CREATING AN EVACUATION PLAN DURING AN EMERGENCY BY COORDINATING VEHICLES

A Thesis

by

Hazal Bacaksız

Submitted to the
Graduate School of Sciences and Engineering
In Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in the
Department of Industrial Engineering

Özyeğin University
October 2018

CREATING AN EVACUATION PLAN DURING AN EMERGENCY BY COORDINATING VEHICLES

Approved by:

Assoc. Prof. Dr. Ali Ekici, Advisor
Department of Industrial Engineering
Özyeğin University

Dr. Dilek Günneç
Department of Industrial Engineering
Özyeğin University

Dr. Hatice Tekiner Moğulkoç
Department of Industrial Engineering
Istanbul Şehir University

Date Approved: 9 August 2018

To my family

ABSTRACT

As disaster relief operations required quick and effective service, especially evacuating victims from disaster area will be more problematic. In this paper, the problem is about evacuating the people who need service after a disaster by using best routes. The problem based on the Pickup and Delivery Problem with consideration of critical operational constraints. The problem is NP Hard and exact proposal for the solution of real life problem is not achievable. The best routes which only contain generalized Pickup and Delivery Problem is based on the established Traveling Salesman Problem(TSP) methodology. For our research, we have two types of patients and instead of create an evacuation plan with one vehicle, we developed our approach for two vehicle with two end points. The vehicles can carry all types of patient moreover, the patient locations can contain both type of patients so, some points visited twice. For minimize the total transportation time, we regulated evacuation plan as the vehicles can help each other and we proposed a change point for swap the patients to carry their own end points. So, our solution methodology is provide new routes for determine a switch point. Especially, when we consider these critical operational constraints mentioned above the TSP can be insufficient. Thus, to make this problem more practicable, we created initial routes by using Christofides' Algorithm then presented a mathematical model which applied our critical elimination process on the Hamiltonian paths that we acquired in the first phase. This implementation improved the solution of TSP. We also described two effective and fast heuristic algorithms. As a result of these heuristics, we improved the quality and efficiency of TSP solution and the best routes that contained the critical constraints.

ÖZETÇE

Afet sonrası yardım operasyonlarının hızlı ve etkili olması gerekmektedir, özellikle kurtarılması gereken kişiler yaralı olduğu durumlarda operasyonlar daha problemli olabilir. Bu araştırmada, problem afet sonrasında yardıma ihtiyacı olan bireylerin kurtarılması için en iyi rotalamanın oluşturulmasıdır. Problemin konusu Toplama ve Dağıtım Problemini göz önünde bulundurarak kritik operasyonel kısıtlar üstünde durmaktadır. Bu problem NP Hard tipi bir problem olup, kesin çözümü gerçek dünya problemi bazında yapılması çok zordur. Klasik Toplama ve Dağıtım Problemi için en iyi sonucu veren rotalar Gezen Satıcı Problemini (TSP) methodolojisi kullanılarak bulunur. Bu çalışmada iki tip felaketzede bulunmaktadr, bir araba ile kurtarma planı yapmak yerine, biz çözümümüzü iki son nokta için iki araba ile geliştirdik. Araçlar her tip kurbanı taşıyabilmektedir aynı zamanda talep noktaları iki tip talebi de barındırdığından bazı noktalara iki kez uğranmaktadır. Toplam kurtarma süresini minimize etmek için kurtarma planını araçların birbirine yardım etmesine izin verecek şekilde düzenledik ve kurbanları gidecekleri son noktaya bırakabilmesi adına bir değiştirme noktası belirledik. Böylece, çözüm metodolojimiz değiştirme noktasını belirleyerek yeni rotaları düzenler. Özellikle bahsedilen kritik operasyonlar göz önüne alındığında TSP metodolojisi tek başına yeterli olmaz. Çözümü daha pratik hale getirmek için, Christofides Algoritması kullanılarak ilk rotalar elde edilir. Kritik eleme operasyonu için ilk adımda oluşturulan Hamiltonian rotalara matematiksel model uygulanır. Bu uygulama ile birlikte TSP den elde edilen çözüm geliştirilmiş olunur. Ayrıca sonucu hem çözüm süresi bakımından hem de kalitesi açısından daha da iyileştirmek için kritik eleme kısıtlarını içeren iki tane sezgisel algoritma oluşturulmuştur.

ACKNOWLEDGEMENTS

Thanks to my advisor for his support during my master journey.

I am grateful to my mother and my father who have provided me through moral and emotional support in my life. I am also grateful to my other family members and friends who have supported me along the way.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Nowadays, humanitarian and disaster relief operations are gaining more importance because of the increasing number of disaster occurred around the world. This consequence becomes more critical when the focus is the evacuation of people who is injured or disabled after a disaster. They are the most vulnerable community in disasters or conflicts because they cannot easily access the humanitarian responses and efforts. Moreover, when the disaster occurs non-disabled people can also become disabled, in the other words the number of handicapped people in a crisis situation is increasing concomitantly. Generally, most of the studies about humanitarian logistics focuses on minimization of the inventory costs and maximization of accessible infrastructure. However, the nature of the handicapped people humanitarian logistics has different preferences than the general scope, as any wasted time they are exposed to in a crisis environment affects their security and health concerns sharply. Thus, financial costs cannot be the favored objective, the minimization of evacuation plan time has to be main objective for the evacuation scope. Furthermore, right along with the objective other situations should be addressed as constraints. Does sufferer need first aid on the emergency vehicle or not? Is victim bedfast or not? Both injured and handicapped people might need inmate treatment or not. All of these questions are help to understand situation about how to carry those people and giving descriptions about demand types.

This research focuses on the problem of assisted evacuation in a short-notice disaster. This is discrete from the self-evacuation problem where the concern is with how individuals can maximize their survival chances by leaving from the disaster area on their own capability, on foot or self-driven vehicles. Generally, an assisted evacuation plan requires such people to assemble at selected central locations to board vehicles in order to be mass-evacuated. Unfortunately, this type of plan may not be conformable to those who are unable to move themselves to the designated assembly locations. At the same time, local authorities face many constraints such as limited number and variety of evacuation vehicles, diverse mobility level of evacuees, available time, etc. Key to minimizing loss of life often relies on fast and optimal determination of vehicle assignment and routes. Thus, our motivation for this research determines an evacuation plan that consider these conditions.

In this paper, the aim is to gather all victims of the disaster on a specified assembly point which can be hospitals, refugee centers or shelters. Because of that it should be preferred more flexible models such as vehicle routing problems and its variants on the evacuation transportation management. The main goal of this research is to minimize the total traveled time of created routes which send vehicles to pick up and evacuate as many people as possible from their homes to a hospital or a common shelter, according to their conditions, within given constraints.

In this research, we will solve the non-capacitated vehicle routing problem with two end points (hospital and refugee center). If the patients injured or need first aid then send them to the hospital, else they are delivered to refugee center. For the first step, we created initial solution by Christofides algorithm for these two end points with two vehicles. These two vehicles are homogeneous and they can visit each other's patient nodes and both vehicle can carry every type of patient but at the end they must go to their end points. These nodes that visited twice in our evacuation plan are called common nodes. Because of the vehicles must visit their end point lastly, there has to be one common node for exchange the patients. Thus, determined mathematical model which based on our critical constraints which contains select a change point for swap the patients with using the initial solution for see the improvement of the objective. The selection of exchange node is critical because it can be minimizing the total transportation time. This problem aim is to find best common node will be selected for exchange. After the selection of exchange point, the model eliminate the common nodes which are visited twice except exchange point but ensure that two vehicles must visit all common nodes at once in the total schema. Also, there cannot be a common node which will be visited after the our exchange point. Our solution approach continues with other greedy heuristic algorithms with consideration of all constraints mentioned and their solutions. In the next sections, we provide a review of the related literature and state our contributions, the problem definition, and present the solution approach and the numerical computational results of the solution approach.

CHAPTER II

LITERATURE REVIEW

2.1 Disaster and Humanitarian Aid Trends

In recent years, an appreciable number of the worlds population has suffered by cause of the increasing frequency and significance of disasters. The U.S. Federal Emergency Management Agency (FEMA) determined a disaster being as an occurrence that causes 100 deaths or 100 human injuries. It could be more sensitive when the case of evacuate injured and disabled people from disaster areas. Thus, fast and effective evacuation plan required in this point of view [1]. These evacuation plan could be before the disaster or after the disaster. For instance before Hurricane Katrina destroyed New Orleans, there are injured patients and disabled people who have no ambulatory needed relief operations. Unfortunately, some of them died because of the lack of evacuation before the disaster. They tried to stand untreated for days [2]. Within the time, the budgets of the humanitarian agencies increasing significantly, the logistics of aid has attracted increasing scrutiny [3]. Moreover, recent humanitarian responses to the 2010 Haitian and 2011 Turkey earthquakes, the 2005 Hurricane Katrina in the United States, and the 2004 Indian Ocean have largely been neither effective nor efficient. Causes of these inefficiencies are many, including the sheer size and scope of such disasters, but with rising scrutiny, reports of how public officials are ill-prepared and fail to mitigate the resulting damage and loss of lives has become plentiful [4].

2.2 Humanitarian Logistics as a Supply Chain

Nowadays, the field of humanitarian logistics has more and more become a topic of interest to academics. Because, the scope of humanitarian logistics has form a large integral part that contain disaster response and humanitarian relief [5]. The operational relief actions based on mostly transportation so that the academics progressively interests transportation solutions and systems [6]. Although supply chains for humanitarian logistics are debatable among the most dynamic and complex supply chains in the world [7], proper logistics preparation before a disaster strikes could better coordinate processes, technologies, and communications capabilities. This would improve the effectiveness and efficiency of the supply chains, and thus that of authorities response.

Our research says that the vehicles will departure from same depot, visit all patients who needs assistance then arrive to two different end points which are refugee center and hospital. The vehicles can carry both type of patient in the condition of change at an uncertain common node. But, [1] focuses on the evacuation of injured people with general capacitated vehicle routing systems. It is not assumed that a vehicle has to pick up all of them simultaneously. Also, [8] further integrated time solving a dynamic, time-dependent transportation problem during ongoing aid delivery. More recently, [9] examined the problem of coordinating transportation of commodities from major supply centers to distribution centers in affected areas and the transport of wounded people from affected areas to temporary and permanent emergency unit and extended the earlier model as a mixed integer, multi-commodity network flow problem treating vehicles as integer commodity flows in the first stage and providing schedules using a vehicle splitting algorithm. The objective was to minimize delay in supplying critical commodities and health services. [10] presented a heuristic iterative algorithm Capacity Constrained Route Planner (CCRP) that finds the minimum time horizon that ensures 100% evacuation. However, resulting evacuation paths are not necessarily useful in practice because the evacuation paths from CCRP allow intersection nodes to hold flow for some periods of time, which is not possible in practice [11].

2.3 Evacuation Modeling

In the area of evacuation planning, literature research has focused on evacuation departure scheduling and traffic assignment [12], flow optimization, and classic ambulance routing [13]. Formulations of evacuation planning problems range from network flow models [14], cell-transmission-models [15], traffic assignment models [14], multi objective path selection models [16], and transshipment models [17]. Optimization-based solution algorithms include those based on Capacity Constrained Route Planning [10], contraflow network reconfiguration[18]. More realistic but complicating scenarios in the form of multiple commodities, customer priorities, and time-dynamic networks are occasionally considered. Moreover, [19] presented a large-scale multi-commodity, multi-modal network flow problem with time windows to transport a range of critical supplies using a vehicle fleet from depots to affected areas, while developed a mathematical model to efficiently plan crew/fleet configuration and flight routes for disaster relief helicopter missions [20].

Actually, the evacuation process does not end when they transferred to shelter or hospital. After the evacuation, they could need first aid or special treatment according to the damage. This essentials the disabled and injured people and their families to plan for their evacuation [21]. Although FEMA advises that during emergency situations disabled people form a self-help network which contains friends, family and neighbors to help them, injured and disabled people often do not like to be determined for fear of evolving vulnerable to crime or and also unwilling to leave their homes [22]. Thus, the importance of evacuation operations by the authorities, especially for the injured and disabled people, becomes progressively conspicuous.

2.4 Related Solution Approaches

The routes of visits to patients have been considered under different variations of the Vehicle Routing Problem (VRP) [1]. The variations of the VRP applied to the Pick up and Delivery Problem have been studied independently are the Multi Traveling Salesman Problem with Time Windows (MTSPTW), the Vehicle Routing Problem with Multi-Depot (VRPMD) and the Vehicle Routing Problem with Multi-Period (VRPMP), which intend to characterize multiple staff and multiple points in which the staff start and end each route respectively [23]. As in our research, created two routes that were executed by Travelling Salesman Problem structure. With using these two TSP routes, we will determine the efficiency and improvement our solution approach.

In [24], the scope is synchronized routing problem for humanitarian logistics operations for delivering medication and supervisors. The vehicles pick up and deliver with synchronized routing plan. The difference from our problem is that, there is no such a node for exchange the patients who are different type from each other. In [25], there is an arc routing problem which aims to make the connectivity of the road components by clearing a debris. In this problem, the solution approaches are mixed integer problem and Lagrangian relaxation with considering synchronize the vehicles. The difference is that the problem is not dependent in terms of nodes, so there is no common nodes or demand types for each vehicles. The similarity is in the solution approach which is synchronize the vehicles according the best arc routing plan.

The VRP with Simultaneous Pick-up and Delivery (VRPSPD) represents the case when no precedence constraints are imposed on the order in which the pickup and delivery must be performed [26]. Customers require not only the delivery of goods but also the simultaneous pick up of goods from them. A general assumption is that all delivered goods originate from the depot and all pickup goods must be transported back to the depot. Difference of our problem is the patients must be arrived to the their end points. The vehicles pickup and delivery patients at the uncertain patient node. Moreover, [27] first introduced this variant to solve a distribution problem of a public literature, with the objective of minimizing the total travel distance/ time of the route by considering the vehicle capacity as the problem constraint.

The VRP with mixed Pickup and Delivery (VRPMDP) represents the case where line-hauls and back-hauls can occur in any sequence on a vehicle route [28]. The VRP-MDP can be considered the special case of the VRPSDP where either the delivery demand or the pick-up demand of each customer equals zero. Even though the VRP-MDP is closely related to the VRPSDP, none of the solution approaches towards the VRPMDP can be applied directly for the strict VRPSDP, although some basic ideas can be transferred [29]. VRPSPD is a generalization of the VRPMPD [30]. Thus, mixed and simultaneous VRPPD problems can generally be modeled using the same framework. Mixed problems can be thought of as simultaneous cases with either the pickup or the delivery load being zero; while the customers of simultaneous problems can be divided into pickup and delivery entities to give a mixed formulation [31].

Essentially, application of humanitarian logistics solutions based on creating best routes for to minimize the transportation time. Since the VRP looks for the description of an optimal set of routes to be accomplished by a fleet of vehicles, located in a depot(s), to fulfill the requirements of a given set of geographically-dispersed customers, subject to operational constraints. The objective is typically to minimize the total transportation cost or distance traveled [32]. When the creating the vehicles' routes, the distance matrix is accepted the triangle inequality. Simultaneously, different types of relief are allowed participation to be carrying with same vehicle. Some of these academic researches are about create best possible routes for carrying of disabled and elderly people from their homes to shelters. There can be different types of users and routes that created cannot exceed the maximum duration of journey [33]. Also, [34] was presented a cluster-first-route-second heuristic where clusters are combined by solving an auxiliary assignment problem, using information provided by a proposed Lagrangian relaxation. The initial routes are built through a modified TSP heuristic. The final set of routes is then obtained through exchanging the intra-route, inter-route and outer-route arcs to improve the solution quality. Differentiation of this paper, there are different type users who can be carried with homogeneous vehicles but they have to transfered their end points. Thus, we describe one uncertain change node which is also user node, it will help to decrease of total transportation time. Because of the complexity of VRP, heuristic algorithms can be more practicable for this problem [35]. For the phase of creation the initial routes, the algorithm by Christofides could be useful. Since the best known approximation algorithm for the single TSP is create Hamiltonian paths with using Christofides' Algorithm. The algorithm developed a 5/3-approximation algorithm for a single depot, single terminal Hamiltonian path problem (SDSTHPP), but for our problem has two end points one depot so creation of two Hamiltonian path will be effective [36].

This research seeks to develop efficient models that contains a critical operation that can be used efficiently in post disaster situations and solve the developed model using heuristics. These operations include vehicle delivery and wounded patients and regular patients evacuation.

CHAPTER III

PROBLEM DEFINITION

When a disaster occurs at an uncertain time, one of the main problem is that reach incident locations where roads are still traversable for evacuate as many disabled and non-disabled people as possible. Therefore, the goal is to create the best routing plan that sends vehicles to pick up and evacuate people from their homes within the shortest time. If these people injured or need first aid then send them to the hospital, else they are delivered to refugee center. Thus, the routing plan has to contain two different routes for two different vehicles. One of the vehicle's route is end with hospital, the other one is end with refugee center. In our problem, these two vehicles can visit each other's patient nodes. Even though they do not have to visit the same location, helping each other might be better for the overall objective. Since, our problem focuses on evacuate people in the minimum time limit, this condition will save the time. In real world case, vehicles can be heterogeneous, but in this problem vehicles are accepted homogeneous. Both vehicle can carry every type of patient but at the end they must go to their end points. Because of that, there has to be one common node for exchange the patients. The patient who is injured cannot go to the shelter so, the exchange node is important for swap the patients. The selection of exchange node is critical because it can be minimizing the total transportation time. This problem aim is to find best common node will be selected for exchange.

Demand nodes are known and there are two types of demand, one of type is injured people, other one is uninjured people. There is no prioritisation of people during evacuation. These nodes can include both type of demands at the same time. Also, vehicles can be pick up all type of demand, but they have to exchange them

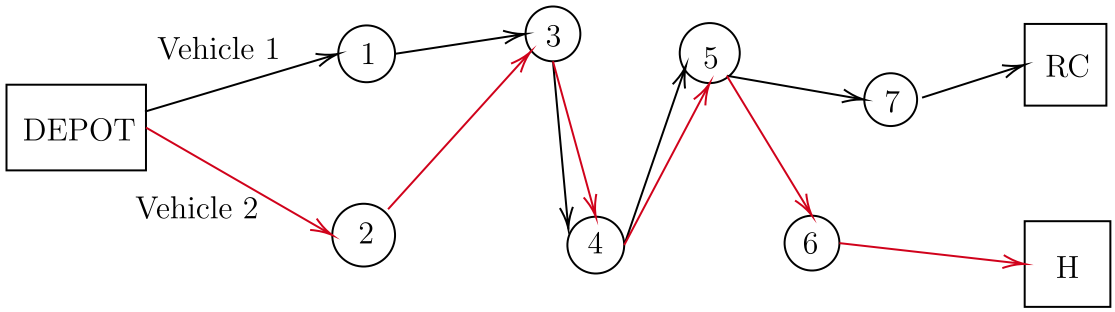

Figure 1: Small scaled example.

who do not belong the vehicle's route in an uncertain demand location. It is also assumed that a vehicle has to pick up everyone at the same location simultaneously. Since all vehicles are identical, their travel times between the demand locations are assumed known and same as well. The evacuation planning horizon must take place within one-time window constrained by total available time.

As shown in Figure 1, there are two vehicles, one depot node, two sink nodes which are refugee center(RC) and hospital(H). The vehicle which carry injured people has to end with hospital, and the other vehicle has to end with refugee center. Nodes which have injured patients are 2, 3, 4, 5 and 6. Nodes that have non-injured people 1, 3, 4, 5 and 7. As seen in the instance, nodes that 3, 4, 5 include both type of patient, so these nodes have visited two times and we called them common nodes. Firstly, we created initial routes which are two Hamiltonian paths. These routes contain the common nodes which are visited twice by the vehicles. Since the aim is to minimize the total travel time, our solution approaches will be determine a change point for swap the patients and ensure that there are common nodes which will be visited one time except that change point. If the vehicle's end point is hospital, it must be drop off non-injured patients in the exchange point. Then, pick up injured patients from that point. The process is the same for the vehicle which will be end at the refugee center. After determine the exchange point for our patients, we modify our two routes with eliminate the common nodes except exchange point but ensure that two vehicles must visit all common nodes at once in the total schema. Also, there cannot be a common node which will be visited after the our exchange point. The detailed explanation about determine the exchange point is in the Solution Approach section.

CHAPTER IV

SOLUTION APPROACH

In this research, because of the complexity of the problem we used Christofides Algorithm and created two different routes for two different end points. These created routes are the initial solution for our solution approach. As we know, vehicles have to visit all locations which can contain different type of patient. So, in the initial solution, there will be nodes that visited by both vehicles which are called common nodes. Since, the goal is to minimize the total time, we have to eliminate some common nodes, except one of the common node. Because, that uncertain common node will be the exchange node for the vehicles. The elimination is important because, this will avoid the unnecessary visits and minimize the total transportation cost of routes. Thus, we determined the mathematical model that will do elimination of these nodes from routes and make the certain the exchange point also tries to find the best routes for these vehicles. Moreover, we derive feasible solutions with using two greedy heuristic algorithms.

4.1 Christofides' Algorithm

Initial solutions are obtained with using Christofides' Algorithm. With Christofides' heuristic we derived two Hamiltonian paths for determine the initial routes. For the dedication of a Hamiltonian path, Christofides' heuristic has to be adapted to assure that the union of the tree T and the matching M contains exactly two vertices of odd degree. Furthermore, any prespecified endpoint has to be among those odd-degree vertices. The presentation of the modification of Christofides' heuristic is following:

1. Devise a minimum spanning tree T of the graph G.

2. First, define the set S of vertices that are of wrong degree in T, i.e., the aggregation of fixed endpoints of even degree and other vertices of odd degree. Next, build a minimum matching M on S that leaves 2- k vertices exposed, where k is the number of fixed endpoints. Note that such a matching can be found by building a minimum perfect matching on S augmented with 2 - k dummy vertices.

3. Consider the graph that is the union of T and M. This graph is connected and has either two or zero odd-degree vertices.

4. Find an Eulerian path in the resulting graph. This path traverses each edge exactly once and has the two odd-degree vertices as its endpoints.

5. Transform the Eulerian path into a Hamiltonian path by applying shortcuts. This path will be denoted by depending on the number of prespecified endpoints [36].

4.2 Mathematical Model to Determine the Exchange Point

4.2.1 The Exchange Point

To determine the our change point we developed a mathematical model that will choose best possible common node for the exchange and avoid visits twice to other common nodes but ensure that two vehicles must be visited all common nodes at once in the total schema. The exchange point helps to swap the patients between vehicles. Therefore, the vehicles can carry injured and non-injured patients until that point. For instance, the vehicle's end point is refugee center, this vehicle collect all patients from its nodes when it will arrive the exchange point it must be drop off injured patients and pick up non-injured patients from that point. Because of the collecting all patients until that change point, other vehicle which will be end up at hospital node does not have to visit common nodes that refugee center's vehicle is already visited. So, the elimination of these common nodes will be helps to avoid unnecessary visits to that nodes. With determine the best exchange point and routing plan that contains elimination of unnecessary visits will be decrease the total time of both routes.

4.2.2 Mathematical Model

The model starts with two initial routes which are coming from Christofides' Algorithm. Then, the model is updating our both routes according to our constraints. There are some critical terms for using this model. One of them is common node terminology which is explained there are nodes that visited for both routes in our model. K will be represent the set of common nodes. Other one is feasible patients points which will be chosen from set of K. There is a rule for select feasible patient points. The rule says that the feasible patient point cannot be coming before the all other common nodes for both routes. For instance, the point which is in set of K is positioned first order in terms of common nodes' order in the first route and also for the second route, that point cannot be a feasible point for our solution.

Sets

R : Set of routes, $R = \{1, 2\}$.

P_r : Set of patient positions in route r, $P_r = \{1, 2, .., n_r\}$.

K : Set of patients that are visited in both routes.

F : Set of feasible patients that are visited in both routes.

H_f : Set of patients that visited after feasible customer f.

Parameters

c_{ij} : Distance or time it takes for any vehicle to traverse arc (i, j) $\forall$ i,j $\in$ V , $i \neq j$.

$V_r(k)$: Visiting order of patient k in route r. $\forall k \in K$

$l_r(p)$: Index of patient visited at the p^{th} position of route r.

M : Big number.

Decision variables

Y_r: Total distance of route $r \quad \forall r \in R$

$$X_p^r = \begin{cases} 1, & \text{If the vehicle which is in route } r \text{ visited the patient at } p^{th} \text{ position of route } r. \\ 0, & \text{otherwise.} \end{cases}$$

In decision variable $X_p^r \; \forall \; p \in \{p : p = V_r(k)$ for some $k \in$ K $\}$

T_p^r: Distance traveled until position p on route $r \; \forall p \in P_r$

$$Z_f = \begin{cases} 1, & \text{If the common patient } f \text{ visited for both route } \forall f \in F \;. \\ 0, & \text{otherwise.} \end{cases}$$

The decision variable X_p^r is binary variable, if the value equals to 1 the vehicle which belongs to route r visited common node at position p in the route r.

Mathematical Formulation

$$Min \sum_{r \in R} Y_r \tag{1}$$

Subject to

$$Y_r \geq T_{n_r}^r \qquad \forall r \in R \tag{2}$$

$$T_p^r \geq T_q^r + c_{l_r(q),l_r(p)} X_p^r - \mathcal{M}(1 - X_q^r) \qquad \forall \quad q,p \in P_r \quad ,r \in R, q < p \tag{3}$$

$$\sum_{k \in K} \sum_{r \in R} X_{V_r(k)}^r = |K| + 1 \tag{4}$$

$$\sum_{r \in R} X_{V_r(k)}^r \geq 1 \qquad \forall k \in K \tag{5}$$

$$X_p^r = 1 \qquad \forall p \in \{p : p \neq V_r(k) \quad for \quad some \quad k \in K\} \tag{6}$$

$$X_{V_r(f)}^r \geq Z_f \qquad \forall f \in F, \quad r \in R \tag{7}$$

$$X_{V_r(h)}^r \leq 1 - Z_f \qquad \forall h \in H_f, \quad r \in R, f \in F \tag{8}$$

$$\sum_{f \in F} Z_f = 1 \tag{9}$$

$$X_p^r \in \{0,1\}, \quad Z_f \in \{0,1\}, \quad T_p^r \geq 0, \quad Y_r \geq 0, \quad \forall \quad p \in P_r{}' \quad r \in R \quad f \in F \tag{10}$$

In the objective function (1), the goal is to minimize the total time of routes. First constraint (2) ensures that the covered distance until end point must be less than equal to total distance of route r. In the second constraint (3), covered distance until position p must be greater than equal to covered distance until position q, plus distance between that positions.The constraint (4), ensures that vehicles must visit number of common nodes plus 1 nodes in set of some nodes for both routes. The constraint (5) ensures the vehicle must visit all common nodes for both routes. In the constraint (6), vehicles must visit all demand nodes once except common ones. The constraint (7) says that if the model choose to visit that feasible node then the vehicle must visit that node. The constraint (8) ensures if that feasible node chosen to visit then the vehicle cannot visit the nodes that after chosen node. And, the constraint (9) says that there can be just one feasible node. And, last constraint (10) are about sign restrictions.

In Figure 2, there is a small example for our problem with implementation of mathematical model approach. The first vehicle has to start with depot node and has to cover 1, 3, 5, 6 and refugee center, second vehicle starts with depot node and has to cover 2, 3, 4, 5, 6 and hospital. The initial solution which contains two routes created by Christofides' Algorithm is shown in the figure. First route has depot, 1, 3, 6, 5 and refugee center, second route has depot, 2, 4, 3, 6, 5 and hospital. Our aim is minimize the total transportation cost so, the elimination will be reduce our total cost. In this instance, number of common node is 3. The elimination process which will be for these common nodes contains choose best exchange node and eliminate other common nodes for the minimize total transportation cost. Thus, after the elimination with mathematical model the updated first route will be depot-1-3-6-5-Refugee Center and second route will be depot-2-4-3-5-Hospital. As solution shows in Figure 3, common node 3 eliminated from route 1 and common node 6 eliminated from route 2. The exchange point is common node 5 which is chosen from mathematical model, there is no possible solution that can give better than this elimination. Because the mathematical model minimize the total transportation cost for both vehicles.

4.3 Implementation of Some Greedy Heuristics

The mathematical model is particularly challenging because it requires the determination of vehicle routes and eliminate common nodes except one uncertain node which

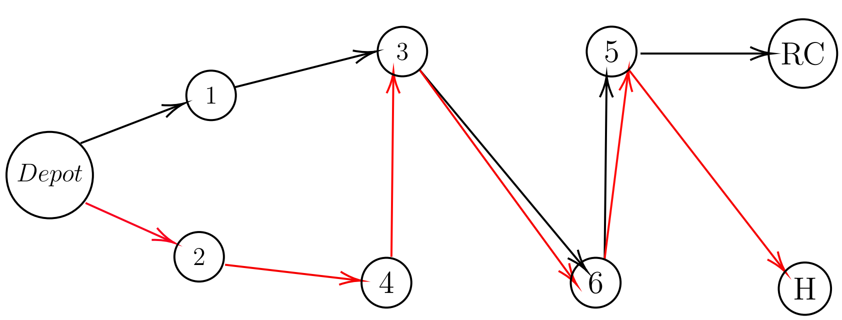

Figure 2: The initial solution for two vehicles.

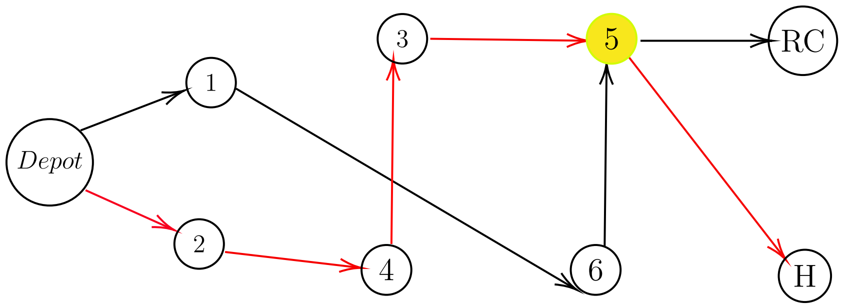

Figure 3: Two routes after the elimination.

is also change node for vehicles. Small scale problems may be solved optimally with CPLEX in the given solution time, but for the large scaled problems the computation time exceed the given solution time. So, the heuristic methods can be more helpful for improve the time constraint. Moreover, these algorithms assist to compare the solutions with TSP Solver's and mathematical model.

4.3.1 Heuristic 1

As shown in Table 1, the algorithm begins with Christofides' Algorithm which is generated initial solution. Then, the algorithm determines the common nodes and select randomly one of them. And remove all other common nodes from both routes. So, the initial solution is updated, both routes only contain one common node which is called selected node the other points will have different demand type from each other. Afterwards, the removed common nodes will be added in the initial solution which is positioned before the selected common node. The issue of positioning is critical, because the selected node will be our change node for vehicles. Thus, there cannot be any common node after the selected node, last visiting common node for both routes will be selected common node. Moreover, the position of appendage nodes will be arranged according to minimum value of distance. This process will continue until there is $K+1$ common nodes for two routes. Because of the triangle inequality, the elimination of these common nodes certainly will improve our initial solution. The heuristic algorithm can be easily implemented to large scaled problems and gives the

Table 1: Heuristic 1

Procedure H1(depot,nodes,end points,distances)
1.Get two routes that contain nodes,depot and end points using by Christofides' Algorithm, called initial solution. 2. Select one common node from initial solution, called X^r_{chosen} 3. Modify the initial solution by removing all common nodes except chosen node from both route 4. Repeat 5. - Add one common node which is called X^r_i to best possible point(min distance) into route r 6. - If $X^r_{chosen} < X^r_i$ in terms of position for route r then 7. - Try other best possible point for X^r_i into routes until find the $X^r_{chosen} < X^r_i$ in terms of position for route r 8. - Else, continue steps 9. - Until there are K+1 common nodes in both routes (K: number of common nodes in one route) 10. Record initial solution to best feasible solution 11. Continue until find the routes that have minimum distance 12. Return best feasible solution 13. End H1

feasible solutions for comparison. Additionally, the computation time will be decrease compared to mathematical model.

In Figure 4, there are two routes that covered all demand points. Vehicle 1 visits Depot-1-2-3-6-5-Refugee center and vehicle 2 visits Depot-2-4-3-5-Hospital. The common nodes are 2, 3 and 5, for starting the procedure we choose randomly one common node which is node 2. This node will be our chosen node for exchange , then all common nodes will be destroyed from both routes. After that the insertion

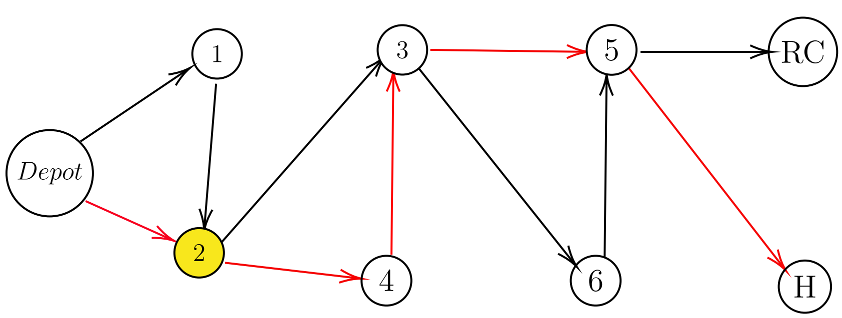

Figure 4: Small scaled example for Heuristic 1.

Table 2: Heuristic 2

Procedure H2(depot,nodes,end points,distances)
1. Get two routes that contain nodes,depot and end points using by Christofides Algorithm, called initial solution
2. Select one common node from initial solution, called X^r_{chosen}
3. Repeat
4. - Choose one common node (except X^r_{chosen}) which is called X^r_i to best possible point (min distance) into routes
5. - If $X^r_{chosen} < X^r_i$ in terms of position then
6. - Remove X^r_i from that route r
7. - Add best possible point that before the X^r_{chosen} (min distance)
8. - Record the initial solution to the best feasible solution
9. - Else, record initial solution to best feasible solution
10. - Remove common nodes except X^r_{chosen} that caused of long distance
11. - Until there are K+1 common nodes in both routes (K: number of common nodes in one route)
12. Until find the routes that have minimum distance
13. Return best feasible solution
14. End H2

procedure will be start by adding nodes which are removed from routes. For minimize the total transportation time, the common node which will be adding the route has to be positioned to best point for reduce the cost and its position has to be before the chosen node's position in that route. For this instance, after the implementation of the heuristic the vehicle 1 visits Depot-1-3-2-6-Refugee center and the route 2 visits Depot-5-2-4-Hospital. Since, there is 3 common nodes for this example, the procedure continue until there are 4 common nodes in the total for the both route. Thus, there will be two elimination for this instance. For our problem, we will be work with at least 3 common node. So, this small example just shows the implementation of procedure.

4.3.2 Heuristic 2

The Heuristic 2 procedure as presented in the Table 2 begins with Christofides Algorithm which is generated initial solution. Then, the algorithm determines the common

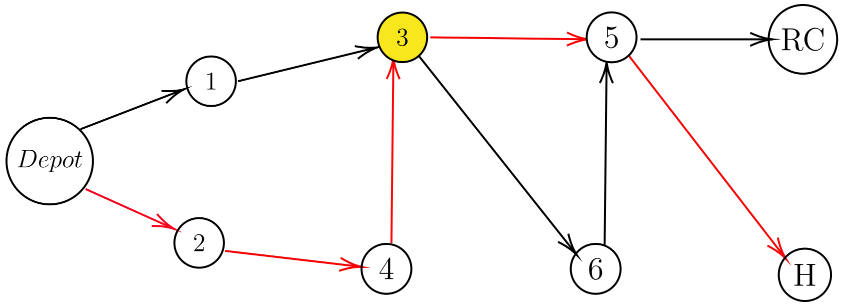

Figure 5: Small scaled example for Heuristic 2.

nodes and select randomly one of them. And remove all other common nodes which has the position after the selected node from both routes. Afterwards, the removed common nodes will be add in the initial solution with positioning before the selected common node. The added nodes position will be arranged according to value of minimum distance. This process will continue until there are $K+1$ common nodes for both routes.

In Figure 5, Vehicle 1 visits Depot-1-3-6-5-Refugee center and vehicle 2 visits Depot-2-4-3-5-Hospital. The common node 3 is chosen randomly for start the procedure, the common nodes which is coming after the node 3 will be destroyed from both routes. Then, the insertion procedure will be start by adding nodes which are removed from routes. For the minimize the total transportation time, the common node which will be adding the route is finding best position for reduce the cost. After the implementation of the heuristic, the vehicle 1 visits Depot-5-1-3-6-Refugee center and the route 2 visits Depot-2-4-3-Hospital. Since, there is 2 common nodes for this example, the procedure continue until there are 3 common nodes in the total for the both route. Thus, there will be one elimination from one route at this example and it is common node 5.

The difference between these two heuristic algorithms is the Heuristic 1 removes all common nodes from the route plan except chosen exchange point, on the other hand, the Heuristic 2 only removes common nodes which are positioning after the chosen exchange point. Thus, in some scenarios Heuristic 2 can be stay same structure if there is no common nodes after the chosen exchange point except elimination of common nodes to avoid the common nodes that visited two times.

CHAPTER V

COMPUTATIONAL RESULTS

For this research, a solution instance contains; one depot node which the vehicles are departed, demand nodes which include patients, two end points which are refugee center and hospital. The demand nodes are not identical, they contain two types of demand, these are injured patients, non-injured patients or they can include both of them. In this problem, there is no vehicle capacity, so the structure of problem doesn't have any demand amount. Thus, the demand values are represented as binary variables. And, they are known generated randomly with code. The distances between nodes are given and also generated discrete uniform distribution between [0, 1000] and the available vehicle number is two.

Small and medium problem instances are solved with CPLEX solver in JAVA using an Intel Core 6500U CPU, 2.50 GHz computer with 8.0 GB RAM. There is a standard problem which is Travelling Salesman Problem (TSP) to compare the solutions of heuristic methods with its solutions. So eighty randomly generated examples were considered in order to indicate the efficiency of heuristic method among the current method, by comparing the solutions of MATLAB with TSP Solver's.
The solution of the Christofides Algorithm determines the initial solution which creates routes needed to meet the demand of visits that patients require for two vehicles. Each route is carried out by a member of the medical staff who begins at depot and ends at hospital or refugee center. Then mathematical model eliminates nodes which are common for these two routes except one uncertain exchange node. The model determines the best route plan for these two vehicles. Additionally, there are 2 heuristic algorithms for see the improvement comparison with TSP Solver's solution. Table 3

Table 3: Comparison of Algorithms' solutions with TSP Solver's

INSTANCES	Math. Model Elimination	Elim. with H. 1	Elim. with H. 2
Number of Nodes	Improv.(%)	Improv.(%)	Improv.(%)
10	14.23	7.61	12.19
20	11.01	4.49	2.07
30	8.08	3.67	5.84
40	15.74	8.55	13.29
50	20.52	12.26	17.53
100	29.40	24.22	25.79
200	31.12	28.00	27.68
300	31.28	28.12	29.87

shows that the average values of improvement of mathematical model and heuristics for each instances. The average improvement values which are percentage values determine the difference between TSP Solver's solutions with elimination mathematical model and heuristics. The improvement values can be calculated as;

$$\text{Improvement} = \frac{(\text{ TSP Solver Value - Elimination Objection Function Value})}{\text{TSP Solver Value}} \text{ x } 100$$

As shown in Table 3, the improvement values of the elimination with mathematical model gives the best value according to other solution approaches. The improvement values for the small scaled instances (10 and 20 nodes) are up to 14.2 % , 20.5 % for the medium scaled instances (30, 40 and 50 nodes) and 31.2 % for the large scaled instances (100, 200 and 300 nodes) . All of these average improvement values show that the mathematical model can reduce the objection function value efficiently. Most of the cases, small scaled instances' improvement values show that Heuristic 2 works better than Heuristic 1. When the number of nodes are increasing, the gap between of the heuristics' improvement values are decreasing.

Table 4 and 5 show the values of improvements and computational time values for all instances. The computational time is in terms of seconds. It is clear that the computational time values are better for heuristic algorithms compared with mathematical model. In the Table 4, there are values of comparison for small and medium scaled instances. The elimination with mathematical model improvement values are better than heuristic approaches solutions for that instance set. However, the computational time values for mathematical model are higher than TSP Solver solution and both heuristic algorithms. Thus, even in case of small scaled instances the computational time of mathematical model is the worst. As shown in Table 4, in some of the solution instances the improvement values of Heuristic 2 and mathematical model are the equal, because of the implementation of Heuristic 2 the modified routes of evacuation can be similar to mathematical model solution. As seen in Table 5, when the number of nodes are 100 and number of common nodes are over the 60 the mathematical model will be exceed the time horizon. Thus, we only get the feasible solution for our instance. So, the heuristic algorithms will be work better with large scaled instances. But, the improvement percentages show that the mathematical model gives best values for our problem. Because, it will optimize the elimination of common nodes from both routes except one common node which is our aim change point to minimize the distance with elimination. To sum up, in case of consider the improvement of objection function the mathematical model improvement values are the best, but the case is computational time heuristic algorithms work better than mathematical model.

Table 4: Comparison values of Small-Medium scaled Instances

INSTANCES	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
10 nodes	1.4	3.2	16.02	2.1	1.89	2.7	10.75
	1.1	3.1	15.65	2.2	3.16	2.1	15.65
	1.3	2.7	2.20	2.4	0.06	2	-0.64
	1.1	2.2	33.46	1.6	25.71	2.1	29.27
	1	2.4	14.40	1.4	9.93	2.2	14.40
	1.1	2.2	11.92	1.5	5.59	2	8.80
	1.4	2	18.99	1.8	13.06	2.1	14.76
	1.5	3.2	15.52	1.6	8.88	2	15.52
	1.1	3	7.99	1.4	4.18	2.4	7.24
	1	3.4	6.15	2.1	3.66	2.7	6.15
Average	1.2	2.74	14.23	1.81	7.61	2.23	12.19
	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
20 nodes	1.3	9.4	14.26	2.1	7.31	2.4	10.88
	1	10.5	12.26	2.5	14.11	2.5	5.30
	1.2	11.8	5.38	2.8	2.69	2.7	2.83
	1	5.1	1.21	3.1	1.06	2.5	1.21
	1.2	9.4	10.97	3	0.56	2.6	10.97
	1.1	10.6	11.69	2.4	2.85	2.7	9.80
	1	15.5	5.71	2.2	1.53	3	5.07
	1.4	13.7	12.42	3.4	2.83	2.4	12.42
	1.2	21.6	10.80	3	2.09	2	10.63
	1	12.6	25.42	3.2	9.86	2.6	23.07
Average	1.14	12.02	11.01	2.77	4.49	2.54	9.22
	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
30 nodes	1.5	4.1	6.29	4	0.83	4.2	6.29
	1.2	100.7	13.98	3.3	8.17	3.5	8.17
	1.4	103.5	4.09	3.8	-9.05	2.8	-9.80
	1.6	128.2	14.05	4.1	7.62	3	14.05
	1.7	95.2	1.39	4	0.64	3.2	1.39
	1.8	100.5	2.45	3.4	0.58	4	2.37
	1.5	135	6.07	3.2	5.04	3.1	5.74
	1.4	121.1	8.24	3	5.87	4	8.08
	1.8	98.3	6.53	4.2	4.21	4.3	6.24
	1.7	104.2	17.67	3.3	12.84	3.2	15.89
Average	1.56	99.08	8.08	3.63	3.67	3.53	5.84
	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
40 nodes	2.8	310	21.00	9	10.76	12	12.95
	2.9	210.1	19.76	8.4	19.76	14	13.22
	2.4	308.7	22.24	8	10.83	12	22.24
	3	411.2	6.36	8.2	4.19	9.4	5.82
	2.5	310.5	6.86	7.9	1.05	13.5	6.86
	2.7	323.9	9.61	9.1	5.15	11.4	8.70
	3	310	25.24	7.4	13.13	12.5	22.29
	2.7	415.4	24.32	12	10.08	13	18.99
	2.5	316.4	3.62	11.7	2.31	10.1	3.41
	2.9	218.1	18.45	13.4	8.19	15	18.45
Average	2.74	313.43	15.74	9.51	8.55	12.29	13.29

Table 5: Comparison values of Medium-Large scaled Instances

INSTANCES	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
50 nodes	4.1	598.2	25.00	8	16.12	10	19.21
	5.2	601.4	16.37	8.5	9.96	12	11.27
	4.7	1065.1	20.94	12.1	11.46	14.1	14.65
	5.3	987.4	16.46	10.2	8.24	8.7	13.22
	4.8	902.5	8.37	11.9	6.05	9.1	8.37
	4.3	567.4	9.41	9.5	7.19	9.4	7.98
	5.6	1209.8	25.14	17.4	15.84	14.4	25.14
	5.1	1356.4	32.32	14.2	17.01	16.1	28.99
	4.9	1298.7	28.04	16.7	16.53	15.1	25.10
	4.6	1226.2	23.15	15.4	14.19	16.2	21.32
Average	4.86	981.31	20.52	12.39	12.26	12.51	17.53
	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
100 nodes	10.1	5674.1	22.90	22	20.55	25.1	19.99
	15.2	6101.4	26.12	21.5	19.88	22.4	21.53
	11.4	7065.1	28.67	32.1	18.16	34	24.14
	10.3	8987.4	31.56	32.4	28.24	31.5	31.56
	9.8	43200	29.36	43.9	26.05	41.4	28.66
	8.5	7567.4	29.41	31.5	17.94	30.4	22.98
	9.6	43200	32.84	48.4	32.84	44.3	27.14
	10.2	8356.4	33.14	45.2	27.90	50.1	28.19
	10.6	7298.7	29.91	28.7	26.79	29.8	25.10
	8.6	6226.2	30.10	29.5	23.87	31.2	28.65
Average	10.43	14367.67	29.40	33.52	24.22	34.02	25.79
	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
200 nodes	19.7	15482.1	24.06	135.3	20.80	151.3	24.06
	29.4	18564.7	29.98	146.6	26.87	140.6	28.11
	26.5	43200	30.11	151.9	27.04	148.8	18.16
	27.6	43200	31.09	154.7	26.98	137.4	28.03
	26.9	43200	33.65	198.3	31.64	181.1	29.13
	28.1	43200	32.50	176.4	29.32	167.9	28.35
	27.3	43200	34.02	184.3	32.10	180.3	34.02
	29.8	43200	34.95	197.5	34.30	167.4	31.74
	30.4	43200	28.93	192.4	25.02	187.2	26.71
	28.5	43200	31.95	176.2	25.97	180.1	28.46
Average	27.42	37964.68	31.12	171.36	28.00	164.21	27.68
	TSP SOLVER	Elimin. with Math. Model		Elimin.with Heuristic 1		Elimin. with Heuristic 2	
	Comp. Time	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)	Comp. Time	Improv.(%)
300 nodes	21.4	24582.2	22.34	261.4	20.55	244.1	22.34
	23.9	24651.1	23.97	234.3	19.72	236.2	21.99
	28.1	43200	31.81	248.1	28.62	267.1	29.87
	28.4	43200	29.11	254.7	29.04	249.5	27.66
	26.7	43200	30.39	201.6	28.13	223.3	29.05
	32.4	43200	32.46	228.4	27.79	216.7	28.66
	36.7	43200	36.10	271.2	33.55	280.5	35.07
	33.9	43200	39.36	264	34.06	245.4	37.19
	36.8	43200	34.10	278.1	29.11	276	32.96
	35.1	43200	33.10	241.7	30.66	246.3	33.95
Average	30.34	39483.33	31.28	248.35	28.12	248.51	29.87

CHAPTER VI

CONCLUSION

We defined a new vehicle routing problem that to create the best evacuation plan for humanitarian logistics in field of post disaster. The problem focuses on prepare the evacuation plan with homogeneous vehicles facilitate logistic operations which include pick up patients from their homes and deliver to refugee center or hospital. Since, the aim of this problem is minimize the total covered distance with elimination of common nodes which has contained two patient types. Furthermore, this process has to require keep one common node which will help to exchange patients between vehicles. Because of the complexity of the problem, we developed initial solution. Christofides Algorithm created initial solution to solve the problem. The elimination phase will be with mathematical model which begins with initial solution. This model can only solve small and medium scale problems effectively with a given time. For large scale problems, the model can give feasible solution but the time horizon will be exceeding. Thus, we developed two different heuristic methods for elimination of common nodes. The heuristics used to eliminate common nodes and delivery to end points, and generates a good feasible solution in a reasonable time. The elimination mathematical model gives the best values for route plan. Moreover, both heuristics provide a good feasible solution. In our work, because of the limitations of the problem we didn't provide an exact solution approach. These limitations are basically determine an uncertain change point for swap the patients and recreate the evacuation plan. But future works could be dedicated to testing an exact solving approach.

Bibliography

[1] A. Pico and Y. H. R. Tan, "Heuristics for solving problem of evacuating non-ambulatory people in a short-notice disaster," tech. rep., Graduate School of Business and Public Policy, Naval Postgraduate School, Monterey, California, Dec. 2012.

[2] L. McGuire, E. Ford, and C. Okoro, "Natural disasters and older u.s. adults with disabilities: Implications for evacuation.," *American Journal of Geriatric Psychiatry*, vol. 31, no. 1, pp. 49–56, 2007.

[3] A.Thomas and M. Mizushima, "Logistics training: Necessity or luxury?," *Forced Migration Review*, vol. 22, pp. 60–61, 2005.

[4] A. Apte, "Humanitarian logistics: A new field of research and action.," *Foundations and Trends in Technology, Information and Operations Management*, vol. 3, pp. 1–100, 2009.

[5] G. Kovacs and K. M. Spens, "Humanitarian logistics in disaster relief operations," *International Journal of Physical Distribution and Logistics Management*, vol. 37, no. 2, pp. 99–114, 2007.

[6] P. Trunick, "Special report: delivering relief to tsunami victims," *Logistics Today*, vol. 46, no. 2, pp. 1–38, 2005.

[7] A.Thomas, "Humanitarian logistics: Enabling disaster response," *Fritz Institute*, pp. 15–17, 2003.

[8] L. Ozdamar, E. Ekinci, and B. Kucukyazici, "Emergency logistics planning in natural disaster.," *Annals of Operations Research*, pp. 217–245, 2004.

[9] L. Ozdamar and W. Yi, "Greedy neighborhood search for disaster relief and evacuation logistics.," *IEEE Intelligent Systems*, vol. 23, pp. 14–23, 2008.

[10] Q. Lu, Y. Huang, and S. Shekhar, "Evacuation planning: a capacity constrained routing approach.," *ISI 2003. LNCS Springer*, vol. 2665, pp. 111–125, 2003.

[11] Q. Lu, B. George, and S. Shekhar, "Capacity constrained routing algorithms for evacuation planning: A summary of results.," *SSTD 2005. LNCS Springer*, vol. 3633, pp. 291–307, 2005.

[12] A. Bental, B. D. Chung, S. R. Mandalab, and T. Yao, "Robust optimization for emergency logistics planning: Risk mitigation in humanitarian relief supply chains.," *Transportation Research Part B: Methodological*, vol. 45(8), pp. 1177–1189, 2011.

[13] S. N. Parragh, K. F. Doerner, and R. F.Hartl, "A survey on pickup and delivery problems. part i: Transportation between customers and depot.," *Journal fr Betriebswirtschaft*, vol. 58, pp. 21–51, 2008.

[14] Y. C. Chiu and H. Zheng, "Real-time mobilization decision for multi-priority emergency response resources and evacuation groups: Model formulation and solution.," *Transportation Research: Part E*, vol. 43, pp. 710–736, 2007.

[15] Y. Chiu, H. Zheng, J. Villalobos, and B.Gautam, "Rmodeling no-notice mass evacuation using a dynamic traffic flow optimization model.," *IIE Transactions*, vol. 39, pp. 83–94, 2007.

[16] Y. Yuan and D. Wang, "Path selection model and algorithm for emergency logistics management.," *Computers and Industrial Engineering*, vol. 56, pp. 1081–1094, 2009.

[17] B. Hoppe and E. Tardos, "The quickest transshipment problem.," *Mathematics of Operational Research*, vol. 25, pp. 36–62, 2000.

[18] S. Kim and S. Shekhar, "Contraflow network reconfiguration for evacuation planning: a summary of results.," *Proceedings of 13th Annual ACM International Workshop on Geographic Information Systems*, pp. 250–259, 2005.

[19] A. Haghani and S. C. Oh, "Formulation and solution of a multi-commodity, multimodal network flow model for disaster relief operations.," *Transportation Research*, vol. 30, pp. 231–250, 1996.

[20] 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*, vol. 140, pp. 118–133, 2002.

[21] R. Eldar, *The needs of elderly persons in natural disasters: Observations and recommendations*, vol. 16. 1992.

[22] B. Morrow, "Identifying and mapping community vulnerability.," *Disaster*, vol. 23, no. 1, pp. 1–18, 1999.

[23] Y. Kergosien, C. Lent, and J.-C. Billaut, "Home health care problem: An extended multiple traveling salesman problem," *MISTA*, pp. 85–92, 2009.

[24] J. Clarke, V. Gascon, and J. A. Ferland, "A capacitated vehicle routing problem with synchronized pick ups and drop-offs: The case of medication delivery and supervision in the dr congo," *IEEE Transactions on Engineering Management*, vol. 64, no. 3, 2017.

[25] V. Akbari and F. Salman, "Multi-vehicle synchronized arc routing problem to restore post-disaster network connectivity," *European Journal of Operational Research*, vol. 257, pp. 625–640, 2017.

[26] N. Bianchessi and G. Righini, "Heuristic algorithms for the vehicle routing problem with simultaneous pick-up and delivery.," *Computers and Operations Research*, vol. 34, pp. 587–594, 2007.

[27] H. Min, "The multiple vehicle routing problem with simultaneous delivery and pick-up points.," *Transportation Research A*, vol. 23A, pp. 377–386, 1989.

[28] A. C. Wade and S. Salhi, "An investigation into a new class of vehicle routing problem with backhauls.," *Omega*, vol. 30, pp. 479–487, 2002.

[29] J. Dethloff, "Vehicle routing and reverse logistics: The vehicle routing problem with simultaneous delivery and pick-up.," *OR Spectrum*, vol. 23, pp. 79–96, 2001.

[30] G. Nagy and S. Salhi, "Heuristic algorithms for single and multiple depot vehicle routing problems with pickups and deliveries.," *European Journal of Operational Research*, vol. 162, pp. 126–141, 2005.

[31] G. Nagy and S. Salhi, "Location-routing: Issues, models and methods.," *European Journal of Operational Research*, vol. 177, p. 649672, 2007.

[32] J. W. Joubert and S. J. Classen, "A sequential insertion heuristic for the initial solution to a constrained vehicle routing problem," *Orion*, vol. 22, no. 1, pp. 105–116, 2006.

[33] P. Toth and D. Vigo, "Heuristic algorithms for the handicapped persons transportation problem," *Transportation Science*, vol. 31, Feb. 1997.

[34] P. Toth and D. Vigo, "A heuristic algorithm for the symmetric and asymmetric vehicle routing problems with backhauls.," *European Journal of Operational Research*, vol. 113, pp. 528–543, 1999.

[35] Q. Lu, "A new insertion-based construction heuristic for solving the pickup and delivery problem with hard time windows.," *European Journal of Operational Research*, vol. 175, pp. 672–687, 2005.

[36] J. Hoogeveen, "Analysis of christofides' heuristic:some paths are more difficult than cycles," *Elsevier Operations Research Letters*, vol. 10, no. 5, 1991.

VITA

HAZAL BACAKSIZ

EDUCATION

OZYEGIN University, Istanbul, Turkey

Master of Science, Industrial Engineering, Sept 2018

Minors in International Trade and Logistics

G.P.A. 3.3/4.0

ISIK University, Istanbul, Turkey

Bachelor of Science, Industrial Engineering, Jan 2016

Minors in International Trade and Logistics

G.P.A. 3.43/4.0

EXPERIENCE

Turkish Airlines, Database Specialist, Jun 2018 - Current

Ozyegin University, Teaching Assistant, Feb 2016 - Jun 2018

Nitto Automotive, Quality Intern, Jun 2014 - Sept 2014

DHL Express Turkey, Finance Intern, Jul 2013 - Sept 2013

COMPUTER SKILLS

Knowledge of database programming (Oracle and SQL)

Programming skills in JAVA, MATLAB and Optimization Tools(CPLEX,GAMS)

LANGUAGE

English, French and native Turkish

HONORS AND AWARDS

Government full scholarship during Bachelor's degree

University full scholarship during Master's degree