

G. H. Tzeng, H. J. Cheng, and T. D. Huang. Multi-objective optimal planning for designing relief delivery systems. *Transportation Research Part E*, 43:673–686, 2007.

B. Vitoriano, M. T. Ortuno, G. Tirado, and J. Montero. A multi-criteria optimization model for humanitarian aid distribution. *Springer - J Glob Optim*, 2010.

L. Wen and F. Meng. An improved particle swarm optimization for the multi-depot vehicle routing problem with time windows. *IEEE*, 2008.

F. Wex, G. Schryen, S. Feuerriegel, and D. Neumann. Emergency response in natural disaster management: Allocation and scheduling of rescue units. *European Journal of Operational Research*, 2013.

M. J. Widener and M. W. Horner. A hierarchical approach to modeling hurricane disaster relief goods distribution. *Journal of Transport Geography*, 19:821828, 2011.

S. Yan and Y. L. Shih. Optimal scheduling of emergency roadway repair and subsequent relief distribution. *Computers and Operations Research*, 36:2049–2065, 2009.

W. Yi and A. Kumar. Ant colony optimization for disaster relief operations. *Elsevier-Transportation Research*, Part E 43:660 and 672, 2007.

W. Yi and L. Ozdamar. A dynamic logistics coordination model for evacuation and support in disaster response activities. *European Journal of Operational Research*, 179: 1177–1193, 2007.

Y. Yuan and D. Wang. Path selection model and algorithm for emergency logistics management. *Computers and Industrial Engineering*, 56:1081–1094, 2009.

Q. H. Zhao, S. Chen, and C. X. Zang. Model and algorithm for inventory/routing decision in a three-echelon logistics system. *European Journal of Operational Research*, 191:623–635, 2008.

Appendices

Appendix A

Large Scale Set- HLVRPSF Model

Table A.1: Large scale – set parameters

Time Periods $\|T\|$	**Wounded Levels** $\|E\|$	**Commodities Types** $\|C\|$	**workers Categories** $\|W\|$	**Vehicles** $\|V\|$	**Satellite Facilities** $\|F\|$	**Demand Nodes** $\|D\|$	**Supply Nodes** $\|S\|$	**Hospital Nodes** $\|H\|$	**SF Locations** $\|L\|$
30	2	3	2	20	6	20	4	3	12

Table A.2: Demand – first type (d^C_{1it})

	Time 1-30																													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	0	240	200	100	300	300	340	320	120	140	340	220	80	360	100	340	60	360	100	300	180	320	260	0	320	300	240	180	0
2	0	100	200	0	200	340	240	220	120	120	0	0	160	220	260	220	140	140	260	100	160	0	280	0	220	280	100	0	280	0
3	0	0	300	200	320	340	100	60	100	60	260	60	80	280	260	140	320	320	0	260	180	360	320	180	0	0	340	300	0	0
4	0	360	320	300	0	60	360	240	0	340	160	0	80	160	0	160	160	260	60	340	160	180	140	100	160	240	280	0	360	0
5	0	300	220	140	160	220	260	80	0	0	240	140	0	220	300	0	360	180	80	240	340	240	340	240	60	120	320	300	200	0
6	0	280	260	320	100	260	160	320	100	240	280	140	120	180	340	140	80	200	260	300	0	240	60	0	100	320	280	300	0	0
7	0	60	300	80	320	220	0	80	180	220	120	60	240	100	260	220	240	260	240	220	220	80	0	120	120	100	180	0	340	0
8	0	360	0	160	320	0	160	200	0	220	220	360	80	300	160	0	0	200	240	80	280	300	240	200	220	340	0	0	140	0
9	0	80	0	0	0	220	0	180	120	160	260	260	320	180	80	340	140	280	160	120	60	300	340	220	100	0	0	140	280	0
10	0	0	120	0	80	60	100	60	180	0	0	0	360	0	360	360	300	320	340	340	0	140	0	0	140	120	0	100	180	0
11	0	180	160	0	100	340	0	340	0	100	80	280	0	140	100	140	80	60	300	240	140	340	120	260	240	240	100	0	120	0
12	0	360	360	220	180	280	120	200	0	340	240	120	100	180	100	160	340	280	0	340	220	280	240	340	320	320	140	220	0	0
13	0	0	140	80	120	100	80	280	200	0	280	80	80	0	0	200	180	60	140	0	200	240	180	140	0	100	340	300	240	0
14	0	120	220	360	0	240	0	220	0	0	300	80	0	0	360	160	80	260	100	0	0	100	280	300	0	120	0	120	120	0
15	0	80	0	180	0	360	320	200	140	240	200	140	0	0	80	360	160	200	120	200	160	280	0	100	140	220	0	180	0	0
16	0	200	80	320	320	180	360	0	340	300	0	320	300	0	360	220	180	260	280	360	220	0	80	80	140	60	0	180	0	0
17	0	340	160	0	280	220	0	60	220	260	80	200	0	360	360	300	360	100	360	160	180	0	320	80	220	360	0	260	280	0
18	0	80	0	160	160	0	360	200	160	300	260	100	0	360	300	80	0	140	100	0	320	100	0	100	360	0	100	0	0	0
19	0	320	60	260	340	320	140	300	220	80	0	240	240	240	280	360	260	260	0	360	60	0	200	300	240	260	320	160	340	0
20	0	0	280	340	0	240	220	100	360	0	0	0	0	0	280	340	340	60	300	360	260	0	100	320	140	300	180	60	240	0

Table A.3: Demand – second type (d^C_{2it})

	Time 1-30																													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	260	120	0	0	100	0	0	60	120	320	100	0	340	260	260	0	0	320	140	240	0	140	80	0	0	280	320	280	0
2	0	0	80	100	80	220	340	300	260	200	140	60	0	220	280	0	240	300	0	200	320	120	0	240	60	0	340	260	140	0
3	0	180	340	360	260	240	240	80	100	300	0	320	0	320	240	320	60	200	120	0	120	360	260	240	0	240	80	160	80	0
4	0	120	340	300	100	0	340	60	300	340	200	260	60	0	300	0	80	80	0	160	340	320	80	0	0	100	220	0	0	0
5	0	0	300	60	340	0	340	160	0	220	120	0	360	80	200	0	0	260	80	160	0	120	260	0	340	0	280	180	0	0
6	0	0	0	360	100	140	360	0	140	260	80	80	240	140	0	180	100	0	60	300	280	0	320	320	100	0	60	100	180	0
7	0	360	280	0	120	100	200	60	0	60	360	300	160	60	0	0	0	340	360	180	220	100	180	360	0	0	100	180	300	0
8	0	320	80	320	340	0	360	0	280	0	0	260	120	120	160	0	80	140	320	100	320	60	60	360	0	180	220	160	320	0
9	0	220	200	100	0	0	260	120	200	0	0	240	220	160	320	0	160	200	200	220	0	0	360	320	220	0	0	300	200	0
10	0	140	180	180	200	180	80	140	0	200	240	100	0	280	0	0	0	300	100	240	60	220	320	120	60	280	0	360	280	0
11	0	300	100	320	340	80	220	0	100	0	80	60	220	240	240	100	80	360	80	100	280	200	140	140	80	280	360	340	0	0
12	0	280	220	0	0	140	60	160	0	140	360	240	200	180	60	300	240	60	140	240	0	180	340	200	0	240	80	320	260	0
13	0	340	0	100	240	240	260	60	240	0	60	280	0	0	160	120	60	0	240	0	0	0	160	360	120	0	240	300	180	0
14	0	320	340	360	180	0	0	0	60	140	220	260	280	60	0	360	80	0	240	0	0	240	180	0	240	160	160	0	120	0
15	0	340	300	100	0	280	280	340	180	0	260	320	320	360	0	320	140	0	0	140	340	60	280	320	100	60	280	300	0	0
16	0	320	280	160	80	320	200	140	140	0	60	80	160	0	140	300	360	280	0	160	360	60	340	320	140	140	300	160	80	0
17	0	100	180	200	300	80	300	0	180	60	180	200	240	60	140	100	0	140	0	360	300	120	80	0	280	0	240	280	180	0
18	0	320	80	220	80	0	0	80	180	280	240	60	200	220	300	340	240	60	360	0	180	80	60	260	140	100	0	0	280	0
19	0	0	140	60	340	320	0	80	260	160	240	260	200	320	0	160	0	160	100	0	160	360	280	240	100	0	0	180	260	0
20	0	120	340	60	340	0	0	260	360	80	0	320	360	200	0	320	60	0	240	340	260	260	320	200	0	340	140	80	0	

Table A.4: Demand – third type (d^C_{3it})

	Time 1-30																													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	320	0	280	260	200	0	260	0	360	240	320	360	240	200	180	0	360	320	180	140	280	120	120	280	200	240	160	360	0
2	0	240	340	0	240	0	280	300	280	300	180	80	0	0	120	60	200	80	180	120	240	340	200	280	260	60	360	320	320	0
3	0	360	360	200	300	0	320	280	0	180	140	200	80	180	80	0	0	0	0	140	0	360	0	220	0	60	0	160	0	0
4	0	360	0	260	180	0	0	160	200	180	80	0	120	0	340	140	220	280	180	360	100	200	0	280	320	280	0	80	160	0
5	0	120	80	200	100	100	0	0	140	320	0	60	260	80	320	180	260	100	160	220	0	0	60	100	220	0	260	340	220	0
6	0	0	0	0	280	340	0	340	0	0	100	0	260	240	200	200	200	300	300	360	360	280	120	100	0	100	140	60	300	0
7	0	260	260	300	280	80	0	220	0	140	140	340	0	0	100	0	60	220	300	60	320	0	100	220	0	320	0	60	360	0
8	0	320	260	80	220	200	160	260	80	80	280	180	360	140	360	60	0	320	280	100	300	320	0	220	0	240	360	0	0	0
9	0	360	120	0	120	340	280	0	0	360	0	300	100	140	260	180	360	0	240	100	220	80	0	280	300	260	0	320	100	0
10	0	120	140	0	140	280	300	0	200	340	220	340	120	240	320	100	200	240	0	160	60	120	140	0	300	0	120	200	0	0
11	0	280	360	340	320	240	0	100	160	360	120	220	60	360	80	200	360	60	140	0	140	120	260	300	0	360	200	80	120	0
12	0	240	320	200	0	300	300	60	200	160	260	60	80	80	360	120	0	120	0	140	180	280	80	100	180	300	0	260	140	0
13	0	60	60	0	0	340	280	180	180	0	60	360	0	240	80	360	60	300	260	0	200	100	180	240	60	160	180	300	300	0
14	0	0	280	120	120	360	260	240	240	0	280	360	140	160	160	0	360	0	280	120	340	160	0	140	320	140	320	240	220	0
15	0	60	180	100	260	120	300	60	240	60	280	0	0	120	140	0	240	360	340	0	360	0	180	0	360	300	260	240	140	0
16	0	220	360	320	60	60	140	220	260	0	340	120	0	0	320	360	260	320	220	200	180	280	0	140	120	200	120	300	0	0
17	0	280	0	140	340	260	160	0	260	140	140	0	240	160	80	360	60	320	360	100	340	100	0	0	0	140	360	100	280	0
18	0	120	300	200	180	260	120	160	280	160	220	200	360	120	360	220	280	0	340	60	200	0	120	360	0	340	300	0	280	0
19	0	320	200	360	60	100	120	300	0	140	340	200	220	80	360	80	200	0	220	60	340	240	300	100	0	120	0	0	340	0
20	0	340	260	300	0	0	300	220	0	0	160	100	0	100	280	160	360	120	260	120	0	140	180	180	100	280	100	360	60	0

Table A.5: Supply – first type (s^C_{1it})

	Time 1-30																													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	10923	201	0	0	0	0	613	0	0	0	359	0	0	0	434	0	0	89	437	0	0	0	520	0	0	0	289	277	0	0
2	12245	212	504	323	0	153	409	0	0	178	0	203	0	0	0	391	0	0	0	133	0	0	0	492	165	0	0	335	0	0
3	7986	268	322	0	275	0	587	0	0	0	149	434	0	0	0	459	0	0	377	0	0	127	278	668	0	0	0	636	0	0
4	7116	64	373	0	0	624	0	300	341	0	0	0	0	0	623	0	0	95	176	89	0	0	513	448	201	0	0	448	0	0

Table A.6: Supply – second type (s^C_{2it})

	Time 1-30																													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	4465	0	191	0	425	592	385	0	290	0	591	0	631	350	0	0	327	0	633	0	339	0	0	0	0	148	212	0	0	0
2	14162	61	0	74	0	493	0	0	147	0	214	0	373	536	251	0	0	0	103	179	0	0	360	0	0	0	0	0	0	0
3	16748	447	191	294	0	53	0	0	596	442	0	154	0	589	154	0	608	649	218	0	0	112	0	0	98	659	0	0	0	0
4	8266	586	0	0	0	655	663	0	663	0	182	0	0	0	0	491	653	0	0	73	522	217	0	0	0	0	166	223	0	0

Table A.7: Supply – third type (s^C_{3it})

	Time 1-30																													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	14865	255	365	635	0	315	143	644	381	603	0	0	0	0	259	585	0	635	444	0	0	247	459	562	0	0	0	0	0	0
2	13178	0	617	0	663	0	0	0	0	0	193	0	523	0	480	377	0	0	234	0	479	0	0	0	0	63	0	528	0	0
3	7809	600	352	447	175	0	0	189	0	174	555	361	125	0	0	390	431	147	0	0	0	72	526	0	0	0	0	382	0	0
4	16339	98	0	0	564	293	335	173	260	0	0	0	0	624	254	581	384	0	475	276	546	194	481	570	0	0	0	0	0	0

Table A.8: Available workers – first category (s^W_{1it})

	Time 1-30																													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	11	4	3	4	0	0	2	0	1	2	0	4	0	4	0	0	3	4	2	0	3	1	0	0	0	3	2	1	0	0
2	14	1	0	0	1	3	0	1	3	0	0	2	0	0	5	3	4	3	3	4	5	0	0	0	0	0	0	0	0	0
3	35	5	3	0	3	0	0	0	0	0	0	2	1	0	5	0	0	0	3	0	4	5	1	4	0	0	4	3	0	0
4	34	0	0	0	0	0	0	3	3	1	0	0	0	4	0	1	5	0	4	3	0	0	0	0	2	0	0	0	0	0

Table A.9: Available workers – second category (s^W_{2it})

	Time 1-30																													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	26	1	0	0	0	5	5	0	0	2	1	0	0	0	5	2	5	5	1	0	0	0	0	0	0	4	4	0	0	0
2	15	0	1	0	5	5	5	0	0	0	0	0	1	0	5	0	0	0	0	0	3	0	1	2	1	3	0	5	2	0
3	37	0	0	0	0	4	0	2	0	0	2	4	0	0	4	3	2	4	4	3	1	1	0	0	0	2	0	3	5	0
4	43	5	0	0	2	0	0	0	3	0	2	1	5	4	0	2	0	0	0	4	1	2	0	0	3	5	2	2	0	0

Table A.10: Requested workers – first category (d^W_{1it})

$i \in D$	Time 1-30																													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	3	6	2	6	3	1	8	5	5	6	3	6	4	2	8	5	4	3	8	7	8	8	0	4	7	0	8	0	0
2	0	4	7	8	5	3	1	0	4	2	8	1	5	5	4	2	8	4	8	2	7	2	1	5	0	0	3	4	7	0
3	0	3	3	6	5	0	5	1	1	4	1	5	4	1	6	0	4	0	0	3	2	7	5	0	7	6	3	7	6	0
4	0	6	3	3	8	4	7	2	2	3	4	1	7	3	7	2	2	2	0	7	0	0	8	3	7	5	1	6	0	0
5	0	5	4	5	0	5	8	6	8	6	0	8	7	2	1	3	3	8	5	6	8	5	2	0	3	1	3	2	4	0
6	0	2	6	5	7	8	8	6	3	7	1	2	2	1	1	7	1	2	1	5	8	4	0	8	0	2	6	3	1	0
7	0	7	3	6	0	7	0	6	7	8	1	1	4	2	1	4	4	0	2	3	1	1	8	0	5	6	6	3	6	0
8	0	1	4	8	8	6	3	7	4	1	2	0	7	3	8	2	5	0	4	7	8	4	2	0	5	8	7	8	6	0
9	0	3	2	1	4	6	7	2	1	1	7	6	0	0	6	7	3	4	7	8	4	2	7	1	6	0	1	2	8	0
10	0	0	1	3	1	1	5	5	6	1	5	7	1	3	4	1	3	0	0	6	4	7	6	6	1	2	8	5	2	0
11	0	7	8	8	5	7	1	6	0	4	3	6	5	6	2	6	1	5	6	4	5	6	0	7	2	4	2	1	6	0
12	0	1	7	6	0	4	3	5	2	4	1	0	6	4	4	1	8	7	7	0	3	4	3	6	8	3	4	0	7	0
13	0	6	8	4	6	4	1	4	6	2	7	0	5	8	7	2	1	3	3	1	8	0	8	2	2	2	6	0	5	0
14	0	1	7	1	5	4	5	0	0	4	2	6	7	8	4	3	7	1	3	7	4	5	6	3	5	5	3	5	6	0
15	0	0	3	0	8	1	2	2	6	5	1	4	1	3	1	6	2	4	7	8	5	8	6	7	4	1	8	7	4	0
16	0	2	2	1	0	5	2	6	7	2	8	4	7	0	8	6	2	7	3	4	2	8	3	5	8	7	3	1	6	0
17	0	2	0	2	2	2	1	2	7	3	8	3	3	6	5	2	4	2	8	6	1	1	0	1	0	1	7	6	7	0
18	0	1	8	4	4	6	6	6	8	6	7	4	7	4	8	2	8	4	4	4	7	3	8	6	4	8	7	3	1	0
19	0	3	0	8	5	6	3	7	3	8	2	2	3	7	5	1	3	4	3	2	6	7	4	2	0	4	8	2	1	0
20	0	5	3	2	8	2	8	2	8	1	7	3	0	8	3	3	6	8	2	7	1	6	8	8	2	3	8	0	5	0

Table A.11: Requested workers – second category (d^W_{2it})

$i \in D$	Time 1-30																													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	8	3	7	4	4	7	1	6	7	4	6	8	0	7	6	8	1	7	6	8	0	2	0	4	1	6	7	3	0
2	0	6	5	6	3	6	2	5	2	1	6	8	8	8	3	5	0	1	2	8	1	0	3	0	7	4	7	3	5	0
3	0	3	8	6	7	4	2	8	2	4	4	2	5	8	1	2	6	3	7	6	2	0	3	3	7	5	1	4	0	0
4	0	7	5	3	1	4	8	6	6	1	5	6	5	7	8	0	6	1	2	1	2	8	7	4	6	0	8	5	3	0
5	0	7	7	3	5	3	4	4	5	3	8	2	2	2	0	6	0	8	6	5	7	6	6	7	5	3	3	3	1	0
6	0	0	6	4	7	4	5	2	5	0	4	1	2	2	3	4	4	1	1	5	8	5	8	4	1	3	3	4	6	0
7	0	4	7	5	4	2	0	0	4	5	0	0	4	3	1	6	5	3	8	0	2	8	3	1	4	0	4	3	4	0
8	0	5	8	8	0	6	5	2	7	3	2	2	0	1	3	2	4	2	8	0	5	7	7	8	6	0	7	0	0	0
9	0	2	3	4	7	0	2	5	5	7	7	3	1	1	5	8	0	6	8	4	0	7	2	5	4	7	2	8	7	0
10	0	8	8	6	1	1	8	7	1	1	1	6	6	0	7	6	8	4	5	8	1	3	1	8	1	1	5	3	6	0
11	0	5	3	5	4	0	0	4	8	8	0	1	1	1	5	7	1	2	4	7	4	8	4	3	2	5	3	1	4	0
12	0	8	5	2	2	8	5	7	6	5	0	6	4	0	5	5	1	1	2	1	1	4	6	5	3	2	0	3	7	0
13	0	3	5	1	0	1	3	2	7	8	7	4	4	7	8	8	7	4	3	7	4	3	6	5	7	3	2	2	5	0
14	0	2	5	2	5	8	3	3	7	4	5	3	3	4	6	5	0	5	2	8	1	5	4	5	8	1	1	5	2	0
15	0	3	7	8	3	1	8	8	8	2	2	6	4	6	8	7	8	5	3	8	1	3	5	2	0	0	5	6	8	0
16	0	7	0	2	8	7	8	3	7	7	0	4	7	1	8	2	7	7	7	4	3	8	3	3	2	7	5	0	5	0
17	0	0	7	5	7	5	5	6	2	4	7	0	0	8	2	7	7	1	7	5	0	5	7	1	2	8	4	4	6	0
18	0	8	5	3	8	1	6	4	6	0	8	8	2	7	6	2	6	8	7	4	8	3	7	6	8	3	5	8	2	0
19	0	1	3	0	7	6	1	4	7	5	8	3	5	7	0	7	3	7	7	0	4	5	2	1	8	7	7	5	1	0
20	0	2	4	4	1	5	2	8	3	3	1	8	6	0	0	2	5	1	7	0	6	5	7	8	8	8	1	5	4	0

Table A.12: Waiting evacuees – first level (d^E_{1it})

	Time 1-30																													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	5	3	6	2	5	1	2	5	4	4	6	1	2	5	2	4	5	1	5	6	6	0	4	4	5	0	3	0	0
2	0	1	6	3	6	2	1	1	5	2	1	3	0	6	1	1	6	6	1	1	2	2	0	1	1	5	4	5	2	0
3	0	4	6	2	5	5	4	2	0	3	1	3	3	3	0	3	0	6	2	6	5	3	6	5	3	6	5	4	2	0
4	0	2	0	4	4	5	5	1	3	2	1	2	3	1	3	6	4	3	1	2	0	1	6	3	3	5	2	6	2	0
5	0	0	2	5	0	2	2	2	5	0	1	2	0	3	2	3	4	5	1	6	0	2	1	0	3	0	4	6	4	0
6	0	4	4	6	4	6	4	2	6	0	4	5	0	6	5	1	0	5	2	4	3	3	1	1	5	2	2	0	0	0
7	0	4	4	4	1	1	4	3	5	6	5	5	6	0	1	0	4	6	6	4	4	1	6	5	3	0	0	1	0	0
8	0	0	6	1	4	4	3	3	3	5	4	2	5	0	5	4	0	6	2	5	5	6	0	0	6	0	5	2	5	0
9	0	3	1	6	3	1	5	5	3	1	1	4	5	3	6	3	3	2	5	2	1	6	5	4	3	5	4	2	3	0
10	0	1	4	2	4	6	1	6	5	4	4	1	3	4	3	1	0	3	2	2	3	6	4	5	5	2	2	1	5	0
11	0	5	2	2	4	6	2	6	3	1	5	6	5	1	5	1	5	2	3	3	3	3	5	6	2	2	4	0	2	0
12	0	5	0	1	1	0	1	5	6	3	2	1	4	1	0	2	0	6	3	5	1	4	1	4	1	5	1	3	0	0
13	0	6	2	1	2	0	2	3	0	3	6	4	6	1	3	1	0	4	3	0	1	4	3	0	0	5	2	6	3	0
14	0	3	0	1	2	0	2	2	0	2	5	5	3	4	3	0	4	6	1	4	1	2	3	2	0	6	2	5	2	0
15	0	2	4	3	6	2	5	6	3	5	2	3	6	0	2	2	3	3	3	0	0	2	2	2	5	5	2	3	3	0
16	0	3	1	5	5	3	2	4	5	5	4	1	1	6	3	0	4	3	1	0	6	4	5	6	6	6	6	2	4	0
17	0	2	5	5	5	4	4	3	0	4	6	4	0	3	5	1	0	6	0	2	2	1	1	1	3	6	6	0	5	0
18	0	5	3	1	5	6	6	3	4	1	5	2	5	4	6	3	5	3	3	5	2	3	0	3	2	1	2	3	6	0
19	0	1	3	2	5	4	3	3	2	1	0	6	0	5	6	4	0	4	0	5	5	3	1	5	4	6	1	6	6	0
20	0	4	0	5	5	4	5	3	6	0	5	1	1	5	5	1	1	3	5	6	0	4	4	5	0	3	3	3	2	0

Table A.13: Waiting evacuees – second level (d^E_{2it})

	Time 1-30																													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	3	0	1	0	1	4	3	3	1	5	2	1	3	2	0	6	0	6	0	1	3	4	1	0	1	4	5	2	0
2	0	1	1	4	4	2	4	2	3	6	5	4	0	3	6	1	4	6	1	3	5	1	1	6	4	5	1	2	4	0
3	0	5	0	6	4	2	2	6	2	6	1	5	5	5	2	6	6	6	5	4	6	5	0	2	4	0	1	1	5	0
4	0	2	3	1	6	1	0	3	3	2	1	5	6	2	1	5	5	1	2	5	6	5	2	3	3	0	5	0	0	0
5	0	6	6	4	0	0	5	6	2	3	0	3	6	1	0	3	2	6	1	0	1	1	3	5	5	3	1	6	4	0
6	0	6	0	2	3	4	6	3	5	2	0	5	6	1	6	3	0	6	6	0	6	6	6	5	5	2	3	3	6	0
7	0	2	3	1	1	1	3	2	5	1	6	1	1	4	4	0	5	4	1	4	1	1	2	0	0	1	3	3	2	0
8	0	6	0	1	1	1	0	0	2	3	3	5	2	0	5	4	4	0	2	1	2	4	3	4	5	5	2	3	0	0
9	0	6	6	2	5	4	1	5	3	6	3	3	2	4	2	3	4	5	0	0	5	2	6	6	4	2	3	2	5	0
10	0	5	3	5	4	1	5	1	5	4	6	2	3	2	5	4	0	5	5	2	1	3	0	5	5	6	4	3	6	0
11	0	0	3	5	5	0	1	1	6	5	2	4	0	6	4	2	6	3	6	4	6	2	5	1	5	5	6	1	3	0
12	0	3	2	0	1	6	3	4	4	5	5	3	1	5	5	1	2	3	3	2	4	0	4	3	2	0	2	0	4	0
13	0	1	2	0	2	4	5	3	1	2	1	3	5	4	6	6	1	3	5	3	6	0	3	1	0	6	4	1	6	0
14	0	0	1	3	6	1	1	0	4	0	3	5	0	2	2	5	5	6	2	6	2	0	0	6	0	4	0	6	3	0
15	0	3	0	2	1	6	4	0	6	5	0	3	3	2	6	3	2	1	6	5	6	1	4	6	0	5	4	5	0	0
16	0	4	4	3	5	2	3	6	2	0	5	1	4	3	2	0	3	1	4	6	1	1	2	0	3	0	4	1	3	0
17	0	1	6	1	4	2	2	2	2	5	0	4	4	5	3	1	6	3	6	3	5	1	0	6	3	2	4	4	0	0
18	0	1	5	1	3	2	2	0	4	4	0	0	1	0	2	3	3	4	2	3	0	1	6	5	3	4	2	6	6	0
19	0	6	3	5	1	6	6	2	1	2	0	6	4	0	4	5	1	4	1	4	1	1	5	0	3	4	3	4	6	0
20	0	6	3	6	3	4	2	2	1	1	4	2	1	4	6	4	3	3	0	2	1	0	4	0	1	3	0	4	5	0

Table A.14: Vehicle depots (i^V_v)

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
$i \in S$	1	1	1	1	1	2	2	2	2	3	3	3	3	3	3	4	4	4	4	4

Table A.15: Vehicle speed factors

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Speed Factor	2	2	2	2	1	2	2	2	2	2	1	2	1	2	1	1	2	2	1	2

Table A.16: Vehicle capacities (m_v^V)

$v \in V$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Capacity	1200	1000	1000	1100	1000	900	1300	800	800	900	900	800	1400	1100	1000	800	1200	1300	1300	1300

Table A.17: Satellite facility depots (i_f^F)

$f \in F$	1	2	3	4	5
$i \in S$	1	2	3	3	3

Table A.18: Satellite facility speed factors

$f \in F$	1	2	3	4	5
Speed Factor	4	2	3	3	3

Table A.19: Satellite facility capacities (m_f^F)

$f \in F$	1	2	3	4	5
Capacity	4200	4300	3900	3000	3800

Table A.20: Mass of commodities, workers, and wounded (m_c^C, m_e^E, and m_w^W)

Type	c_1	c_2	c_3	w_1	w_2	e_1	e_2
Mass (lb)	3	8	9	200	200	200	200

Table A.21: Priorities (p_{ci}^C, p_{ei}^E, and p_{wi}^W)

$i \in D$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
c_1	6	10	6	7	5	4	8	10	6	1	7	2	10	8	7	4	10	7	10	6
c_2	10	7	6	5	1	7	5	6	2	3	5	9	4	2	5	10	7	4	9	3
c_3	4	7	6	4	4	4	9	5	10	8	2	10	6	10	4	6	8	1	3	9
w_1	700	800	900	850	500	650	800	800	800	800	500	600	650	800	850	900	950	750	750	950
w_2	700	800	500	950	850	750	800	750	750	900	650	950	850	600	800	850	850	700	750	750
e_1	550	800	850	800	600	800	700	650	550	950	700	850	900	700	900	750	600	800	600	850
e_2	750	800	950	700	500	850	650	950	600	900	700	650	700	700	950	900	500	750	600	700

Table A.22: Distance matrix

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39
1	0	2	1	1	1	2	1	1	1	2	2	2	1	1	2	1	1	2	2	2	3	3	2	2	2	1	1	2	1	1	2	2	1	1	1	2	1	2	2
2	2	0	2	2	2	1	1	1	1	1	1	2	1	1	2	1	1	2	1	1	3	3	3	3	2	1	1	2	1	1	2	1	2	2	1	2	1	2	2
3	1	2	0	1	1	2	1	2	2	2	2	2	1	1	1	1	2	1	1	1	2	2	2	2	2	2	1	1	1	2	2	2	2	1	1	2	1	1	2
4	1	2	1	0	1	2	2	2	2	1	2	1	1	1	2	1	1	2	1	2	2	3	2	3	1	1	1	1	2	2	2	1	1	1	1	1	1	2	2
5	1	2	1	1	0	1	2	2	2	1	1	1	2	1	2	1	2	2	1	2	3	2	2	3	2	2	2	1	1	1	1	1	2	2	1	1	1	1	1
6	2	1	2	2	1	0	1	2	1	1	2	1	1	2	2	1	1	2	1	2	2	2	2	2	1	1	2	1	2	2	1	1	1	2	1	2	1	2	1
7	1	1	1	2	2	1	0	2	2	1	2	1	1	1	2	1	1	1	2	2	3	3	2	2	2	2	1	1	1	1	2	1	2	2	1	2	2	1	2
8	1	1	2	2	2	2	2	0	1	2	1	2	2	1	1	2	2	1	2	1	3	2	2	2	1	2	2	1	1	2	2	1	2	2	1	2	1	1	1
9	1	1	2	2	2	1	2	1	0	1	2	1	1	1	2	1	2	1	2	1	2	2	3	2	2	2	1	1	1	1	2	2	1	1	2	2	1	2	2
10	2	1	2	1	1	1	1	2	1	0	2	2	1	1	2	2	2	2	2	2	3	3	2	3	1	1	1	1	1	1	1	1	2	2	2	1	2	2	1
11	2	1	2	2	1	2	2	1	2	2	0	2	1	2	2	2	2	1	2	1	2	2	3	3	1	1	2	2	1	1	1	2	1	1	2	2	1	2	1
12	2	2	2	1	1	1	1	2	1	2	2	0	1	1	2	1	1	1	2	2	3	3	2	2	1	1	2	2	2	1	1	1	2	1	2	1	1	1	2
13	1	1	1	1	2	1	1	2	1	1	1	1	0	2	2	2	1	1	2	2	2	2	3	2	1	2	2	1	1	2	1	1	1	2	2	1	2	2	2
14	1	1	1	1	1	2	1	1	1	1	2	1	2	0	1	1	2	1	2	2	3	2	3	3	1	1	1	2	1	1	2	2	2	1	1	1	2	2	1
15	2	2	1	2	2	2	2	1	2	2	2	2	2	1	0	1	1	2	1	1	2	2	2	3	2	1	1	2	2	1	1	2	2	1	2	2	2	1	2
16	1	1	1	1	1	1	1	2	1	2	2	1	2	1	1	0	2	2	2	2	3	3	2	2	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1
17	1	1	2	1	2	1	1	2	2	2	2	1	1	2	1	2	0	2	2	1	3	3	3	3	2	2	1	1	1	2	1	1	2	2	1	2	2	2	2
18	2	2	1	2	2	2	1	1	1	2	1	1	1	1	2	2	2	0	1	2	3	3	3	3	2	2	2	1	1	2	1	2	1	1	1	1	2	1	2
19	2	1	1	1	1	1	2	2	2	2	2	2	2	2	1	2	2	1	0	2	2	2	2	2	2	1	1	2	2	2	1	2	2	1	1	1	2	1	2
20	2	1	1	2	2	2	2	1	1	2	1	2	2	2	1	2	1	2	2	0	3	3	3	3	2	2	1	2	1	2	2	2	1	2	1	1	2	2	2
21	3	3	2	2	3	2	3	3	2	3	2	3	2	3	2	3	3	3	2	3	0	1	1	1	1	2	1	1	1	1	1	2	1	1	1	2	1	2	2
22	3	3	2	3	2	2	3	2	2	3	2	3	2	2	2	3	3	3	2	3	1	0	2	1	1	1	1	1	1	1	1	2	1	2	2	2	2	1	2
23	2	3	2	2	2	2	2	2	3	2	3	2	3	3	2	2	3	3	2	3	1	2	0	2	2	1	1	1	2	2	2	2	2	1	2	2	2	1	2
24	2	3	2	3	3	2	2	2	2	3	3	2	2	3	3	2	3	3	2	3	1	1	2	0	2	2	1	1	2	2	1	2	2	2	1	1	1	1	2
25	2	2	2	1	2	1	2	1	2	1	1	1	1	1	2	1	2	2	2	2	1	1	2	2	0	1	2	1	2	2	1	1	2	2	2	1	1	2	1
26	1	1	2	1	2	1	2	2	2	1	1	1	2	1	1	1	2	2	1	2	2	1	1	2	1	0	2	2	2	1	1	2	1	2	2	1	1	1	2
27	1	1	1	1	2	2	1	2	1	1	2	2	2	1	1	1	1	2	1	1	1	1	1	1	2	2	0	1	2	1	2	2	1	1	1	1	1	2	2
28	2	2	1	1	1	1	1	1	1	1	2	2	1	2	2	1	1	1	2	2	1	1	1	1	1	2	1	0	2	1	2	1	1	1	1	1	1	2	2
29	1	1	1	2	1	2	1	1	1	1	1	2	1	1	2	1	1	1	2	1	1	1	2	2	2	2	2	2	0	1	2	2	1	2	2	1	2	2	2
30	1	1	2	2	1	2	1	2	1	1	1	1	2	1	1	1	2	2	2	2	1	1	2	2	2	1	1	1	1	0	1	2	2	1	2	1	1	2	1
31	2	2	2	2	1	1	2	2	2	1	1	1	1	2	1	1	1	1	1	2	1	1	2	1	1	1	2	2	2	1	0	2	1	1	2	1	1	1	2
32	2	1	2	1	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	2	2	2	2	2	1	2	2	1	2	2	2	0	1	1	2	1	2	1	1
33	1	2	2	1	2	1	2	2	1	2	1	2	1	2	2	2	2	1	2	1	1	1	2	2	2	1	1	1	1	2	1	1	0	1	2	2	1	2	2
34	1	2	1	1	2	2	2	2	1	2	1	1	2	1	1	1	2	1	1	2	1	2	1	2	2	2	1	1	2	1	1	1	1	0	2	2	1	1	1
35	1	1	1	1	1	1	1	1	2	2	2	2	2	1	2	1	1	1	1	1	1	2	2	1	2	2	1	1	2	2	2	2	2	2	0	1	2	2	1
36	2	2	2	1	1	2	2	2	2	1	2	1	1	1	2	1	2	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	2	2	1	0	1	2	1
37	1	1	1	1	1	1	2	1	1	2	1	1	2	2	2	2	2	2	2	2	1	2	2	1	1	1	1	1	2	1	1	2	1	1	2	1	0	1	1
38	2	2	1	2	1	2	1	1	2	2	2	1	2	2	1	2	2	1	1	2	2	1	1	1	2	1	2	2	2	2	1	1	2	1	2	2	1	0	2
39	2	2	2	2	1	1	2	1	2	1	1	2	2	1	2	1	2	2	2	2	2	2	2	2	1	2	2	2	2	1	2	1	2	1	1	1	1	2	0

Appendix B

Medium Scale Set- HLVRPSF Model

Table B.1: Medium scale – set parameters

Time Periods $\lvert T\rvert$	**Wounded Levels** $\lvert E\rvert$	**Commodities Types** $\lvert C\rvert$	**workers Categories** $\lvert W\rvert$	**Vehicles** $\lvert V\rvert$	**Satellite Facilities** $\lvert F\rvert$	**Demand Nodes** $\lvert D\rvert$	**Supply Nodes** $\lvert S\rvert$	**Hospital Nodes** $\lvert H\rvert$	**SF Locations** $\lvert L\rvert$
23	3	5	4	13	3	15	4	3	8

Table B.2: Demand – first type (d^C_{1it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	60	280	200	160	220	100	300	220	0	360	60	180	360	80	240	360	100	240	320	160	0	0
2	0	200	160	180	0	220	80	0	100	240	240	280	140	80	320	80	0	60	260	0	320	220	0
3	0	100	0	0	180	280	120	140	60	120	320	300	260	0	320	180	0	220	120	160	120	140	0
4	0	200	320	360	340	80	140	60	120	280	360	320	300	300	100	0	220	260	220	360	160	360	0
5	0	260	0	260	260	200	0	160	120	0	200	60	0	180	360	260	140	0	280	340	360	0	0
6	0	120	260	180	360	80	160	320	300	0	320	260	60	320	320	0	220	60	220	140	0	0	0
7	0	160	0	0	0	340	300	160	0	340	220	320	140	220	220	80	0	360	140	280	340	360	0
8	0	0	80	100	0	260	0	180	340	360	0	60	240	320	160	100	80	80	260	300	0	0	0
9	0	360	60	100	0	80	320	340	280	300	0	340	0	0	0	240	200	120	220	160	0	0	0
10	0	200	0	300	0	180	180	140	120	120	200	80	280	160	320	200	320	120	80	0	0	0	0
11	0	240	140	180	120	260	320	80	80	340	180	0	0	220	300	320	360	0	120	340	340	140	0
12	0	180	0	0	180	260	0	140	300	200	220	0	360	80	180	0	280	180	140	300	300	80	0
13	0	160	200	60	160	260	320	100	0	60	0	140	120	240	180	120	60	140	0	180	140	60	0
14	0	140	0	200	280	220	280	360	280	80	260	100	260	280	220	0	320	360	260	0	80	140	0
15	0	320	160	140	140	0	360	320	180	280	0	360	60	100	0	320	260	180	0	60	0	300	0]

Table B.3: Demand – second type (d^C_{2it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	0	200	140	360	200	0	80	80	140	260	280	180	80	280	240	180	200	220	220	360	200	0
2	0	320	0	180	320	160	320	280	120	0	200	220	0	200	60	240	200	160	220	80	340	220	0
3	0	140	220	280	0	360	120	60	140	340	60	280	60	0	140	240	260	100	100	80	60	280	0
4	0	220	160	200	260	0	360	220	100	160	60	0	160	360	60	240	0	80	220	360	280	320	0
5	0	340	200	180	260	240	140	160	100	260	60	100	0	0	360	260	320	100	0	300	320	160	0
6	0	160	220	220	280	0	320	360	100	120	0	140	340	100	0	300	80	140	60	100	200	300	0
7	0	0	160	360	240	120	120	100	300	300	360	0	0	300	280	240	120	220	320	0	280	340	0
8	0	220	360	60	160	360	360	180	120	100	0	360	120	320	60	320	320	260	260	280	0	80	0
9	0	240	200	360	200	180	300	220	60	120	280	240	0	140	360	200	0	320	0	140	260	0	0
10	0	0	300	280	100	320	260	0	200	340	220	220	0	220	180	240	300	120	80	360	140	320	0
11	0	200	0	240	100	140	0	320	100	220	0	180	280	0	0	320	140	160	260	260	360	200	0
12	0	0	280	280	140	0	220	340	80	280	60	80	360	200	240	280	100	60	120	300	340	200	0
13	0	60	80	100	300	0	340	240	80	0	360	80	200	280	320	280	220	160	0	0	280	340	0
14	0	80	300	360	200	360	340	140	300	140	300	360	80	200	0	160	320	220	100	180	200	240	0
15	0	100	320	0	60	320	260	320	240	220	240	80	200	160	300	160	300	0	320	120	180	340	0

Table B.4: Demand – third type (d^C_{3it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	0	340	140	160	100	300	0	0	0	220	300	80	120	360	220	320	60	0	100	260	300	0
2	0	360	240	160	320	0	60	160	0	0	100	120	220	260	240	240	0	240	300	220	60	200	0
3	0	60	260	280	160	200	120	60	220	0	100	340	0	200	180	280	280	100	320	80	300	0	0
4	0	300	260	260	280	280	360	60	80	0	180	80	0	0	260	360	220	220	0	0	260	300	0
5	0	360	220	240	0	120	300	0	0	280	200	280	160	220	0	260	0	300	0	240	360	120	0
6	0	100	0	80	80	140	200	180	0	0	260	340	300	320	140	200	0	120	180	360	80	340	0
7	0	0	160	0	120	180	320	280	0	300	0	100	140	240	140	340	280	200	340	0	120	0	0
8	0	80	340	120	0	260	180	200	260	360	180	180	160	160	280	220	100	100	200	240	260	180	0
9	0	260	0	0	80	300	140	340	220	0	360	280	280	300	240	160	60	0	260	0	240	80	0
10	0	320	160	320	220	280	0	0	0	0	360	300	140	140	360	260	0	260	0	320	0	180	0
11	0	140	360	140	0	0	220	0	60	60	220	320	100	140	120	360	280	340	340	0	0	280	0
12	0	140	80	340	0	280	160	100	260	0	160	360	340	200	180	360	120	260	200	320	0	180	0
13	0	100	260	220	260	140	360	280	320	180	320	160	240	0	280	160	220	180	180	120	160	260	0
14	0	260	60	60	60	0	240	0	0	220	120	200	0	260	0	180	260	120	60	0	240	260	0
15	0	200	280	180	0	220	220	260	200	320	60	280	120	80	300	360	280	120	160	160	180	280	0]

Table B.5: Demand – fourth type (d^C_{4it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	220	0	200	160	0	160	160	120	100	280	160	0	0	0	120	160	320	0	100	0	340	0
2	0	0	220	140	160	160	120	220	200	80	200	0	0	0	140	160	360	320	100	280	0	260	0
3	0	240	360	320	0	340	360	0	200	280	300	340	240	160	260	120	100	120	0	220	0	0	0
4	0	240	180	0	300	60	220	260	140	160	0	220	0	0	200	120	0	0	60	260	100	100	0
5	0	300	240	260	260	80	120	80	120	140	80	320	280	340	80	220	300	140	0	200	0	120	0
6	0	360	260	360	280	320	140	140	300	180	100	340	240	240	340	360	80	0	100	200	0	0	0
7	0	180	160	180	0	60	260	260	0	340	240	100	280	240	340	200	160	280	240	100	180	60	0
8	0	240	160	220	140	240	0	200	360	60	280	0	0	160	0	0	60	0	160	120	140	240	0
9	0	260	340	140	180	0	180	200	220	300	240	340	200	200	0	120	80	320	200	240	160	100	0
10	0	200	0	300	80	300	300	120	140	260	120	180	240	220	200	260	140	140	160	200	0	340	0
11	0	120	0	80	140	160	180	300	220	360	220	160	140	140	360	180	140	60	180	0	220	220	0
12	0	300	0	320	360	80	340	100	240	100	100	0	140	120	0	300	60	160	140	360	140	0	0
13	0	360	60	320	160	280	0	180	260	180	280	0	0	100	180	160	60	300	0	120	360	160	0
14	0	220	340	0	260	220	340	0	0	60	180	0	0	240	140	0	280	0	80	120	0	160	0
15	0	140	100	280	80	0	140	0	360	220	240	120	240	200	100	0	320	0	140	220	0	280	0]

Table B.6: Demand – fifth type (d^C_{5it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	160	320	220	340	100	100	0	160	0	340	80	220	200	240	360	240	180	0	340	0	220	0
2	0	0	240	60	220	240	280	80	120	300	160	120	60	220	0	0	280	0	60	300	260	220	0
3	0	260	260	160	240	200	0	120	360	180	340	340	200	200	60	0	240	360	200	120	320	260	0
4	0	140	180	0	240	0	280	100	240	80	260	0	160	100	160	260	260	0	240	0	260	120	0
5	0	80	360	0	120	300	60	280	280	120	0	160	0	360	100	140	240	60	240	100	140	0	0
6	0	0	160	320	200	0	320	240	240	140	140	260	100	240	280	260	340	60	60	320	60	100	0
7	0	300	0	160	140	0	300	320	100	0	280	160	340	100	180	0	60	120	220	200	0	140	0
8	0	300	240	240	340	60	60	280	200	200	0	80	0	140	0	60	240	0	240	220	340	140	0
9	0	160	0	260	220	280	120	200	200	300	120	120	120	140	140	360	200	0	100	0	0	160	0
10	0	240	120	100	220	140	80	300	80	160	0	160	140	300	100	240	340	360	200	240	220	260	0
11	0	360	80	360	280	140	280	320	120	280	220	120	300	340	240	0	340	0	0	80	0	0	0
12	0	80	360	280	200	180	280	0	300	0	120	260	340	60	80	0	180	100	240	0	320	120	0
13	0	320	0	360	280	0	160	60	180	360	200	100	0	60	140	160	360	80	140	0	260	220	0
14	0	180	120	0	180	280	300	100	360	300	260	60	0	320	0	0	320	0	140	260	320	60	0
15	0	0	0	360	120	100	160	300	140	120	140	80	280	100	80	80	0	120	60	160	0	180	0

Table B.7: Supply – first type (s^C_{1it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	4640	359	0	123	0	194	0	90	0	0	0	0	192	0	0	0	116	205	236	85	0	0	0
2	7196	0	251	0	0	0	0	77	417	0	269	0	0	0	269	148	417	0	0	429	0	0	0
3	4462	0	131	0	0	362	0	0	463	144	0	245	206	0	472	88	119	418	0	0	0	0	0
4	8149	0	107	0	0	0	262	0	0	272	0	403	0	337	0	0	79	0	0	0	139	0	0

Table B.8: Supply – second type (s^C_{2it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	10336	0	0	386	0	0	0	538	0	0	0	0	0	0	328	476	220	355	0	183	0	0	0
2	4366	531	218	0	0	113	0	0	271	0	343	180	102	459	0	0	0	468	0	0	150	0	0
3	4329	384	321	487	238	244	380	237	0	289	0	0	54	0	0	504	330	0	146	0	324	0	0
4	8315	0	287	454	133	0	0	53	288	0	109	161	494	0	201	0	0	109	0	0	206	0	0

Table B.9: Supply – third type (s^C_{3it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	10312	0	270	0	0	301	390	83	0	0	0	82	0	224	539	0	429	0	0	0	146	0	0
2	10263	0	119	499	0	0	0	160	0	201	274	83	357	192	51	0	0	0	0	0	0	0	0
3	4574	0	278	538	0	0	145	0	0	290	0	470	0	379	185	516	241	0	0	0	138	0	0
4	5547	153	237	0	0	0	422	250	0	0	355	0	0	0	321	0	188	263	531	317	81	0	0

Table B.10: Supply – fourth type (s^C_{4it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	6682	308	412	0	0	0	0	450	0	211	431	0	0	0	185	419	0	0	349	0	0	0	0
2	7467	0	0	101	224	0	0	0	187	454	0	496	0	0	0	0	0	0	0	0	353	0	0
3	2775	478	0	519	519	0	255	0	0	473	0	423	233	194	0	0	392	0	0	211	372	0	0
4	8629	0	57	0	240	119	0	346	0	0	0	159	0	0	0	502	72	539	0	0	427	0	0

Table B.11: Supply – fifth type (s^C_{5it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	6554	103	0	0	189	396	0	223	202	0	222	0	336	275	0	152	0	0	0	157	0	0	0
2	5723	0	406	0	70	414	0	312	0	0	202	0	0	0	0	421	0	362	0	0	0	0	0
3	8240	0	0	0	479	0	0	0	59	123	0	58	488	505	0	108	0	408	0	480	0	0	0
4	6542	487	0	0	0	422	0	291	364	0	0	326	0	466	0	0	0	390	82	440	287	0	0

Table B.12: Available workers – first category (s^W_{1it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	21	0	0	0	1	0	0	3	0	0	0	3	0	3	0	0	3	2	0	0	3	3	0
2	57	2	0	0	4	3	0	0	3	0	0	5	0	0	5	4	0	4	0	0	4	0	0
3	30	0	1	2	2	0	2	3	3	5	0	5	0	3	5	2	3	1	4	0	0	0	0
4	59	0	5	0	0	1	0	2	0	1	2	4	4	0	4	5	0	4	0	4	1	2	0

Table B.13: Available workers – second category (s^W_{2it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	24	0	0	1	3	0	0	3	0	2	0	4	0	2	0	0	2	0	0	0	0	0	0
2	61	0	0	2	0	0	4	3	0	0	0	4	0	0	5	0	0	4	1	1	2	1	0
3	43	0	4	0	0	0	0	0	0	2	1	2	3	3	0	0	1	0	5	0	0	3	0
4	19	0	0	5	3	0	0	1	0	0	0	4	0	1	0	0	0	0	3	0	0	0	0

Table B.14: Available workers – third category (s^W_{3it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	59	0	0	0	2	0	1	0	1	0	3	0	0	3	0	0	0	0	2	4	5	4	0
2	39	0	0	0	5	4	4	5	0	1	0	0	0	1	0	3	3	5	4	1	4	0	0
3	47	5	0	4	1	0	0	0	0	1	0	0	0	0	0	1	2	2	0	0	0	0	0
4	52	0	5	3	4	0	2	0	2	0	4	3	0	5	5	0	0	0	0	0	0	1	0

Table B.15: Available workers – fourth category (s^W_{4it})

	Time 1-23																						
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	16	4	0	1	3	5	0	0	3	0	0	4	2	1	3	1	3	5	0	2	0	1	0
2	41	0	2	0	0	0	0	1	1	0	0	5	2	4	0	2	0	1	0	0	0	0	0
3	26	3	4	5	0	3	5	4	2	2	0	0	1	5	0	3	0	0	5	0	0	0	0
4	57	4	0	0	3	0	0	0	1	4	5	4	4	1	0	0	4	4	4	0	1	4	0

Table B.16: Requested workers – first category (d^W_{1it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	3	8	3	8	5	0	6	6	8	5	8	2	2	0	1	7	8	5	3	4	1	0
2	0	3	1	1	1	1	1	1	6	8	1	0	5	3	0	0	1	4	4	0	0	4	0
3	0	3	2	2	2	7	8	5	2	4	7	3	5	6	4	4	8	3	1	5	5	0	0
4	0	0	6	0	0	7	4	4	7	2	6	8	3	8	1	8	6	5	8	1	3	2	0
5	0	4	7	4	7	6	8	8	1	2	8	1	8	6	8	6	8	1	2	0	8	2	0
6	0	3	5	1	2	2	6	2	1	7	2	6	4	5	4	8	2	1	0	4	8	1	0
7	0	1	3	0	5	3	2	5	1	8	7	4	2	7	4	3	2	4	4	8	7	8	0
8	0	3	1	1	2	3	3	1	5	0	2	4	3	1	7	4	1	3	5	7	0	7	0
9	0	0	7	3	3	7	7	6	4	3	5	7	2	7	8	3	8	0	6	6	0	1	0
10	0	7	8	8	3	0	1	6	7	1	5	8	6	6	0	4	2	6	0	4	1	5	0
11	0	6	8	2	1	5	2	5	2	1	7	0	0	4	1	1	5	6	6	6	0	3	0
12	0	1	6	4	6	6	8	4	1	0	0	6	8	3	5	2	3	1	2	4	6	1	0
13	0	5	2	2	4	5	6	1	1	6	5	2	1	7	6	6	6	1	7	7	0	2	0
14	0	4	1	7	7	2	0	0	7	6	8	1	6	0	5	1	6	4	2	2	7	2	0
15	0	3	5	0	7	3	8	6	1	6	6	5	7	5	1	1	5	0	6	0	8	7	0

Table B.18: Requested workers – third category (d^W_{3it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	2	2	2	2	7	8	4	6	4	4	3	8	1	0	2	5	0	5	4	3	4	0
2	0	1	0	6	5	4	7	8	5	4	6	5	4	7	8	0	6	1	7	8	4	1	0
3	0	7	5	2	8	8	2	4	4	3	6	5	2	1	8	6	8	7	0	1	3	4	0
4	0	6	1	1	4	5	0	2	5	4	2	3	1	2	2	0	2	4	2	3	8	5	0
5	0	5	0	4	3	8	1	1	8	2	5	3	3	6	7	8	7	8	2	0	1	6	0
6	0	1	1	6	0	3	2	0	6	1	6	3	0	8	4	6	0	3	5	2	0	8	0
7	0	3	4	7	1	0	6	3	1	5	7	0	6	5	7	0	5	8	4	4	5	5	0
8	0	2	2	7	0	1	2	5	1	0	3	5	4	1	4	5	5	5	6	1	4	4	0
9	0	5	7	3	5	1	2	7	3	5	4	6	7	2	6	8	2	0	1	2	3	4	0
10	0	7	2	8	1	7	2	5	6	6	0	2	2	3	5	1	3	4	5	8	6	2	0
11	0	5	6	6	2	0	6	3	2	1	5	7	3	2	8	0	5	2	6	0	3	7	0
12	0	3	4	3	2	8	5	7	5	2	7	1	0	2	4	7	0	5	0	8	2	8	0
13	0	0	4	5	0	7	8	5	8	0	3	0	2	6	2	1	1	8	5	3	4	6	0
14	0	1	7	8	8	5	5	0	4	5	6	4	0	0	3	8	6	8	5	4	0	5	0
15	0	7	4	5	6	5	4	2	7	0	0	8	5	8	8	1	2	6	5	7	1	7	0

Table B.17: Requested workers – second category (d^W_{2it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	5	8	1	6	6	3	6	6	2	8	7	7	6	6	1	6	1	0	3	7	4	0
2	0	0	3	5	1	6	5	5	5	5	1	1	2	2	7	6	3	4	3	5	1	2	0
3	0	2	8	8	1	3	0	2	4	5	6	4	0	0	3	4	6	8	0	0	0	8	0
4	0	0	0	4	7	4	6	1	7	8	1	0	5	0	0	8	7	2	3	4	6	8	0
5	0	2	4	0	4	8	0	3	8	7	2	7	8	7	5	1	4	4	6	1	6	7	0
6	0	6	4	5	5	1	7	7	3	2	4	3	6	4	7	6	4	1	3	1	4	8	0
7	0	0	0	4	8	4	7	5	6	2	1	1	6	6	7	5	2	3	8	2	7	2	0
8	0	0	2	8	4	5	0	5	6	2	5	4	2	7	3	5	5	6	0	5	8	1	0
9	0	3	3	6	6	4	0	6	6	7	6	4	8	3	6	4	4	3	1	4	6	5	0
10	0	5	4	6	1	8	3	8	4	0	0	5	2	5	3	6	3	7	1	0	2	6	0
11	0	8	6	3	3	1	6	2	3	3	5	8	6	2	0	5	3	8	0	2	7	4	0
12	0	2	1	7	6	4	5	7	4	5	4	1	2	8	2	1	3	2	5	5	7	4	0
13	0	0	7	3	5	0	0	3	0	5	7	2	6	3	8	0	6	4	2	3	0	4	0
14	0	5	6	4	5	7	7	1	1	5	3	1	2	6	6	2	5	8	2	1	4	2	0
15	0	8	6	8	8	3	3	8	4	1	3	8	5	8	4	4	6	3	5	0	6	7	0

Table B.19: Requested workers – fourth category (d^{W}_{4it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	6	8	8	3	4	5	8	8	5	4	6	1	7	2	6	3	4	4	1	2	2	0
2	0	6	0	8	5	2	3	8	8	4	4	5	1	4	8	5	0	5	5	6	7	0	0
3	0	5	5	2	2	6	5	5	7	7	5	2	7	4	5	8	7	4	7	0	0	1	0
4	0	1	2	7	7	2	3	1	6	1	8	2	4	2	3	2	5	6	7	3	2	8	0
5	0	0	6	4	6	4	7	4	2	5	3	3	7	1	8	0	2	0	5	1	0	7	0
6	0	5	0	1	5	3	7	4	6	7	1	4	4	3	1	6	1	3	8	6	6	1	0
7	0	2	5	0	1	7	8	6	8	6	4	3	4	4	8	7	0	1	2	8	2	7	0
8	0	1	6	6	8	7	8	5	3	5	4	5	0	3	6	7	2	3	5	6	6	8	0
9	0	1	8	5	6	6	7	8	5	0	4	7	4	0	4	1	8	7	4	2	3	7	0
10	0	2	6	3	8	6	4	4	3	1	1	2	7	6	8	5	4	5	8	3	1	4	0
11	0	7	1	8	8	7	5	1	0	6	7	3	3	1	0	7	5	4	8	5	3	1	0
12	0	3	0	7	6	3	3	6	4	2	1	2	1	8	0	8	4	8	0	1	6	1	0
13	0	2	7	8	7	2	3	6	7	4	7	8	2	3	6	5	6	1	0	0	2	1	0
14	0	1	1	8	1	3	7	8	2	3	7	4	1	6	0	1	7	6	8	2	2	6	0
15	0	4	5	1	8	3	2	6	1	4	5	2	4	4	1	7	3	7	1	6	5	3	0

Table B.20: Waiting evacuees – first level (d^{E}_{1it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	1	0	1	1	0	0	4	6	6	3	4	6	6	1	5	5	1	6	4	1	3	0
2	0	6	6	6	1	4	4	5	1	5	6	2	3	5	1	3	6	3	2	3	5	4	0
3	0	2	4	4	5	2	3	5	0	4	6	4	1	3	5	3	5	1	5	4	0	0	0
4	0	5	6	0	2	3	3	2	6	1	5	6	5	2	2	6	5	0	6	0	5	3	0
5	0	1	1	6	4	5	5	2	0	6	1	5	3	1	0	4	4	1	1	4	6	0	0
6	0	0	1	2	6	4	1	3	4	6	4	5	5	3	2	1	2	3	1	6	4	0	0
7	0	0	5	5	4	0	6	5	2	5	3	3	6	3	0	3	4	4	5	1	1	3	0
8	0	5	3	4	6	3	5	1	0	2	6	0	5	4	2	3	4	5	6	2	1	0	0
9	0	0	2	0	1	5	2	0	4	2	1	2	5	3	0	6	1	6	6	1	5	4	0
10	0	6	2	6	1	6	4	0	0	3	5	0	3	3	6	1	4	6	6	6	6	6	0
11	0	2	2	6	1	2	5	5	3	3	2	3	4	1	4	1	3	2	1	4	5	6	0
12	0	0	1	6	2	5	3	6	2	2	5	4	3	5	3	5	1	1	1	3	3	2	0
13	0	0	2	4	1	5	4	1	0	2	0	1	4	4	1	0	1	0	3	1	5	0	0
14	0	2	3	2	0	3	3	0	6	0	0	6	0	5	5	4	0	6	4	3	5	5	0
15	0	5	0	6	3	1	6	6	1	3	5	3	4	0	2	0	3	0	6	1	0	3	0

Table B.21: Waiting evacuees – second level (d^{E}_{2it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	0	3	2	4	4	1	1	5	4	5	3	5	2	6	4	0	4	3	3	0	0	0
2	0	0	0	0	6	1	5	3	1	5	0	1	0	2	5	2	1	4	0	4	2	1	0
3	0	2	3	5	6	3	2	1	4	0	1	2	0	6	6	0	4	3	1	0	3	0	0
4	0	5	3	3	0	2	0	5	6	1	6	1	2	3	6	5	3	0	0	4	6	2	0
5	0	2	3	2	2	5	3	1	5	6	6	4	2	2	2	4	1	1	2	0	5	3	0
6	0	2	6	0	5	3	5	5	5	2	5	0	5	5	1	3	1	0	0	5	0	4	0
7	0	5	0	4	1	1	5	3	6	2	4	1	1	5	6	2	3	4	0	4	1	1	0
8	0	2	4	0	6	6	0	6	2	5	1	1	4	5	2	3	2	5	3	4	2	4	0
9	0	3	5	2	6	0	6	6	4	5	5	6	3	5	3	0	4	0	2	0	6	3	0
10	0	2	5	5	6	5	1	2	2	2	4	5	0	6	4	0	4	2	2	2	0	0	0
11	0	3	4	3	3	1	2	6	6	1	0	2	4	6	1	2	5	1	2	0	3	6	0
12	0	6	3	3	4	5	5	0	5	4	0	2	1	1	3	0	3	2	6	5	3	6	0
13	0	0	0	5	3	5	4	5	4	1	4	3	2	6	0	0	2	0	5	4	5	5	0
14	0	5	0	2	3	1	2	1	6	3	0	5	1	4	1	5	1	4	2	2	0	3	0
15	0	2	4	3	2	4	2	6	2	0	2	5	5	4	2	0	5	3	4	1	3	2	0

Table B.22: Waiting evacuees – third level (d^E_{3it})

	Time 1-23																						
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	0	3	5	1	1	0	4	1	0	2	4	3	6	0	5	1	0	2	3	6	5	0	0
2	0	4	0	2	2	5	5	0	5	6	0	1	5	0	0	3	4	1	3	6	5	6	0
3	0	3	3	5	2	2	5	6	1	3	4	3	4	6	6	0	2	4	5	6	2	4	0
4	0	4	2	4	0	6	3	2	3	6	1	4	1	4	0	3	3	4	4	4	1	5	0
5	0	6	0	2	0	0	6	3	6	0	1	2	2	5	0	2	2	2	3	1	4	1	0
6	0	2	1	1	3	2	5	5	0	6	4	6	4	6	4	4	4	1	3	4	2	5	0
7	0	6	5	6	6	0	1	3	0	3	4	0	3	3	4	5	1	2	5	5	4	3	0
8	0	2	2	5	6	4	6	0	6	1	4	3	0	3	3	5	2	4	3	4	6	2	0
9	0	0	2	6	5	3	6	2	1	2	3	1	4	1	5	6	1	5	5	0	2	1	0
10	0	5	3	4	2	4	6	5	1	5	0	6	0	4	2	1	2	4	0	2	5	1	0
11	0	6	0	6	5	1	3	1	6	5	2	3	0	0	5	4	4	1	3	3	0	0	0
12	0	1	4	2	3	4	5	3	6	3	3	3	3	2	6	2	5	0	2	2	3	5	0
13	0	2	1	1	4	5	2	5	6	2	5	1	5	0	4	2	5	5	0	0	1	3	0
14	0	3	2	1	6	0	1	6	0	2	2	2	3	3	4	0	5	2	6	6	0	5	0
15	0	4	6	0	4	2	6	4	2	5	6	4	0	0	1	6	6	0	6	2	0	0	0

Table B.23: Vehicle depots (i^V_v)

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
$i \in S$	1	1	1	1	2	2	2	2	3	3	4	4	4

Table B.24: Vehicle speed factors

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Speed Factor	1	2	1	2	1	1	2	2	2	2	2	2	2

Table B.25: Vehicle capacities (m^V_v)

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Capacity	900	900	1100	1400	800	1200	900	800	1200	1000	1300	800	1400

Table B.26: Satellite facility depots (i^F_f)

$f \in F$	**1**	**2**	**3**
$i \in S$	1	2	3

Table B.27: Satellite facility speed factors

$f \in F$	**1**	**2**	**3**
Speed Factor	2	4	3

Table B.28: Satellite facility capacities (m_f^F)

$f \in F$	**1**	**2**	**3**
Capacity	5000	4700	3200

Table B.29: Mass of commodities, workers, and wounded (m_c^C, m_w^W, and m_e^E)

Type	c_1	c_2	c_3	c_4	c_5	$w_1 - -w_4$	$e_1 - -e_3$
Mass (lb)	5	8	6	4	10	200	200

Table B.30: Priorities (p_{ci}^C, p_{wi}^W, and p_{ei}^E)

$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
c_1	4	2	4	10	7	5	9	5	10	9	9	4	9	2	8
c_2	10	9	9	3	2	1	10	8	10	10	8	4	7	5	7
c_3	6	9	9	2	10	5	8	10	1	7	8	1	2	8	3
c_4	9	7	3	9	2	5	1	3	2	1	2	1	6	9	6
c_5	3	6	6	3	9	5	9	6	5	9	2	2	10	4	10
w_1	650	650	850	750	700	900	550	700	500	650	800	700	750	600	700
w_2	500	800	950	750	500	900	600	900	750	800	900	850	950	950	600
w_3	500	700	850	900	500	550	900	550	900	550	800	700	750	700	800
w_4	550	800	700	500	700	700	500	800	700	800	600	750	750	650	700
e_1	950	700	950	800	700	550	500	700	700	900	750	650	600	600	850
e_2	550	650	650	850	800	850	600	900	650	900	700	850	650	550	550
e_3	500	600	850	550	550	550	600	550	750	900	550	650	550	650	850

Table B.31: Distance matrix

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0	2	1	2	2	2	2	2	2	2	1	2	1	1	2	3	3	2	3	1	1	1	1	1	1	1	1	2	2	2
2	2	0	2	1	1	2	1	2	1	2	2	1	2	1	2	3	2	3	2	1	1	2	1	1	2	1	2	2	2	1
3	1	2	0	1	1	1	2	1	2	2	2	1	2	1	2	3	3	3	3	1	1	1	2	1	1	1	2	1	2	2
4	2	1	1	0	1	1	2	2	2	1	2	1	2	2	1	2	2	3	2	2	1	1	1	2	1	1	1	1	1	1
5	2	1	1	1	0	2	1	1	2	1	1	2	1	2	2	3	2	2	2	1	2	2	1	1	1	1	1	2	2	1
6	2	2	1	1	2	0	2	1	1	1	2	1	1	1	1	3	2	2	2	2	1	2	1	1	1	1	2	1	1	1
7	2	1	2	2	1	2	0	1	1	1	2	1	2	1	1	3	3	3	3	1	2	2	2	2	1	2	1	2	1	1
8	2	2	1	2	1	1	1	0	2	1	1	2	1	1	2	3	2	3	2	2	1	2	2	1	1	1	2	1	1	2
9	2	1	2	2	2	1	1	2	0	1	1	2	2	1	2	2	3	3	2	1	1	2	2	1	1	1	2	2	1	1
10	2	2	2	1	1	1	1	1	1	0	2	1	1	2	2	3	2	3	2	1	2	2	2	2	1	2	2	1	1	2
11	1	2	2	2	1	2	2	1	1	2	0	1	1	2	1	2	2	2	2	2	1	1	1	2	2	2	1	2	1	2
12	2	1	1	1	2	1	1	2	2	1	1	0	1	1	1	3	2	2	2	2	2	1	1	1	2	2	1	1	2	2
13	1	2	2	2	1	1	2	1	2	1	1	1	0	2	2	2	2	3	2	2	1	1	2	2	2	2	1	2	1	1
14	1	1	1	2	2	1	1	1	1	2	2	1	2	0	1	3	2	3	2	2	1	2	2	1	1	1	2	2	2	2
15	2	2	2	1	2	1	1	2	2	2	1	1	2	1	0	2	2	3	2	1	2	1	2	2	2	2	1	2	2	1
16	3	3	3	2	3	3	3	3	2	3	2	3	2	3	2	0	1	1	1	2	2	2	2	1	1	1	1	2	2	2
17	3	2	3	2	2	2	3	2	3	2	2	2	2	2	2	1	0	2	1	2	2	1	1	2	1	1	1	2	2	1
18	2	3	3	3	2	2	3	3	3	3	2	2	3	3	3	1	2	0	1	1	1	2	2	1	1	2	2	2	1	2
19	3	2	3	2	2	2	3	2	2	2	2	2	2	2	2	1	1	1	0	2	2	1	1	2	1	2	2	1	2	1
20	1	1	1	2	1	2	1	2	1	1	2	2	2	2	1	2	2	1	2	0	1	2	1	2	2	2	2	2	2	2
21	1	1	1	1	2	1	2	1	1	2	1	2	1	1	2	2	2	1	2	1	0	2	1	1	2	1	1	1	2	2
22	1	2	1	1	2	2	2	2	2	2	1	1	1	2	1	2	1	2	1	2	2	0	2	2	2	1	1	1	2	2
23	1	1	2	1	1	1	2	2	2	2	1	1	2	2	2	2	1	2	1	1	1	2	0	1	1	1	2	2	1	2
24	1	1	1	2	1	1	2	1	1	2	2	1	2	1	2	1	2	1	2	2	1	2	1	0	1	2	1	1	1	2
25	1	2	1	1	1	1	1	1	1	1	2	2	2	1	2	1	1	1	1	2	2	2	1	1	0	1	2	1	2	1
26	1	1	1	1	1	1	2	1	1	2	2	2	2	1	2	1	1	2	2	2	1	1	1	2	1	0	1	1	1	1
27	1	2	2	1	1	2	1	2	2	2	1	1	1	2	1	1	1	2	2	2	1	1	2	1	2	1	0	1	1	2
28	2	2	1	1	2	1	2	1	2	1	2	1	2	2	2	2	2	2	1	2	1	1	2	1	1	1	1	0	2	1
29	2	2	2	1	2	1	1	1	1	1	1	2	1	2	2	2	2	1	2	2	2	2	1	1	2	1	1	2	0	1
30	2	1	2	1	1	1	1	2	1	2	2	2	1	2	1	2	1	2	1	2	2	2	2	2	1	1	2	1	1	0

Appendix C

Small Scale Set- HLVRPSF Model

Table C.1: Small scale – set parameters

Time Periods $\lvert T\rvert$	**Wounded Levels** $\lvert E\rvert$	**Commodities Types** $\lvert C\rvert$	**workers Categories** $\lvert W\rvert$	**Vehicles** $\lvert V\rvert$	**Satellite Facilities** $\lvert F\rvert$	**Demand Nodes** $\lvert D\rvert$	**Supply Nodes**$\lvert S\rvert$	**Hospital Nodes** $\lvert H\rvert$	**SF Locations** $\lvert L\rvert$
17	2	3	2	7	2	8	3	1	7

Table C.2: Demand – first type (d^C_{1it})

	Time 1-17																
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	0	140	240	360	200	0	100	220	120	0	0	360	200	0	120	360	0
2	0	240	200	0	160	60	240	300	360	0	140	320	120	300	60	280	0
3	0	340	0	140	340	260	0	140	0	240	0	360	180	180	0	60	0
4	0	240	260	200	100	360	220	300	140	300	300	80	180	220	240	60	0
5	0	140	200	240	0	240	300	340	280	100	180	240	280	0	240	120	0
6	0	0	120	160	0	0	0	360	60	0	160	120	360	0	200	0	0
7	0	180	0	0	240	200	340	280	220	140	0	320	160	220	240	200	0
8	0	260	240	260	0	360	240	80	300	0	340	260	0	360	0	360	0

Table C.3: Demand – second type (d^C_{2it})

	Time 1-17																
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	0	100	160	360	360	340	0	240	0	80	160	0	340	260	300	100	0
2	0	300	100	100	240	240	0	220	0	280	160	120	220	0	180	120	0
3	0	360	260	360	0	200	280	280	240	180	220	0	180	140	0	0	0
4	0	220	160	160	60	300	300	80	0	120	60	160	260	100	80	80	0
5	0	240	0	220	280	340	300	300	0	360	120	340	340	160	200	200	0
6	0	60	360	160	320	100	100	100	340	80	180	360	360	0	280	0	0
7	0	340	60	160	180	180	180	100	0	200	100	140	280	0	80	0	0
8	0	180	100	160	0	80	160	340	0	60	0	240	300	300	80	240	0

Table C.4: Demand – third type (d^C_{3it})

	Time 1-17																
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	0	60	260	220	100	180	300	180	240	260	280	280	0	140	160	0	0
2	0	120	160	160	0	340	360	140	280	0	0	320	360	340	60	200	0
3	0	160	180	260	0	300	320	0	360	360	60	240	360	140	160	300	0
4	0	160	300	0	0	180	0	340	300	0	260	300	180	0	280	340	0
5	0	320	100	160	220	0	360	360	260	200	80	340	0	120	0	0	0
6	0	180	100	360	0	180	260	80	240	240	300	0	320	360	0	280	0
7	0	60	0	0	320	280	180	300	160	260	300	100	80	120	60	80	0
8	0	340	60	80	240	180	0	0	220	60	160	340	120	320	60	100	0

Table C.5: Supply – first type (s^C_{1it})

	Time 1-17																
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	4700	372	0	0	324	63	0	0	323	223	0	0	259	143	175	0	0
2	3748	0	212	0	0	0	340	394	0	0	64	101	0	0	149	0	0
3	2738	56	0	0	127	0	260	0	0	0	0	0	225	0	344	0	0

Table C.6: Supply – second type (s^C_{2it})

	Time 1-17																
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	4399	0	230	353	393	0	368	0	289	0	101	93	92	181	336	0	0
2	3519	0	386	0	0	0	320	277	148	381	287	0	84	297	58	0	0
3	1676	323	382	354	387	142	153	0	0	341	315	0	0	0	323	0	0

Table C.7: Supply – third type (s^C_{3it})

	Time 1-17																
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	4327	0	0	345	0	157	0	0	0	0	246	0	0	196	212	0	0
2	4093	354	0	92	0	0	0	0	98	218	0	98	0	0	0	0	0
3	3377	0	0	315	0	0	325	238	93	275	0	0	206	185	182	0	0

Table C.8: Available workers – first category (s^W_{1it})

	Time 1-17																
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	13	0	0	5	5	2	2	1	0	0	5	0	1	0	0	0	0
2	13	2	0	0	2	4	3	0	2	0	0	0	3	0	4	3	0
3	11	0	0	5	2	0	0	0	0	1	0	0	0	2	2	0	0

Table C.9: Available workers – second category (s^W_{2it})

	Time 1-17																
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	25	0	0	0	0	5	4	0	2	4	1	0	0	2	4	0	0
2	9	0	0	0	5	5	3	0	1	3	2	2	5	5	3	1	0
3	22	0	1	0	0	0	0	0	2	0	3	0	0	0	3	0	0

Table C.10: Requested workers – first category (d^{W}_{1it})

	Time 1-17																
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	0	7	2	2	1	6	1	6	5	4	0	3	6	5	6	5	0
2	0	8	6	5	4	2	0	0	3	2	1	8	6	3	0	2	0
3	0	8	5	2	1	6	6	2	3	2	4	3	5	1	7	1	0
4	0	4	6	7	7	8	0	7	6	4	1	8	1	7	2	1	0
5	0	7	1	4	0	0	1	6	0	2	6	4	6	1	3	2	0
6	0	2	8	6	7	6	6	6	3	1	8	4	0	0	0	1	0
7	0	1	8	0	3	6	1	4	2	8	6	8	4	1	7	5	0
8	0	3	7	2	1	6	7	5	3	1	4	2	5	5	2	3	0

Table C.11: Requested workers – second category (d^{W}_{2it})

	Time 1-17																
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	0	4	1	0	4	4	5	3	6	7	3	3	4	5	3	3	0
2	0	8	4	1	2	3	5	0	8	8	1	4	8	4	7	1	0
3	0	7	0	0	6	2	4	2	4	8	0	5	1	2	8	4	0
4	0	3	7	8	3	0	1	8	7	7	6	6	0	5	1	7	0
5	0	5	7	5	5	2	8	8	4	1	7	2	6	8	4	5	0
6	0	3	6	3	1	0	2	2	8	0	0	3	5	8	0	6	0
7	0	4	5	2	1	1	4	7	0	6	8	8	8	5	7	2	0
8	0	8	0	8	2	8	8	2	8	5	1	6	0	6	5	7	0

Table C.12: Waiting evacuees – first level (d^{E}_{1it})

	Time 1-17																
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	0	1	3	4	5	6	6	4	5	6	2	1	1	5	3	4	0
2	0	0	1	0	5	4	1	4	2	0	0	4	4	5	4	6	0
3	0	5	3	0	2	2	6	0	4	2	6	5	3	0	3	4	0
4	0	2	1	6	2	6	1	1	1	4	1	1	1	3	6	3	0
5	0	0	3	0	0	3	0	4	3	4	6	0	2	3	0	5	0
6	0	0	0	4	6	0	2	6	1	3	3	0	5	4	4	2	0
7	0	0	2	5	5	3	2	5	0	3	3	0	4	5	1	2	0
8	0	2	6	3	6	4	3	1	3	3	5	6	3	1	1	5	0

Table C.13: Waiting evacuees – second level (d^{E}_{2it})

	Time 1-17																
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	0	3	6	1	0	5	2	2	3	0	3	4	5	0	1	6	0
2	0	3	3	6	4	2	1	5	2	4	1	0	3	5	6	2	0
3	0	3	2	1	4	2	4	4	2	1	5	6	3	3	4	4	0
4	0	1	5	0	5	0	1	6	6	3	1	0	1	4	3	0	0
5	0	4	0	0	5	2	1	3	5	3	2	3	0	5	4	3	0
6	0	1	5	6	1	1	0	0	0	6	1	1	4	0	3	1	0
7	0	5	0	6	6	4	6	0	5	4	1	0	0	0	3	5	0
8	0	3	4	1	2	4	3	0	2	1	6	4	1	2	4	4	0

Table C.14: Vehicle depots (i^{V}_{v})

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**
$i \in S$	1	1	2	3	3	3	3

Table C.15: Vehicle speed factors

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Speed Factor	2	1	2	1	1	1	2

Table C.16: Vehicle capacities (m_v^V)

$v \in V$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Capacity	800	900	1300	900	1400	1300	800						

Table C.17: Satellite facility depots (i_f^F)

$f \in F$	**1**	**2**
$i \in S$	1	2

Table C.18: Satellite facility speed factors

$f \in F$	**1**	**2**
Speed Factor	2	3

Table C.19: Satellite facility capacities (m_f^F)

$f \in F$	**1**	**2**
Capacity	4500	3200

Table C.20: Mass of commodities, workers, and wounded (m_c^C, m_w^W, and m_e^E)

Type	c_1	c_2	c_3	$w_1 - -w_2$	$e_1 - -e_2$
Mass (lb)	7	7	3	200	200

Table C.21: Priorities (p_{ci}^C, p_{wi}^W, and p_{ei}^E)

$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
c_1	9	10	9	9	9	8	9	7
c_2	2	3	6	2	7	5	10	8
c_3	7	4	10	10	8	10	6	7
w_1	900	850	650	850	750	950	500	700
w_2	550	500	700	950	850	600	900	500
e_1	750	750	650	650	550	650	600	950
e_2	900	600	900	750	550	700	650	950

Table C.22: Distance matrix

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	0	1	2	2	2	2	1	1	2	3	2	1	1	2	1	1	1	1	1
2	1	0	2	1	1	2	1	1	3	2	2	2	2	2	1	2	2	1	2
3	2	2	0	2	2	2	2	2	2	2	2	2	2	2	1	1	2	2	2
4	2	1	2	0	2	1	2	1	3	3	3	2	1	1	2	2	1	2	2
5	2	1	2	2	0	1	1	2	3	2	3	2	1	1	2	1	2	2	2
6	2	2	2	1	1	0	2	1	3	3	2	2	2	2	2	2	2	1	1
7	1	1	2	2	1	2	0	2	3	2	3	2	2	2	2	1	1	1	1
8	1	1	2	1	2	1	2	0	2	2	3	1	1	1	1	1	2	1	2
9	2	3	2	3	3	3	3	2	0	1	1	2	2	1	2	2	2	2	2
10	3	2	2	3	2	3	2	2	1	0	2	2	1	1	1	1	2	2	1
11	2	2	2	3	3	2	3	3	1	2	0	2	2	1	2	2	2	1	1
12	1	2	2	2	2	2	2	1	2	2	2	0	2	1	2	2	2	1	1
13	1	2	2	1	1	2	2	1	2	1	2	2	0	1	1	1	2	2	2
14	2	2	2	1	1	2	2	1	1	1	1	1	1	0	1	2	1	1	1
15	1	1	1	2	2	2	2	1	2	1	2	2	1	1	0	2	1	2	2
16	1	2	1	2	1	2	1	1	2	1	2	2	1	2	2	0	1	2	1
17	1	2	2	1	2	2	1	2	2	2	2	2	2	1	1	1	0	2	1
18	1	1	2	2	2	1	1	1	2	2	1	1	2	1	2	2	2	0	2
19	1	2	2	2	2	1	1	2	2	1	1	1	2	1	2	1	1	2	0

Appendix D

Tiny Scale Set- HLVRPSF Model

Table D.1: Tiny scale – set parameters

Time Periods $\lvert T \rvert$	**Wounded Levels** $\lvert E \rvert$	**Commodities Types** $\lvert C \rvert$	**workers Categories** $\lvert W \rvert$	**Vehicles** $\lvert V \rvert$	**Satellite Facilities** $\lvert F \rvert$	**Demand Nodes** $\lvert D \rvert$	**Supply Nodes**$\lvert S \rvert$	**Hospital Nodes** $\lvert H \rvert$	**SF Locations** $\lvert L \rvert$
14	1	2	2	4	1	6	1	2	3

Table D.2: Demand – first type (d_{1it}^{C})

	Time 1-14													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	0	360	0	80	240	0	260	0	100	260	200	320	160	0
2	0	0	260	80	120	300	80	240	180	260	240	180	140	0
3	0	100	280	160	300	200	240	260	0	260	320	300	280	0
4	0	220	360	220	200	300	200	300	160	0	260	260	360	0
5	0	340	0	0	240	160	100	0	240	180	280	260	260	0
6	0	0	300	180	300	320	360	0	220	100	360	260	80	0

Table D.3: Demand – second type (d_{2it}^{C})

	Time 1-14													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	0	240	60	60	60	160	0	320	360	280	0	0	0	0
2	0	100	100	300	0	60	140	300	0	0	240	80	240	0
3	0	200	140	200	200	0	160	360	220	180	340	240	80	0
4	0	0	180	160	0	160	60	320	60	0	0	120	0	0
5	0	0	320	360	360	0	120	340	160	160	220	140	140	0
6	0	240	240	80	60	180	120	0	260	280	60	0	0	0

Table D.4: Supply – first type (s_{1it}^{C})

	Time 1-14													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	6344	236	0	0	469	469	0	500	0	0	127	0	0	0

Table D.5: Supply – second type (s_{2it}^{C})

	Time 1-14													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	4178	251	495	0	528	684	729	553	0	738	0	0	0	0

Table D.6: Available workers – first category (s^W_{1it})

	Time 1-14													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	38	0	1	5	0	0	5	5	0	0	0	5	4	0

Table D.7: Available workers – second category (s^W_{2it})

	Time 1-14													
$i \in S$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	62	0	2	1	4	2	0	0	0	2	3	0	0	0

Table D.8: Requested workers – first category (d^W_{1it})

	Time 1-14													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	0	4	4	7	4	7	5	1	3	2	4	3	2	0
2	0	8	5	2	7	0	7	1	3	5	1	5	7	0
3	0	7	8	2	0	1	1	4	3	5	2	6	1	0
4	0	5	7	2	6	0	3	8	0	7	1	5	7	0
5	0	7	5	1	3	4	4	2	0	3	2	1	4	0
6	0	1	3	6	6	4	3	5	0	1	5	6	2	0

Table D.9: Requested workers – second category (d^W_{2it})

	Time 1-14													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	0	8	3	0	6	5	5	3	1	8	4	2	4	0
2	0	7	4	4	1	4	3	4	5	7	1	0	2	0
3	0	2	3	0	3	8	7	3	8	8	3	3	2	0
4	0	7	6	3	6	0	6	8	7	8	4	6	2	0
5	0	7	1	5	3	0	4	5	2	7	4	4	5	0
6	0	0	7	2	8	0	5	2	5	3	3	0	3	0

Table D.10: Waiting evacuees – first level (d^E_{1it})

	Time 1-14													
$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	0	0	0	6	3	5	4	6	6	3	5	0	3	0
2	0	6	0	2	3	6	3	1	6	3	6	0	0	0
3	0	5	2	3	0	2	1	2	2	6	1	5	3	0
4	0	3	3	2	4	1	0	1	6	6	1	0	5	0
5	0	2	6	4	5	5	2	4	1	3	0	2	5	0
6	0	6	2	0	6	1	3	2	4	4	2	2	6	0

Table D.11: Vehicle depots (i^V_v)

$v \in V$	**1**	**2**	**3**	**4**
$i \in S$	1	1	1	1

Table D.12: Vehicle speed factors

$v \in V$	**1**	**2**	**3**	**4**
Speed Factor	1	1	1	2

Table D.13: Vehicle capacities (m_v^V)

$v \in V$	**1**	**2**	**3**	**4**
Capacity	1200	1200	900	800

Table D.14: Satellite facility depots (i_f^F)

$f \in F$	**1**
$i \in S$	1

Table D.15: Satellite facility speed factors

$f \in F$	**1**
Speed Factor	2

Table D.16: Satellite facility capacities (m_f^F)

$f \in F$	**1**
Capacity	4500

Table D.17: Mass of commodities, workers, and wounded (m_c^C, m_w^W, and m_e^E)

Type	c_1	c_2	$w_1 - w_2$	e_1
Mass (lb)	8	2	200	200

Table D.18: Priorities (p_{ci}^C, p_{wi}^W, and p_{ei}^E)

$i \in D$	**1**	**2**	**3**	**4**	**5**	**6**
c_1	6	9	3	9	1	2
c_2	4	5	9	6	2	2
w_1	800	850	700	900	600	900
w_2	500	950	500	950	850	800
e_1	750	950	950	900	700	900

Table D.19: Distance matrix

Node	1	2	3	4	5	6	7	8	9	10	11	12
1	[0	1	2	1	1	1	1	2	1	1	2	3
2	1	0	1	2	1	2	2	1	2	1	1	2
3	2	1	0	2	1	2	3	1	2	2	2	3
4	1	2	2	0	2	1	2	1	3	2	2	1
5	1	1	1	2	0	1	3	2	3	2	2	1
6	1	2	2	1	1	0	2	2	2	2	1	3
7	1	2	3	2	3	2	0	3	1	2	1	1
8	2	1	1	1	2	2	3	0	2	2	1	2
9	1	2	2	3	3	2	1	2	0	1	2	2
10	1	1	2	2	2	2	2	2	1	0	2	1
11	2	1	2	2	2	1	1	1	2	2	0	1
12	3	2	3	1	1	3	1	2	2	1	1	0